Appearance based Techniques for Face Recognition: A Comparative Study

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ABSTRACT
In these days, appearance based approaches gain popularity in many computer vision problems, more in particular on face recognition techniques. In this context, a study on face recognition techniques based on appearance based paradigm is addressed in our work. More focus is provided to principal component analysis (PCA) based techniques where the principle of PCA is well received by pattern recognition community for most of the dimensionality reduction problems or for feature selection in a large collection of features set. We have seen several variants of PCA in the literature applied to the domain of face recognition considering variety of natural problems that would occur during face recognition. In our work, we have made an attempt to study the problem of face recognition under different situations. The study is conducted with varying dimension of features on a variety of face databases which include pose, illumination and occlusion problems. The effect of varying training samples is also addressed in our study. We have considered the standard PCA, two dimensional PCA (2D PCA) which works in row directions, alternative 2D PCA that works in column directions and bidirectional PCA for comparative analysis on many of the standard face databases such as AT&T, UMIST and IITK datasets. Extensive experimental results on each of these datasets along with computing time and their recognition accuracy under different dimension of feature vectors with varying number of training samples is reported in our work.

General Terms
Pattern Recognition, Image Processing, Biometrics.

Keywords
Principal Component Analysis, Two-dimensional PCA, bidirectional PCA, Eigen face, Face recognition.

1. INTRODUCTION
In the current technological advancements, we have witnessed the growth of usage of biometric techniques to provide authentication for many of the secured transactions such as banking, airport transfer, defense entry criminal investigation etc. The usage of face as a biometric along with other traits such as plam-print, iris, speech etc is quite common in most of these authentication systems. This is due to the fact that the face is one of the biometric which can be captured without user intervention and without user acceptance too. In this context, researchers developed many of the algorithms for face recognition to address several problems such as orientation, non-uniform illumination etc, that exists in real scenario. Face recognition is very challenging because of its interclass recognition problem and distinctiveness of face is quite low when compared to other biometrics [1].

Among the existing face recognition approaches, appearance based paradigm is found to be dominant because of ease of implementation and also its simplicity, and computational efficiency. However, we have seen plethora of algorithms under this broad stream where PCA is found to be one of the natural solution to the dimensionality reduction technique and hence a study on the suitability of PCA to different types of face datasets would be a very interesting and also useful for the research community. This issue motivates us to take a study of PCA and its variants to address the well known face recognition problem which is commonly referred as 'eigen – face' or manifold learning technique in the field of pattern recognition and image processing.

In the process of image representation, recognition and retrieval, vector-space model may be the most popular one and is used in most of the existing algorithms designed for these tasks. The most popular vector space model in use is PCA. Kirby and Sirovich [2] first showed that PCA can be effectively used to represent images of human faces. The main idea of PCA for face recognition is that it transforms 2D facial image matrix into large 1D vector of pixels and expresses the 1-D vector as the compact principal components of the feature space [3]. Thus, it reduces the large dimensionality of data space into small dimensionality of feature space. Rajkiran and Vijayan [4] proposed to divide the face images into sub images and then applying PCA on each of the sub images which possess an improved recognition rate when compared to conventional PCA. Changjun Zhou et al., [5] combined the PCA, LDA and Support vector machine (SVM) to obtain the improved recognition accuracy in comparison to PCA and LDA. The work involves: computation of residual images by subtracting reconstructed images and obtaining images through reconstruction from original face images. The performances of various PCA and LDA algorithms are analyzed using different standard public databases by Steven Fernandes et al., [6] and proved that, among various PCA algorithms analyzed, manual face localization gives the best face recognition rate of 100% and among various LDA algorithms analyzed, Illumination Adaptive Linear Discriminant Analysis (IALDA) gives the best face recognition rate of 98.9%. Bartlett et al. [7] and Draper et al., [8] showed that, ICA for face representation is better than PCA using cosines as the similarity measure. Yang [9] used Kernel PCA for face feature extraction and recognition and showed that the Kernel Eigen faces method outperforms the classical Eigen faces method. However, computational complexity is higher in ICA and Kernel PCA than PCA.

