Journal of Engineering and Sustainable Development
www.jeasd.org
Vol. 20, No.05, September 2016
ISSN 2520-0917

A COMPARATIVE STUDY OF HUMAN FACES RECOGNITION USING PRINCIPLE COMPONENTS ANALYSIS AND LINEAR DISCRIMINANT ANALYSIS TECHNIQUES

Anas Fouad Ahmed*

Assist lect., Computer Engineering Department, Al-Iraqia University, Baghdad, Iraq.

Abstract: This paper presents a comparative study of human faces recognition using two feature extraction techniques: Principle Components Analysis (PCA), and Linear Discriminant Analysis (LDA). The performance of these techniques is evaluated and compared to find the best technique for human faces recognition. The experiments are carried out on the Olivetti and Oracle Research Laboratory (ORL), University of Manchester Institute of Science and Technology (UMIST), and Japanese Female Facial Expression (JAFFE) face databases, which include variability in affectation, facial details, and expressions. The obtained results for the two techniques have been compared by varying the train images/test images ratio in a three levels: 80/20, 60/40, and 40/60. The experimental results show that the LDA feature extraction technique gives better performance than PCA technique. The highest recognition rate is recorded for the LDA technique (recognition rate=95.981%) when the train images/test images ratio is (80/20). On the other side, the highest recognition rate that is recorded for PCA technique is 94.027% when the train images/test images ratio is (80/20). The PCA, and LDA techniques are implemented and their performance is measured using MATLAB (2013) program.

Keywords: *Face Recognition, Principle Components Analysis, and Linear Discriminant Analysis.*

دراسة مقارنة لتميز الوجوه البشرية بأستخدام تقنيات مبدأ تحليل المكونات و تحليل التمايز الخطي

الخلاصة: هذا البحث يقدم دراسة مقارنة لتميز الوجوه البشرية بأستخدام تقنيتين للأستخلاص السمات: تقنية مبدأ تحليل المكونات (PCA) وتقنية تحليل التمايز الخطي (LDA). تم ايجاد ومقارنة اداء هاتين التقنيتين لأيجاد التقنية الأفضل لتميز الوجوه البشرية. اجريت التجارب على قواعد البيانات التالية: مختبر أبحاث أوليفيتي واوراكل (ORL)، معهد جامعة مانتشستر للعلوم والتكنلوجيا (UMIST) و تعابير وجوه ألاناث اليابانيات (JAFFE) حيث ان قواعد البيانات تحوي العديد من صور الوجوه بتعابير وملامح مصطنعة ومختلفة. تمت مقارنة النتائج المستحصلة من التقنيتين عن طريق تغير نسبة صور التدريب/صور الاختبار(train images/test images ratio) وبثلاث مستويات: ٨٠/٢٠، ٦٠/٤٠ و ٤٠/٦٠. أظهرت النتائج أن أداء تقنية تحليل التمايز الخطي (LDA) أفضل من تقنية مبدأ تحليل المكونات (PCA). أعلى نسبة تميز سجلت لتقنية التمايز الخطي وبلغت (%٩٥,٩٨١) عندما كانت نسبة صور التدريب/صور الاختبار (train images/test images ratio=80/20). في الجانب الأخر أعلى نسبة تميز لتقنية مبدأ تحليل المكونات (PCA) بلغت (94.027%) عندما كانت نسبة صور التدريب/صور الاختبار (train images/test images ratio=80/20). تم قياس ومقارنة أداء تقنية مبدأ تحليل المكونات وتحليل التمايز الخطي بأستخدام برنامج (2013) MATLAB.

