

Full Length Research Paper

Scatter-difference discriminant locality preserving projections for palmprint recognition

JianXin Zhang, XiaoPeng Wei and Qiang Zhang*

Key Laboratory of Advanced Design and Intelligent Computing, Dalian University, Ministry of Education, Dalian 116622, P. R. China.

Accepted 11 October, 2011

We develop an improved LPP method called scatter-difference discriminant locality preserving projections (SDLPP) for palmprint recognition. SDLPP has better classification capability which benefits from discriminant information obtained by maximizing the difference of between-class separability and within-class similarity. SDLPP 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 discriminant information. Comparative recognition performance results obtained on public PolyU palmprint database also confirm the effectiveness of the proposed SDLPP approach.

Key words: Palmprint recognition, scatter-difference criteria, locality preserving projections, singularity problem.

INTRODUCTION

In information society, biometrics technique is one of the most important and effective solutions for automatic personal recognition. It has been successfully used in many fields including civil, commercial and martial applications. Palmprint recognition is a relatively new biometric technique, which is also regarded as a potential technique. Recently, palmprint recognition has been widely investigated (Kong et al., 2009) owing to its advantages such as high recognition accuracy, low-cost and user friendliness.

According to feature extraction methods, current palmprint recognition algorithms mainly can be classified into line-, texture-, subspace- and statistic-based palmprint recognition. Line-based approaches (Han et al., 2003; Huang et al., 2008) employ edge detectors to extract palm lines. The extracted lines are either matched directly or represented in other formats for matching. Because it is very difficult to extract structural features exactly, texture analysis is introduced to palmprint recognition. Zhang et al. (2003) propose a texture-based approach called PalmCode for palmprint recognition using Gabor filter. Palmprint FusionCode (Kong et al., 2006), Orientation Code (Yue et al., 2009) etc are then

proposed for better representation of palmprint texture. Statistical-based approaches transform palmprint images into another domain using Fast Fourier transform (FFT), discrete cosine transform (DCT), discrete wavelets, etc (Chen and Kegl, 2010; Manisha et al., 2009; You et al., 2010). The transformed images are generally divided into small regions, and the statistic values of each small region are calculated as recognition features. The subspace-based approaches employ subspace methods such as principal component analysis (PCA), linear discriminant analysis (LDA) and locality preserving projections (LPP) etc (Belhumeur et al., 1997; He and Niyogi, 2003; Jolliffe, 1986). The subspace coefficients are used as features for palmprint recognition (Hu et al., 2007; Lu et al., 2003). Some researches also apply DCT, wavelets or Gabor wavelets on the subspace methods to improve feature discriminant (Aykut and Ekinici, 2009; Leng et al., 2010; Murat and Murat, 2008; Zheng et al., 2007). The subspace-based approaches are considered to be one of the most important approaches for palmprint recognition. Among subspace-based approaches, EigenPalms (Lu et al., 2003) and FisherPalms (Wu et al., 2003) map palmprint image data into a low-dimensional linear subspace while it preserve the global structure of data space. However, EigenPalms and FisherPalms, which are linear models, fail to discover intrinsic nonlinear data structures of palmprint images. He and Niyogi

*Corresponding author. E-mail: zhangq30@hotmail.com.

(2003) propose a new linear subspace technique called LPP, which shares many advantages of nonlinear methods. LPP can effectively preserve the local structure of image data and may achieve better recognition performance than PCA (He et al., 2005; Wang and Yau, 2008). However, LPP has its limitations to image recognition for considering less classification information and having singularity problem. Zheng et al. (2007) absorb the class labels of within-class image data to enhance the discriminant power of LPP and present a supervised locality preserving projections (SLPP) for face recognition. Yu et al. (2006) present a discriminant locality preserving projections (DLPP) to improve the classification capability of LPP algorithm by maximizing the between-class distance while minimizing the within-class distance. However, both SLPP and DLPP mentioned previously are confronted with the singularity problem similar to LPP's. One possible method reducing the dimension of data space by utilizing PCA as preprocessing step (He et al., 2005; Wang et al., 2008; Wong and Zhao, 2011; Yu et al., 2006) is used to overcome this singularity problem. Thus, these LPP-based approaches are generally called PCA plus LPP, SLPP and DLPP. Because of the essentially difference between objectives of PCA and LPP, the PCA preprocessing could result in the loss of some important information for LPP, SLPP or DLPP that follows PCA. In view of this, Hu et al. (2007) propose a novel LPP-based algorithm called two dimensional locality preserving projections (2DLPP) for palmprint recognition. 2DLPP employs smaller feature dimensions to provide more accurate approximation of the original image data than LPP. 2DLPP can solve the singularity problem of LPP but considers less classification information than SLPP and DLPP.

In the paper, an improved LPP algorithm called scatter-difference discriminant locality preserve projections (SDLPP) for palmprint recognition is put forward. SDLPP considers discriminant information through maximizing the difference of between-class separability and within-class similarity, what makes it more suitable for data classification. SDLPP avoids singularity problem in high dimensional data matrix by scatter-difference discriminant criteria. Thus, SDLPP can be directly applied to palmprint image recognition while providing more compact representation of original image data. The experiment results obtained on the public PolyU palmprint database also prove the effectiveness of the proposed SDLPP method.

LOCALITY PRESERVING PROJECTIONS (LPP)

Given C classes input data $X = [x_1, x_2, \dots, x_N]$ with x_i being d dimensional column vector, LPP seeks a linear transformation matrix A to project high-dimensional input data X into a low-

dimensional subspace Y in which the local structure of input data can be well preserved. The transformation matrix A can be obtained by minimizing the following objective function (He and Niyogi, 2003)

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

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 $\omega_{ij} = \exp(-\|x_i - x_j\|^2 / t)$, where t is a suitable constant, otherwise, $\omega_{ij} = 0$. Weight matrix W is a sparse symmetric matrix formed by ω_{ij} . For more details of LPP and weight matrix, please refer to reference (He and Niyogi, 2003) and (He et al., 2005). The minimizing aforementioned objection function is an attempt to ensure that if x_i and x_j are 'close' then y_i and y_j are 'close' as well. This minimization problem can be converted to solving a generalized eigenvalue problem as follows (He and Niyogi, 2003)

$$XLX^T A = \lambda XDX^T A \tag{2}$$

In Equation 2, $D_{ii} = \sum_j \omega_{ij}$ is a diagonal matrix and $L = D - W$ is called the Laplacian matrix. The transformation vector a_i that minimizes this objective function is given by the minimum eigenvalue solutions to the generalized eigenvalue problem. LPP provides an intrinsic compact representation of high-dimensional samples using low-dimensional data. However, LPP has no direct connection to classification information and often fails to preserve within-class local structure as k -nearest neighbors may belong to different classes. As the dimension of matrix XDX^T ($d \times d$) is generally much larger than matrix D 's ($N \times N$) for image recognition, the solution to LPP also has its singularity for high-dimensional matrix XDX^T .

SCATTER-DIFFERENCE DISCRIMINANT LPP (SDLPP)

To overcome the limitations of LPP, we define the objective function of the given SDLPP algorithm as follows

$$J = \max_A (S_{B1} - \alpha S_{W1}) \tag{3}$$

$$S_{W1} = \sum_{i=1}^N \sum_{j=1}^N (y_i - y_j)^2 R_W(i, j) \tag{4}$$

$$S_{B1} = \frac{1}{C} \sum_{i=1}^C \sum_{j=1}^C (\mu_i - \mu_j)^2 R_B(i, j) \tag{5}$$

S_{B1} and S_{W1} are respectively defined to describe the between-

class separability and within-class similarity. μ_i is the projection vector of m_i where $m_i = (\sum_{k=1}^{N_i} x_k) / N_i$ is the average vector of class i . The C classes average vector can be represented as $M = [m_1, m_2, \dots, m_C]$. R_B and R_W are between-class weight matrix and within-class weight matrix, respectively. The SDLPP subspace can be obtained by maximizing objective function J with its purpose to seek efficient discrimination among different classes while preserving the local structure of within-class data. α is a non-negative constant to balance the contribution of S_{B1} and S_{W1} . When $\alpha = 0$, between-class separability plays a key role; otherwise SDLPP subspace is mainly decided by within-class data while $\alpha \rightarrow \infty$. In SDLPP subspace, projection data from the same class should be 'close' with each other while from the different classes should be 'far' from each other in consideration of class-specified information. Then, we reduce the within-class similarity matrix S_{W1} into

$$S_{W1} = \sum_{i=1}^N \sum_{j=1}^N (y_i - y_j)^2 R_W(i, j) = \sum_{i=1}^N \sum_{j=1}^N A^T (x_i - x_j) R_W(i, j) (x_i - x_j)^T A$$

$$= A^T (\sum_{i=1}^N x_i D_{ii}^W x_i^T - \sum_{i,j} x_i W_{ij}^W x_j^T) A = A^T X (D_W - W_W) X^T A$$

$$= A^T X L_W X^T A \tag{6}$$

In Equation 6, $R_W(i, j)$ is the within-class weight coefficient between x_i and x_j that are from the same class. $D_{ii}^W = \sum_j R_W(i, j)$ is a diagonal matrix and $L_W = D_W - W_W$ is within-class Laplacian matrix. To make projection data from the same class be 'close' with each other, $R_W(i, j)$ is defined as

$$R_W(i, j) = \begin{cases} \frac{1}{2N_i} \exp(-\|x_i - x_j\|^2 / t_w) & x_i, x_j \in c_i \\ 0 & \text{others} \end{cases} \tag{7}$$

Then, between-class separability matrix S_{B1} can be reduced to

$$S_{B1} = \frac{1}{C} \sum_{i=1}^C \sum_{j=1}^C R_B(i, j) (\mu_i - \mu_j)^2 = \frac{1}{C} \sum_{i=1}^C \sum_{j=1}^C R_B(i, j) (A^T m_i - A^T m_j)^2$$

$$= \frac{1}{C} A^T (\sum_{i=1}^C m_i D_{ii}^B m_i^T - \sum_{i,j} m_i W_{ij}^B m_j^T) A = \frac{1}{C} A^T M (D_B - W_B) M^T A$$

$$= \frac{1}{C} A^T M L_B M^T A \tag{8}$$

$R_B(i, j)$ is the between-class weight coefficient between class i and class j which can be computed by the following equation

$$R_B(i, j) = \begin{cases} \frac{N_i N_j}{(N_i + N_j)} \exp(-\|m_i - m_j\|^2 / t_b) & u_j \in u_i \text{ k-nearest neighbor classes} \\ 0 & \text{others} \end{cases} \tag{9}$$

where t_b is a suitable constant that can be decided by experiment tests. The purpose of defining $R_B(i, j)$ is to make the two classes which are 'close' in original high-dimensional space be 'far' in low-dimensional SDLPP subspace. Then, between-class weight matrix R_B is constructed through the k-nearest neighbors graph $D_{ii}^B = \sum_j R_B(i, j)$ is a $C \times C$ dimensional diagonal matrix and $L_B = D_B - W_B$ is the between-class Laplacian matrix. According to Equations 6 and 8, the objective function of SDLPP can be rewritten as

$$J = \max_A A^T (\frac{1}{C} M L_B M^T - \alpha X L_W X^T) A \tag{10}$$

Maximizing Equation 10 can be converted to the generalized eigenvalue problem as following equation with a constrain condition $A^T A = I$ to get the effective solution

$$(\frac{1}{C} M L_B M^T - \alpha X L_W X^T) A = \lambda A \tag{11}$$

The problem of SDLPP is then equivalent to find the leading eigenvectors of matrix $M L_B M^T / C - \alpha X L_W X^T$. SDLPP need not compute the inverse of high-dimensional matrix which brings singularity problem. Thus, SDLPP is not limited by the number of training samples when it is applied to palmprint recognition.

EXPERIMENTS AND RESULTS

To test the performance of the proposed SDLPP algorithm, we perform it on the PolyU palmprint database which is the largest and most authoritative public palmprint database (Hong Kong Polytechnic University, 2004). Our experiments were performed on a subset of this database. This subset consists of 1000 images evenly from 100 different palms. The central part of each palm image is cropped and resized to 32×32 pixels, which is called ROI (Region of Interest) image. Thus, each ROI image can be represented by a 1024-dimensional vector in image space. Figure 1 shows some cropped ROI images of two typical palms in PolyU palmprint database. The experiments also compare SDLPP with PCA, LDA, LPP, SLPP and DLPP. The nearest neighbor rule with L_2 norm distance is employed

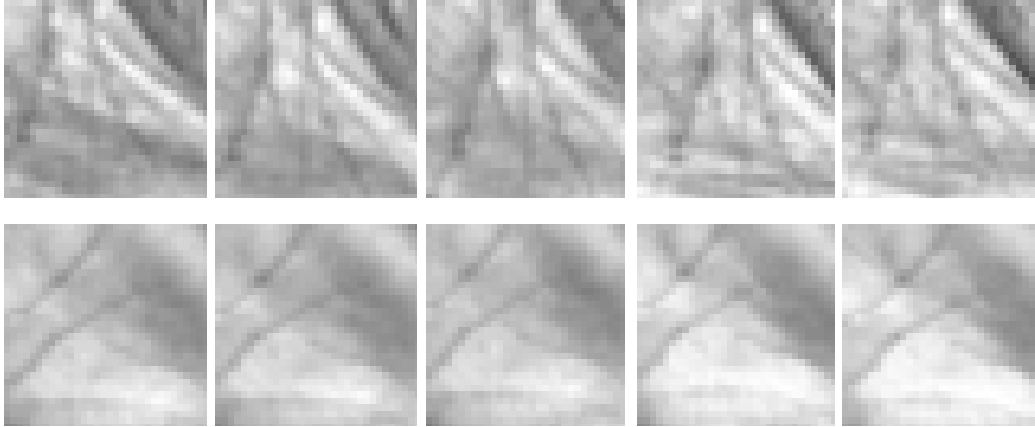


Figure 1. Samples of the cropped ROI images in PolyU palmprint database.

Table 1. Relationship between recognition rate and α value in SDLPP.

α (%)	0	0.001	0.01	0.1	1	10	100	1000
Round 1	89	89	89	89.83	91.67	81.83	75.5	73.5
Round 2	89.33	90.33	90.33	91.33	91.33	83.83	76.17	75.17
Round 3	88	89.33	89.33	89.33	91.33	80	74.83	73.67
Average	88.78	89.56	89.56	90.16	91.44	81.89	75.5	74.11

for the feature classification step by the six algorithms in experiments. Note that LDA, LPP, SLPP and DLPP involve a PCA as preprocessing step to avoid the singular matrix. The optimum PCA preprocessing dimension is extensively witness by experiment results.

We randomly choose 4 samples of each palm for training while the remaining 6 images are used for testing. This process is repeated three times and three different sample sets are obtained for experiments. The first experiment is designed to determine the parameters of

proposed SDLPP algorithm. In SDLPP, parameter t_w and t_b can be approximatively estimated by the average distance of within-class sample data and class-mean sample data, respectively. Then, the final values of t_w

and t_b are set to 10^6 and 10^7 in experiment. The number of between-class nearest neighbors is generally set to a small positive integer. In our experiments; this value equals 5. Then, we use the aforementioned parameters to determine appropriate balance parameter α which is designed to balance the contribution of between-class separability and within-class similarity. Table 1 gives the relationship between recognition rate (100-dimensional subspace features) and α value in SDLLP.

Table 1 shows that SDLPP can achieve its best

recognition performance when α equals 1. Smaller α values for SDLPP can also preserve satisfied recognition rates, while bigger α will rapidly influence the effectiveness of SDLPP. Hence, it can be concluded that the between-class separability takes a more important role for palmprint recognition. Figure 2 illustrates the relationship between the average recognition rate and feature dimension corresponding to different balance parameter values. The average recognition rate is the average value of three recognition rates obtained on three sample sets under the same subspace dimension.

In our second experiment, we vary PCA dimensions from 30 to 80 with 5 spaces to choose the optimum PCA preprocessing dimension for LDA, LPP, SLPP and DLPP according to the average top recognition rates. The average top recognition rates are the average value of three top recognition rates respectively achieved on three sample sets. The corresponding subspace dimensions for three top recognition rates are generally different from each other. Figure 3 shows the relationship of the average top recognition rates and corresponding PCA processing dimensions for each algorithm. From Figure 3, we can choose the optimum PCA preprocessing dimensions for LDA, LPP, SLPP and DLPP to be 40, 40, 30 and 40, respectively.

Finally, we compare the recognition performance of SDLPP algorithm with the PCA and these four algorithms by employing each determined optimum parameter.

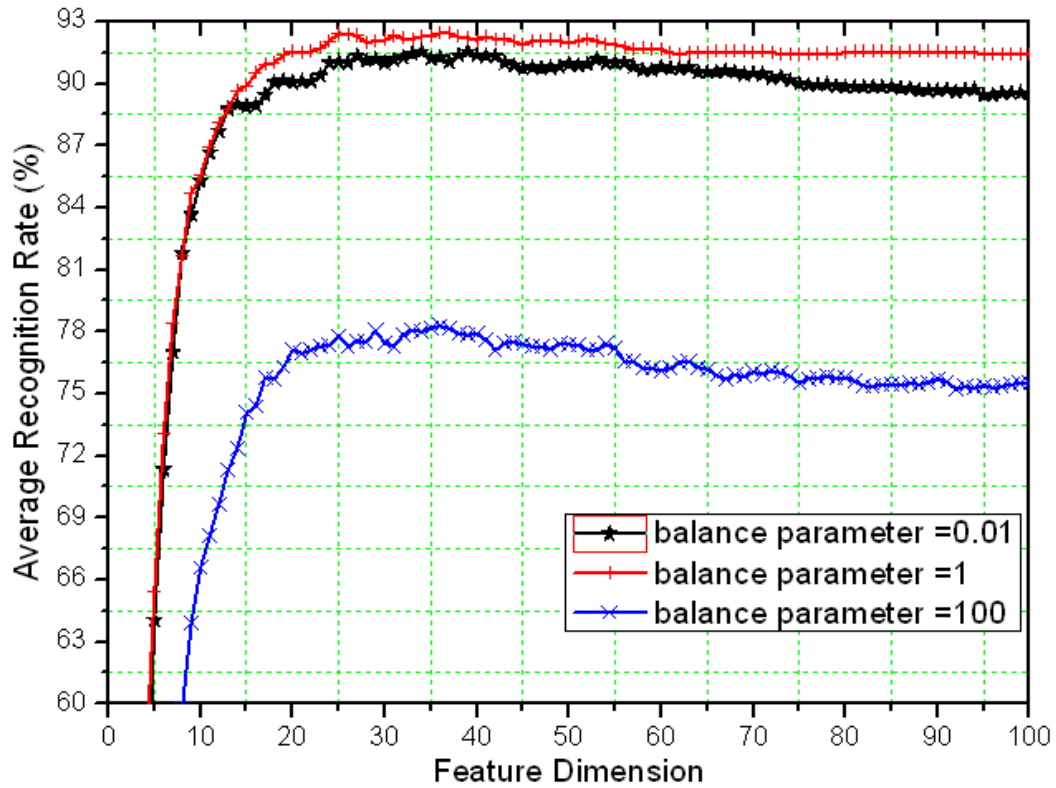


Figure 2. The average recognition rates vs. feature dimension obtained on different balance parameter values.

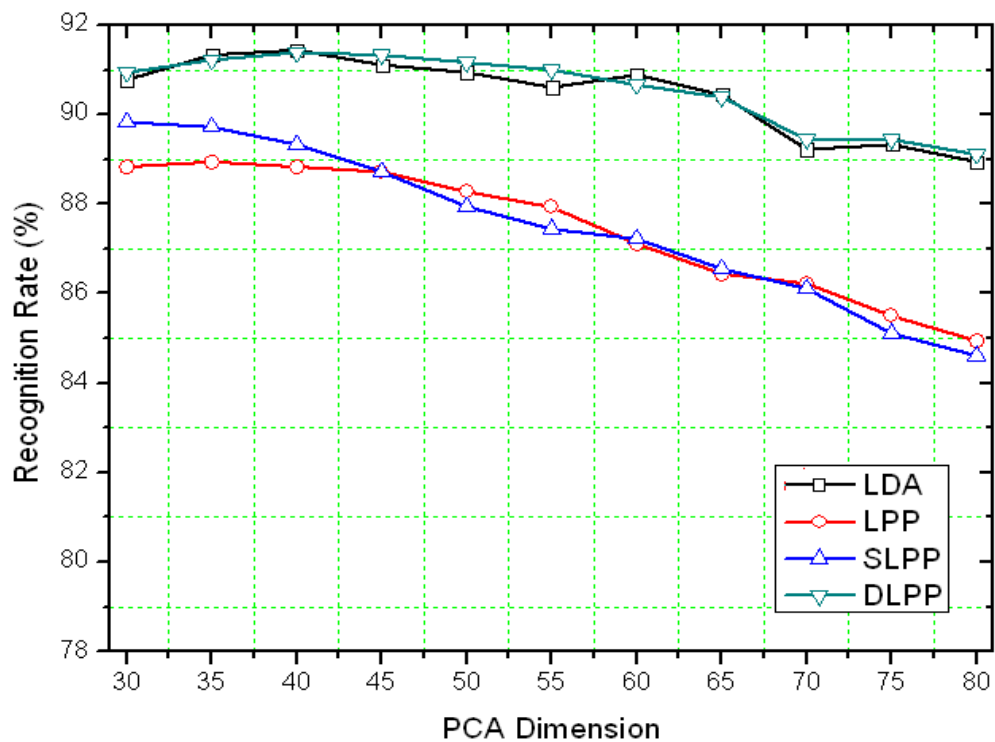


Figure 3. The average top recognition rates vs. PCA dimensions.

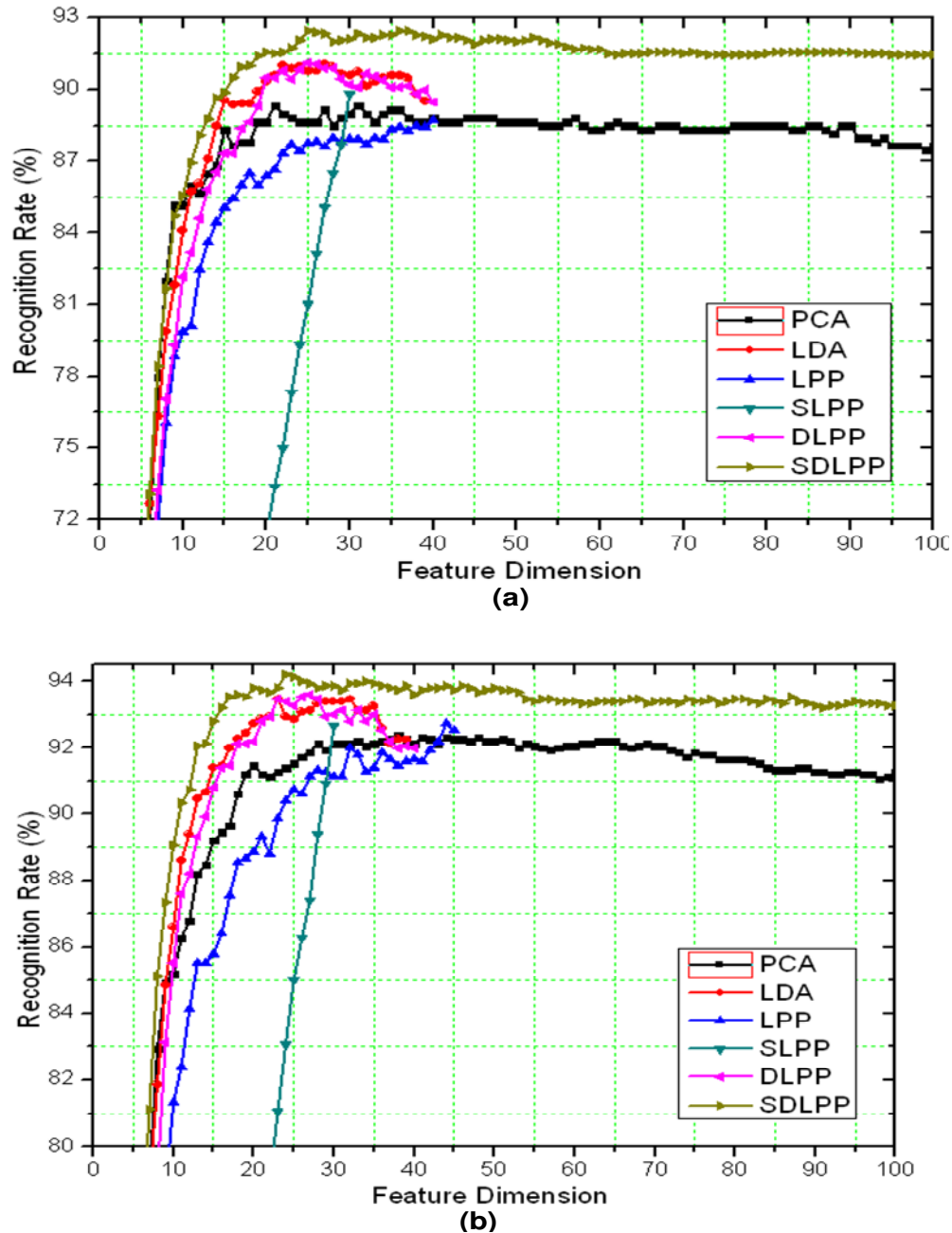


Figure 4. Comparative average recognition rates vs. feature dimension; (a) 4 samples per palm for training, and (b) 5 samples per palm for training.

Figure 4a shows the comparative average recognition rate results of the six algorithms. Then, we change the training sample number per palm to 5 to get more comparative results. Under this condition, the optimum PCA preprocessing dimensions for LDA, LPP, SLPP and DLPP are chosen to be 40, 45, 30 and 40, respectively. Furthermore, the comparative average recognition rate results vs. feature dimension for all algorithms are displayed in Figure 4b.

Figure 4 illuminates that SDLPP achieves the best and

most stable recognition performance in these six algorithms. When using 4 samples per palm for training, SDLPP obtains the top average recognition rate of 92.44%, while PCA, LDA, LPP, SLPP and DLPP obtain the top average recognition rates of 89.33%, 91.06%, 88.72%, 89.83% and 91.11%, respectively. Higher recognition rates can be achieved by the six algorithms when we employ more samples for training. Furthermore, the supervised LDA, SLPP, DLPP and SDLPP achieve higher recognition performance than that of unsupervised

PCA and LPP.

Conclusions

An improved subspace approach named SDLPP is presented for palmprint recognition in this paper. SDLPP considers discriminant information by maximizing the difference of between-class separability and within-class similarity. SDLPP avoids singularity problem of high-dimension matrix and can be directly applied to small sample size problem. As less important information is lost, SDLPP provides a more accurate approximation of original image than the presentation given by PCA plus LPP. Experiment results obtained on PolyU palmprint database demonstrate stable and effective recognition performance of SDLPP.

ACKNOWLEDGEMENT

This work is supported by the National Natural Science Foundation of China (No.60875046), the Key Project of Chinese Ministry of Education (No.209029), the Program for Liaoning Excellent Talents in University (No.LR201003), the Program for Liaoning Science and Technology Research in University (No.LS2010008, 2009S008, 2009S009, LS2010179), the Program for Liaoning Innovative Research Team in University (No.2009T005, LT2010005), the "Liaoning BaiQianWan Talents Program (2010921010)" and the Doctoral Fund of Dalian University.

REFERENCES

- Aykut M, Ekinci M (2009). Kernel principal component analysis of Gabor features for palmprint recognition. In Proceedings of Third International Conference on Advances in Biometrics, Alghero, Italy. pp. 685-694.
- Belhumeur PN, Hespanha JP, Kriegman DJ (1997). Eigenfaces vs. Fisherfaces: recognition using class specific linear projection. *IEEE Trans. Patt. Anal. Mach. Intell.*, 17(7): 711-720.
- Chen GY, Kegl B (2010). Invariant pattern recognition using contourlets and AdaBoost. *Patt. Recog.*, 43(3): 579-583.
- Han CC, Chen HL, Lin CL, Fan KC (2003). Personal authentication using palm-print features. *Patt. Recog.*, 36(2): 371-381.
- He XF, Niyogi P (2003). Locality preserving projections. In Proceedings of Advances in Neural Information Processing Systems, Vancouver, Canada. pp. 585-591.
- He XF, Yan SC, Hu Y, Niyogi P, Zhang H (2005). Face recognition using Laplacian faces. *IEEE Trans. Patt. Anal. Mach. Intell.*, 27(3): 328-340.
- Huang DS, Jia W, Zhang D (2008). Palmprint verification based on principal lines. *Patt. Recog.*, 41(4): 1316-1328.
- Hu DW, Feng GY, Zhou ZT (2007). Two-dimensional locality preserving projections (2DLPP) with its application to palmprint recognition. *Patt. Recog.*, 40: 339-342.
- Jolliffe IT (1986). *Principal Component Analysis*. Springer, New York, USA.
- Kong A, Zhang D, Kamel M (2006). Palmprint identification using feature-level fusion. *Patt. Recog.*, 39(3): 478-487.
- Kong A, