Face Recognition using Artificial Intelligent Techniques

Laheeb Mohammad Ibrahim **Ibrahim A. Saleh**
College of Computer Sciences and Mathematics
University of Mosul, Iraq

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ABSTRACT

Face recognition is considered one of the visual tasks which humans can do almost effortlessly while for computers it is a difficult and challenging task. This research deals with the problem of face recognition. A novel approach is presented for both face feature extraction and recognition, first, we introduce Principal Component Analysis (PCA) for face feature extraction, Generalized Regression Artificial Neural network for face recognition. The performance of the whole system was done after training with 120 color images (40 human faces with 3 poses) and testing using 40 color images. The images were taken from Collection of Facial Images: Faces95 by Computer Vision Science Research Projects. Experimental results for proposed human face recognition confirm that the proposed method lends itself to good extraction and classification accuracy relative to existing techniques.

Keyword: Face Recognition, Artificial Intelligent Techniques

تمييز الوجه باستخدام التقنيات الذكائيه الاصطناعيه

لهيب محمد ابراهيم **ابراهيم احمد صالح**
كليه علوم الحاسوب والرياضيات، جامعه الموصل

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الملخص

يعتبر تمييز الوجه أحد المهام البصرية التي يمكن ان ينجزها الانسان دون مشقة مع أنها من أصعب المهام أداء في الحاسوب. وقد تم تقديم طريقة مبتكرة لكل من استخلاص خواص الوجه وتمييزه ، إذ تم أولا تناول مشكله استخلاص الخواص لصورة الوجه باستخدام تحليل المكونات الأساسية (Principal Component Analysis (PCA)،. وثانيا تمييز الوجه باستخدام الشبكة العصبية الاصطناعية (Generalized Regression Artificial Neural network) باستخدام قاعدة البيانات (faces95) في تقييم كفاءة النظام المقترح حيث قسمت قاعدة البيانات الى مجموعتين، المجموعة الأولى مجموعة التدريب بواقع (120) صورة ملونة بمعدل (40) صورة لكل وجه بثلاثة أوضاع ، اما المجموعة الثانية فهي مجموعة الاختبار التي تضم (40) صورة. و تم الحصول على نتائج جيدة في التجارب التي انجزت على النظام المقترح لتمييز الوجه.

وأثبتت النتائج ان الطرائق المستخدمة لاستخلاص الوجه وتمييزه جيدة ودقه تصنيفها عالية مقارنة بالتقنيات المتاحة حاليا.

الكلمات المفتاحيه: تمييز الوجه، الشبكات العصبيه الاصطناعيه

1. Introduction

Humans have been using physical characteristics such as face, voice, gait, etc. to recognize each other for thousands of years. With new advances in technology, biometrics has become an emerging technology for recognizing individuals using their biological traits. This technology makes use of the fact that each person has specific unique physical traits that are one's characteristics which can't be lost, borrowed or stolen. By using biometrics it is possible to confirm or establish identity based on "who the individual is", rather than by "what the individual possesses"[2].

Several systems require authenticating a person before giving access to their resources. Biometrics has been long known to recognize persons based on their physical and behavioral characteristics. Examples of different biometric systems include fingerprint recognition, face recognition, iris recognition, retina recognition, hand geometry, voice recognition, signature recognition …etc. [2].

Automated Face recognition in particular, has received a considerable attention in recent years both from the industry and the research communities. Automated face recognition is an interesting computer vision problem with many commercial and law enforcement applications. Mugshot matching, user verification and user access control, crowd surveillance, enhanced human computer interaction all become possible if an effective face recognition system can be implemented. While research into this area dates back to the 1960's, it is only very recently that acceptable results have been obtained. However, face recognition is still an area of active research since a completely successful approach or model has not been proposed to solve the face recognition problem. Face recognition is one of the visual tasks which humans can do almost effortlessly while for computers it is a difficult and challenging task. [7].

Face perception is an important part of the capability of human perception system and is a routine task for humans, while building a similar computer system is still an on-going research area. The earliest work on face recognition can be traced back at least to the 1950's in psychology and to the 1960's in the engineering literature. But research on automatic machine recognition of faces really started in the 1970's after the seminal work of Kanade and Kelly . Over the past thirty years extensive research has been conducted by psychophysicists, neuroscientists, and engineers on various aspects of face recognition by humans and machines. Psychophysicists and neuroscientists have been concerned with issues such as whether face perception is a dedicated process (this issue is still being debated in the psychology community and whether it is done holistically or by local feature analysis). Many of the hypotheses and theories put forward by researchers in these disciplines have been based on rather small sets of images,[14].

