Using Locality Preserving Projections in Face Recognition

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ABSTRACT

Human recognition has become an essential part of variety of applications ranging from security, surveillance, control etc. It has become an important aspect when it comes to issues like authentication and identification. Human face can play an important role in identification. By developing better dimensionality reduction and feature extraction techniques, a large number of face recognition systems have come into existence. In this paper we discuss and elaborate a recently proposed method based on Locality Preserving Projection (LPP) and Laplacianfaces. In LPP, the face images are mapped into a face subspace for analysis. An unsupervised linear dimensionality reduction method, LPP, preserves the local structure of face image space. Other methods like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) work only on the Euclidean structure of face space. The Laplacianfaces are the optimal linear approximations to the eigen functions of the Laplace Beltrami operator on the face manifold. Unwanted variation from facial expression, lighting etc. may be eliminated or reduced using this method. This paper is focused on systematic analysis of LPP. We have also compared Laplacianface approach with some previously developed methods like EigenFace and Fisherface on Yale dataset. Experimental results prove significant improvement in face recognition performance when using Laplacianfaces.

KEYWORDS
Subspace Learning, Face Recognition, Linear Discriminant Analysis, Face Manifold, Principal Component Analysis, Locality Preserving Projections

INTRODUCTION

Biometrics has become an important component in order to establish authentication and security. Though several biometric technologies can be used in security applications, face recognition is
one of the most recommended and is considered impeccable among several. In face recognition systems, the identity of a person is verified by matching a test face with already available database of known training faces[28][16]. It involves statistical and geometric features unearthed from face image for personal identity. Over the period of time numerous face recognition techniques have developed. Appearance based methods have been considered widely used and most successful. In appearance based methods, the image of size $m \times n$ pixels is represented by vector in $m \times n$ dimensional space. As these dimension spaces are very large to have efficient face recognition, dimensional reduction techniques are used. Two important algorithms, Principal Component analysis (PCA) and Linear Discriminant analysis (LDA) [2], have been used for both dimensionality reduction and feature extraction. In PCA, dimensionality reduction is performed by projecting original $n$-dimensional data onto $j (<<n)$ dimensional linear subspace. Mutually orthogonal basis functions are figured out which capture the directions of maximum variance and the coefficients are then pairwise decorrelated. Matthew Turk and Alex Pentland have used PCA to describe face images in terms of “eigenfaces”. LDA, on the other hand, is a supervised learning. LDA encodes discriminating information in a linear separable space different from PCA which encodes in orthogonal linear space. Research has analyzed that face images reside on nonlinear submanifold. Both PCA and LDA, fail to discover the underlying structure [1][2][8][11][12][14][22][26]. They are only able to see the Euclidean structure. In this paper, we a discussing a novice approach to face recognition which works well on manifold layer structure [7][10][18]. This new algorithm called, Locality Preserving Projections (LPP) obtains a face subspace by modeling the manifold structure by a nearest-neighbor graph which preserves the local structure of image space. In LPP, each face data is mapped to a low-dimensional face subspace, called Laplacianfaces.

The rest of this paper is organized as follows: Section 2 describes the Locality Preserving Projections (LPP) algorithm. Section 3 presents the manifold ways of face analysis using Laplacianfaces. A variety of experimental results and comparative analysis are presented in Section 4. Finally, we provide some concluding remarks and suggestions for future work in Section 5.

LOCALITY LEARNING PROJECTIONS

Locality Preserving Projections (LPP) involves linear projective maps arising after solving a variational problem that is optimally preserved by the neighborhood structure of the database. Linear approximation of non-linear Laplacian eigenmap is introduced by LPP. It is a method used in manifold learning. Laplace Beltrami operator is used in finding the linear approximations of the eigen functions. Local structure of the data set is preserved in LPP. Taking into consideration LPP, we will discuss Laplacianfaces method which is used in face recognition in locality preserving subspace [9]. Manifold structure of data set is modeled by making an adjacency graph. This adjacency graph is used to express the local nearness of the data set. The image set is first projected to a PCA subspace so as to make a nonsingular matrix. Noise and unwanted data points is also used with the help of PCA preprocessing.
Optimal subspace for face recognition can be learnt with the help of Laplicianfaces [11][14].

The algorithm for Laplicianfaces is as follows:

1. **PCA projection**: The smallest principal component is thrown and the image set \( \{ Y_i \} \) is projected onto the PCA subspace. We will be using \( Y \) to signify images in PCA subspace. The transformation matrix of PCA can be denoted by \( X_{abc} \).

