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Statistical Measures to Test the Stability of Face Recognition Approach: Duplicating Human Faces based on Cross-correlation Study

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Abstract

This literature work suggests a novel approach for rearranging train set developed by us. The rearrangement of train set is based on cross-correlation study of facial images of individual subjects. The new approach, tried five factual human face acknowledgment techniques with standard and Senthilkumar, face databases. Further, the stability of our proposed method tested with different statistical measures such as rank, kurtosis, mean, median, mode and skewness using large face database FERET. The experimental results show that, our approach of rearranging train sets certainly improves recognition accuracy compared to traditional approaches.

Keywords: *Correlation study, face database, face recognition, face recognition algorithms, kurtosis, rank, recognition accuracy, skewness, training set*

INTRODUCTION

In order to test existing standard Face Recognition Algorithms (FRA), we have developed three small face databases, Senthil database version1.0 [1], Senthil IRTT face database version1.1 [2] and Senthil IRTT face database version1.2 [3]. These databases are created based on the case study of standard face databases discussed in [4, 5].

In our proposed approach, we have shown improved recognition rate by performing correlation studies on Yale face database [6]. Each subject in face databases is treated as classes. The class has many faces. Each face of all classes is performed correlation with faces in inter class and intra classes. The low correlated faces affect classification accuracy and the faces to be trained are arranged according to correlation coefficient. Performance of different face recognition algorithms and suggest an approach based on correlation between facial images, to improve face recognition accuracy [7]. The proposed approach and traditional approaches are tested with a small face database contains simple frontal images like Yale database. Then they are tested with large database contains occluded, illuminant variant and different pose variant face images like FERET (Face Recognition Technology Face Database) [8, 9]. The observational results are tabulated in section 4, which shows that the proposed approach significantly improves the recognition accuracy for small and large standard face databases. Section 5 draws conclusions and future work.

OUR OWN FACE DATABASES

Senthil Face Database

The first set database consists of 80 face images and are cropped to 160x188 pixel size. Each human face has 16 different sets. An example face is shown in Fig. 1.

Senthil IRTT Face Database

The second version of Senthil data set consists of 317 faces for 13 IRTT college under graduate students. The digital camera which has been used for capturing faces has resolution of 14:1 Megapixels. The 2D faces are cropped to 550x780 and downscaled by 5. Face dataset consists of 12 males and 1 female. Example faces of first subject are shown in Fig. 2. The faces have different expressions with little makeup, scarf, poses and hat also.

Senthil IRTT Female Face Database

The third version of Senthil data set consists of both color and gray scale faces. The ten subjects used for testing consist of ten faces per subject, totally 100. The pixel resolution of the faces captured through digital camera is 480x640 and they are resized to 100x100. The ten female faces in this database are shown in Fig. 3.

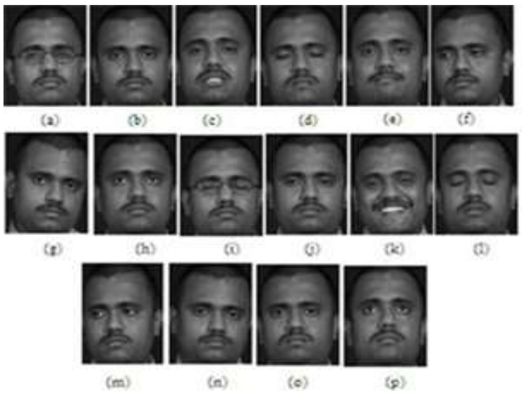

Figure 1: *Sample images for one subject of the Senthil database.*

Figure 2: *Sample faces of subject01 in Senthil IRTT face database version 1.1.*

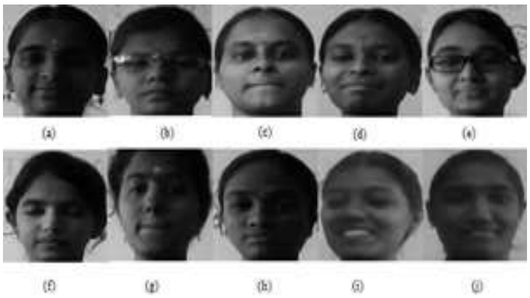

Figure 3: *10 subjects of Senthil IRTT Female face database version 1.2.*

FACE RECOGNITION ALGORITHMS

Eigen Face Recognition

The 1DPCA depends on the Eigen vectors and Eigen values of 2D face images [10, 11]. The face identification work consists of two phases: Training and Recognition Phases. The Eigen vectors are obtained from the covariance matrix as in eq (1):

$$covA = A^T A \qquad (1)$$

Where, 'A' is the set of 'M' training images. The Eigen vectors, then arranged in ascending order (i.e.) the top Eigen vectors have maximum power. This is done in the training phase.