There are many methods for face recognition. These methods are namely correlation, Eigenface methods, Template matching, … etc. [9], in template matching technique is effective only when the test images have the same scale, orientation, as training images. But this technique is cumbersome and time consuming and not at all robust. Elastic Bunch graph matching method gives appreciable results for less distortion invariant object recognition, if data base size is moderate. The correlation method is the simplest method for image classification, where the test set is classified by assigning it to the label of the closest point in the learning set. Here distances are measured in the image space. This technique has several disadvantages, first is, if the trained and test images are taken under varying moderate lighting conditions, then the corresponding points in the image may not be tightly clustered. Secondly, it requires large storage and is computationally more expensive. Hence an alternative method for dimension reduction scheme is used. The most commonly used technique for dimension reduction is Principal Component Analysis (PCA), which chooses a dimension reducing linear projection that maximizes the scatter of all projected samples. The advantage of PCA comes from its generalization ability. It reduces the feature space dimension by considering the variance of the input data [9,14]. Principal components analysis (PCA) is a technique that can be used to simplify a dataset; more formally it is a transform that chooses a new coordinate system for the data set such that the greatest variance by any projection of the data set comes to lie on the first axis (then called the first principal component), the second greatest variance on the second axis, and so on. PCA can be used for reducing dimensionality in a dataset while retaining those characteristics of the dataset that contribute most to its variance by eliminating the later principal components, which have the least variation in the data set and speeds up the computational time [1].

In this research, we propose a human face recognition system using Principal Component Analysis (PCA) to extract best characteristics from input images, after that feature vectors used as input to Generalized Regression Artificial Neural network to work as classifier for human face.

2. GENERAL FACE RECOGNITION SYSTEM

The general face recognition system has been designed to perform recognition on images. Figure (1) presents a block diagram of the general face recognition system that includes three major tasks [7,8,11]:

- **Face Detection** : The ultimate goal of the face detection is finding an object in an image as a face candidate that its shape resembles the shape of a face.
- **Feature Extraction** : Feature extraction abstracts high level information about individual patterns to facilitate recognition. Selection of feature extraction method is probably the single most important factor in achieving high recognition performance. To design a face recognition system with low to moderate complexity the feature vectors should contain the most pertinent information about the face to be recognized.
- **Classifier**: Comparison of the face to a database of known faces

3. Proposed Face Recognition System

The architecture of the proposed system is depicted in figure (2). The face recognition system developed comprises three major processing modules which are:

3.1. Face Detection

The problem of face recognition is all about face detection, before face recognition is possible, one must be able to reliably find a face and its landmarks. Most face detection systems attempt to extract a fraction of the whole face, thereby eliminating most of the background and other areas of an individual's head such as hair that are not necessary for the face recognition task. With static images, this is often done by running a '*window'* across the image. [4]

A manual face detection system is implemented by measuring the facial proportions of the average face. To detect a face, a human operator would identify the locations of the subject's eyes in an image and using the proportions of the average face, the system would segment an area from the image. In the ideal frontal view segmented facial image for face recognition, the lower edge of each eye is 27% from the top of the image and the left and right eyes are 20% and 80% from the left border of the image respectively [3], see Figure (3). Operator instructed to click under a subject's left and right eye. However, just use a single statistic (vector between lower edges of eyes) so as not to lose the natural variation between human faces.

3.2. Feature Extraction

Feature selection in pattern recognition involves the derivation of certain features from the input data in order to reduce the amount of data used for classification and provide discrimination power [3, 6]. Feature extraction methods try to reduce the feature dimensions used in the classification step. This is a specially used method in pattern recognition to reduce the feature dimensions; Principal Component Analysis (PCA) [6]. The advantage of PCA comes from its generalization ability. It reduces the feature space dimension by considering the variance of the input data. The method determines which projections are preferable for representing of the structure of the input data. Those projections are selected in such a way that the maximum amount of information (i.e. maximum variance) is obtained in the smallest number of dimensions of feature space. In order to obtain the best variance in the data, the data is projected to a subspace (of the image space)which is built by the eigenvectors from the data. In that sense, the eigenvalue corresponding to an eigenvector represents the amount of variance that eigenvector handles [6].

