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Face Recognition Based on Eigen Features of Multi Scaled Face Components and an Artificial Neural Network

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Abstract

Face recognition has been a very active research area in the past two decades. Many attempts have been made to understand the process of how human beings recognize human faces. It is widely accepted that face recognition may depend on both componential information (such as eyes, mouth and nose) and non-componential/holistic information (the spatial relations between these features), though how these cues should be optimally integrated remains unclear. In the present study, a different observer's approach is proposed using eigen/fisher features of multi-scaled face components and artificial neural networks. The basic idea of the proposed method is to construct facial feature vector by down-sampling face components such as eyes, nose, mouth and whole face with different resolutions based on significance of face component, and then subspace Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) method is employed for further dimensionality reduction and to acquire a good representation of facial features. Each face in the database to be recognized is projected onto eigenspace or fisherface to find its weight vector. The weight vectors of face images to be trained become the input to a neural network classifier, which uses back propagation/radial basis functions to recognize faces with variation in facial expression, and with / without spectacles. The proposed algorithm has been tested on 400 faces of 10 subjects of the ORL database and results are encouraging compared to the existing methods in literature.

Key Words: *Radial Basis Function, Back Propagation, Neural Network, PCA and LDA, Feature Extraction, Face Recognition.*

1. Introduction

Automated face recognition aims at exploiting face images to identify human subjects. A number of approaches such as appearance/ holistic based, feature/ component based and hybrid face recognition approaches have been proposed in literature for automated face recognition and these three approaches are discussed in the following sections.

1.1 Holistic Approach

Among appearance-based face recognition approaches, PCA and LDA are very popular and have been applied extensively. Face recognition using PCA [1-2], LDA [3-5], Independent Component Analysis (ICA) [6] are among the representative techniques that have been developed. PCA is especially widely used in face recognition system to extract features from original face images and for dimension reduction. It captures the variance between training samples and turns them into a small set of characteristic feature images called principal components or 'eigenfaces' [2]. A subspace formed by these eigenfaces is used to project training and testing face images into lower dimensional face

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templates for classification. Successful demonstration of this method resulted in growth of research in holistic based face recognition since 1991 [7].

The main draw backs of PCA are its lack of discrimination ability and retention of unwanted features such as light variation facial expression etc. Belhumeur et al. [3] proposed fisher face method (FLD) to enhance discriminating ability by utilizing class information. The algorithms are heavily based on maximizing the ratio of 'between class scatter matrix' to that of 'within class scatter matrix' to find another subspace that best discriminates input data. Similar works [4-5] have shared the same basic idea in which LDA is applied on PCA-transformed face data for classification, so called 'PCA+LDA'.

PCA and LDA face recognition methods involves matrix calculations with very high dimension of face image. If the face image is represented by a *m by n* matrix, the covariance matrix of PCA and the between-class and within-class scatter matrices will all be *mn* by *mn* matrices. Note that face images are usually much fewer than dimensions of the covariance matrix of PCA and the between-class and within-class scatter matrices. As a result, these very high-dimensional matrices cannot be evaluated accurately [6] and it is difficult for LDA-based face recognition to obtain a high accuracy. LDA-based face recognition usually also suffers from the small sample size (SSS) problem [8-12] i.e. if face images in the training set are fewer than dimensions of the between-class and within-class scatter matrices, the within-class scatter matrix will be singular and the transforming axes of LDA cannot be obtained directly. This mathematical complexity can be reduced by different dimension-reduction techniques. In [13] it is found that resizing conventional face images into smaller sizes allowed discriminating performance of LDA to be improved.

In face classification, ANN is widely used with PCA/LDA for its good learning ability and generalization. In face recognition, PCA or LDA is used to extract facial features and is classified by ANN using radial basis function (RBF) network [14-15] or back-propagation (BP)[16-17]. In paper [18] when back-propagation neural network was used to classify 40 subjects of human faces using facial features provided by both PCA & LDA, the face recognition results have been proven to be better than Euclidean distance.

Recently, work has been done on face recognition [19] using holistic approach with large dimensional reduction using low resolution and single neural network, but recognition rate is only 90.25% for 40 images. In low resolution neural network, face has been resized to 400 samples using Bicubic Interpolation. These 400 samples are used as inputs to artificial neural networks. In this method, as equal emphasis is given (uniform sampling is used in image resizing) on all the parts of a face, there has been a redundancy of the image data from discrimination point of view and hence suffers from unwanted equal weightage on whole face portion of the image, resulting in low recognition rate. In the proposed method, this problem is overwhelmed by using different samplings for different components based on their significance in face recognition.