It shall be noted from the above mentioned PCA-based face recognition techniques, the 2D face image matrices need to be transformed into 1D image vectors. The resulting image vectors of faces usually lead to a high dimensional image vector space, which also causes difficulty in evaluating the covariance matrix accurately. To overcome this problem, Jian Yang et al. [10] proposed an alternative method for image feature extraction called 2D-PCA which differs from conventional PCA where the image matrix does not need to be transformed into 1D vector. The image covariance matrix can be directly obtained using the original image matrices and it is much smaller in size as compared to that obtained using PCA. Their work also showed that 2D-PCA achieves better performance than one dimensional PCA in face recognition when the number of samples is small. However, there still remain several problems in 2D-PCA such as requirement of more coefficients to represent an image in 2D-PCA than in one dimensional PCA. Many variants of two dimensional PCA have been proposed and are reviewed below. However, the basic principle in all the variants of 2D-PCA is one and the same, but differs by representation and nomenclature.

Hui Kong et al. [11] proposed generalized 2D Principal Component Analysis (G2DPCA) as an extension of the original 2D-PCA and introduced a bilateral 2DPCA scheme to reduce number of coefficients in representing an image. An algorithm of face recognition based on the variation of 2DPCA (V2DPCA) is proposed by Y. Zeng et al [12], which make the most useful discriminant information of covariance, and use the fewer coefficient to represent an image. Zhang and Zhou [13] proposed two-dimensional two directional PCA ($2D^2$-PCA) to overcome the limitation of 2D-PCA. The work indicated that $2D^2$-PCA works in both row and column directions of face images. It also showed that by simultaneously considering row and column directions, the proposed $2D^2$-PCA has better recognition accuracy than PCA and 2D-PCA. $2D^2$-PCA which uses global feature extraction mechanism may fail to preserve local features of face images. Hence, blockwise $2D^2$-PCA improves the performance of $2D^2$ PCA by preserving the local informative variations [14]. Bidirectional PCA (BPCA) or $2D^2$-PCA works only in Euclidean space. To enhance the robustness of these techniques, Laplacian BPCA was proposed [15] in which the two techniques are extended to non-Euclidean space.

In this paper, we have considered the conventional PCA and its two variants 2D-PCA and BPCA for comparative study. The three approaches are experimentally analyzed. The study is conducted with varying dimension of features on a variety of face databases such as AT&T, UMIST and IITK, which include pose, illumination and occlusion problems. The effect of varying training samples is addressed in our study and the suitability of different variants of PCA to different situations is also considered in our work.

In the following, we discuss the PCA in section 2, 2D-PCA in section 3, $2D^2$-PCA in section 4, the experimental results with comparative analysis in section 5, and finally section 6 includes conclusion.

2. PRINCIPAL COMPONENT ANALYSIS BASED FACE RECOGNITION

The PCA method of Turk and Pentland [3] has been extensively used for feature extraction and face recognition purposes. It treats the face images as 2-D data, and classifies the face images by projecting them to the eigen-space which is composed of eigen vectors obtained by the variance of the face images. This variance is obtained by getting the eigen vectors of the covariance matrix of all the images. In the standard eigen-face procedure suggested by Turk and Pentland [3], Euclidean distance is used for the classification of test images.

Let $f_1, f_2, f_3, \ldots, f_M$ be M training samples, each of size r x c. Each 2D image matrix f_i (i=1,2,…,M) is converted into 1D image vector of size N x 1 (N= r*c) as

$$f_i = [f_{i1}, f_{i2}, \ldots, f_{iN}]^T \quad (1)$$

The images are mean centered by subtracting the mean image from each image vector.

$$\bar{f}_i = f_i - m \text{, where } m = \frac{1}{M}\sum_{i=1}^{M} f_i \quad (2)$$

These vectors are then concatenated side by side to form data matrix of size N x M (M is the number of training images).

$$\bar{X} = [\, \bar{f}_1 \mid \bar{f}_2 \mid \mid \bar{f}_3 \mid \ldots. \mid \bar{f}_M \,] \quad (3)$$

The data matrix and its transpose are multiplied to obtain the covariance matrix.

$$C = \bar{X}\,\bar{X}^T \quad (4)$$

The eigen vectors of the covariance matrix are computed and the k eigen vectors corresponding to the k largest eigen values are ordered from high to low to form the eigen-face model. Let $V = [V_1|V_2| \ldots |V_k]$ where $k \le M$, be the eigen-face space.

