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FACE RECOGNITION USING GABOR-BASED IMPROVED SUPERVISED LOCALITY PRESERVING PROJECTIONS

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Abstract. A novel Gabor-based Improved Supervised Locality Preserving Projections for face recognition is presented in this paper. This new algorithm is based on a combination of Gabor wavelets representation of face images and Improved Supervised Locality Preserving Projections for face recognition and it is robust to changes in illumination and facial expressions and poses. In this paper, Gabor filter is first designed to extract the features from the whole face images, and then a supervised locality preserving projections, which is improved by two-directional 2DPCA to eliminate redundancy among Gabor features, is used to augment these Gabor feature vectors derived from Gabor wavelets representation. The new algorithm benefits mostly from two aspects: One aspect is that Gabor wavelets are promoted for their useful properties, such as invariance to illumination, rotation, scale and translations, in feature extraction. The other is that the Improved Supervised Locality Preserving Projections not only provides a category label for each class in a training set, but also reduces more coefficients for image representation from two directions and boost the recognition speed. Experiments based on the ORL face database demonstrate the effectiveness and efficiency of the new method. Results show that our new algorithm outperforms the other popular approaches reported in the literature and achieves a much higher accurate recognition rate.

Keywords: Face recognition, Gabor wavelets, two-directional 2DPCA, Locality Preserving Projections (LPP), Gabor-based Improved Supervised Locality Preserving Projections (Gabor-based ISLPP)

1 INTRODUCTION

In the last several years, automatic face recognition technology has developed rapidly for the need of surveillance and security, human-computer intelligent interaction, access control, telecommunication and digital libraries, and smart environments. A successful face recognition algorithm aims at representing the facial feature effectively and extracting the most discriminant information from the face images. Numerous algorithms have been proposed for face recognition, such as principal component analysis (PCA) [1] and linear discriminant analysis (LDA) [2], independent component analysis (ICA) [3] and so on. Simultaneously, Gabor wavelets have proven to be good at local and discriminate image feature extraction as they have similar characteristics to those of the human visual system.

Gabor wavelet transform [10–13] allows description of spatial frequency structure in the image while preserving information about spatial relations which is known to be robust to some variations, e.g., pose and facial expression changes. Although Gabor wavelet is effective in many domains, it nevertheless suffers from a limitation. The dimension of the feature vectors extracted by applying the Gabor wavelet to the whole image through a convolution process is very high. To solve this dimension problem, subspace projection is usually used to transform the high dimensional Gabor feature vector into a low dimension one. Principal component analysis (PCA) [1], linear discriminant analysis (LDA) [2], Two-dimensional Principal component analysis (2DPCA) [15, 16] and Two-dimensional linear discriminant analysis (2DLDA) [19, 20] which are typical subspace projection methods for feature extraction and dimension reduction have been used in face recognition successfully.

Recently, some nonlinear methods have been developed to discover the nonlinear structure of the manifold algorithms, e.g. Isomap [4], locally linear embedding (LLE) [5], and Locality Preserving Projections (LPP) [6–9]. The first two algorithms are nonlinear but the LPP algorithm is a linear dimensionality reduction algorithm. PCA aims at preserving the global structure of the face image space, and the LDA method aims at preserving the discriminating information, but the goal of the LPP method is to preserve the local structure of samples. LPP method aims at preserving the local structure of samples. Experiments show that LPP is able to extract nonlinear features in the local and nonlinear manifold and can thus perform better in face recognition [7]. Xiaofei He etc. [6, 7] has used Locality Preserving Projections to describe face images by mapping the face data onto a low-dimensional face feature subspace called "Laplacianfaces".

This paper presents a novel, hybrid scheme for face recognition by combining Gabor wavelets and an improved Supervised LPP method called Gabor-based improved locality preserving projections. Since LPP represents an image by a vector in high-dimensional space which is often confronted with the difficulty that sometimes the matrix is singular, different than with Laplacianfaces which uses PCA as a preprocessing step, we improved the LPP method by two-directional 2DPCA [15, 16] to overcome this problem. In our method, face images are first decomposed into their spatial/frequency domains by Gabor wavelet transforms and then a two-directional

2DPCA algorithm [17, 18] is utilized to reduce the dimension of the Gabor feature vectors from horizontal direction and vertical direction. Eventually, LPP is applied to the resultant feature vectors to extract robust and discriminative features for recognition. Experiments on the ORL database also demonstrate the discrimination power of the new algorithm we proposed in this paper. Figure 1 shows the system structure of our method for face recognition.

