Concordia University

Computer Science and Software Engineering Department

COMP 6321

Machine Learning

Project Report

Face recognition using Laplacianfaces

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Contents

ABSTRACT

Human face recognition systems have gained a considerable attention during last few years. There are very few applications with respect to security, sensitivity and accuracy. Face recognition systems are built on computer programs that analyze images of human faces for the purpose of identifying them. In this paper, Laplacian faces method is used for face recognition. Each face image in the image space is mapped to a low-dimensional face subspace using locality preserving projection (LPP), which is characterized by a set of feature images, called Laplacianfaces. The result of this study will build a system for recognizing faces by matching to an image database. This system can be used in any security systems and can be compared to fingerprint or eye iris recognition system.

MOTIVATION FOR THE PROJECT

The face recognition is a fairly controversial subject right now. A system such as this can recognize and track dangerous criminals and terrorists in a crowd, but some contend that it is an extreme invasion of privacy. The proponents of large-scale face recognition feel that it is a necessary evil to make our country safer. It could benefit the visually impaired and allow them to interact more easily with the environment. Also, a computer vision-based authentication system could be put in place to allow computer access or access to a specific room using face recognition. Another possible application would be to integrate this technology into an artificial intelligence system for more realistic interaction with humans.

This paper proposes an appearance-based face recognition method called the Laplacianface approach. By using Locality Preserving Projections (LPP), the face images are mapped into a face subspace for analysis. Different from Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) which effectively see only the Euclidean structure of face space, LPP finds an embedding that preserves local information, and obtains a face subspace that best detects the essential face manifold structure. The Laplacian faces are the optimal linear approximations to the Eigen functions of the Laplace Beltrami operator on the face manifold. In this way, the unwanted variations resulting from changes in lighting, facial expression, and pose may be eliminated or reduced.

Theoretical analysis shows that PCA, LDA, and LPP can be obtained from different graph models. We compare the proposed Laplacianface approach with Eigenface and Fisher face methods on three different face data sets. Experimental results suggest that the proposed Laplacianface approach provides a better representation and achieves lower error rates in face recognition.

Principal Component Analysis (PCA) is a statistical method under the broad title of factor analysis. The purpose of PCA is to reduce the large dimensionality of the data space (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which are needed to describe the data economically. This is the case when there is a strong correlation between observed variables. The jobs which PCA can do are prediction, redundancy removal, feature extraction, data compression, etc. Because PCA is a known powerful technique which can do something in the linear domain, applications having linear models are suitable, such as signal processing, image processing, system and control theory, communications, etc.

The main idea of using PCA for face recognition is to express the large 1-D vector of pixels constructed from 2-D face image into the compact principal components of the feature space. This is called Eigen space projection. Eigen space is calculated by identifying the eigenvectors of the covariance matrix derived from a set of fingerprint images (vectors).

But the most of the algorithm considers somewhat global data patterns while recognition process. This will not yield accurate recognition system.

LOCALITY PRESERVING PROJECTION

Locality Preserving Projections (LPP) are linear projective maps that arise by solving a variational problem that optimally preserves the neighborhood structure of the data set. LPP should be seen as an alternative to Principal Component Analysis (PCA) -- a classical linear technique that projects the data along the directions of maximal variance. When the high dimensional data lies on a low dimensional manifold embedded in the ambient space, the Locality Preserving Projections are obtained by finding the optimal linear approximations to the Eigen functions of the Laplace Beltrami operator on the manifold. Locality Preserving Projection (LPP) is a new algorithm for learning a locality preserving subspace. LPP seeks to preserve the intrinsic geometry of the data and local structure. The objective function of LPP is as follows,

$$\text{Min } \Sigma(y_i + y_j)^2 S_{ij}$$

Where yi is the one-dimensional representation of image xi and the matrix S is a similarity matrix. A possible way of defining S is as follows:

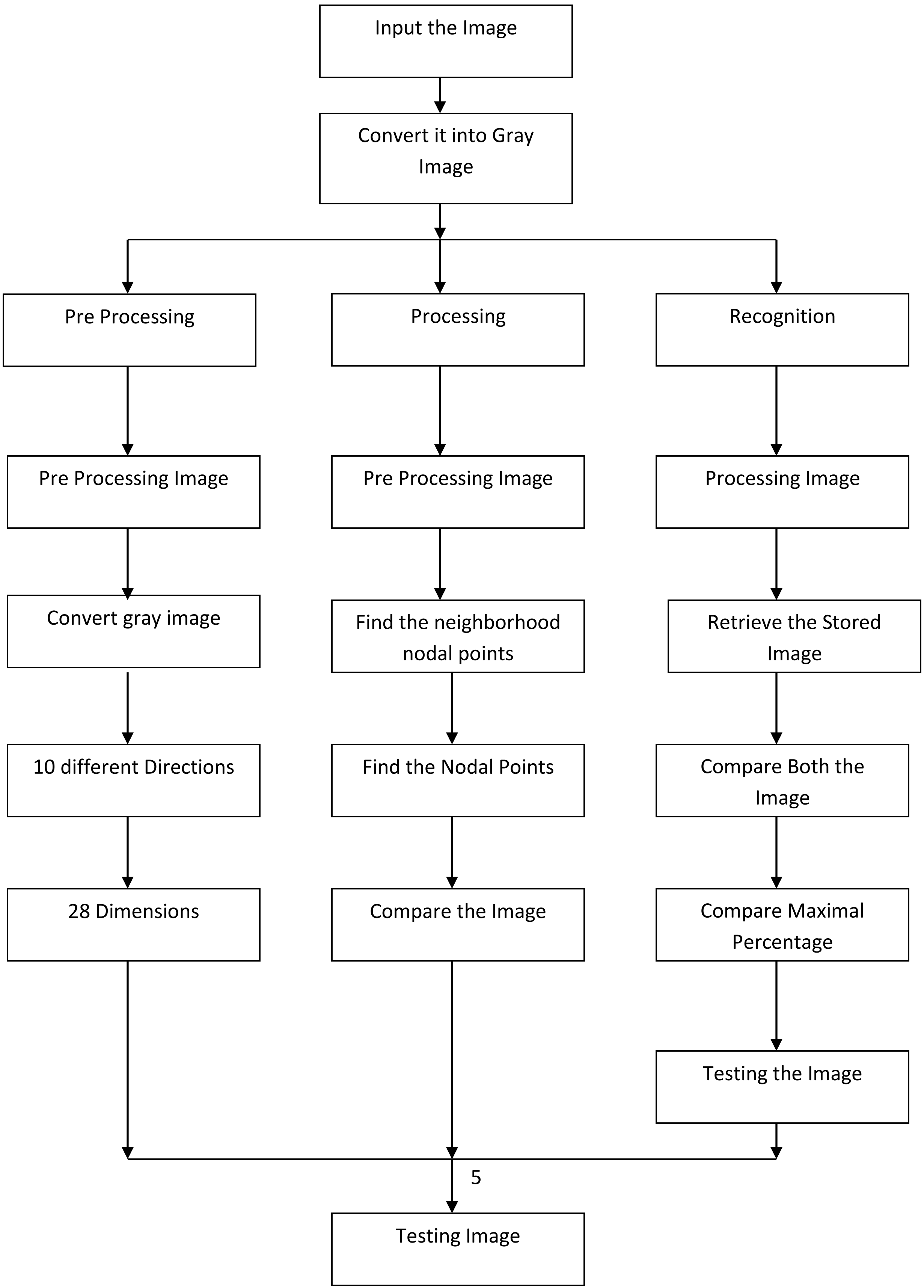
$$S_{ij} = \{\exp(||x_i-x_j||^2 /t), \; ||x_i-x_j||^2 < \varepsilon$$

$$= 0$$

Where exp $(||x_i-x_j||^2 /t)$, means if x_i is among k nearest neighbors of x_j or x_j is among k nearest neighbors of x_i. ε is sufficiently small, and ε > 0. Here, ε defines the radius of the local neighborhood.

Here, ε defines the radius of the local neighborhood. In other words, ε defines the “locality”. The objective function with our choice of symmetric weights S_{ij} ($S_{ij} = S_{ji}$) incurs a heavy penalty if neighboring points x_i and x_j are mapped far apart, i.e. if $(y_i - y_j)^2$ is large. Therefore, minimizing it is an attempt to ensure that if x_i and x_j are "close" then y_i and y_j are close as well.