Once eigen space is obtained, each of the centered training image vectors ($\bar{f}_i$) are projected into the eigen space.

$$\tilde{f}_i = V^T \bar{f}_i \quad (5)$$

To identify the test image, initially it is mean centered by subtracting the mean image from the test image vector. It is then projected into the obtained eigen vector space.

$$\bar{t}_i = t_i - m \text{, where } m = \frac{1}{M}\sum_{i=1}^{M} f_i \quad (6)$$

And

$$\tilde{t}_i = V^T \bar{t}_i \quad (7)$$

The comparison is done between the projected test image and each of the training images using similarity measure. The training image found to be closest to the test image is used to classify the test image. The most well known similarity measure is Euclidean distance.

3. TWO DIMENSIONAL PRINCIPAL COMPONENT ANALYSIS BASED FACE RECOGNITION

The two dimensional Principal Component Analysis (2D-PCA) (Yang et al., 2004), a variant of the conventional PCA, is another linear image projection technique for face recognition. The 2D-PCA uses matrix based representation model rather than simply the 1D vector based one. When performing 2DPCA, the original 2D image matrix does not need to be transformed into 1D vector. The covariance matrix is constructed by using the 2D image matrices directly. As mentioned in (Yang et al., 2004), 2DPCA can achieve better performance than PCA in face recognition when the number of samples is small. However, is shall be observed that the 2D-PCA need more coefficients to represent an image than PCA. This means that a lower compression rate could be achieved in representing an image.

Consider an m by n random image matrix X. Let V is an n-dimensional unitary column vector with orthonormal columns. Projecting X onto V yields an m x d matrix

$$Y = XV \quad (8)$$

In 2DPCA, the total scatter of the projected samples is used to determine a good projection matrix V.

Suppose that there are M training face images, denoted by m by n matrices X_k, (k=1, 2… M), and the average image is given as

$$\overline{X} = \frac{1}{M}\sum_k X_k \quad (9)$$

Then, image covariance matrix C is defined as,

$$C = \frac{1}{M}\sum_{k=1}^{M}(X_k - \overline{X})^T (X_k - \overline{X}) \quad (10)$$

This is an n by n nonnegative definite matrix. Then the orthonormal eigen vectors $V_1, V_2,\ldots,V_d$ corresponding to the d largest eigen values of C are obtained which forms projection matrix: $V=[V_1, V_2,\ldots,V_d]$.

Thus, an m-dimensional projected vector Y is obtained, which is called the projected feature vector of image X.

Suppose $X_k = [(X_k^{(1)})^T, (X_k^{(2)})^T \ldots (X_k^{(m)})^T]^T$ and $\overline{X} = [(\overline{X}^{(1)})^T, (\overline{X}^{(2)})^T \ldots. (\overline{X}^{(m)})^T]^T$, where $X_k^{(i)}$ and $\overline{X}^{(i)}$ denote the i^{th} row vector of X_k and $\overline{X}$ respectively, then we can rewrite C given by Eq. (10) as

$$C = \frac{1}{M}\sum_{k=1}^{M}\sum_{i=1}^{m}(X_k^{(i)} - \overline{X}^{(i)})^T (X_k^{(i)} - \overline{X}^{(i)}) \quad (11)$$

The Eq. (11) indicates that C can be obtained from the product of row vectors of the images, assuming the training images have zero mean. Thus, one can notice here that the 2D-PCA works in the row direction of images.