In the testing phase, the test images are projected into feature space and feature vectors are calculated. The classification is based on the distance as in (2) between the train set feature vectors and test set feature vectors.

$$D(j,i) = \sqrt{\sum_{i=1}^{M2} \sum_{j=1}^{M} \left(R(:,i) - T(:,j)\right)^2} \qquad (2)$$

From eq(2), 'R' and 'T' are the test and train feature vectors respectively. The number of face images in the test set is 'M2'.

Fischer Discriminant Analysis

In LDA [12, 13], a set of vectors 'W_{LDA}' are found out, such that the Fisher Discriminant Criterion is maximized as in eq(3).

$$W_{LDA} = \arg\max_x \frac{W^T \bullet S_B \bullet W}{W^T \bullet S_W \bullet W} \qquad (3)$$

From eq(3), 'S_B' is the between class scatter matrix defined in (4) and 'S_W' is the within class scatter matrix defined in eq(5). The 'W' is the weighted principle components and 'x' is the data belongs to a particular class, to be maximized.

$$S_B = \sum_{i=1}^{c} N_i \bullet (\mu_i - \mu) \bullet (\mu_i - \mu)^T \quad (4)$$

$$S_W = \sum_{i=1}^{c} N_i \bullet (x_i - \mu_i) \bullet (x_i - \mu_i)^T \quad (5)$$

The 'μ_i' in eq(4) is the mean vector of samples belonging to class 'i' and 'μ' is the mean image of complete database. In eq(4), 'N_i' is the number of training samples in class 'i', 'c' is the number of distinct classes and 'x_i' represents the set of samples belonging to the class 'i'. The classification is based on the minimum Euclidean distance as in eq(2).

Independent Component Analysis

The matrix eq(6) obtained in ICA is important [14]. This removes the statistics like mean and covariance and equalize the variances.

$$W_z = 2*(COV(P_m^T))^{-1/2} \quad (6)$$

The matrix W_z is calculated from the covariance of principle components P_m as given in eq(6). The weight matrix learned by ICA is 'W' and it is updated by the gradient update rule given in eq(7).

$$W = W+L\ (I+Y\ U^T)W \quad (7)$$

In eq(7), 'L' is the learning rate, 'I' is the identity matrix and 'Y' is the postsynaptic activation function. The ICA representation of the face images 'B' based on the set of 'M' statistically independent feature images 'U' is given in eq(8).

$$B = R_m W_I^{-1} \quad (8)$$

In eq(8), 'R_m' is the feature projected vector and 'W_I' is the whitening matrix, The human face recognition performance is calculated for the coefficient vectors 'B' by the nearest neighbor algorithm, with cosine similarity measure.

Kernel Principal Component Analysis

The KPCA face recognition is similar to the 1DPCA face recognition method, except that Eigen vectors are evaluated from polynomial kernel 'K' matrix as in eq(9) [15].

$$K_{ij} = K(X_i,X_j) = \Phi(X_i) .\Phi(X_j) \quad (9)$$

From eq(9), 'X' is the training samples of size (N_1, pxq), 'Φ' is the polynomial function of 'X', 'N_1' is the number of individuals in the train set. The 'pxq' gives the dimension of the face image.

Two Dimensional Principal Component Analysis

Let 'A' be the given set of 2D train images of equal sizes 'p'x 'q'. The average image of all training image samples is denoted by $\overline{A}$. Then the covariance matrix in 2DPCA of size 'q'x'q' is in (10) as [16],

$$COV_{2D} = \frac{1}{M} \sum_{j=1}^{M} \left(A_j - \overline{A}\right)\left(A_j - \overline{A}\right)^T \quad (10)$$

The nearest classifier is used for the classification of test images based on the minimum distance between train set and test set.

EXPERIMENTAL RESULTS

Performance Comparison of Different FRAs

The experiments are conducted on following five databases: ORL face database Yale face database, Senthil database version1.0, Senthil IRTT database version1.1 and Senthil IRTT database version1.2 [17].

