Face Recognition and Facial Expression Identification using PCA

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***Abstract* - The face being the primary focus of attention in social interaction plays a major role in conveying identity and emotion. A facial recognition system is a computer application for automatically identifying or verifying a person from a digital image or a video frame from a video source. The main aim of this paper is to analyse the method of Principal Component Analysis (PCA) and its performance when applied to face recognition. This algorithm creates a subspace (face space) where the faces in a database are represented using a reduced number of features called feature vectors. The PCA technique has also been used to identify various facial expressions such as happy, sad, neutral, anger, disgust, fear etc. Experimental results that follow show that PCA based methods provide better face recognition with reasonably low error rates. From the paper, we conclude that PCA is a good technique for face recognition as it is able to identify faces fairly well with varying illuminations, facial expressions etc.**

Keywords – Principal Component Analysis (PCA), Eigen faces, Face recognition

I. INTRODUCTION

Over the last decade, face recognition has been extensively used in applications like identity authentication, access control, face-based video indexing/browsing, as well as in human-computer interaction and communication. Unlike other forms of personal identification such as fingerprint analysis or iris scanning, face recognition is non-intrusive and can be performed even the subjects reject to, which is indeed a g reat advantage, especially for law enforcement purposes. However, developing a computational model of face recognition is quite difficult, because faces are complex, multidimensional and meaningful visual stimuli. Two issues are central to all face recognition algorithms: a) feature selection for face representation and b) classification of a new face image based on the chosen feature representation.

Principal Component Analysis (PCA) is a classical feature extraction and data representation technique widely used in the areas of pattern recognition and computer vision. The purpose of PCA is to reduce the large dimensionality data space into the smaller dimensionality feature space, needed to describe the data economically [1] .This approach is based on the concept of eigenfaces, it can locate and track a s ubject's face, and then recognize the person by comparing the characteristics of the face to those of known individuals. This algorithm treats face recognition as a two-dimensional (2-D) recognition problem considering that fact that faces are upright and its characteristic features are used for calculation.

Facial expressions play an important role in communication between people. Generally, for the purpose of identifying the expression, features such as the contours of the mouth, eyes and eyebrows obtained from eigenfaces are used [2]. In this paper we have taken into account various facial expressions such as ha ppy, s ad, d isgust, fear, anger a nd surprise whereas ab sence of a ny expression i s c onsidered to be the ne utral expression.

II. PCA ALGORITHM

A. Overview

The main idea of Principal Component Analysis (PCA) is to find the vectors which best account for the distribution of face images within the entire image space, as stated in [1][3]. These vectors define the subspace of face images, which we call "face space" [4]. In this approach, the faces are represented as a l inear combination of weighted eigenvectors called eigenfaces. The eigenfaces are nothing but the principal components of a distribution of faces, or equivalently, the eigen vectors of the covariance matrix of the set of face images, where an image of size N by N pixels is considered a point in the N^2 dimensional space.

B. Principle of the algorithm

The 2-D facial images of size N x N in the training set are represented as column vectors of size N^2. Suppose we have M images, they can be represented as $P_1, P_2, \ldots P_M$.
The average face image is calculated as

$$m = \frac{1}{M}\sum_{i=1}^{M} P_i \tag{1}$$

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Next, the mean-centered images are obtained by subtracting the mean image from each image vector and it can be defined as

$$\varphi_i = P_i - m \quad (2)$$

The matrix A is the set of all these mean-centered images

$$A = [\varphi_1\, \varphi_{2.....}\varphi_M\,] \quad (3)$$

$C = AA^T$ results in a covariance matrix of dimensions N^2 X N^2 and determining the N eigenvectors and eigenvalues is tedious task for typical image sizes. Therefore for simplicity, we compute $C = A^T A$ which would be a much smaller matrix of size M x M matrix and would result in lesser number of computations.