Alternatively, we can define covariance matrix C from product between the column vectors of images. Let $X_k = [X_k^{(1)}, X_k^{(2)} \ldots X_k^{(m)}]$ and $\overline{X} = [\overline{X}^{(1)}, \overline{X}^{(2)} \ldots. \overline{X}^{(m)}]$, where $X_k^{(j)}$ and $\overline{X}^{(j)}$ denote the j^{th} column vector of X_k and $\overline{X}$ respectively, then the covariance matrix C is defined as

$$C = \frac{1}{M}\sum_{k=1}^{M}\sum_{j=1}^{n}(X_k^{(j)} - \overline{X}^{(j)})(X_k^{(j)} - \overline{X}^{(j)})^T \quad (12)$$

Let U be a matrix of size m x q with orthonormal columns. We project the image matrix X onto U to get q x n matrix Z as $Z=U^TX$.

We now obtain the orthonormal eigen vectors $U_1, U_2,\ldots,U_q$ corresponding to the q largest eigen values of C (Eq. (12)) to form projection matrix $U=[U_1, U_2,\ldots,U_q]$. Hence, we say that the alternative 2D-PCA is working in column direction of images.

4. BIDIRECTIONAL PRINCIPAL COMPONENT ANALYSIS BASED FACE RECOGNITION

As mentioned in section 3, the 2D-PCA and its alternative versions respectively works in row and column directions of image matrix. That is, the optimal projection matrix V is obtained from the product between the row vectors of the images. Projecting an m by n image X onto V, yielding an m by d matrix Y= XV. Similarly, the projection matrix U is obtained from the product of column vectors of images. We project image matrix X onto U to obtain q x n matrix $Z=U^TX$.

In $2D^2$-PCA approach [13], a different mechanism to project the image matrix is used, which results in reduced coefficients for image representation. Suppose V and U are obtained projection matrices, then m x n image matrix X can be projected onto both projection matrices simultaneously to get q x d matrix P as follows:

$$P = U^T XV \quad (13)$$

The matrix P is also called coefficient matrix or feature matrix for image representation. Let P_k (k=1… M) be the feature matrices obtained by projecting the training samples X_k (k=1,…,M) onto both projection matrices V and U simultaneously. Given a test image X, we use Eq. (13) to obtain the feature matrix P. We use the Euclidean distance measure for classification, where the distance between P and P_k is given by d (P, P_k) = $\sqrt{\sum_{i=1}^{q}\sum_{j=1}^{d}(P^{i,j} - P_k^{i,j})^2}$

5. EXPERIMENTAL RESULTS

In this section, we present the experimental results obtained due to PCA, 2D-PCA, alternative 2D-PCA and $2D^2$-PCA. The experiments are performed on ORL, UMIST and IITK face databases. In all our experiments, we used the Euclidian distance as the similarity measure for classification.

5.1 Experiments on ORL Database

The ORL face database consists of gray-scale images of 40 individuals each with 10 samples. They represent some variation in facial expressions, facial details, scale and also limited rotation. All images are cropped to size of 112 x 92 pixels. Fig. 1 shows the subset of one such subject of the ORL database.

Fig 1: Ten images of one person in ORL face database.

The experiments are carried out by varying the number of training samples and testing samples under each subject. We have chosen five different samples of each person for training such as (1) alternate samples (1, 3, 5, 7, 9 and 2, 4, 6, 8, 10), (2) last 5 samples, (3) initial 5 samples and remaining as testing. Similarly, experiments are conducted with seven random samples (i.e. total 280 training samples) and three (i.e. 120 training samples) random samples of each individual for training and the remaining samples for testing. In all the cases, the recognition accuracy is measured for varying dimensions and the results obtained due to $2D^2$-PCA is shown in Fig. 2.

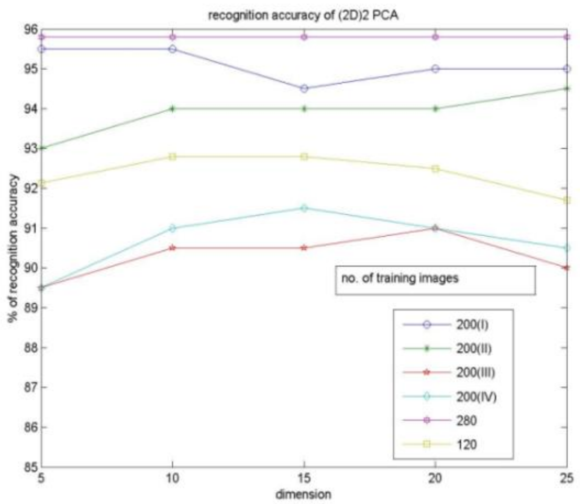

Fig 2: Recognition accuracy of $2D^2$ PCA for ORL dataset.