Out of five databases, the last three databases are developed by us. Five statistical face recognition algorithms 1DPCA, FDA, KPCA, ICA and 2DPCA are used to try these databases [18]. Table 1 compares the recognition time, feature vector size, number of faces in test set recognized and recognition rate.

The recognition rate is used to evaluate the performance of face recognition techniques. The recognition time varies depending on face recognition methods. The recognition time is high for FDA due to Eigen vectors calculation from scatter matrices. The ORL database requires more time to test, compared to other databases due to its size of the train set and the test set. The ICA method shows better results for Senthil IRTT student database version1.1. This is due to it removes second order statistics of face images of individuals.

Our Approach Based on Correlation Study

The correlation is an important statistical parameter to measure the similarity between two images. The fact is correlations between the faces of the subjects, decide the recognition accuracy in face recognition. A detail correlation study has been made using the Yale database in order to know its effect on face recognition.

The correlation between any two images can be calculated using the following formula,

$$r = \frac{\sum_p \sum_q (A_{pq} - \bar{A})(B_{pq} - \bar{B})}{\sqrt{\sum_p \sum_q (A_{pq} - \bar{A})^2 \sum_p \sum_q (B_{pq} - \bar{B})^2}} \quad (11)$$

In eq(11), $\bar{A}$ is the mean of whole image A and $\bar{B}$ is the mean of the whole image B.

Let X_i be the set of face images, where, i =1, 2,..n individuals and each set has 'm' number of subsets $\{x_1, x_2 \ldots x_m\}$. The subsets in sets, are all of equal dimension [p, q]. Since 'n' sets there will be 'n' number of classes 'Cn'.

The following decisions are included in our approach:

- If correlation of a face image x_j with intra class face images is $r(x_j,x_l)<0.5$ and with inter class are $r(x_j,X_i)<0.5$, then the corresponding face image from the database must be in the train set.
- If $r(x_j,x_l)$ is $\min\{r(C_n)\}$, the corresponding face image should be duplicated in train set in order to improve recognition accuracy. The third and sixth face image of each subject has very low correlation in a class, because they are occluded faces (they have background image themselves). A sample from subject02 is shown in Fig. 4.
- The face images 3 shown in Fig. 5 and 47 shown in Fig. 6 have very low correlation in both the cases (i.e.) they have less than 50% correlation coefficient with intra class faces and inter class faces shown in Fig. 7. The face image 3 of subject01 is placed in train set and face image 47 belongs to subject05 is also placed in the train set.
- The better recognition accuracy is obtained for all FRAs, when the train set is formed from first image to the 6^{th} image of each subject (s_1 to s_6). The corresponding result is tabulated in Table 2.

From the above experiment on the Yale face database using standard statistical FRAs, we suggest following two corollaries:

Corollary 1: Facial images with very low correlation coefficient must affect the recognition rate.

Corollary 2: Facial images with very low correlation coefficient must be in the train set in order to improve the recognition accuracy.

Table 1: *Experimental results for various face databases testes with different face recognition algorithms.*

Face Databases Face Recognition Algorithms		**ORL Database**	**Yale Database**	**Senthil Database**	**Senthil IRTT Female Student Database**	**Senthil IRTT Student Database Ver1.1**
No. of Faces in Train and Test set	Train set	5	5	8	5	Varies for Different Subjects
	Test set	5	5	8	5	
Eigen Face	Recognition time(sec)	77.3	36.533	42.588	27.737	73.343
	Feature vector	37	37	37	37	37
	No. of Faces Recognized	187	61	36	41	31
	Recognition rate	93.5	81.33	90	82	65.957
FDA	Recognition time(sec)	106.917	62.525	70.88	52.203	51.06
	Feature vector	200x37	75x37	40x37	50x37	47x37
	No. of Faces Recognized	192	59	37	33	24
	Recognition rate	96	78.66	92.5	66	51.06
KPCA	Recognition time(sec)	10.1875	43.65	2.125	5.79	8.828
	Feature vector	200x37	75x37	40x37	50x37	47x37
	No. of Faces Recognized	185	61	36	41	32
	Recognition rate	94	81.33	90	82	68
ICA	Recognition time(sec)	69.608	61.136	20.731	35.658	53.125
	Feature vector	200x37	75x37	40x37	50x37	47x37
	No. of Faces Recognized	170	64	34	39	37
	Recognition rate	85	85.33	85	78	78.72
2DPCA	Recognition time(sec)	64.99	85.33	18.476	50.774	54.91
	Feature vector	112x3	320x3	140x3	103x3	100x3
	No. of Faces Recognized	192	64	38	43	29
	Recognition rate	96	85.33	95	86	65.77

(The algorithms are implemented in Open Source software Scilab and Its Atoms IPD, SIVP. The Scilab software programs are tested with CPU i3 core with 4GB RAM).