1.2. Component Based Approach

For the component-based algorithms, the main idea is to compensate for pose changes by allowing a flexible geometrical relation among the components in the classification stage. In paper [20] face recognition was performed by independently matching templates of three facial regions (eyes, nose and mouth). The configuration of the components during classification was unstrained since the system did not include a geometrical model of the face.

A method of face recognition using a Weighted Modular Principle Component Analysis (WMPCA) is presented in paper [21]. The proposed method has a better recognition rate, compared to conventional PCA, for faces with large variation in expression and illumination. The face is divided into horizontal sub-regions such as forehead, eyes, nose and mouth. Then each of them are separately analyzed using PCA. The final decision is taken based on a weighted sum of errors obtained from each sub-region. A method to calculate these weights is proposed, which is based on the assumption that different regions in a face vary at different rates with expression, pose and illumination.

1.3. Hybrid Approach

In paper [22], Mehrtash et.al proposed a hybrid recognition system which tries to find the human recognition behavior by efficiently combining the facial components in the recognition task. In this method the decision system uses the weighted majority strategy to fuse the results of whole image and facial component classifier. Simulation studies justify the superior performance of the proposed method as compared to that of Eigenface method.

In paper [23] Mazloom et.al presents a hybrid approach for face recognition by handling three issues put together. For preprocessing and feature extraction stages, a combination of wavelet transform and PCA are applied. During the classification phase, the Neural Network (MLP) is explored for robust decision in the presence of wide facial variations. The experiments that have been conducted on the Yale database and ORL database vindicated that the combination of Wavelet, PCA and MLP exhibits the most favorable performance. This is on account of the fact that it has the lowest overall training time, the lowest redundant data, and the highest recognition rates compared to similar methods introduced so far. The proposed method in comparison with the present hybrid methods enjoys a low computation load in both training and recognizing stages.

In paper [24], Suvendu Mandal et. al have proposed a hybrid face recognition system. The proposed method combines the structural features with holistic features. In that experiment, the facial image is partitioned into a number petals considering *nose tip* as the origin. From each petal, intensity profile is computed by radial projection and then they are more compactly represented by applying Discrete Cosine Transform (DCT) on them. To classify the images, correlation between the vectors is used as the 'similarity' measure. The proposed method is simple to implement and is efficient. The performance of the proposed method is encouraging and gives scope for further study.

In this paper a hybrid method for face recognition is proposed in which pre-processed face image is cropped to extract facial components - eyes, nose and mouth. These features and whole face are down sampled using different resolutions and a feature vector is formed which is used to train Artificial Neural Network for face classification.

This paper is organized as follows:

Section 2 describes the pre-processing phase. Section 3 talks about application of PCA & LDA methods for face recognition. Section 4 explains about Artificial Neural Network in face recognition. Section 5 describes the proposed algorithms for face recognition. Section 6 reports experimental conditions and results, and finally the conclusion is stored in section 7.

2. Pre-processing Phase

In preprocessing stage, initially average filtering is applied to produce blurry effect, and contrast of the image is enhanced through histogram equalization process. Then image size is reduced using Bi-cubic Interpolation down sampling method in order to make it light but efficient and best suited for PCA/LDA subspace processing and neural network classification stage.

2.1. Average Filtering

After retrieving images from the database, each image undertakes smoothing process. The mean/averag filter is applied in order to produce the blurry effect, as resizing (down sampling) is included in later stages while maintaining the quality of face image. The 5*5 mask is used for average filter process.

$$R = \frac{1}{25}\sum_{i=1}^{25} Z_i \tag{1}$$

Equation (1) calculates the average value of the pixels, whereas 'z' is the mask, and 'i' are mask elements. The output 'R' is then convolved with image to produce filtering effect. A 5*5 mask used in the implementation calculates average of 25 neighboring pixels in image.

2.2. Histogram Equalization

After average filtering stage all images undertake the process of histogram equalization. This equalization process is done in order to have uniform distribution of intensities and to enhance contrast of the images. Mathematically histogram equalization can be expressed as:

$$S_k = T(r_k) = \sum_{j=0}^{k} \frac{n_j}{n} \text{ where } k = 0,1,2\ldots \text{L}-1 \tag{2}$$

Here in equation (2) n is the total number of pixels in an image, n_j is the number of pixels that have gray level r_k , and L is the total number of possible gray levels in the image.

