Face Recognition Using Various Feature Extraction Approaches

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Abstract

This paper introduces an experimental study on the recognition of the person's face by utilizing three
Techniques of extraction: Principle Components Analysis (PCA), Linear Discriminant Analysis (LDA) and Contourlet- Curvelet Transform (CCT). The results of these approaches were observed and compared to discover the perfect scheme for identification of human faces. The tests have been carried out on the
faces databases of (ORL) ,(UMIST), and (JAFFE). The results acquired by the methods were quantified by altering the ratio of train to test photos in three categories: 75/25, 55/45 and 35/65. The evaluation results showed that the CCT extraction method provides better results than the others. The highest recognition rate was recorded for the CCT approach (recognition rate=98.980%) when the (train /test) photos ratio is (75/25). Furthermore, the best recognition rates for the LDA and PCA were 96.391% and 95.127% respectively. The Matlab R2019b program was used for implementing and testing the algorithms.

Keywords: Contourlet -Curvelet Transform, CCT, LDA, PCA and Face Recognition.

1. Introduction

Our faces are the centre of attention in culture and play a significant role in communicating identity and feelings. Though this ability to deduce intellect or nature from the face feature is misleading, the human ability to identify faces is significant. A human can identify millions of faces learned in his or her lifespan and recognize famous faces upon years of absence quickly. Excluding significant visual stimulus changes due to visual situations, gestures, maturity or disturbances, such as glasses, bars or modifications in hairstyle, this skill is very strong. In many application areas, recognition system is becoming an important Consideration, such as terrorist recognition, security systems and payment card confirmation. Indeed the ability to just remember faces could be valuable as opposed to recognizing them. Even though it is obvious that human recognize their faces well, it is really not clear how face is encrypted or decrypted by a brain human. Recognition of person's faces has also been studied over 20 years. It is extremely hard to formulate a super-computing model for facial recognition since faces are complex and multidimensional visual stimuli. Consequently, facial recognition is now a high-level image processing challenge, covering multiple initial vision techniques [1]. The first process involves extraction of important characteristics from face images. A major challenge is to quantify the facial characteristics so that a computer can identify a face with a group of features. The researches that done by several researchers in recent years have shown that human beings use particular facial characteristics to identify faces [2].

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2. Principle Components Analysis (PCA)

PCA involves the use of an orthogonal transformation mathematical method. The PCA method aims to reduce the dimensionality using different compression principles and shows the most effective low-dimensional facial pattern structure. Such reduced dimensions remove data which is not relevant and decomposes precisely the facial structure, which consists of converting the number of associated variables possible into a smaller number of orthogonal (unconnected) components called primary components. Any face image can be "exemplified as a scaled sum (feature vector) of the eigenfaces that can be stored in one dimension matrix". The test photos are exemplified by these scaled sums. When the test photo is known, the scales are determined by extrusion the photo upon the eigenface vectors. The spacing between the scaled photo vectors and the database photo is calculated. Therefore, with the aid of eigenfaces the face image can be reconstructed to fit the intended image [3]. The PCA's numerical expressions as follows:

Assume the training set of facial imagesA_1, A_2,........., A_n, then the average of this set is described by Eq. (1) [4]:

$$\mathrm{B} = \frac{1}{C}\sum_{i=1}^{C} \mathrm{A_i} \tag{1}$$

Each face is distinguished from the average by the following vector [4]:

$$\mathrm{D_i} = \mathrm{A_i} - \mathrm{B} \tag{2}$$

This collection of very large vectors is subordinated to the PCA which looks for a group of orthonormal C vectors, E_{L1}, "the best definition of data distribution".