The block diagrammatic representation in Fig. 13 gives an overview of our method. The faces of each individual are treated as a separate class and correlation of faces is performed between faces in the same class and different classes.

The pseudo code is shown in Fig. 14 and the Table 2, compares our approach and the traditional approach for Yale database. The Table 3 shows four strategies. In the third strategy, the first six faces of each subject are arranged in train set. This strategy shows better result in all four strategies we used. The fourth strategy also gives a good recognition accuracy along with the third. The second strategy shows poor performance in all four strategies. The Table 3 also shows the number of faces in the test set and the number of faces recognized correctly. Note that, the equal number of faces per class is used in both train set and test set.

Figure 4: *Faces 3 and 6 of subject02 (occluded faces).*

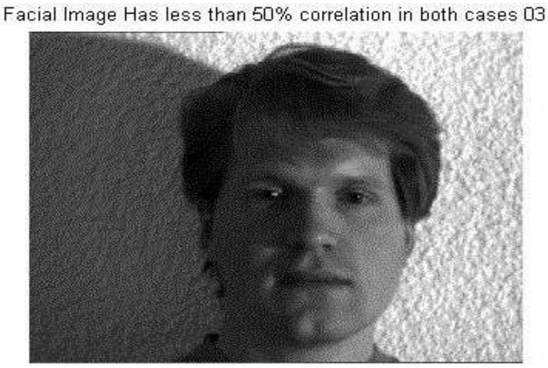

Figure 5: *Face image03 of Subject01 has less than 50% correlation in both inter class and intra class with both intra class and inter class faces.*

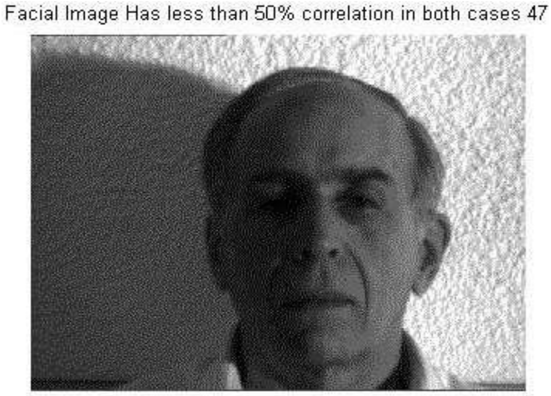

Figure 6: *Face Image03 of Subject05 has less than 50% correlation with both intra class and inter class faces.*

From Table 3, the Eigen face, KPCA and 2DPCA show better performance for strategies 3 and 4. ICA shows best performance for strategies 1 and 3. The FDA has shown better accuracies for strategies 2 and 4. The Scilab function for automatic rearrangement of faces in a train set from the complete set of face database based correlation study is shown in Fig. 9.

