ISSN 2250-3153

Gender Classification of Human Faces Using Class Based PCA

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Abstract- Gender classification is a binary classification system where system has to assign a given test image to one of the two classes (male or female). The gender classification system with large set of training data normally gives good accuracy. But to achieve good accuracy with small training data is a difficult task. This paper proposes an algorithm for gender classification with small training data and it gives good accuracy even with one image per person for training. The system contains mainly two parts: feature vector generation and classification. Feature vector generation is done with PCA (Principal Component Analysis). Generally all training images are organized as a columns of a matrix and then PCA is applied to generate feature vectors of those training images. To reduce the computational complexity, PCA is separately applied to each individual training class. The paper proposes a new approach of classification where, after a given test image is reconstructed with different Eigen coordinate systems, lowest MSE(mean square error) between given image and reconstructed image, indicate the output class for that image. The proposed method is also compared with nearest neighbor classification using different similarity criteria such as Euclidean, Manhattan, Chebyshev, Canberra, Cosine Correlation and Bray-Curtis distance. These all algorithms are applied on two databases. Indian face database (664 images) and local database (1000 images). Results show that the proposed method significantly improves the overall classification accuracy.

Index Terms- Feature Vector, Nearest neighbor classifier, Principal Component Analysis, Similarity Measures, Supervised Classification.

I. INTRODUCTION

Face is a most important biometric feature of human beings and used for identification in many applications such as surveillance, security, human computer interaction, object based video coding etc. For a human, to recognize whether a given image is of man or woman, is very easy but for the system it is complex to recognize a gender. In recent years, a lot of research is done on this topic. Gender classification using the frontal still facial image is a challenging task. Two main steps of gender classification are feature extraction and pattern classification. Let the image 'I' is of size NxN. This image can be represented as a point in N^2-dimensional space. So face image of 256x256 can be represented as a point in 65,536-dimensional space. But being a lot of similarity involved in facial images, these images are not randomly distributed in huge image space and can be represented by relatively low dimension space. The face image can be represented by feature vector. The feature extraction can be done in two ways either by considering the whole image as given by Ardakany and Joula [1] or by considering the local features of different parts of an image such as eyes, nose, mouth etc.[2][3][4]. Principal component analysis (PCA) is the most popular method for feature extraction in face recognition domain. The goal of the PCA is to reduce the dimension of an image space so that new basis better describes the typical model of the image space. Beginning with Matthew Turk's and Alex Pentland's [5] early system, Eigen faces have been created using PCA and used for face recognition. Later PCA method has been extensively used in this domain[6][7]. For classification task the traditional pattern classifiers such as nearest-neighbor classifier[8][9], decision tree classifier[10] as well as modern techniques like neural networks[11] and support vector machine (SVM)[12] have been used. The proposed methods of gender classification are based on PCA and nearest neighbor classification. Initially PCA is applied to training images of male and female class separately so named as **Class Based PCA**. The Eigen faces are calculated which define the male face space and female face space. Then for each male training image a set of weights (feature vector) is calculated by projecting that image onto each of the Eigen faces of male face space. Similar process is done with female training images. After generating the one feature vector for each training image, two feature vectors are generated for a given testing image by projecting that image on both the face spaces. Nearest neighbor classification is done with different similarity criteria and the results obtained are compared. The paper is organized as follows : Section II gives a brief idea about PCA. Section III gives the equations of different distance criteria. Section IV proposes the methodologies of the system. Section V discusses the results. Finally Section VI describes the conclusion followed by references.

II. PRINCIPAL COMPONENT ANALYSIS (PCA)

PCA is a mathematical and statistical technique used for finding patterns in high dimensional data. It is generally accepted that the earliest descriptions of the technique now known as PCA were given by Karl Pearson in 1901[13] and it was later researched by Harold Hotelling [14] in the 1930s. A lot of information about PCA is given in a book by I.T.Jolliffe [15].