Consider the eigenvectors V_i of $A^T A$ such that

$$A^T AX_i = \lambda_i X_i \quad (4)$$

Now multiplying the above equation by A on both sides,

$$AA^T AX_i = A(\lambda_i X_i)$$
$$AA^T (AX_i) = \lambda_i (AX_i) \quad (5)$$

Eigen vectors corresponding to AA^Tcan be easily calculated now with reduced dimensionality where AX_i is the eigen vector, denoted by U_i and λ_i is the Eigen value. It is observed that U_i resembles facial images which look ghostly and are called eigenfaces .These eigenfaces are ranked according to their usefulness in characterizing the variation among the images.

It has to be noted here that although the number of possible eigen faces is equal to the number of face images in the training set, the faces can also be approximated by using the best eigenfaces, those that have the largest Eigen values, and which therefore account for the most variance between the set of face images. The different eigenfaces seem to accentuate different features of the face. The reason for using fewer Eigen faces is improve computational efficiency. Each face image in the training set is now be projected onto this face space using

$$\omega_k = U^T (P_k - m)\ ,\ k=1,2,\ldots M \quad (6)$$

where $(P_k - m)$ represents the mean-centered image. Hence projection of each image can be obtained using the above equation, as ω_1 for the first image, ω_2 for the second image and so on.

C. Recognition

The new face image during testing, P, is projected onto the face space to obtain a vector ω defined as

$$\omega = U^T (P - m) \quad (7)$$

The distance between the projected test image and each of the projected images obtained during training is computed using the Euclidean distance measure $\in$ and it is defined as

$$\in_k^2 = \|\omega - \omega_k\|^2,\ \ k=1,2,\ldots.M \quad (8)$$

A face is classified as belonging to class k when the minimum Euclidean distance $\in_k$ is below some chosen threshold defined as

$$\theta = \frac{1}{2} max_{j,k} \|\omega_j - \omega_k\| \quad (9)$$

where j , k =1,2,….M

The major advantage of using PCA is that the eigenface approach helps in reducing the size of the database required for recognition of a t est image. The trained images are not stored as raw images, rather they are stored as their weights which are found by projecting each image in the training set onto the set of eigenfaces obtained [5].

III. FACE RECOGNITION

A. Steps in face recognition

The steps involved in the recognition process can be summarized as follows:

a) Acquire the face images of the training set and compute the average face image.
b) Calculate the deviation of each image from the mean face image, this constitutes the set of mean-centered images.
c) Obtain the eigenfaces corresponding to this training set, this consitutes the face space.
d) Now find the projection of the mean-centered images onto the face space.
e) During testing, for a new face image, in a similar way, find the mean-centered image and project this onto the face space.
f) Calculate the Euclidean distance between the projected test image and each projected training image as found in step d) and find the minimum of these distances.
g) The threshold value is calculated as half the maximum distance between any two face images.
h) If the minimum Euclidean distance calculated in step f) is below the specified threshold, the corresponding test image is considered to be present in the database and the closest matching image is displayed. Otherwise, it means that the test image is not recognized.

Fig.1. Mean face image

Fig. 2. Eigenfaces

B. Calculating similarity score for performance evaluation

The similarity between any pair of face images can be calculated by finding the Euclidean distance $\|y1 - y2\|$ between their corresponding feature vectors y1 and y2; the smaller the distance between the feature vectors, the more similar are the faces[15]. We define a s imple similarity score to measure the extent to which the face is recognized and it is calculated as

$$s(y1, y2) = \frac{1}{1 + \|y1 - y2\|} \in [0,1] \qquad (10)$$

To perform face recognition, the similarity score is calculated between an input face images and each of the training images. The matched face is the one with the highest similarity, and the magnitude of the similarity score indicates the confidence of the match, with a unit value indicating an exact match.

IV. FACIAL EXPRESSION IDENTIFICATION

The following steps have been used for detecting the facial expression [8].

A. Training process

a) Read all the faces of a person in the training database.
b) Normalize all the faces.
c) Using Principal Component Analysis on the training set, calculate the eigenvalues.
d) Calculate the eigenvectors of the covariance matrix.
e) Obtain the corresponding Eigen faces and the projection of the training images onto the face space.