The L^{th} vector, E_L, is chosen in such away [5]:

$$\alpha_\mathrm{L} = \frac{1}{\mathrm{C}} \sum_{\mathrm{i=1}}^{\mathrm{C}} (\mathrm{E_L^T D_i})^2 \tag{3}$$

is the greatest value, Subordinate to

$$\mathrm{E_J^T E_L} = \begin{cases} 1 \mathrm{if\, J = L} \\ 0 \ \ \mathrm{otherwise} \end{cases} \tag{4}$$

The vectors E_L and scalars α_L are the eigenvectors and eigenvalues, sequentially of the covariance matrix [5]:

$$\mathrm{F} = \frac{1}{\mathrm{C}} \sum_{\mathrm{i=1}}^{\mathrm{C}} \mathrm{D_i D_i^T} = \mathrm{GG^T} \tag{5}$$

The matrix G =[$\mathrm{D_1}$ $\mathrm{D_2}$.... $\mathrm{D_C}$]. The covariance matrix F however is $\mathrm{O}^2 \times \mathrm{O}^2$ Real symmetric matrix and O^2 evaluation is a hard process for the standard image dimensions.

The developers need a method that is arithmetically feasible to compute these vectors.

Assume the eigenvectors w_j of $\mathrm{GG^T}$ such that [5]:

$$\mathrm{G} \,.\, \mathrm{G^T} \,.\, w_j = \beta_j \,.\, w_j \tag{6}$$

We obtain Eq. (7) by pre-multiplying each side by G:

$$\mathrm{G} \,.\, \mathrm{G^T} \,.\, w_j \,.\, \mathrm{G} = \beta_j \,.\, w_j \,.\, \mathrm{G} \tag{7}$$

It is evident that G w_j is the eigenvectors and β_j is the eigenvalues of $F= G \,.\, G^T$.
After this process, we are able to construct the C × C matrix H= G^T G, where H_{ci} = D_i^T D_i , and evaluate the C eigenvector, w_j of H. These vectors generate linear configurations of the C training group face images to determine the eigenvalues E_J [5].

$$E_J = \sum_{L=1}^{C} W_{JL} D_L, J = 1, \dots C \tag{8}$$

With all of this process, computations are reduced considerably, from the amount of the overall pixels in the images (O^2) to the amount of overall images in the training group (C).

The training collection of face images will be relatively small ($C<<O^2$) and the computations will be comparatively controllable.

The relevant eigenvalues allow us to rank the eigenvectors in terms of their usefulness in describing the alterations in the images [5]. An updated face image A is converted into its eigenface components by a simple process [5]:

$$X_L = D_L^T(A - B) \tag{9}$$

for L = 1,...,C'. The weights form a projection vector can be defined as the following [5]:

$$\mu^T = [X_1 X_2 \dots \dots X_{C'}] \tag{10}$$

Explaining the contribution of each individual eigenface in the image representation, which deals with the characteristics as a basis for face images. The projection function in a standard pattern recognition system is used to decide which facial classes are best represented in a certain predefined face class.
By averaging the outcomes of the eigenface class definition over a few face images of each person, the face class μ_L can be evaluated. The classification is accomplished by comparing the projection vectors of the training face photos with the reference face projection vector. This differentiation is based on the distance between the face classes and the face image of the input which can be defined in Eq.(11) [5]. The aim is to determine the face class L that decreases the distance [5]:

$$M_L = |\mu - \mu_L| \tag{11}$$

Where μ_L is a vector representing the L^{th} faces class.

3. Linear Discrimination Analysis (LDA)

The LDA is a strategy for minimizing dimensionality that used for classification tasks. Another name of LDA is the fisher's discriminant analysis that searches certain vectors which are the finest discrimination between classes in the underlying domain. LDA combines the individual feature, leading to the highest average differences among the most desired classes. LDA is a linear conversion based on the analyses of the scatter matrix. The LDA's task is to maximize the scatter matrix measurement between the classes and to minimize the scatter matrix measurement between the classes. The LDA is produced fish linear classifier form which increases the ratio of scatters between and within classes. It is typically used in the area of face recognition [6]. The LDA attempts to maximize the percentage difference rate of the determinant of the between-class scatter matrix for the estimated samples and the scatter matrix of the samples estimated within the class. The discriminant Fisher gathers images of the same class and distinguishes images of different classes. Images are "predicted from O^2 to F dimensional domain (where F is the number of image classes)". For example, let that two groups of points are projected on a single line in two-dimensional domain. The points can be merged together or secluded according to the direction of the line as demonstrated in Fig.1. Fisher discriminant finds the line that finest separates the points.
To differentiate a test photo of the Input, the projected photo is compared to the numerous projected training photos and the test photo is then stated to the nearest training photo. Just like eigenspace placing, the training photos are positioned into a spatial space. The test photos are demonstrated in the same spatial space and identified with a similitude metric. The major difference is the evaluation of spatial

