A Systematic Review of PCA and Its Different Form for Face Recognition

Reecha Sharma, M.S. Patterh

ABSTRACT: Face recognition is an important part of our daily life. Face recognition is used either for verification (one-to-one matching) or for identification (one-to-many). Mainly face recognition consists of two categories feature based and appearance based. Feature-based method first process the input image to identify and measure distinctive facial features such as the eyes, mouth, nose, etc., as well as other fiducial marks and then compute the geometric relationships among those facial points, thus reducing the input facial image to a vector of geometric features. Appearance based method used holistic features of 2D image attempt to identify faces using global representations, i.e., descriptions based on the entire image rather than on local features of the face. In this paper holistic method is discussed using Principle Component Analysis. This paper presents a systematic review of different forms of Principle Component Analysis (PCA) for face recognition. Based on the brief review of different forms of PCA, comparison table of recognition rate for ORL and FERET database are prepared.

Keywords: eigenface, principal component analysis, PCA, face recognition

1 INTRODUCTION

Face is an important biometric trait used in many applications such as General identity verification, Criminal justice system, Image database investigation, Smart card etc. The human ability to recognize faces is awesome. A human can recognize thousands of faces learned throughout the lifetime and identify familiar faces at a glance even after years of separation. This skill is quite robust, despite large changes in the visual stimulus due to viewing conditions, expression, aging, and distractions such as glasses, beards or changes in hair style. Developing a computational model for face recognition is difficult. Over the last few decades, a lot of researchers have been working in this area. Principal component analysis (PCA) is holistic method. Holistic method tries to identify face using global representation. It describes the entire face rather than on local features such as eyes, nose, lip etc of the face. One of the simplest and most effective PCA approaches used in face recognition systems is the eigenface approach. This approach transforms faces into a small set of essential characteristics. Recognition is done by projecting a new image in the eigenface subspace, after which the person is classified by comparing its position in eigenface space with the position of known individuals.
Initially Sirovich and Kirby (1987) and Kirby and Sirovich (1990) exploited PCA to effectively characterize geometry of the faces[1][2]. According to them, faces can be easily reconstructed by only considering few eigen vector. Turk and Pentland (1991) motivated from Kirby and Sirovich made use of Eigenfaces for face detection[3]. The rest of paper is organized as section 2 in which general steps of PCA are discussed. It tell how eigenfaces are calculated, section 3 describes various forms of PCA. It briefly explains different forms of PCA and section 4 shows comparison results of different forms of PCA on ORL and FERET face database. Section 5 gives conclusion.

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2 GENERAL STEPS FOR PCA ALGORITHM

The algorithm used for face recognition using principal component analysis [4] is as follows:
(i) Acquire an initial set of M face images (the training set) & Calculate the eigenfaces for each training set, keeping only M' eigenfaces that correspond to the highest eigenvalues.
(ii) Calculate the corresponding distribution in M'-dimensional weight space for each known individual, and calculate a set of weights based on the input image
(iii) Classify the weight pattern as either a known person or as unknown, according to its distance to the closest weight vector of a known person.
Let the training set of images be $\Gamma_1, \Gamma_2, \Gamma_3 \dots\dots \Gamma_M$. The average face of the set is defined by

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

Each face differs from the average by vector

$$\Phi_i = \Gamma_i - \Psi \quad (2)$$

The co- variance matrix is formed by

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

where the matrix $A = [\Phi_1, \Phi_2, \Phi_3 \dots\dots \Phi_M]$.
This set of large vectors is then subject to principal component analysis, which seeks a set of M orthonormal vectors u1............um .To obtain a weight vector Ω of contributions of individual eigen-faces to a facial image Γ, the face image is transformed into its eigenface components projected onto the face space by a simple operation

$$\omega_k = u_k^T(\Gamma - \Psi) \quad (4)$$

For k=1,.., M', where M' ≤ M is the number of eigen-faces used for the recognition. The weights form vector Ω = [ω1,ω2,....ωM] that describes the contribution of each Eigen-face in representing the face image Γ, treating the eigenfaces as a basis set for face images. The simplest method for determining which face provides the best description of an unknown input facial image is to find the image k that minimizes the Euclidean distance εk.