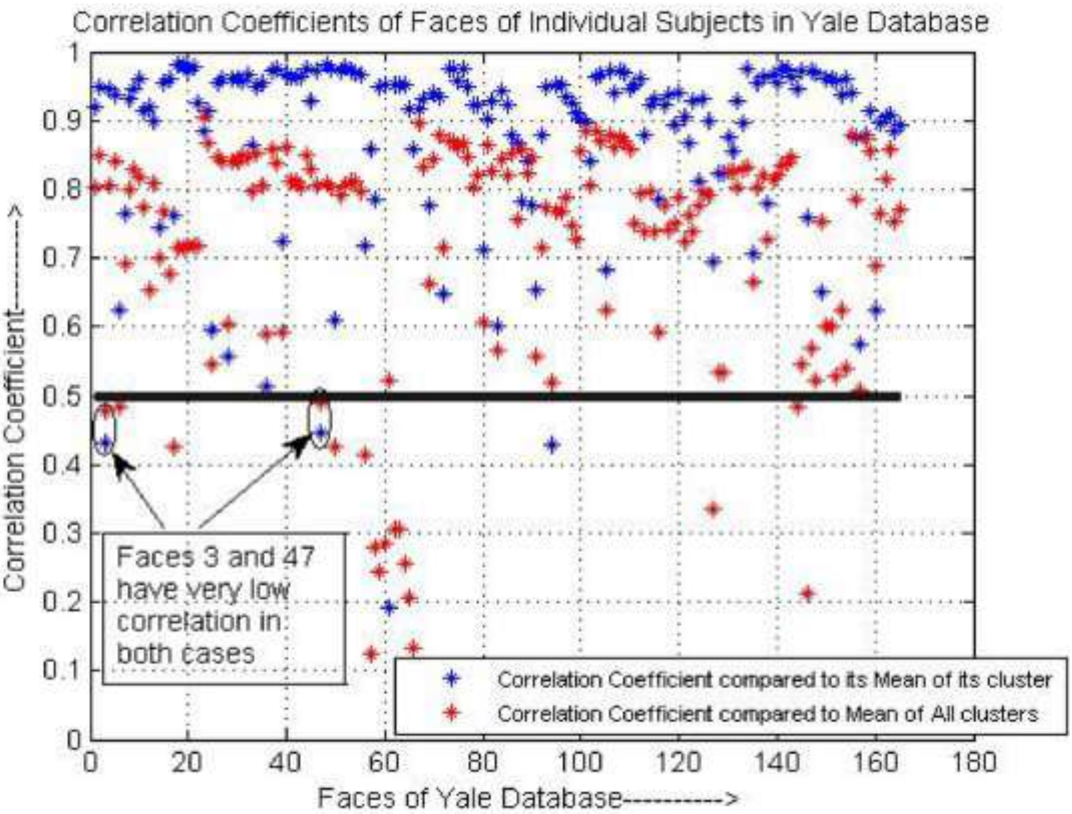

Figure 7: *Correlation coefficients of faces of individual subjects in Yale database.*

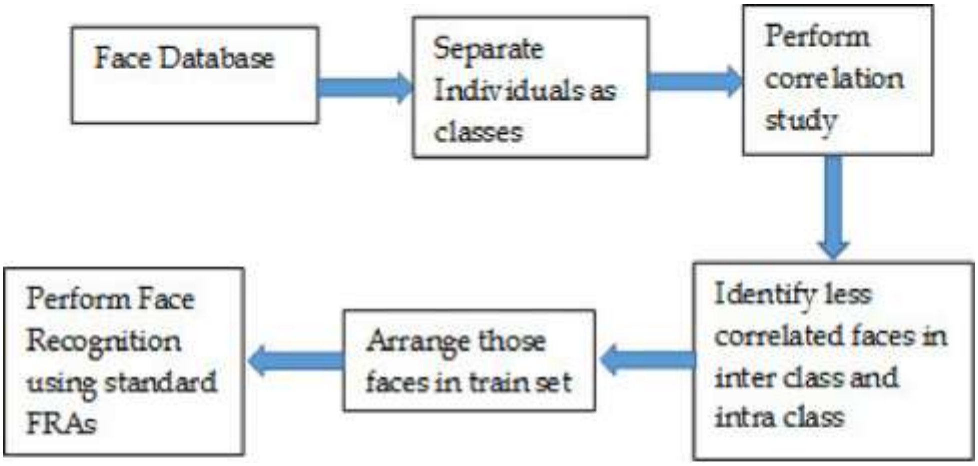

Figure 8: *Block schematic representation of our approach.*

```
function [ ]= trainset(X, threshold, corr_coeff1, corr_coeff2,
                        numimgs)
   //X is the face image to be placed in train set or test set
   //threshold = 0.5 for Yale face database
  //corr_coeff1- is the correlation coefficient obtained for the
given face/image with mean image its own cluster
 //corr_coeff2- is the correlation coefficient obtained for the
given face
   //image with mean image of entire database
   //numimgs- number of images in database

for i =1:numimgs
  imgname = getstring(i);
  if((corr_coeff1(i)<threshold)&(corr_coeff2(i)<threshold))
        imwrite(X(i,:,:),'trainset\imgname');
   end if
end
endfunction
```

Figure 9: *Scilab function for automatic rearrangement of face images.*

Table 2: *Comparison of recognition accuracy for our approach and traditional approach.*

Approach	FRA	Recognition Accuracy for Yale database
Traditional Approach (First Five in train set)	EigenFace	81.33
	FDA	78.66
	KPCA	81.33
	ICA	85.33
	2DPCA	85.33
Our Approach (Low Correlated faces in train set)	Eigen Face	95.55
	FDA	80.00
	KPCA	95.55
	ICA	93.33
	2DPCA	96.66

