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Performance Analysis of Feature Extraction Techniques: PCA and LDA for Face Recognition

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Abstract: **- Feature extraction is one of the most important steps in image pattern recognition. Some sources of difficulty are the presence of irrelevant information and the relativity of a feature set to a particular application. Feature extraction and description are essential components of various computer vision applications. The concept of feature extraction and description refers to the process of identifying points in an image (interesting points) that can be used to describe the image's contents. The One major goal of feature extraction is to increase the accuracy of learned models by compactly extracting prominent features from the input data, while also possibly removing noise and redundancy from the input. Additional objectives include low-dimensional representations for data imagining and compression for the purpose of reducing data storage requirements as well as increasing training and implication speed. The aim of this paper is to report the result analysis of the most popular feature extraction techniques PCA and LDA using MATLAB to extract face features which are generally used in human recognition.**

Keywords: **Feature extraction, PCA Algorithm, LDA Algorithm, human recognition.**

I. INTRODUCTION

Feature extraction is playing a vital role in image pattern recognition applications. The aim of feature extraction is to find the most pertinent data from the original data and represent that data in low dimensional space [1]. When the input data to the algorithm is very large and redundant then the input data to be transformed into reduced set of features. The process of transforming the input data into a reduced set of features is called feature extraction. Feature extraction has been given as extracting from the raw data information that is most suitable for classification purpose. Thus, selection of a suitable feature extraction technique according to the input to be applied need to be done with utmost care. Taking into consideration all these factors, it becomes essential to look at the various available techniques for feature extraction in a given domain, covering vast possibilities of cases. The efficiency of feature extraction method enhances the further processing of an image to a great extent. Face recognition is an integral part of biometrics. In biometrics basic traits of human is matched to the existing data and depending on result of matching recognition of a human being is traced. In Face Recognition, the very first step is to reduce the dimensionality of the original face space with respect to a certain criterion. Because of the huge dimensionality of a face image, it may contain redundant or noisy information, and its processing requires a high computational cost. A feature reduction is performed by applying some standard algorithms of pattern recognition. Face recognition algorithms are used in a wide range of applications viz., security control, crime investigation, and entrance control in buildings, access control at automatic teller machines, passport verification, identifying the faces in a given databases [2], [3]. This paper discusses the experimental performance analysis of feature extraction techniques PCA & LDA for appearance based face recognition on small training data set. The result obtained showed that PCA outperforms LDA for small training database.

II FEATUE EXTRACTION TECHNIQUES PRINCIPAL COMPONENT ANALYSIS (PCA)

The main aim of a Principal Component Analysis [4] [5] [6] is finding the directions of maximum variance in high-dimensional (n) dataset and project it onto a smaller dimensional subspace while retaining most of the information. In other words, it is a procedure that uses an orthogonal transformation to convert a set of possibly M correlated variables into a set of K uncorrelated variables are called as principal components / eigen vectors (K < M). The flowchart of Principal Component Analysis is given in figure 1.

Principal Component Analysis Algorithm

Inputs : a set of images visualized as a set of coordinates in a in high-dimensional(n) dataset.

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Outputs : produces a lower dimensional picture a shadow (eigen images) of given m images when viewed from its most informative points.

