Research Journal of Applied Sciences, Engineering and Technology 4(24): 5572-5577, 2012
ISSN: 2040-7467

Submitted: April 27, 2012 Accepted: May 16, 2012 Published: December 15, 2012

Discriminant Locality Preserving Projection

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Abstract: In this study, we proposed an improved LPP method named Scatter-Difference Discriminant Locality Preserving Projection (SDDLPP). It considers discriminant information by maximizing the scatter-difference, which makes it have better classification capability. SDDLPP also avoids the singularity problem for the high-dimensional data matrix and can be directly applied to the small sample size problem while preserving more important information. Comparative recognition performance results on public face and palmprint databases also demonstrate the effectiveness of the proposed SDDLPP approach.

Keywords: Image recognition, Locality Preserving Projection (LPP), Scatter-Difference Discriminant LPP (SDDLPP)

INTRODUCTION

Subspace analysis (Turk and Pentland, 1991; Belhumeour *et al*., 1997; Lu *et al*., 2003; He and Niyogi, 2003; Fu and Huang, 2005) seeks to find meaningful low-dimensional subspace. Among subspace analysis methods, Principle Component Analysis (PCA) (Turk and Pentland, 1991; Belhumeour *et al*., 1997) and Linear Discrininant Analysis (LDA) (Lu *et al*., 2003) are the most popular approaches, which can map image data into a low-dimensional linear subspace.

As linear models, PCA and LDA fail to discover intrinsic data structures for nonlinear data. However, lots of experiment results show that image data in real-world may have nonlinear structures. Recently, some manifold techniques have been proposed to discover the nonlinear structure of data space e.g., ISOMAP (Balasubramanian *et al*., 2002), Locally Linear Embedding (LLE) (Roweis and Saul, 2000) and Laplacian Eigenmap (LE) (Belkin and Niyogi, 2001). These methods are appropriate for presentation of nonlinear data but not suitable for new data, which limits their application to image recognition.

He and Niyogi proposed a new manifold learning-based technique called Locality Preserving Projection (LPP) (He and Niyogi, 2003; He *et al*., 2003) which successfully solved the difficulty that how to map a new test sample to low-dimensional space. The main idea of LPP is to detect an intrinsic embedded subspace which can preserve the local structure of manifold. As a linear manifold learning technique, LPP shares many advantages of the data representation properties of nonlinear techniques. However, LPP has its limits to image recognition for containing no classification information and having singularity problem for the high-dimensional matrix. To overcome the singularity problem, one possible method is to reduce the dimension of data space by utilizing PCA as a preprocessing step (He *et al*., 2005). Since the objective of PCA and LPP are essentially different, the preprocessing using PCA could result in the loss of some important information for LPP algorithm which follows the PCA.

This study proposes an improved LPP algorithm called Scatter-Difference Discriminant Locality Preserving Projection (SDDLPP). SDDLPP considers discriminant information by maximizing the difference of the between-class scatter and the within-class scatter, which makes it more capable for data classification. Using the scatter-difference discriminant rule, SDDLPP also avoids the singularity problem of the high-dimensional data matrix. Thus, SDDLPP can be directly applied to image recognition while providing more accurate compact representation of the original data for few important information lost. The proposed algorithm is tested on the ORL and Yale face databases and PolyU palmprint database. Experiment results also prove the effectiveness of the proposed method.