Mathematically, PCA finds the principal components of the distribution of faces. It is based upon the Eigen vector decomposition of a covariance matrix of the set of face images. These Eigen vectors can be rearranged to generate Eigen face. The number of Eigen faces is same as the number of training images. To reconstruct the original training face image, we need to calculate the weighted sum of all Eigen faces. The set of the weight coefficients required for reconstruction, is called as the feature vector of that image.

III. DISTANCE CRITERIA

Many similarity measures have been proposed by X.Chen and T.J.Cham [16], E.Deza and M.Deza [17], and John P.Van De Geer [18] in literature for image classification. This section describes the six distance measures used by H.B.Kekre et al. [19]. Consider P ($P_1,P_2,....,P_n$) and Q ($Q_1,Q_2,...., Q_n$) are two feature vectors.

A. Euclidean Distance

Euclidean distance as given in Eq.1, is a standard metric for geometrical problems.

$$D_{Euc}(P,Q)=\sqrt{\sum_{i=1}^{n}\left|P_i-Q_i\right|^2} \tag{1}$$

B. Manhattan Distance

It is a distance between two points measured along axes at right angles. It is also known as rectilinear distance or city block distance. It is given in Eq.2.

$$D_{Man}(P,Q)=\sum_{i=1}^{n}\left|P_i-Q_i\right| \tag{2}$$

C. Chebyshev Distance

Chebyshev distance (Eq. 3) between two vectors is the greatest of their differences along any coordinate dimension.

$$D_{Cheb}(P,Q)=\max_{i}\left|P_i-Q_i\right| \tag{3}$$

D. Canberra Distance

It is similar to the Manhattan distance as shown in Eq.4. The distinction is that the absolute difference between the variables of the two objects is divided by the sum of the absolute variable values prior to summing.

$$D_{Can}(P,Q)=\sum_{i=1}^{n}\frac{\left|P_i-Q_i\right|}{\left|P_i\right|+\left|Q_i\right|} \tag{4}$$

E. Cosine Correlation Distance

Eq. 5 gives Cosine similarity which is a measure of similarity between two vectors by measuring the cosine of the angle between them.

$$D_{Corr}(P,Q)=\frac{\sum_{i=1}^{n}P_iQ_i}{\sqrt{\sum_{i=1}^{n}P_i^2}\sqrt{\sum_{i=1}^{n}Q_i^2}} \tag{5}$$

F. BrayCurtis Distance

The distance based on Bray-Curtis dissimilarity[20] is given in Eq.6. It is also known as *Sorensen* distance.

$$D_{BC}(P,Q)=\frac{\sum_{i=1}^{n}\left|P_i-Q_i\right|}{\sum_{i=1}^{n}\left|P_i+Q_i\right|} \tag{6}$$

IV. PROPOSED SYSTEM

Proposed algorithm is explained in two sections. First section describes the procedure of generation of feature vectors and second section explains the classification methods.

A. Generation of feature vectors

Image database is divided into two parts: training set and testing set. The training and testing set consists images of two classes (male and female).Consider there are 'n' images in training set in each class. All images are converted into gray scale and of 256x256 size. In the beginning Eigen images for each class are generated using the procedure given below.

Step1 : Find the average image 'I_{avg}' .

Step2 : Find zero mean images by subtracting average image from each image of that class

Step 3: Each zero mean image is converted into one dimensional vector by arranging its columns one below the other.

Step 4: Form the matrix say Φ whose columns are the one dimensional vectors obtained in step 3.

Step 5: Calculate the covariance matrix A given by Eq.7

$$\mathrm{A}=(1/\mathrm{n})\times\Phi^{t}\times\Phi \qquad \text{where } n=\text{Number of columns of matrix}\,\Phi \tag{7}$$

Step 6: Find the Eigen vectors using Eq.8. Arrange the Eigen vectors in decreasing order of corresponding Eigen values. Discard the last Eigen vector corresponding to the smallest Eigen value (It is negligible because of very small value compared to others).

$$[\mathrm{A}-\lambda\mathrm{I}]\mathrm{V}=0 \tag{8}$$

Step 7: Each Eigen vector is converted into two dimensional matrix i.e. Eigen image by dividing it into n parts and organizing those parts as columns of matrix.