The result of histogram equalization is shown in Fig. 1.

Original Image Histogram Equalized Image

Fig. 1 Histogram Equalization

2.3. Bi-Cubic Interpolation

The process of histogram equalization is followed by image resizing process. The key advantage of resizing through bicubic interpolation is that it produces smoother surfaces than any other interpolation technique. Reducing the actual resolution of the image [21], e.g. 112X92 to 56X46/28X23. Bicubic Interpolation takes into account 16 pixels in the rectangular grid, takes weighted average of pixels and replaces them with a single pixel, and it is that pixel which has actually got the flavor of all the replaced pixels.
This reduction is done to reduce redundant information and to reduce mathematical complexity in PCA/LDA process. Here the actual resolution of an image is also reduced to ease complexity in convergence and significant effects on time required for training the neural network.

3. PCA and LDA Methods

3.1. Principal Component Analysis

PCA is used to represent face data in lower dimension [22-26]. Given a total of M images with (N_x x N_y) pixels, they are converted into training set $\Gamma = \Gamma_1 \Gamma_2 \ldots \Gamma_M$ with lexicographic ordering of the pixel elements. Ψ is the mean of whole data in vector form and Φ is the images data with mean removed, as given by

$$\Psi = \frac{1}{M_i}\sum_{i=0}^{M_i}\Gamma_i \tag{3}$$

$$\Phi_i = \Gamma_i - \Psi \tag{4}$$

Covariance matrix is computed from Φ as in

$$C = \frac{1}{M_i}\sum_{i=1}^{M_i}\Phi_i\Phi_i^{\,T} \tag{5}$$

However, covariance matrix computed in (5) lie in a very high dimension, gets sized up to *(N_x* x *N_y)*(N_x* x Ny) pixels. Unwieldy of this excessive data has been solved by [23] which uses a small dimension covariance, L to replace C. Eigenvectors, v computed from covariance L are multiplied with A to obtain principal component υ which is able to represent the actual eigenvectors of covariance C, as given by

$$A = [\Phi_1 \quad \Phi_2 \quad \ldots \quad \Phi_M] \tag{6}$$

$$L = A^T.A = \frac{1}{M}\sum_{i=1}^{M_i}\Gamma_i^{\,T} \tag{7}$$

$$v_i = A.V_i \tag{8}$$

v becomes PCA projection basis in which both training and testing samples are projected on it, yielding corresponding weights of each subject, ω_k, which are arranged in sets, as in

$$\omega_k = v_k^{\ T}.\Phi = v_k^{\ T}.(\Gamma - \Psi) \tag{9}$$

$$\Omega = [\omega_1 \quad \omega_2 \quad \ldots \quad \omega_M] \tag{10}$$

Equation (10) shows M sets of sample weights with a dimension of M. This dimension can be reduced to M' if only M' principal components are selected in (8). Through this method, computational cost can be greatly reduced because of $M' \ll (N_x x N_y)$.

3.2. Linear Discriminant Analysis

LDA uses face class information to find a subspace for better discrimination of different face classes. Thus at least two training samples are required to calculate between-class scatter matrix S_b and within-class scatter matrix, S_w. For c subjects having q_i training samples, S_b and S_w are obtained by using mean image per class, m_i and total mean, m_o, which are given by

$$m_i = \frac{1}{q_i}\sum_{k=1}^{q_i}\Omega_k \tag{11}$$

$$m_o = \frac{1}{M_i}\sum_{k=1}^{M_i}\Omega_k \tag{12}$$

$$S_w = \sum\nolimits_{i=1}^{c} P(C_i)(\Omega - m_i).(\Omega - m_i)^T \tag{13}$$

$$S_b = \sum\nolimits_{i=1}^{c} P(C_i)(m_i - m_o).(m_i - m_o)^T \tag{14}$$

As shown in the above equations, S_b and S_w are computed using PCA extracted features obtained in (8), which lie in M' dimension. Applying LDA on PCA features not only improves computational efficiency but also alleviates the complication of S_w singular problem [24]. LDA creates another subspace to further project the data based on Fisher Linear Discriminant criterion:

$$W = \arg\max(J(T)) = \frac{\left|w^T.S_b.W\right|}{\left|w^T.S_w.W\right|} \tag{15}$$

In other words, $W_{opt} = [W1\ W_2\ \ldots\ W_M']$ is the set of eigenvectors of $S_b{*}S_w^{-1}$ that corresponds to M' largest eigenvalues. There are at most c-1 non-zero generalized eigenvalues, thus LDA subspace's dimension is spanned by c-1 at most. For examples if there are 10 subjects trained, LDA subspace dimension is limited at 9.

