Eigenvectors of Covariance Matrix using Row Mean and Column Mean Sequences for Face Recognition

Dr. H. B. Kekre hbkekre@yahoo.com
Senior Professor, Computer EngineeringDepartment
MPSTME, SVKM'S NMIMS University
Mumbai 400056, India

Sudeep D. Thepade sudeepthepade@gmail.com
Ph.D. Research Scholar and Assistant Professor,
Computer Engineering Department
MPSTME, SVKM'S NMIMS University
Mumbai 400056, India

Akshay Maloo akshaymaloo@gmail.com
Student, B. Tech (Computer Engineering)
MPSTME, SVKM'S NMIMS University
Mumbai 400056, India

Abstract

Face recognition has been a fast growing, challenging and interesting area in real-time applications. A large number of face recognition algorithms have been developed from decades. Principal Component Analysis (PCA) [2][3] is one of the most successful techniques that has been used in face recognition. Four criteria for image pixel selection to create feature vector were analyzed: the first one has all the pixels considered by converting the image into gray plane, the second one is based on taking row mean in RGB plane of face image, the third one is based on taking column mean in RGB plane finally, the fourth criterion is based on taking row and column mean of face image in RGB plane and feature vector were generated to apply PCA technique. Experimental tests on the ORL Face Database [1] achieved 99.60% of recognition accuracy, with lower computational cost. To test the ruggedness of proposed techniques, they are tested on our own created face database where 80.60% of recognition accuracy is achieved.

For a 128 x 128 image that means that one must compute a 16384 x 16384 matrix and calculate 16,384 eigenfaces. Computationally, this is not very efficient as most of those eigenfaces are not useful for our task. Using row mean and column mean reduces computations resulting in faster face recognition with nearly the same accuracy.

Keywords: Face recognition, eigenvectors, covariance matrix, row mean, column mean.

1. INTRODUCTION

The term face recognition refers to identifying, by computational algorithms, an unknown face image. This operation can be done by means of comparisons between the unknown face and faces stored in a database.

Face recognition systems have a wide range of application, especially when dealing with security applications, like computer and physical access control, real-time subject identification and authentication, and criminal screening and surveillance. Biometrical identification based on iris, fingerprint and other attributes all suffer from a series of drawbacks, including need of high precision image acquisition equipment's, difficulty to use with video images and need of agreement when doing the image acquisition. Systems that use face recognition don't have any of these restrictions.

Face recognition is a difficult task, because it cannot be performed by pixel to pixel comparison of two images. Some aspects of the scene must be irrelevant when doing the recognition, like illumination, pose, position, scale, environment, accessories and small age differences. So, face recognition systems require use of accurate and robust methods.Principal component Analysis is usually used because of its acceptable performance, but it is very time consuming. Particularly, our coefficient selection experiments register an accuracy of over 99.00% in controlled database with using less than 95% coefficients, so reduced computational cost and 80% in non-controlled database.

In the area of human computer interaction, an ultimate goal is for machine to understand, communicate with and react to humans in natural ways. Although there are many other avenues to person identification – gait, clothing, hair, voice, and height are all useful indication of identity of the person, none are as compelling as face recognition.

2. PRINCIPAL COMPONENT ANALYSIS (PCA) [6][7]

The task of facial recognition is discriminating input signals (image data) into several classes (persons). The input signals are highly noisy (e.g. the noise is caused by differing lighting conditions, pose etc.), yet the input images are not completely random and in spite of their differences there are patterns which occur in any input signal. Such patterns, which can be observed in all signals could be in the domain of facial recognition, like the presence of some objects (eyes, nose, mouth) in any face as well as relative distances between these objects. These characteristic features are called eigenfaces in the facial recognition domain (or principal components generally). They can be extracted out of original image data by means of a mathematical tool called Principal Component Analysis (PCA).

The idea of using principal components to represent human faces was developed by Sirovich and Kirby [4] in 1987 and used by Turk and Pentland [2][3] in 1991 for face detection and recognition. The Eigenface approach is considered by many to be the first working facial recognition technology, and it served as the basis for one of the top commercial face recognition technology products. Since its initial development and publication, there have been many extensions to the original method and many new developments [7] in automatic face recognition systems.

