Chapter 2 PCA based Face Recognition Techniques

"The power of intuitive understanding will protect you from harm until the end of your days" – (Laozi)

2.1 Introduction

Face recognition has been studied extensively for more than 40 years. Now it is one of the most imperative sub-topics in the domain of face research [1] [2]. Face recognition is a technology which recognize the human by his/her face image. Face recognition can be divided into two core approaches namely, content-based and appearance based [1].

- Content-based recognition is based on the relationship between facial features like eyes, mouth & nose etc.

- In appearance based recognition the face is treated as a two dimensional pattern of intensity variation. The face matching is done through its underlying statistical regularities.

Principal Component Analysis (PCA) has been proven to be an effective approach for the face recognition [1]-[5].

2.2 Principal Component Analysis

Principal Component Analysis (PCA), also known as Hotelling Transform or Karhunen-Loeve expansion, is a well known data representation and feature extraction technique widely used in the areas of pattern recognition, computer vision, etc [1]-[3]. The purpose of PCA is to reduce the data dimensionality with reveal its essential

characteristics i.e. to extract the relevant information from high dimension data set.

2.3 PCA based face recognition techniques

The Eigenface (PCA) based Method of Turk and Pentland [4] is one of the foremost successful method applied in the literature which is based on the Karhunen-Loeve expansion and their study was motivated by the earlier work of Sirowich and Kirby [3] [5]. It is based on the application of Principal Component Analysis to the human faces. It treats the face images as 2-D data, and classifies the face images by projecting them to the eigenface space which is composed of eigenvectors obtained by the variance of the face images. Eigenface recognition derives its name from the German prefix eigen, meaning own or individual. The Eigenface method of facial recognition is considered the first working facial recognition technology [6].

When the method was first proposed by Turk and Pentland [4], they worked on the image as a whole. Also, they used Nearest Mean classifier two classify the face images. By using the observation that the projection of a face image and non-face image are quite different, a method of detecting the face in an image is obtained. They applied the method on a database of 2500 face images of 16 subjects, digitized at all combinations of 3 head orientations, 3 head sizes and 3 lighting conditions. They conducted several experiments to test the robustness of their approach to illumination changes, variations in size, head orientation, and the differences between training and test conditions. They reported that the system was fairly robust to illumination changes, but degrades quickly as the scale changes [4]. This can be explained by the correlation between images obtained under different illumination conditions; the correlation between face images at different scales is

rather low. The eigenface approach works well as long as the test image is similar to the training images used for obtaining the eigenfaces.

The following steps of eigenface approach summarize the process:

1. Let a face image $X(x, y)$ be a two dimensional $m \times n$ array (8-bit Gray Scale) of intensity values. An image may also be considering the vector of dimension mn. Let the training set of images $\{X_1, X_2, X_3 \ldots X_N\}$. The average face of the set $\overline{X}$ is defined by

$$\overline{X} = \frac{1}{N} \sum_{i=1}^{N} Xi \tag{1}$$

2. Calculate the covariance matrix to represent the scatter degree of all feature vectors related to the average vector. The covariance matrix C is defined by

$$C = \frac{1}{N} \sum_{i=1}^{N} (Xi - \overline{X})(Xi - \overline{X})^T \tag{2}$$

3. The Eigenvectors and corresponding eigenvalues are computed by using

$$CV = \lambda V \tag{3}$$

Where V is the set of eigenvectors associated with its eigenvalue λ.

4. Sort the eigenvector $V_i \in V$ according to their corresponding eigenvalues $\lambda_i \in \lambda$ from high to low

5. Each of the mean centered image project into eigenspace using

$$W_i = V_i^T (X_i - \overline{X}) \tag{4}$$

6. In the testing phase each test image should be mean centered, now project the test image into the same eigenspace as defined during the training phase.

This projected image is now compared with projected training image in eigenspace. Images are compared with similarity measures. The training image that is close to the test image will be matched and used to identify. ***Later, derivations of the original PCA (eigenfaces approach) approach has been revolutionize.***

View based and Modular eigenspaces [7] [8]: In 1994 Alex Pentland, Baback Moghaddam, and Thad Starner proposed view-based multiple-observer eigenspace technique for use in face recognition under variable pose. Till to that date, most face recognition experiments have had at most a few hundred faces. Thus how face recognition performance scales with the number of faces is almost completely unknown. In order to have an estimate of the recognition performance on much larger databases, they have conducted tests on a database of 7,562 images of approximately 3,000 people. They were used two different testing methodologies to judge the relative performance of the parametric and view-based eigenspace methods.