4. ANN for Face Recognition

Artificial neural network is a branch of artificial intelligence which has fast emerged with wide range of applications in pattern recognition and data processing. It is popular because of its adaptive learning, self organizing, real time operations and fault tolerance via redundant information coding. There are many efficient algorithms using which ANN can be implement, but multi layer neural network (back propagation algorithm) and radial basis function network are used in proposed method because of their better classification efficiency for descriminant facial features.

4.1. Back Propagation:

Neural networks-based methods have been widely used in classification for its learning ability and good generalization. A three layer ANN with back propagation training (BPNN) is used in this work. The network architecture consists of I input layer neurons, H hidden layer neurons and O output layer neurons as depicted Figure 2. Number of output nodes is same as the number of subjects in training set.

During training stage, back propagation or RBF algorithm is used to update weights of ANN based on the errors traced at each neuron output. Every subject is trained towards getting an output "1" at its own corresponding output node. No threshold is set for output layer neurons. In fact, our ANN classification is based on maximum selection. When there is a new input feed into ANN, only one output layer node which yields maximum value will get "1" and the rest get "0".

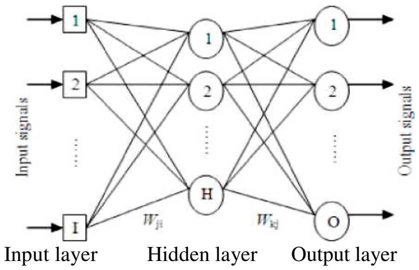


Figure 2. Three layer ANN architecture

4.2. Radial Basis Function Network

A radial basis function network is an artificial neural network, which uses radial functions as activation functions. A Radial Basis Function (RBF) is a real- valued function whose value depends only on the distance from the origin. RBF networks are claimed to be more accurate than those based on Back- Propagation (BP), and they provide a guaranteed, globally optimal solution via simple, linear optimization. One advantage of radial basis networks over back propagation is that, if the input signal is non-stationary, the localized nature of the hidden layer response makes the networks less susceptible to the learning rate and tolerance for errors.

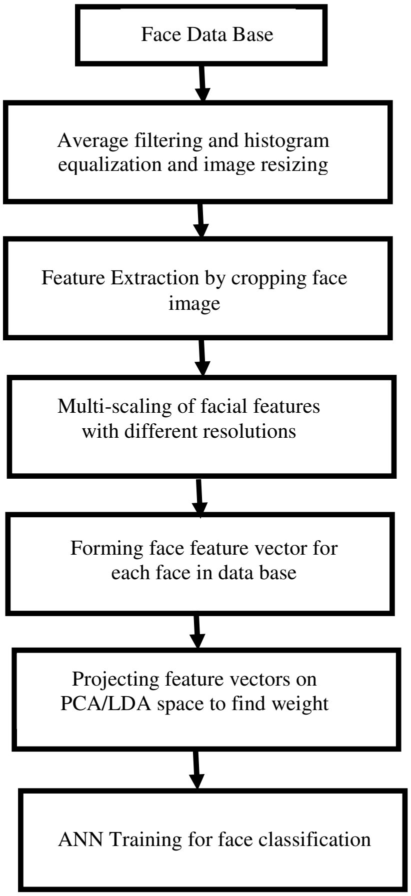
5. Proposed Algorithm for Face Recognition

In this study hybrid face recognition technique is proposed combining both componential cues (such as eyes, mouth and nose) and holistic information.
In the proposed method, initially face images are pre-processed (Average Filtering, Histogram Equalization and Image resized using Bicubic Interpolation) then based on eye co-ordinates face features (eyes, nose and mouth) are extracted by cropping techniques, then image patches of eyes, nose, mouth and whole face are down sampled using different sampling rates based on components significance (Ex eye 1:1, nose 1:2, mouth 1:4 and whole face 1:8). These 2D face image patches are represented by a matrix $A = [\overline{a_1}, \overline{a_2}, \ldots \ldots \overline{a}_n]$ where $\overline{a_1}$ represents a one-dimensional image column obtained from the two-dimensional image patches scanned in lexicographic order and written into a column vector.

