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Face Recognition Using Combined Global Local Preserving Projections and Compared With Various Methods

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Abstract— In appearance-based methods, we usually represent an image of size n x m pixels by a vector in an n x m - dimensional space. However, these n x m-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. The most prominent existing techniques for this purpose are Principal Component Analysis (PCA) and Locality Preserving Projections (LPP). We propose a new combined approach for face recognition which aims to integrate the advantages of the global feature extraction technique like PCA and the local feature extraction technique LPP . It has been introduced here (CGLPP- Combined Global Local Preserving Projections. Finally, Comparison is done with various recognition methods. Experimental evaluations are performed on the ORL and UMIST data sets with 400 images and 40 subjects.

Index Terms— CGLPP, Dimensionality reduction, Face recognition, Locality Preserving Projection, ORL, Principal Component Analysis, UMIST.

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1 Introduction

FACE recognition research started in the late70s and has become one of the active and exciting research are as in computer science and information technology areas since 1990. Basically, there are two major approaches in automatic recognition of faces by computer, namely, constituent- base recognition (we called as local feature approach) and face-based recognition (we called as global feature approach).

Face recognition can significantly impact authentication, monitoring and indexing applications. Much research on face recognition using global or local information has been done earlier. By using global feature preservation techniques like principal component analysis (PCA) [1] the authors can effectively preserve only the Euclidean structure of face space that suffers lack of local features, but which may play a major role in some applications. On the other hand, the local feature preservation technique namely locality preserving projections (LPP) preserves local information and obtains a face subspace that best detects the essential face manifold structure [2]. However, it also suffers loss in global features which may also be important in some of the applications.

Here in the proposed method, we are using both global and local features for recognition. A new combined approach for recognition faces that integrates the advantages of the global feature extraction technique like PCA and the local feature extraction technique LPP has been introduced here (CGLPP-Combined Global Local Preserving Projections).In Proposed method, the authors had to extract discriminating features that yields improved facial image recognition results. This has been verified by making a fair comparison with the existing methods like PCA, LPP.

The rest of this paper is organized as follows: In Section 2, we give a brief review of PCA and LPP. Section 3, The proposed method CGLPP – Combined Global Local Preserving Projections. The experimental results are shown in Section 4. Finally, we give concluding remarks and future work in Section 5.

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2 Brief Review of PCA and LPP

2.1 Principal Component Analysis

Principal Component Analysis is a well-known method for dimension reduction. PCA has been used widely in computer vision applications. PCA is a mathematical procedure that transforms a larger number of (possibly) correlated variables into a smaller number of uncorrelated variables called principal components. The objective of principal component analysis is to reduce the dimensionality (number of variables) of the dataset but retain most of the original variability in the data. It is a classical statistical method widely used in data analysis and compression. Principal component analysis is based on the statistical representation of a random variable. A 2-D facial image can be represented as 1-D vector by concatenating each row (or column) into a long thin vector. Let's suppose we have *M* vectors of size *N* (= rows of image £ columns of image) representing a set of sampled images. P_i's represent the pixel values.

$$x_i = P_1 \ldots P_N{}^t, i = 1 \ldots M \quad (1)$$

The images are mean centered by subtracting the mean image from each image vector. Let m represent the mean image.

$$m = \frac{1}{M}\sum_{i=1}^{M} x_i \quad (2)$$

And let W_i be defined as mean centered image

$$W_i = x - m \quad (3)$$

Our goal is to find a set of e_i's which have the largest possible projection onto each of the W_i's. We wish to find a set of *M* orthonormal vectors e_i for which the quantity

$$\lambda_i = \frac{1}{M}\sum_{n=1}^{M}\left(e_i^T w_n\right)^2 \quad (4)$$

is maximized with the orthonormality constraint

$$e_l^T e_k = \delta_{lk} \quad (5)$$

It has been shown that the e_i's and λ_i's are given by the egenvectors and eigen values of the covariance matrix

$$C = WW^T \quad (6)$$

Where, W is a matrix composed of the column vectors W_i placed side by side. The size of C is N * N which could be enormous. It is not practical to solve for the eigenvectors of C directly. A common theorem in linear algebra states that the vectors e_i and scalars λ_i can be obtained by solving for the eigenvectors and eigen values of the $M * M$ matrix W^TW. Let d_i and μ_i be the eigenvectors and eigen values of W^TW, respectively.

$$W^TWd_i = \mu_i d_i \quad (7)$$

By multiplying left to both sides by W

$$WW^T(Wd_i) = \mu_I(Wd_i) \quad (8)$$

which means that the first M-1 eigenvectors e_i and eigen values¸λ_i of WW^T are given by Wd_i and μ_i, respectively. Wd_i needs to be normalized in order to be equal to e_i. Since we only sum up a finite number of image vectors, M, the rank of the covariance matrix cannot exceed M - 1 (The -1 come from the subtraction of the mean vector m).