B. Testing process

a) Read all the faces of the person in the test folder.
b) Project the test image onto the face space. As a r esult, all the test images are represented in terms of selected principal components.
c) Calculate the Euclidean distance of the projected test image from all the projected train images.
d) The train image with the minimum value of Euclidean distance is taken as the face image with the closest match to the test image.
e) If the test image closely represents the face image, it is assumed to fall in the same training set as that of the face image and the expression of the test image is the expression corresponding to that particular class.

V. FACE DATABASES USED

For analysing the performance of PCA for face recognition, two public databases ATT and CSU have been used. For facial expression identification, we use small MPI database.

A. ATT Database

a) Number of individuals: 40
b) Total no. of images: 400
c) Image resolution: 92 x 112 pixels, grayscale
d) Contains images of male and female subjects
e) Considerable variation in head turn, tilt and slant
f) Image lighting variation is very little[13]

Fig. 3. Sample images from ATT database

B. CSU Database

a) No. of individuals: 59
b) Total no. of images: 590
c) Image resolution: 64 x 58, grayscale
d) Contains i mages of male and female subjects
e) Significant variation in head turn, tilt and slant
f) Image lighting variation is very little[14]

Fig. 4. Sample images from CSU database

C. Small MPI Facial Expression Database

a) No. of individuals considered: 2
b) Total no. of images: 200
c) Image resolution: 768 x 576 pixels, RGB
d) Contains cropped face images of male and female subject
e) Includes expressions such as neutral, happy, sad, disgust and surprise[14]

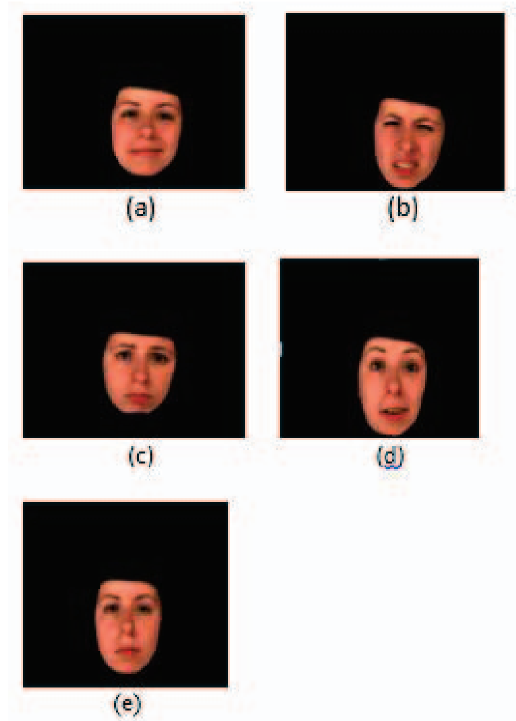

Fig. 5. Sample images from Small MPI database showing expression (a) happy, (b) disgust, (c) sad, (d) surprise, (e) neutral

VI. EXPERIMENTAL RESULTS

A. Face Recognition

To evaluate the performance of the face recognition algorithm, as proposed in [7], we calculate a measure called recognition accuracy (RA) which can be defined as follows

$$RA = \frac{No.of\ test\ images\ correctly\ recognized}{Total\ no.of\ test\ images} \quad (11)$$

Table I shows the comparative results of PCA implementation on ATT and CSU databases. The system is trained by considering 3 randomly picked images for each individual and assigning them to one class. In our experiment, we have used 40 classes for ATT and 59 classes for CSU database.

TABLE I – Recognition accuracy for ATT and CSU databases

Database	Training samples per class	Total number of classes	PCA recognition accuracy
ATT	3	40	85.5%
CSU	3	59	81.3%

(a) (b)
(c) (d)
Fig. 6. Two sets of test images (b), (d) and corresponding recognized images (a), (c)

B. Facial Expression Identification

Here, the expressions such as happy, disgust, sad, surprise and neutral of a particular person are taken into consideration. Initially these 5 prototypic expressions are trained using the train database. The system is then checked by giving the test images as input. A total of 30 images with each prototypic expression containing 6 images are used for training and 200 images are used for testing. The algorithm has been tested on various facial expressions of one male and one female subject. Tables II and III show the corresponding confusion matrices.