By means of PCA one can transform each original image of the training set into a corresponding eigenface. An important feature of PCA is that one can reconstruct any original image from the training set by combining the eigenfaces. But one can also use only a part of the eigenfaces and reconstruct an approximate of the original image[12,13]. However, one can ensure that losses due to omitting some of the eigenfaces can be minimized, by choosing only the most important features (eigenfaces). The jobs which PCA can do are prediction, redundancy removal, feature extraction, data compression, etc. Because PCA is a classical technique which can do something in the linear domain, some applications [14] include signal processing, image processing, system and control theory, communications, etc.

3. PCA ALGORITHM [2]

The various steps to calculate eigenfaces are:

A. Prepare the data

A 2-D facial image can be represented as 1-D vector by concatenating each row (or column) into a long thin vector. Let's suppose we have M vectors of size N (= rows of image × columns of image) representing a set of sampled images.

Then the training set becomes: $\Gamma_1, \Gamma_2, \Gamma_3 \ldots\ldots \Gamma_M$.

B. Subtract the mean

The average matrix Ψ has to be calculated, then subtracted from the original faces (Γ_i) and the result stored in the variable Φ_i:

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

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

C. Calculate the co-variance matrix
In the next step the covariance matrix A is calculated according to:

$$A = \Phi^T\Phi \quad (3)$$

D. Calculate the eigenvectors and eigenvalues of the covariance matrix
In this step, the eigenvectors (eigenvectors) X_i and the corresponding eigenvalues λ_i should be calculated.

E. Calculate eigenfaces

$$[\Phi]X_i = f_i \quad (4)$$

where X_i are eigenvectors and f_i are eigenfaces.

F. Classifying the faces
The new image is transformed into its eigenface components. The resulting weights form the weight vector Ω_{new}^T. Where ω_k is the sum of element wise product of 'Γ_{new}' and 'f_k'.

$$\Omega_{new}^T = [[\omega]_1\omega_2\omega_3 \dots \omega_{M'}] \quad (5)$$

$$\omega_k = \Omega_k^T(\Gamma_{new}|f_k)\ k = 1,2 \dots M' \quad (6)$$

The Euclidean distance between two weight vectors $d(\Omega_i,\Omega_j)$ provides a measure of similarity between the corresponding images i and j. If the Euclidean distance between Γ_{new} and other faces exceeds some threshold value θ, one can assume that Γ_{new} is not a face at all, $d(\Omega_i,\Omega_j)$ also allows one to construct "clusters" of faces such that similar faces are assigned to one cluster.