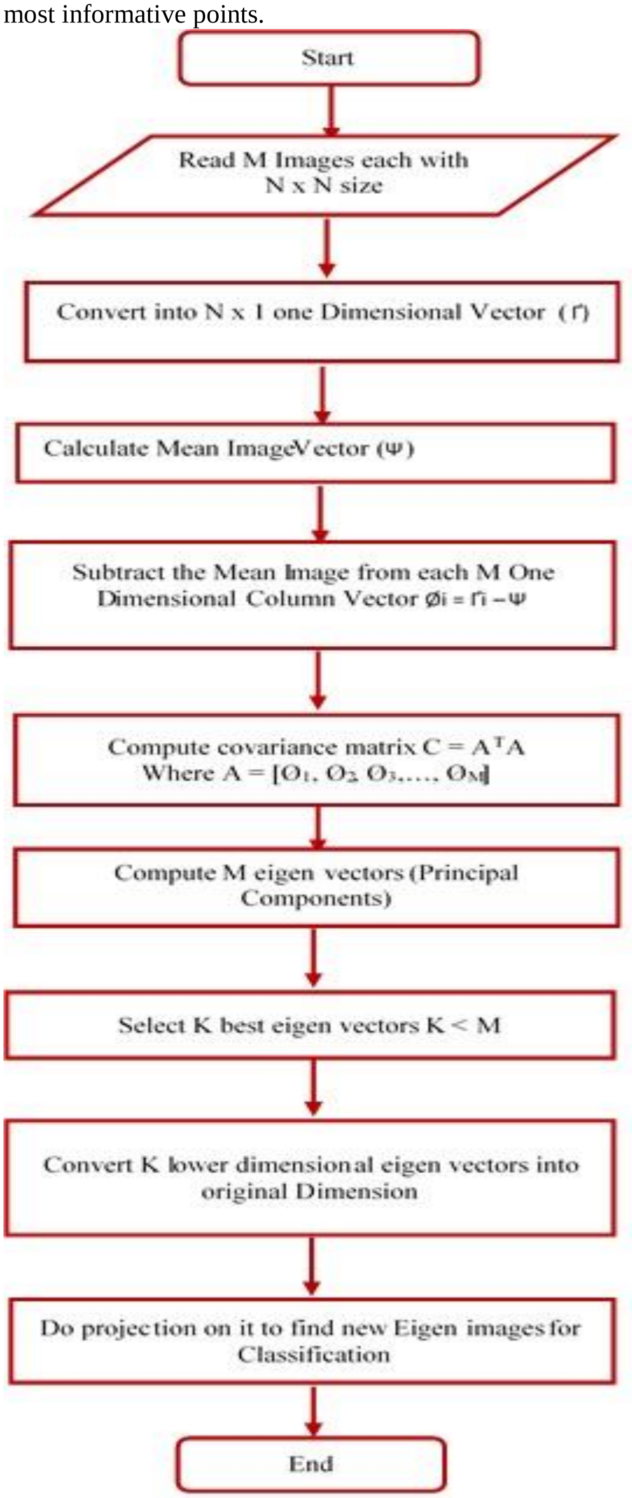

Figure 1. Flowchart of Principal Component Analysis

Steps :

1. Convert each m input images (I1,I2,…,Im) of size N X N into N X 1 one dimensional column vectors (Ґ1, Ґ2…, Ґm)
2. Normalize N X 1 column vector. It means that the all the common features from each M images are removed so that each image has only unique features.
   i. Calculate an average/mean image vector (Ψ)
   ii. Subtract the average/mean image vector (Ψ) from each M one dimensional column vectors Ґ (i.e.) Normalized Image Vectors Øi = Ґi – Ψ
3. Calculate K significant Eigen Vectors (principal components/axes) and eigen values (variance) from a covariance with reduced dimensionality

Eigen vectors => Determines the direction of the new feature space

Eigen Values => Determines the magnitude / variance of the data along the new feature space

Calculate the Covariance matrix C = ATA

where A = [Ø1, Ø2, Ø3,…, ØM]

Dimension of A = N2 M & AT = M N2

Hence C = (MN2) (N2 M) => (M M)

ii) Generate M eigen vectors (Principal Components)

4. Select K best Eigen Vectors K < M
5. Convert lower dimensional K eigen vectors into original dimensionality and do projection along these eigen images to find new features for classification

B. LINEAR DISCRIMINANT ANALYSIS (LDA)

The goal of the Linear Discriminant Analysis technique is to project the original data matrix onto a lower dimensional space. The Linear discriminant analysis technique [7] [8] [9] is developed to transform the features into a lower dimensional space, which maximizes the ratio of the between-class variance to the within-class variance, thereby guaranteeing maximum class separability. To achieve this goal, three steps to be performed.

The first step is to calculate the separability between different classes (i.e. the distance between the means of different classes), which is called the between-class variance or between-class matrix. The second step is to calculate the distance between the mean and the samples of each class, which is called the within-class variance or within-class matrix. The third step is to construct the lower dimensional space which maximizes the between-class variance and minimizes the within class variance. The flowchart of Linear Discriminant Analysis is given in figure 2.

Linear Discriminant Analysis Algorithm

Input : Given a data matrix N X M. Where N denotes number of samples $X = (x_1, x_2, x_3, \ldots\ldots x_N)$. Each sample xi is represented as a vector with a length of M.