In the first experiments the interpolation performance was tested by training on a subset of the available views { ±90°, ±45° , 0°) and testing on the intermediate views {±68°, ±23°). The average recognition rates obtained were 90% for the view-based and 88% for the parametric eigenspace methods. In a second experiments tested the extrapolation performance by training on a range of views (e.g., -90°' to +45°) and testing on novel views outside the training range (e.g., +68°' and +90°). For testing views separated by ±23° from the training range, the average recognition rates were 83% for the view-based and 78% for the

parametric eigenspace method. For ±45° testing views, the average recognition rates were 50% (view-based) and 43% (parametric).

Kernel Principal Component Analysis (KPCA) [9] [10]: A kernel principal component analysis (PCA) was recently proposed by Kwang In Kim et.al and Ming-Hsuan Yang in 2002, which was the nonlinear extension of a PCA. The basic idea was to first map the input space x into a feature space F via nonlinear mapping Φ and then compute the principal components in that feature space F. This letter adopts the kernel PCA as a mechanism for extracting facial features. The basic idea was to first map the input space into a feature space via nonlinear mapping and then compute the principal components in that feature space.

They have performed their experiments on ORL [11] [12] and Yale [13] [14] Databases. For the evaluation of the algorithm they have calculated the error rate which is 2.5% for the ORL and 24.4% for the Yale database.

Illumination Normalization technique based on PCA [15]: Chen, T et.al proposed the Illumination Normalization technique based on PCA in 2002 to remove the limitations traditional well-controlled illumination system. They show that it is very useful to preprocess any face image by normalizing its illumination before its use for the face recognition. For the experiments a subset PIE database [16], including 24 people and 21 illuminations with the image size 32x32 is used. Out of these illuminations six are used as training and other for testing. The recognition error rate has been reduced to 0.8%, compared to 21% if the original image were used.

Image principal component analysis (IMPCA) [17]: In 2002 Yang, J. and Yang, J.-Y proposed a straight forward image projection technique, called as image principal component analysis(IMPCA), to overcome the

weakness of the conventional PCA. The main idea was to construct the image total covariance matrix directly based on original image matrices, and then to utilize it as generation matrix to perform principal component analysis. As the scale of image total covariance matrix of IMPCA is generally much smaller that of PCA, therefore much computational time will be saved. The IMPCA was tested on ORL Face database [11] [12] with two classifier. The maximal recognition rate using Nearest Neighbor was 95.5% and Distance 91%.

Improved Modular PCA [18]: Rajkiran G et.al in 2004 proposed a face recognition algorithm based on modular PCA approach, a similar method called modular eigenspaces [7] [8], in this method PCA was performed on the eyes and nose of the face images. The performance was evaluated with two face databases, UMIST and Yale [13] [14]. All the images in both the databases were normalized and cropped to a size of 64x64 pixels. Averagely 85% of recognition rate has been obtained.

Principal Component Analysis and Feedforward Neural Networks [19]: Oravec M and Pavlovic□ová J in 2004 presented an original method for internal representation of input data by multilayer perceptron (MLP). It uses MLP for block compression of image data and it was based on formation of outputs of MLP hidden layer to an image, which was then further processed by PCA. They used the face database from MIT (Massachusetts Institute of Technology) [4], which consists of face images of 16 people, 27 of each person under various conditions of illumination, scale, and head orientation. It means total number of face images is 432. Each image was 64 (width) by 60 (height) pixels, eight-bit grayscale. 83.07% faces were recognized successfully.

Two-Dimensional Principal Component Analysis (2DPCA) [20]: In 2004 Yang, J et.al proposed a new technique 2DPCA for face representation and recognition. As opposed to PCA, 2DPCA was based on 2D image

matrices rather than 1D vector so the image matrix does not need to be transformed into a vector prior to feature extraction. An image covariance matrix was constructed directly using the original image matrices and its eigenvectors were derived for feature extraction. For the performance evaluation of 2DPCA a series of experiments were performed on the three face databases ORL [11] [12], AR [21] [22], and Yale [13] [14] face databases. The recognition rate was 98.3%, 84.24% and 84.5% respectively on the databases ORL, AR, and Yale was obtained.