Subspace analysis PCA/LDA are employed to the matrix A. PCA is used for further dimensionality reduction and good representation. LDA is used for better discrimination information.

The weight vector obtained by projecting training face on PCA/LDA subspace is used as input to the Artificial Neural Network which is trained by Back-propagation (BP) or Radial basis function (RBF) network for recognizing faces. The flow chart and implementation steps are given as follows.

5.1. Flow chart for Proposed method



5.2. Implementation:

The algorithm is described in the following steps:

Training Phase

1. Pre-process the selected face images from database (Average Filtering, Histogram Equalization, image resizing using Bi-cubic interpolation method).
2. Crop the eyes, Nose patch and Mouth patch from the above image. The locations of the Nose and Mouth patches are kept identical for all images.
3. Change the resolution of extracted features and whole face.
4. Convert the above image patches obtained in step-3 into a single face feature vector of dimension N X 1, N changes with resolution.
5. Repeat steps 1 to 4 for all faces to be trained in data base to form face feature vectors.
6. Project each face feature vector on PCA or LDA subspace to find weight vector.
7. Use the weight vector found in step 6 as inputs to artificial neural network and train the network to classify the faces using back propagation or RBF network algorithm.

Testing Phase

In the testing phase, the face image is selected from test data base and steps 1 to 6 are carried out as it is done in the training phase. But in the last step, Artificial Neural Network training is not required, weight vector is fed directly to the already trained Artificial Neural Network to recognize the test face.

6. Results and Discussion

6.1. Experimental Setup

AT & T Database of Faces [25] (formerly known as ORL face database) is used to evaluate PCA, LDA and ANN. This database contains 10 different images of 40 distinct subjects. The images vary in terms of lighting, facial expressions including open/closed eyes, facial details such as with glasses/without glasses, and different time of snapping pictures. In the proposed experiment, these images were converted from 112 x 92 pixels to 56 x 46 pixels. Average percentage of face recognition is calculated based on 10 attempts. Figure 3 shows 10 images of a single subject in ORL database.

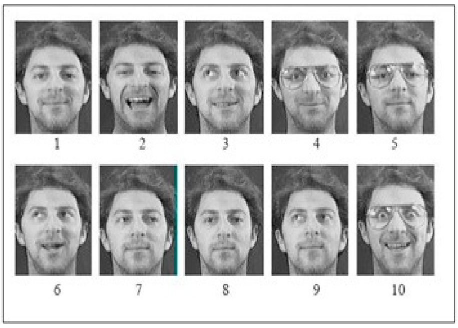


Figure 3: Example of a subject in ORL data base

6.2. Simulation Result

Number of training faces Vs percentage of Recognition

Image Size: 56x46
Multi-scaling: Eye-1:1, Nose-1:2, Mouth-1:4,
Whole Face-1:8
ANN Structure: 40: 50:40
Number of Training Faces for each class: Variable
Number of Testing Faces : Variable
Number of Principle Components : 40
Data Base : ORL

Table No-1: Number of training faces vs percentage of recognition for four different methods

Number of		PCA +BP	PCA +RBF	LDA +BP	LDA +RBF
Train faces	Testing faces				
2	8	84.50	84.70	83.75	84.00
3	7	86.10	87.35	85.65	87.00
4	6	93.20	94.85	93.00	93.10
5	5	96.35	96.55	96.85	97.10
6	4	96.95	97.00	97.10	97.50
7	3	97.10	97.35	97.55	97.95
8	2	98.00	98.10	98.20	98.40

From the results cited in table number 1, the following inferences can be made

- Face recognition percentage increases with number of training faces in all four methods as the network adoptability capacity increases with training faces
- When number of training faces are small compared to testing faces PCA performs better than LDA.
- LDA+RBF method outperforms the other methods (98.40) as face discrimination ability of LDA is more compared to PCA and RBF network classification efficiency is more compared to BP
- When number of training & testing faces are equal to 5, the face recognition percentage is better compared to the other methods in literature.

