A COMPARATIVE STUDY ON ICA AND LPP BASED FACE RECOGNITION UNDER VARYING ILLUMINATIONS AND FACIAL EXPRESSIONS

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***Abstract*—Dimensionality reduction has been a key problem in Face Recognition. Independent Component Analysis (ICA) is a recent approach for dimensionality reduction. Locality Preserving Projections (LPP) is also a recently proposed new method in pattern recognition for feature extraction and dimension reduction. In this paper we have developed and analyzed the face recognition rate of ICA and LPP under varying illuminations and facial expressions. Analyzes is performed on YALEB databases which contains 64 illuminations conditions (5760 images) and ATT databases which contains major facial expressions (400 images). From the results we conclude that the best algorithm to recognize images with varying illuminations is ICA. On the other hand to recognize image with varying facial expressions, LPP is better to use because it has better recognition rate.**

Keywords-Face recognition, Independent Component Analysis, Locality Preserving Projections, Illuminations, Facial expressions

I. INTRODUCTION

Face recognition has become a hot research topic in the area of computer vision. For face recognition, searching and retrieval of the relevant images from large databases forms the major task [1]. In the existing approaches, computational requirements for performing such tasks are greatly related to the dimensionality of the original data and the number of training samples [2].Methods of face recognition can be divided into two approaches namely, subspace analysis techniques and feature based. Subspace analysis approach attempts to capture and define the face as a whole. The face is treated as a two dimensional pattern of intensity variation. The original image representation is highly redundant, and the dimensionality of this representation could be greatly reduced when only the face pattern is of interest. The features represented in such subspace will be more salient and richer information than original data making recognition task easier and effective [3].Thus dimensionality reduction has been a key problem in face recognition. The classification is usually performed according to a simple distance measure in the multidimensional space. Principal component analysis (PCA) [9-14] and linear discriminant analysis (LDA) [15-23] methods are two classical statistic approaches to reduce the feature dimension. Independent Component Analysis (ICA) [6-7] is a recent approach to face recognition that use feature subspaces. Locality Preserving Projections (LPP) [8] is also a recently proposed new method in pattern recognition for feature extraction and dimension reduction.

ICA is proposed by Jutten and Herault firstly to solve the cocktail lounge problem; its basic intension is to separate the mixed signals into some independent components by optimization algorithm according to statistical independence principle, and take the separated components as the approximate estimation of source signals. The function of ICA is to extract corresponding independent signals from the source mixed signals. One of the applications of ICA is feature extraction. ICA is a method in which statistical characteristics in second order or higher order are considered. Basis vectors decomposed from face images obtained by ICA are more localized in distribution space than those by PCA. Localized characteristics are favorable for face recognition, because human faces are non-rigid bodies, and because localized characteristics are not easily influenced by face expression changes, location, position, or partial occlusion.

LPP is a linear manifold learning approach [8]. LPP is used to generate an unsupervised neighborhood graph on training data, and then finds an optimal locality preserving projection matrix under certain criterion. LPP aims to disclose the low dimensional local manifold structures embedded in high dimensional feature space. This method is to preserve the local structure of image space by explicitly considering the manifold structure, which is transformed into solve a generalized eigenvalue problem using a long. It can be viewed as a linear approximation of Laplacian eigenmaps

The face recognition rate is analyzed on 5760 images of YALE B database which contains 64 illuminations conditions and 400 images of ATT database which contains major facial expressions**.** The remaining of the paper is organized as follows: Section II provides a brief overview of ICA, Section III presents ICA based algorithm for face recognition, Section IV provides brief overview of LPP, Section V presents LPP based algorithm for face recognition. Section VI describes the features of YALEB and ATT databases. Section VII presents results and discussions. Section VIII describes the experimental implementations of ICA and LPP based algorithms finally Section IX draws the conclusion.

