Face Recognition Using PCA and Minimum Distance Classifier

Shalmoly Mondal and Soumen Bag

Abstract Face is the most easily identifiable characteristic of a person. Variations in facial expressions can be easily recognized by humans, while it is quite difficult for machines to recognize faces portraying varying facial expressions, pose, and illumination conditions efficiently. Face recognition works as a combination of feature extraction and classification. The selection of a combination of feature extraction technique and classifier to obtain maximum accuracy rate is a challenging task. This paper presents a unique combination of feature extraction technique and classifier that yields a satisfactory and more or less same accuracy rate when tested on more than one standard database. In this combination, features are extracted using principle coponent analysis (PCA). These extracted features are then fed to a minimum distance classification system. The proposed combination is tested on ORL and YALE datasets with an accuracy rate of 95.63% and 93.33%, respectively, considering variations in facial expressions, poses as well as illumination conditions.

Keywords Eigenface · Face datasets · Minimum distance classifier · Face recognition · Principle component analysis

1 Introduction

Face recognition system is an application of biometric technology, which is equipped for distinguishing or confirming a man from a picture or a video outline from a video source. Face recognition is one of the most successful applications of image analysis and has received significant attention, during the last several years. A face recognition system is comprised of two parts: feature extraction and recognition. There are several factors that affect the face recognition process like illumination conditions,

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pose, and various facial expressions. Various methods for face recognition are categorized as holistic methods, feature-based methods, and hybrid methods [6]. In the holistic method, the face recognition system takes the whole face as an input. One of the most widely used representations of the face region is eigenfaces, which are based on principal component analysis (PCA) [2]. In the feature-based methods, facial features such as eyes, ears, and nose are extracted and their locations are given as input to a classifier. The hybrid method makes use of both local features as well as the whole face as input to recognize a face.

Turk and Pentland [6] have developed an eigenface based face recognition method, which uses PCA to decompose face images into a small set of characteristic feature images called eigenfaces. These eigenfaces are used as feature vectors for the purpose of face recognition by comparing the features of the test face with those of known individuals.

Zhao et al. [8] have given a detailed survey of face recognition from still images as well as from a video frame. Later et al. [5] have proposed a way of recognizing faces using the concept of two thresholds (acceptance and rejection) in order to increase the recognition rate and decrease the rejection rate of the existing eigenface method.

Kukreja and Gupta [3] have proposed a PCA with KNN classifier based method for face recognition. Experiment is done on ORL database [9] and YALE database [10]. PCA and KNN when tested on the ORL database has given an accuracy rate of 92% whereas the same combination when tested on the YALE database has given a lower accuracy rate of 81.33%.

Latha et al. [4] have proposed a way to deal with ways to detect frontal view of faces. The dimensionality of face image is reduced by PCA and the recognition procedure is carried out by the back propagation neural network (BPNN). This neural network-based face recognition approach has better performance of more than 90% acceptance ratio.

Face recognition is basically done in two steps: feature extraction followed by classification [1]. The selection of a combination of feature extraction technique and a classifier to obtain maximum accuracy rate is a challenging task. Many such combinations have been obtained and tested on various face datasets. Some of these combinations have given very high accuracy on one database and low accuracy when the experiment with the same combination is performed on some other database. In our proposed method, we have tried to find out a combination of a feature extraction technique and a classifier that will yield a satisfactory and more or less same accuracy rate when tested on more than one databases.

This paper is organized as follows. Section 2 describes the proposed methodology of face recognition. The experimental results on two independent databases are shown in Sect. 3. We conclude this paper with some remarks on the proposed method in Sect. 4.

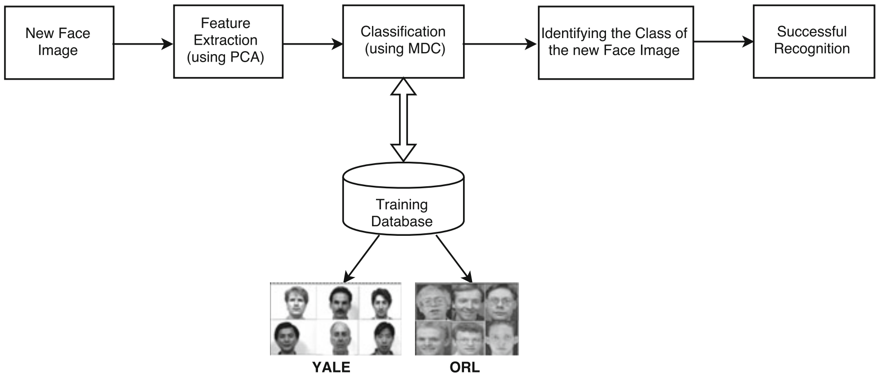

Fig. 1 System architecture of the proposed method

2 Proposed Method

Our objective is to recognize a person with various facial expressions, pose, and illumination conditions using a statistical pattern recognition approach. Our proposed system aims to implement face recognition with the combination of PCA as a feature extraction technique and MDC as the recognition method. We then compare the performance on two independent face datasets named YALE [10] and ORL databases [9]. Figure 1 shows the system architecture of the proposed methodology for face recognition.

