ORL database and UMIST database are reduced to 92 pixels in both heights and width as shown in Fig.1.

Fig. 1An original image in UMIST database and its cropped form

2. Calculating the Mean Face: The mean face is calculated by taking the pixel-by-pixel average of all the faces in the database. Let the training set of *M* face images *be* Γ_1, Γ_2, $\Gamma_3 \ldots \Gamma_M$. The average face ψ of the set is defined by:

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \text{ .... (1)}$$

During the calculations, the average of all the pixel values for the same point across the faces is taken, i.e., the values of the (*x*,*y*) the pixel for all the faces are added and the sum is divided by the number of faces. The number of pixels in the mean image in both the ORL and UMIST databases is 92 x 92 = 8464. The total number of pixels is same in both the mean face and original faces.

In the ORL database, number of images is 250 (10 faces per person for 25 persons), so M = 250. For the UMIST face database, 19 faces are taken for each person and number of persons considered is 15 so M = 285. The mean faces for ORL and UMIST face databases are shown in fig. 2.

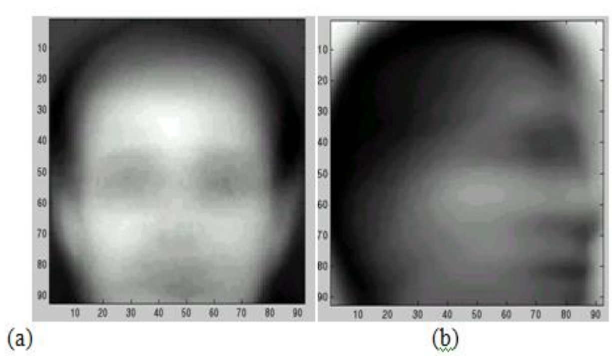

Fig. 2 (a) The ORL mean face (b) The UMIST mean face

3. Calculation of Difference Images: Once the mean image has been calculated, the mean image is subtracted from the individual face images one by one resulting in the difference images. Each face differs from the average by the vector Φ_i given by:

$$\Phi_i = \Gamma_i - \Psi \text{ .... (2)}$$

where Γ_i is the i[th] face image and Ψ is the mean face image.This difference is calculated on a pixel-by-pixel basis, i.e., the value of the (*x*,*y*)th pixel of the mean face is subtracted from the value of the (*x*,*y*)th pixel of the original face image. Fig. 3 shows the original face image of the first person in ORL face database and also the difference image obtained after subtraction by the mean face image.

Fig. 3 (a) The original ORL database image (b) Corresponding difference image

The difference images capture the deviation of the original faces from the mean face. So the faces can be represented in terms of their deviations from the average face. An important property of the difference images is that the difference in the pixel values of the original and means image can be positive as well as negative, indicating positive or negative deviation from the mean image.

4. Calculation of the Covariance Matrix: After the calculation of the difference images for all the faces in the training set, we begin the calculation of the covariance matrix C. The covariance matrix stores the difference images in a matrix form, thus capturing the deviations of the face images from the mean face. The covariance matrix represents the variations across the faces of the face database.

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T \text{ .... (3)}$$

The above equation makes it clear that the covariance matrix is the element-by-element product between the difference matrix and transpose of the difference matrix calculated over all the M training faces. If a matrix A is considered such

$A = [\Phi_1\ \Phi_2 \ldots\ldots \Phi_M]$. Then the covariance matrix can be represented as

$$C = AA^T \text{ ....(4)}$$

The Eigenvectors and Eigenvalues are defined for the covariance matrix. The matrix *C*, however, is N^2 *by* N^2 (where *N* is the number of pixels in both width and height of each face image), and determining the N^2eigenvectors and Eigenvalues is an intractable task for typical image sizes. We need a computationally feasible method to find these eigenvectors. For the ORL and UMIST databases the faces have been cropped to 92 pixels each in width and height, so the covariance matrix is of the order 8464.