II. INDEPENDENT COMPONENT ANALYSIS

ICA is a recently developed statistical technique that can be viewed as an extension of standard PCA [4] and does not consider LDA [5]. Using ICA, one tries to model the underlying data so that in the linear expansion of the data vectors the coefficients are as independent as possible. ICA bases of the expansion must be mutually independent while the PCA bases are merely uncorrelated. ICA has been widely used for blind source separation and blind convolution. Blind source separation tries to separate a few independent but unknown source signals from their linear mixtures without knowing the mixture coefficients. Fig. 1 sets the fundamental ground for ICA face recognition.

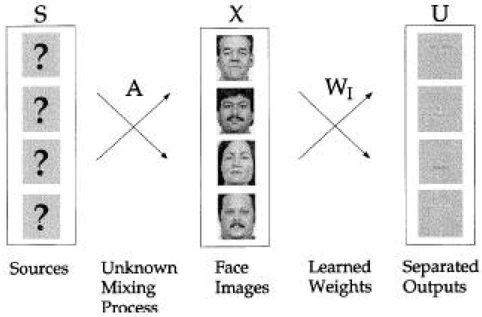

Figure 1. Image synthesis model for ICA face recognition

The model of independent component analysis is: suppose there are *n* random variables as x= (x_1, x_2, x_3,...x_n) which is obtained from the other n independent non-Gaussian variables s= (s_1, s_2, s_3, …s_n)

$$x_i = a_{i1}s_1 + a_{i2}s_2 + \ldots + a_{in}s_n,\ i= 1, 2,\ldots, n$$

where i,j = 1,2,…,n, a_{ij} are the mixed coefficients and it can also be written as:

$$x = As$$

In order to estimate one of the independent component, considering linear combination with x_i as $y = b^T x$ where *b* is the unsure vector. Thus the relation $y = b^T As$ can be got. Assuming $q=b^T A$ there is

$$y = b^T x = q^T s$$

In face recognition, every face image as a column, there are n training set and n observation set. Vector X can be thus obtainred, then using the ICA we can get m basic images as:

$$U = WX$$

where *W* is the mixed matrix. For a given test image y which is being bleached and centered, and then projected on the m basic images, the face feature vector is given as below:

$$z = Uy$$

For optimizing independent components, ICA Component Subspace Optimization or Sequential Forward Floating Selection (SFFS) is used.

III. ALGORITHM FOR ICA BASED FACE RECOGNITION

Step 1: Start
Step 2: Read face samples from face databases
Step 3: Pretreat face samples
Step 4: Obtain matrix using PCA and carryout whitening process
Step 5: Compute the un-maxing matrix W
Step 6: Compute ICA feature samples
Step 7: Classify using classifiers and output the result.
Step 8: End

IV. LOCALITY PRESERVING PROJECTIONS

LPP is an unsupervised manifold dimensionality reduction approach, which aims to find the optimal projection matrix W by minimizing the following criterion function:

$$J_1(W) = \sum_{i,j} \left\| y_i - y_j \right\|^2 S_{ij}.,$$

Substituting $y_i = W^T x_i$ into above objection function. Direct computation yields

$$J_1(W) = 2trace(W^T XLX^T W),$$

Where L=D-S is called Laplacian matrix, *D* is a diagonal matrix defined by

$$D = diag\{D_{11}, D_{22}, \cdots, D_{NN}\}$$

where $D_{ii} = \sum_i S_{ij}$. Matrix D provides a natural measure on the data points. The bigger the value D_{ii} (corresponding to y_i) more important is y_i. Thereby, the projection matrix W should maximize the following constraint objective function simultaneously:

$$J_2(W) = \sum_{i=1}^{N} y_i^T D y_i = trace(Y^T DY)$$

$$= trace(W^T XDX^T W).$$

Solving problems min $J_1(W)$ and max $J_2(W)$ simultaneously is equivalent to minimizing the following criterion function:

$$J(W) = \frac{trace(W^T XLX^T W)}{trace(W^T XDX^T W)},$$

The optimal locality preserving projection matrix

$$W_{LPP} = \arg\min_{W \in R^{d \times l}} J(W)$$

can be obtained by solving the following generalized eigen-value problem:

$$XLX^T W = (XDX^T) W \Lambda.$$

where is Λ a diagonal eigenvalue matrix. While in most cases, the number of training data is smaller than the dimension of feature vector, i.e. d << N. When this 3S problem occurs, the matrix XDX^T is not full rank.