*Corresponding Author anasfuad33eng@yahoo.com

1. Introduction

The face is the focus of consideration in the society, playing an essential role in transmission identity and emotion. Although the capability to infer intelligence or nature from facial appearance is suspect, the human aptitude to recognize faces is notable. A person can recognize thousands of faces learned during the life time and identify familiar faces at a quick look even after years of separation. This talent is quite forceful, in spite of big changes in the visual stimulus due to viewing situations, expressions, aging, and distractions for example glasses, beards or changes in hair style. Face recognition has become a significant issue in several applications for example criminal recognition, safety systems, and credit card verification. Even the aptitude to just detect faces, as contrasting to recognizing them, can be important. Although it is obvious that people are fine at face recognition, it is not at all understandable how faces are encoded or decoded by a person brain. Human face recognition has been studied for above twenty years. Developing a computational formula of face recognition is relatively hard, because faces are complex, multi-dimensional visual stimuli. Therefore, face recognition is an extremely high level computer vision task, in which various early vision techniques can be concerned [1]. For face recognition the first stage includes extraction of the significant features from facial images. A great challenge is the quantizing of the facial features so that a computer is capable to recognize a face, given a collection of features. Investigations by many researchers over the past several years show that particular facial characteristics are used by human beings to recognize the faces [2].

2. Principle Components Analysis (PCA)

Principal component analysis (PCA) is an arithmetical algorithm that uses an orthogonal transformation. The PCA approach is used to minimize the dimension of the data by means of data compression principles and reveals the most useful low dimensional structure of facial patterns. This minimizing in dimensions eliminates information that is not significant and accurately decomposes the face structure, which consists of transformation of number of possible correlated variables into a lesser number of orthogonal (uncorrelated) components called as Principal Components. Each face image may be “represented as a weighted sum (feature vector) of the eigenfaces, which are saved in a 1D array”. The test image is represented by these weighted sums of eigenfaces. When a test image is known, the weights are evaluated by projecting the image upon eigenface vectors. The distance between the weighted vectors of the test image and that of the database images are compared. Thus, one can reconstruct original image with the help of eigenfaces so that it matches the desired image [3]. The mathematical model of the PCA as the following:

Let the training set of face images be $\Gamma 1$, $\Gamma 2$,…., Γm, then the average of the set is defined by (1): [4]

$$\Psi = \frac{1}{M} \sum_{n=1}^{M} \Gamma n \tag{1}$$

Every face differs from the average by the vector [4]:

$$\Phi_i = \Gamma_i - \Psi \tag{2}$$

This set of a very big vectors is then subjected to principal component analysis, which searches a set of M orthonormal vectors, Um, which "best describes the distribution of the data". The kth vector, U_k , is selected such that [5]:

$$\lambda_k = \frac{1}{M} \sum_{n=1}^{M} (U_k^T \Phi_n)^2 \tag{3}$$

is a maximum, subject to

$$U_I^T U_k = \begin{cases} 1 & \text{if } I = k \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The vectors U_k and scalars λ_k are the eigenvectors and eigenvalues, respectively of the covariance matrix [5]:

$$C = \frac{1}{M} \sum_{n=1}^{M} \Phi_n \Phi_n^T = A A^T \tag{5}$$

where the matrix A =[Φ1 Φ2....ΦM]. The covariance matrix C, however is $N^2 \times N^2$ real symmetric matrix, and calculating the N^2 eigenvectors and eigenvalues is a difficult task for typical image sizes. We need a mathematically practicable method to calculate these eigenvectors. Let the eigenvectors v_i of $A A^T$ such that [5]:

$$A^T . A . v_i = \mu_i v_i \tag{6}$$

Pre-multiplying both sides by A, we have (7) [5]:

$$A . A^T . A . v_i = \mu_i A v_i \tag{7}$$

It is obvious that Av_i are the eigenvectors and μ_i are the eigenvalues of $C = A . A^T$.
Following these analysis, we create the M × M matrix $L = A^T A$, where $Lmn = \Phi_n^T \Phi n$, and find the M eigenvectors, v_i of L. These vectors create linear combinations of the M training set face images to evaluate the eigenfaces U_I [5].

$$U_I = \sum_{k=1}^{M} V_{IK} \Phi_k \text{ , I=1,….., M} \tag{8}$$

With this analysis, the calculations are very much reduced, from the order of the total pixels in the images (N^2) to the order of the total images in the training set (M). Practically, the training set of face images will be comparatively small ($M \ll N^2$), and the calculations become fairly controllable. The related eigenvalues let us to rank the eigenvectors according to their effectiveness in characterizing the variations in the images [4]. A new face image Γ is transformed into its eigenface components (projected onto “face space”) by an easy operation: [5]

$$w_k = U_k^T (\Gamma - \Psi) \quad (9)$$

for k = 1,...,M'. The weights form a projection vector: [4]