$$\varepsilon_k = \|\Omega - \Omega_k\|^2 \quad (5)$$

where Ω_k is a weight vector describing the kth face from the training set. A face is classified as belonging to person k when the ε_k is below some chosen threshold Θε otherwise, the face is classified as unknown. The algorithm functions by projecting face images onto a feature space that spans the significant variations among known face images. The projection operation characterizes an individual face by a weighted sum of eigenfaces features, so to recognize a particular face, it is necessary only to compare these weights to those of known individuals. The input image is matched to the subject from the training set whose feature vector is the closest within acceptable thresholds.

Eigen faces have advantages over the other techniques available, such as speed and efficiency. For the system to work well in PCA, the faces must be seen from a frontal view under similar lighting.

3 OTHER FORMS OF PCA

PCA method has been a popular technique in facial image recognition. But this technique is not highly accurate when the illumination and pose of the facial images vary considerably. There are many extended forms of traditional PCA. They are for the purpose of betterment and for removing drawbacks in traditional one.

Kwang et.al. purposed a kernel principal component analysis (KPCA) as a nonlinear extension of a PCA. 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. It adopts the kernel PCA as a mechanism for extracting facial features. Through adopting a polynomial kernel, the principal components can be computed within the space spanned by high-order correlations of input pixels making up a facial image, thereby producing a good performance. KPCA can be applied in supervised and unsupervised learning. In this paper performance of PCA and KPCA for face recognition were compared using ORL database. The error rate KPCA is 2.5% as compare to PCA is 10% [5].

Rajkiran Gottumukkal et.al. proposed a face recognition algorithm based on modular PCA approach. The PCA based face recognition method is not very effective under the conditions of varying pose and illumination, since it considers the global information of each face image and represents them with a set of weights. In modular PCA, the face images are divided into smaller sub-images and the PCA approach is applied to each of these sub-images. Recognition rate of modular PCA is 89% and of PCA is 70% for YALE database. The recognition rate is increasing in both PCA and modular PCA methods as there increases the number of eigenvector Mo, and there is not much improvement for Mo > 30. In particular, the modular PCA method will be useful for identification systems subjected to large variations in illumination and facial expression [6].

Jian YanG et.al. developed two-dimensional principal component analysis (2DPCA) for image representation. 2DPCA is 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. Instead, an image covariance matrix is constructed directly using the original image matrices, and its eigenvectors are derived for image feature extraction. 2DPCA gives 96% top recognition accuracy rate (%) as compared to PCA which is 93% on ORL database. Image features is computationally more efficient using 2DPCA than PCA. The main disadvantage of 2DPCA is that it needs many more coefficients for image representation than PCA. For example, suppose the image size is 100×100, then the number of coefficients of 2DPCA is 100×d, where d is usually set to no less than 5 for satisfying accuracy. Although this problem can be alleviated by using PCA after 2DPCA for further dimensional reduction, it is still unclear how the dimension of 2DPCA could be reduced directly [7].

Hui Konga et.al proposed Generalized 2D Principal Component Analysis (G2DPCA). It overcomes the limitations of the 2DPCA from the following aspects: (1) the essence of 2DPCA is clarified and the theoretical proof why 2DPCA is better than Principal Component Analysis (PCA) is given; (2) 2DPCA often needs much more coefficients than PCA in representing an image. In this work, a Bilateral-projection-based 2DPCA (B2DPCA) is proposed to remedy this drawback; (3) a Kernel-based 2DPCA (K2DPCA) scheme is developed and the relationship between K2DPCA and KPCA (Scholkopf et al., 1998) is explored. Experimental results in face image representation and recognition show the excellent performance of G2DPCA [9].

Daoqiang Zhang et.al proposed diagonal principal component analysis (DiaPCA) for face recognition. PCA, DiaPCA directly seeks the optimal projective vectors from diagonal face images without image-to-vector transformation. DiaPCA reserves the correlations between variations of rows and those of columns of images. DiaPCA gives 90.5% top recognition accuracy on FERET database whereas PCA and 2DPCA gives 85.5% on same database. It can further improved (91.5%) by combining DiaPCA with 2DPCA [10].