V. ALGORITHM FOR LPP BASED FACE RECOGNITION

Step 1: Start
Step 2: Construct neighborhood graph G.
Step 3: Use k-nearest neighbor criterion and €-ball neighborhood graph.
Step 4: Perform Edge weight assignment.
Step 5: Applying simple-mind
Step 6: Solve the generalized eigenvalue problems.
Step 7: End

VI. FACE DATABASES

For analysing the performance of ICA and LPP we have considered 2 public databases YALEB and ATT.

A. YALEB Database

- Number of individuals: 39
- Image resolution: 180x200 pixels (portrait format)
- Contains images of male and female subjects

- Backgrounds: the background is grey
- Head Scale: small head scale variation
- Head turn, tilt and slant: images are 5 degree from right profile (defined as +90°) to left profile (defined as -90°) in the pan rotation.
- Position of face in image : some right and some left
- Image lighting variation: 64 illumination condition.
- Expression Variation: minor expression variation
- Each person's image is taken with 9 pose x 64 illumination condition
- Total images: 5760

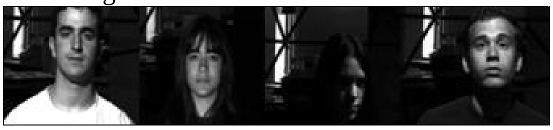

Figure 2. YALEB databases

B. *ATT Database*

- Number of individuals: 40
- Image resolution: 92x112 pixels, with 256 grey levels per pixel (portrait format)
- Contains images of male and female subjects
- Backgrounds: the background is grey
- Head Scale: small head scale variation
- Head turn, tilt and slant: considerable variation in these attributes
- Image lighting variation: very little
- Expression Variation: major expression variation
- Total images: 400

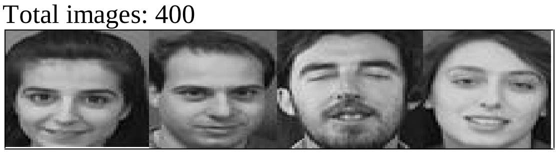

Figure 3. ATT databases

VII. RESULTS AND DISCUSSIONS

ICA and LPP face recognitions are analyzed on YALEB database which contains 5760 images and ATT database which contains 400 images. YALEB contains 39 different individuals and ATT contains 40 different individuals. Each individual in YALEB and ATT databases is assigned a separate class number. Hence after YALEB database is trained there would be 39 classes and after ATT database is trained there would be 40 classes. Each class would contain 5 randomly picked images of each individual. Databases info would display the images for which each class when the class number is specified. This is shown in Fig. 4 for ATT database and Fig. 5 for YALEB database.