$$\Omega^T = [w1\ w2\ \ldots\ldots w_{M'}] \quad (10)$$

Describing the participation of each eigenface in representing the input face image, dealing the eigenfaces as a basis set for face images. The projection vector used in a typical pattern recognition algorithm to recognize which of a number of predefined face classes, if any, better describes the face. The face class Ω_k can be determined by averaging the results of the eigenface representation over a little number of face images of each individual. The classification is done by comparing the projection vectors of the training face images with the projection vector of the input face image. This comparison is depending on the Euclidean Distance between the face classes and the input face image. This is given in (11) [4]. The idea is to find the face class k that reduces the Euclidean distance: [4]

$$E_k = |\Omega - \Omega_k| \quad (11)$$

Where Ω_k is a vector describing the kth faces class.

3. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is a dimensionality minimization method, which is used for classification purposes. The other name of LDA is fisher’s discriminant analysis and it seeks those vectors in the underlying space that are the finest discriminant between classes. LDA merge the independent feature, which leads the biggest mean differences between the most wanted classes. LDA is a linear transformation following the through scatter matrix analysis. The objective of LDA is to increase the between-class scatter matrix measure and to reduce the within-class scatter matrix measure. LDA is a derived form of fisher linear classifier it increases the ratio of the between- and within-class scatters. It is usually used in face recognition field [6]. LDA tries to increase the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples. Fisher discriminant collects images of the identical class and separates images of dissimilar classes. Images are “projected from N^2-dimensional space to C dimensional space (where C is the number of classes of images)”. For instance, assume two sets of points in Two-dimensional space that are projected onto a single line.

Based on the orientation of the line, the points can either be mixed together fig. 1(a) or separated fig. 1(b). Fisher discriminant evaluates the line that best splits the points.

To distinguish an input test image, the comparison is done between the projected test image and the various projected training images, then the test image is specified to the closest training image. As with eigenspace projection, training images are projected into a subspace. The test images are projected into the similar subspace and recognized using a similarity measure. The main difference is how the subspace is determined. Unlike the PCA technique that extracts features to best characterize face images; the LDA technique tries to determine the subspace that best discriminates the various face classes as illustrated in fig. 1(b).

The within-class scatter matrix, also called intra-personal, represents changes in appearance of the same individual caused by various illumination and face expression, whereas the between-class scatter matrix, also known as the extra-personal, represents changes in appearance caused by a difference in identity. By applying this technique, we get the projection directions that on one hand increase the distance between the face images of various classes. on the other hand reduce the distance between the face images of the identical class. In other word, they increase the between-class scatter matrix Sb, while decrease the within-class scatter matrix Sw in the projective subspace. Fig. 2 illustrates a good and bad class separation [4].

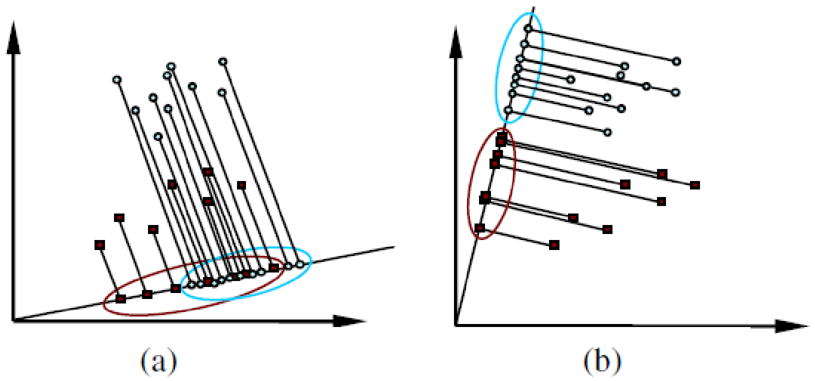

Figure 1. (a): Points mixed when projected onto a line. (b): Points separated when projected onto another line [5].