After forming the Eigen coordinate system for male and female class, the feature vector is generated for each image in training set and testing set. The generation of feature vector for training image is done using the corresponding Eigen coordinate system where as the generation of feature vector for testing image is done using both the Eigen coordinate system. Hence for each training image one feature vector is generated and for each testing image two feature vectors are generated. The stepwise procedure is given below:

Step 1: Find zero mean images by subtracting the average image of each class from the given image.

Step 2: Calculate the feature vectors of given image for each class 1 and 2 using the Eq.9

$$W1=\begin{bmatrix} w1_1 \\ w1_2 \\ M \\ w1_{(n-1)} \end{bmatrix} \quad W2=\begin{bmatrix} w2_1 \\ w2_2 \\ M \\ w2_{(n-1)} \end{bmatrix} \tag{9}$$

where each coefficient $w1_j$ is given in Eq.10

$$\begin{aligned} w1_j &= \frac{1}{\mu_j}\sum_{x,y} Z_{t1}(x,y)F_j(x,y) \\ \textit{where } \mu_j &= \textit{Cumulative energy of the} \\ &\quad \textit{eigen image } F_j \textit{ of class} 1 \\ Z_{t1} &= \textit{Zero mean test image for class } 1 \\ \textit{for } j &= 1..n-1 \end{aligned} \tag{10}$$

In similar way the coefficients of feature vector w2 is calculated.

B. Classification Methods

After finding the two feature vectors for each image in testing set, classification can be done to find an appropriate class for testing image. Since the number of training images in male and female category is not equal, the sizes of two feature vectors are different. The two methods of classification have been applied. The first method is nearest neighbor classification where nearest neighbor of testing image feature vector gives the class for the testing image as given by Kekre et al. [21]. Different similarity criteria are applied such as Euclidean distance, Manhattan distance, Chebyshev distance, Canberra distance, Cosine similarity and Bray Curtis distance. In the second method of classification, mean square error is calculated between the given test image and reconstructed image (image reconstructed by sum of weighted Eigen images and average image of that class). Lowest mean square error indicates the final output class for given test image [22].

V. RESULTS

The implementation of the proposed method is done in MATLAB 7.0 using a computer with Intel Core i5, CPU (2.50GHz and 6 GB RAM). The proposed technique is tested on two face databases. First one is Indian face database created by Vidit Jain and Amitabha Mukherjee [23].This database contains human face images captured in February, 2002 in the campus of Indian Institute of Technology Kanpur. This database contains face images of 61 people. All the images have a bright homogeneous background and the subjects are in an upright, frontal position. Different poses such as looking front, looking left, looking right, looking up and different emotions such as - neutral, smile, laughter and sad - are also included in the database for every individual. There are total 664 images (422 male and 242 female). Second one is a local database created by H.B.Kekre and K.Shah[24] without any constraints of lighting condition and pose variations. The faces have been selected from long video clips where the object is asked to move the face with different angle and expressions. This database contains face images of 100 people. There are total 1000 images (620 male and 380 female) in this database. Fig.1 shows the sample images from first data base and Fig.2 shows the sample images from second database.

From the first database, each person's single face is considered for training. So there are total 61 training images (male 39 and female 22). Remaining 603 images are used for testing purpose. Table I shows the number of correctly classified images for male, female and both for different algorithms. Fig.3 shows the accuracy for different methods.

Figure 1: Sample images from first database

Figure 2: Sample images from second database

Then two faces of each individual person are considered for training. So now 122 images (male 78 and female 44) are used for training and remaining 542 images are used for testing. Number of correctly classified images and their accuracy is shown in table II. The performance is also tested and tabulated in table III when training images are increased by considering 3 faces of each individual for training purpose.