***Table 3:** Comparison of different strategies for different FRAs using Yale face database.*

Strategy	Eigen Face	FDA	KPCA	ICA	2DPCA
1. First Five Faces of Each class in train set	81.33 (61/75)	78.66 (59/75)	81.33 (61/75)	85.33 (64/75)	85.33 (64/75)
2. 6th Face to 10th Face of Each class in train set	72 (54/75)	85.33 (64/75)	72 (54/75)	72 (54/75)	74.66 (56/75)
3. First Six Faces of Each class in train set	95.55 (86/90)	80.00 (72/80)	95.55 (86/90)	93.33 (84/90)	96.66 (87/90)
4. 6th Face to 10th Face of Each class + including low correlated occluded Face (3rd face) in train set	90 (81/90)	86.66 (78/90)	90 (81/90)	78.88 (71/90)	91.11 (82/90)

Testing Our Approach with Large Database FERET

The proposed approach also tested with large set of face database FERET (Face Recognition Technology Face Database) developed by National Institute of Standards and Technology. The total number of subjects available is 994 and total 11,338 face images available in entire database. A sample of 100 subjects, each with 5 faces are selected to test our approach. First, the recognition rate for different face recognition algorithms tested with FERET database are obtained.

A sample of 5 tests (n=5) is done for different feature vector size. Then, based on these sample tests, the following statistical parameters are evaluated: mean, median, mode, range, standard deviation, variance and confidence intervals [19, 20]. The mean is calculated by taking the average value of recognition rate obtained for five tests. The median is the center value and mode are the most frequent value. Range can be calculated from the highest recognition rate and lowest recognition rate for a particular FRA and approach. The mean and standard deviation are unknown and for small ample size student's t-distribution is preferred to find intervals for 95% confidence. The confidence limits are the lower and upper boundaries of a confidence interval. A two-tail test is performed. In a t-distribution for a sample of size 'n', the t-distribution will have n-1 degrees of freedom. The critical value for 95% confidence is 0.025. In this case, the standard deviation 'σ' is equal to the estimated standard deviation 'S_t' is given in eq (12).

A population with unknown mean and unknown standard deviation, a confidence interval for the population mean '$\bar{x}$', in a simple random sample(SRS) with size 'n' is given in eq(13), where 't*' is the upper critical value of the t-distribution with n-1 degrees of freedom, t(n-1).

$$S_t = \frac{\sigma}{\sqrt{n}} \tag{12}$$

$$Confidence\_Interval = \left[\left(\bar{x} - t^* * S_t\right), \left(\bar{x} + t^* * S_t\right)\right] \tag{13}$$

The face images are used as it is in downloaded database. Since, the face images are tested without face portions cropped, low recognition accuracies are obtained for face recognition algorithms such as Eigen Face, KPCA and 2DPCA. For all the three algorithms the proposed approach shows better recognition rate compared to traditional approach as given in Table 4. The recognition rate can still be improved by cropping the face portions alone in the images. The mean value is high for a 2DPCA method for both approaches. Since in 2DPCA feature extraction directly done from 2D image, the range is very high for 2DPCA. Due to this similar reason, the sample standard deviation and variance are also very high for 2DPCA.

The Fig. 10 shows the confidence interval bar plot for different FRAs. The upper limit for proposed approach is more or less same for all FRAs. The range plot is shown in Fig. 11. For KPCA and Eigen Face, the range is minimum comparing proposed approach with existing methods, whereas, for 2DPCA the same range is obtained for both approaches. Fig. 12 shows a comparison of face recognition accuracy for different FRAs and for various feature sizes tested with FERET database.