5. Determining the Eigenfaces: Rather than calculating the covariance matrix which is of the order of is N^2 by N^2, we try to reduce the dimensionality of the matrix based on the approach of principal components. If the number of data points in the image is less than the dimension of the space, there will be only *M-1*, where *M* is the number of faces in the training set, rather than N^2, meaningful eigenvectors. (The remaining eigenvectors will have associated eigenvalues of zero.) So we can solve for the N^2–dimensional eigenvectors by solving for the eigenvectors of an *M* by *M* matrix and then taking appropriate linear combinations of the face images Φ_i. So the dimensionality of the covariance matrix can be reduced to the order of images in training set from the total number of pixels in the face image. We construct the *M* by *M* matrix $L = A^T A$, where

$$L_{mn} = \Phi_m^T \Phi_n \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

and find the M eigenvectors, v_i, of *L*, these vectors determine linear combinations of the M training set face images to form the Eigenfaces u_i.

$$u_l = \sum_{k=1}^{M} v_{lk} \Phi_k \quad , l = 1, \ldots\ldots , M \ldots\ldots\ldots\ldots(6)$$

The eigenfaces are just like the faces but are somewhat "ghostly" and are not as clear as the original faces. The eigenfaces are of the same size as the original faces, so they also have 92 pixels in width as well as in height.

For the ORL database, *M* = 250 and total number of pixels (N^2) = 8464 and for the UMIST database, *M* = 285 and total number of pixels (N^2) = 8464. So the numbers of eigenfaces that are needed to capture the variation of the ORL database are reduced from 8464 to 250 and for the UMIST face database only 285 eigenfaces are sufficient to represent the variations in the faces.

6. Sorting the Eigenfaces by Using Eigen Values: As a property of the eigenface, each of them has an eigenvalue associated with it. More important, eigenvectors with from the graph shown in Fig.4, where x-axis represents number of eigenfaces and y-axis represents the corresponding eigenvalues, the number of eigenfaces having maximum eigenvalues is very less and the eigenvalues drop significantly after the top 50 eigenfaces.

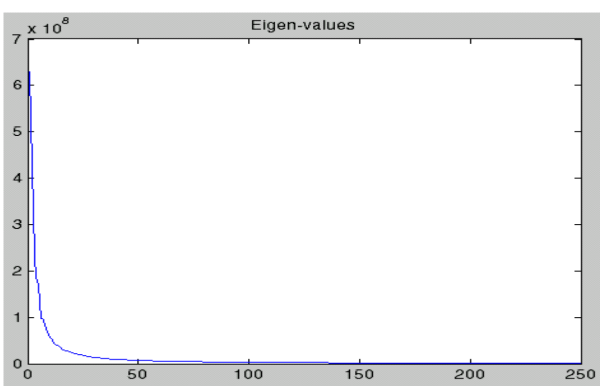

Fig. 4The variation in the Eigenvalues for ORL database

So, the faces are being represented using about 50 eigenfaces only. The eigenfaces with largest eigen values capture maximum variation of the faces while the eigenfaces with low eigen values are insignificant and do not represent much information about the faces. If we use the maximum number of eigenfaces then the faces can be most correctly reconstructed and recognized. For maximum accuracy, the number of eigenfaces should be equal to the number of images in the training set. In practice, a smaller *M'* is sufficient for identification. Therefore, the most significant *M'* eigenvectors of the *L* matrix are chosen as those have the largest associated eigenvalues.

7. Face Reconstruction: After the calculation of the Eigenfaces, the original face images are reconstructed using the most significant eigenfaces. This is achieved by multiplying the eigenfaces with some multipliers (both negative and positive) and adding the products. In order to determinethe multipliers a new face image (Γ) is transformed into its eigenface components by a simple operation,

$$\omega_k = u_k^T (\Gamma - \Psi) \text{ for} k = 1,\ldots,M'. \ldots\ldots\ldots\ldots\ldots\ldots(7)$$

The multipliers form a feature vector,

$$\Omega^T = [\omega_1, \omega_2 \ldots\ldots \omega_{M'}] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

that describes the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images. Once the feature vector has been obtained, the original faces can be reconstructed by multiplying the Eigenfaces with the multipliers and adding up the products thus obtained. The number of multipliers will be same for all the faces and is equal to the number of eigenfaces that are sufficient for the reconstruction. In Fig.5, the original face and its reconstruction using the Eigenfaces is shown.