In the proposed system we use **Principle Component Analysis** (PCA) to extract feature from the derived sub images. Therefore this approach can extract characteristics of face images for classification purpose.

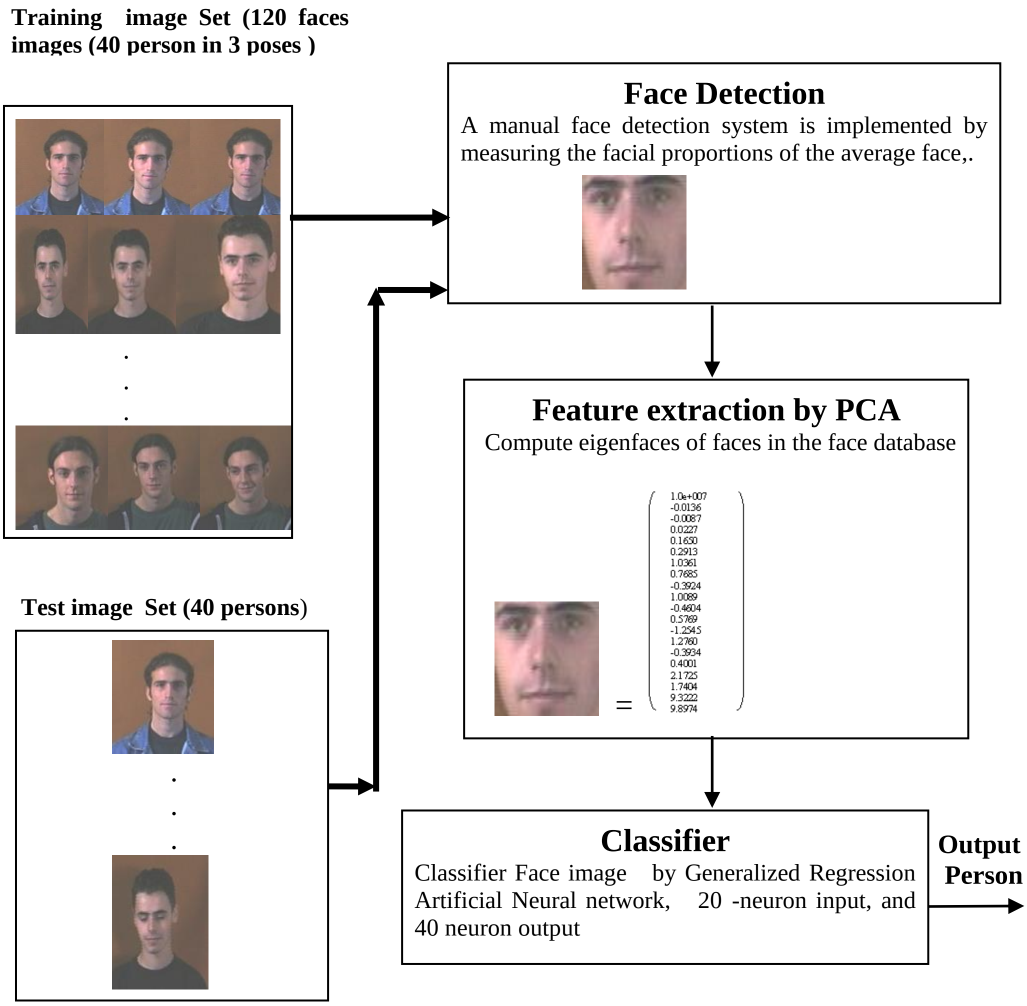
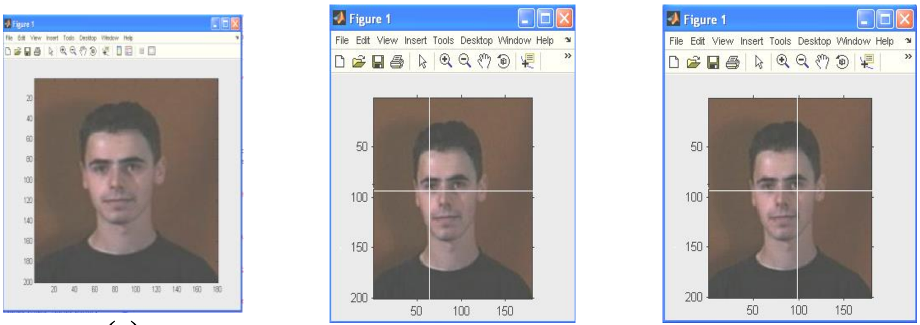


Figure 2 : Proposed Face Recognition System



(a) (b) (c)

Figure 3: Manual Face Detection a- Original Image b- Click Under Eye on left , c- Click Under Eye on Right

3.2.1. Principle Component Analysis

PCA aims to determine a set of orthogonal vectors that optimally represent the distribution of the data. Any face image can then be theoretically reconstructed by projections onto the new coordinate system, in search of a technique that extracts the most relevant information in a face image to form the basis vectors.

In Mathematic, a two dimension facial image can be represented as one dimension vector by concatenating each row (or column) into a long thin vector. Let's suppose we have M vectors of size N (= rows of image x columns of image) representing a set of sampled images. p^j's represent the pixel values [10,13].

$$xi = [p1 \ldots pN]^T, \quad i = 1, \ldots, M \qquad \ldots(1)$$

The images are mean centered by subtracting the mean image from each image vector. Let m represent the mean image.

$$m = \frac{1}{M}\sum_{i=1}^{M} x_i \qquad \ldots(2)$$

And let w_i be defined as a mean centered image

$$w_i = x_i - m \qquad \ldots(3)$$

Our goal is to find a set of e_i's which have the largest possible projection onto each of the w_i's. We wish to find a set of M orthonormal vectors e_i for which the quantity

$$\lambda_i = \frac{1}{M}\sum_{n=1}^{M}(e_i^T w_n)^2 \qquad \ldots(4)$$

is maximized with the orthonormality constraint

$$e_l^T e_k = \delta_{lk} \qquad \ldots(5)$$

It has been shown that the e_i's and λi's are given by the eigenvectors and eigenvalues of the covariance matrix

$$C = WW^T \qquad \ldots(6)$$

where W is a matrix composed of the column vectors w_i placed side by side. The size of C is N x N which could be enormous. For example, images of size 64 x 64 create the covariance matrix of size 4096 x 4096. It is not practical to solve for the eigenvectors of C directly. A common theorem in linear algebra states that the vectors e_i and scalars λi can be obtained by solving for the eigenvectors and eigenvalues of the M x M matrix W^TW. Let d_i and μ_i be the eigenvectors and eigenvalues of W^TW, respectively.

$$W^T W d_i = \mu_i d_i \qquad \ldots(7)$$

By multiplying left to both sides by W

$$WW^T(Wd_i) = \mu_i(Wd_i) \qquad \ldots(8)$$

which means that the first M - 1 eigenvectors ei and eigenvalues λi of WW^T are given by Wd_i and μ_i, respectively. Wd_i needs to be normalized in order to be equal to e_i. Since we only sum up a finite number of image vectors, M, the rank of the covariance matrix cannot exceed M - 1 (The -1 come from the subtraction of the mean vector m).

The eigenvectors corresponding to **nonzero eigenvalues** of the covariance matrix produce an orthonormal basis for the subspace within which most image data can be represented with a small amount of error. The eigenvectors are **sorted from high to low** according to their corresponding eigenvalues. The eigenvector associated with the largest eigenvalue is one that reflects the greatest variance in the image. That is, the smallest eigenvalue is associated with the eigenvector that finds the least variance. They decrease in exponential fashion, meaning that the roughly 90% of the total variance is contained in the first 5% to 10% of the dimensions.

A facial image can be projected onto M' (<< M) dimensions by computing

$$\Omega = [v_i v_2 .... v_{M^i}] \qquad \ldots(9)$$

where $vi = e^T_i w_i$. v_i is the i^{th} coordinate of the facial image in the new space, which came to be the principal component. The vectors e_i are also images, so called, *eigenimages*, or *eigenfaces*

3.2.2. PCA Feature Extraction on Database for Proposed Face Recognition System

If the dimension of the input vector is too large, the network can be quite complex and therefore difficult to train and may take more time for classification; hence it is required to reduce the input vector dimension. In our research we used Principal Component Analysis (PCA) technique for dimension reduction in face recognition.