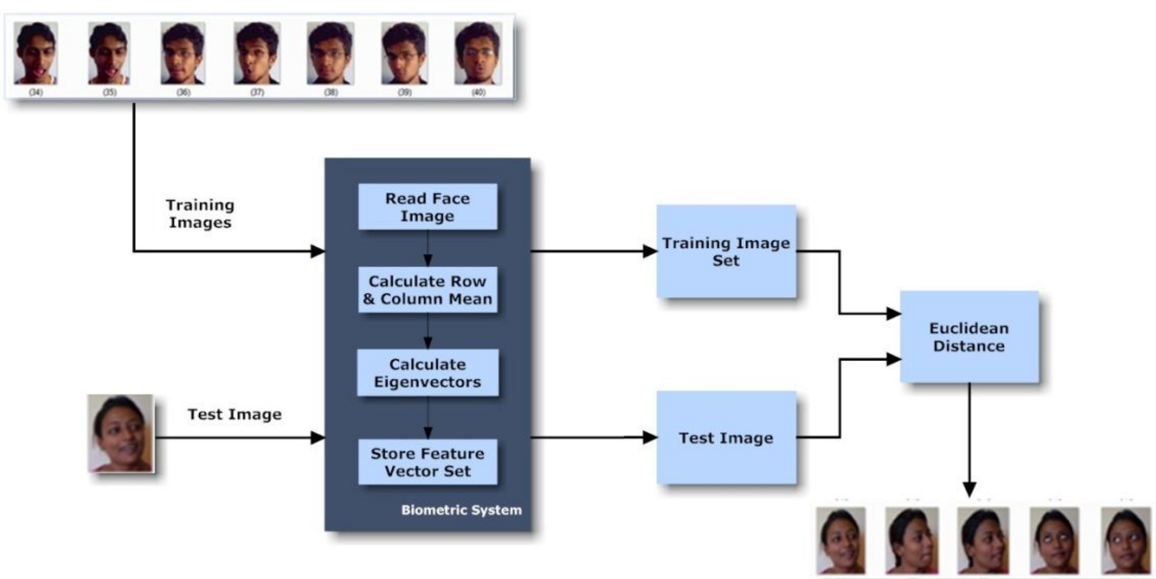

FIGURE 1: System using the proposed technique

4. ROW MEAN (RM)/COLUMN MEAN (CM) [5][11]

The row mean vector is the set of averages of the intensity values of the respective rows [8,9,10]. The column mean vector is the set of averages of the intensity values of the respective columns. Fig. 2 is representing the sample image with 4 rows and 4 columns, the row and column mean vectors for this image is given below.

$$\text{Row Mean Vector} = [\text{Avg(Row 1), Avg(Row 2), ..., Avg(Row n)}] \quad (7)$$

$$\text{Column Mean Vector} = [\text{Avg(Col. 1), Avg(Col. 2), ..., Avg(Col. n)}] \quad (8)$$

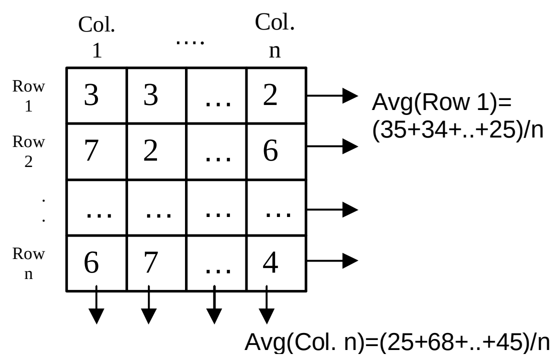

FIGURE 2: Sample Image Template (with size nxn)

5. PROPOSED TECHNIQUES

The various proposed techniques are:

A. All image pixels in grey scale

Here the face image is transformed into grey scale and then eigenfaces are generated. Then Euclidean Distance was used to find the best match. This is how PCA is generally implemented we propose new techniques (explained below) to reduce eigenfaces generated so that with nearly the same accuracy faster face recognition techniques are implemented. These calculations are used for comparing proposed techniques with standard PCA technique.

B. Row Mean in RGB Plane

Here row mean is calculated of all image pixels in RGB plane. The feature vectoris used to generate eigen mean sequences for row mean. Then Euclidean Distance was used to find the best match.

C. Column Mean in RGB Plane

Here column mean is calculated of all image pixels in RGB plane. The feature vector is used to generate eigen mean sequences for column mean. Then Euclidean Distance was used to find the best match.

D. Row Mean & Column Mean in RGB Plane

Here row&column mean is calculated in red plane, then green and finally blue plane to create a feature vector which is then used to generate eigen row and column sequence. Then Euclidean Distance was used to find the best match.

Partial coefficients	No of image coefficients	No. of elements in Eigen Sequence
All	16384	16384
RM	384	384
CM	384	384
RMCM	768	768

TABLE 1: Complexity analysis for proposed technique for 128*128 Image

6. IMPLEMENTATION

A. Platform

The experiments were performed using Matlab R2009b, on a machine with Intel Core 2 Duo T8100 (2.1 Ghz) and 2GB ram.

B. Databases

The experiments were performed on two databases:

1) ORL Database[1]: This database has 100 images (each with 180 pixels by 200 pixels), corresponding to 20 persons in five poses each, including both males and females. All the images are taken against a dark or bright homogeneous background, little variation of illumination, different facial expressions and details (open/closed eyes, smiling/non smiling, glasses/no glasses). The five poses of ORL's database are shown in Figure 3.