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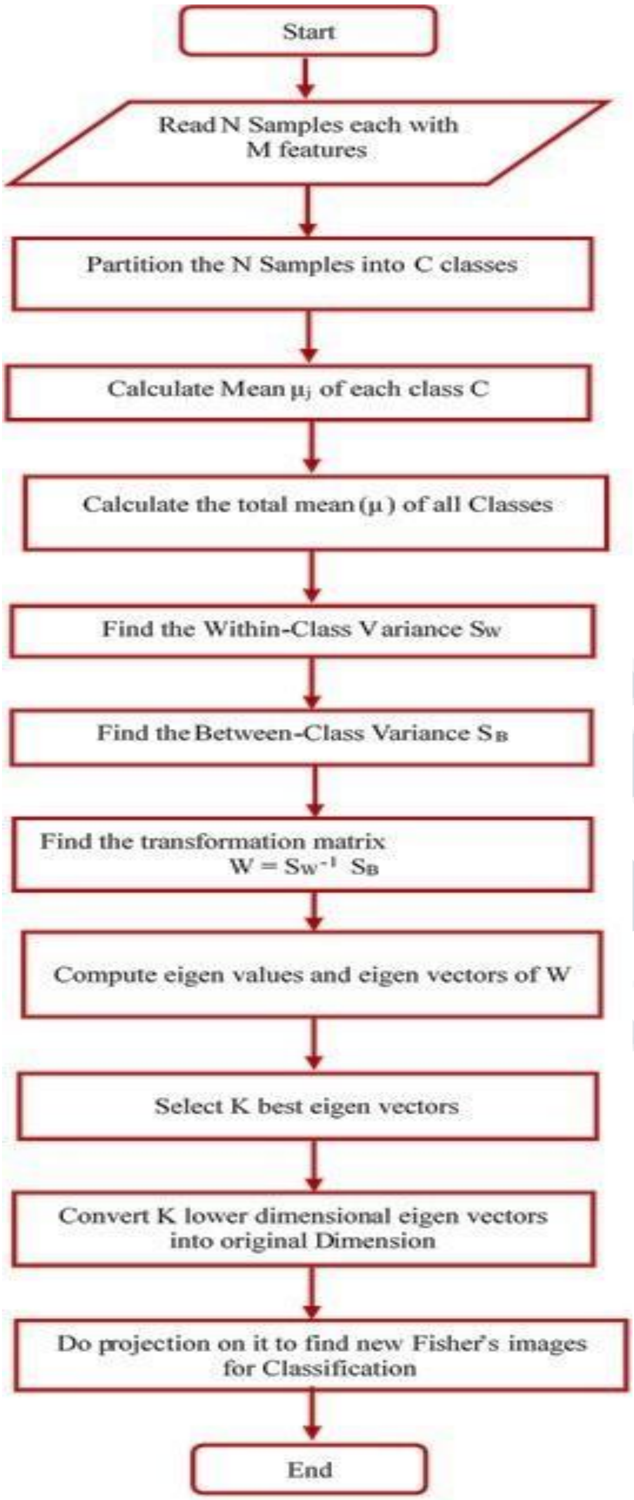

Figure 2. Flowchart of Linear Discriminant Analysis

Output : Generates a lower dimensional picture a shadow (fisher images) of given N images.

Steps :

1. Read N sample images. Each image is represented as a row vector with a length of M features and form a data matrix X with a size of N X M.

2. Partition the data matrix into c classes (ie x1, x2, … xc). Each class xj has M features. Find the mean of each class μj (1×M) using the equation

$$\mu_j = \frac{1}{n_j} \sum_{i=1}^{M} x_i$$

3. Find the total mean of all data μ(1×M) using the equation

$$\mu = \frac{1}{c} \sum_{i=1}^{c} \mu_i$$

4. Find the within-class variance SW. It represents the difference between the mean and the samples of that class using the equation

$$S_W = \sum_{j=1}^{c} \sum_{i=1}^{n_j} (x_{ij} - \mu_j)(x_{ij} - \mu_j)^T$$

5. Find the between-class variance (SB). Represents the difference between the mean and the samples of that class using the equation

$$S_B = \sum_{i=1}^{c} n_i (\mu_i - \mu)(\mu_i - \mu)^T$$

6.Find the transformation matrix (W) $W = S_W^{-1} S_B$

7. The eigenvalues (λ) and eigenvectors (V) of W are then calculated.

Where the eigen values are $\lambda = \{\lambda_1, \lambda_2, \lambda_3 .... \lambda_M\}$

and eigen vectors are $V = \{v_1, v_2, v_3 .... v_M\}$

8. Sorting the eigenvectors in descending order according to their corresponding eigenvalues. The first k eigenvectors are then used as a lower dimensional space (V_k). $Y = XV_k$

9. Project all original samples (X) onto the lower dimensional space of LDA using the equation

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Where each sample (Xi) which was represented as a point a M-dimensional space will be represented in a k-dimensional space by projecting it onto the lower dimensional space (V_k) as follows, $Yi = X_i V_k$.