Gabor based Kernel PCA [23]: Chengjun Liu (2004) proposed Gabor-based kernel Principal Component Analysis (PCA) method by integrating the Gabor wavelet representation of face images and the kernel PCA method for face recognition. Gabor wavelets first derive desirable facial features characterized by spatial frequency, spatial locality, and orientation selectivity to cope with the variations due to illumination and facial expression changes. The kernel PCA method is then extended to include fractional power polynomial models for enhanced face recognition performance. The feasibility of the Gabor based kernel PCA method with fractional power polynomial models has been successfully tested on both frontal and pose-angled face recognition, using two data sets from the FERET database [24] and the CMU PIE database [16], respectively. The FERET data set contains 600 frontal face images of 200 subjects, while the PIE data set consists of 680 images across five poses (left and right profiles, left and right half profiles, and frontal view) with two different facial expressions (neutral and smiling) of 68 subjects. The Gabor-based kernel PCA method works better with fractional power of polynomial.

2-Directional 2-Dimensional PCA (2D^{2}PCA) [25]: In 2005 Daoqiang Zhang and Zhi-Hua Zhou developed the 2-Directional 2DPCA, i.e.

2D^{2}PCA, for efficient face representation and recognition. The experiments has been done on two face databases ORL [11] [12] and a subset of FERET [24]. 2D^{2}PCA achieves the same or even higher recognition accuracy than 2DPCA, while the number of coefficients needed by the former for image representation is much less than that of the latter. The experimental results also indicate that 2D^{2}PCA is more computationally efficient than both PCA and 2DPCA.

Generalized 2D principal component analysis (G2DPCA) [26]:Hui Kong et.al in 2005 proposed G2DPCA i.e. Bilateral-projection-based 2DPCA (B2DPCA) and kernel-based 2DPCA (K2DPCA). This G2DPCA overcomes the limitations of 2DPCA i.e. 2DPCA needs much more coefficients than PCA in representing an image. But B2DPCA can effectively remove the redundancies among both rows and columns of the images and thus lower the number of coefficients used to represent an image. These two methods are evaluated on three well known face databases: ORL [11] [12], UMIST, and Yale database [13] [14].

Gabor-Based Kernel PCA With Doubly Nonlinear Mapping [27]: Xudong Xie and Kin-Man Lam in 2006 proposed this Gabor-Based Kernel PCA With Doubly Nonlinear Mapping, which not only consider the statistical property of the input features, but also adopts an eigenmask to emphasize those important facial feature points. Therefore, after this mapping, the transformed features have a higher discriminating power, and the relative importance of the features adapts to the spatial importance of the face images. The proposed algorithm has been evaluated on the face databases: Yale [13] [14], ORL [11] [12], AR [21] [22], and YaleB database, which gives the 94.7%, 82.8%, 98.8%, and 98.8% recognition rate respectively.

The Face-Specific Subspace Based Two-Dimensional Principal Component Analysis (FSS+2DPCA) [28]: P. Sanguansat et.al in 2006

proposed the Face-Specific Subspace (FSS) concept of class-specific subspace. Each subspaces learned from the training images which correspond to only one class, thus the number of these subspaces is equal to the number of classes. Since the information of class labels are considered in FSS, so the discriminant power can be improved. Experiments were done on Yale face database [13] [14] which show the FSS + 2DPCA and FSS+B2DPCA gives the better accuracy as compared to 2DPCA and B2DPCA. But the disadvantage of this method is it requires more memory for storing each class and recognition time.

Gabor wavelet based Modular PCA [29]: Neeharika Gudur and Vijayan Asari (2006) proposed a Gabor wavelet based Modular PCA approach for face recognition improves the efficiency of face recognition, under varying illumination and expression conditions for face images when compared to traditional PCA techniques. The performance of the proposed technique was evaluated under conditions of varying illumination, expression and variation in pose up to a certain range using standard face databases: ORL [11] [12] and AR [21] [22]. The Gabor wavelet approach has been proved to be a better approach to achieve improved recognition rate for variations in illumination and expressions and especially for occlusions.

PCA of Multi-view Face Images [30]: Takio Kurita et.al (2006) consider the problem of recognising a specific human face in different poses when only one frontal image exists in the face database and solved it by using PCA on a set of multi-view images to obtain aligned principal component. For the experiments face images from Softpia Japan were divided into two independent data sets; one for learning and other for testing. 2520 face images (9 orientations x 280 subjects) were used for learning. The best recognition rate, 76.9% was achieved with 100 principal components.

