Face Recognition using local features by LPP approach

M.E. Ashalatha
Dept. of Biomedical Engineering
Bapuji Institute of Engineering & Technology
Davanagere, Karnataka, India
meashalatha@rediffmail.com

MallikarjunS.Holi
Dept. of Electronics & Instrumentation Engineering
University B.D.T.College of Engineering
Davanagere, Karnataka, India
msholi@yahoo.com

Praveen R.Mirajkar
Microelectronics and Control Systems
PES Institute of Technology
Bangalore, Karnataka, India
praveen.mirajkar11@gmail.com

***Abstract*—In the present work, appearance-based face recognition method called the Laplacianface approach is used. The face images are mapped into a face subspace for analysis by using Locality Preserving Projections(LPP). The technique is different from Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) which effectively see only the Euclidean structure of face space.The main goal of LPP is to preserve neighbourhood structure of the data set optimally and hence obtain a face subspace that best detects the essential face manifold structure. The Laplacianfaces are the optimal linear approximations to the Eigen functions of the Laplace Beltrami operator on the face manifold. Hence, by using this approach undesired variations because of facial expression, changes in lighting conditions, and pose may be eliminated or reduced.**

Performance analysis of face recognition is carried out on standard databases using both LPP technique and PCA technique. For comparison purpose, PCA with ANN classifier based on Back Propagation Feed Forward Neural Network is also developed and being used for training the input face images and then testing.LPP approach outperforms PCA with ANN, and provides better face representation and also achieves lower error rate.

***Keywords*—Principal Component Analysis, Locality Preserving Projections, Laplacianfaces, Face manifold, Subspace learning.**

I. INTRODUCTION

Face recognition is a relevant subject in pattern recognition, neural networks, computer graphics, image processing and analysis. Generally, there are three phases for face recognition, mainly face representation, face detection and identification. Face representation is the first task, that is, how to model a face. There are a variety of approaches for face representation, which can be classified in to three categories: template based, feature based and appearance based.

Appearance-based methods represent a face in terms of several raw intensity images. An image is considered as a high dimensional vector. Then statistical techniques are used to derive a feature space from the image distribution. The face vectors are projected to the basis vectors, the projection coefficients are used as the feature representation of each face image. Eigenface or PCA approach is one of the earliest appearance-based face recognition method, which was developed by M. Turk and A. Pentland [2] and aims to preserve the global structure.This method retains the global features and is sensitive to scale and illumination. The Locality Preserving Projections introduced by X. He and P. Niyogi [10] is an alternative to PCA and is designed to preserve locality structure. Pattern recognition algorithms usually make a search for the nearest pattern or neighbours. Therefore the locality preserving quality of LPP can quicken the recognition.

Face detection is to locate a face in a given image and to separate it from the remaining scenes.

In face identification stage, a new face is compared to the face models stored in database and then classified as a known individual if a correspondence is found. The performance of face identification is affected by several factors such as scaling, pose, illumination and facial expression. Since LPP works on local manifold structure, it overcomes some of the drawbacks present in PCA approach.

II. LITERATURE SURVEY

One of the most successful technique to face recognition is the appearance-based method [1],[2],[3]. When using appearance-based methods, an image of size M x N pixels is represented by a vector in an M x N dimensional space. In practice, however, these M x N dimensional spaces are too large to allow robust and fast face recognition. A common way to attempt to resolve this problem is to use dimensionality reduction techniques [2],[3],[4],[5],[6],[7],[8]. Two of the most popular techniques for this purpose are Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) [4],[5],[7]. PCA is an eigenvector based method designed to model linear variation in high-dimensional data. PCA performs dimensionality reduction by projecting the original n-dimensional data onto the k (<<n) dimensional linear subspace spanned by the leading eigenvectors of the data covariance matrix. Its goal is to find a set of mutually orthogonal basis functions that capture the directions of maximum variance in the data and for which the coefficients are pair wise decorrelated. For linearly embedded manifolds, PCA produces a compact representation. Turk and Pentland

used PCA [2],[3] to describe face images in terms of a set of basis functions, or "eigenfaces".

LDA is a supervised learning algorithm. LDA searches for the project axes on which the data points of different classes are far from each other while requiring data points of the same class to be close to each other. Unlike PCA which encodes information in an orthogonal linear space, LDA[4],[7] encodes discriminating information in a linear separable space using bases that are not necessarily orthogonal.