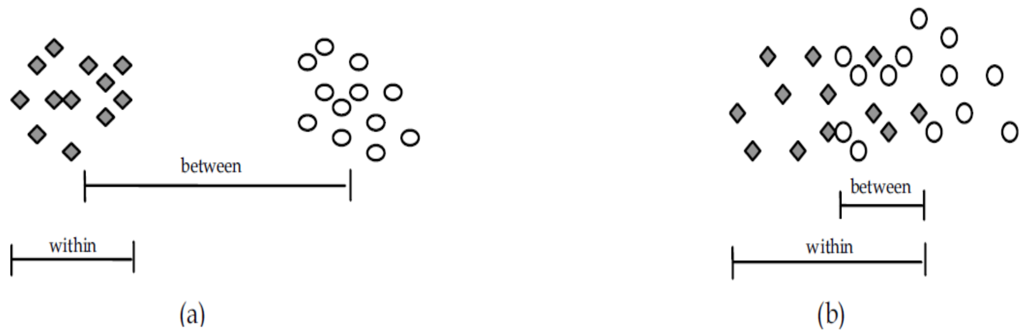

Figure 2. (a): Good class separation. (b): Bad class separation [5].

The within-class scatter matrix Sw and the between-class scatter matrix S_b are given by (12), and (13): [5]

$$Sw = \sum_{j=1}^{C} \sum_{i=1}^{Nj} (\Gamma_i^j - \mu_i)^T \ (\Gamma_i^j - \mu_i) \qquad (12)$$

Where Γ_i^j is the i^{th} sample of class j, μ_i is the mean of class j, C is the number of classes, N_j is the number of samples in class j.

$$S_b = \sum_{i=1}^{C} (\mu - \mu_i)(\mu - \mu_i)^T \qquad (13)$$

where μ represents the mean of all classes. The subspace for LDA is extended by a set of vectors W = [W1, W2, … , Wd], satisfying : [5]

$$w = \arg\max = \left| \frac{W^T \ S_b \ w}{W^T \ S_w \ w} \right| \qquad (14)$$

The within class scatter matrix describes how face images are allocated nearly within classes and the between class scatter matrix depicts how classes are distinguished from each other. When face images are projected into the discriminant vectors W, face images must be allocated nearly within classes and must be distinguished between classes, as much as possible. In other word, these discriminant vectors reduce the denominator and increase the numerator of (14). W can therefore be formed by the eigenvectors of $S_{w^{-1}}$ Sb. There are different approaches to solve the problem of LDA for instance the pseudo inverse approach, the subspace approach, or the null space approach.

The LDA approach is similar to the eigenface method, which takes advantage of projection of training images within a subspace. The test images are projected within the similar subspace and recognized using the likeness measure. The only distinction is the method of evaluating the subspace that defining the face image. The face which has the smallest distance with the test face image is distinguished with the identity of that image. The smallest distance can be determined using the Euclidean distance approach as given in (11).

4. Proposed System

The block diagram of the proposed system is shown in fig. 3. It involves applying the PCA, and LDA features extraction techniques to a huge and various face databases. The train images/test images ratio is varied in a three levels (80/20), (60/40), and (40/60) to test the performance of both techniques by evaluating the recognition rate in each level. The Euclidean distance classifier is used in this work for comparing the projection vector of the training face images with the projection vector of the input face image as given in (11).