Resolution of face components vs Percentage of recognition

Image Size: 56x46
Multi-scaling: Variable
ANN Structure: 40: 50:40
Number of Training Faces for each class: 5
Number of Testing Faces : 5
Number of Principle Components : 40
Data Base : ORL

Table No-2: Resolution of face components vs percentage of recognition

Row No.	Eye (R)	Eye (L)	Nose	Mouth	Whole face	PCA +BP	PCA +RBF
1	1:1	1:1	1:2	1:4	1:8	96.35	96.55
2	1:1	1:1	1:4	1:8	1:16	93.75	94.00
3	1:2	1:1	1:4	1:8	1:8	88.60	87.00
4	1:2	1:2	1:8	1:8	1:16	84.45	85.10
5	1:2	1:2	1:2	1:4	1:8	85.00	85.20
6	1:1	1:1	1:2	1:8	1:16	89.95	91.00

Row No.	Eye (R)	Eye (L)	Nose	Mouth	Whole face	LDA +BP	LDA +RBF
1	1:1	1:1	1:2	1:4	1:8	96.85	97.10
2	1:1	1:1	1:4	1:8	1:16	94.10	94.25
3	1:2	1:1	1:4	1:8	1:8	88.10	88.40
4	1:2	1:2	1:8	1:8	1:16	85.70	87.15
5	1:2	1:2	1:2	1:4	1:8	88.80	87.50
6	1:1	1:1	1:2	1:8	1:16	93.60	94.10

From the results cited in table number 2, the following inferences can be made

- Percentage of face recognition decreases with decrease in resolution for eyes, nose, mouth and whole face for all the four methods
- LDA+RBF method outperforms other methods with percentage of recognition as 97.10 when resolution of eye is 1:1, nose is 1:2, mouth is 1:4 and whole face is 1:8
- It can be seen from the first and 5^{th} row of results that the change in resolution of eye results in drastic change in the percentage of recognition of face.
- It can be observed from first and 6^{th} row of results that the change in resolution of mouth and whole face changes face recognition rate slightly.

Resolution of face vs percentage of recognition

Image Size: Variable
Multi-scaling: Eye-1:1, Nose-1:2, Mouth-1:4, Whole Face-1:8
ANN Structure: 40: 50:40
Number of Training Faces for each class: 5
Number of Testing Faces : 5
Number of Principle Components : 40
Data Base : ORL

Table No-3: Resolution of face vs percentage of recognition

Resolution of Face	PCA +BP	PCA +RBF	LDA +BP	LDA +RBF
28X23	85.10	87.30	88.00	88.30
42X35	90.05	91.25	91.40	92.00
56X46	96.35	96.55	96.85	97.10
84X69	96.60	97.00	97.50	98.00
112X92	97.00	97.15	98.10	98.25

From the results cited in table number 3, the following inferences can be made

- Percentage of face recognition increases with increase in resolution of face image for all the four methods.
- LDA+RBF method outperforms other methods with percentage of face recognition 98.25% when face image resolution is 112X92.
- The face recognition rate is increasing with the face image resolution and level off when arriving at one certain resolution 56X40 it is concurring with conjecture that the face discrimination information increases with the face image resolution and remains stable when reaching one specific resolution.

Variation in training set vs percentage of recognition

Image Size: 56X46
Multi-scaling: Eye-1:1, Nose-1:2, Mouth-1:4, Whole Face-1:8
ANN Structure: 40: 50:40
Number of Training Faces for each class: 5 by changing different faces in set
Number of Testing Faces : 5 by changing different faces in set
Number of Principle Components : 40
Data Base : OR

Table No-4: Variation in training set vs percentage of recognition

Set	Training Set	Testing Set	PCA +BP	PCA +RBF	LDA +BP	LDA +RBF
1	1,2,3,4,5	6,7,8,9,10	96.10	96.20	96.25	96.85
2	2,3,4,5,6	1,7,8,9,10	97.00	97.25	97.95	98.00
3	3,4,5,6,7	1,2,8,9,10	97.25	97.40	98.30	98.40
4	4,5,6,7,8	1,2,3,9,10	98.50	98.85	98.00	98.20
5	5,6,7,8,9	1,2,3,4,10	98.30	98.55	98.00	97.50
6	6,7,8,9,10	1,2,3,4,5	96.35	96.55	96.85	97.10
		Average=	97.25	97.46	97.55	97.67

From the results cited in table number 4, the following inferences can be made

- The face recognition rate changes based on training set and testing set used.
- The maximum face recognition rate (98.85%) is achieved when training set and testing set are balanced with respect to facial expression and spects that is 4,5,6,7,8 for training and 1,2,3,9,10 for testing PCA method outperforms the LDA as discrimination information is less in training set
- When discrimination information is high in set number 1 and 6, the percentage of face recognition is found to be maximum and LDA+RBF method outperforms other methods.