5.2 Experimentation on UMIST Face Dataset:

The UMIST face dataset consists of 564 images of 20 people with large pose variations. In our tests, we have considered a partial set of face images consisting of 15 images each of 20 different individuals from the UMIST face database. The Fig. 3 shows 15 such samples of a single person in UMIST database.

Fig 3: Samples of a person in UMIST

We have conducted the experiments by considering alternate samples (even and odd), continuous samples (last 8 and first 7 samples) and random samples (11 and 4 samples of each person) for training and remaining samples are considered for testing. In all the above experiments, we recorded the recognition accuracy for $2D^2$-PCA under varying dimensions of feature vectors. The experimental results are shown in Fig. 4.

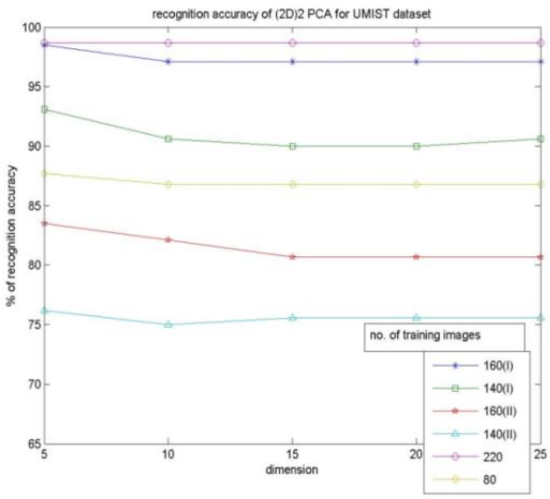

Fig 4: Recognition accuracy of $2D^2$ PCA for UMIST dataset.

5.3 Experimentation on IITK Face Dataset:

The IITK dataset consists of 242 images of 22 persons with 11 samples for each individual. The samples represent face appearance with variations in pose and expression. The Fig. 5 shows 11 such samples of a single person in real database.

The same set of experiments that are performed on ORL and UMIST datasets are also conducted on IITK dataset and recognition rate is found for each experiment and the results are reported in Fig. 6.

For the purpose of providing a comparative study, we have conducted similar experimentation considering PCA and 2D-PCA (row wise and column wise) models, using different face datasets such as ORL, UMIST and IITK datasets. The recognition accuracy of all experiments for these models is recorded.

Fig 5: Samples of a person in IITK dataset

The recognition performances of row wise 2D-PCA, column wise 2D-PCA and conventional PCA techniques with varying dimensions of feature vectors for ORL dataset are plotted in Fig. 7, Fig. 8 and Fig. 9 respectively and for UMIST dataset are plotted in Fig. 10, Fig. 11 and Fig. 12 respectively.

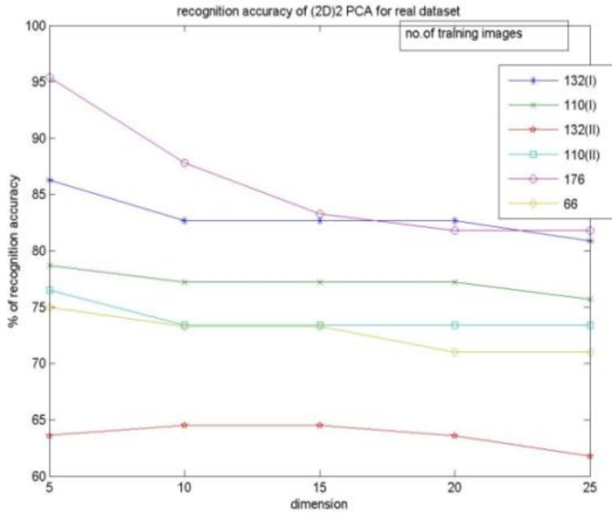

Fig 6: Recognition accuracy of $2D^2$ PCA for IITK dataset.