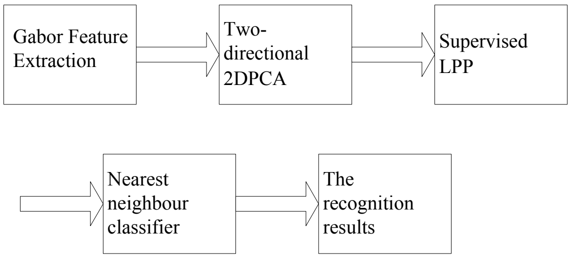


Fig. 1. The structure of the Gabor-based Improved Supervised Locality Preserving Projections for face recognition

The paper is organized as follows. In Section 2, Gabor wavelets are defined and the extractions of Gabor features from face images are outlined. Section 3 introduces Improved Supervised Locality Preserving Projections, while the strategy to combine the Gabor and Improved Supervised Locality Preserving Projections is given in Section 4. Experimental results for recognition using the ORL face database are given in Section 5, and conclusion are drawn in Section 6.

2 GABOR FEATURE EXTRACTION

2.1 Gabor Wavelet Transforms

Gabor wavelet representation of face images derives desirable features gained by spatial frequency, spatial locality, and orientation selectivity. These discriminative features extracted from the Gabor filtered images could be more robust to illumination and facial expression changes. In the spatial domain, the Gabor wavelet is a two-dimensional plane wave with wavelet vector $\vec{z}_j$ restricted by a Gaussian envelope function with relative width σ that can be defined as follows [9–11]:

$$\Psi_{\mu,\nu}(\vec{z}) = \frac{\|\vec{k}_{\mu,\nu}\|^2}{\sigma^2} exp(\frac{\|\vec{k}_{\mu,\nu}\|^2 \|\vec{z}\|^2}{2\sigma^2})[exp(i\vec{k}_{\mu,\nu}\vec{z}) - exp(-\frac{\sigma^2}{2})] \tag{1}$$

where μ and ν define the orientation and scale of the Gabor kernels $\vec{z} = (x, y)$, $\|\cdot\|$denotes the norm operator, and the wave vector $\vec{k}_{\mu,\nu}$is defined as

$$\vec{k}_{\mu,\nu} = k_\nu e^{i\phi_\mu} \tag{2}$$

where $k_\nu = k_{max}/f_\nu$ and $\phi_\mu = \pi\mu/8$. $k_{max}$is the maximum frequency, and f is the spacing factor between kernels in the frequency domain [10]. In most face recognition cases, parameters of Gabor wavelets $\sigma = 2\pi, k_{max} = \pi/2, f = \sqrt{2}$ are used by most researchers [10, 11]. By different scaling and rotation via the wave vector $\vec{k}_{\mu,\nu}$, Gabor kernel is generated from a Gaussian envelope and a complex plane wave. In Equation (1), the first term in the square brackets determines the oscillatory part of the kernel and the second term makes the wavelets DC-free.

2.2 Gabor Feature Representation

Let $I(z)$be a gray level face image. The Gabor wavelet representation of I is the convolution of the image with a family of Gabor kernel filters in Equation (1) and can be defined as

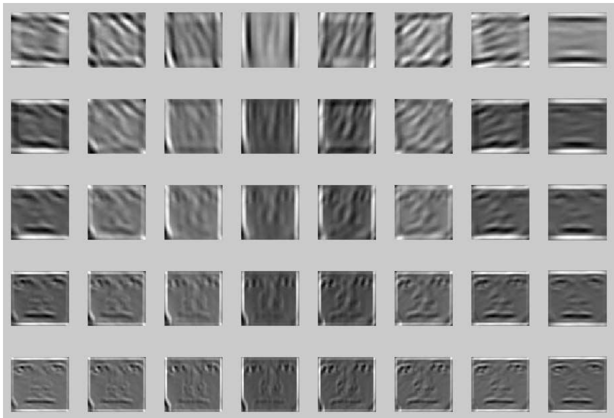
$$G_{\mu,\nu} = I(z) * \Psi_{\mu,\nu} \tag{3}$$

where $z = (x, y)$, $*$ denotes the convolution operator, and $G_{\mu,\nu}$ is the convolution result corresponding to the Gabor filter at orientation μ and scale ν [10, 11]. In this paper, experimental results show that Gabor wavelets of five different scales, $\nu \in \{0, \dots, 4\}$ and eight orientations, $\mu \in \{0, \dots, 7\}$ should be used. The convolution outputs (the real part and the magnitude) of a sample image are shown in Figure 2. The outputs exhibit desirable characteristics of spatial locality, scale and orientation selectivity as a result of the Gabor wavelet transforms. Since the outputs $G_{\mu,\nu}$ consist of different local, scale and orientation features, we choose the best one in order to derive an optimal feature vector. Therefore, the face image $I(\vec{z})$ is represented by a set of Gabor coefficients $\{G_{\mu,\nu} : \mu \in \{0, \dots, 7\}, \nu \in \{0, \dots, 4\}\}$ and the magnitude of each $G_{\mu,\nu}$ is then sampled, normalized to zero mean and unit variance.