LAPLACIANFACES



In the face analysis and recognition problem one is confronted with the difficulty that the matrix XDX^T is sometimes singular. This stems from the fact that sometimes the number of images in the training set n is much smaller than the number of pixels in each image m. In such a case, the rank of XDX^T is at most n, while XDX^T is an m×m matrix, which implies that XDX^T is singular.

To overcome the complication of a singular XDX^T, we first project the image set to a PCA subspace so that the resulting matrix XDX^T is non-singular. Another consideration of using PCA as preprocessing is for noise reduction. This method is called Laplacian faces, can learn an optimal subspace for face representation and recognition.

THE ALGORITHMIC PROCEDURE OF LAPLACIANFACES

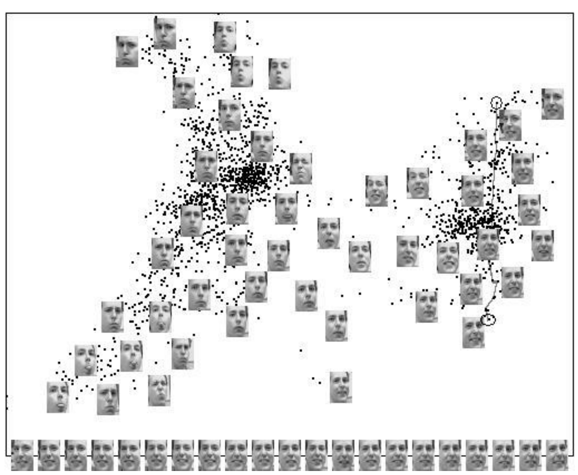
PCA Projection:

Project the image set $\{x_i\}$ into the PCA subspace by throwing away the smallest principal components.

In the preprocessing step, Take the single gray image in 10 different directions and measure the points in 28 dimensions of each gray image.

Construct the nearest neighbor graph:

Let G denote a graph with n nodes. The i^{th} node corresponds to the face image x_i and put an edge between nodes i and j if x_i and x_j are "close", i.e. x_i 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.



In this step, the system does not use the **neighborhood** to construct the graph. This is simply because it is often difficult to choose the optimal in the real-world applications, while k nearest-neighbor graph can be constructed more stably.

The disadvantage is that the k nearest-neighbor search will increase the computational complexity of our algorithm.

Choosing the weights:

As I have mentioned in Locality preserving projects section,

$$S_{ij} = \{\exp(||x_i\text{-}x_j||^2 /t),\ ||x_i\text{-}x_j||^2 < \varepsilon$$

$$= 0$$

Where t is a suitable constant. Otherwise, put $S_{ij} = 0$.

Eigen map:

Compute the eigenvectors and eigenvalues for the generalized eigenvector problem:

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

Where D is a diagonal matrix.

L = D − S is the Laplacian matrix. The i^{th} row of matrix X is x_i.

These eigenvalues are equal to or greater than zero, because the matrices XLX^T and XDX^T are both symmetric and positive semi-definite. Thus, the embedding is as follows:

$$x \to y = W^T x \ {}^{W = W}PCA^{W}LPP$$

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

Where y is a 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 the so called Laplacian faces.

This principle is implemented with unsupervised learning concept with training and test data.

Recognize the image

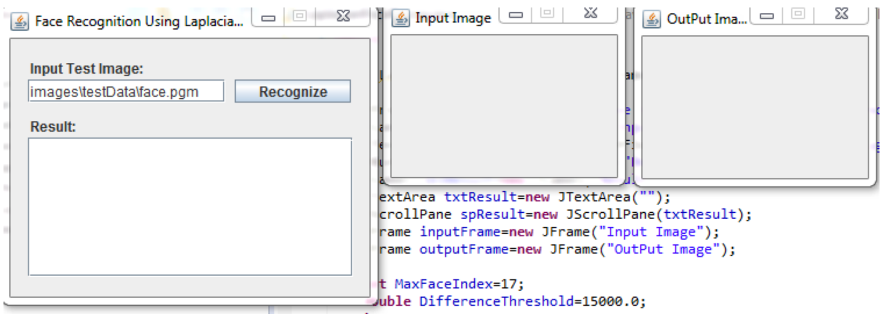
Then measure the value as from test directory which contain grayer image if it is match with any gray image then it is recognized and show the image or else it is not recognized.