METHODOLOGY

Outline of LPP: LPP is a linear approximation of Laplacian Eigenmap. Given input data $X = [x_1, x_2, ..., x_N]$ with x_i being the d dimensional column vector, LPP seeks a linear transformation A to project high-dimensional input data X into a low-dimensional subspace Y in which the local structure of the input data can be preserved. The transformation A can be obtained by minimizing the following objective function:

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$$\min \sum_{ij} \left(y_i - y_j\right)^T \omega_{ij} \tag{1}$$

where, $y_i = A^T x_i$ is the low-dimensional projection of x_i . If x_i is among the k-nearest neighbors of x_j , weight coefficient ω_{ij} can be computed by the following equation:

$$\omega_{ij} = \exp\left(-\left\|x_i - x_j\right\|^2 / t\right) \tag{2}$$

where, parameter t is a suitable constant, otherwise, ω_{ij} = 0. The weight matrix can be simply set as $\omega_{ij} = 1$ while x_i and x_j are the k-nearest neighbors. Then the weight matrix W can be constructed through the k-nearest neighbor graph. For more details of LPP and weight matrix, please refer to He and Niyogi (2003). Minimizing the objection function is an attempt to ensure that if x_i and x_j are 'close' y_i and y_j will be 'close', too. This minimization problem can be converted to solving the generalized eigenvalues problem as follows:

$$XLX^T A = \lambda XDX^T A \tag{3}$$

Refer to (3), $D_{ii} = \sum_j \omega_{ij}$ is a diagonal matrix and $L = D - W$ is called the Laplacian matrix. The transform vector a_i minimized the objective function is given by the minimum eigenvalues solution to the generalized eigenvalues problem.

LPP provides an intrinsic compact representation of the high-dimensional sample using a low-dimensional data. However, LPP has no direct connection to classification information and often fails to preserve within-class local structure for the k-nearest neighbors may belong to different classes due to influence of complex variations, such as lighting, expression and pose. Another problem with LPP is that the dimension of the matrix XDX^T ($d \times d$) is generally much larger than matrix D ($N \times N$) for image recognition. Thus, the solution to LPP has its singularity for this high-dimensional matrix XDX^T.

Scatter-difference discrininant LPP: Firstly, we define the objective function of the given SDDLPP method as follows:

$$\begin{aligned} J &= S_B - kS_W \\ &= \sum_{i,j=1}^{C} \left(m_i^{'} - m_j^{'}\right)^2 \omega_{ij}^{'} - k \sum_{i,j=1}^{N} \left(y_i - y_j\right)^2 \omega_{ij} \end{aligned} \tag{4}$$

where, S_B and S_W is called the between-class scatter and within-class scatter, respectively. The SDDLPP subspace can be obtained by maximizing the objective function J with its purpose to seek efficient discrimination among the different classes while preserving the local structure of the data. The scatter-difference discriminant rule is consistent with maximizing the between-class scatter while minimizing the within-class scatter. k is a nonnegative constant to balance the contribution of S_B and S_W. When k = 0, the between-class scatter plays a key role, otherwise, the SDDLPP subspace is mainly decided by the within-class scatter while $k \to \infty$. In this low-dimensional SDDLPP subspace, the projection data from the same class should be 'close' with each other while from the different classes should be 'far' with each other for considering the class-specified information.

For within-class scatter S_W, $y_i = A^T x_i$ is the projection of x_i onto the transformation matrix A and ω_{ij} is the within-class weight coefficient between the data x_i and x_j that are from the same class. The within-class scatter S_W can be reduced to:

$$\begin{aligned} S_W &= \sum_{i,j=1}^{N} \left(y_i - y_j\right)^2 \omega_{ij} \\ &= \sum_{i,j=1}^{N} \left(A^T x_i - A^T x_j\right)^2 \omega_{ij} \\ &= A^T \left[\sum_{i,j=1}^{N} \left(x_i x_i^T - x_i x_j^T - x_j x_i^T + x_j x_j^T\right) \omega_{ij}\right] A \\ &= 2A^T \left(\sum_{i=1}^{C} x_i D_{ii} x_i^T - \sum_{i,j=1}^{C} x_i w_{ij} x_j^T\right) A \\ &= 2A^T \left(XDX^T - XWX^T\right) A \\ &= 2A^T X (D - W) X^T A \\ &= 2A^T XLX^T A \end{aligned} \tag{5}$$

In order to make the projection data from the same class be 'close' with each other, the within-class weight matrix ω_{ij} is defined as $\omega_{ij} = \exp(-\|x_i - x_j\|^2 / t)$. If data x_i and x_j belong to the same class, otherwise, $\omega_{ij} = 0$. $D_{ii} = \sum_j \omega_{ij}$ is a diagonal matrix and $L = D - W$ is called within-class Laplacian matrix.