The recognition performances of row wise 2D-PCA, column wise 2D-PCA and conventional PCA techniques with varying dimensions of feature vectors for IITK dataset are plotted in Fig. 13, Fig. 14 and Fig. 15 respectively.

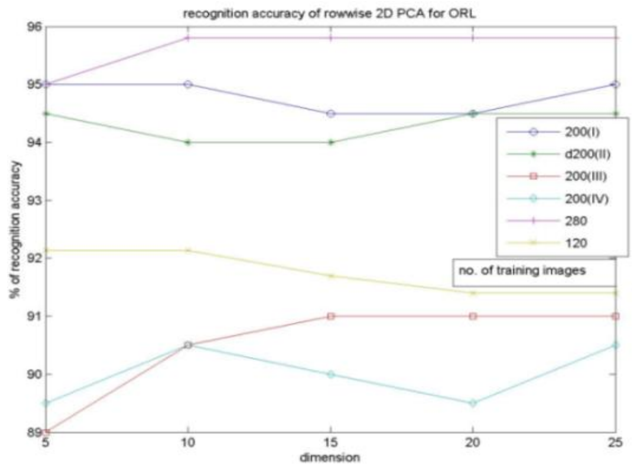

Fig 7: Recognition accuracy of row wise2D PCA for ORL dataset

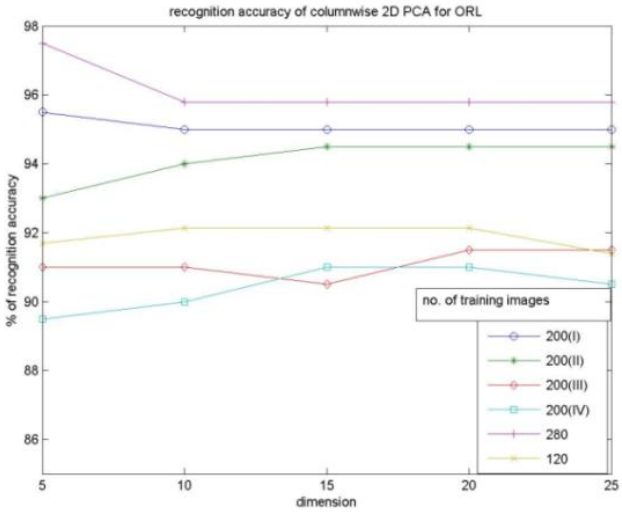

Fig 8: Recognition accuracy of column wise 2D PCA for ORL dataset

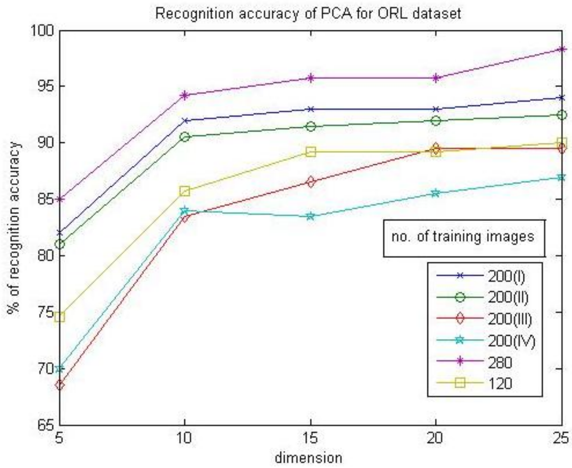

Fig 9: Recognition accuracy of PCA for ORL dataset

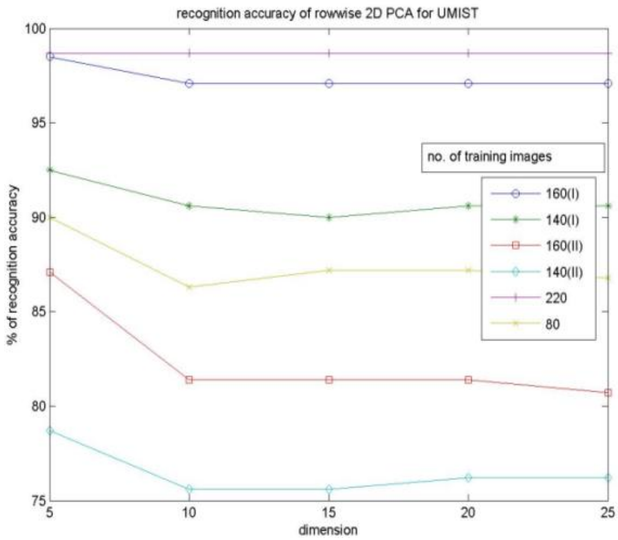

Fig 10: Recognition accuracy of row wise2D PCA for UMIST dataset

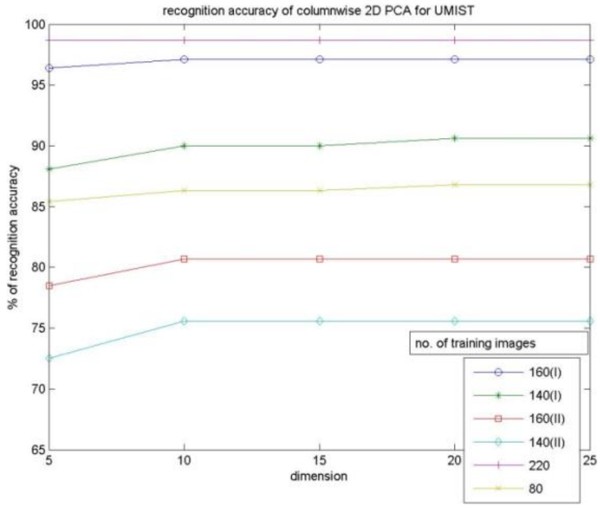

Fig 11: Recognition accuracy of column wise2D PCA for UMIST dataset

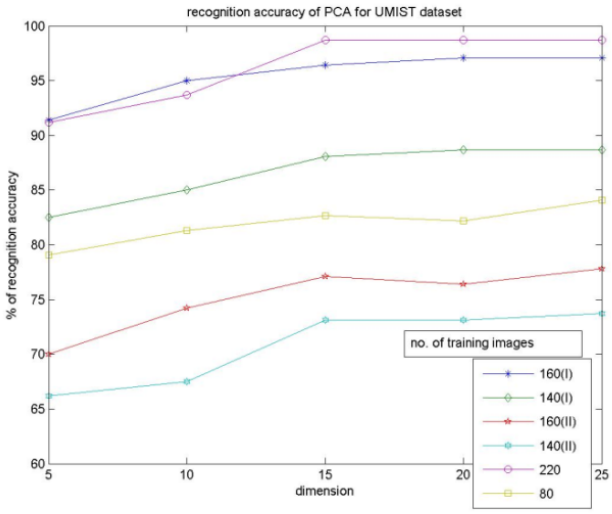

Fig 12: Recognition accuracy of PCA for UMIST dataset

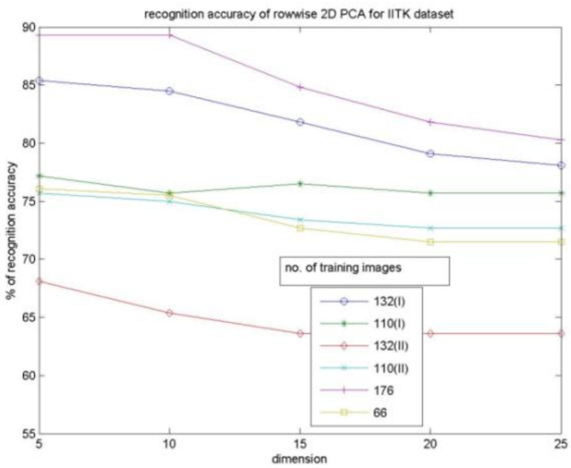

Fig 13: Recognition accuracy of row wise 2D PCA for IITK dataset

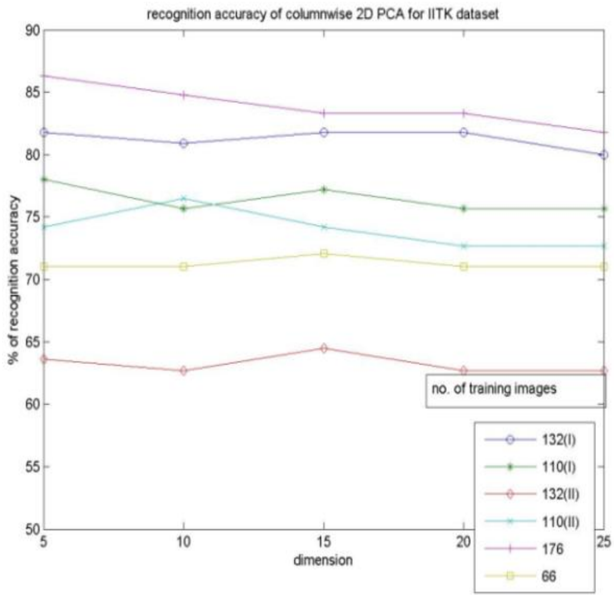

Fig 14: Recognition accuracy of column wise 2D PCA for IITK dataset

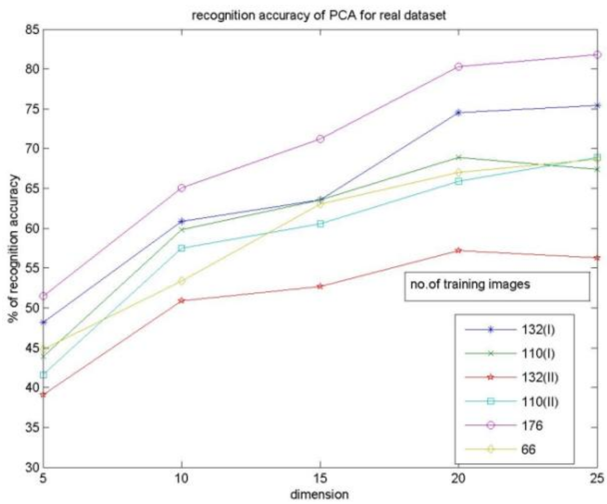