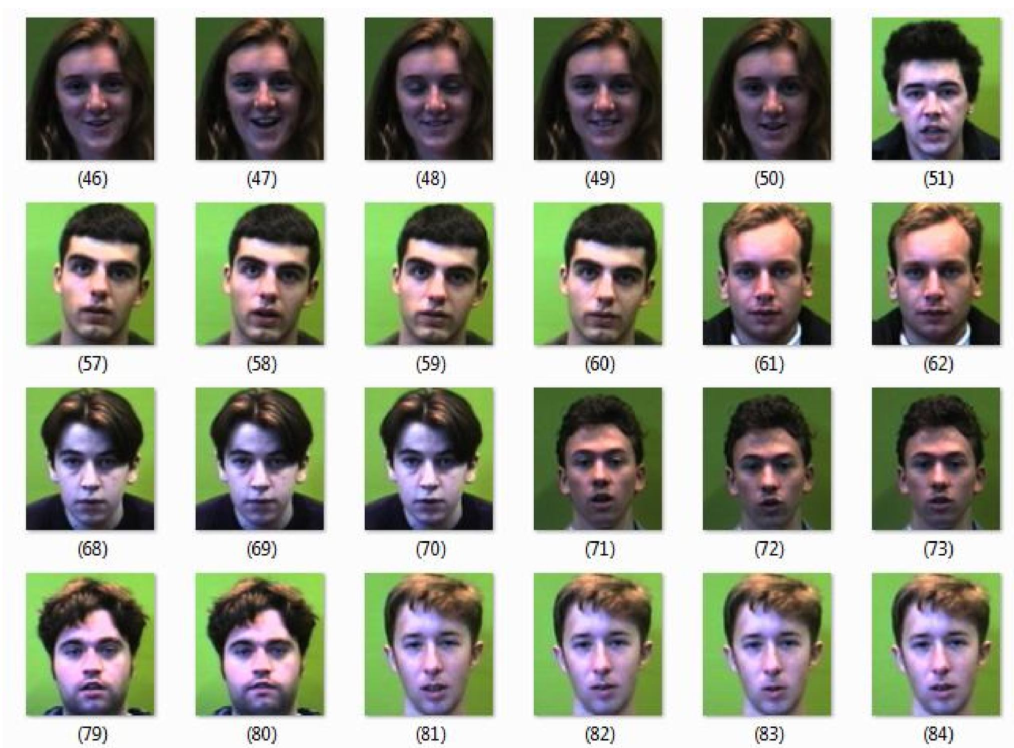

FIGURE 3: Sample Images from ORL Database

2) Our Own Database [7]: This database has 85 images (each with 128 pixels by 128 pixels), corresponding to 20 persons in five poses each, including both males and females. All the images are taken against a dark or bright homogeneous background, with variation of illumination, highly different facial expressions and details (open/closed eyes, smiling/non smiling, glasses/no glasses). Our database has many variations in intensity, the image sizes are varying and it is

non-controlled, this was done to test the ruggedness of our algorithm used for face recognition. The five poses of our database are shown in Figure 4.