EXPERIMENTAL SETUP

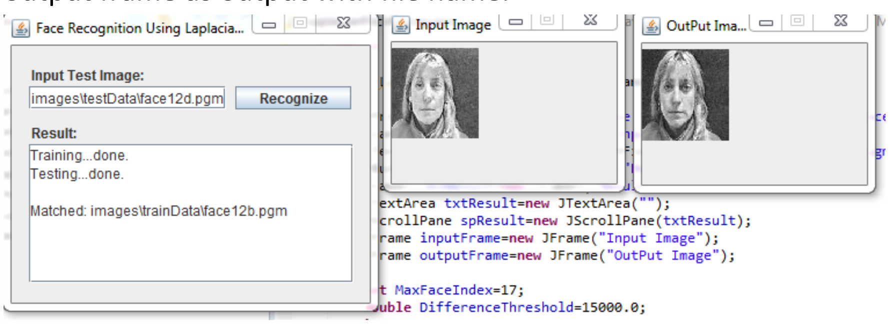
For the project, I have used java as a programming language and for the user interface part, I have used swing component of java.

Steps to evaluate the system,

- Run the program by clicking on executable file.



- Select an image from test data folder in a given textbox and click on “recognize” button.
- If the program finds matching image from the train data folder, it will display it in the output frame as output with file name.



- Try to use different images to evaluate the program.

Programming Components:

- mainProgram.java: Contains the main method to start the execution.
- LaplacianFaces.java: Contains methods to recognize test image from testData folder and give the result from trainData folder if the matching image exists.
- imageFunctions.java: Contains methods to read image, write image, getPixel information of the image, etc...
- imageFilterFunctions.java: Contains methods to set input-output image file paths, resize an image, etc…
- commonFunctions.java: Contains drawImage method.

CONCLUSION

One of the central problems in face manifold learning is to estimate the intrinsic dimensionality of the nonlinear face manifold, or, degrees of freedom. We know that the dimensionality of the manifold is equal to the dimensionality of the local tangent space. Some previous works show that the local tangent space can be approximated using points in a neighbor set. Therefore, one possibility is to estimate the dimensionality of the tangent space. Face recognition methods are still far to address all the challenges like pose, scale, rotation and illumination. However, Laplacian faces is robust and can minimize some of the problems with pose, scale, rotation and illumination as it preserves the local structure of the face but it cannot eliminate it. Laplacian faces is interesting for further research and development activities.

The system is proposed to use Locality Preserving Projection in Face Recognition which eliminates the flaws in the existing system. This system make the faces to reduce into lower dimensions and algorithm for LPP is performed for recognition. The application is developed successfully and implemented as mentioned above.

This system seems to be working fine and successfully. This system can able to provide the proper training set of data and test input for recognition. The face matched or not is given in the form of picture image if matched and text message in case of any difference.

FUTURE WORK

As I mentioned during the presentation,

- To estimate the dimensionality of tangent space.
- To determine an algorithm for the unlabeled samples.

In the project, according to the paper we have used a general method for face analysis (face representation and recognition) by discovering the underlying face manifold structure. Learning the face manifold is essentially an unsupervised learning process. And in many practical cases, one finds a wealth of easily available unlabeled samples. These samples might help to discover the face manifold.

REFERENCES

- He, X., Yan, S., Hu, Y., Niyogi, P. and Zhang, H.J. (2005). Face Recognition Using Laplacianfaces. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 27, no. 3, pp. 328-340
- http://people.cs.uchicago.edu/~niyogi/papersps/Laplacianface.pdf
- http://www.lv-nus.org/papers%5C2005%5C2005_J_4.pdf
- http://www.globalcis.org/ijncm/ppl/01_IJNCM1-052IP.pdf
- http://www.cad.zju.edu.cn/home/xiaofeihe/LPP.html
- http://papers.nips.cc/paper/2359-locality-preserving-projections.pdf
- http://www.mjret.in/v1i1/m14-1-1-4-2014.pdf
- http://www.face-rec.org/databases/
- http://www.stat.columbia.edu/~fwood/Teaching/w4315/Fall2009/pca.pdf
- http://joewan.weebly.com/my-research.html (for programming help)