With the first database, it has been observed that in Euclidean, Manhattan, Canberra, Cosine correlation and Bray-Curtis, more accuracy is achieved in female class compared to male class. In Chebyshev and classification using MSE more accuracy is achieved in male class compared to female class. In Canberra, the male accuracy is below 2% so the overall accuracy is lowest . The classification using MSE gives the best overall results. In this method both male and female accuracy is above 88% even when just 9% training data is used. Similar procedure is carried out for second database. Performances are shown in table IV, table V, table VI and Fig.4.

Table I Performance of different methods for **first database** for 61 training images and 603 testing images

Classification Methods		Number of correctly classified images					
		Male (out of 383)	%Accuracy	Female (out of 220)	%Accuracy	Total (out of 603)	%Accuracy
Nearest Neighbor using	**Euclidean**	191	49.87	214	97.27	405	67.16
	Manhattan	50	13.05	220	100	270	44.78
	Chebyshev	341	89.03	125	56.82	466	77.28
	Canberra	10	2.61	220	100	230	38.14
	Cosine Correlation	199	51.95	206	93.64	405	67.16
	Bray-Curtis	167	43.6	204	92.73	371	61.53
Classification using MSE		381	99.48	195	88.64	576	95.52

Note : Numbers in pink indicate highest number of correctly classified images and green indicate highest accuracy.

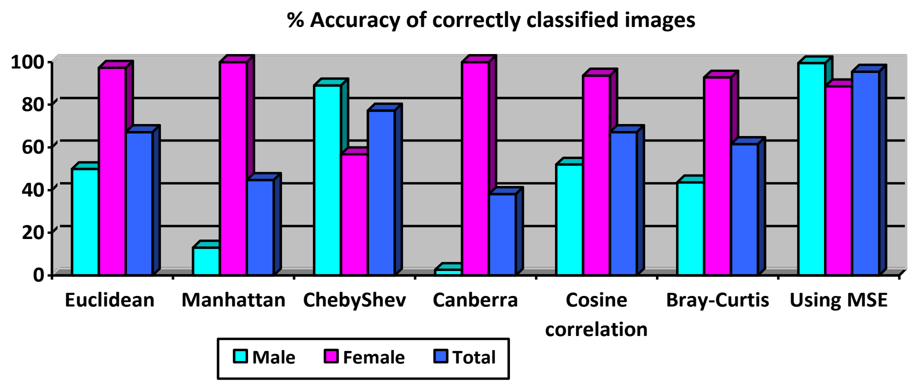

Figure 3: Accuracy of different methods for first database for 61 training images

Table II Performance of different methods for **first database** for 122 training images and 542 testing images

Classification Methods		Number of correctly classified images					
		Male (out of 344)	%Accuracy	Female (out of 198)	%Accuracy	Total (out of 542)	%Accuracy
Nearest Neighbor using	**Euclidean**	175	50.87	198	100	373	68.82
	Manhattan	47	13.66	198	100	245	45.20
	Chebyshev	317	92.15	123	62.12	440	81.18
	Canberra	3	0.87	198	100	201	37.08
	Cosine Correlation	176	51.16	188	94.95	364	67.16
	Bray-Curtis	151	43.90	188	94.95	339	62.55
Classification using MSE		342	99.42	180	90.91	522	96.31

Note : Numbers in pink indicate highest number of correctly classified images and green indicate highest accuracy.

Table III Performance of different methods for **first database** for 183 training images and 481 testing images

Classification Methods		Number of correctly classified images					
		Male (out of 305)	%Accuracy	Female (out of 176)	%Accuracy	Total (out of 481)	%Accuracy
Nearest Neighbor using	**Euclidean**	154	50.49	176	100	330	68.61
	Manhattan	35	11.48	176	100	211	43.87
	Chebyshev	285	93.44	105	59.66	390	81.08

	Canberra	6	1.97	176	100	182	37.84
	Cosine Correlation	158	51.80	167	94.89	325	67.57
	Bray-Curtis	152	49.84	164	93.18	316	65.70
Classification using MSE		305	100	161	91.48	466	96.88

Note : Numbers in pink indicate highest number of correctly classified images and green indicate highest accuracy.