Daoqiang Zhang et.al proposed a new technique called 2-Directional 2DPCA, i.e. (2D)2PCA for efficient face representation and recognition by simultaneously considering the row and column directions. Experimental results on ORL and a subset of FERET face databases show that (2D)2PCA achieves the same or even higher recognition accuracy than 2DPCA, while the former needs a much reduced coefficient set for image representation than the latter [11].

M. Safayani et.al. proposed Extended Two- Dimensional PCA (E2DPCA) which was an extension to the original 2DPCA. It was stated that the covariance matrix of 2DPCA is equivalent to the average of the main diagonal of the covariance matrix of PCA. This implies that 2DPCA eliminates some covariance information that can be useful for recognition. E2DPCA instead of just using the main diagonal considers a radius of 'r' diagonals around it and expands the averaging so as to include the covariance information within those diagonals. The parameter 'r'

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unifies PCA and 2DPCA. r=1 produces the covariance of 2DPCA, r=n that of PCA. Hence, by controlling r it is possible to control the trade-offs between recognition accuracy and energy compression (fewer coefficients), and between training and recognition complexity. Experiments on ORL face database show improvement in both recognition accuracy and recognition time over the original 2DPCA.This paper shows the comparisons of six methods PCA, 2DPCA (row based), alternative 2DPCA (column based), E2DPCA (row based), alternative E2DPCA (column based) and 2D2PCA. This paper shows top accuracy of E2DPCA is better than that of other methods which is because of using more local geometric structure information [12].

Yue ZENG et.al. proposed an algorithm of face recognition based on the variation of 2DPCA (V2DPCA) which make the most useful of the discriminant information of covariance, and use the fewer coefficient to representing a image. It discusses the symmetry of face, the Characteristic of PCA (Principal Component Analysis) and 2DPCA(2-Dimensional PCA). It is proved that the covariance matrix of 2DPCA is equivalent to the average of the main diagonal of PCA and the covariance of 2DPCA eliminates some covariance information that is useful for recognition [13].

4 Results

On the basis of above studies comparison tables of different forms of PCA are prepared. The comparison tables show the recognition rate of PCA's extended forms on ORL and FERET database. Table-I gives comparison of Recognition rate (%) in Different Methods of PCA on ORL Database. In this table PCA gives recognition rate of 84.3% when dimensions of feature vector are 32 and 85.0% when dimension of feature vector are change to 34 but it gives recognition rate of 88% when dimension of feature vector are increased up 110. 2DPCA gives better results as compare to PCA. 2DPCA (row based) gives recognition rate of 92.9%. Alternative 2DPCA (column based) gives 91.5% recognition. Extended 2PCA gives 93% recognition rate. Table shows that variation of 2DPCA (V2DPCA) gives better recognition of 98.1% when feature dimensions are 10. It gives better results as compared to other forms of PCA.

TABLE-I
COMPARISON OF RECOGNITION RATE (%) IN DIFFERENT METHODS OF PCA ON ORL DATABASE

Method	Recognition rate (%)	Dimension
PCA(eigenface) [12][13][11]	85.0	34
	84.3	32
	88	110
2DPCA[13][12][11] (Row based)	92.9	92*10=920
	91.5	112*8=896
	90.5	27X112
Alternative 2DPCA[12][11] (column based)	91.5	92*4=368
	90.5	26X92
2D2PCA[12]	92	16*16=256
(2D)2PCA[11]	90.5	27X26
E2DPCA(r=21)[12] (Row based)	93	6*20=120
AlternativeE2DPCA(r=6)[12] (column based)	92.5	16*18=288
V2DPCA[13]	98.1	2*10=10

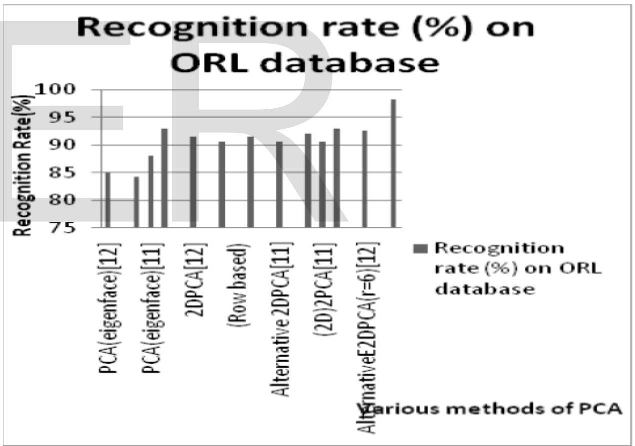

FIG.1: RECOGNITION RATE (%) ON ORL DATABASE.

