FACE RECOGNITION USING PCA AND LDA: ANALYSIS AND COMPARISON

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Abstract: Computer recognition of the human faces has evolved as the most successful and demanding field in the computer science world and in particular Computer Vision. A lot of research work has been done in this field in the last two decade. Numerous algorithms have been projected and they have been experimented with different face image database available. In this paper, a comparative study has been carried out using the two basic and the most important appearance based face recognition methods viz, PCA and LDA. These two techniques for face recognition has been implemented and evaluated with different databases like UMIST, Yale etc. The outputs are compared by using accuracy rate.

Keywords: Face Recognition, PCA, LDA, ORL, FERET, Scatter Matrices

INTRODUCTION

In the last decade biometric based technology like fingerprint, iris recognition, RFID cards, voice recognition and retina recognition has emerged as the most promising option for the recognition of the individual. But in many applications the biometric technique will be unsuccessful because they are quite time consuming, inefficient and could be costly as well. One of the most important drawback of the biometric technique is that one cannot ask the individual to come and put his/her finger on a slide for the finger recognition or an eye in front of the camera for iris recognition or do something similar. So, a system is needed which is similar to the human eye in some sense to identify a person. Thus, in order to carter this need and by observing the human psychophysics, face recognition emerged as a triumphant technique. Here the system does not need the voluntary action by the individual because the face image can be acquired from a distance by a camera.

There are diverse approaches for face recognition, but appearance based face recognition technique has delivered a lot in this field.

FACE RECOGNITION TECHNIQUES

Appearance Based Approach

This approach by and large operates directly on an image based representation (array of pixel intensities), such as PCA and LDA based methods. PCA approach dates back to H. Murase and S.K. Nayar [1] and LDA approach was first proposed by Swets, J. Weng [2]. The comparison between these two techniques has also been done by Martinez and Kak [3]. Thus this paper presents a comparative analysis on the two basic face recognition methods, PCA and LDA and their variants using the different databases used for face recognition as under:

PRINCIPLE COMPONENT ANALYSIS

Principal components analysis (PCA) is a technique commonly used for dimensionality reduction in computer vision, particularly in face recognition as described in M. Turk and A. Pentland [4].

VARIANTS OF PCA

Sppca

Songcan Chen and Yulian Zhu [5] proposed a subpattern-based principle component analysis (SpPCA). This method directly operates on a set of partitioned subpatterns of the original pattern rather than whole pattern itself. These subpatterns are formed from a partition for an original whole pattern and utilized to compose multiple training subpattern sets for the original training pattern set. In this way, SpPCA can separately be performed on individual training subpattern sets and finds equivalent local projection sub-vectors, and then uses them to extract local sub-features from any given pattern. These extracted sub-features from individual subpatterns are synthesized into a global feature of the original whole pattern for subsequent classification.

The proposed method has been experimented with a number of datasets. ORL database was used for face image dataset and SpPCA gave 95.45 % accuracy which is higher than that of PCA which gave only 93.05% accuracy.

2DPCA

J. Yang and D. Zhang [6] developed two-dimensional principal component analysis (2DPCA) for image feature extraction. The essence of 2DPCA is that it computes the eigenvectors of the so-called image covariance matrix without matrix-to-vector conversion. Instead, an image covariance matrix can be constructed directly using the original image matrices. In comparison to the covariance matrix of PCA, the size of the image covariance matrix using 2DPCA is much smaller. As a result, 2DPCA has three important advantages over PCA. Firstly, the 2D spatial information of the sample is well conserved by directly via original two dimensional image matrices rather than one-dimensional vector. Secondly, the 2DPCA method is working on the row direction of image, the dimension of which is much smaller than that of covariance in PCA. The last one is that 2DPCA can effectively avoid the small sample size (SSS) problem, which will achieve good recognition accuracy when even only one sample is contained in each class.

The method proposed was tested against three image database namely ORL, AR and Yale. These three databases were used to test for different purposes. The ORL database was used to evaluate the performance of 2DPCA under conditions where the pose and sample size are varied which gave the following result as shown in table 1:

Strategy	Method	Recognition rate
Using the first five images for training set	Fisherfaces	94.5%
	ICA	85.0%
	Kernel Eigenfaces	94.0%
	2DPCA	96.0%
Leave-one-out	Fisherfaces	98.5%
	ICA	93.8%
	Eigenfaces	97.5%
	Kernel Eigenfaces	98.0%
	2DPCA	98.3%

Table 1: Comparison of 2DPCA with other method using ORL Database

The AR database was employed to test the performance of the system under conditions where there is a variation over time, in facial expressions, and in lighting conditions which gave the following result as shown in table 2:

The Yale database was used to examine the system performance when both facial expressions and illumination are varied which gave the following result as shown in table 3:

Auto-Associative Neural Networks and Eigenbands Fusion

G. D. C. Cavalcanti and E. C. B. C. Filho [7] describe an approach for the verification of the faces using Auto-associative Neural Networks and Eigenbands fusion. The problem of frontal face verification was tried to solve. Each face was partitioned in horizontal bands in order to select discriminative facial features as shown in the figure 1. Each band has a facial feature associated to it like hair, forehead, eyes, nose, mouth and chin. Over these bands Principal Component Analysis (PCA) was applied. The best principal components of each band were selected which was based on a cutoff point calculated by the total amount of the variance in order to form a representative face vector (eigenband vector). For the classification purpose, it used an Auto-associative Neural Network.