Fast incremental principal non-Gaussian directions analysis algorithm (IPCA-ICA) [31]: Issam Dagher and Rabih Nachar (2006) introduced a fast incremental principal non-Gaussian directions analysis algorithm, called IPCA-ICA, which computes the principal components of a sequence of image vectors incrementally without estimating the covariance matrix (so covariance-free) and at the same time transforming these principal components to the independent directions that maximize the non-Gaussianity of the source. Two major techniques (principal component analysis (PCA) and independent component analysis (ICA)) are used sequentially in a real-time fashion in order to obtain the most efficient. Three popular face databases (ORL [11] [12], UMIST, and Yale [13] [14]) were used to demonstrate the effectiveness of the proposed IPCA_ICA algorithm. IPCA_ICA achieves higher average success rate than the Eigenface, the Fisherface, and the FastICA methods with very efficient in memory usage.

The Discrete Wavelet Transform and the Support Vector Machines for PCA based face recognition [32]: Hong Wang, Su Yang, and Wei Liao (2007) proposed an improved PCA face recognition algorithm based on the Discrete Wavelet Transform and the Support Vector Machines. The 2-D Discrete Wavelet Transform has been used to process the face images to form the low frequency sub images by extracting the low frequency component. Then the PCA method was used to obtain the characterizations of these sub images. And at last, the extracted eigenvectors are put into the SVM classifier for training and recognition. The ORL [11] [12] standard face database was chosen in that experiment. The experiments show that this algorithm can improve the calculation speed and recognition rate.

IMAGE PCA [33]: In 2007 Ying Wen and Pengfei Shi proposed IMAGE PCA (The projective feature image obtained by 2DPCA on the original

images) for efficient face representation and recognition. Experiments are performed on two face image database: ORL [11] [12] and Yale [13] [14] face databases. The experimental results show that image PCA achieves the same or even higher recognition rate than 2DPCA, while the former needs fewer coefficients for feature vectors than the latter.

Laplacian PCA [34]: Deli Zhao, Zhouchen Lin, and Xiaoou Tang (2007) proposed the Laplacian PCA (LPCA) algorithm which is the extension of PCA to a more general form by locally optimizing the weighted scatter. The LPCA algorithm is based on the global alignment of locally Gaussian or linear subspaces via an alignment technique borrowed from manifold learning. Based on the coding length of local samples, the weights can be determined to capture the local principal structure of data. The experiments has been performed on a subset of facial data in FRGC version 2 [35] face database.

Curvelet Based PCA [36]: Tanaya Mandal and Q. M. Jonathan Wu (2008) introduced the Face Recognition using Curvelet Based PCA. In which Decomposing images into its curvelet subbands and applying PCA (Principal Component Analysis) on the selected subbands in order to create a representative feature set. Experiments have been carried out on two well-known databases: Essex Grimace [37] and ORL [11] [12] Database. Proposed method gives 100% recognition rate on Essex Grimace and 96.6% on ORL Database which supersede Traditional PCA and also wavelet based PCA scheme.

Combination of Wavelet, PCA, and Neural Networks for face recognition [38]: Masoud Mazloom, and Saeed Ayat (2008) proposed a method to increase the face recognition accuracy using a combination of Wavelet, PCA, and Neural Networks. For preprocessing and feature extraction steps, they apply a combination of wavelet transform and PCA. During the classification stage, the Neural Network (MLP) was

explored to achieve a robust decision in presence of wide facial variations. The computational load of the proposed method was greatly reduced as comparing with the original PCA based method. To evaluate the performance of the proposed method, they used the face-image database of Yale University [13] [14] and ORL face database [11] [12]. the combination of Wavelet, PCA and MLP exhibits the most favorable performance, on account of the fact that it has the lowest overall training time, the lowest redundant data, and the highest recognition rates when compared to similar so far introduced methods.

A Statistical PCA Method [39]: Chunming Li et.al (2008) proposed Statistical Principal Component Analysis Method (SPCA) to overcome the two disadvantages of standard PCA i.e. one is computing complexity, The other is it can only process the faces have the same face expression. In SPCA First, an improved PCA algorithm is used to compute the eigen- vector and eigen-values of the face. Second, Bayesian rule is used to design the classification designer. For the experiments the CVL face database [40] was used. The experimental result shows that the method introduced has the advantages of simple computation and high recognition rate. It can also process the faces have different expression with the recognition rate up to 95.08%.