Face Database **:** Face image databases (containing both training (120 faces image) and test (40 faces image) data) used from the Collection of Facial Images : Faces95 database is one that was created by Computer Vision Science Research Projects on Face Recognition [15] , see figure (4). This database was widely used by researchers to test face detection and recognition systems, see appendix (B).

Faces95 database Description : Number of individuals: 72, (40 individual are used in this research), image resolution: 180 by 200 pixels , contains images of male and female subjects

Figure 4: Samples of Database used in Proposed Face Recognition System

Input and Output Data of Feature Extraction (PCA) **:** Image resolution for database is 180 by 200 pixels and segmented images is 73 x 65 pixels. The column matrix of all images is converted from (73 x 65) to a vector (4745, 1). This vector is used as an input matrix. The size of the input matrix depends on the number of poses 'n' of 'N' persons. If database has 'n' poses of 'N' persons, then size of the input matrix becomes (4745, n × N). The first n columns represent the n poses of 1st person, 2nd n columns represent the n poses of 2nd person and so on. In our research 3 poses of 40 persons will be taken for training then, the size of the input matrix will become (4745, 3 × 40) or (4745, 120). The output from Feature extraction PCA is 20 values represent Eigen vectors of the covariance matrix of the training database.

Output Data from Classifier : The target matrix is to identify the person to whom that test vector belongs. If N persons are to be identified, then size of target vector is (N, 1). If there are 120 image in the input matrix, then the size of target matrix is (40, 120 (where 120 represents 3 poses of 40 persons). The target matrix elements are all zeros except one element whose value is 1, which indicates the position of the corresponding person.

PCA Feature Extraction : Figure (5) illustrates principal components algorithm performing on input vectors to extracted features. The input vectors consist of only these principal components. The size of the input vectors is reduced from (4745, 120) to (20, 120) Principle Component Analysis (PCA) is programmed using Matlab system.

3.3. Proposed Classifier of Face by Generalized Regression Artificial Neural Network (GRNN)

Neural networks have been employed and compared to conventional classifiers for a number of classification problems. The results have shown that the accuracy of the neural network approaches equivalent to, or slightly better than, other methods. Also, due to the simplicity, generality and good learning ability of the neural networks, these types of classifiers are found to be more efficient [5, 14]. Due to the above reasons **Generalized Regression Artificial Neural Network** is used as a classifier and it serves as an excellent candidate for pattern applications and attempts have been carried out to make the learning process in this type of classification faster.

- **Generalized Regression Artificial Neural Network Architecture (GRNN)**

The generalized regression neural network (GRNN) was introduced by Nadaraya and Watson. The GRNN was applied to solve a variety of problems like prediction, control, plant process modeling or general mapping problems, and classification. The concept of the GRNN is based on nonparametric estimation commonly used in statistics [12]

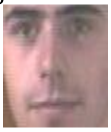
A generalized regression neural network has a radial basis layer and a special linear layer. The architecture of **Generalized Regression** ANN, see figure (6), is similar to the radial basis network, but has a slightly different second layer. The first layer operates radial basis layer. Each neuron's weighted input is the distance between the input vector and its weight vector. Each neuron's net input is the product of its weighted input with its bias. If a neuron's weight vector is equal to the input vector, its weighted input will be 0, its net input will be 0, and its output will be 1.

A second hidden layer contains units that help to estimate the weighted average. This is a specialized procedure. Each output has a special unit assigned in this layer that forms the weighted sum for the corresponding output. To get the weighted average from the weighted sum, the weighted sum must be divided through by the sum of the weighting factors. A single special unit in the second layer calculates the latter value. The output layer then performs the actual divisions (using special division units). Hence, the second hidden layer always has exactly one more unit than the output layer.

The GRNN copies the training cases into the network to be used to estimate the response on new points. The output is estimated using a weighted average of the outputs of the training cases, where the weighting is related to the distance of the point from the point being estimated.

Enter Segmented image from Face Detection step with size of (73 x 65) , for 120 (3 poses x 40 persons) images in the training database the length of one dimension vectors is 4745 and it will be (4745 x 120) Two Dimensional matrix. or enter Segmented image with size (73 x 65) for test image .

Example of Segmented image



Calculate mean for image by using matlab function **mean** to computing the average face image

Calculate deviation of each image from mean image by computing the difference image for each image in the training set

Calculate eigenvalues and eigenvector : This is programmed by using matlab function . Syntax : [V,D] = eig(A)
produces matrices of eigenvalues (D) and eigenvectors (V) of matrix A see appendix (A)

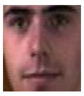
Sorting and eliminating eigenvalues : All eigenvalues of matrix X are sorted and those who are less than a specified threshold (less than 1), are eliminated.