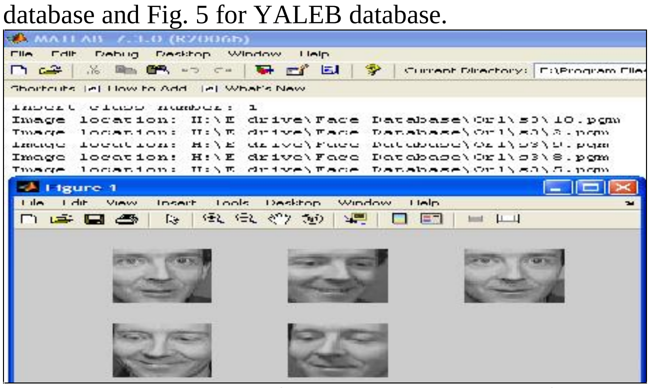

Figure 4. Training 5 images of each individual into one class from ATT databases

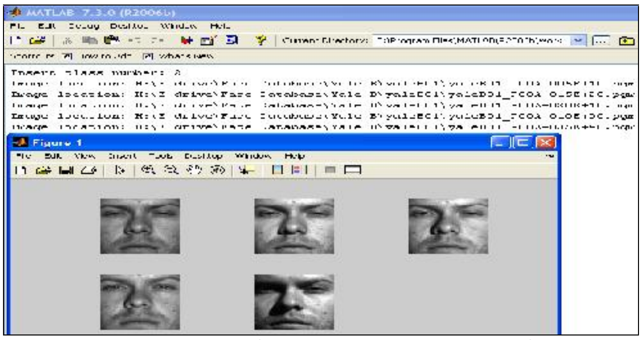

Figure 5. Training 5 images of each individual into one class from YALEB databases

VIII. EXPERIMENTAL RESULTS

A. *ICA Implementation*

Training is performed by taking 5 randomly picked images for each individual and assigning them to one class, there by forming 39 classes for YALEB database and 40 classes for ATT database. ICA implementation is carried out on 5760 images of YALEB database and 400 images of ATT database. Out of 5760 images, 5218 images of YALEB database were accurately recognized while ICA implementation was performed. Hence the total recognition accuracy for YALEB database was 5218/5760 = 90.5%. Out of 400 images, 340 images of ATT database were accurately recognized while ICA implementation was performed. Hence the total recognition accuracy for ATT database was 340/400 = 85%. Each output of ICA implementation contains the input image and recognized image as shown in Fig. 6 and Fig. 7 for ATT and YALEB database respectively.

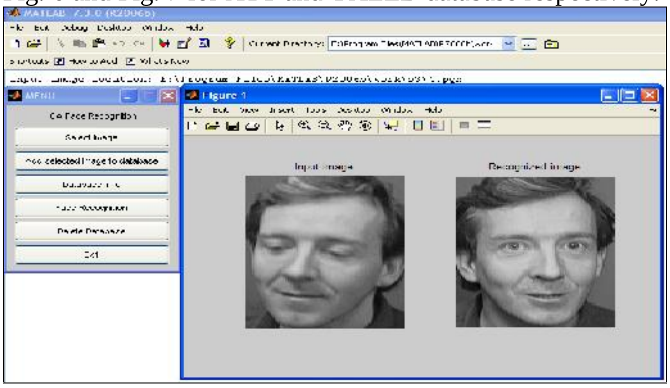

Figure 6. ICA Implementation on ATT databases

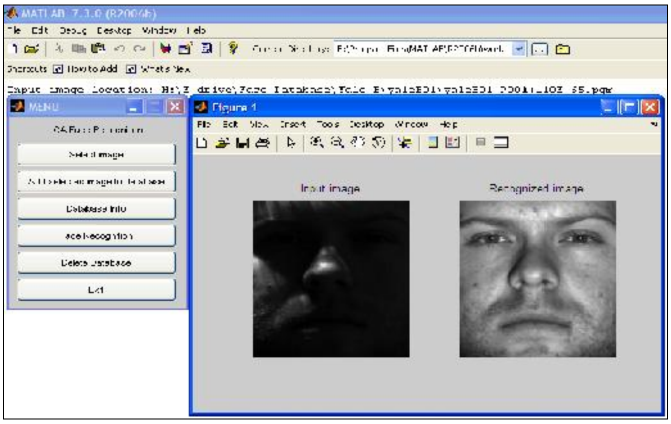

Figure 7. ICA Implementation on YALEB databases

B. LPP IMPLEMENTATION

Training is again performed by taking 5 randomly picked images for each individual and assigning them to one class, there by forming 39 classes for YALEB database and 40 classes for ATT database. LPP implementation is carried out on 5760 images of YALEB database and 400 images of ATT database. Out of 5760 images, 5069 images of YALEB database were accurately recognized while LPP implementation was performed. Hence the total recognition accuracy for YALEB database was 5069/5760 = 88%. Out of 400 images, 362 images of ATT database were accurately recognized while LPP implementation was performed. Hence the total recognition accuracy for ATT database was 362/400 = 90.5%. Each output of LPP implementation contains the input image and recognized image as shown in Fig. 8 and Fig. 9 for ATT and YALEB database respectively.

