FACE RECOGNITION USING LAPLACIANFACES

ABSTRACT

We propose 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 Laplacianfaces are the optimal linear approximations to the eigenfunctions 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 Fisherface 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.

SOFTWARE REQUIREMENTS

Language : J2SDK 1.4

Operating System : Windows 98.

HARDWARE REQUIREMENTS

Processor : Intel Pentium III Processor

Random Memory : 128MB

Hard Disk : 20GB

Processor Speed : 300 min

EXISTING SYSTEM

Facial recognition systems are computer-based security systems that are able to automatically detect and identify human faces. These systems depend on a recognition algorithm. 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 eigenspace projection. Eigenspace 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 some what global data patterns while recognition process. This will not yield accurate recognition system.

- ✓ Less accurate
- ✓ Does not deal with manifold structure
- ✓ It doest not deal with biometric characteristics.

PROPOSED SYSTEM

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 Locality Preserving Projection (LPP) [9], a new algorithm for learning a locality preserving subspace. The complete derivation and theoretical justifications of LPP can be traced back to [9]. LPP seeks to preserve the intrinsic geometry of the data and local structure. The objective function of LPP is as follows:

LPP is a general method for manifold learning. It is obtained by finding the optimal linear approximations to the eigenfunctions of the Laplace Betrami operator on the manifold [9]. Therefore, though it is still a linear technique, it seems to recover important aspects of the intrinsic nonlinear manifold structure by preserving local structure. Based on LPP, we describe our Laplacianfaces method for face representation in a locality preserving subspace. In the face analysis and recognition problem, one is confronted with the difficulty that the matrix XDXT is sometimes singular. This stems from the fact that sometimes the number of images in the training set ðnÞ is much smaller than thenumberof pixels in eachimageðmÞ. Insuch a case, the rank ofXDXT is at most n, whileXDXT is anm _ mmatrix, which implies that XDXT is singular. To overcome the complication of a singular XDXT , we first project the image set to a PCA subspace so that the resulting matrix XDXT is nonsingular. Another consideration of using PCA as preprocessing is for noise reduction. This method, we call Laplacianfaces, can learn an optimal subspace for face representation and recognition. The algorithmic procedure of Laplacianfaces is formally stated below:

1. PCA projection. We project the image set fxig into the PCA subspace by throwing away the smallest principal components. In our experiments, we kept 98 percent information in the sense of reconstruction error. For the sake of simplicity, we still use x to denote the images in the PCA subspace in the following steps. We denote by WPCA the transformation matrix of PCA.

2. Constructing the nearest-neighbor graph. Let G denote a graph with n nodes. The ith node corresponds to the face image xi. We put an edge between nodes i and j if xi and xj are "close," i.e., xj is among k nearest neighbors of xi, or xi is among k nearest neighbors of xj. The constructed nearest neighbor graph is an approximation of the local manifold structure. Note that here we do 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.

When the computational complexity is a major concern, one can switch to the "-neighborhood.

3. Choosing the weights. If node i and j are connected, put

Sij ¼ e_

xi_xj k k2

t ; ð34Þ

column (or row, since S is symmetric) sums of S, Dii ¼ Pj Sji. L ¼ D _ S is the Laplacian matrix. The ith row of matrix X is xi. Let w0;w1; . . . ;wk_1 be the solutions of (35), ordered according to their eigenvalues, 0 _ _0 _ _1 _ _ _ _ _ _k_1.

These eigenvalues are equal to or greater than zero because the matrices XLXT and XDXT are both symmetric and positive semidefinite. Thus, the embedding is as follows: x ! y ¼ WTx; ð36Þ

W ¼ WPCAWLPP ; ð37Þ

WLPP ¼ ½w0;w1; _ _ _ ;wk_1_; ð38Þ

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

Modules

1. Pre processing

In the preprocessing take the single gray image in 10 different directions and measure the points in 28 dimensions of each gray image

2. PCA projection (Principal Component Analysis)

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3. Constructing the nearest-neighbor graph

Let G denote a graph with n nodes. The ith node corresponds to the face image xi. We put an edge between nodes i and j if xi and xj are "close," i.e., xj is among k nearest neighbors of xi, or xi is among k nearest neighbors of xj. The constructed nearest neighbor graph is an approximation of the local manifold structure. Note that here we do 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.

4. Choosing the weights of neighboring pixel

If node i and j are connected, put

Sij ¼ e_

xi_xj k k2

t ; ð34Þ

column (or row, since S is symmetric) sums of S, Dii ¼ Pj Sji. L ¼ D _ S is the Laplacian matrix. The ith row of matrix X is xi. Let w0;w1; . . . ;wk_1 be the solutions of (35), ordered according to their eigenvalues, 0 _ _0 _ _1 _ _ _ _ _ _k_1.

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5. <u>Recognize the image</u>

Then measure the value as from test DIR which contain more gray image. If it is match with any gray image then it recognize and show the image or else it not recognize