Table IV Performance of different methods for **second database** for 100 training images and 900 testing images

Classification Methods		**Number of correctly classified images**					
		Male (out of 558)	%Accuracy	Female (out of 342)	%Accuracy	Total (out of 900)	%Accuracy
Nearest Neighbor using	**Euclidean**	468	83.37	310	90.64	778	86.44
	Manhattan	223	39.96	342	100	565	62.78
	Chebyshev	541	96.95	115	33.63	656	72.89
	Canberra	15	2.69	342	100	357	39.67
	Cosine Correlation	397	71.15	297	86.84	694	77.11
	Bray-Curtis	353	63.26	300	87.72	653	72.56
Classification using MSE		551	98.75	258	75.44	809	89.89

Note : Numbers in pink indicate highest number of correctly classified images and green indicate highest accuracy.

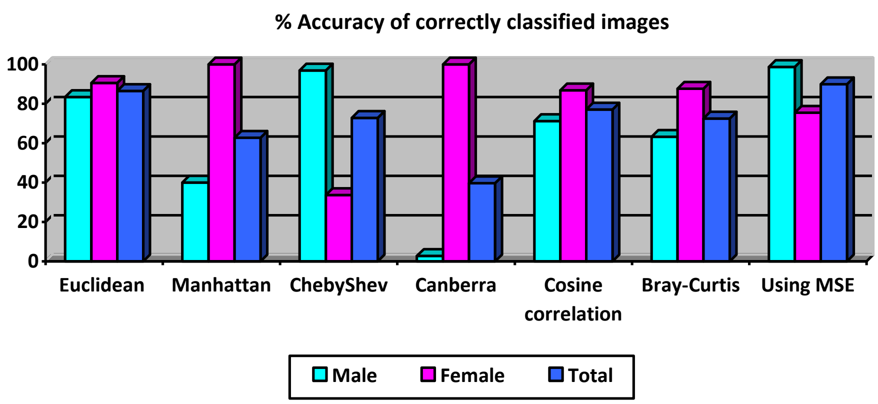

Figure 4: Accuracy of different methods for second database for 100 training images

Table V Performance of different methods for **second database** for 200 training images and 800 testing images

Classification Methods		**Number of correctly classified images**					
		Male (out of 496)	%Accuracy	Female (out of 304)	%Accuracy	Total (out of 800)	%Accuracy
Nearest Neighbor using	**Euclidean**	454	91.53	286	94.08	740	92.5
	Manhattan	187	37.70	304	100	491	61.38
	Chebyshev	495	99.80	78	25.66	573	71.63
	Canberra	9	1.81	304	100	313	39.12
	Cosine Correlation	370	74.60	286	94.08	656	82
	Bray-Curtis	335	67.54	287	94.41	622	77.75
Classification using MSE		495	99.80	233	76.64	728	91

Note : Numbers in pink indicate highest number of correctly classified images and green indicate highest accuracy.

Table VI Performance of different methods for **second database** for 300 training images and 700 testing images

Classification Methods		**Number of correctly classified images**					
		Male (out of 434)	%Accuracy	Female (out of 266)	%Accuracy	Total (out of 700)	%Accuracy

Nearest Neighbor using	**Euclidean**	406	93.55	257	96.62	663	94.71
	Manhattan	176	40.55	266	100	442	63.14
	Chebyshev	433	99.77	53	19.92	486	69.43
	Canberra	9	2.07	263	98.87	272	38.86
	Cosine Correlation	327	75.35	253	95.11	580	82.86
	Bray-Curtis	329	75.81	248	93.23	577	82.43
Classification using MSE		434	100	217	81.58	651	93

Note : Numbers in pink indicate highest number of correctly classified images and green indicate highest accuracy.