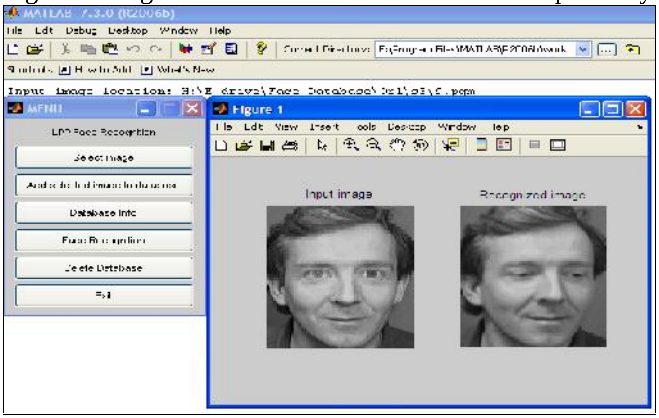

Figure 8. LPP Implementation on ATT database

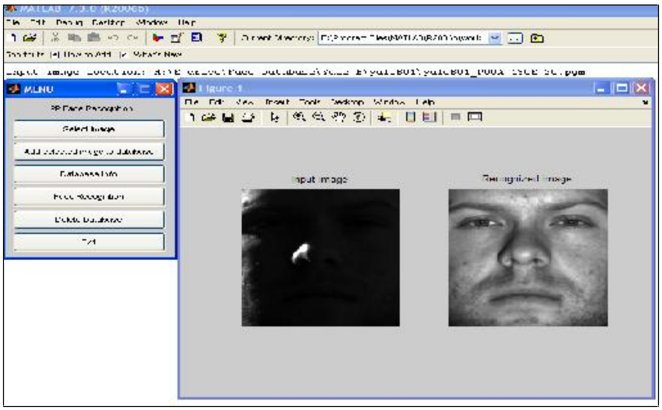

Figure 9. LPP Implementation on YALEB database

Table I shows the comparative results of ICA implementation and LPP implementation on ATT and YALEB database. Each of the system is trained by considering 5 randomly picked images for each individual and assigning them to one class. ATT forms 40 classes and YALEB forms 39 classes. ICA based recognition gives 90.5 % for YALEB databases which contains 64 illumination condition compared to LPP based recognition which gives 88 %. But LPP based recognition gives 90.5 % for ATT databases which contains major expression variations compared to ICA based recognition which gives 85 %.

TABLE I
FACE RECOGNITION ACCURACY OF ICA AND LPP ON YALEB AND ATT FACE DATABASES

Databases	Training samples per class	Total number of classes	ICA recognition accuracy	LPP recognition accuracy
YALEB	5	39	90.5	88
ATT	5	40	85	90.5

IX. CONCLUSION

In this paper we have developed and analysed ICA based face recognition and LPP based face recognition on YALEB which contains 5760 images of 39 different individuals and ATT face database which contains 400 images of 40 different individuals. ICA based recognition gives 90.5 % for YALEB databases which contains 64 illumination condition compared to LPP based recognition which gives 88 %. But LPP based recognition gives 90.5 % for ATT databases which contains major expression variations compared to ICA based recognition which gives 85 %. Thus we conclude that the best algorithm to recognize images with varying illuminations is ICA. On the other hand to recognize image with varying facial expressions, LPP is better to use because it has better recognition rate.

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