Experiment		Recognition Rate (%)	Time of Feature extraction (s)	Size of the Matrix
Varation over time	PCA	66.2	434.87	840X840
	2DPCA	67.6	16.26	40X40
Facial Expression	PCA	94.7	130.42	240X240
	2DPCA	96.1	7.25	40X40
Illumination (mean)	PCA	78.0	129.56	240X240
	2DPCA	89.8	8.32	40X40

Table 2: Comparison of 2DPCA with PCA using AR Database

Method	Recognition accuracy
Eigenfaces	71.52%
ICA	71.52%
Kernel Eigenfaces	72.73%
2DPCA	84.24%

Table 3: Comparison of 2DPCA with other method using YALE Database

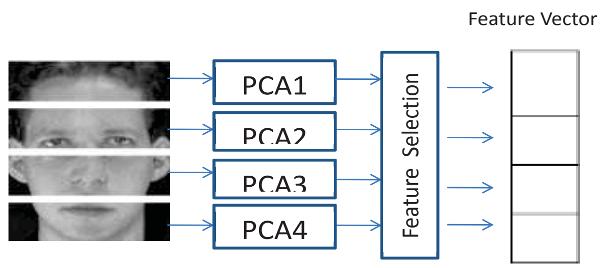

Fig. 1 Feature vector construction [7].

The combination of eigenbands approach to extract discriminant features from faces and auto-associative neural network for classification gave the lower error verification rates than that of PCA.

mPCA

Rajkiran Gottumukkal and Vijayan K.Asari [8] proposed a new face recognition method named Modular Principal Components Analysis (mPCA). This paper curb out the problem of inaccuracy in face recognition by PCA due to varying facial expression, illumination and head pose. In the modular PCA method the face images are divided into smaller images and the

PCA method is applied on each of them. Since, some of the local facial features of an individual do not vary even when the pose, lighting direction and facial expression vary. Therefore, variations in expression or illumination in the image will only affect some sub-images rather than the whole image in PCA, and thus the local information of a face image can be better represented. This method experimented against PCA technique with UMIST and Yale image database. Though, the proposed method did not show the significant improvement over the PCA method under the condition of varying pose. But, for the variation in illumination and facial expression the proposed method had shown the better result than that of the PCA.

WPCA

V. D. M. Nhat and S. Lee [9] proposed a new PCA-based method for face recognition. The proposed method is PCA-based which can overcome weakness of the traditional PCA method. PCA may fail to emphasize the discrimination between the clusters. The directions that maximize the scatter of the data might not be as adequate as to discriminate between clusters. Thus, the new PCA-based scheme can straightforwardly take into consideration data labelling, and makes the performance of recognition system better. The proposed method is tested on the ORL and Yale face image database and compared with the traditional PCA. WPCA gave better recognition rate than PCA.

WMPCA

A. P. Kumar, S. Das, and V. Kamakoti [10] proposed Weighted Modular Principle Component Analysis (WMPCA). The proposed method focuses on recognizing the face with large variation in expression and illumination. First of all, the image is horizontally divided into sub-regions of forehead, eyes, nose and mouth. Then they are separately analysed using PCA and covariance matrix, eigenvectors and weight vector. The most important advantage is that all the computation can be implemented in parallel. The final decision is taken based on a weighted sum of the errors vectors obtained from each sub-region. The proposed algorithm was experimented on Yale face database where WMPCA achieved an accuracy of over 86% which was much higher than PCA and MPCA.

Aw-SpPCA

K. R. Tan and S. C. Chen [11] proposed Adaptively Weighted Sub-pattern PCA (Aw-SpPCA) for face recognition. This method operates directly on its subpatterns partitioned from an original whole pattern and separately extracts features from them. It can adaptively computes the contributions of each part and then endows them to a classification task in order to enhance the robustness to both expression and illumination variations. There are three main steps in Aw-SpPCA algorithm: (1) partitioning the face images into sub-patterns, (2) computing contributions of each sub-pattern, and (3) classifying an unknown image. In this method, the spatially related information in a face image are considered and preserved in each sub-pattern and the different contributions made by different parts of the face are emphasized. In addition, these different contributions make classification accuracy much improved. The method was experimented with the three face database namely AR, ORL and Yale and the comparison was done with mPCA, SpPCA and PCA. The comparison is shown as the result in table 4:

	σ(%)	**Aw-SpPCA**	**mPCA**	**SpPCA**	**PCA**
AR	100	0.9357	0.8586	0.7814	0.7814
	75	0.9300	0.8586	0.7814	0.7757
	50	0.9200	0.8614	0.7786	0.7729
	25	0.9043	0.8614	0.7757	0.7757
ORL	100	0.9650	0.9115	0.9423	0.9423
	86	0.9645	0.9133	0.9423	0.9395
	71	0.9648	0.9167	0.9413	0.9380
	57	0.9675	0.9180	0.9433	0.9373
Yale	100	0.8788	0.8667	0.8121	0.8121
	80	0.8788	0.8667	0.8121	0.8121
	70	0.8848	0.8667	0.8121	0.8121
	60	0.8909	0.8727	0.8121	0.8061

Table 4: Accuracy Comparison of Aw-SPPCA, mpca, sppca and PCA

Dia-PCA

D. Zhang, Z.-H. Zhoua, and S. Chen [12] propose a new face recognition technique called Diagonal Principle Component Analysis (Dia-PCA). The problems posed by the PCA and 2DPCA are solved by obtaining the optimal projective vectors from diagonal face images as shown in the figure 2. Doing so, the correlation between the variation of rows and correlation between the variations of column is preserved. The proposed algorithm has been experimented with FERET database and comparison was made among PCA, 2DPCA, Dia-PCA and Dia-PCA +2DPCA as follows.

Method	**Recognition accuracy (%)**	**Dimension**	**Time (s)**
PCA	85.50	16	7.77
2D PCA	85.50	60 X 4	0.79
Dia PCA	90.50	60 X 4	0.87
DiaPCA+ 2DPCA	91.50	16 X 5	0.73

Table 5: Comparison of Recognition Accuracy Rate among different face recognition

The above result shows that Dia-PCA is much better than that of PCA and 2DPCA, but the Dia-PCA can further be improved by combining it with 2DPCA.

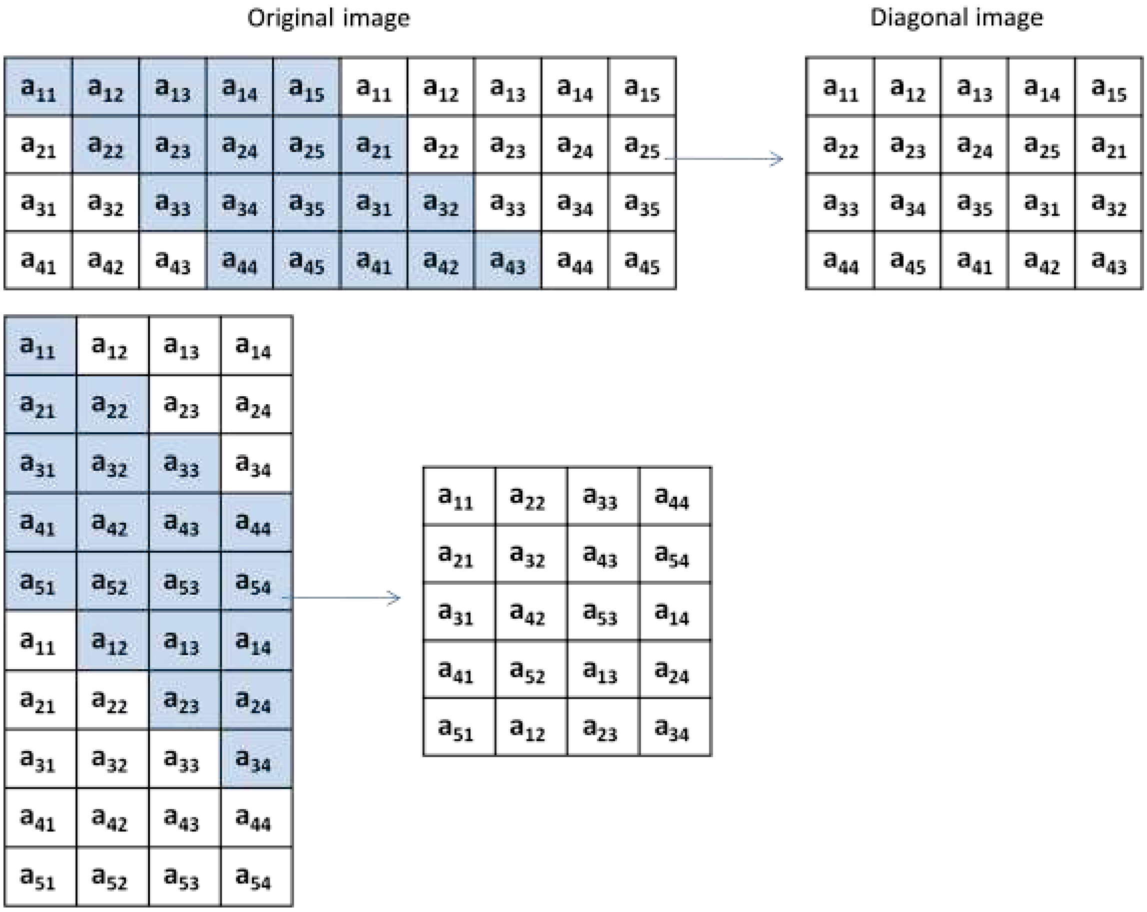

Fig. 2 Deriving the diagonal face image [12].