Gabor Features and Two-Dimensional PCA [41]: Yi-Chun Lee and Chin-Hsing Chen (2008) proposed a new face recognition method based on Two-Dimensional Principal Component Analysis (2DPCA) and Gabor filters. In the method, an original image is convolved with 40 Gabor filters corresponding to various orientations and scales to give its Gabor representation. Then, the Gabor representation is analyzed by the 2DPCA in which the eigenvectors are computed using the Gabor image covariance matrix without matrix to vector conversion. For the experiments ORL [11] [12] face database was used on which it achieves

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98.5% recognition rate by using 25 principal components of 2DPCA using the 1-norm distance classifier.

Combining Wavelet Transform and Image Principle Component Analysis [42]: Yang Jun et.al (2008) proposed a face recognition method that combing wavelet and IMPCA. The proposed method firstly transforms face image with wavelet and gets coefficients of different frequency, then horizontal detail coefficient is enhanced. The image generated by wavelet inverse transform is as new object and is recognized using IMPCA. The experiment result on ORL [11] [12] face database presents the proposed method is efficient and the recognition accuracy rate is better than IMPCA only.

$2D^2PCA$ and Wavelet Packet Decomposition (WPD) [43]: Dongjian He et.al (2008) introduced the Face Recognition Using $2D^2PCA$ and Wavelet Packet Decomposition. First, plot images are obtained via two-levels WPD on original image. And then, the feature matrixes of these plot images are extracted using $2D^2PCA$. Finally, the method is constructed by fusing the feature matrixes of 'successful' plot images properly chosen. For the experiments PIE [16], Yale [13] [14], and UMIST face databases was used with different illumination, expressions, and poses. This method obtains better performance than 'standard' method under these conditions. It performs best under different illumination whereas its performance decreases slightly under different expressions and is worst when poses change.

Contourlet-Based Feature Extraction with PCA [44]: Walid Riad Boukabou and Ahmed Bouridane (2008) proposed the Contourlet Transform with a view to extract more discriminant features in order to further enhance the performance of the well known Principal Component Analysis method. Two different databases: Yale Face [13] [14] Database and FERET [24] Database have been used to evaluate the proposed

method. The experiment results suggest that the Contourlet Transform outperforms significantly the original PCA method. Moreover, when combined with PCA, it yields much improved classification results than most existing and similar methods.

Wavelet transform weighted modular PCA [45]: Minghua ZHAO et.al (2008) proposed wavelet transform weighted modular PCA. Firstly, the training images and the testing image are preprocessed with wavelet transform and the LL band and the LH/HL average band are divided into sub-images with the same size. Secondly, the prospective classify contribution of each sub-model of the two bands are computed. Thirdly, each sub-image of the two bands of the testing image is projected to its corresponding subspace and the confidence values with each image are obtained. Finally, the two confidence values with each image are added with a weight and the total confidence value is obtained to classify the testing image. ORL [11] [12] and Yale [13] [14] face databases were used for experiments, on ORL face database best WTWMPCA result 92.5%, which is 4% superior to PCA and on Yale face database the best WTWMPCA result 93.33%, which is 5.33% superior to PCA.

All the above PCA based face recognition methods summarized in Table 2.1.

	Database	Pre-processing	Feature Extraction	Post Processing	Classifier/ Distance	Best Performance
M Kirby. et al. 1987 M. Kirby et.al 1990	Self developed of 150 images	--	KL Expansion & PCA	--	--	Error Rate **4%**
M Turk et.al. 1991	Self developed of 2500 images	--	PCA	--	L2	**81.66%**
A pentland et.al. 1994	Database of 7562 images with 3000 individuals	--	View based and Modular PCA	--	--	**92%**
Kwang Kim et.al 2002	ORL	--	KPCA	--	SVM	Error Rate **2.5%**
Ming Yang et.al 2002	ORL, Yale	--	KPCA	--	--	Error Rate ORL **2.5%** Yale **24.4%**
T Chen et.al 2002	Subset of PIE	Illumination Normalization	PCA	--	--	EER = **0.006%**

