An Efficient Algorithm for Face Recognition using Modular PCA

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Abstract: **Principal Component Analysis is one of the most successful techniques that have been used in image recognition. The purpose of PCA is to reduce the large dimensionality of the data space to the smaller dimensionality of the feature space. The proposed paper presents a face recognition algorithm based on modular PCA. It provides improved recognition rate for face images with large variations. The variations may be with respect to the lighting, direction and facial expression. In the Modular PCA approach original face images are divided into sub images and then the PCA approach is applied to each of these sub images.**

Keyword: **Face recognition, Illumination variation, facial expression, pose invariance, PCA , Modular PCA.**

I.   INTRODUCTION

The Face recognition becomes a tedious job when similar shape of faces is combined with the numerous variations between images of the same face. The image of a face changes with respect to facial expression, age, viewpoint, illumination conditions, noise etc. The aim of the face recognition system is to recognize a face in a manner that is as independent as possible of these image variations. One of the fundamental problems in computer vision and pattern analysis is the automatic recognition of faces. The other methods which can be used for face recognition are statistical based, neural network based and feature based methods. In PCA approach face images are expressed as a subset of their eigen vectors, and are called as eigen faces. PCA has also been used for handprint recognition, human made object recognition, and robotics. But recognition rate is not satisfactory for pose variations and extreme changes in illumination. To improve the accuracy of the face recognition under the condition of varying facial expression, illumination and pose the proposed method i.e. modular PCA approach can be used. In this modular PCA approach the face images are divided into smaller images and the PCA method is applied on each of them. Since the original image is divided into sub images the variations in the pose or illumination in the image will affect only some of the sub images, hence this method is expected give better results.

This paper is organized as follows. Section 2 describes the conventional PCA approach. Section 3 describes the modular PCA approach. Section 4 describes the face databases used for testing and section 5 provides comparison between the methods. Section 6 presents the final conclusion.

II.   CONVENTIONAL PCA APPROACH

A.   General Review

The PCA method has been commonly applied for the face recognition process. Approximate reconstruction of the faces was performed using the weighted combination of eigen vectors. The weights that characterize the expansion of the given image in-terms of eigen images are seen as global facial features. Al the face images in the face database are represented as very long vectors, instead of the usual matrix representation. This makes up the entire image space where each image is a point. Since the faces have similar structure the vectors representing them will be correlated. The faces of the same class will group at a certain location in the image space as shown in Fig.1. Hence the face images are represented by a set of eigen vectors developed from a covariance matrix formed by training of face images.
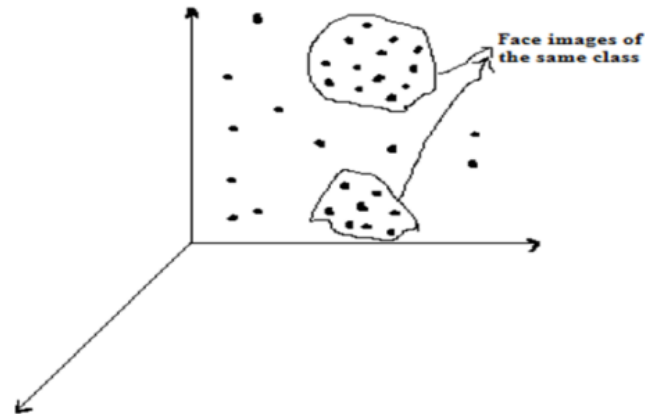
Fig.1. Image space and the face space co-ordinate system

B. Computation of Eigen faces

Consider that the face image in the face database is of size Lx L. These images can be represented as a vector of dimension L^2, or a point in L^2 dimension space. Therefore a set images corresponds to a set of points in this high dimensional space. Since facial images are similar in structure, these points will not be randomly distributed, and therefore can be described by a lower dimensional subspace. PCA gives the basis vector for this subspace.. each basis vector is of length L^2 and is eigen vector of the covariance matrix corresponding to the oriinal face images. Let $I_1, I_2,....I_m$ be the training set of face images. The average face is defined by,

$$Avg= (1/m) \sum I_i \text{ for all } i=1,2,......m \tag{1}$$

Each face differs from the average face by the vector Di=Ii-A. the covariance matrix c is obtained as

$$C=(1/m) \sum Di. Di^T \text{ for all } i=1,2,..... m \tag{2}$$

The eigen vectors of the covariance matrix are computed and M' significant eigenvectors are chosen as those with the largest corresponding eigenvalues. From these eigenvectors, the weights for each image in the training set are computed as,

$$Wik= E_k^T(Ii-A) \tag{3}$$

Where Ek's are the eigen vectors corresponding to the M' largest eigenvalues of C and K varies from 1to M'.