VM-2DPCA

2DPCA-based face recognition approaches works with the feature extraction. But it fails in case of classification measures. The typical classification measure used in 2DPCA-based face recognition is the sum of the Euclidean distance between two feature vectors in a feature matrix, called distance measure (DM). But this measure is not compatible with the high-dimensional geometry theory. A new classification measure compatible with high-dimensional geometry theory and based on matrix volume is developed by J. Meng and W. Zhang [13] for 2DPCA-based face recognition. This classification measure called as Volume measure is based on high-dimensional Pythagora's theorem and the definition of the high-dimensional parallel solid's volume, which is compatible with the high-dimensional geometry theory. The propose method was evaluated by using Yale and FERET database. From the experiment it was seen that 2DPCA + DM performed better than that of PCA, and also performed better than 2DPCA + DM for both the databases.

LINEAR DISCRIMINANT ANALYSIS

Linear Discriminant Analysis (LDA) [2] is a class specific method in the sense that it can represent data in form which is more useful for classification.

VARIANTS OF LDA

CASCADE LDA

W. C. Zhang, S. G. Shan, W. Gao, Y. Z. Chang, and B. Cao [14] proposed a new face recognition method based on cascade Linear Discriminant Analysis (LDA). In this method first of all, the image is divided into four components with an overlap at the neighboring area. After that PCA is applied to reduce the dimension of each of the four components. Then LDA is performed on each component individually to extract component discriminant features. These features are further combined and are subjected to LDA in order to extract the final face descriptor.

Cascaded LDA technique has been tested for identification and verification on the FERET test set. Thus for the verification problem, the proposed algorithm achieved 1.6% equal error rate while LDA achieved 2.0% equal error rate. Here, equal error rate is the point at which the percentage of correct verifications equals one minus the percentage of false alarms. For the recognition the proposed algorithm achieved 93.47% recognition rate which is higher than 91.8% for LDA.

BLDA

A new method called Block Linear Discriminant Analysis (BLDA) is proposed by V. D. M. Nhat and S. Lee [15] for image feature extraction. It is based on 2D matrices where the original image is divided into blocks and then images are transformed into a vector of blocks. By using row vector to represent each block, a new matrix is obtained which is representation of the image. At last, LDA is applied directly to these matrices. Doing so, BLDA gives three important advantages over LDA: (1) it is easier to evaluate the between-class and within-class covariance matrices accurately (2) less time is needed to determine the corresponding eigenvectors and (3) block size could be changed to get the best results. ORL database has been used for the experiment. First of all the recognition rate was tested with different number of training samples and fixed block size of 3X3. It gave the following result outperforming the LDA.

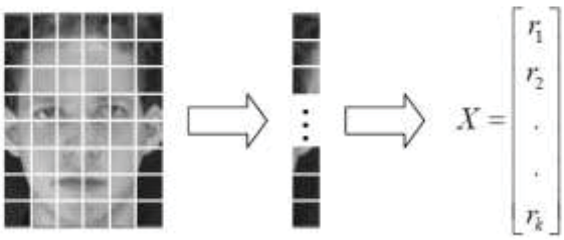

Fig. 4 Representation of each block of image [15]

Training samples	2	3	4	5
LDA	78.83	86.9	91.03	93.6
BLDA (3X3)	86.22	89.61	93.53	95.83

Table 6: Recognition Rate for LDA and BLDA on ORL Database

Again the BLDA approach was tested with different block size like 2X2, 3X3, 5X5, 10X10 etc. and it was found that test with 5x5 produces the best recognition result.

DLDA

A Direct, exact LDA algorithm for the high dimensional data asset has been proposed by H. Yu and J. Yang [16]. The algorithm accepts high dimensional data as an input and optimizes Fisher's criterion directly, without any feature extraction or dimensionality reduction steps. The proposed algorithm takes the advantages of all the information present within and outside of the within – class scatter (S_w). This algorithm can still be used if S_w is not singular. For the proposed algorithm, experiment was carried out with ORL database, which produce 90.8% average recognition rate without the dimensionality reduction and 86.6% with dimensionality reduction. This shows that null space of within-class scatter (S_w) is important and discriminative information really exist outside $S_{w.}$

	Training samples			
Size of block	2	3	4	5
2X2	86.77	90.4	94.23	96.48
3X3	86.22	89.61	93.53	95.83
5X5	87.88	90.92	94.86	96.89
10X2	86.17	90.41	93.6	95.98
10X10	83.51	88.52	90.55	93.57

Table 7: Recognition Rate with Different Block Size

DF-LDA

J. W. Lu, K. N. Plataniotis, and A. N. Venetsanopoulos [17] have combined the merits of D-LDA and F-LDA approaches. It also overcomes the shortcoming and limitation of these two methods. In DF-LDA first of all the dimensionality of the original input space is lowered by introducing a new variant of D-LDA. It results in a low dimensional SSS ("small sample size") free subspace when most discriminatory features are preserved. After that F-LDA is applied to reorient the SSS-free subspace resulting in a set of optimal discriminant features for face representation. They used the ORL and UMIST database and demonstrated the efficiencies of the proposed DF-LDA framework. It is compared with the popular feature selection methods namely DLDA, Eigenface, Fisherface and average percentage of the error rate of DF-LDA over the other method was found as follows:

Method	Eigenface	Fisherface	DLDA
% of error rate(A) (ORL Database)	74.18%	38.51%	80.03%
% of error rate(B) (UMIST Databse)	26.75%	47.68%	79.60%
(A+B)/2	50.47%	43.10%	79.82%

Table 8: Average of Error Rate of DF-LDA

2D-LDA

A statistical linear discriminant analysis for image matrix has been discussed by Li and B. Yuan [18] which directly extracts the proper features from image matrices based on Fisher's Linear Discriminant analysis. 2D-LDA uses the Fisher linear projection criterion which is based on two parameters: the between-class scatter matrix and the within-class scatter matrix. Because the dimension of between-class and within-class scatter matrix is much low, therefore the problem of singularity in within-class scatter matrix has been addressed. The use of the Fisher Linear Discriminant Analysis enhanced the effect of variation caused by different individuals, rather than by expression, illumination, orientation, etc. This method uses the image matrix instead of the image vector to compute the between-class scatter matrix and the within-class scatter matrix. The ORL database has been used to evaluate the performance of 2D-LDA, 2D-PCA, Eigenface, Fisherface .For this experiment the authors have neither used any optimized algorithm nor did any preprocessing on the face image. The size of training set and testing set has been kept equal as 200 each and the size of between-class scatter matrix and within-class scatter matrix are 92 X 92. The best result given by 2D-LDA is 94.0% which is much better than 2D-PCA which is only 92.5%. The following result also gave advantage over other methods.

	2D-LDA	**2D-PCA**	**Eigenface**	**Fisherface**
Computing cost (CPU time in sec)	0.4210	0.4210	28.5000	32.5310
Memory Cost (Bytes)	6720	6720	60	60

Table 9: Comparison of Computing Cost and Memory Cost for different Face Recognition Technique using ORL Database.

FOURIER - LINEAR DISCRIMINATION ANALYSIS (FLA)

X. Y. Jing, Y. Y. Tang, and D. Zhang [19] have proposed Fourier-linear discrimination analysis (FLA) which is composed of the two commonly used techniques for image processing and recognition, namely Fourier Transform and Linear Discrimination Analysis (LDA). In this method an appropriate Fourier frequency bands is selected with favourable linear separability by using a two-dimensional separability judgment. Then two dimensional linear discriminative features are extracted to perform the classification. The author has compared the experimental result of FLA with four different methods namely DLDA, Eigenface, Fisherface and UODV. They used ORL database to get the separability of frequency bands and Fisher discrimination values of FLA and found that that the selected bands are located primarily in the low-frequency region. On the other hand, doing the comparison among the classification performance of all the four methods gave the result in favour of FLA. FLA gave 6.5%, 14%, 8.5%, and 6% more recognition rates than Eigenface, Fisherface, DLDA, and UODV respectively.

IGLDA

Y. W. Pang, L. Zhang, M. J. Li, Z. K. Liu, and W. Y. Ma [20] presented a face recognition method based on Gabor-wavelet and Linear Discriminant Analysis (LDA). In this method first of all by using LDA discriminant vectors are computed from the given training images. This discriminant vectors plays two important roles. First of all, they are used as a transform matrix and LDA features are extracted by projecting original grey level image onto discriminant vectors. Second, it is used to select discriminant pixels. Here, the selected discriminant pixels are quite less than that of the whole image. After this Gabor features are extracted on these discriminant pixels. Then reduced Gabor-LDA is obtained by applying LDA on the Gabor features. At the end, a combined classifier is formed based on local features (Gabor-LDA features) and global feature (Intensity-LDA features) which is illustrated in the figure 5. In this paper the experiment has been carried out with FERET database and the proposed method has been compared with PCA, LDA and GLDA as in the table 10.

Form the experimental result it has been seen that LDA outperformed PCA and GLDA outperformed LDA. This is because Gabor features used in GLDA is robust than original intensity features. But overall IGLDA outperform all other Face recognition method. This is because IGLDA combines both GLDA and LDA and the final classification decision is formed from integrating both local features and global features.

PD-LDA

F. Song, D. Zhang, J. Wang, H. Liu, and Q. Tao [21] proposed the improved version of D-LDA. It has been seen that in D-LDA regulating matrices in D-LDA are either redundant or probably harmful. Thus the new method "PD-LDA" has been proposed which solves the above mentioned problem by inheriting two of the most important advantages of D-LDA. These advantages are: (1) it can be directly applied to high-dimensional input spaces (2) it can be implemented with great efficiency.

The proposed PD-LDA face recognition method is tested on AR and FERET face image databases and it is compared with D-LDA, KLB, Eigenface, and Fisherface. For the AR database, the PD-LDA gave the higher average recognition rate than that of other face recognition method. For FERET database, PL-LDA outperformed in case of average recognition rate and standard derivations as shown in Table 11.