space. In contrast to the PCA method, which extracts characteristics to best recognize face photos, the LDA approach seeks to find the spatial space that most discriminates between the different facial classes, as shown in Fig.2. The intra-class scatter matrix reflects the alterations in form of the same demarcation induced by different illumination and facial manifestations, while the inter-class scatter matrix, sometimes called as "extra-singular" matrix describes the variations in attribute due to alterations in identity. The utilization of this method, we can get a direction in which the the intra-class scatter matrix reflects the alterations in form of the same demarcation induced by different illumination and facial manifestations, while the inter-class scatter matrix, sometimes called as "extra-singular" matrix describes the variations in attribute due to alterations in identity. The utilization of this method enables us to get a direction in which the distance between the face photos of different groups increases. While, it decreases the distance between the similar classes. In another meaning, they maximize the P_q scatter matrix between classes, and minimize the S_t scatter matrix within classes in the projective spatial space.
Fig. 3 demonstrates the positive and negative class Splitting [6].

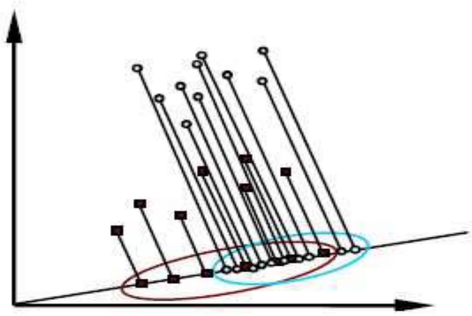

Fig.1: Points that are combined on a line when they projected [7].

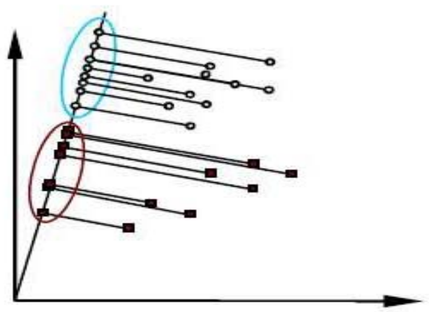

Fig. 2: Points those are detached on another line when they projected [7].

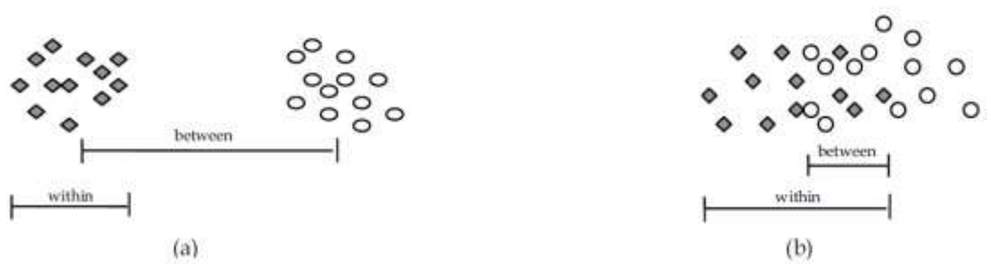

Fig3. (a): Positive class splitting. (b): Negative class splitting [7].

The intra-class scatter matrix P_q and the among-class scatter matrix S_t are given by Eq. (12), and Eq. (13): [7]

$$P_q = \sum_{k=1}^{F} \sum_{i=1}^{Ok} (A_i^k - \sigma_i)^T (A_i^k - \sigma_i) \tag{12}$$

$$S_t = \sum_{i=1}^{F} (\sigma - \sigma_i)\,(\sigma - \sigma_i)^T \tag{13}$$

Where σ is the average of the all classes.