Calculate eigenvectors of covariance matrix : Eigenvectors of covariance matrix (or so-called "Eigenfaces") can be recovered from X's eiegnvectors.

All centered images are projected into facespace by multiplying in Eigenface basis's. Projected vector of each face will be its corresponding feature vector.

Save Resulte in three Variables 1) Eigenface: Eigen vectors of the covariance matrix of the training database, 2) Mean : Mean of the training database, 3) Centered image : Matrix of centered image vectors

Example of output



$$= \begin{pmatrix} 1.0e+007 \\ -0.0136 \\ -0.0087 \\ 0.0227 \\ 0.1650 \\ 0.2913 \\ 1.0361 \\ 0.7685 \\ -0.3924 \\ 1.0089 \\ -0.4604 \\ 0.5769 \\ -1.2545 \\ 1.2760 \\ -0.3934 \\ 0.4001 \\ 2.1725 \\ 1.7404 \\ 9.3222 \\ 9.8974 \end{pmatrix}$$

Figure 5: Flow chart for PCA Feature Extraction

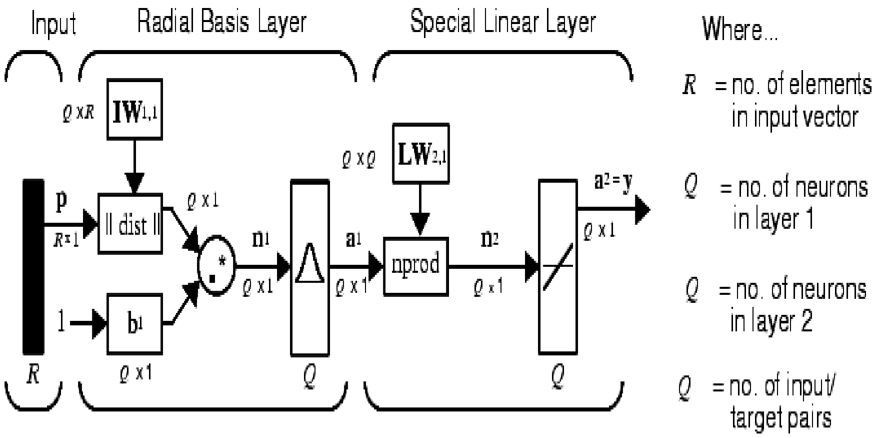


Figure 6 : Generalized Regression Artificial Neural Network Architecture

- **Design Proposed Generalized Regression Artificial Neural Network**

We built a face recognition system using a GRNN. The task is to teach the neural network to recognize 40 faces; output is used to recognize one face from 40 faces. For designing a classifier based on GRNN, we have set the number of input nodes in the input layer of neural network equal to the number of feature vector elements. The number of nodes in the output layer is set to the number of image classes

The neural network consists of Radial basis layer with 20 neurons input (represent PCA), Special linear layer with 40 neurons output, such that its outputs y1 … y40. The structural diagram of neural network is given in Figure (6).

To train the network we will use 120 face images (40 persons in 3 poses). To check whether the network has learned to recognize errors we will use 40 face images. To train the network to recognize faces we applied 20 values represents PCA to the input of the network.

After many experiments we apply the following parameters :

Learning rate parameter is 0.00001,

Performance function is 'MSE',

The performance goal (or tolerance limit) is 0.1.

The network is trained for 1850 epochs.

It is trained with standard data sets 20 -neuron input (represent PCA of segmented image), and 40 neuron output.

These parameters make the algorithm converge and it is trained and tested the network with a set of train and test data. After the training, then next comes the simulation part, where the network identifies a person when a pattern is to be presented to it. Before presenting the input pattern it must be converted to a form acceptable by the neural net. The input pattern may be one of the trained patterns or unknown pattern. The unknown image feature PCA is selected. By presenting this as an input pattern, the neural network computes the output using the set values of weights. The output vector has only one element having value 1 and remaining elements are zeros, which indicates to which class.