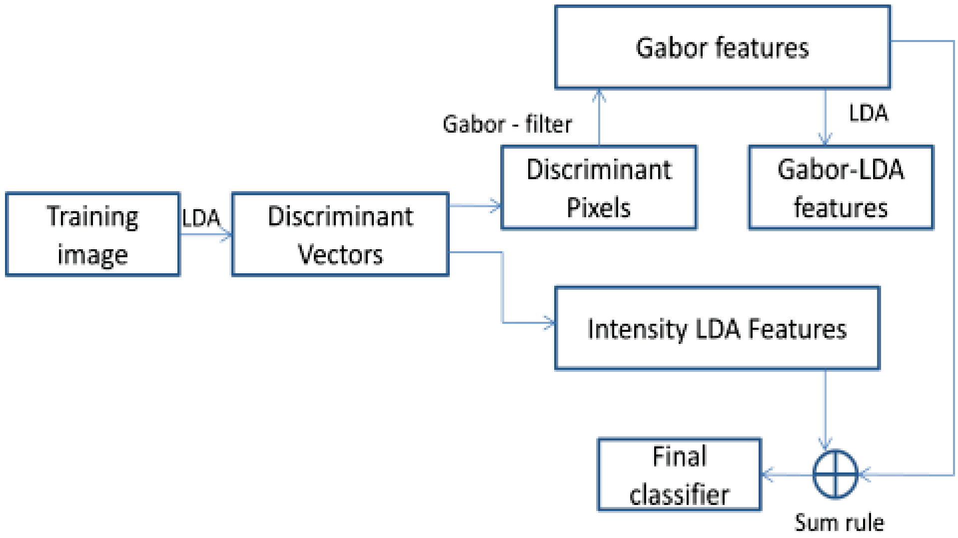

Fig. 5 IG-LDA process [20].

Method	PCA	LDA	GLDA	IGLDA
Recognition rate (%)	88-92	92.50	95.11	97.01

Table 10: Comparison of Recognition Rate for different Face Recognition

DISCUSSION

Here the basic Eigenface PCA face recognition technique and basic Fisherface LDA face recognition technique has been implemented and tested with five different databases whose description is given in the table 12:

Method	D-LDA	KLB	Eigenface	Fisherface	PD-LDA
No. of feature	199	199	799	199	199
Mean	0.4762	0.5910	0.5619	0.5219	0.6445
Std. Derivation.	0.1305	0.0640	0.0070	0.1160	0.0890

Table 11: Comparison of Average Recognition Rate and Standard Deviation for Different Face Recognition.

Name of database	Image format	Image size	Image type
IFD [22]	jpg	110X75	Color
Face94 [23]	jpg	90X100	Color
Yale [24]	gif	320X243	Gray
Face 1999 [25]	jpg	300X198	Color
UMIST [26]	jpeg	92X112	Gray

Table 12: Database Used in PCA Experiment

Both the experiments were carried out using MATLAB R2008a with different number of samples kept in the training set. The test images were kept in the testing set. Both sets were loaded and test image was provided for the recognition. The experimental results are given in the table 13 and14: The result of PCA shows that the recognition rate is quite low in the case of one image per individual in the training set. But as the number of sample is increased, the recognition rate also gets increased and for almost all databases the recognition rate is best for around ten images per individual in the training set.

In case of more than ten images per individual in the training set, time required for the recognition increases too much which cannot be accepted for the real time application. As far as image format, image size and image type is concerned; the eigenface technique can work in all cases.