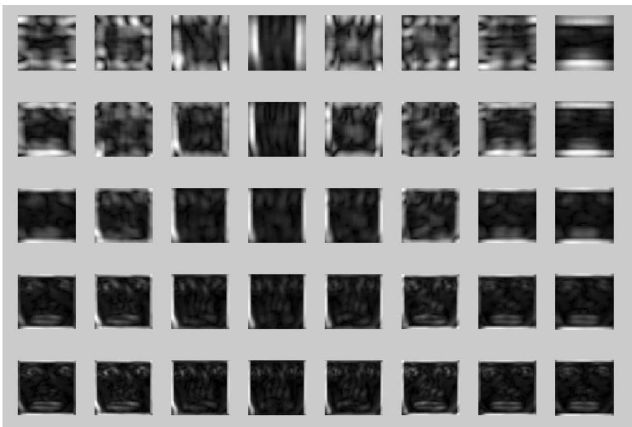
The discriminative Gabor feature can be derived to represent the image by using different combination of μ and ν. However, the dimension of the feature is quite high. Then, a supervised locality preserving projections, which is improved by two-directional 2DPCA to eliminate redundancy among Gabor features, is introduced to reduce the feature dimension.

3 IMPROVED SUPERVISED LOCALITY PRESERVING PROJECTIONS

When the discriminative features are extracted from the Gabor filtered images, Locality Preserving Projections which is then improved by two-direction 2DPCA is performed for classification and recognition. The concept of two-directional 2DPCA method which does not need to stretch image vector before projecting is to construct image covariance matrix and image scatter matrices directly using the original face image matrices. The primary difference between classical PCA and the 2DPCA algorithm is in the representation of face image. The face image should be stretched into one-dimensional image vectors in classical PCA; however, 2DPCA deals with the



a)



b)

Fig. 2. Gabor wavelet transformation of a sample face image. a) The real part of the transformation. b) The magnitude of the transformation.

data in matrix representation. For an image of size 112×92 a 10 304 dimensional vector space will be formed using the classical PCA, and the size of the scatter matrices is $10\,304 \times 10\,304$. When using the 2DPCA algorithm, the size of the scatter matrices is 112×112 or 92×92. Since the image covariance matrix and image scatter matrices have a much smaller size, the calculation complexity is greatly reduced. Therefore, the 2DPCA algorithm is less time-consuming and avoids the singularity problem simultaneously.

3.1 Two-Directional 2DPCA Algorithm [16]

The goal of two-directional 2DPCA is to extract features that can well preserve the principal information in a matrix form. Let X denote an n-dimensional unitary column vector and $A_i (i = 1, \ldots, M)$ denote the $m \times n$ Gabor feature based image matrix, an dim1 $\times$ dim2 projected vector D can be obtained from the following linear transformation:

$$D_i = V^T A_i U = [Y_1^T, \ldots, Y_{dim2}^T] A_i [X_1^T, \ldots, X_{dim1}^T]. \tag{4}$$

First, in order to get the optimal projection vector $U = [X_1^T, \ldots, X_{dim1}^T]$, one directional 2DPCA is performed by maximizing the following criterion function J_x

$$J_x = X^T S_x X \tag{5}$$

where $S_x = \frac{1}{M} \sum_{i=1}^{M} (A_i - \bar{A})^T (A_i - \bar{A})$.

Analogously, the projective function and criterion function of the other directional 2DPCA can be defined as

$$J_y = Y^T S_y Y \tag{6}$$

where $S_y = \frac{1}{M} \sum_{i=1}^{M} (A_i - \bar{A})(A_i - \bar{A})^T = S_x^T$. The optimal vector set $X_1^T, \ldots, X_{dim1}^T$ and $Y_1^T, \ldots, Y_{dim2}^T$ should be the eigenvectors of S_x and S_y corresponding to the largest dim1 and dim2 eigenvalues. Thus, the feature vector gained by two-directional 2DLDA algorithm $dim1 \times dim2$ image matrix can be seen.