2.1 Computing Eigenfaces Using PCA

Eigenface approach utilizes the idea of PCA and decomposes face images into a small set of feature images called eigenfaces. These eigenfaces are used for mapping images from image space to face space. A new face when obtained is also projected to a low dimensional face space. Recognition is performed by computing the minimum distance between the projection of the new image in the face space and the projections of known faces in the training database. The steps of computing eigenfaces using PCA are as follows:

1. We create a training set of N face images and represent each image I_i as a vector Γ_i. A 2-D facial image can be represented as 1-D vector by concatenating each row (or column) into a long vector. The training set now becomes as $\Gamma_1, \Gamma_2, \ldots, \Gamma_M$, where M is the number of images.
2. After forming column vectors, we calculate the mean face ψ (Fig. 2a) from the training set using Eq. 1.

$$\psi = \frac{1}{M}\sum_{i}^{M} \Gamma_i \tag{1}$$

3. We normalize the training set (Fig. 2b) by subtracting the mean face from all vectors corresponding to the original faces using Eq. 2.

$$\boldsymbol{\Phi}_i = \Gamma_i - \psi \tag{2}$$

where $\boldsymbol{\Phi}_i$ is the ith normalized training image.

4. A covariance matrix is then computed in order to extract a limited no of eigenvectors corresponding to largest eigenvalues. Covariance Matrix is given as

$$Cov = \frac{1}{M}\sum_{n=1}^{M} \phi_n \phi_n^T = AA^T \tag{3}$$

$$\text{where}\, A = [\phi_1, \phi_2, \ldots, \phi_M]$$

AA^T is a very large matrix of dimension $N^2 \times N^2$. So the computation of eigenvectors of this matrix is very difficult. To avoid this computational complexity, we instead form a covariance matrix A^TA of reduced dimensionality which is a $M \times M$ matrix as shown in Eq. 4.

$$Cov = A^TA \tag{4}$$

5. Covariance matrix which was of size $N^2 \times N^2$ is now of size $M \times M$, where $M << N^2$. We now compute 'M' eigenvalues and 'M' eigenvectors of this covariance matrix to form the eigenspace using Eq. 5. Eigen decomposition of covariance matrix C is performed to determine the eigenvectors (eigenfaces) u_i and the corresponding eigenvalues λ_i. The eigenfaces (Fig. 2c) must be normalized so that they are unit vectors, i.e., they are of length one.

$$u_i = Av_i. \tag{5}$$

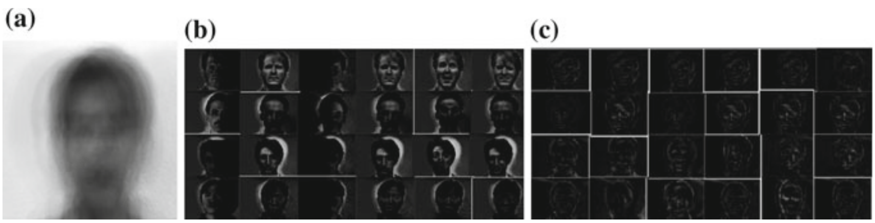

Fig. 2 **a** Mean face; **b** Normalized images of the training set; **c** Eigenfaces of the training set

6. We keep only ‘k’ eigenvectors (corresponding to the k largest eigenvalues). Number of eigenfaces is always less than or equal to the number of original images, i.e., $k << M$. The first few eigenfaces shows the most dominant features of training set of images. Among M eigenvectors (eigenfaces) the one with the highest eigenvalues are chosen and rest are discarded. After ‘k’ eigenfaces are determined, the training phase of the algorithm is completed. Therefore, the training set of ‘M’ images is now represented by only ‘k’ eigenfaces.
7. In order to carry out face recognition, we now find out the training images projection by mapping the training images from image space to face space. Mapping is done by the eigenfaces obtained in step 6 using Eq. 6.

$$\Omega_i = u^T \Phi_i. \tag{6}$$

where i = 1 to M, $u = [u_1, u_2, u_3, \ldots, u_k], k << M, \Omega_i$ = face space training images. These ‘k’ eigenfaces can safely represent the whole training set because they depict the major features that make up the dataset.

2.2 Face Classification Using Minimum Distance Classifier

The following steps demonstrates the process of face recognition.

1. Normalization of test image is done by Eq. 7.

$$\phi_{test} = \Gamma_{test} - \psi \tag{7}$$

where Γ_{test} represents the vector form of our test image, ϕ_{test} is the normalized test image, and ψ is the mean of the training set.
2. Mapping test image into face space by Eq. 8.

$$\Omega_{test} = u^T \Phi_{test} \tag{8}$$

where $u = [u_1, u_2, u_3, \ldots, u_k,]$ and Ω_{test} = mapped test image in the face space.
3. Finding the difference between test image projection and the projections of the training set.

$$Distance = \Omega_{test} - \Omega_i \tag{9}$$

where, Ω_{test} is the test image projection and Ω_i is the projection of images of the training set.
4. Computing the minimum value among all the distance computed in Step 3 using the Eq. 10.

$$D_{min} = Min(Distance) \tag{10}$$

where D_{min} = minimum value among all distances

5. Recognizing known or unknown faces.
   If D_{min} is less than or equal to the threshold (Θ), then it is a known image; hence, display the class which has minimum difference value. Otherwise it is an unknown image.

$$If D_{\min} <= \Theta, \quad (11)$$

   then Ω_{test} belongs to the database of images.