The eigenvectors corresponding to nonzero eigen values of the covariance matrix produce an orthonormal basis for the subspace within which most image data can be represented with a small amount of error. The eigenvectors are sorted from high to low according to their corresponding eigen values. The eigenvector associated with the largest eigenvalue is one that reflects the greatest variance in the image. That is, the smallest eigenvalue is associated with the eigenvector that finds the least variance. They decrease in exponential fashion, meaning that the roughly 90% of the total variance is contained in the first 5% to 10% of the dimensions.

A facial image can be projected onto M'(<<M) dimensions by computing

$$\Omega = \left[v_1 v_2 ....v_{MI}\right]^T \quad (9)$$

Where, $v_i = e_I^T w_I$, v_i is the i^th^ coordinate of the facial image in the new space, which came to be the principal component. The vectors e_i are also images, so called, eigen images, or eigenfaces in our case, which was first named by [3]. They can be viewed as images and indeed look like faces.

So, it describes the contribution of each eigenface in representing the facial image by treating the eigenfaces as a basis set for facial images. The simplest method for determining which face class provides the best description of an input facial image is to find the face class k that minimizes the Euclidean distance

$$\varepsilon_K = \left\|\Omega - \Omega_K\right\| \quad (10)$$

Where, Ω_K is a vector describing the k_{th} face class. If ε_K is less than some predefined threshold μ^2, a face is classified as belonging to the class k.

2.2 Locality Preserving Projections

Linear dimensionality reduction algorithm, called Locality Preserving Projections (LPP) [4]. It builds a graph incorporating neighborhood information of the dataset [5], [6]. Using the notion of the Laplacian of the graph, we then compute a transformation matrix, which maps the data points to a subspace. This linear transformation optimally preserves local neighborhood information in a certain sense. The representation map generated by the algorithm may be viewed as a linear discrete approximation to a continuous map that naturally arises from the geometry of the manifold [4], [7]. The locality preserving character of the LPP algorithm makes it relatively insensitive to outliers and noise.

Actually, the local features preserving technique seeks to preserve the intrinsic geometry of the data and local structure. The following are the steps to be carried out to obtain the Laplacian [8] transformation matrix W_{LPP}, which we use to preserve the local features.

Constructing the nearest-neighbor graph: Let G denote a graph with k 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, which will be used by the distance preserving spectral method to add the local manifold structure information to the feature set.

Choosing the weights: The weight matrix S of graph G models the face manifold structure by preserving local structure. If node i and j are connected, put

$$S_{ij} = e^{\frac{-\left\| x_i - x_j \right\|^2}{t}} \quad (11)$$

Eigen map: The transformation matrix WLPP that minimizes the objective function is given by the minimum Eigen value solution to the generalized Eigen value problem. The detailed study about LPP and Laplace Beltrami operator is found in [9], [10]. The Eigen vectors and Eigen values for the generalized eigenvector problem are computed.

$$XLX^TW_{LPP} = \lambda XDX^TW_{LPP} \quad (12)$$

Where, D is a diagonal matrix whose entries are column or row sums of S, $D_{ii} = \Sigma_j S_{ji}$, $L = D - S$ is the Laplacian matrix. The i^{th} row of matrix X is x_j. Let $W_{LPP} = w_0, w_1, ..., w_{k-1}$ be the solutions

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of the above equation, ordered according to their Eigen values, $0 \le \lambda_0 \le \lambda_1 \le \ldots \le \lambda_{k-1}$. These Eigen values are equal to or greater than zero because the matrices XLX^T and XDX^T are both symmetric and positive semi-definite. Note that the two matrices XLX^T and XDX^T are both symmetric and positive semi-definite since the Laplacian matrix *L* and the diagonal matrix *D* are both symmetric and positive semi-definite.

By considering the transformation space W_{PCA} and W_{LPP}, the embedding is done as follows:

$$x \rightarrow y = W^T x,$$

$$W = W_{LDA} W_{LPP},$$

$$W_{LPP} = [w_0, w_1, \ldots, w_{k-1}] \quad (13)$$

where *y* is a *k*-dimensional vector, W_{PCA}, W_{LPP} and *W* are the transformation matrices of PCA, LPP and CGLPP algorithms respectively.

3 Formation OF Combined Global And Local Preserving Projections (CGLPP)

Earlier works based on PCA suffer from not preserving the local manifold of the face structure whereas the research works on LPP [8], [9], [11] lacks to preserve global features of face images. Where as our proposed work uses the combination of PCA and LPP and the distance preserving spectral method LPP, that captures the most discriminative features which plays a major role in face recognition. Also, those works that uses alone PCA captures the variation in the samples without considering the variance among the subjects. Hence, in our proposed work, for the first time up to our knowledge, we employ the combination of global feature extraction technique PCA and local feature extraction technique LPP to achieve a high quality feature set called Combined Global and Local Preserving Projections (CGLPP) that captures the discriminate features among the samples considering the different classes in the subjects which produces the considerable improved results in facial image representation and recognition. The proposed combined approach that combines global feature preservation technique PCA and local feature preservation technique LPP to form the high quality feature set CGLPP is described in this section. Actually, the CGLPP method is to project face data to a PCA space for preserving the global information and then projecting to Locality Preserving Projection (LPP) space by using the distance preserving spectral methods, to add the local neighborhood manifold information which may not be interested by PCA alone.