2. **Construction of nearest-neighbor graph**: Let \( U \) is a graph with \( m \) nodes. The \( i^{th} \) node of the graph corresponds to the face image \( y_i \). We put an edge between nodes \( i \) and \( j \) if \( x_i \) and \( x_j \) are neighbors. The word “neighbor” means \( x_j \) is among \( k \) nearest neighbors of \( x_i \) or \( x_i \) is among \( k \) nearest neighbors of \( x_j \). Local manifold structure can be depicted with the help of nearest neighbor graph. \( \varepsilon \) – neighborhood is not used to construct the graph since it is difficult to choose correct and optimal \( \varepsilon \) in real world applications. The use of \( k \) nearest neighbor search will have a negative impact and will increase the complexity of the algorithm.

3. **Choosing the weights**: If the two nodes \( I \) and \( j \) are connected, then

\[
S_{ij} = e^{-\frac{||x_i-x_j||^2}{t}}
\]

where \( t \) is a suitable constant. Else put \( S_{ij} = 0 \). The face manifold structure of graph \( U \) is modeled by weight matrix \( S \).

4. **Eigenmap**: eigenvectors and eigenvalues are computed for the generalized eigenvector problem:

\[
XLX^T w = \lambda XDX^T w
\]

where \( D \) is a diagonal matrix whose entries are column sums of \( S \),
\[
D_{ii} = \sum j S_{ji} . L = D - S \text{ is the Laplacian matrix. The } i^{th} \text{ row of matrix } X \text{ is } x_i.
\]

Let \( w_0, w_1, \cdots, w_{k-1} \) be the solutions of equation, ordered according to their eigenvalues, \( 0 \leq \lambda_0 \leq \lambda_1 \leq \cdots \leq \lambda_{k-1} \). 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:

\[
x \rightarrow y = W^T x
\]

\[
W = WPCAWLPP
\]

\[
WLPP = [w_0, w_1, \ldots, w_{k-1}]
\]
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 [21][24]. The column vectors of $W$ are the so called Laplacianfaces.

FACE MANIFOLD ANALYSIS
Assume that a set of human faces have been generated when the face is rotated. As there is only one degree of freedom, the angle of rotation, the set of faces correspond to continuous curve in image space. As, studies have revealed that face images reside on low dimensional submanifold, an algorithm is required to check nonlinear manifold structure. The already developed Approaches analyze only the Euclidean structure and not the underlying submanifold low dimension [15][13][20]. Laplacianfaces, because of its neighborhood preserving character is able to capture intrinsic face manifold structure. Figure 1 has a set of faces and mapping on two dimensional subspace. This data set has 1965 faces, with each image of $20 \times 28$ pixel. Each face image is represented by a point in the 560- dimensional ambient space. We take 10 testing and remaining 1955 images for training.

These face images are mapped into two dimensional space and are divided into two parts. The right part has faces with open mouth and left has images with closed mouth [1][3][20]. The images at the bottom are points along the right path, defining one particular mode of variability in expression.

These ten samples can be located in reduced representation space by the Laplacianfaces. The results can be noted in figure 2.
These image testing samples figure out there coordinates that reflect their properties like expression and pose. This approves that Laplicianfaces can capture the face manifold structure, not completely, but to some extent [18][19][21][27].

Both LPP and Laplician Eigenmap are capable to find a map which preserves the local structure of the image. They both have the same objective function as:

$$\min_{f} \sum_{ij} (f(x_i) - f(x_j)) S_{ij}$$

The major difference is Laplician Eigenmap is non-linear whereas LPP is linear. To what extent Laplician Eigenmaps can be approximated by LPP, can be figured out with the help of eigenvalues. Figure 3 depicts the eigenvalues derived by two methods.
Clearly, though the difference between the eigenvalues of the two methods is smaller, the eigenvalues of Laplician eigenmaps is lower than that of LPP.

**COMPARATIVE ANALYSIS**

Experiments have shown that LPP can discriminate more in comparison to PCA but could be less sensitive to outliers. This section shows the results of several experiments being carried out to propose the effectiveness of Laplicianfaces method in face recognition.