ANN structure vs percentage of recognition

Image Size: 56X46
Multi-scaling: Eye-1:1, Nose-1:2, Mouth-1:4, Whole Face-1:8
ANN Structure: Variable

Number of Training Faces for each class: 5
Number of Testing Faces : 5
Number of Principle Components : 40
Data Base : ORL

Table No-5: ANN structure Vs percentage of recognition

ANN Structure	PCA +BP	PCA +RBF	LDA +BP	LDA +RBF
40:10:40	90.65	91.15	91.45	91.65
40:20:40	91.05	93.10	93.25	93.55
40:30:40	95.25	95.75	95.95	96.85
40:40:40	95.30	95.80	95.95	96.85
40:50:40	96.10	96.25	96.60	97.10
40:70:40	94.50	95.25	95.50	96.00

*for LDA instead of 40 inputs 39 inputs are used in ANN structure
From the results cited in table number 5, the following inferences can be made

- The face recognition rate increases with number of hidden layer nodes as dimension of weight matrix increases with hidden layer nodes but after certain dimension the percentage of recognition decreases and maximum recognition rate is achieved for 40:50:40 ANN structure.
- LDA+RBF outperforms other methods as the discrimination information is high in training set (1,2,3,4,5).

Number of principle components vs percentage of recognition

Image Size: 56X46
Multi-scaling: Eye-1:1, Nose-1:2, Mouth-1:4, Whole Face-1:8
ANN Structure: Variable
Number of Training Faces for each class: 5
Number of Testing Faces : 5
Number of Principle Components : Variable
Data Base : ORL

Table No-6: Number of principle components vs percentage of recognition

No. of principle components	ANN Structure	PCA +BP	PCA +RBF	LDA +BP	LDA +RBF
15	15:40:40	60.00	62.05	63.25	67.85
25	25:40:40	94.60	94.60	94.15	94.90
30	30:35:40	95.25	93.50	94.20	94.90
35	35:50:40	95.50	95.00	96.20	96.95
40	40:50:40	95.50	95.90	96.10	96.50
50	50: 40:40	96.35	96.55	96.85	97.10
100	100:60:40	92.00	93.00	94.00	94.25

*For LDA 39:50:40 ANN structure is used

From the results cited in table number 6, the following inferences can be made

- The face recognition rate increases with principle components upto 30, that is 15% of 200 faces and then levels off. But once principle components crosses 50, the percentage of recognition decreases due to the structure of ANN.
- LDA+RBF outperforms other methods and achieves maximum recognition rate of 97.10% for 40 principle components when structure of ANN is 40:50:40.

Table No-7: Comparison of recognition rate of the proposed method with the available previous methods.

S.No:	Method	%age of Recognition
1	Weighted modular principle component analysis [21]	87
2	Wavelet +PCA+ANN [23]	97.68
3	Hybrid method based on structural and holistic [24]	90.30
4	Hybrid model using facial components [22]	88.57
5	PCA, LDA and Neural Network for face identification [18]	95.80
6	Low resolution single neural network based on face recognition [19]	94.50
7	Proposed method [When five faces are used for training and five faces for testing]	97.10

7. Conclusion

In this paper, face identification performance using PCA+BP, PCA+RBF, LDA+BP and LDA+RBF is investigated for multi-scaled features of ORL Face Database, 200 faces of 40 subject are used for training and another 200 faces are used for testing. In the proposed method face images are pre-processed and cropped to extract face features (eyes, nose and mouth) and these features and whole face are multi-scaled to reduce dimension. Then the feature vector formed by face components and whole face is projected on PCA/LDA subspace to find PCA/LDA weight vector. PCA is used to reduce dimensions of data while LDA improves its discrimination ability. PCA & LDA features are trained using ANN (BP & RBF) for classification. Besides, effect of varying number of principle components, multi-scaling resolution of face features, image sizes, training and testing face sets and number of hidden layer neurons are studied. From the experiment it is found that LDA+RBF improves performance reasonably over PCA+BP. PCA+RBF and LDA+BP methods of face recognition. LDA+RBF method achieved a recognition rate of 98.40% for 40 subjects with image size 112X92 for 40:50:40 ANN structure.

The prime advantage of LDA+RBF method for multi-scaled features of low resolution face image over other existing hybrid face recognition techniques is that proposed method involves less mathematical complexity and hence processing time, with slightly higher recognition rate.

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