ISSN 2229-5518

Image-Cuebik: System adapting Laplacian Faces to Face Recognition

Vishu Kukkar, Vipin Goyal

Abstract— We propose a new analysis for recognition of an input image by comparing it with a prepared database. The technique uses the linear projective maps which arise by solving a variational problem that optimally preserves the neighborhood structure of the data set termed as Locality Preserving Projections. By using Locality Preserving Projections (LPP), the face images are mapped into a face subspace for analysis. This approach is quite different from Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) which effectively see only the Euclidean structure of face space while LPP finds an embedding that preserves local information, and obtains a face subspace that best detects the essential face manifold structure.

Index Terms— face recognition, laplacianfaces, LDA, LPP, MSRA, PCA, PGM,

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1 Introduction

The existing PCA and LDA aim to preserve the global structure. However, in many real-world applications, the local structure is more important. In this section, we describe an image search engine that employs Locality Preserving Projection (LPP), a new algorithm for learning a locality preserving subspace. Our image cuebik is used to find the set of images from a given image collection that is similar to the given query image, where similarity is very subjective.

2 Objective of LPP

The structure is modeled by a nearest neighbor graph that tends to preserve the local image space structure. Locality preserving projections provide a face subspace. Each face image in this image space is mapped to a low dimensional face subspace characterized by a feature images set termed as *laplacianfaces*. Our developed system is based on this method that aims to preserve the local structure of the image space.

3 Algorithm

3.1 PCA Projection

The image set is projected into the PCA subspace by discarding the principal components. In our system, we kept 98% information.

3.2 Nearest Neighbor Graph

Let G be a graph containing n nodes. We put an edge between node x_i and x_j if x_j is among k neighbors of x_i.

3.3 Choosing Weights

$$S_{ij} = e^{-\|x_i - x_j\|^2} / t$$

If node i and j are connected. Otherwise, S_{ij}=0. The weight matrix S of graph G models the face manifold structure by preserving local structure. The justification for this choice of weights can be traced.

$$XLX^T w = \lambda XDX^T w,$$

Where D is a diagonal matrix given by,

$$D = \sum jS_{ij}$$

And finally laplacian matrix is given by

$L=D-S.$

We get the following embedding,

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

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

$$W_{LPP} = \; w_0, w_1, \cdots, w_{k-1} \;,$$

Where W is a transformation matrix and y is a k-dimensional vector.

The manifold's estimated intrinsic geometry is preserved best by this linear mapping in a linear sense. The column vectors of W are so called *laplacianfaces*. Our image cuebik system implements this with unsupervised learning concept with training and test data.

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ISSN 2229-5518

4 Implementation

Image cuebik is a java based system that implements the algorithm explained above. The unsupervised learning here employs the use of PGM extension for images. The fig 1 shows the system procedure implemented.

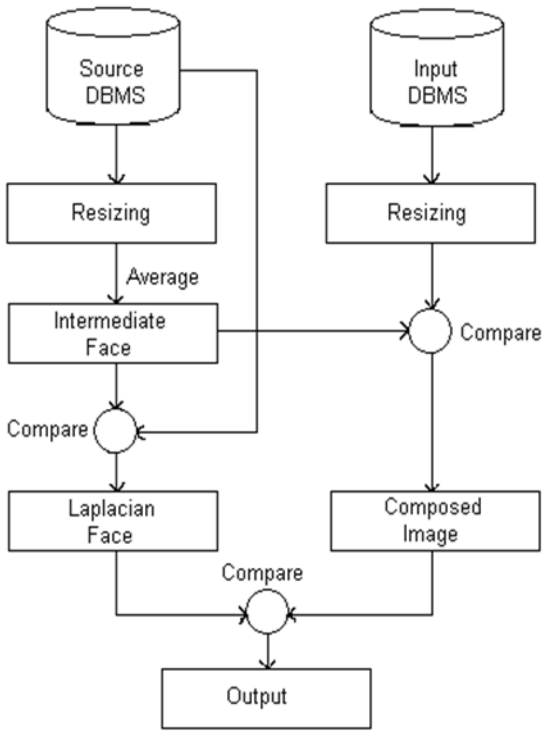

Fig 1

5 Database Employed

We made use of database collected at Microsoft Research Asia (MSRA). 64 to 80 face images were collected in each session for each individual. Fig 2 below shows the sample cropped face images taken from this database. In our system, one session was used for training and the other was used for testing.