**Representing Faces using Laplicianfaces**

A point image in space can represent a face image. Generally, an image of m x n size is described as a point in m x n dimensional image space. But, due to unwanted variations resulting from facial expressions, change in lightning or pose, the image space might not be perfect for visual representation [2][14][28][29]. The face images in training set are used to learn locality preserving subspace. The subspace is spanned by a set of eigenvectors i.e. \( w_0, w_1, \ldots, w_{k-1} \). Images can be displayed as eigenvectors. Such images are called Laplicianfaces. Working on Yale face database, figure 4 represents first 10 eigenfaces, fisherfaces and laplicianfaces. As, can be seen, fisher and laplician faces resemble.

![Figure 4. The first 10 Eigenfaces (first row), Fisherfaces (second row) and Laplacianfaces (third row) calculated from the face images in the YALE database.](image)

**Using Laplacianfaces in Face Recognition**

After creation of laplacianfaces, face recognition is a classification problem. In this section, we will compare the performance of laplacianfaces with eigenfaces and fisherfaces. This comparative study is based on the Yale face database. The faces need to be preprocessed; the images are normalized in orientation and scale so as to align two eyes at the same position. The facial part is then cropped to make the final image used for matching. The size is reduced to 32 x 32 pixels, with 256 grey levels per pixel[17]. After cropping, no more preprocessing is required. An example of original and cropped is shown in figure 5.
Though various classification methods like Bayesian classification, support vector machine etc. are available, we have used nearest neighbor in this paper as this is easy and simple to implement [2][5][15][20]. Therefore, the recognition is a three step process. Initially, Laplacianfaces are calculated from training set, next, the image to be identified is projected onto the face subspace spanned by the Laplacianfaces; and finally, new faces are identified using the nearest neighbor classification.

### YALE DATABASE

Yale Center for Computational Vision and Control created Yale face database [11][14]. This database has 165 grayscale images of 15 individuals. Various images show variations in facial expression (happy, normal, sad, surprised etc.), lightning condition (right-light, left-light, centre-light) and with or without glasses. A total of 90 images (Six images per individual) were taken to form training set and were used to learn the laplacianfaces. The remaining database is used for testing purpose. These testing samples were projected onto low-dimensional subspace and nearest neighbor classification is used for recognition. 20 random splits were generated. In case of LDA, c-1 non zero generalized eigenvalues can be generated, hence, the upper limit on the dimension of reduced space is c-1, where c is number of individuals. The performance of Laplacianfaces and Eigenfaces changes with number of dimensions. Table 1 shows the recognition results.

<table>
<thead>
<tr>
<th>APPROACH USED</th>
<th>DIMENSIONS</th>
<th>ERROR RATE</th>
</tr>
</thead>
<tbody>
<tr>
<td>FisherFaces</td>
<td>14</td>
<td>20.0%</td>
</tr>
<tr>
<td>EigenFaces</td>
<td>33</td>
<td>25.3%</td>
</tr>
<tr>
<td>LaplacianFaces</td>
<td>28</td>
<td>11.3%</td>
</tr>
</tbody>
</table>

This can easily be seen in table that LaplacianFaces has the minimum error rate in comparison to other methods. The best results of recognition can be achieved with 28, 14, 33 dimensions for Laplacianfaces, Fisherfaces and Eigenfaces respectively. Error rates of Laplacianfaces, eigenfaces and fisherfaces are 11.3%, 25.3% and 20% respectively. No substantial improvement can be seen if dimensions are increased. The plot of error rate vs. percentage of training tuples can be seen in figure 6.
Figure 6. Performance comparison on the Yale database with different number of training samples. The results in this experiment clearly show that Laplacianfaces method outperforms to other approaches of face recognition. Similar results can be derived when doing the same experimental work on other databases like PIE, AT&T or MSRA. The relationship between accuracy rate and dimensions of feature vectors used in three algorithms is further shown in figure 7.

Figure 7. Recognition rate over dimensions of feature vectors (expressions).

CONCLUSION AND FUTURE WORK

An important manifold way of face recognition called, LPP has been discussed in this paper. Adjacency graph is created from the data points. A transformation matrix, which is mapping of the face images onto face subspace, is then created. Optimal linear approximations to the
eigenfunctions of the Laplace Beltrami operator on face manifold are derived which are then used to find Laplacian faces[12][16][18]. Experimental results on Yale database shows how the Laplacian faces method has lower error rate in comparison to other approaches. One possible extension of this work is to blend the LPP with MPCA technique to yield better recognition results. Also the use of unlabeled samples can be considered. Currently we are exploring these options for future work and practice.

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