With second database it has been observed that, as the number of training images is increased from 10% to 30%, the accuracy of male and female class in Euclidean increases above 90%. If 10% data is used for training purpose then the classification using MSE gives the highest accuracy of 90%. Like with the first database, it has also been observed that in Euclidean, Manhattan, Canberra, Cosine correlation and Bray-Curtis, more accuracy is achieved in female class compared to male class. In Chebyshev and classification using MSE more accuracy is achieved in male class compared to female class. In both the databases the number of male faces is more than the number of female faces. So the number of training images for male is more than female. To test whether this factor affects the results, a subset of second database, say third database, is considered. This third database contains the faces of 30 males and 30 females. Total number of images is 600. In the beginning training is done with single faces for each individual. Then two faces and at last three faces for each individual are considered for training. Table VII, table VIII, table IX and Fig. 5 gives the results obtained with this third database.

Table VII Performance of different methods for **third database** for 60 training images and 540 testing images

Classification Methods		**Number of correctly classified images**					
		Male (out of 270)	%Accuracy	Female (out of 270)	%Accuracy	Total (out of 540)	%Accuracy
Nearest Neighbor Using	**Euclidean**	248	91.85	205	75.93	453	83.89
	Manhattan	248	91.85	219	81.11	467	86.48
	Chebyshev	238	88.15	180	66.67	418	77.41
	Canberra	179	66.3	203	75.19	382	70.74
	Cosine Correlation	235	87.04	203	75.19	438	81.11
	Bray-Curtis	221	81.85	213	78.89	434	80.37
Classification using MSE		251	92.96	263	97.41	514	95.19

Note : Numbers in pink indicate highest number of correctly classified images and green indicate highest accuracy.

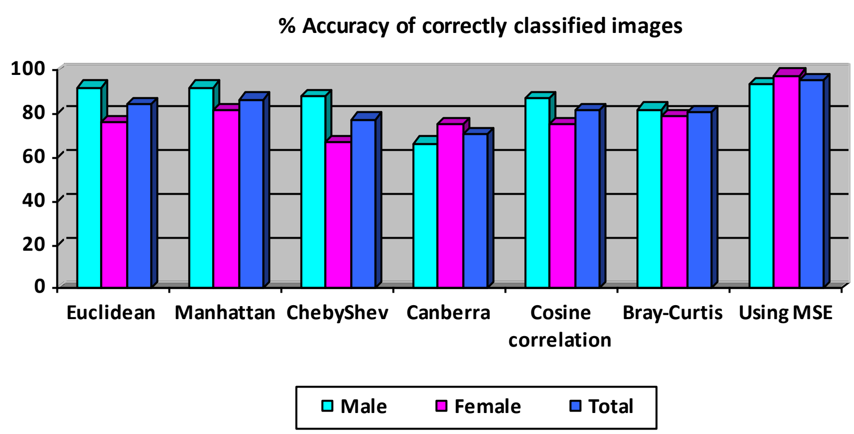

Figure 5: Accuracy of different methods for third database for 60 training images

Table VII Performance of different methods for **third database** for 120 training images and 480 testing images

Classification Methods	**Number of correctly classified images**					
	Male (out of 240)	%Accuracy	Female (out of 240)	%Accuracy	Total (out of 480)	%Accuracy

Nearest Neighbor using	**Euclidean**	237	98.75	171	71.25	408	85
	Manhattan	238	99.17	168	70	406	84.58
	Chebyshev	217	90.42	144	60	361	75.21
	Canberra	182	75.84	174	72.5	356	74.17
	Cosine Correlation	216	90	188	78.33	404	84.17
	Bray-Curtis	206	85.83	189	78.75	395	82.29
Classification using MSE		232	96.67	239	99.58	471	98.13

Note : Numbers in pink indicate highest number of correctly classified images and green indicate highest accuracy.