	Database	Pre-processing	Feature Extraction	Post Processing	Classifier/ Distance	Best Performance
		Pixel wise Gaussian and PCA based				
Jian Yang et al 2002	ORL	--	IPCA	--	Nearest Neighbor, Distance	Nearest Neighbor **95.5%** Distance **91%**
RajKiran G et.al 2003	UMIST, Yale	--	Improved Modular PCA	--	--	**85%**
M Oravec et.al 2004	MIT	--	PCA	--	MLP and RBF Network	**83.07%**
Jian Yang et.al 2004	ORL ,AR, Yale	--	2DPCA	--	--	Yale **84.24%** AR **84.5%** ORL **98.3%**
Chengjun Liu 2004	FERET, PIE	--	Gabor based KPCA	--	Nearest Neighbor, L1, L2, Cosine	**99.7%**
Daoqiang Zhang et.al 2005	ORL, FERET	--	(2D)^{2}PCA	--	L2	ORL **90.5%** FERET **85.5**
Hui Kong et.al 2005	ORL ,UMIST, Yale	--	Generalized 2DPCA	--	--	ORL **95%** UMIST **93%** Yale **94%**
X Xie et.al 2006	Yale, AR, ORL, YaleB		GW + DKPCA		--	Yale **94.7%** AR **98.8%** ORL **82.8%** YaleB **98.8%**
P Sanguansat et.al. 2006	Yale	--	2DPCA B2DPCA 2DPCA+FSS B2DPCA+FSS	--	Nearest Neighbor classifier & Euclidean	2DPCA **87.78%** B2DPCA **92.22%** 2DPCA+FSS **92.22%** B2DPCA+FSS**94.44%**
N Gudur et.al 2006	ORL, AR	--	GW based Modular PCA	--	Mahalanobis	ORL **88.90%** AR **89.95**
T. Kurita er.al. 2006	Softpia Japan	--	PCA of Multi-View	--	--	**76.9%**
Issam Dagher et.al. 2006	ORL, UMIST, Yale	--	IPCA_ICA	--	Nearest Neighbor classifier & Cosine	ORL **88.37%** UMIST **94.36%** Yale **98.24%**
Hong Wang ey.al. 2007	ORL	--	Wavelet PCA	--	SVM	94.2%
Ying Wen et.al. 2007	ORL ,Yale	--	Image PCA	--	Nearest Neighbor classifier & Euclidean	ORL **90%** Yale **85%**
Deli Zhao et.al. 2007	FRGC Version 2	--	Laplacian PCA	--		**88%**
T Mandal et.al. 2008	Essex Grimace, ORL	--	Curvelet PCA	--	K-NN and L1	Essex Grimace **100%** ORL **96.6%**
M Mazloom et.al. 2008	Yale, ORL	--	Wavelet PCA	--	ANN	ORL **97.68%** Yale **90.35%**
Chunming Li et.al. 2008	CVL	--	Statistical PCA	--	Bayes Rule	Frontal **100%** Expression **95.08** Pose **72.44%**
Yi-Chun Lee et.al 2008	ORL	--	2DPCA+GF 2DPCA+MGF	--	--	2DPCA+GF **93%** 2DPCA+MGF **98.5%**
Yang Jun et.al. 2008	ORL	--	WT + Image PCA	--	Nearest Neighbor	**93.5%**

	Database	Pre-processing	Feature Extraction	Post Processing	Classifier/ Distance	Best Performance
					classifier	
Dongjian He et.al. 2008	PIE, Yale, UMIST	--	$(2D)^2$+PCA and WPD	--	L1 and L2	**98.79%**
Walid Riad et.al. 2008	Yale, FERET	--	Contourlet+PCA	--	Nearest Neighbor classifier	**91.67%**
Minghua Zhao et.al. 2008	ORL, Yale	--	WT Weighted Modular PCA	--	--	ORL **92.5%** Yale **93.33%**

Table 2-1Comparison of various PCA based face recognition techniques

2.4 Summary

PCA based face recognition has been studied for many years as discussed, the research into the PCA has helped to revolutionize face recognition algorithm. It is a subspace based method, when studying this PCA based methods as interesting question arise. *Under what conditions does projecting an image into a subspace improve performance? What specified combinations improve the performance?* For some problems the variations within the subspace also affect the performance, The variations between the images of the same face due to illumination and viewing direction are almost always larger than the image variation due to change in face identity. This variability makes it difficult to extract the basic information of the face objects from their respective images. The traditional PCA based face recognition techniques are unable to preserve the non-convex variations of face necessary to differentiate among individuals, it also unable to characterize unseen images of the same individual.