Fig 15: Recognition accuracy of PCA for IITK dataset

From all the experiments conducted on standard face datasets ORL, UMIST and IITK dataset, we can analyze that $2D^2$-PCA performs better than PCA in terms of recognition accuracy and also proved that under the same dimensions of feature vectors, $2D^2$-PCA obtains same or better accuracy than both variants of 2D-PCA. Also, the performance of $2D^2$-PCA does not reduce with reduction in dimension of feature vector. That is, we obtained improved recognition rates even with the small dimension of feature vector. It shall be noted here that the dimensionality of $2D^2$-PCA is quite less when compared to row-wise and column-wise 2D-PCA techniques and hence is certainly will be the better choice from efficiency point of view. In addition, as $2D^2$-PCA does not require conversion of image data to vector form and hence the covariance matrix can be computed efficiently within a reasonable period of time and accurately. In this context, $2D^2$-PCA is shown to perform much better when compared to conventional PCA also. The experimental results conducted on various datasets reveals the performance of bi-directional PCA over conventional PCA.

6. CONCLUSION

In this paper, we have discussed the variants of PCA considering face recognition problem and analyze the performance. The $2D^2$-PCA is proven to be the better approach for face representation and recognition as compared to the conventional PCA, 2D-PCA and alternate 2D-PCA. Our experiments also showed that the $2D^2$-PCA achieves greater accuracy than PCA, 2D-PCA and its alternate version with reduced number of coefficients for image representation. The main advantage of $2D^2$-PCA over 2D-PCA is that the number of coefficients needed by the former for face representation and recognition is much reduced than the latter and the $2D^2$-PCA directly processes the 2D image matrix, eliminating the need to transform into 1D vector. It also evaluates the covariance matrix more accurately. The experimental results are presented considering some of the standard face datasets such as ORL, UMIST and IITK dataset. The $2D^2$-PCA outperforms the other methods in terms of accuracy and computational efficiency.

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