The LDA spatial space is expanded by a group of vectors:

V = [V1, V2, … , Vz], achieving: [7]

$$V = \arg\max = \left|\frac{Q^T\ S_t q}{Q^T\ P_q q}\right| \tag{14}$$

4. Contourlet Transform

This is a convenient, orientation wavelet expansion. Wavelets are not efficient to display images in various orientations with the sleek contours. The orientation and anisotropy features are treated by contourlet transform. There are two major stages for implementing the contourlet transform, the first one is the Laplacian Pyrarmid and the second one is the orientation filter banking as illustrated in Fig.4. Firstly, the input photo is segmented into low-pass and band-pass photos, and then every band-pass photo is more segmented by the orientation filter banking. For the following grade of segmentation, first low pass photo is down-sampled and threaded during the same filter package texture. The process is repeated for every following grade of segmentation [8].

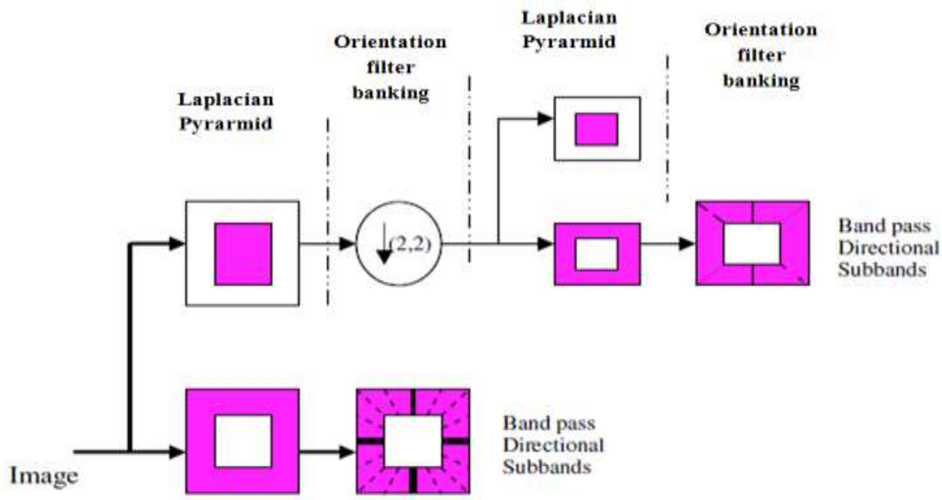

Fig.4: Segmentation diagram of contourlet transform.

5. Curvelet Transform

The curvelet transform is a multiple orientations and multiple level transformations that describe edges and other features on the curves better than other multistage transforms. The application of the curvelet transform includes evaluating the two dimensional FFT of the image. In the following stage, the (2D-FFT) domain is segmented into parabolic pegs, then the inverse FFT is calculated at every scale Δ and angle δ as illustrated in Fig.5 [9].

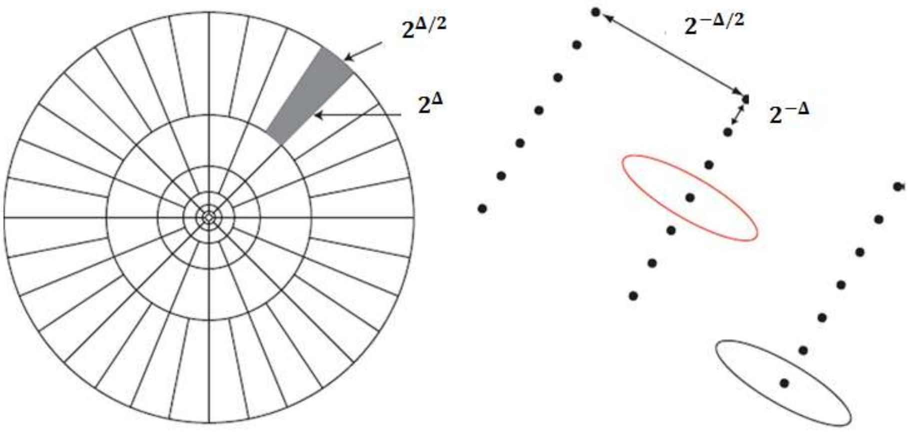

Fig.5: The curvelet cladding of space and frequency[9].