TABLE II – Facial expression confusion matrix for male face

MALE FACE	Hap py	Disg ust	Sa d	Sur pris e	Neutr al
Happy	44	0	0	0	0
Disgust	0	44	0	0	0
Sad	0	0	43	1	0
Surprise	0	0	0	44	0
Neutral	0	0	3	2	39

TABLE III – Facial expression confusion matrix for female face

FEMAL E FACE	Hap py	Disgu st	Sa d	Surp rise	Neut ral
Happy	33	0	0	0	1
Disgust	0	39	0	0	0
Sad	0	0	67	0	1
Surprise	2	0	0	18	3
Neutral	0	0	0	0	36

The figure below shows a sample of the results of facial expression identification, the test images and the corresponding recognized images for happy and surprise expressions.

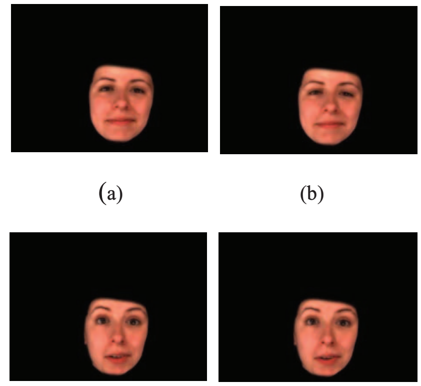

Fig. 7. Test images (a) and (c) and corresponding recognized images (b) and (d)

VII. DISCUSSION

In the above experiments for face recognition, the number of classes considered is 40 f or ATT database, with each class containing 10 facial images. So the total number of test images considered in our study is 40 x 10 = 400. For the purpose of training, 3 f aces of each person are taken in the training database which makes it a total of 40 x 3 =120 training images. Out of the 400 test images, 342 are recognized correctly, and so the recognition rate for the above database has been found to be 85.5%. The same procedure is adopted for CSU database in which the number of classes considered is 59, with each class containing 10 facial images. So the total number of facial images considered for testing is 59 x 10 = 590. In the training set, 3 faces of each person are taken into consideration making it a total of 59 x 3 = 177 training images. For CSU database, the images correctly recognized are 480 ou t of 590 a nd the recognition rate is observed to be 81.36%. This comparatively lower recognition accuracy can be accounted for the fact that CSU database contains facial images of people with more amount of head tilt and rotation. Even the similarity score is observed to be 1 for two sets of images that are similar and less than 1 for images with variations which depends on the difference of their characteristic features.

PCA has been extended for the identification of facial expressions as well. Tables II and III s how the number of images properly recognized with different prototypic expressions such as happy, disgust, sad, surprise and neutral. Table II contains the expressions of a male face where happy, disgust and surprise are properly classified whereas sad and neutral have a variation in the no of facial images recognized. The same algorithm has been implemented for a female face with the same prototypic expressions and the results can be observed in Table III. Here, expressions such as disgust and neutral have been properly classified whereas happy, sad and surprise expressions suffer minor variations in recognition of the number of test images.

VIII. CONCLUSION

In this paper, the technique of Principal Component Analysis for face recognition has been thoroughly studied and implemented. The same algorithm has also been adopted for facial expression detection for both male and female faces. The eigenface approach provides a p ractical solution that is well suited for the problem of face recognition. This method is fast, reliable but works well in a constrained environment. Experimental results show that PCA based methods provide better representations and achieve lower error rates for face recognition. This is mainly because principal components have proven the capability to provide significant features and reduce the input size of the images. The algorithm proposed in this paper has the advantage of good recognition rate, simple calculations and quick speed. Certain issues of robustness to changes in lighting, head size, and head orientation , the trade-offs between t he number o f ei genfaces n ecessary f or unambiguous cl assification ar e a matter o f concern.

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