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A Comparative Study on Face Recognition using Subspace Analysis

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Abstract— Face recognition has become a field of interest in pattern recognition and artificial intelligence. One of the vital steps involved in face recognition is that of 'Feature Extraction'. Feature extraction is imperative because handling data whose dimensions are inherently high, is rather a tedious process and therefore we adopt strategies for the purpose of dimensionality reduction. This process of studying data by reducing dimensions is called subspace analysis. Two such subspace methods are Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). PCA extracts the most significant components or those components which are more informative and less redundant, from the original data. While LDA is used to find a linear combination of features that characterizes or separates two or more classes in the data. Both PCA and LDA are studied in this paper. For our data set, distance measure is used as a classifier. Euclidean distance, Manhattan distance, Chi square distance are some examples for distance measures.

Keywords— Face recognition, Feature extraction, Dimensionality reduction, Subspace methods, PCA, LDA, Classification,

I. INTRODUCTION

Recognizing faces is a very easy task for human beings like us. However for computers it is not quite easy. There are a lot of calculations and computations required for this process. Despite all these calculations, there are factors such as variations in expression or pose in faces which affect the recognition accuracy.

Face recognition is a technology of using computer to analyze the face images and extract the features for recognizing the identity of the target [1]. Now we discuss some of the existing and previously used methods or techniques for face recognition. Bayesian analysis is a statistical procedure which endeavors to estimate parameters of an underlying distribution based on the observed distribution. It is one of the common subspace based face recognition method. It takes into account the intrapersonal variations and extrapersonal variations modeled as a Gaussian distribution [2]. Linear Discriminant Analysis (LDA) is most commonly used as dimensionality reduction technique in the pre-processing step for pattern-classification and machine learning applications [3]. One more method uses a combination of Gabor wavelets, Direct Linear Discriminant Analysis(DLDA) and Support Vector Machine(SVM). Gabor based extracted features are tolerant against distortions caused by pose, illumination and expression [4].Yet another way for face recognition is the use of combination of Radon and discrete cosine transforms (DCT). The low frequency components are enhanced using Radon transform. Lower dimensional feature vector is obtained by using the data compaction property of DCT [5]. Face recognition using Pixel selection method in a face image based on discriminant features could also be done. The features are extracted by studying the relationships between the pixels in the face images [6].

One of the crucial steps in pattern recognitions as applied to face recognition is that of the feature extraction. For face recognition, image features are first extracted and then matched to those features in a gallery set. The amount of information and the effectiveness of the features used will determine the recognition performance. There are various ways for feature extraction. A combination of Linear Discriminant Analysis (LDA) and Locally Linear Embedding (LLE) is one of the non-linear methods of feature extraction [7]. The primary goal of linear discriminant analysis (LDA) in face feature extraction is to find an effective subspace for identity discrimination [8]..Another approach is using information about face images at higher and lower resolutions so as to enhance the information content of the features that are extracted and combined at different resolutions [9]. The fractional Fourier feature extraction is also a method that could be employed. Developed from the conventional Fourier transform, the fractional Fourier transform is a powerful signal analysis and processing technique [10]. Another effort in feature extraction is the use of hybrid feature extraction using Two-Dimensional Complex Wavelet Transform (2D-CWT). This recognition system congregates three Artificial Neural Network classifiers
(ANNs) and a gating network [11].

Several papers also talk about skin detection methods. A method for skin detection in color images which consists in spatial analysis using the texture-based discriminative skin-presence features was proposed. Color-based skin detection has been widely explored and many skin color modeling techniques are developed so far [12]. There is another method proposed for a reliable color pixel clustering model for skin segmentation under unconstrained scene conditions which can overcome sensitivity to variations in lighting conditions and complex backgrounds [13].

There are various problems which are encountered in the process of detecting faces. One of them is misalignment. A method was proposed to overcome this problem. For a given subspace derived from training data in a supervised, unsupervised, or semi-supervised manner, the embedding of a new datum and its underlying spatial misalignment parameters are simultaneously inferred by solving a constrained optimization problem, which minimizes the error between the misalignment-amended image and the image reconstructed from the given subspace along with its principal complementary subspace [14]. Yet another problem is that of variations in pose. A fast and efficient method was published to overcome this problem. It involves the use of Gabor filters and PCA [15].