6. Methodology

The suggested block diagram of this work is demonstrated in Fig.6. It consists of implementing the PCA, LDA and CCT feature extraction schemes. The validation for the performance of the aforementioned methods is done using different face databases. The ratio of (Train/Test) images is altered in a three grades (75/25), (55/45) and (35/65). The type of the classifier that has been used is the conventional Euclidean distance.

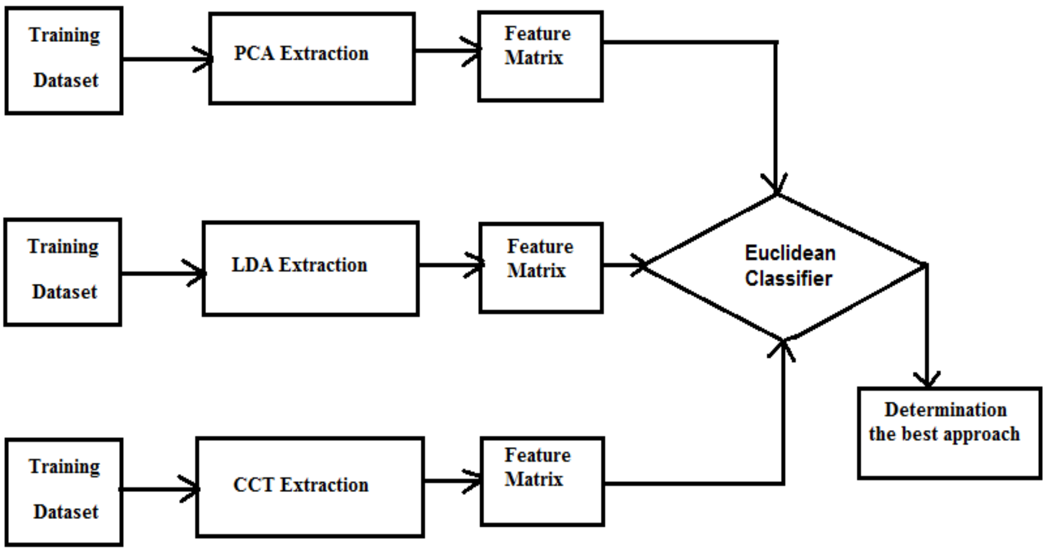

Fig.6: The suggested framework.

7. The ORL Face Group

This database comprises four hundred gray-scale face photos of forty persons. Every person has ten photos, with two hundred and fifty six levels and resolution of 112 x 92. The photos are captured with different characteristics, such as altering partially the lightening, various face manifestations i.e. flickering eyes, fake, and non-fake smile, with or without wearing glasses. Fig. 7 shows the photos of face for two persons (male and female) from this database [10].

Fig.7: ORL Face photos for two persons male and female [10].

8. The UMIST Face Group

This is a multiple-sight database. It composed of five hundred and forty-six gray-scale photos of twenty men, each including a fair range of situations: side to direct sights. Every individual involves a range of descent, sex, and manifestation. Every photo has two hundred and fifty six levels and resolution of 112 x 92. In contrast to the ORL database, the group of photos per individual is not constant. Fig. 8 displays a specimen photos for one man from this database [11].

Fig.8: Photos of One man from UMIST collection [11].

9. The JAFFE Face Group

This database implicates two hundred and thirteen gray-scale photos of seven face features (six primary manifestations plus one neutral) pretended by ten Japanese females. Every photo has been predestined on six emotions adjectives by 60 Japanese citizens. Fig. 9 displays specimen photos of one female of the JAFFE database [12].

Fig. 9: Specimen photos of one female of the JAFFE collection [12].