3 Experimental Analysis

3.1 Face Databases

We have carried out our experiment on two independent face databases, the YALE Database [10] and the ORL Database [9]. The YALE Database contains 165 images of 15 individuals (each person has 11 different images) under various facial expressions, lighting conditions, and images with and without glasses. All images are in grayscale with a resolution of 320 × 243 pixels. The ORL Database contains 10 different images each of 40 distinct subjects. The facial expressions (open/closed eyes, smiling/non smiling) as well as the facial details (glasses/no glasses) are varied. The images are taken with a tolerance of some tilting and also a rotation of about 20°. All images are in grayscale and normalized to a resolution of 92 × 112 pixels. All the programs are written using Matlab R2015a.

3.2 Recognition Results

The experiment is first performed on the YALE database by considering 150 images. The database has been divided into training and test sets. Out of 10 images of a person, we have used six images for training and the rest four images for testing. Therefore, the training set consists of 90 images and the test set consists of 60 images. Figure 3a, b show the set of images of a person from the YALE database that has been used for training and testing, respectively. The features of the database are extracted using PCA. The features are classified using MDC and the classification accuracy is 93.33% for test images of the YALE Database.

Fig. 3 **a** Sample images from YALE training database; **b** sample images from YALE test database

Fig. 4 **a** Sample images from ORL training database; **b** Sample images from ORL test database

The experiment is again performed on the ORL database. The experiments are performed with six training images and four test images per person. Figure 4a, b show the set of images of a person that has been used for training and testing, respectively. There are no overlaps between the training and test sets. Since the recognition performance is affected by the selection of the training images, the reported results are obtained by randomly selecting six images per subject, out of the total images. The overall classification accuracy is 95.63% for test images of the ORL database. The proposed method is computationally efficient in terms of time complexity.

3.3 Comparison with Other Methods

We have done a comparative study on the basis of the rate of recognition accuracy in between our proposed method and other existing methods. We have observed that the performance of these combinations highly depends on the experimental databases. For example, the combination of PCA and KNN [3] gives an accuracy rate of 92% for ORL database, whereas the same combination performs less significantly (81.33%) for the YALE database. Our main focus was to select a unique combination of feature extraction technique and classifier, which can perform similarly well for more than one databases. In our proposed method, we have chosen the combination of PCA and MDC for face recognition. We have shown that this proposed combination gives an accuracy rate of about 93.33% and 95.63% for YALE and ORL databases, respectively. So, we can conclude that our proposed method can handle different datasets in a similar way. Table 1 shows the performance measurement among other methods. It shows that our method has achieved the highest recognition rate compared to the other methods. Comparative results obtained by testing PCA and MDC on both YALE and ORL databases are shown in Fig. 5.

Table 1 A comparative study of experimental results of the two databases

Database	Method	Feature extraction	Classification	Recognition rate (%)
ORL [9]	Kukreja and Gupta [3]	PCA	KNN	92
	Yang and Zhang [7]	ICA	MDC	85
	Proposed method	**PCA**	**MDC**	**95.63**
YALE [10]	Kukreja and Gupta [3]	PCA	KNN	81.33
	Yang and Zhang [7]	ICA	MDC	71.52
	Proposed Method	**PCA**	**MDC**	**93.33**

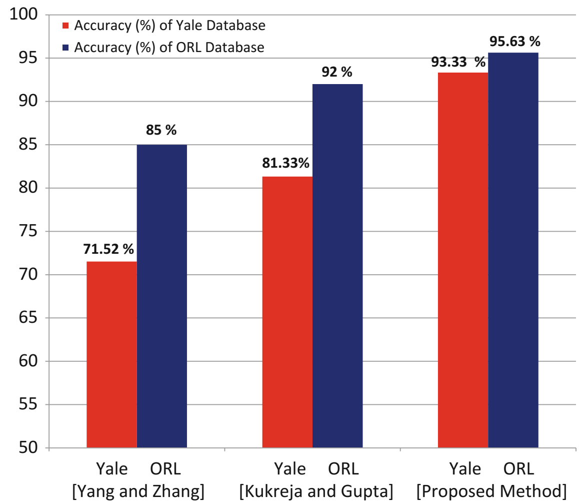

Fig. 5 Comparison of the accuracy rate of our proposed system on two databases using the combination of PCA and MDC

4 Conclusion

This paper presents a unique combination of feature extraction technique and classification method that perform well on more than one standard face datasets. We have performed feature extraction and classification using PCA and MDC, respectively. We have also successfully handled the cases where the input face is an unknown face, i.e., the face of a person is not present in the database. The experiment is successfully performed on two databases named YALE and ORL databases. The experimental results show that our selected combination gives more or less same recognition accuracy for both the datasets.

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