Recently, a number of research efforts have shown that the face images possibly reside on a nonlinear submanifold [8],[9],[10],[11],[12],[13],[14]. But both PCA and LDA effectively see only the Euclidean structure. They fail to discover the underlying structure, if the face images lie on a nonlinear submanifold hidden in the image space. A new approach to face analysis (representation and recognition) explicitly considers the manifold structure. The manifold structure is modeled by a nearest- neighbor graph which preserves the local structure[15] of the image space. A face subspace is obtained by LPP[10]. Each face image in the image space is mapped to a low dimensional face subspace, which is characterized by a set of feature images, called Laplacianfaces[5], which preserves the local structure and seems to have more discriminating power than the PCA approach for classification purpose.

III. METHODOLOGY

In this section, LPP, an efficient algorithm for learning a locality preserving subspace is described. Each face image in the image space is mapped to a low dimensional face subspace, which is characterized by a set of feature images, called Laplacianfaces. LPP is a general method for manifold learning. It is obtained by finding the optimal linear approximations to the Eigenfunctions of the Laplace Beltrami operator on the manifold [5].

Therefore, though it is still a linear technique, it seems to recover important aspects of the intrinsic nonlinear manifold structure by preserving local structure. While the Eigenface method (PCA) aims to preserve the global structure of the image space, and the Fisherfaces method (LDA) aims to preserve the discriminating information. The present work uses Laplacianface method which aims to preserve the local structure of the image space. In many real world classification problems, the local manifold structure is more important than the global Euclidean structure, especially when nearest neighbor classifiers are used for classification. LPP seems to have more discriminating power although it is unsupervised.

In this work, PCA is used as preprocessing step in LPP in order to overcome the complication of singularity of $\mathbf{XDX^T}$. So, first step is to project the image set to a PCA subspace so that the resulting matrix XDX^T is nonsingular. Another consideration is for noise reduction.

LPP algorithm is implemented in two phases: Training and Testing.

A. Training

1. Read Training set of images:

Let the training set consists of P images. Each of these images can be represented as matrix of size M x N. Let these images be $I_1, I_2, \ldots I_P$.

2. Apply image enhancement techniques:
   - RGB to GRAY Conversion
   - Wiener Filtering for image deblurring
   - Histogram Equalization
   - Median filtering to remove the noise

3. Formation of training data matrix:

The enhanced grayscale training 2D image matrices of dimension M x N are first converted into 1D image vectors of dimension M*N x 1.Let these1D image vectors be $\Gamma_1, \Gamma_2, \ldots \Gamma_P$. All these 1D image vectors are concatenated to form 2D training data matrix of dimension M*N x P.

4. Computing average face image:

The average face image vector of all the image vectors of training set is given by

$$\Psi = (1/P)\ \sum_{i=1}^{p} \Gamma i \tag{1}$$

5. Formation of covariance matrix:

Each face image differs from the average face of the distribution, and this distance is calculated by subtracting the average face image vector from each face image vectors. This gives us new image space.

$$\Phi_I = \Gamma_i - \Psi \ (i=1, 2, \ldots, P) \tag{2}$$

From new image space of P Φ_i images (Each with dimension M*N x 1), the matrix A is formed with dimension M*N x P by taking each of image vectors Φ_i and placing them in each column of matrix A.

$$A = [\Phi_1\ \Phi_2\ \Phi_3 \ldots\ldots \Phi_M] \tag{3}$$

This matrix is called Matrix of Centered Images. Using matrix A, it is important to set up the covariance matrix C. This is given by product of matrix A with matrix A^T. The dimension of such covariance matrix will be M*N x M*N.

$$C = A\,A^T \tag{4}$$

6. Formation of surrogate matrix:

As the dimension of covariance matrix is M*N x M*N, which means it will result in M*N eigenvalues and M*N eigenvectors. Since the value of M*N is very large, it would be better to reduce this overhead by considering matrix

$$Z = A^T A \tag{5}$$

This matrix is called surrogate matrix and has a dimension of P x P.

7. Eigenvalues and Eigenvectors of surrogate matrix:

We have the equation,

$$(Z - \lambda I)\,X = 0 \tag{6}$$

where I is the P x P identity matrix and X is vector of dimension P x 1. This is a homogeneous system of equations, and from fundamental linear algebra, we know that a nontrivial solution exists if and only if

$$\det(Z - \text{eigenvalue} * I) = 0 \quad (7)$$

where, det ( ) denotes determinant. When evaluated, becomes a polynomial of degree P. Since Z is P x P, then there are 'P' solutions or 'P' roots of the characteristic polynomial. Thus there are 'P' eigenvalues of Z satisfying the equation,

$$Z x_i = \lambda_i x_i \quad (8)$$

Thus we have P eigenvalues and P eigenvectors.