III FACE FEATUE EXTRACTION USING PCA FOR RECOGNITION

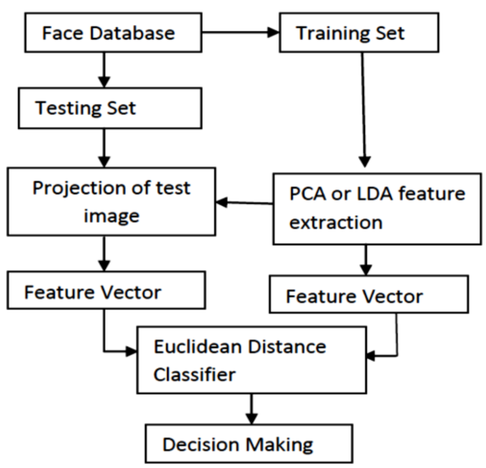

Figure 3. Flowchart for PCA and LDA approach

Face recognition has a number of advantages over other biometrics. Firstly, it is non-intrusive. While many biometrics require the subject's co-operation and awareness in order to perform identification, such as looking into an eye scanner or placing their hand on a fingerprint reader, face recognition could be performed even without the subject's knowledge [10]. Secondly, the biometric data used to perform recognition is in a format that is readable and understood by humans. The steps involved in the face recognition system are first the system needs to be initialized by feeding it a set of training images of faces. This is used to define the face space of face images. Next when a test face image is encountered, it calculates an eigen face for it. Then it compares the test image with known faces and using some statistical analysis it can be determined whether the test face is recognized or not. The flowchart to show the steps involved in the PCA and LDA approaches for face recognition is given in figure 3.

C. Role of PCA for Face Recognition

The main idea of using PCA for face recognition is to express the large 1-D vector of pixels constructed from 2-D facial image into the compact principal components of the feature space [11] [12]. Face Images are projected into a feature space ("Face Space") that best encodes the variation among known face images. The face space is defined by the "EigenFaces", which are the eigenvectors of the set of faces. EigenFaces is calculated by identifying the eigenvectors of the covariance matrix derived from a set of facial images (vectors). Then the distance between the test and training images are found using the distance measures like Euclidean, Mahalanobis and Angle Negative to find the similarity match[13] [14]. The training image which has the maximum similarity is the recognized face image for the given test image. The face feature extraction and recognition using PCA is shown in figure 4.

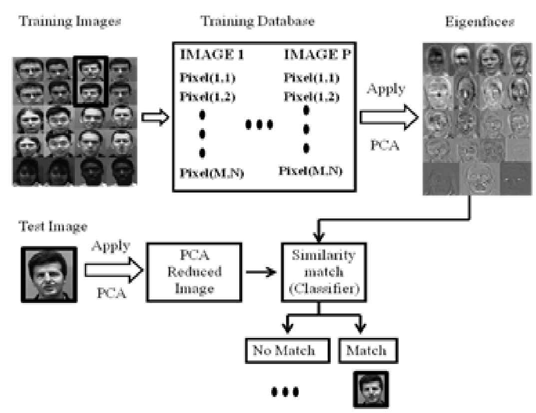

Figure 4. Face feature extraction and recognition using PCA

Steps :

1. Read the test image and separate face from it.
2. Calculate the feature vector of the test face. The test image is transformed into its eigenface components. First we compare line of our input image with our mean image and multiply their difference with each eigenvectors [2].
3. Each value would represent a weight and would be saved on a vector Where, is the ith Eigenfaces and i=1, 2, 3 . . . . . .K.
4. Compute the average distance (Euclidean distance) between test feature vector and all the training feature vectors. Mathematically, recognition is finding the minimum Euclidean distance , between a testing point and a training point given in the following equation Where, i = 1, 2, 3. . . . . . K. The Euclidean distance between two weight vectors thus provides a measurement of similarity between the corresponding images.
5. The face class with minimum Euclidian distance shows similarity to test image.