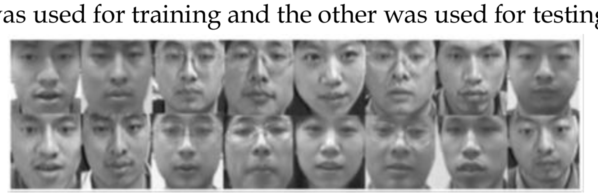

Table 1 shows the recognition results

Approach	Dims	Error Rate
EigenFaces	142	35.4%
FisherFaces	11	26.5%
LaplacianFaces	66	8.2%

Table-1

6 Why PGM?

The name PGM is an acronym derived from "Portable Gray Map". A PGM image represents a grayscale graphic image. This format is a lowest common denominator grayscale file format. It is designed to be extremely easy to learn and write programs for. This format is easy to port and requires lesser memory.

7 System Screenshots

Fig 3

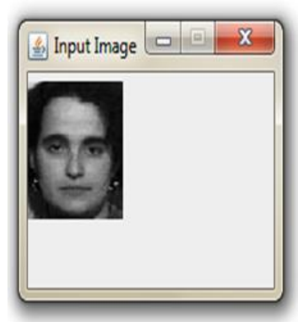

Fig 4

Fig 5

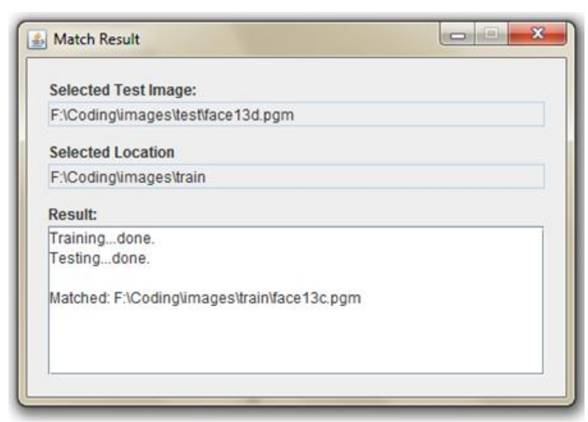

Fig 6

ISSN 2229-5518

8 Product Scope

Facial recognition system is an important field in computer sciences. It is widely used in robotics, doctor helping systems, liar detection system and advance integration in interrogation system for intelligence agencies. It is also used on airports to detect smugglers and terrorists.

9 Future Implementations

For more advancement in image cuebik, we propose the integration of other image extensions as well as higher accuracy.

10 Conclusion

Here we explain the implementation of the linear dimensionality reduction algorithm called LPP. This system provides possible advantages over recent nonparametric techniques.

Acknowledgment

The authors wish to thank Mrs. Kamaljit Kaur, Asst. Professor, Panjab University who supported us all through our work and provided her best efforts to bring us to this level of knowledge.

References

[1] P.N. Belhumeur, J.P. Hepanha, and D.J. Kriegman, "Eigenfaces vs. fisherfaces: recognition using class specific linear projection,"IEEE.Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 711-720, July 1997.
[2] M. Belkin and P. Niyogi, "Laplacian Eigenmaps and Spectral Techniques for Embedding and Clustering ," Advances in Neural Information Processing Systems 14,
Vancouver, British Columbia, Canada, 2002.
[3] C. L. Blake and C. J. Merz,"UCI repository of machine learning databases,"http://www.ics.uci.edu/mlearn/ MLRepository.html. Irvine,CA, University of California, Department of Information and Computer Science, 1998.
[4] Fan R. K. Chung, Spectral Graph Theory, Regional Conference Series in Mathematics, number 92, 1997.
[5] Sam Roweis, and Lawrence K. Saul, "Nonlinear Dimensionality Reduction by Locally Linear Embedding," Science, vol 290, 22 December 2000.
[6] Joshua B. Tenenbaum, Vin de Silva, and John C. Langford, "A Global Geometric Framework for Nonlinear Dimensionality Reduction," Science, vol 290, 22 December
2000.
[7] M. Turk and A. Pentland, "Eigenfaces for recognition," Journal of Cognitive Neuroscience,
3(1):71-86, 1991.