3.2 Supervised Locality Preserving Projections Algorithm

Let us consider the samples $x_1, x_2, \ldots, x_n$ with zero mean are in a vector form. A linear transformation

$$y_i = W^T x_i. \tag{7}$$

is found from the d-dimensional space to a line. The objective function of LPP is as follows:

$$\min_y \sum_{ij} (y_i - y_j)^2 S_{ij} \tag{8}$$

where y_i is the one-dimensional representation of x_i and the matrix S is a similarity matrix. The objective functions with the choice of S_{ij} result in a heavy penalty if neighboring points x_i and x_j are mapped far apart.Therefore, minimizing it is an attempt to ensure that if x_i and x_j is 'close' then y_i and y_j is close too. If nodes i and j are connected, define the weighted similarity matrix:

$$S_{ij} = \begin{cases} \exp -\|x_i - x_j\|^2 / t & \text{if } i, j^{\text{th}} \text{ data from positive class} \\ 0 & \text{if } i, j^{\text{th}} \text{ data from different class} \end{cases} \tag{9}$$

where ε is sufficiently small, and $\varepsilon > 0$. Therefore, the objective function can be reduced by the following algebra formulation:

$$\begin{aligned} 1/2\sum_{ij}(y_i - y_j)^2 S_{ij} &= 1/2\sum_{ij}(W^T x_i - W^T x_j)^2 S_{ij} \\ &= \sum_i W^T x_i S_{ij} x_i^T W^T - \sum_{ij} W^T x_i S_{ij} x_j^T W^T \\ &= \sum_i W^T x_i D_{ii} x_i^T W^T - \sum_{ij} W^T x_i S_{ij} x_j^T W^T \\ &= W^T X(D - S)X^T W \\ &= W^T XLX^T W \end{aligned} \tag{10}$$

where $X = x_1, x_2, \ldots, x_n$ and D is a diagonal matrix; its entries are column (or row, since S is symmetric) sums of S, $D_{ii} = \sum_{ij} S_{ij}$. $L = D - S$ is the Laplacian matrix [3]. Besides, a constraint is imposed as follows:

$$y^t Dy = 1 \Longrightarrow W^T XDX^T W = 1. \tag{11}$$

Therefore, Supervised Locality Preserving Projections can be formulated as the following optimization problem:

$$\min_W W^T XLX^T W \qquad s.t. W^T XDX^T W = 1. \tag{12}$$

The transformation vector w that minimizes the objective function is obtained by minimizing the generalized eigenvalues problem:

$$XLX^T W = \lambda XDX^T W. \tag{13}$$

Note that the two matrices XLX^T and XDX^T are both symmetric and positive semi-definite.

Thus, according to their first k largest eigenvalues, the embedding is as follows:

$$x_i \rightarrow y_i = W^T x_i, W = [w_0, w_1, \ldots, w_{k-1}] \tag{14}$$

where y_i is a k-dimensional vector, and W is a $N \times k$ matrix.

4 COMBINING GABOR FEATURE AND IMPROVED SUPERVISED LOCALITY PRESERVING PROJECTIONS

In our algorithm we propose to transform the Gabor feature space into the Supervised Locality Preserving Projections which is then improved by two-direction 2DPCA to reduce Gabor feature dimension for face recognition. Compared with the features obtained by classical subspace methods such as principal component analysis (PCA) and linear discriminant analysis (LDA), Gabor features contain more discriminant information and are thus more robust against variations in illumination, pose and expressions.

Given a Gabor feature vector extracted from a face image and a subspace projection matrix derived from the Improved Supervised LPP subspace analysis, a new feature with low dimension can be derived by:

$$y = W^T x, W = W_{(2D)^2PCA} W_{LPP}. \tag{15}$$

Since face recognition requires a similarity measure reflecting the differences between two facial features in the projection subspace, the Euclidean Distance is utilized to calculate the distance between the two sample projections y_1 and y_2.

Euclidean Distance (Eu):

$$D_E(y_1, y_2) = \sqrt{(y_1 - y_2)^T (y_1 - y_2)}. \tag{16}$$

While the simple nearest neighbour classifier is used in our work for face recognition, the result is output due to the shortest distance of the test sample and the standard sample.

5 EXPERIMENTAL RESULTS

The performance of the proposed Gabor-based Improved Supervised locality preserving projection method is analyzed using the ORL face database. The ORL database (http://www.cam-orl.co.uk) contains images from 40 individuals, each providing 10 different images. For some subjects, the images were taken at different times with different expressions and decorations.

5.1 Turning Gabor Filter Parameters: Orientation μ and Scale ν

In the first experiment, the goal is to find the optimal Gabor filter parameters for face recognition purpose. The experiment is performed using the first five images samples per class for training, while the remaining five images are used for testing. A proper dim of the LPP as the optimal projective directions and the nearest neighbour classifier are used to test the parameters. The range of frequency information the Gabor filter extracted is defined by the number of scales of the filter, while the directional information is specified by the number of orientations of the filter. The lager the number of scales, the more information from low frequency bands will be extracted.