Similar to S_W, the between-class scatter S_B can be reduced to:

$$\begin{aligned} S_B &= \sum_{i,j=1}^{C} \left(m_i^{'} - m_j^{'}\right)^2 \omega_{ij}^{'} \\ &= \sum_{i,j=1}^{C} \left[A^T \left(m_i - m_j\right)\right]^2 \omega_{ij}^{'} \\ &= 2A^T \left(\sum_{i=1}^{c} m_i D_{ii}^{'} m_i^T - \sum_{i,j=1}^{c} m_i \omega_{ij}^{'} m_i^T\right) A \\ &= 2A^T \left(MD' M^T - MW' M^T\right) A \\ &= 2A^T M (D' - W') M^T A \\ &= 2A^T ML' M^T A \end{aligned} \tag{6}$$

where, $m_i^{'} = A^T m_i$ is the projection vector of m_i with $m_i = \left(\sum_{k=1}^{Ni} x_i\right) \Big/ N_i$ being the average data of the class i. $\omega_{ij}^{'}$ is the between-class weight coefficient between the class i and class j . If m_i and m_j are the k-nearest neighbors, $\omega_{ij}^{'}$ can be defined as:

$$\omega_{ij}^{'} = \exp\left(- \left\| m_i - m_j \right\|^2 / t' \right) \quad (7)$$

$\omega_{ij}^{'}$ can also be simplified as $\omega_{ij}^{'} = 1$ if m_i and m_j are the k-nearest neighbors. Parameter t' is a suitable constant that can be decided by experiment results. The purpose of defining $\omega_{ij}^{'}$ is to make the two classes which are 'close' in original high-dimensional space be 'far' in the low-dimensional SDDLPP subspace. Then, between-class weight matrix W' is constructed through the k-nearest neighbors graph whose nodes are the class average data. $D_{ii}^{'} = \sum_j \omega_{ij}^{'}$ is a $C \times C$ dimensional diagonal matrix and $L' = D' - W'$ is the between-class Laplacian matrix.

Refer to (5) and (6), the objective function of the SDDLPP algorithm can be rewritten by:

$$J = A^T \left(ML' M^T - kXLX^T \right) A \quad (8)$$

Maximizing (8) can be converted to the generalized eiguevalues problem as following equation with a constrain condition $A^T A = I$ to get the effective solution:

$$\left(ML' M^T - kXLX^T \right) A = \lambda A \quad (9)$$

Then, the problem of SDDLPP is equivalent to find the leading eigenvectors of matrix $ML' M^T - kXLX^T$. The proposed approach has no need to compute the inverse of the high-dimensional matrix which generally brings singularity problem to image recognition. Thus, the SDDLPP algorithm is not limited by the number of training samples when it is applied to image recognition.

EXPERIMENTAL RESULTS

Our method is performed on pubic ORL and Yale face databases and PolyU palmprint database. We also compare the proposed method with LPP and another two important linear subspace analysis methods PCA and LDA. For these subspace methods, LDA and LPP involve PCA as preprocessing step to avoid the singular matrix. It should be emphasized that how to determine proper preprocessing dimension is still a hard problem. Generally, this dimension is selected through experiments. For the SDDLPP approach, if two notes are connected with each other, the weight coefficient between them is simply set as 1. In the feature classification step, the nearest neighbor rule in L_2 norm distance is then employed.