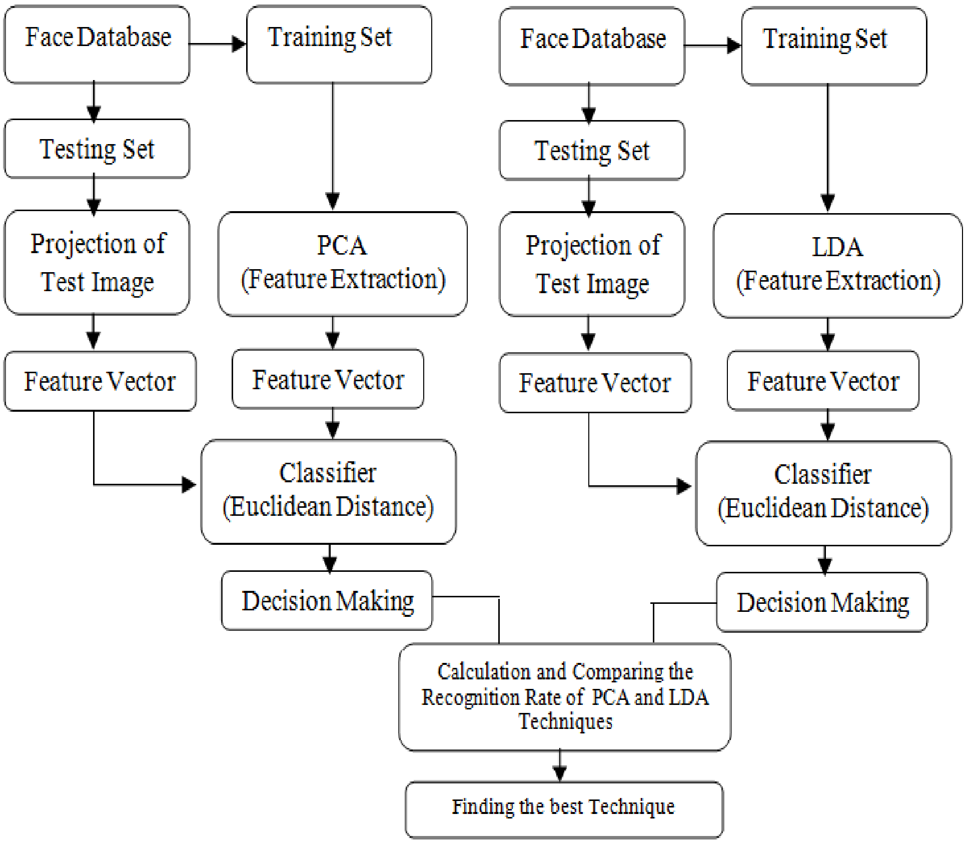

Figure 3. Block diagram of the proposed system.

5. Olivetti Research Laboratory (ORL) Database

The ORL face database is picked up at the Olivetti Research Laboratory in Cambridge, United Kingdom. This database contains 400 gray-scale images of 40 subjects. Each subject has 10 images, each having a resolution of 112 x 92, and 256 gray levels. The images are picked up at altered times with various specifications: including varying slightly illumination, different facial appearances i.e. open, closed eyes, simper, and non-simper, and facial minutiae i.e. glasses, and no-glasses. All images were picked up against a dark uniform background with the individuals in an upright, forward position, also tolerance for a little orientation and variation reach to 20 degrees. There is some difference in scale reach to about 10%. Fig. 4 shows sample images of two persons from the ORL face database [7].

Figure 4. Sample images of two persons from the ORL face database.

6. University of Manchester Institute of Science and Technology (UMIST) Database

The UMIST face database is a various-view database. It consists of 564 gray-scale images of 20 person, each covering a broad range of attitudes from the side to frontal views. Each person also covers a range of race, gender, and appearance. Each image has a resolution of 112 x 92, and 256 gray levels. Unlike the ORL database, the collection of images per person is not firm. Fig. 5 shows sample images of one subject from the UMIST face database [8].

Figure 5. Sample images of one subject from the UMIST face database.

7. Japanese Female Facial Expression (JAFFE) Databases

The JAFFE face database is picked up at the psychology department Kyushu University, Japan. The database contains 213 gray-scale images of 7 facial expressions (6 fundamental expressions + 1 neutral) posed by 10 Japanese female models. Each image has been rated on 6 feeling adjectives by 60 Japanese subjects. Fig. 6 shows sample images of one subject from JAFFE face database [9].

Figure 6. Sample images of one subject from JAFFE face database.

8. Results and Discussion

Many experiments have been performed on ORL, UMIST, and JAFFE face databases with various numbers of training and testing images. The ORL database is used to evaluate the performance of the proposed system against the conditions of minor differences of rotation and scaling. The UMIST database is used to test the performance of the proposed system when the angle of rotation of the facial image is quite large. The JAFFE database is used to examine the performance of the proposed system when the images contain many facial expressions.

The eigen faces and fisher faces are calculated using PCA, and LDA techniques respectively. These techniques are implemented using MATLAB (2013). In the empirical set-up for all the databases, the number of training images is changed from 80 percent to 40 percent i.e. firstly 80% of the total images are used in training and the resting 20% are used for testing then the ratio is changed as 60/40 and 40/60. The experimental results show that the recognition performance of the proposed system improved due to increase in face images in the training set. This is clear, because more samples of images can identify the classes of the subjects better in the face space.