References

1. W. Zhao, R. Chellappa, A. Rosenfeld, and P. J. Phillips, "Face recognition: a literature survey" ACM Computing Surveys, Vol. 35, No. 4, pp. 399–458, December 2003.

2. A. S. Tolba, A.H. El-Baz, and A.A. El-Harby, "Face Recognition: A Literature Review", International Journal Of Signal Processing Volume 2 Number 2 ISSN 1304-4494, 2005.

3. M. Kirby and L. Sirovich, "Application of the KL procedure for the characterization of human faces," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 12, no. 1, pp. 103-108, Jan. 1990.

4. M. Turk and A. Pentland, "Eigenfaces for recognition", J. of Cognitive Neuroscience, Vol. 3, No. 1, pp. 71-86, 1991.

5. Sirovich, L. & Kirby, M. "A low-dimensional procedure for the characterization of human face", Journal of the Optical Society of America A, Vol. 4, No. 3, pp.519-524 1987.

6. B. Kepenekci, "Face Recognition Using Gabor Wavelet Transform", MSc. Thesis, METU, September 2001.

7. A. Pentland, B. Moghaddam, T. Starner, "View-based and modular eigenspaces for face recognition", Proceedings of IEEE, CVPR, 1994.

8. B. Moghaddam and A. Pentland, "Face Recognition using View-Based and Modular Eigenspace", Automatic Systems for the Identification and Inspection of Humans, 2277, 1994.

9. Kim, K.I., Jung, K., Kim, H.J. "Face recognition using kernel principal component analysis", IEEE Signal Processing Letters, 9 (2), pp. 40-42, 2002.

10. Ming - Hsuan Yang, "Kernel eigenfaces vs. Kernel Fisherfaces: Face recognition using kernel methods", Proceedings of the fifth international conference on automatic face and gesture recognition 2002.

11. The ORL Database of Faces, Available:

    http://www.uk.research.att.com/facedatabase.html

12. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman. "Eigenfaces vs. fisherfaces: recognition using class specific linear projection", IEEE Transactions on Pattern Analysis and Machine Intelligence, 19(7):711–720, July 1997.Fgfgg

13. The Yale database, Available: http://cvc.yale.edu/

14. F. Samaria and A. Harter. "Parameterisation of a stochastic model for human face identification", In 2nd IEEE Workshop on Applications of Computer Vision, Sarasota, FL, 1994.

15. Chen, T., Hsu, Y.J., Liu, X., Zhang, W. "Principle component analysis and its variants for biometrics" IEEE International Conference on Image Processing, 1, pp. I/61-I/64 2002.

16. T. Sim, S. Baker, and M. Basat, "The CMU pose illumination and expression (PIE) database of human faces", Technical report CMU-RI-TR-01-02, Robotics Institutes, Carnegie Mellon University, Pittsburgh, PA, January 2001.

17. Yang, J., Yang, J.-Y. "From image vector to matrix: A straightforward image projection technique-IMPCA vs. PCA" Pattern Recognition, 35 (9), 2002

18. Gottumukkal, Rajkiran. Asari, V.K. "An improved face recognition technique based on modular PCA approach" Pattern Recognition Letters, 25 (4), pp. 429-436, 2004.

19. Oravec, M., Pavlovic☐ová, J. "Face recognition methods based on principal component analysis and feedforward neural networks" IEEE International Conference on Neural Networks - Conference Proceedings, 1, pp. 437-441, 2004.

20. Yang, J., Zhang, D., Frangi, A.F., Yang, J.-Y. "Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition" EEE Transactions on Pattern Analysis and Machine Intelligence, 26 (1), pp. 131-137, 2004.

21. SA.M. Martinez and R. Benavente, "The AR Face Database," CVC Technical Report, no. 24, June 1998.

22. A.M. Martinez and R. Benavente, "The AR Face Database," http://rvl1.ecn.purdue.edu/~aleix/aleix_face_DB.html.

23. Liu, C. "Gabor-based kernel PCA with fractional power polynomial models for face recognition" IEEE Transactions on Pattern Analysis and Machine Intelligence, 26 (5), pp. 572-581, 2004.

24. P.J. Phillips, H. Wechsler, J. Huang, and P. Rauss, "The FERET Database and Evaluation Procedure for Face-Recognition Algorithms," Image and Vision Computing, vol. 16, pp. 295-306, 1998.