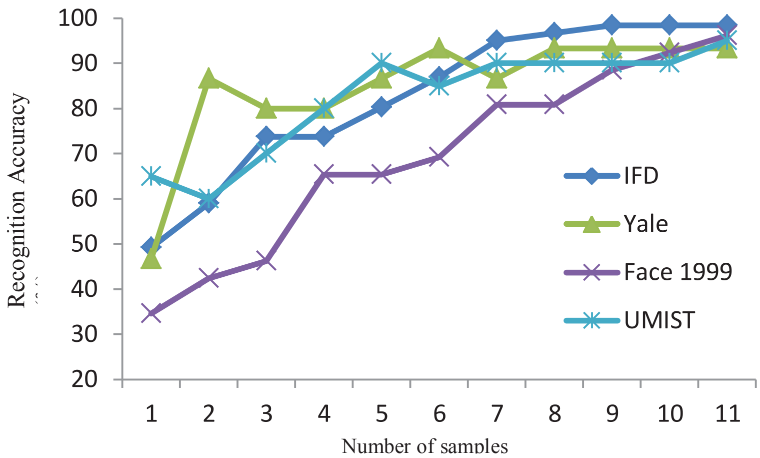

Fig. 6 Recognition Accuracy for PCA

Name of database	Total No. of unique person	No. of samples of each image in training set	No. of image in training set	No. of False recognition	Accuracy rate (%)
IFD	60	1	61	31	49.18
		2	122	25	59.01
		3	183	16	73.77
		4	244	16	73.77
		5	305	12	80.32
		6	366	8	86.88
		7	427	3	95.08
		8	488	2	96.72
		9	549	1	98.36
		10	610	1	98.36
		11	671	1	98.36
Face94	152	1	152	47	69.07
		2	304	29	80.92
		3	456	12	92.10
		4	608	11	92.76
		5	760	11	92.76
		6	912	10	93.42
		7	1064	10	93.42
		8	1216	9	94.07
		9	1368	8	94.73
		10	1520	8	94.73
		11	1672	6	96.05
Yale	15	1	15	8	46.66
		2	30	2	86.66
		3	45	3	80.00
		4	60	3	80.00
		5	75	2	86.66
		6	90	1	93.33
		7	105	2	86.66
		8	120	1	93.33
		9	135	1	93.33
		10	150	1	93.33
		11	165	1	93.33
Face 1999	26	1	26	17	34.61
		2	52	15	42.30
		3	78	14	46.15
		4	104	9	65.38
		5	130	9	65.38

		6	156	8	69.23
		7	182	5	80.76
		8	208	5	80.76
		9	234	3	88.46
		10	260	2	92.30
		11	286	1	96.15
UMIST	20	1	20	7	65.00
		2	40	8	60.00
		3	60	4	70.00
		4	80	2	80.00
		5	100	3	90.00
		6	120	2	85.00
		7	140	2	90.00
		8	160	2	90.00
		9	180	2	90.00
		10	200	2	90.00
		11	220	1	95.00

Table 13: Experimental Result of PCA

Name of database	Total No. of unique person	No. of samples of each image in training set	No. of image in training set	No. of False recognition	Accuracy rate (%)
IFD	60	1	61	59	3.27
		2	122	51	16.39
		3	183	58	4.91
		4	244	37	39.34
		5	305	29	52.45
		6	366	32	47.54
		7	427	17	72.13
		8	488	14	77.04
		9	549	12	80.32
		10	610	9	85.20
		11	671	8	86.88
Face94	152	1	152	143	5.92
		2	304	131	13.81
		3	456	141	7.23
		4	608	123	19.07
		5	760	113	25.65
		6	912	109	28.28
		7	1064	96	37.5
		8	1216	94	38.15
		9	1368	65	57.23
		10	1520	33	78.28
		11	1672	25	83.55
Yale	15	1	15	6	60.00
		2	30	4	73.33
		3	45	5	66.66
		4	60	2	86.66
		5	75	2	86.66
		6	90	2	86.66
		7	105	1	93.33
		8	120	0	100.00
		9	135	0	100.00
		10	150	0	100.00
		11	165	0	100.00
Face 1999	26	1	26	22	15.38

		2	52	23	11.53
		3	78	18	30.76
		4	104	22	15.38
		5	130	11	57.69
		6	156	9	65.38
		7	182	11	57.69
		8	208	6	76.92
		9	234	9	65.38
		10	260	4	84.61
		11	286	6	76.92
UMIST	20	1	20	17	15.00
		2	40	13	35.00
		3	60	16	20.00
		4	80	10	50.00
		5	100	11	45.00
		6	120	9	55.00
		7	140	6	70.00
		8	160	3	85.00
		9	180	5	75.00
		10	200	4	80.00
		11	220	2	90.00

Table 14: Experimental Result of LDA

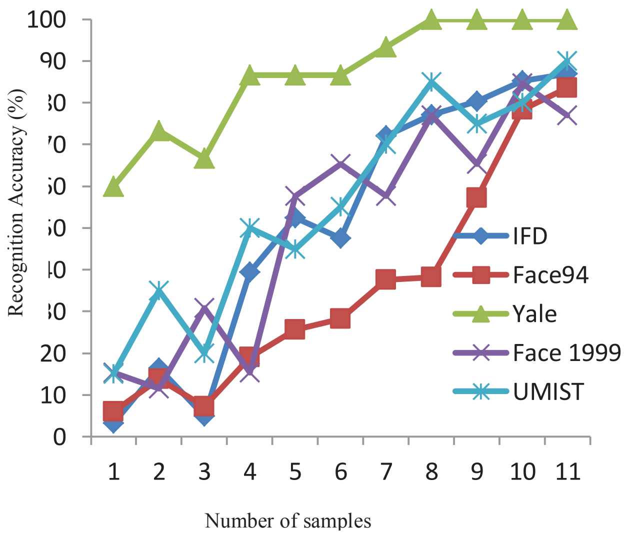

Fig. 7 Recognition Accuracy for LDA

Thus the result of LDA shows that, the recognition rate is quite low in the case of one image per individual in the training set. But as the number of sample is increased, the recognition rate also gets increased and for almost all databases the recognition rate is best for around ten images per individual in the training set. In case of more than ten images per individual in the training set, time required for the recognition increases too much which cannot be accepted for the real time application. As far as image format, image size and image type is concerned; the LDA technique is quite sensitive for the image type. It gives better result for the gray images than the color images.

CONCLUSION

After examining the above mentioned face recognition method it has been observed that PCA gave average results for varying illumination and pose. But PCA did quite well in the case of small training set and large test set. It also outperformed LDA for the images having different background. On the other hand LDA performed well wherever distance measure is taken into account and thus LDA outperformed PCA for computational efficiency. It has also been noticed that combination of two face recognition technique gave better results than the conventional one.