The obtained results of the experiments on ORL, UMIST, and JAFFE face databases are shown in figures (7), and (8), while the detailed results are shown in tables (1), and (2). These results clearly show that the LDA feature extraction technique outperforms the PCA feature extraction technique in face recognition. The highest recognition rate, which is recorded for the LDA technique on the ORL database, is 95.981% when the train images/test images ratio is 80/20, while the highest recognition rate for PCA technique is 94.027%. On the other side, the lowest recognition rate, which is recorded for the LDA technique on the JAFFE database, is 60.905% when the train images/test images ratio is 40/60, while the lowest recognition rate for PCA technique is 51.281%. Figures (9), (10), and (11) show some successful face recognition tests for all the databases.

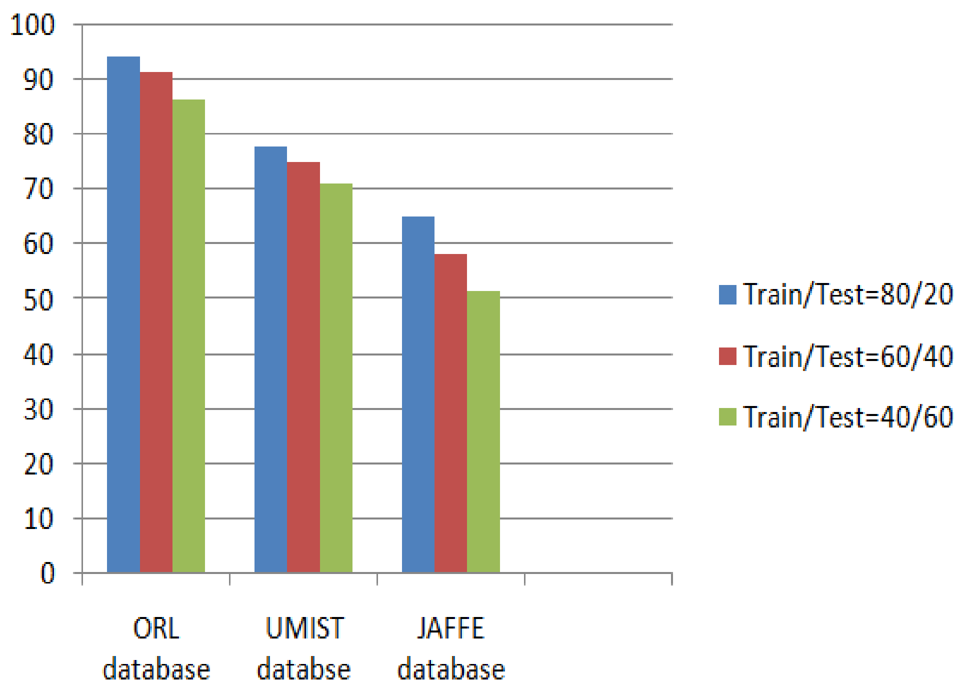

Figure 7. The percentage recognition rate versus various databases using PCA technique.