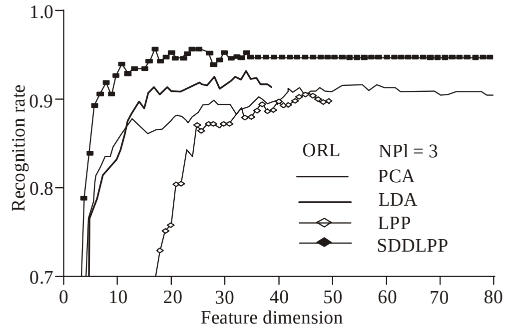
Fig. 1: Sample images of one individual from the ORL database

Fig. 2: Sample images of one individual from the yale database

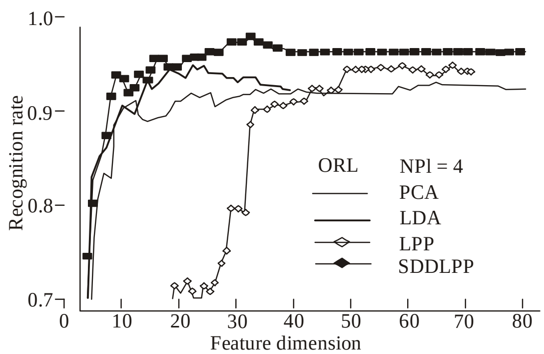
Experiment on the ORL and yale face database: The ORL database contains images from 40 individuals and each person provides 10 different images under various facial expressions and facial details. The Yale face database contains 15 objections with each objection having 11 different images. Both facial expressions and lighting variations exist in the Yale database. In our experiments, each face image was automatically cropped and resized to 32×32 pixels for computational efficiency. Part of images in the ORL and Yale database are given respectively in Fig. 1 and 2. The top group of images belong to the ORL database and the bottom ones are from the Yale database.

The training and testing set are chosen randomly from each individual on both databases. The number of training samples Per Individual (NPI) increases from 3 to 5 on both databases. In each round, the training samples are randomly chosen for training while the remaining images are used for testing. Figure 3 and 4 illustrate the relationship of recognition accuracy versus the dimension of subspace on the ORL and Yale database, respectively.

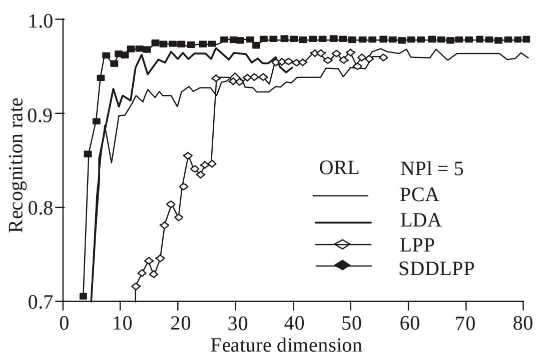
Figure 3 and 4, we can see that the SDDLPP and LDA can obtain effective recognition rate even using limited feature number because of classification



(a)

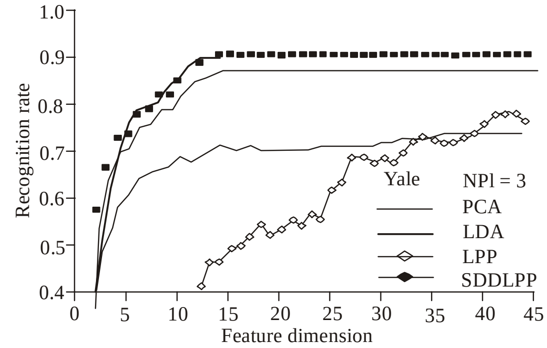


(b)