Figure 1 shows the graphical representation of various methods of PCA versus recognition rate for ORL face database. The graph is generated from the data collected in table –I. From the graph it is analyzed that PCA gives smallest peak and V2DPCA gives highest peak. 2DPCA, alternative 2DPCA, 2D2PCA and $(2D)^2PCA$ gives intermediate peak i.e. between PCA and V2DPCA.

Table-II gives comparison of Recognition rate (%) in Different Methods of PCA on FERET Database. On FERET database simple PCA gives recognition rate of 83% when dimensions of feature vectors are 73 [11]. It also gives 85.5% recognition rate when feature vector dimensions are 16. PCA, 2DPCA, alternate 2DPCA, 2D2PCA,(2D)2PCA gives almost same recognition rate which is below 85%. DiaPCA gives 90.5% recognition but when it is combined with 2DPCA i.e. DiaPCA+2DPCA it improves recognition rate

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which is near about 91.5% when feature vector dimensions are 16X5. If we overall compare the table-I and table-II then it shows that ORL database gives better results as compare to FERET.

TABLE-II
COMPARISON OF RECOGNITION RATE (%), THE CORRESPONDING DIMENSIONS OF FEATURE VECTORS OR MATRICES IN DIFFERENT METHODS OF PCA ON FERET DATABASE [10].

Method	Recognition Rate (%)	Dimensions
PCA[10][11]	83	73
	85.5	16
2DPCA[10][11]	84.5	13X60
	85.5	60X4
Alternate 2DPCA[11]	84.5	14X60
(2D)2PCA[11]	85	13X14
DiaPCA[10]	90.5	60X5
DiaPCA+2DPCA[10]	91.5	16X5

Figure 2 shows the graphical representation of various methods of PCA with recognition rate of FERET face database. This graph is prepared from the data collected in table-II. When recognition rate(%) of FERET face database is analyzed, it is shown in figure 2 that PCA gives smallest peak and DiaPCA+ 2DPCA gives highest peak. 2DPCA, alternative 2DPCA, 2D2PCA and (2D)2PCA gives intermediate peak i.e. between PCA and V2DPCA.

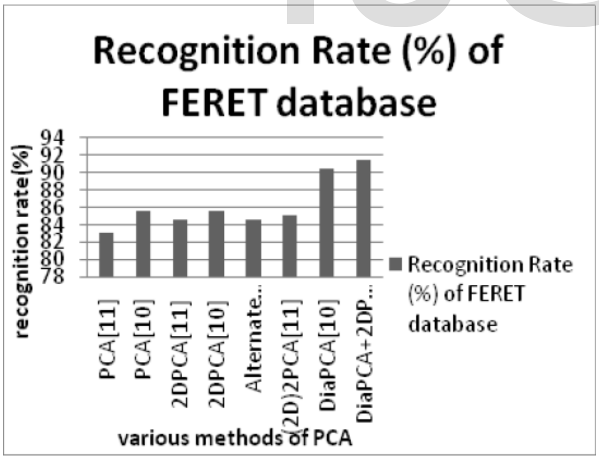

FIG.2: RECOGNITION RATE (%) ON FERET DATABASE.

5 CONCLUSIONS

From this systematic review of different forms of PCA, it is seen that on ORL database V2DPCA gives better recognition rate as compare to other form of PCA. It gives 98% [12] recognition as compare to 2DPCA and PCA. On FERET face database DiaPCA+2DPCA gives high recognition rate as compare to PCA, 2DPCA, DiaPCA. The recognition rate of DiaPCA is 91.5%. so it is concluded when PCA is combined with some other extended form of PCA gives better recognition.

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