III.   PROPOSED 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. Under these conditions the weight vectors will vary considerably from the weight vectors of the images with normal pose and illumination, hence it is difficult to identify them correctly. On the other hand, if the face images were divided into smaller regions and the weight vectors are computed for each of these regions, then the weights will be more representative of the local information of the face.

When there is a variation in the pose or illumination, only some of the face regions will vary and rest of the regions will remain the same as the face regions of a normal image. Hence weights of the face regions not affected by varying pose and illumination will closely match with the weights of the same individuals face regions under normal conditions. Therefore it is expected that improved recognition rates can be obtained by following the modular PCA approach. We expect that if the face images are divided into very small regions the global information of the face may be lost and the accuracy of this method may deteriorate. In this method, each image in the training set is divided into N smaller images. Hence the size of each sub-image will be L^2/N. These sub images can be presented as,

$$Iij(m,n)=Ii(\tfrac{L}{\sqrt{N}}(j-1)+m, \tfrac{L}{\sqrt{N}}(j-1)+n) \text{ for all } i,j \tag{4}$$

Where I varies from 1 to M, M is the number of images in the training set, j varies from 1 to N, N is the number of subimages and m and n vary from 1 to L/sqrt(N)

The average image of all training sub images are obtained as

$$A = (1/M.N) \sum_{i=1}^{M} \sum_{j=1}^{N} Iij \tag{5}$$

The next atep is to normalize each training sub image by subtracting it from the mean

$$Yij = Iij - A \tag{6}$$

From the normalized sub images the covariance matrix is computed as

$$C = 1/(M.N) \sum \sum Y_{ij} Y_{ij}^{T} \tag{7}$$

Next we find the eigen vectors of C that are associated with the M′ largest eigenvalues. We represent the eigen values as $E_1, E_2, \ldots\ldots E_{M'}$. then the weights are computed from the eigenvectors. Mean weightset of each class in the training set is computed from the weight sets of the class. Then the minimum distance is computed.

IV.   BASIC IMAGE DATABASES

There are many databases of images available for use. Proposed approach used Yale and UMIST databeses to study the performances of both conventional PCA and Modular PCA algorithm. The UMIST database consists of images with varying pose and Yale database consists of images with varying illumination and expressions. All the images in both the datbases were normalized and cropped to a size of 64x64 pixels.

The proposed method used a partial set of facial images consisting of 10 images each of 20 different individuals from UMIST database. Each image of a person is taken at different pose, with a normal expression. Out of the ten imagesof a person, only eight were used for training and the remaining two were used to test the recognition. The choice of the training and testing images was made to test both the algorithms with head pose angles that lie outside the head pose angles they were trained with.

The Yale database has 165 gray scale images in GIF format of15 individuals, 11 images per person. The face images vary with respect to facial expression and illumination. There are also image with and without glasses. Out of 11 images of a person, only eight were used for training and the remaining three were used to test recognition rate.

V.   RESULTS

For varying number of eigen vectors the performance of both PCA algorithm and the proposed modular PCA algorithm were tested. By considering more eigenvectors it resulted in increased recognition rate but computational cost is derectly proportional to the number of eigen vectors. Fig. 2 shows the recognition rates of the conventional PCA and the proposed modular PCA. It has been observed that modular PCA algorithms provides better recognition rate and it does not require the detection of specific features like eye, noise, and mouth.
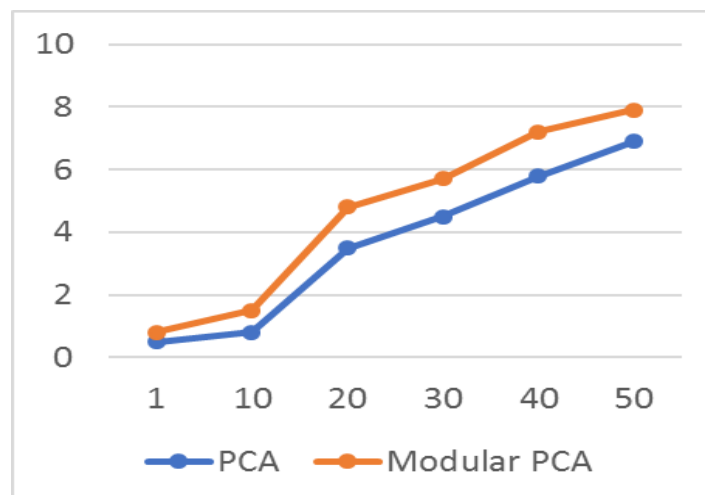

Fig.2. Recognition rate graph

VI. CONCLUSION

The modular PCA method found to perform better than the conventional PCA method under the condition of large variations in expression and illumination. Hence the proposed method can be used as an alternative to the conventional PCA. And it will be useful for identification systems subjected to large variations in illumination and facial expression.

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