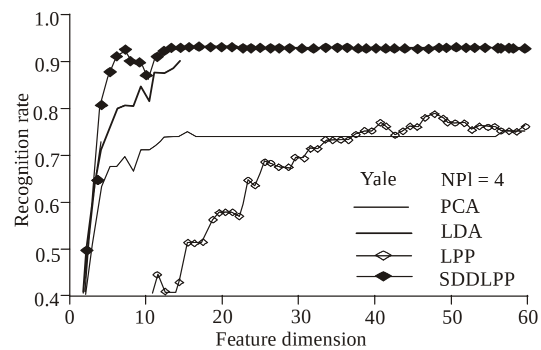


(c)

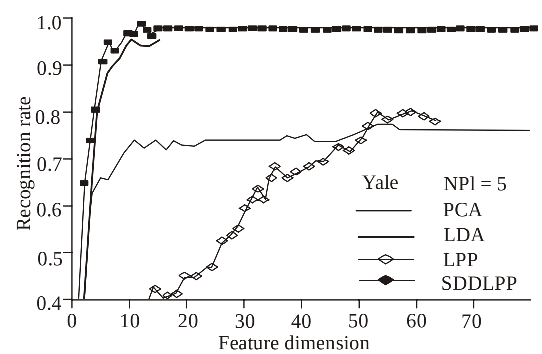
Fig. 3: Recognition accuracy versus the dimension of subspace on the ORL database, (a) Three samples for training, (b) Four samples for training, (c) Five samples for training



(a)



(b)



(c)

Fig. 4: Recognition accuracy versus the dimension of subspace on the Yale database, (a) Three samples for training (b) Four samples for training, (c) Five samples for training

information being considered. Furthermore, recognition rate obtained by SDDLPP is quite stable while the dimension of subspace is larger than a certain value. Thus, it is convenient to decide the dimension of SDDLPP subspace for image recognition problem.

Table 1 and 2 show the top recognition accuracy with corresponding dimension in compact space for each algorithm on the two databases. On both face databases, our SDDLPP algorithm outperforms LPP, PCA and LDA. When using three images per individual for training, SDDLPP achieves the recognition accuracy of 94.58% on ORL database and 90.83% on Yale databases while LPP is 90.36 and 77.5%, PCA is 91.07 and 73.33% and LDA is 92.85 and 89.17%, respectively. Better recognition accuracy can be achieved by using more images for training.

Table 1: Recognition performance results with corresponding feature dimension on ORL face database

	ORL		
Measure	NPI = 3	NPI = 4	NPI = 5
PCA	91.07 (41)	92.92 (64)	96.50 (54)
LDA	92.86 (31)	94.58 (28)	96.50 (26)
LPP	90.36 (45)	94.58 (54)	96.00 (43)
SDDLPP (k = 0.1)	89.29 (28)	92.50 (24)	96.00 (32)
SDDLPP (k = 1)	91.43 (26)	94.58 (31)	96.50 (27)
SDDLPP (k = 10)	93.93 (21)	96.67 (30)	97.50 (28)
SDDLPP (k = 100)	94.58 (24)	97.14 (26)	97.50 (21)
SDDLPP (k = 1000)	94.58 (26)	97.14 (28)	96.50 (26)

Table 2: Recognition performance results with corresponding feature dimension on yale face database

	Yale		
Measure	NPI = 3	NPI = 4	NPI = 5
PCA	73.33 (36)	74.29 (56)	76.67 (49)
LDA	89.17 (12)	89.52 (14)	94.44 (10)
LPP	77.50 (41)	78.10 (47)	80.00 (55)
SDDLPP (k = 0.1)	85.00 (12)	82.86 (12)	88.89 (13)
SDDLPP (k = 1)	86.67 (14)	85.71 (13)	92.22 (12)
SDDLPP (k = 10)	89.17 (13)	89.52 (12)	95.56 (13)
SDDLPP (k = 100)	90.00 (13)	91.43 (13)	96.67 (12)
SDDLPP (k = 1000)	90.83 (14)	92.38 (13)	96.67 (12)