Table 4: *Comparison of our approach and traditional approach for FRAs using FERET face database using different statistical parameters (which are based on recognition accuracy).*

Statistical Parameters	Traditional Approach			Our Approach		
	Eigen Face	**KPCA**	**2DPCA**	**Eigen Face**	**KPCA**	**2DPCA**
1. Mean	28.782	28.782	32.52	62.42	62.3	63.53
2. Median	28.28	27.77	32.82	62.62	62.12	62.62
3. Range	3.03	4.04	9.6	2.52	2.02	9.6
4. Mode	27.77	27.77	28.78	62.62	62.12	62.62
5. Standard Deviation	1.1516	1.5324	3.4498	0.8186	0.7558	1.369
6. Variance	1.3261	2.3483	11.9012	0.67	0.5713	1.8742
7. Confidence Interval	(25.5852,31.9788)	(24.5281,33.0359)	(22.9434,42.0966)	(60.1476,64.6924)	(60.2239,64.4201)	(59.7297,67.3303)

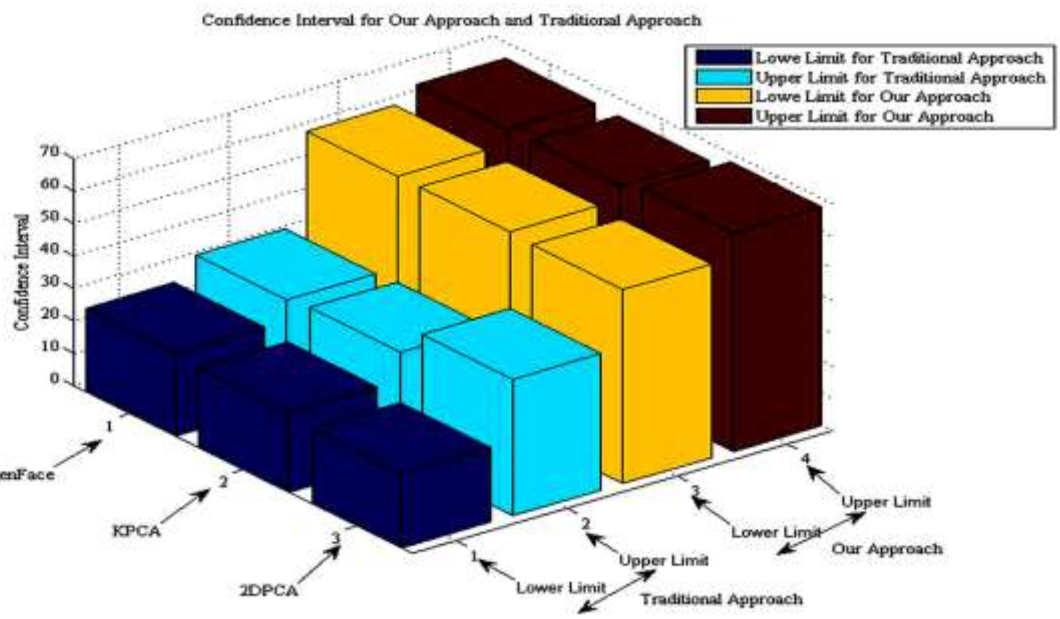

Figure 10: *Confidence interval for proposed and traditional approaches tested with FERET face database for different FRAs.*

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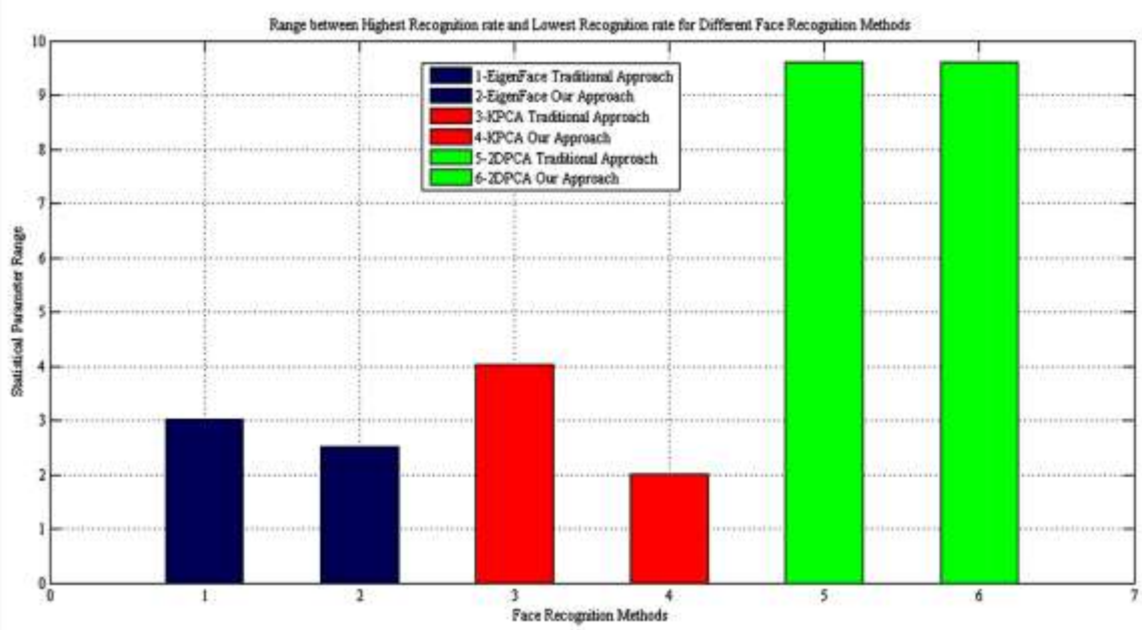