Figure 2 shows the performance of the new method when the number of orientations varies and the number of scales fixed. Figure 3 shows the result when number of scales varies and the number of orientations is fixed. As shown in the figure, the X label stands for the dimensions of the 2DPCA, for example, the number 2 means $dim1 \times dim2$ is 2×2.

In the figures above, it is shown clearly that the new algorithm performs better as the number of dimensions of 2DPCA increases. However, when the number of $dim1 \times dim2$ reaches 8×8, the accurate recognition rate declines. Consequently,

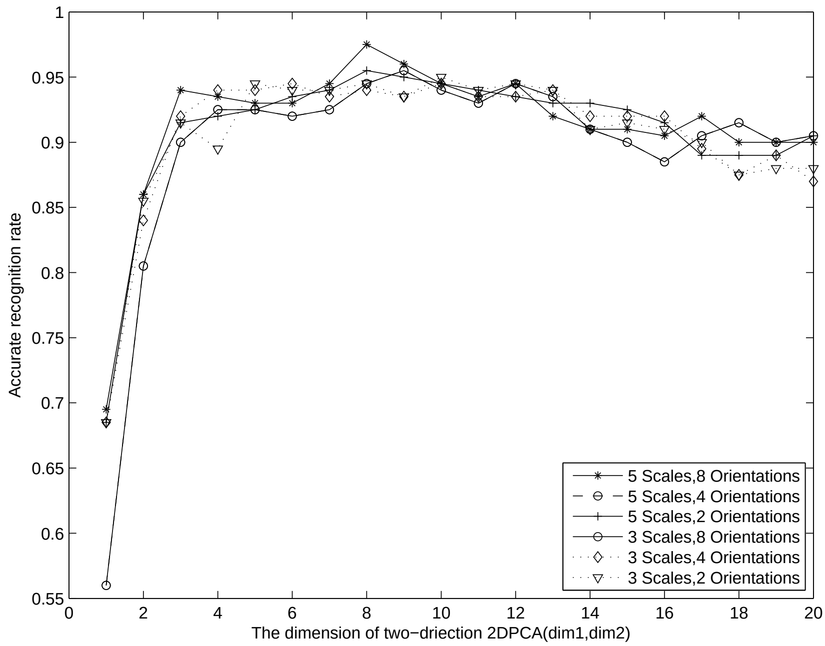


Fig. 3. Performance for different number of orientations

Gabor filters of five scales and eight orientations are chosen to be used in our following experiments for it reaches the top of the accurate recognition rate when the dimension is 8×8.

5.2 Comparison with Other Subspace Methods

In the following section, the Gabor-based Improved Supervised locality preserving projection algorithm is first compared to PCA, LDA and LPP under different feature dimensions.

The experiments are performed using the first five images samples per class for training, while the remaining five images for testing. Figure 5 shows the comparative results. It can be seen that the Gabor-based Improved Supervised Locality Preserving Projections is more competitive than the other three subspace methods. The accurate recognition rate reaches its top of 97.5 % and becomes stable when the number of feature dimension is 32.

To emphasize the discriminating power of the extracted Gabor feature vector, the comparative performance of LPP, Gabor-based LPP, Improved SLPP and Gabor-based Improved Supervised LPP (Gabor-based ISLPP) are also shown in Figure 6.