8. Eigenvalues and Eigenvectors of Covariance matrix:

The M*N eigenvalues obtained from C are same as P eigenvalues with remaining (M*N – P) eigenvalues equals zero. Also if x is eigenvalue obtained from C, then the eigenvectors of L are given by

$$y = A^T x \quad (9)$$

This relationship can be used to obtain eigenvalues and eigenvectors of covariance matrix $C = A A^T$ by calculating eigenvalues and eigenvectors of surrogate matrix $Z = A^T A$. The eigenvectors for C (Matrix U) are obtained from eigenvectors of Z (Matrix V) as given below:

$$W_{PCA} = U = A V \quad (10)$$

The Eigenfaces can be simply defined as the eigenvectors of covariance matrix which represent one of the dimensions of face image space. The Eigenfaces are a group of important characteristics that describe the variation in the group of face images. All eigenvectors have an eigenvalue associated to it, and the eigenvectors with the largest eigenvalues provide more information on the face variation than the ones with smaller eigenvalues.

9. Projecting centered image vectors into facespace:

All the images from the training set are projected to this eigenspace. Images can be represented by linear combination of the Eigenfaces, which have a new descriptor as a point in a great dimensional space. This projection is constructed in the following way:

$$\Omega_i = U^T (\Gamma_i - \Psi) \quad (11)$$

where $i = 1, \ldots\ldots, p$

As the projection on the Eigenface space describes the variation of face distribution, it is possible to use these new face descriptors as feature vectors.

10. Construction of nearest-neighbor graph:

Let G denote a graph with n nodes. The i^{th} node corresponds to the face image x_i. We put an edge between nodes i and j if x_i and x_j are "close," i.e., x_j is among k nearest-neighbors of x_i, or x_i is among k nearest neighbors of x_j. The constructed nearest - neighbor graph is an approximation of the local manifold structure.

11. Choosing the weights:

If node i and j are connected, put

$$S_{ij} = e^{-\frac{\|x_i - x_j\|^2}{t}}, \quad (12)$$

where t is a suitable constant.

Otherwise, put Sij=0.

The weight matrix S of graph G models the face manifold structure by preserving local structure.

12. Eigenmap:

Compute the eigenvectors and eigenvalues for the generalized eigenvector problem:

$$XLX^T w = \lambda XDX^T w \quad (13)$$

where D is a diagonal matrix whose entries are column (or row, since S is symmetric) sums of S, $D_{ii} = \sum_j S_{ji}$. L = D-S is the Laplacian matrix. The i^{th} row of matrix X is x_i.

Let $w_0, w_1, \ldots\ldots, w_{k-1}$ be the solutions of equation (13), ordered according to their eigenvalues ,$0 \le \lambda_0 \le \lambda_1 \le \ldots\ldots \le \lambda_{k-1}$. These eigen values are equal to or greater than zero because the matrices XLX^T and XDX^T are both symmetric and positive semidefinite. Thus, the embedding is as follows:

$$x \rightarrow y = W^T x \quad (14)$$

where , $W = W_{PCA} W_{LPP}$,

$W_{LPP} = [w_0, w_1, \ldots\ldots w_{k-1}]$,

where y is k-dimensional vector. W is the transformation matrix. This linear mapping best preserves the manifold's estimated intrinsic geometry in a linear sense. The column vectors of W are called Laplacianfaces which span the face subspace.

B. Testing

1. Read test face:

A new face image for testing the algorithm is read from a file.

2. Apply image enhancement techniques:

The same image enhancement techniques which are applied during database creation are applied to the test image. Now a pre-processed image of dimension M x N is obtained.

3. Formation of test data matrix:

The pre-processed grayscale 2D image matrix of dimension M x N is first converted into 1D image vector of dimension M*N x 1. Let this 1D image vector be Γ.