Figure 11: *Range (obtained for percentage recognition accuracy) for different FRAs and the two approaches.*

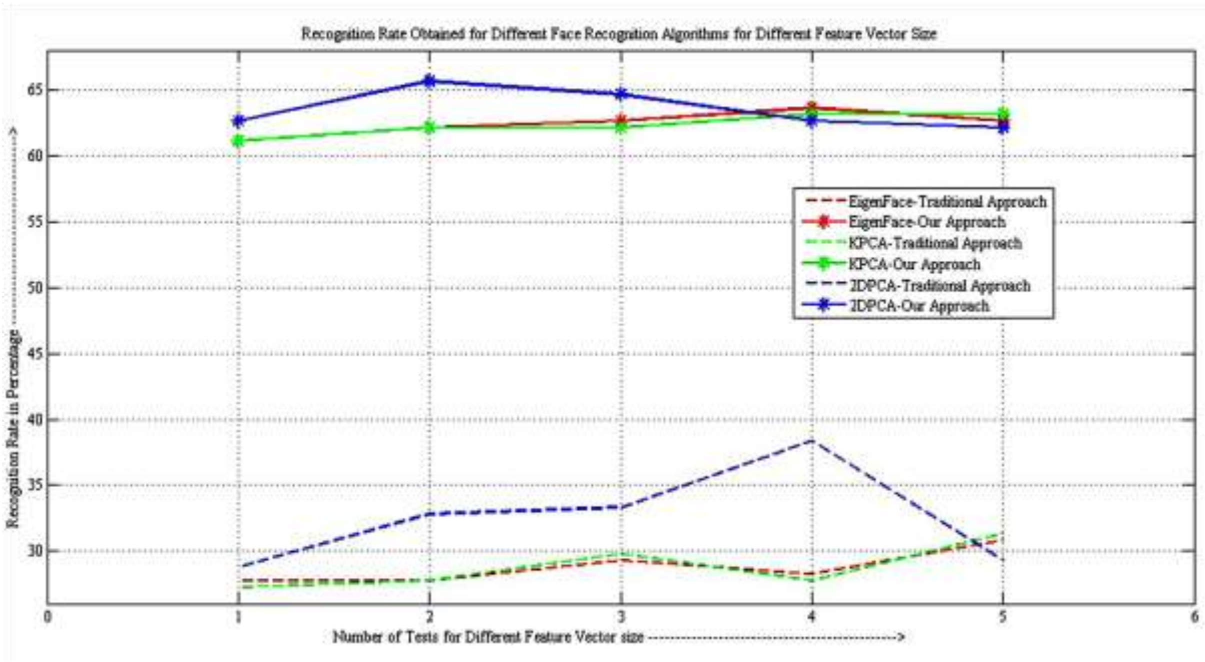

Figure 12: *Recognition rate in percentage for proposed and traditional approaches tested with FERET face database for different FRAs.*

CONCLUSION

After testing the proposed method, other problems may arise depending on the size of facial images and recognition algorithms. Subsequent to performing piece highlight extraction in KPCA, the framework isn't reacting appropriately for facial grouping because of enormous face picture size. We are as yet dealing with these two issues.

From Table 3, the strategy 3 gives the best recognition accuracy. In this strategy, the occluded faces in each subject (i.e.) left light and right light faces are placed in train set, results in better accuracy.

The correlation study has to be extended for all other databases including our databases. Then only the actual stability of our new approach can be found out. Presently we are involved in the development of a new algorithm for automatic rearrangement of train set based on unsupervised learning. Our aim is to make our algorithm fit for other PCA based face recognition methods such as: 2DKPCA, Sparse 2DPCA, Robust PCA, Bi2DPCA, MPCA and multidirectional 2DPCA.

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