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REFERENCES

[1] H. Murase and S.K. Nayar (1991) ‘Visual learning and recognition of 3-D objects from appearance’ International Journal of Computer Vision, 14:5–24, 1995.

[2] D.Swets, J.Weng(1996)‘Using Discriminant Eigen features for Image Retrieval’, IEEE Transactions on Pattern Analysis and Machine Intelligence,18(8), pp. 831-836.

[3] A. Martinez, A. Kak (2001) ‘PCA versus LDA’, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 23, no. 2, pp. 228-233.

[4] M.Turk and A.Pentland(1991) ‘Eigenfaces for recognition’, Journal of Cognitive Neuroscience, vol.3, No.1.

[5] Songcan Chen, Yulian Zhu (2004) ‘Subpattern-based principle component analysis’, Pattern Recognition 37, 1081 – 1083.

[6] J. Yang and D. Zhang (2004) ‘Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition’, IEEE Trans. Pattern Analysis and Machine Intelligence, Vol.28, pp.131- 137.

[7] G. D. C. Cavalcanti and E. C. B. C. Filho (2003) ‘Auto Associative Neural Network and Eigenbands Fusion for Frontal Face Recognition’, Proceedings of IEEE International Conference on Image Processing, Vol.1, pp.665–668.

[8] Rajkiran Gottumukkal and Vijayan K. Asari (2004) ‘An improved face recognition technique based on modular PCA approach’, Pattern Recognition Letters 25,429–436.

[9] V. D. M. Nhat and S. Lee (2005) ‘An Improvement on PCA Algorithm for Face Recognition’, Advances in Neural Networks-ISNN 2005, Vol.3498, Lecture Notes in Computer Science. Chongqing: Springer, pp.1016-1021.

[10] A. P. Kumar, S. Das, and V. Kamakoti (2004) ‘Face recognition using weighted modular principle component analysis’, Neural Information Processing, Vol.3316, Lecture Notes In Computer Science: Springer Berlin / Heidelberg, pp.362-367.

[11] K. R. Tan and S. C. Chen (2005) ‘Adaptively weighted subpattern PCA for face recognition’, Neurocomputing, Vol.64, pp.505-511.

[12] D. Zhang, Z.-H. Zhoua and S. Chen ‘Diagonal principal component analysis for face recognition’.

[13] J. Meng and W. Zhang (2007) ‘Volume measure in 2DPCAbased face recognition’, Pattern Recognition Letters, Vol.28, pp.1203-1208.

[14] W. C. Zhang, S. G. Shan, W. Gao, Y. Z. Chang, and B. Cao (2004) ‘Component-based cascade linear discriminant analysis for face recognition in Advances In Biometric Person Authentication’, Proceedings, Vol.3338, Lecture Notes In Computer Science, pp.288-295.

[15] V. D. M. Nhat and S. Lee (2005) ‘Block LDA for Face Recognition in Computational Intelligence and Bioinspired Systems’, Vol.3512, Lecture Notes in Computer Science: Springer Berlin/Heidelberg, pp.899-905.

[16] H. Yu and J. Yang (2001) ‘A Direct LDA Algorithm for High-dimensional Data with Application to Face Recognition’ Pattern Recognition, Vol.34, pp.2067- 2070.

[17] J. W. Lu, K. N. Plataniotis, and A. N. Venetsano poulos (2003) ‘Face Recognition Using LDA-based Algorithms’, IEEE Trans. On Neural Networks, Vol.14, pp.195- 200.

[18] M. Li and B. Yuan (2005) ‘2D-LDA: A statistical linear discriminant analysis for image matrix’, Pattern Recognition Letters, Vol.26, pp.527-532.

[19] X. Y. Jing, Y. Y. Tang, and D. Zhang (2005) ‘A Fourier- LDA approach for image recognition’, Pattern Recognition, Vol.38, pp.453-457.

[20] Y. W. Pang, L. Zhang, M. J. Li, Z. K. Liu, and W. Y. Ma (2004) ‘A novel Gabor-LDA based face recognition method’, in Advances In Multimedia Information Processing – PCM 2004, Pt 1, Proceedings, vol. 3331, Lecture Notes In Computer Science, pp.352- 358.

[21] F. Song, D. Zhang, J. Wang, H. Liu, and Q. Tao (2007) ‘A parameterized direct LDA and its application to face recognition’, Neurocomputing, Vol.71, pp.191-196.

[22] Vidit Jain, Amitabha Mukherjee (2002) ‘The Indian Face Database’, http://vis-ww.cs.umass.edu/ ~vidit/ IndianFaceDatabase/.

[23] ‘Essex face database -face94’, University of Essex, UK, http://cswww.essex.ac.uk/mv/allfaces/index.ht ml

[24] ‘Yale Database’, http://cvc.yale.edu/projects/ yalefaces/yalefaces.html.

[25] ‘FACE 1999’, http://www.vision.caltech.edu/html-files/ archive.html.

[26] ‘UMIST Face Database’, http://www.sheffield. ac.uk/eee/ research/iel/ research/face.