Table IX Performance of different methods for **third database** for 180 training images and 420 testing images

Classification Methods		**Number of correctly classified images**					
		Male (out of 210)	%Accuracy	Female (out of 210)	%Accuracy	Total (out of 420)	%Accuracy
Nearest Neighbor using	**Euclidean**	209	99.52	173	82.38	382	90.95
	Manhattan	208	99.05	166	79.05	374	89.05
	Chebyshev	196	93.33	125	59.52	321	76.43
	Canberra	177	84.29	163	77.62	340	80.95
	Cosine Correlation	194	92.38	180	85.71	374	89.05
	Bray-Curtis	197	93.81	185	88.10	382	90.95
Classification using MSE		204	97.14	210	100	414	98.57

Note : Numbers in pink indicate highest number of correctly classified images and green indicate highest accuracy.

When equal number of images for male and female is used for training purpose, it has been observed that the accuracy of male classification has increased in nearest neighbor classification methods. Also it has been observed that the difference between male and female classification accuracy is reduced. Classification using MSE gives very high overall accuracy (above 95%). Fig.6 shows the reconstruction of sample male and female test image from the first database using both the Eigen spaces. For female test image, reconstructed image using female Eigen space shows lower MSE compared to the MSE obtained between given test image and reconstructed image using male Eigen space. Similar results are observed for male test image.

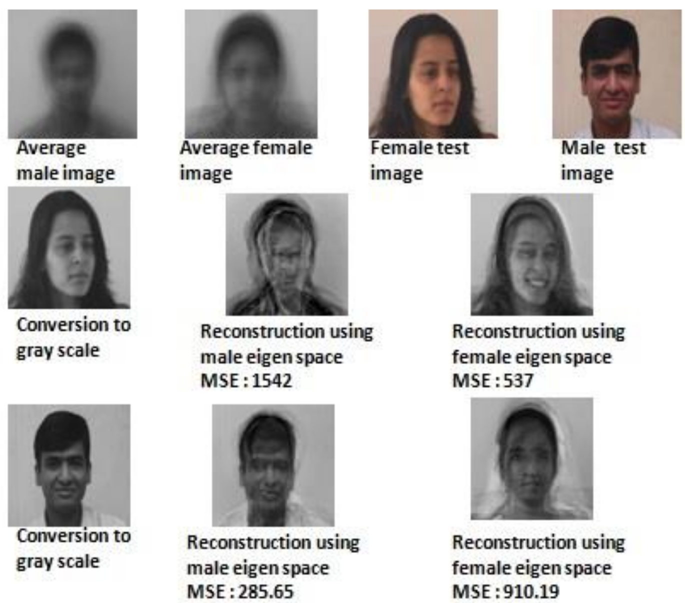

Figure 6: Reconstruction of 2 test images in '**Classification using MSE**' method

VI. CONCLUSIONS

Traditionally PCA is applied to all training images together. This paper presents a method where PCA is applied to each training class separately. Hence male Eigen co-ordinate system and female Eigen coordinate system are made. After forming Eigen face images and feature vectors, a different approach of classification is presented and its performance is tested with traditional nearest neighbor classification method. Even with nearest neighbor classification method, a variety of similarity measures are used and their results are shown. The proposed method is applied on two different databases. All images in the first database have same background whereas second database contains images taken in an uncontrolled environment. All the algorithms are robust since they give equally well performance in second database. After a lot of experimentation, performance wise the nearest neighbor classification methods using distances such as Euclidean, Manhattan, Canberra, Cosine correlation and Bray-Curtis show the high accuracy in female class classification than male class classification. One reason of high accuracy in female category is the number of training images in female category are less. This is verified by using third database with equal number of male and female images where the male and female accuracies are close to each other. With the first database, for 9%, 18%, 27% training data, best method is classification using MSE which gives overall performance from 95% to 97%. With second database, for 10% training data, the best method is classification using MSE which gives overall performance of 90%. For 20% and 30% training data, the best method is nearest neighbor classification using Euclidean distance which gives 93% and 95% overall accuracy. It may be observed that the technique proposed in this paper gives high accuracy of 95% with a very small training data set as low as 9%.

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