4. Calculate centered test image vector:

This new image vector is mean centered by subtracting average face.

$$\Phi = (\Gamma - \Psi) \quad (1)$$

5. Projecting centered test image vector into facespace:

Each of such new face submitted to the face recognition is projected into the facespace, obtaining the feature vector, also known as face key for this image, by using the following equation

$$\Omega = W^T \Phi \qquad (2)$$

6. Compute Euclidean distances:

The test feature vector Ω with dimension P x 1 is compared with each training feature vector Ωi representing face keys for each of training images. The Euclidean distance between two face key vectors can be calculated using square minimal method given by the following equation.

$$\epsilon^2_i = \| \Omega - \Omega_i \|^2 \qquad (3)$$

7. Classification of input image:

If the distance found among Ω and any Ωiis the smallest then there is a facial recognition of belonging to training image i.

IV. Results and Discussion

A. YALE Database

The YALE database includes different images for each of 40 distinct subjects. For same subjects, the images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement).

In the present work , for training, 10 subjects having 10 images per individual without much variation in expression are chosen. A total of 100 images are selected to form training data. For testing,7 images for each individual with much variation in expression and illumination are chosen. A total of 70 images are selected to form test data. Each image is resized to 60X60. The recognition results are shown in Fig.1 and Table I. This illustrates correct face recognition for wide variations in facial expressions.

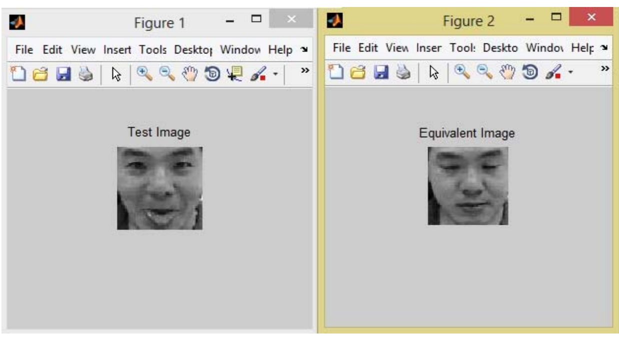

Fig. 1. Projected test image and recognized image of YALE Database

B. ORL Database

The ORL face database is composed of 400 images of size 112 x 92. This includes40 personswith 10 images for each. The images were taken at different times, lighting and facial expressions and facial details. The faces are in an upright position in frontal view, with a slight left or right rotation.

For testing, 6 images per individual are selected without much variation for 12 individuals, which form 72 images in the training data. For testing, 4 images per person with much variation are considered to form 48 images in the test data. The recognition results are shown in Fig. 2 and Table I.

This illustrates correct face recognition for variations in pose and also for person with and without spectacles.

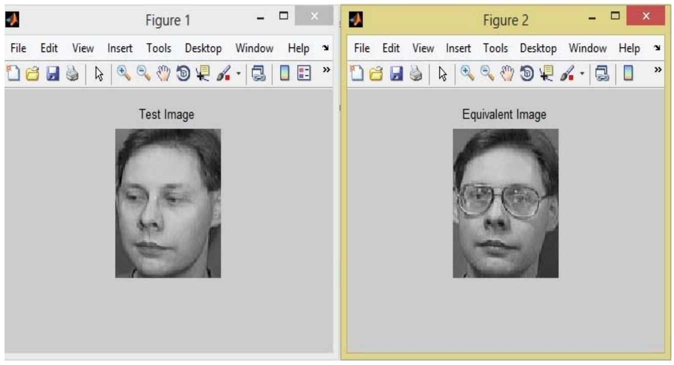

Fig. 2. Projected test image and recognized image of ORL Database

The algorithm is also tested for JAFFE database and the results are tabulated in Table I.

TABLE I: Recognition Rate For Standard Databases with LPP technique

Database	YALE	ORL	JAFFE
No. of Training images	100	72	100
No. of Test images	70	48	50
No. of Test images recognized	68	46	49
Recognition Rate (in %)	97.14	95.83	98
Error Rate (in %)	2.86	4.17	2

C. Discussion on Experimental Results

Performance analysis of face recognition is carried out for the above mentioned standard databases using both LPP technique and PCA technique.

For the purpose of comparison, PCA with Artificial Neural Network classifier based on Back Propagation Feed Forward Neural Network is developed and being used for training the input face images. The feature vectors of the input face images are fed to the neural network.During training procedure, parameters like epochs, learning rate, goal, show, number of neurons in hidden layer are varied and finally implemented with epochs = 1000, learning rate = 0.1, goal = $1e^{-5}$.