D. Role of LDA for Face Recognition

Another important feature extraction technique is Linear Discriminant Analysis (LDA) or fisherface approach, proposed by Kriegmann et al. [15]. LDA constructs a discriminant subspace that minimizes the scatter between images of same class and maximizes the scatter between different class images. LDA is a class based approach in which the faces of the same subjects are grouped into separate classes and the variations between the images of different classes are discriminated using the eigenvectors at the same time minimizing the covariance within the same class. These eigenvectors are called fisherfaces. Linear Discriminant Analysis (LDA) [16], [17] finds the vectors in the underlying space that best discriminate among classes. Then the distance between the test and training images are found using the distance measures like Euclidean, Mahalanobis and Angle Negative to find the similarity match. The training image which has the maximum similarity is the identified face image for the test image. The face feature extraction and recognition using LDA is shown in figure 5.

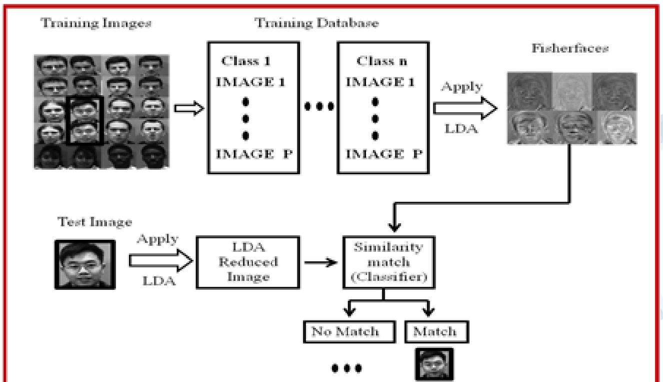

Figure 5. Face feature extraction and recognition using LDA

Steps :

1. Read N number of training images and partition them into C classes and a test image.
2. Compute the average of images for each class as µj and overall classes as µ.
3. Find within-class variance S_W and between class variance S_B.
4. Find transformation matrix W using S_W and S_B.
5. The eigen values (λ) and eigenvectors (V) of W are then calculated.
6. Sort the eigen vectors in decreasing order and select the first K low dimensional eigen vectors.
7. Project all original samples onto the lower dimensional space of LDA.
8. Apply the same process to compute the test image feature vector.
9. Compute the average distance (Euclidean distance) between test feature vector and all the training feature vectors. The Euclidean distance between two weight vectors thus provides a measurement of similarity between the corresponding images.
10. The face class with minimum Euclidian distance shows similarity to test image.

IV EXPERIMENTAL RESULTS AND DISCUSSION

We have used faces from Yale database for present work. MATLAB 2013a is used to carry out this research work. First of all, the image preprocessing steps are carried out on the images for improving performance of algorithms. Then by applying principle component analysis and linear discriminant analysis, face recognition is done [18] [19] [20]. Further the performance of PCA and LDA based algorithms was evaluated with respect to face recognition rate and dimensionality. Figure 6 shows some of the faces from Yale database [21] [22].

Figure 6. Faces from Yale database

After applying PCA and LDA, the recognition process gave the closest matching face from training database for the given test image (as shown in Figure 7 and Figure 8).

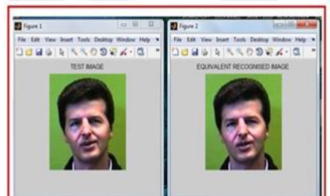

Figure 7. PCA Output

Figure 8. LDA Output

The results obtained shows that PCA outperforms LDA for small training database. But for large training face images and different training data set, LDA shows better result than pure PCA.

VI. CONCLUSION

In this study, we have applied two most popular appearance based face recognition methods i.e. PCA and LDA along with image preprocessing factors on Yale database. The Euclidean Distance based classifier was used for both methods of face recognition systems. The results obtained shows that PCA outperforms LDA for small training database. But for large training face images and different training data set, LDA shows better result than pure PCA. It may be concluded that for some value of dimensionality, PCA gives higher recognition rate than LDA. In future we want to extend our work by combining PCA and LDA for better performance. The work further may be extended for another approach of face recognition like Independent Component Analysis (ICA).

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