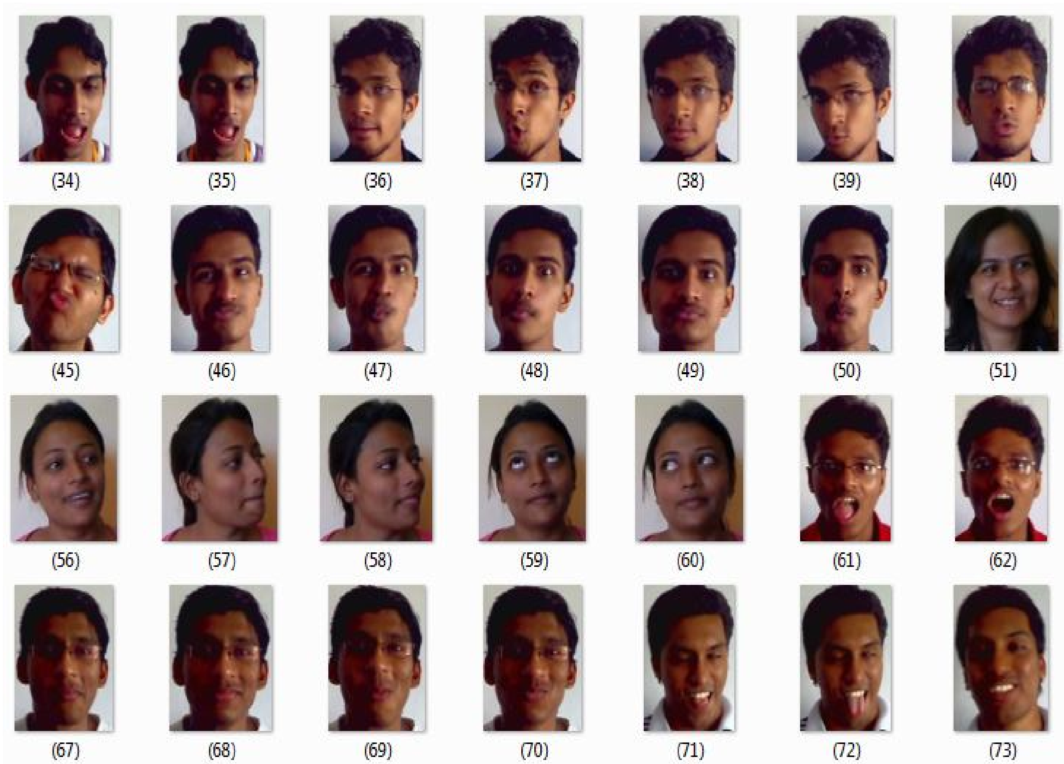

FIGURE 4: Sample Images from Our Own Database

7. RESULTS AND DISCUSSIONS

The false acceptance rate (FAR) [16] is the measure of the likelihood that the biometric security system will incorrectly accept an access attempt by an unauthorized user. A system's FAR typically is stated as the ratio of the number of false acceptances divided by the number of identification attempts.

The false rejection rate (FRR) [15] is the measure of the likelihood that the biometric security system will incorrectly reject an access attempt by an authorized user. A system's FRR typically is stated as the ratio of the number of false rejections divided by the number of identification attempts.

During performance testing a test image was considered and five closest matches were displayed, so percentage correct detection is the percentage of relevant images it returned and percentage incorrect detection is the amount irrelevant images it returned.

1) ORL Database [1]

In all 100 queries were tested on ORL database for analysing the performance of proposed face recognition techniques. Fig 5 gives the percentage of FAR and FRR for face recognition using variations in PCA based techniques. Here it is observed that PCA on full image and on feature vector of RM and RMCM are nearly giving the same performance, the advantage of using proposed technique over PCA applied on full image is reduced feature vector size which gives faster recognition with nearly the same or better accuracy.

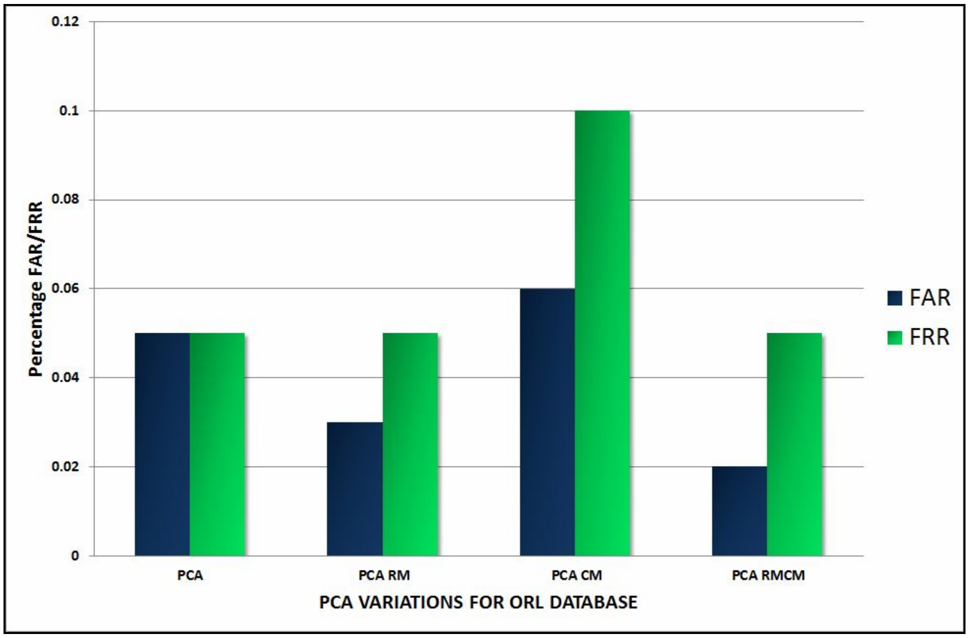

FIGURE 5: FAR/FRR using PCA on ORL database

2) Own Database [7]

In all 100 queries were tested on Our Own database for analysing the performance of proposed face recognition techniques. Fig 6 gives the percentage of FAR and FRR for face recognition using variations in PCA based techniques. Here it is observed that PCA on full image and on feature vector of RGB RMCM are giving nearly the same performance but the advantage of using the proposed RMCM technique is reduced feature vector size which gives faster recognition (refer table. 4) with nearly the same accuracy.

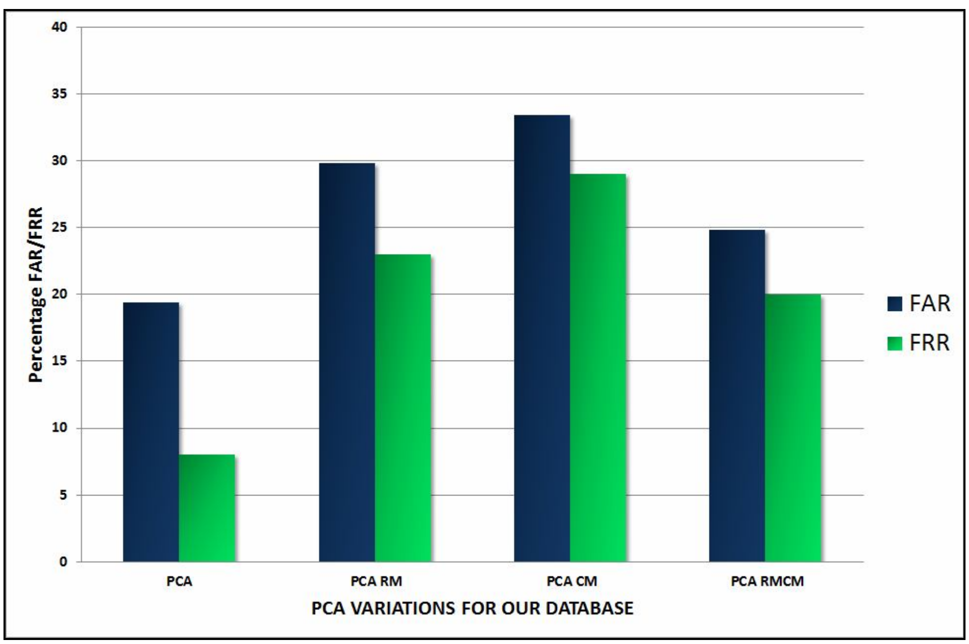

FIGURE 6: FAR/FRR using PCA on Our Own Database

In table 2&3 performance comparisons of PCA on both the databases are shown. Here performance of full image and row mean column mean vector is quite similar and row mean column mean is much faster because of less computations required (table 4)as results are based on less number of eigenfaces generated for comparison.

Partial coefficients	Percentage Correct Detection	Percentage Incorrect Detection
All	99.0%	1.0%
Row Mean	99.4%	0.6%
Column Mean	99.2%	0.8%
Row& Column mean	99.6%	0.4%

TABLE 2: Correct/Incorrect Detection Using PCA on ORL Database

Partial coefficients	Percentage Correct Detection	Percentage Incorrect Detection
All	80.0%	20.0%
Row Mean	70.2%	29.8%
Column Mean	66.0%	34.0%
Row& Column mean	75.0%	25.0%

TABLE 3: Correct/Incorrect Detection Using PCA on Our Own Database

PCA applied on	All	Row Mean	Column Mean	Row& Column mean
Feature Extraction				
No of additions	1,61,07,11,040	99,072	99,072	3,94,752
No of multiplications	80,54,53,824	50,304	50,304	1,98,912
Query Execution				
No of additions	1,96,602	1,530	1,530	3,054
No of multiplications	98,304	768	768	1,530

TABLE 4: Complexity analysis for proposed technique for 128*128 Image

8. CONCLUSION

Recognition accuracy, robust method and computational costs are topics that must be taken into account when analyzing a face recognition method.

The proposed method (RMCM technique) is feasible as it achieves a high recognition accuracy (99.6% when using ORL database and correct classification when the five most similar faces are returned), without any pre-processing step.In a 128*128 face image PCA uses a feature vector of size 16384 coefficients is used and our proposed technique uses only 768 coefficients that is 95.21% less number of coefficients for PCA or eigenvector calculation with nearly the same results.

The proposed method is also suitable for real time applications: in the experimental tests the classification processing time for a face, using 768 coefficients (RMCM technique), is nearly 0.6 seconds in a database of 100 people. The proposed technique so can be used for much real time applications like face recognition in crowded public places where numbers of people moving are high and face recognition is required on the fly, the proposed technique can give guaranteed results instead of using normal PCA with reduced computations and time.

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