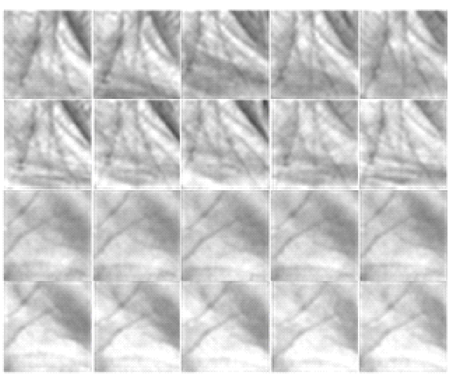


Fig. 5: Samples of the cropped images in the polyU palmprint database

Experiment using the PolyU palmprint database: We also perform the four algorithms on the public PolyU palmprint database. This palmprint database contains 7752 grayscale images corresponding to 386 different palms. Around twenty samples from each of these palms were collected in two sessions, where around 10 samples were captured in the first session and the second session, respectively. Our experiment is tested on a subset of the PolyU database. The subset consists of 1000 images which form 100 palms. Five images of each palm belong to the first session and the remaining are from the second session. In our experiment, the central part of each original image was automatically cropped and resized to 32×32 pixels. Figure 5 shows some sample images of the palms.

Table 3: Recognition performance results with corresponding feature dimension on the poly U palmprint database

Measure	NPI = 3	NPI = 4	NPI = 5
PCA	85.86 (41)	88.67 (36)	91.60 (38)
LDA	85.28 (27)	89.17 (29)	90.80 (27)
LPP	81.00 (48)	86.17 (37)	88.60 (41)
SDDLPP (k = 0.1)	87.14 (28)	90.67 (29)	93.60 (31)
SDDLPP (k = 1)	88.00 (32)	90.67 (31)	93.60 (26)
SDDLPP (k = 10)	86.14 (31)	89.17 (34)	92.80 (28)
SDDLPP (k = 100)	84.43(31)	87.50(28)	90.60 (29)
SDDLPP (k = 1000)	82.14(33)	84.33(29)	88.40 (29)

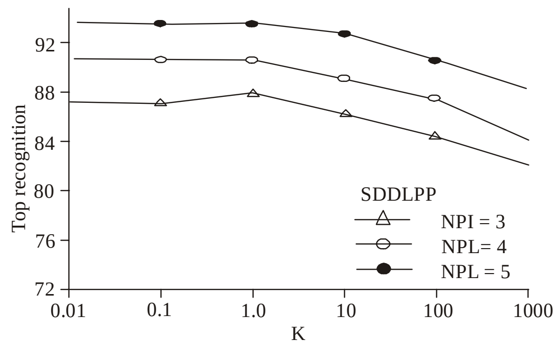


Fig. 6: Top recognitions using different k value obtained on the polyU palmprint database

Similar to the experiment on face databases, we choose training and testing set for each individual with the number of training samples increases from 3 to 5 per palm. The training samples are randomly chosen for training while the remaining images are used for testing in each round. The top recognition rate with corresponding dimension of compact space for each algorithm is given in Table 3. Figure 6 is the corresponding relationship between the top recognition rates and different *k* values for the SDDLLP method. Figure 6 also illuminates that, for palmprint images recognition, the between-class scatter takes a crucial role in SDDLPP space.

CONCLUSION

In this study, a novel subspace analysis approach named SDDLPP is presented. Compared to LPP, SDDLPP has better classification performance for considering the discriminant information of the training data. The proposed SDDLPP approach also avoids the singularity problem of the high-dimension matrix and can be directly applied to small sample size problem. As less important information lost, SDDLPP can provide a more accurate approximation of the original image than the presentation given by PCA plus LPP. Experiment results on the public ORL and Yale face databases and PolyU palmprint database also demonstrate effective performance of the given SDDLPP approach.

ACKNOWLEDGMENT

This study is supported by Foundation of He 'Nan Educational Committee (number 2010A520028). The authors would like to thank the anonymous reviewers for their constructive suggestions.

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