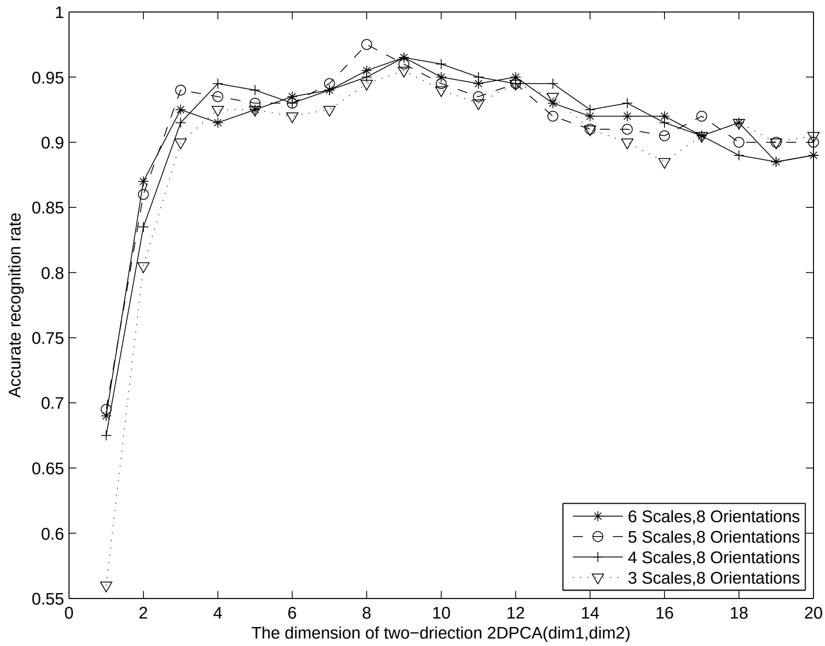


Fig. 4. Performance for different number of scales

It is apparent from the figure above that the performance of the LPP and Improved Supervised LPP is increased by using Gabor feature vector. The highest accurate recognition rate of the four algorithms is 94.00 %, 96.00 %, 96.5 %, 97.5 % separately. The Gabor-based LPP method achieves 2 % higher accuracy than LPP, while 1 % increase is observed for Improved SLPP when Gabor wavelets are applied.

5.3 Comparison Using Different Sets of Training Samples

In the second part of the experiments, for each individual, the first 2, 3, 4, 5, 6 face images are selected for training and the rest are used for testing. For each given sets of training samples, we choose the best dimensions of the dimension parameters. Figure 7 shows the plots of recognition rate versus different training samples for LPP, Improved LPP and Gabor-based Improved Supervised LPP methods.

From the diagram above we can see that the new algorithm present in this paper achieves the highest recognition rate in the three methods when different sets of samples are used for training. Furthermore, a detail of the experiment is shown in Table 1.

It is found that the new method proposed in this paper outperforms the other two methods with different numbers of training samples (the first 2, 3, 4, 5, 6 face images) per individual. The LPP method performs the worst. Extraordinarily,

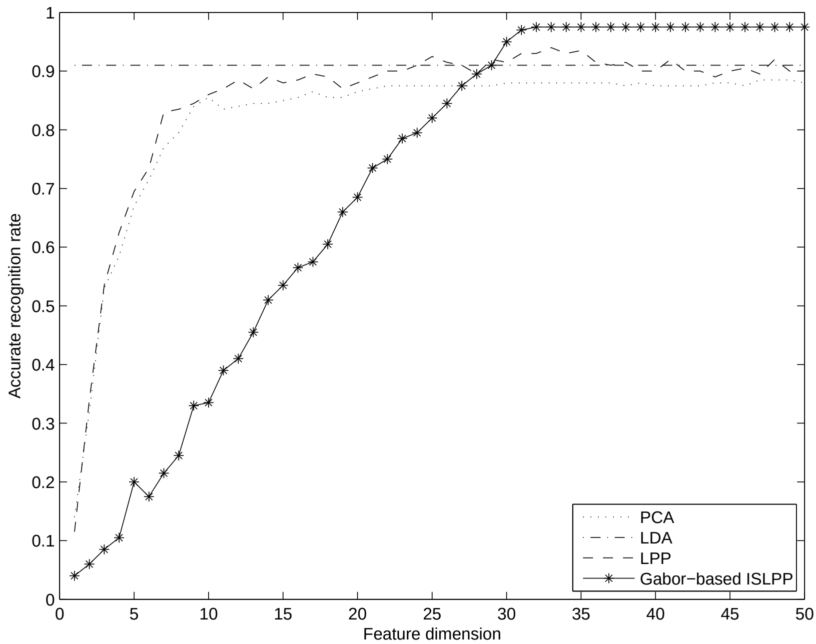


Fig. 5. Performance for different number of scales

	Sets of training samples				
	2	3	4	5	6
LPP	82.19 %	87.14 %	92.92 %	94.00 %	97.50 %
Improved SLPP	83.44 %	90.00 %	94.00 %	96.50 %	98.12 %
Gabor-based LPP	87.50 %	90.71 %	93.75 %	96.00 %	98.12 %
Gabor-based ISLPP	88.12 %	91.43 %	95.83 %	97.50 %	99.38 %

Table 1. Comparison of recognition rates with different algorithm. Note that the best choices of the number of the components for the top recognition accuracy depend on the test data.

	Sets of training samples				
	2	3	4	5	6
LPP	0.2030	0.2650	0.2970	0.3120	0.3014
Improved SLPP	0.1720	0.2340	0.2660	0.2820	0.2786
Gabor-based LPP	0.7245	0.9868	1.0549	1.0654	1.0455
Gabor-based ISLPP	0.6717	0.8152	0.9887	0.9981	0.9875

Table 2. Comparison of recognition time with different algorithm, Note that recognition time depends on the top recognition accuracy.