As shown in Table II, the recognition rate for LPP approach is 97.14% and 98% for YALE and JAFFE databases respectively, and it is 94% for PCA with ANN approach. Results demonstrate that LPP approach outperforms PCA with ANN, and provides better face representation and also achieves lower error rate.

TABLE II: Performance analysis of LPP technique over PCA with ANN

Database	No. of Training images	No. of Test images	Recognition Rate (in %)	
			PCA with ANN	LPP
YALE	100	70	94	97.14
JAFFE	100	50	94	98

V. CONCLUSION

In this work, the Laplacianface approach for face recognition process is implemented. This method is fast and accurate, and works well under constrained environment. It is one of the best practical solutions for the problem of face recognition.LPP finds an embedding that preserves the local information, and obtains a face manifold structure. Therefore, the unwanted variations resulting from changes in lighting, facial expressions and pose may be reduced.The algorithm is developed and tested for the standard databases like YALE,ORL and JAFFE. Experimental results show the effectiveness of the proposed system and works satisfactorily for the images with different illumination conditions, poses, expressions and also occlusions.Performance analysis of local features using LPP technique and global features using PCA technique is carried out for different standard databases. Experimental results demonstrated that LPP approach outperforms PCA with ANN, andprovides better face representation and also achieves lower error rate.

REFERENCES

[1] Richard Johnson Bough and Steve Jost ,"Pattern Recognition and Image analysis".

[2] M. Turk and A. P. Pentland, "Face Recognition Using Eigenfaces", IEEE Conference on Computer Vision and Pattern Recognition, Maui, Hawaii, 1991.

[3] M. A. Turk and A. P. Pentland. "Eigenfaces for Recognition" Journal of Cognitive Neuroscience, 3(1):71 - 86, 1991.

[4] J. Yang, Y. Yu, and W. Kunz, "An Efficient LDA Algorithm for Face Recognition", The sixth International Conference on Control, Automation, Robotics and Vision, Singapore, 2000.

[5] Xiaofei He, Shuicheng Yan, Yuxiao Hu, ParthaNiyogi, Hong-Jiang Zhang, Face Recognition Using Laplacianfaces, IEEE Trans. Pattern Analysis and Machine Intelligence. 27(3) (2005) 328-340.

[6] M. Belkin and P. Niyogi, "Laplacian Eigenmaps and Spectral Techniques for Embedding and Clustering", Advances in Neural Information Processing System 15, Vancouver, British Columbia, Canada, 2001.

[7] A. M. Martinez and A. C. Kak, "PCA versus LDA", IEEE Trans. on Pattern Analysis and Machine Intelligence, 23(2):228-233, 2001.

[8] Sam T. Roweis, and Lawrence K. Saul, "Nonlinear Dimensionality Reduction by Locally Linear Embedding", Science, vol 290, 22 December 2000.

[9] M. Belkin and P. Niyogi, "Using Manifold Structure for Partially Labeled Classification", Advances in Neural Information Processing System 15, Vancouver, British Columbia, Canada, 2002.

[10] Xiaofei He and Partha Niyogi, "Locality Preserving Projections", Advances in Neural Information Processing Systems, Vancouver, Canada, 2003.

[11] Sam Roweis, Lawrence Saul and Geoff Hinton, "Global Coordination of Local Linear Models", Advances in Neural Information Processing System 14, 2001.

[12] A. Shashua, A. Levin and S. Avidan, "Manifold Pursuit: A New Approach to Appearance Based Recognition", International Conference on Pattern Recognition (ICPR), August 2002, Quebec, Canada.

[13] L. Sirovich and M. Kirby, "Low-Dimensional Procedure for the Characterization of Human Faces", Journal of the Optical Society of America A, vol. 4, pp. 519-524, 1987.

[14] Zhengyue Zhang and Hongyuan Zha, "Principal Manifolds and Nonlinear Dimension Reduction via Local Tangent Space Alignment", CSE-02-019, Technical Report, CSE, Penn State Univ., 2002.

[15] Lawrence K. Saul and Sam T. Roweis, "Think Globally, Fit Locally: Unsupervised Learning of Low Dimensional Manifolds", Journal of Machine Learning Research, v4, pp. 119-155, 2003.

[16] T. Sim, S. Baker, and M. Bsat, "The CMU Pose, Illumination, and Expression (PIE) Database", in Proceedings of the IEEE International Conference on Automatic Face and Gesture Recognition, May, 2002.