In this paper two subspace methods namely, PCA and LDA are studied by applying it on a dataset. Results for both of these methods are compared and suitable inferences and conclusions are drawn.

II. PROPOSED METHODOLOGY

Subspace is a “manifold” (surface) embedded in a higher dimensional vector space. Speaking in mathematical sense, a linear subspace (or vector subspace) is a vector space that is a subset of some other higher dimensional vector space.

For the purpose of feature extraction we employ subspace techniques .Here our main focus is on bringing down the dimensions, which makes data handling an easy task and reduces the computational costs. This is achieved by extracting important features from a dataset.

Eigenvectors and eigenvalues play an important role in identifying the “important” or ‘most significant” features. The largest eigenvalue would mean that the corresponding component of the feature is the “most informative” and “least redundant” compared to the rest of the components. The inductively implies that the eigenvectors corresponding to eigenvalues which are small in magnitude would have less information and we may consider dropping them which invariably reduces the dimensions. This is the essence of subspace analysis and dimensionality reduction.
Two such techniques/methods are discussed below.

A. PCA

Principal Component Analysis is a useful statistical procedure which can be used to bring out strong patterns in a dataset and to emphasize variation. Here the main goal is to identify patterns to reduce the dimensions of the dataset with minimal loss of information. Our intention is to project a feature space of our dataset of n-dimensions onto a smaller subspace that best represents our data.

Listed below are the steps for performing PCA.

1. The first step is to acquire the complete dataset of d-dimensions neglecting the class labels.
2. Calculating the d-dimensional mean vector and getting the mean subtracted data.
3. Computing the covariance matrix (also called scatter matrix) of the whole dataset.
4. Calculating the eigenvectors and eigenvalues of the covariance matrix.
5. Rearranging the eigenvectors such that their corresponding eigenvalues are in descending order.
6. Choosing ‘k’ eigenvectors with largest eigenvalues to form a d*k dimensional matrix(say m), where every column represents an eigenvector.
7. Using this d*k eigenvector matrix (i.e. m) to transform the samples onto the new subspace. The corresponding mathematical equation would look like $x=(m^T)*y$ (x is the transformed k*1 dimensional sample in the new subspace and y is a d*1 dimensional vector representing one sample)

B. LDA

Linear Discriminant Analysis is another technique used for dimensionality reduction in the preprocessing stage for pattern classification. Here our aim is to project the dataset onto a lower dimensional subspace with good class separability.

In terms of the approach, LDA is similar to that of PCA, but in LDA in addition to finding the most significant component axes that maximize the variance, we also find the axes that maximize the separation between multiple classes. LDA maximizes the distance between classes and minimizes the distance within class.
Listed below are the steps for performing LDA.

1. Compute the *d*-dimensional mean vectors for the different classes from the dataset.
2. Obtain the “in-between-class” and “within-class” covariance matrices.
3. Calculate the eigenvectors and eigenvalues for the covariance matrix.
4. Sort the eigenvectors by decreasing eigenvalues and choose k eigenvectors with the largest eigenvalues to form a k*d dimensional matrix WW (where every column represents an eigenvector)
5. Use this k*d eigenvector matrix to transform the samples onto the new subspace. This can be summarized by the mathematical equation: YY=XX*WW (where XX is a n*d-dimensional matrix representing the n samples,

and YY are the transformed n*k-dimensional samples in the new subspace).

A few words on Classification

Classification is the process, in which we determine, to which category, out of several set of categories, a new observation belongs. This determination is based on the training set of data (data containing observations or instances).

An algorithm which implements classification is known as a classifier

Steps involved in classification are, preprocessing, detection and extraction of object, training and classification of object.

Listed below are the approaches for image classification.

1. Based on characteristic used
2. Based on training sample used
3. Based on assumption of parameter in data
4. Based on pixel information used
5. Based on number of outputs for each spatial element
6. Based on spatial information

Classification based on training sample used is further subdivided into supervised and unsupervised classification. The process of using samples of known informational classes (training sets) to classify pixels of unknown identity is called supervised classification. Examples include minimum distance algorithm, parallelepiped algorithm, and maximum likelihood algorithm. For our dataset we use minimum distance algorithm in supervised classification.