4. Experimental Results

To check advantages of our proposed algorithm experimental, studies are carried out on the Collection of Facial Images: Faces95 databases (containing both training and test data). 120 face images from 40 individuals in 3 poses, Faces95 database have been used to evaluate the performance of the proposed method. None of the 40 samples are identical to each other. They vary in position, rotation, scale and expression. In this database each person has changed his face expression in each of 40 samples. A PCA feature domains and the **Generalized Regression Artificial Neural Network** has been developed. In this example, for the PCA feature vector has been created based on the 20 largest PCA number for each image. A total of 120 images have been used to train and another 40 for test. Recognition rate of training data set is 99.6% and 94.32 % was obtained for test data set using this proposed technique, see table(1).

Table (1) Face Recognition Accuracy Rate

Number of faces image (person)		**Number of poses**		**Accuracy Rate %**	
Training data set	**Testing data set**	**Training data set**	**Testing data set**	**Training data set**	**Testing data set**
120 face images (3 poses * 40)	40	3	At any poses	99.6%	94.32

5. Comparisons with other algorithms

To check the utility of our proposed algorithm and Experimental results, we compare between proposed algorithm (using PCA and GRNN) with other algorithms used to recognized faces, table (2) Shows that the proposed method is better than other existing methods.

Table (2) Comparisons of Face Recognition Accuracy Rate with other algorithms

Algorithms	Number of faces image (person)		Number of poses		Accuracy Rate %	
	Training data set	Testing data set	Training data set	Testing data set	Training data set	Testing data set
Proposed Algorithm PCA with GRNN	120 face images (3 poses * 40)	40	3	At any poses	99.6%	94.32
PCA [3]	450	30	-	At any poses	100%	93%
SOM+CN" (Self-Organizing Map combined with a CN	ORL + FERET Database	-	-	-	96%	-
BP ANN with Wavelets transform coefficient [9]	30	7	3	7	99%	96%

6. Conclusion

This paper presented a novel method for the recognition of human faces in 2-Dimensional digital images. It employs the **Generalized Regression Artificial Neural Network** and PCA feature domains. The highest recognition rate for training 99.6% and testing 94.32 with the Faces95 database was obtained using this proposed algorithm indicates the usefulness of the proposed technique.

Experimental results have established that PCA and GRNN is a very useful technique for any face recognition system. PCA finds it's most suitable application in extracting image information, the extracted PCA has been used as the discriminate feature of the facial images. The advantage of this PCA is its ability to extract features of faces at any poses. Classification, GRNN has been used. The input to such a classifier is of course the PCA extracted from the faces. The input dimension to this classifier has been reduced by Principal Component Analysis to improve the performance. Experimental results show that the proposed method is better than other existing methods. Indeed it can be efficiently applied to any face recognition system,

For our future work, we are planning to apply the genetic algorithms on a number of interest points of some faces and determine the best features for face. Then these selected features will be used, and another type of ANN for classifier will be used.

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Appendix (A)

MATLAB Function Reference (eig)

Find eigenvalues and eigenvectors

Syntax : [V,D] = eig(A)

produces matrices of eigenvalues (D) and eigenvectors (V) of matrix A, so that A*V = V*D. Matrix D is the canonical form of A--a diagonal matrix with A's eigenvalues on the main diagonal. Matrix V is the modal matrix--its columns are the eigenvectors of A.

Appendix (B)

Collection of Facial Images : Faces95

Collection of Facial Images : Faces95 by Computer Vision Science Research Projects, Designed and maintained by Dr Libor Spacek. Updated Friday, 16-Feb-2007, Http://cswww.essex.ac.uk/mv/allfaces/faces95.html.

Acquisition conditions : Using a fixed camera, a sequence of 20 images per individual was taken. During the sequence the subject takes one step forward towards the camera. This movement is used to introduce significant head (scale) variations between images of same individual. There is about 0.5 seconds between successive frames in the sequence.

Database Description :Number of individuals: 72 , Image resolution: 180 by 200 pixels (portrait format) , Contains images of male and female subjects

Variation of individual's images : Backgrounds: the background consists of a red curtain. Background variation is caused by shadows as subject moves forward. **Head Scale:** large head scale variation , **Head turn,tilt and slant:** minor variation in these attributes , **position of face in image** : some translation , **image lighting variation:** as subject moves forward, significant lighting changes occur on faces due to the artificial lighting arrangement , **expression Variation:** some expression variation, **additional comment:** there is no hair style variation as the images were taken in a single session.