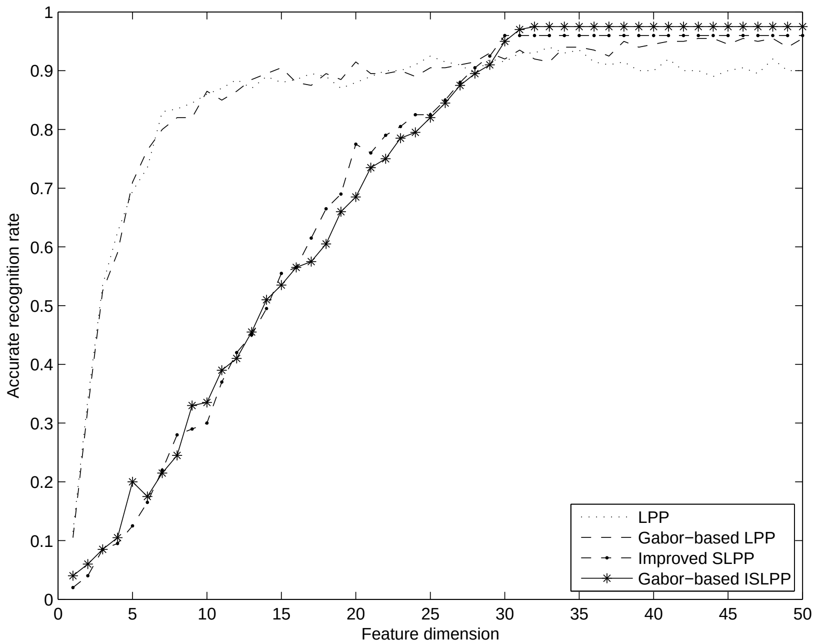


Fig. 6. Comparison of recognition rates with LPP, Gabor-based LPP, improved SLPP and Gabor-based ISLPP under different dimensions

when the first 6 images are used for training, the new method achieves the highest recognition accuracy rate of nearly 100 %. In Table 2, we further tested the new algorithm using different distance such as cosine and Mahalanobis distances,with different numbers of training samples per individual.

	Sets of training samples				
	2	3	4	5	6
Absolute Distance	87.81 %	91.07 %	95.42 %	93.50 %	99.38 %
Eucledian Distance	88.12 %	91.43 %	95.88 %	96.50 %	99.38 %
Cosine Distance	82.81 %	86.43 %	89.17 %	97.50 %	94.38 %
Mahalanobis Distance	89.38 %	92.14 %	96.67 %	98.00 %	100.00 %

Table 3. Comparison of recognition rates with different distance. Note that the best choices of the number of the components for the top recognition accuracy depend on the test data.

6 CONCLUSIONS

In this paper, we proposed Gabor-based Improved Supervised LPP (Gabor-based ISLPP) algorithm to preserve the nonlinear structure of the manifold. For most of

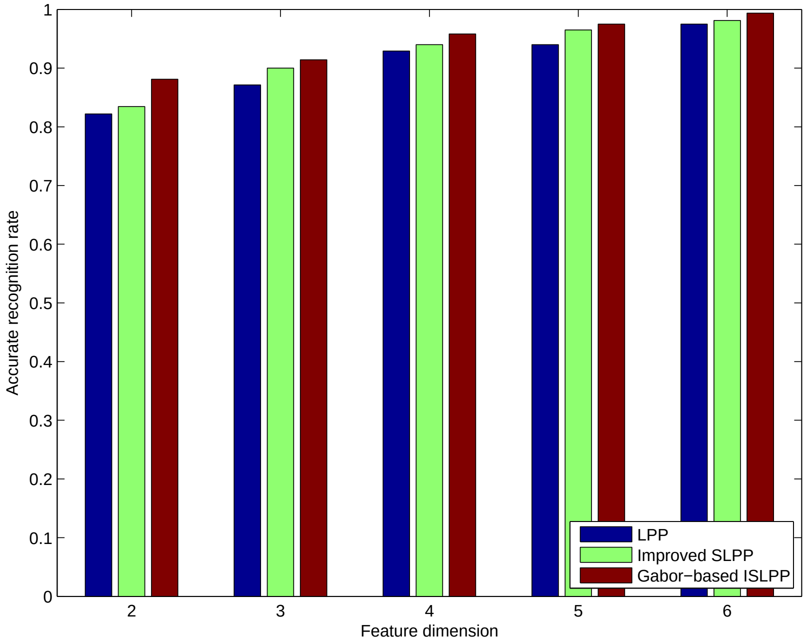


Fig. 7. Comparison of recognition rates with the three methods using different sets of training samples

traditional face recognition methods (i.e. PCA, LDA, and LPP) consider an image as a vector in high dimensional space; in our method the Gabor filtered image is firstly represented as a matrix. Then a two-directional 2DPCA is utilized before SLPP for image matrix compression to remove the inherent redundancy among Gabor features. Important intra-person variations among the Gabor feature space can be captured well and experiments on the ORL database show the new method is more effective and competitive. On the ORL database with six training samples per individual, the Gabor-based improved LPP proposed achieves an accurate recognition rate of 100.00 % using the Mahalanobis Distance.