25. Zhang, D Daoqiang., Zhou, Z.-H. "$(2D)^2$ PCA: Two-directional two-dimensional PCA for efficient face representation and recognition" Neurocomputing, 69 (1-3), pp. 224-231, 2005.

26. Kong, H., Wang, L., Teoh, E.K., Li, X., Wang, J.-G., Venkateswarlu, R. "Generalized 2D principal component analysis for face image representation and recognition" Neural Networks, 18 (5-6), pp. 585-594, 2005.

27. Xie, X., Lam, K.-M. "Gabor-based kernel PCA with doubly nonlinear mapping for face recognition with a single face image" IEEE Transactions on Image Processing, 15 (9), pp. 2481-2492, 2006.

28. Sanguansat, P., Asdornwised, W., Jitapunkul, S., Marukatat, S. "Class-specific subspace-based two-dimensional principal component analysis for face recognition" Proceedings - International Conference on Pattern Recognition, 2, art. no. 1699435, pp. 1246-1249, 2006.

29. Gudur, N., Asari, V. "Gabor wavelet based modular PCA approach for expression and illumination invariant face recognition" Proceedings - Applied Imagery Pattern Recognition Workshop, 2006.

30. Kurita, T., Hosoi, T., Hidaka, A. "Principal component analysis of multi-view images for viewpoint-independent face recognition" Proceedings - IEEE International Conference on Video and Signal Based Surveillance 2006.

31. Dagher, I., Nachar, R. "Face recognition using IPCA-ICA algorithm" IEEE Transactions on Pattern Analysis and Machine Intelligence, 28 (6), pp. 996-1000, 2006.

32. Wang, H., Yang, S., Liao, W. "An improved PCA face recognition algorithm based on the discrete wavelet transform and the support vector machines" Proceedings - International Conference on Computational Intelligence and Security Workshops, pp. 308-311, 2007.

33. Ying, W., Pengfei, S. "Image PCA: A new approach for face recognition" ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings, 1, pp. I1241-I1244, 2007.

34. Zhao, Deli., Lin, Z., Tang, X. "Laplacian PCA and its applications" Proceedings of the IEEE International Conference on Computer Vision, 2007,

35. P. Philips, P. Flynn, T. Scruggs, and K. Bowyer. Overview of the face recognition grand challenge. CVPR, 2005.

36. Mandal, T., Wu, Q.M.J. "Face recognition using curvelet based PCA" 19th International Conference on Pattern Recognition, ICPR 2008.

37. http://cswww.essex.ac.uk/mv/allfaces/grimace.zip

38. Mazloom, M., Ayat, S. "Combinational method for face recognition: Wavelet, PCA and ANN", Proceedings - Digital Image Computing: Techniques and Applications, DICTA 2008, pp. 90-95.

39. Li, C., Diao, Y., Ma, H., Li, Y. "A Statistical PCA Method for face recognition" Proceedings - 2nd International Symposium on Intelligent Information Technology Application, 2008, 3, pp. 376-380

40. CVL FACE DATABASE: http://www.lrv.fri.unilj.si/facedb.html.

41. Lee, Y.-C., Chen, C.-H. "Face recognition based on gabor features and two-dimensional PCA" Proceedings - 4th International Conference on Intelligent Information Hiding and Multimedia Signal Processing, IIH-MSP 2008, pp. 572-576.

42. Jun, Y., Hong-Zhao, Y., Xiu-Qiong, Z., Zhi-Sheng, G. "Face recognition based on wavelet transform and image principle component analysis" Proceedings of the International Conference on Computer and Electrical Engineering, ICCEE 2008, pp. 354-357

43. He, D., Zhang, L., Cui, Y. "Face recognition using (2D)2 PCA and wavelet packet decomposition" Proceedings - 1st International Congress on Image and Signal Processing, CISP 2008, 1, pp. 548-553

44. Boukabou, Walid Riad., Bouridane, A. "Contourlet-based feature extraction with PCA for face recognition" Proceedings of the NASA/ESA Conference on Adaptive Hardware and Systems, AHS 2008, pp. 482-486

45. Zhao, M., Li, P., Liu, Z. "Face recognition based on wavelet transform weighted modular PCA" Proceedings - 1st International Congress on Image and Signal Processing, CISP 2008, 4, pp. 589-593