10. Results and Discussion

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Numerous Tests are conducted on several groups of databases; ORL, UMIST, and JAFFE. The ORL collection was utilized to find the effectiveness of the suggested techniques versus the situations of slight distinction of turning and scaling. Furthermore, the UMIST collection was applied to examine the results of the presented methods when the angle of turning of the face photo is considerable. Finally, The JAFFE collection was utilized to test the efficiency of the introduced approaches when the images comprise multiple face manifestations. The introduced methods were executed using MATLAB (2019b). In the testing set-up for the complete collection of the databases, the training photos was varied from 75 percent to 35 percent i.e. starting with a 75% of the entire images were utilized in the training and the others 25% were used for examination. Furthermore, the attribution was changed as 55/45 and 35/65. The empirical results displayed that the recognition rate of the CCT method improved because of raising the number of images in the training group. This is evident since further specimens of photos can distinguish the classes of the persons utmost in the face scope.

The comprehensive results are demonstrated in tables (1), (2) and (3). The results distinctly exhibit that the CCT feature extraction scheme surpasses the others algorithms in face recognition. The biggest recognition rate was for the CCT scheme on the ORL collection, which is 98.980% when the ratio of the (train /test) photos is 75/25, while the largest recognition proportion for LDA and PCA algorithms were 96.391% and 95.127% respectively. Furthermore, the smallest recognition ratio that is scored for the CCT method on the JAFFE group is 63.200% when the ratio of the (train /test) photos is 35/65. Moreover, the smallest recognition ratio for LDA and PCA approaches were 61.878% and 52.790% in successive. The Figures (10), (11), and (12) display specimens of successful recognition from all groups of the databases.

Table 1. The overall results of the PCA Scheme.

(Train/Test)	Recognition Rate of ORL Database	Recognition Rate of UMIST Database	Recognition Rate of JAFFE Database
75/25	95.127	78.281	65.168
55/45	93.230	76.166	60.010
35/65	87.511	71.884	52.790

Table 2. The overall results of the LDA Scheme.

(Train/Test)	Recognition Rate of ORL Database	Recognition Rate of UMIST Database	Recognition Rate of JAFFE Database
75/25	96.391	80.500	68.121
55/45	94.104	76.878	64.197
35/65	89.005	73.108	61.878

Table 3. The overall results of the CCT Scheme.

(Train/Test)	Recognition Rate of ORL Database	Recognition Rate of UMIST Database	Recognition Rate of JAFFE Database
75/25	98.980	82.611	70.310
55/45	96.210	78.337	66.244
35/65	91.111	75.016	63.200

Fig. 10: Specimen of a successful execution on ORL group.

Fig. 11: Specimen of a successful execution on UMIST group.

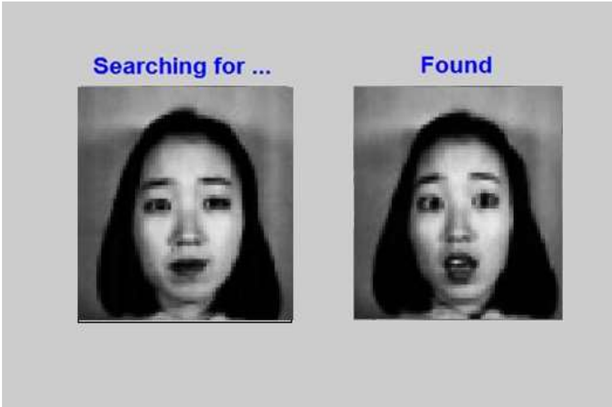

Fig.12: Specimen of a successful execution on JAFFE group.

11. Conclusion

In this work a three feature extraction approaches (PCA, LDA and CCT) have been validated and confronted for face recognition task. The tests were carried out on different collections of databases (ORL, UMIST, and JAFFE). The results were demonstrated that the CCT scheme gives the highest recognition rate than the others. The best recognition rates that are obtained for the CCT method as the following: 98.980% (ORL collection), 82.612% (UMIST collection) and finally, 70.310% (JAFFE collection).

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