Fig. 5 (a) The original image(b) Its reconstruction using the multipliers

C. Generating the Input for the Neural Network: The neural network that is constructed for the face recognition task is supplied with inputs in the form of the multipliers that are generated. The original face images can be represented as the sum of products of the multipliers and the eigenfaces. So these multipliers can be used to differentiate the faces. The multipliers for all the faces of the same person are very much similar while they differ greatly from the multipliers of the faces of another person. The number of multipliers that are supplied to the neural network as the input is equal to the number of Eigenfaces that are sufficient to represent the variation of the faces. Now, we design an optimal multi-layer neural network [15] for face recognition by specifying the parameter like learning rate, momentum, number of hidden layer and number of neurons in input layer, hidden layers and output layer.

IV. EXPERIMENTS AND RESULTS

In this section, we report here the results of our experiments, which were performed on the ORL and UMIST database. The UMIST university face database [12] consists of 564 images of 20 people, each covering a range of poses from profile to frontal views. Subjects cover a range of race/sex/appearance. The files are all in Portable Gray Map (PGM) format, 220 x220 pixels in 256 shades of grey. ORL database [13] contains a set of faces taken between April 1992 and April 1994 at Olivetti Research Laboratory (ORL) in Cambridge, UK. There are 10 different images are variations in facial expression (open/closed eyes, smiling/non-smiling), and facial details(glasses/no glasses) There is some variation in scale of up to about 10%. The images are gray scale with a resolution of 92 x112 pixels UMIST face database. The UMIST face database has a larger number of faces per person and also, the faces are of different poses. So the number of faces that can be used in training is more thus resulting in better recognition accuracy than that for the ORL database. The recognition accuracy is more than 95% as shown in Fig.6.

For the ORL faces, the recognition system performed very well. The recognition value for the correct person is around 0.9 and for all other persons it is very near to 0 (as shown in Fig.7). This clearly indicates that the face belongs to only the person with highest recognition value and not to the other persons.

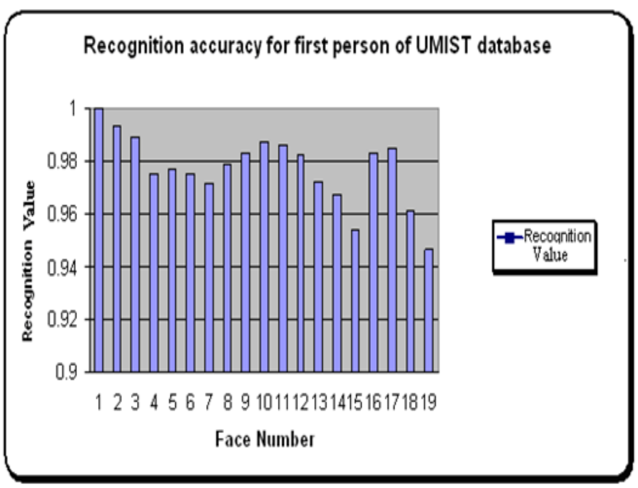

Fig. 6 Recognition value for first person of UMIST database

The number of Eigenfaces that are used in the reconstruction of the original faces plays an important role in determining the accuracy of the recognition system. Each original face is expressed as a sum of the products between the Eigenfaces and the multipliers. It was found that for the ORL face database, 50 Eigenfaces are sufficient as shown in Fig.8, resulting in an accuracy of more than 99.5% for the first person's faces. On the other hand, for the UMIST face database the number of Eigenfaces found to be sufficient is 403.