About the Dataset

A dataset containing 10 images of 10 people (100 images in total) is considered. In each of the 10 images of a person there is a variation in the pose, illumination or expression of the face. This can be clearly observed in the sample dataset shown in *Fig*.

Fig. 1.1

III. RESULTS AND DISCUSSION

Results were taken after applying PCA and LDA separately to the same dataset. *Table.1* shows the results for PCA and *Table. 2* shows results for LDA. The results are plotted as shown in *Fig. 1.2* and *Fig.1.3* for PCA and LDA respectively

TABLE. 1 Results for PCA

Number of train images	Number of test images	Percentage recognition
5	5	100.00
4	6	100.00
3	7	100.00
2	8	97.50
1	9	93.33

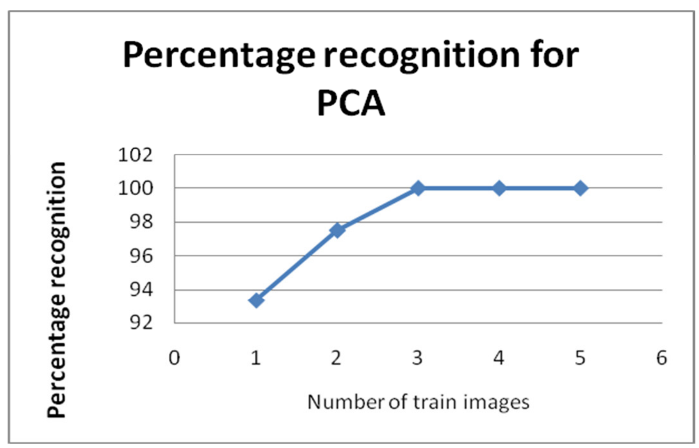

Fig. 1.2

From the results above we can see that, as the number of train images reduces the recognition accuracy slightly reduces. This is because with less train images fewer features are extracted. It is important to recall that PCA does not take care of class labels.

TABLE. 2 Results for LDA

Number of train images	Number of test images	Percentage recognition (based on classification)
5	5	100.00
4	6	81.60
3	7	80.00
2	8	0
1	9	0

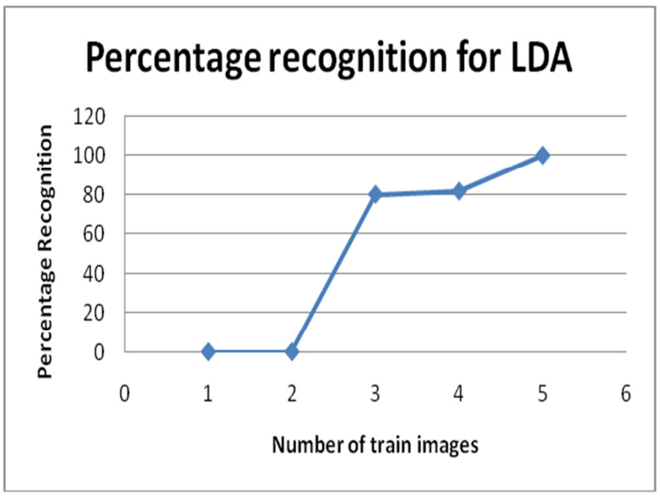

Fig. 1.3

We can see that the percentage for the last two rows is zero. Since distance measure is used as classifier, the test images will be recognized and classified only if it is below a preset threshold value. Moreover as the train images reduces, only those images which belong to that class will be recognized and classified, while for other images the distance value is well above the threshold indicating that they do not belong to that class.

I. CONCLUSION

Both Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) are linear transformation techniques that are commonly used for dimensionality reduction. We can consider PCA as an "unsupervised" algorithm, since it ignores class labels and its objective is to find the principal components that maximize the variance in a dataset. In contrast to PCA, LDA is "supervised" and computes the linear discriminants that will represent the axes that that maximize the separation between multiple classes.

Although it might seem that LDA is superior to PCA for a multi-class classification task where the class labels are known, this might not always the case. For example, comparisons between classification accuracies for image recognition after using PCA or LDA show that PCA tends to outperform LDA if the number of samples per class is relatively small. In practice, we can use PCA and LDA in combination; PCA for dimensionality reduction and LDA for classification.

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