4 Experimental Result

We use, ORL and UMIST face databases with different pose, illumination, and expression for Training and Testing. The second one is the UMIST database (mainly for different orientations, brightness and contrast, hairstyle, glasses, cosmetics). Each of the above two dataset contains 400 images including 40 different subjects of 10 poses or variations. The third one is the combination of ORL + UMIST database, which contain 800 images including 80 different subjects of 10 poses. The size of each used in the proposed method is 50 x 50 pixels, with 256 gray levels per pixel. Finally, each image is represented by a 2500 dimensional vector in image space.

TABLE 1
Overall Comparison Between Existing And Proposed Methods

Database	PCA	LPP	CGLPP
ORL	69	64	87
UMIST	65	57.8	77
ORL+UMIST	67	65.3	82

Fig. 1. Sample Images from ORL face database, used in our experiments.

Fig. 2. Sample Images from UMIST face database, used in our experiments.

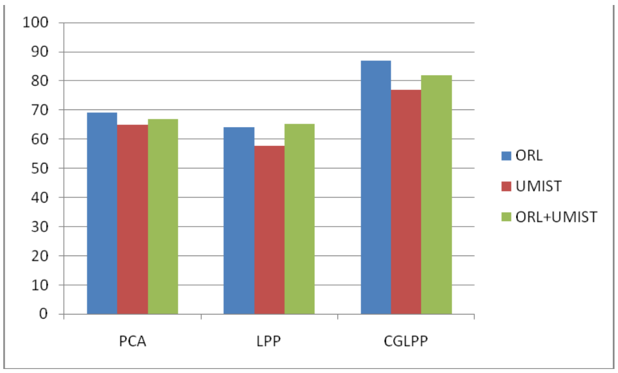

Fig. 3. *Over all Comparison between Existing and Proposed Methods*.

5 CONCLUSIONS

The CGLPP algorithm that combines the global and local information preserving features has been analyzed under using ORL and UMIST facial image database. In this work the main focus is on linear face recognition technique. Currently, we experimented, the face recognition by varying various *dimension reduction* methods like PCA, LPP. Various existing face manifold structure like eigen faces, Laplacian faces, and proposed method CGLPP has been implemented and successfully tested and compared. In future, the same can be experimented by various classifiers like Support Vector Machine [12], Bayesian Methods .We can also use different database like Yale, Ferret containing large number of dataset. In this work, it is mainly concentrate on still images and we can proceed with video images and can also try out in online recognition in unsupervised method.

REFERENCES

[1] A.U. Batur and M.H. Hayes, "Linear Subspace for Illumination Robust Face Recognition," Proc. IEEE Int'l Conf. Computer Vision and Pattern Recognition, Dec. 2001.

[2] M. Belkin and P. Niyogi, "Laplacian Eigenmaps and Spectral Techniques for Embedding and Clustering," Proc. Conf. Advances in Neural Information Processing System 15, 2001.

[3] M.A. Turk and A.P. Pentland, "Face Recognition Using Eigenfaces", IEEE Conf. on Computer Vision and Pattern Recognition, pp. 586-591, 1991.

[4] M. Belkin and P. Niyogi, "Using Manifold Structure for Partially Labeled Classification," Proc. Conf. Advances in Neural Information Processing System 15, 2002.

[5] M. Brand, "Charting a Manifold," Proc. Conf. Advances in Neural Information Processing Systems, 2002.

[6] F.R.K. Chung, "Spectral Graph Theory," Proc. Regional Conf. Series in Math., no. 92, 1997.

[7] Y. Chang, C. Hu, and M. Turk, "Manifold of Facial Expression," Proc. IEEE Int'l Workshop Analysis and Modeling of Faces and Gestures, Oct. 2003.

[8] Jiangfeng Chen Bo Li , Baozong Yuan, "Face recognition using direct LPP algorithm" , 26-29 Oct. 2008.

[9] Xiaofei He., Shuicheng Yan, Yuxiao Hu, Partha Niyogi, Hong-Jiang Zhang, "Face recognition using Laplacian faces" in *IEEE Trans. on Pattern Analysis And Machine Intelligence*, vol. 27, no. 3, (2005), pp. 328–340.

[10] A. Jose, Diaz-Garcia, "Derivation of the Laplace-Beltrami operator for the zonal polynomials of positive definite hermitian matrix argument" in *Applied Mathematics Sciences*, Vol.1, no.4, (2007), pp. 191-200.

[11] B. Moghaddam and A. Pentland, "Probabilistic Visual Learning for Object Representation," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, pp. 696-710, 1997.

[12] P.J. Phillips, "Support Vector Machines Applied to Face Recognition," Proc. Conf. Advances in Neural Information Processing Systems 11, pp. 803-809, 1998.

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