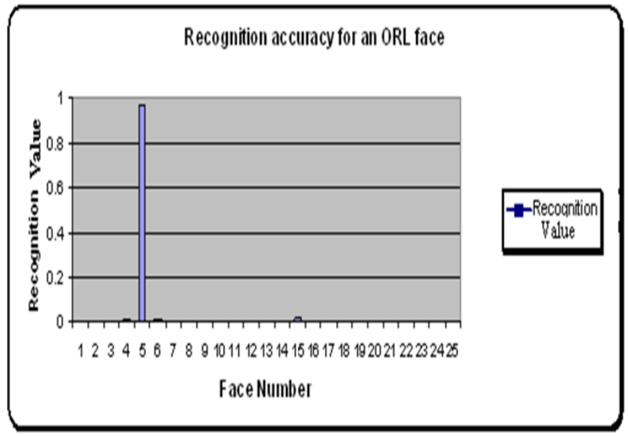

Fig. 7 Recognition accuracy for 25 persons when the face belongs to 5th person

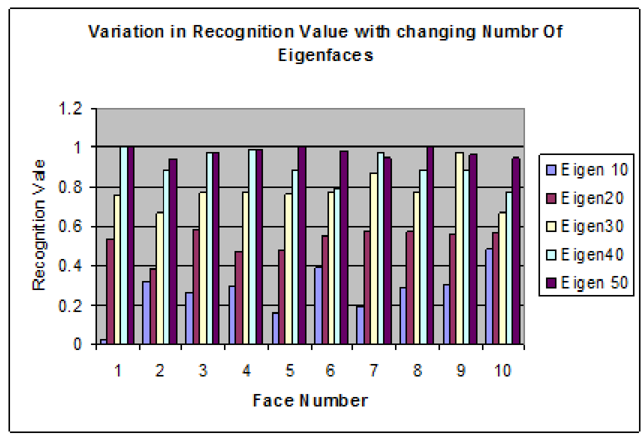

Fig. 8 Recognition value for first person of the ORL database with varying number of Eigenfaces

Now, we discuss the significance of results of the proposed method as shown in Table I in comparison to the results of the well-known face recognition methods as listed in Table II. The proposed method provides with the good accuracy with the less number of images per person in the training dataset, and also with the less number of design parameters for the neural network in comparison to the other techniques. In proposed method, number of input to the neural for the ORL face data base is 50 and the number of hidden layer is 2 and number of neurons units per hidden layer is 10 and 8 respectively. Similarly, for UMIST face database, number of input to the multi-layer perceptron (MLP) are 40 and the number of hidden layer is 1 and the number of neurons per layer is 11 respectively.

V. CONCLUSION

The various face recognition approaches varies in diversity with the diversity of the problems on face recognition. There are approaches like geometric and mathematical approaches but doesn't dwell where the Eigen face values and similar approaches persist. The approaches fail gradually when face recognition is to be done with new faces and not just the trained ones. If illuminations and pose change abruptly, the non-geometric approaches fail vehemently. The input space can also be reduced using PCA. PCA significantly reduces the computing complexity.

Neural networks lend themselves for the task of face recognition by drawing the hyper-surfaces between the faces of the different persons. These methods however simplify the task of face recognition but the constraints are the variation in poses, illumination levels and facial features, thereby making the task quite difficult. This paper focuses on the optimized eigenfaces based approach, which uses the optimized multilayer perceptron for face recognition. This approach is found to be both proficient and efficient compared to the other classical approach.

TABLE I PROPOSED OPTIMIZE METHOD WITH PCA

Type of NN	Input	Number of hidden layer	Unit/ hidden layer	Data Base	Accuracy
MLP	50	2	10,8	ORL	95% to 98%
MLP	40	1	11	UMIST	98.5%

TABLE II DIFFERENT METHOD RESULT

Reference	Type of NN	No. of input	Hidden Unit/ No of unit	Database	Recognition rate
Z.Pen.*et al*.,[6]	MLP	Whole image	One (60 to 80)	ORL	94%to97%
S.Lawrence *et al.*,[7]	ConvolutionNN	Whole image		ORL	96%to98.5%
S. Eickeler*et al.*,[14]	P-2D HMM	Whole image		ORL	98% to 100%
V.Goloko, *et al.*,[9]	RNN	No of image pixel	2 (20 to 30)	ORL	97%
Fu.Jie Huang *et al.*,[11]	Novel NN	No of image pixel	One, 15 to 30	ORL	98.75%

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