REFERENCES

[1] Turk, M.—Pentland A.: Eigenfaces for Recognition. Journal of Cognitive Neuroscience, Vol. 3, 1991, No. 1), pp. 72–86.

[2] Belhumeur, P. N.—Hespanha, J. P.—Kriegman, D. J.: Eigenfaces vs. Fisherface: Recognition Using Class Special Linear Projection. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 19, 1997, No. 7, pp. 711–720.

[3] Bartlett, A. M. S.—Lades, H. M.—Sejnowski, T. J.: Independent Component Representations for Face Recognition. Human Vision and Electronic Imaging III, Bernice E. Rogowitz; Thrasyvoulos N. Pappas, Proc. SPIE, Vol. 3299, 1998, p. 528–539.

[4] Tenenbaum, J. B.—de Silva, V.—Langford, J. C.: A Global Geometric Framework for Nonlinear Dimensionality Reduction. Science, Vol. 290, December 2000, No. 5500, pp. 2319–2323.

[5] Roweis, S. T.—Saul, L. K.: Nonlinear Dimensionality Reduction by Locally Linear Embedding. Science, Vol. 290, 2000, No. 5500, pp. 2323–2326.

[6] He, X.—Niyogi, P.: Face Recognition Using Laplacianfaces. Proceedings of the Conference on Advances in Neural Information Processing Systems 16. Cambridge, MA: MIT Press, 2004.

[7] He, X.—Yan, S. et al.: Face Recognition Using Laplacianfaces. IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 27, 2005, No. 3, pp. 328–340.

[8] He, X.—Yan, S. et al.: Learning a Locality Preserving Subspace for Visual Recognition. Proceedings of the Ninth IEEE International Conference on Computer Vision (ICCV 2003) 2 – Volume Set, 2003.

[9] Yu, W.—Teng, X.—Liu, C.: Face Recognition Using Discriminant Locality Preserving Projections. Image and Vision Computing, Vol. 24, 2006, pp. 239–248.

[10] Jones, J.—Palmer, L.: An Evaluation of the Two-Dimensional Gabor Filter Model of Simple Receptive Fields in Cat Striate Cortex. I.J̇. Neurophysiology, 1987, pp. 1233–1258.

[11] Liu, C.—Wechsler, H.: Gabor Feature Based Classification Using the Enhanced Fisher Linear Discriminant Model for Face Recognition. IEEE Trans. Image Processing, Vol. 11, 2002, No. 4, pp. 467–476.

[12] Liu, C.—Wechsler, H.: A Gabor Feature Classifier For Face Recognition. Proceedings of the Eighth IEEE International Conference on Computer Vision, Vol. 2, July 2001, pp. 270–275.

[13] Liu, C.: Gabor-Based Kernel PCA with Fractional Power Polynomial Models for Face Recognition.IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 26, May 2004, No. 5, pp. 572–581.

[14] Shen, L.—Bai, L.—Fairhurst M.: Gabor Wavelets and General Discriminant Analysis for Face Identification and Verification. Image and Vision Computing, Vol. 25, May 2007, No. 5, pp. 553–563.

[15] Yang, J.—Zhang, D.—Frangi, A. F.—Yang, J. Y.: Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition. IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 26, 2004, No. 1, pp. 131–137.

[16] Xu, D.—Yan, S. et al.: Parallel Image Matrix Compression for Face Recognition. Proceedings of the 11th International Multimedia Modelling Conference (MMM ’05), 2005, pp. 232–238.

[17] Zhang, D. Q.—Zhou, Z. H.: $(2D)^2$PCA: Two-Directional Two-Dimensional PCA for Efficient Face Representation and Recognition. Neuro computing, Vol. 69, 2005, Nos. 1–3, pp. 224–231.

[18] Ye, J. P.: Generalized Low Rank Approximations of Matrices. The Proceedings of the Twenty-First International Conference on Machine Learning (Outstanding Student Paper), Banff, Alberta, Canada, 2004, pp. 887–894.

[19] Xiong, H. L.—Swamy, M. N. S.—Ahmad, M. O.: Two-Dimensional FLD for Face Recognition. Pattern Recognition, Vol. 38, 2005, pp. 1121–1124.

[20] Li, M.—Yuan, B.: 2D-LDA: A Novel Statistical Linear Discriminant Analysis for Image Matrix. Pattern Recognit. Lett., Vol. 26, 2005, No. 5, pp. 527–532.

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