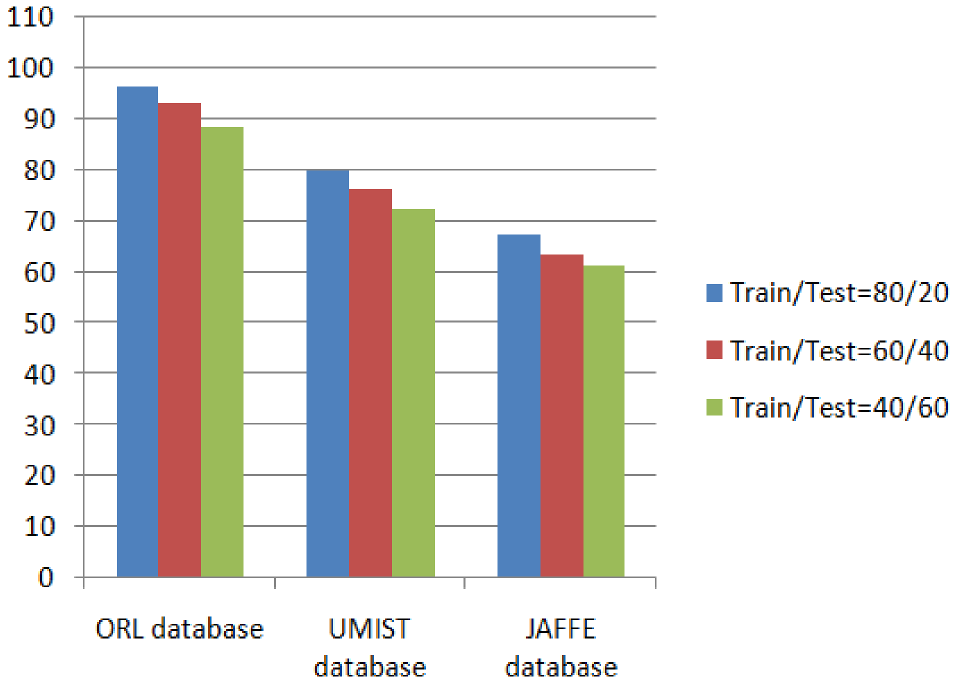

Figure 8. The percentage recognition rate versus various databases using LDA technique.

Table 1. Detailed results of the recognition rate for all databases using PCA technique.

(Train/Test)	Recognition Rate of ORL Database	Recognition Rate of UMIST Database	Recognition Rate of JAFFE Database
80/20	94.027	77.681	64.978
60/40	91.074	74.983	58.035
40/60	86.202	70.994	51.281

Table 2. Detailed results of the recognition rate for all databases using LDA technique.

(Train/Test)	Recognition Rate of ORL Database	Recognition Rate of UMIST Database	Recognition Rate of JAFFE Database
80/20	95.981	79.691	67.052
60/40	93.028	75.991	63.089
40/60	88.107	72.231	60.905

Figure 9. Sample of a successful face recognition test on ORL database.

Figure 10. Sample of a successful face recognition test on UMIST database.

Figure 11. Sample of a successful face recognition test on JAFFE database.

9. Conclusions

In this paper, two feature extraction techniques (PCA, and LDA) are investigated and compared for human face recognition. The experiments performed on ORL, UMIST, and JAFFE face databases. From tables (1), and (2), it can be concluded that the LDA technique provides higher recognition rate than the PCA technique. The highest recognition rates that are recorded for the LDA technique as the following: 95.981% (ORL database), 79.691% (UMIST database), and 67.052% (JAFFE database). On the other side, The highest recognition rates that are recorded for the PCA technique as the following: 94.027% (ORL database), 77.681% (UMIST database), and 64.978% (JAFFE database). The Euclidean distance classifier is used in the proposed system for comparing the projection vector of the training face images with the projection vector of the input face image.

10. References

1. Mayank, A., Nikunj, J., Manish, K. and Himanshu, A. (2010). *"Face Recognition Using Eigen Faces and Artificial Neural Network"*, International Journal of Computer Theory and Engineering (IACSIT), Vol.2, No.4, pp. 624-629.
2. Gunjan, A. and Cyril, V. (2012). *"An efficient Method for Face Recognition Using Principle Component Analysis (PCA)"*, International Journal of Advanced Technology & Engineering Research (IJATER), Vol.2, Issue.2, pp. 23-28.
3. Priyanka, D. and Parsai, P. (2014). *"A MATLAB Based Face Recognition Using PCA with Back Propagation Neural Network"*, International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE), Vol.2, Issue.8, pp. 5291-5297.
4. Alaa, E. and Hasan, D. (2005). *"Face Recognition System Based on PCA and Feed Forward Neural Networks"*, Springer-Verlag, Berlin, Heidelberg, pp. 935-942.
5. Alaa, E. and Hasan, D. (2006). *"PCA and LDA Based Face Recognition Using Feed forward Neural Network Classifier "*, Springer-Verlag, Berlin, Heidelberg, pp. 199-206.
6. Amritpal, K. and Sarabjit, S. (2015). *"Face Recognition Using PCA (Principal Component Analysis) and LDA (Linear Discriminant Analysis) Techniques"*, International Journal of Advanced Research in Computer and Communication Engineering (IJARCCE), Vol.4, Issue.3, pp. 308-310.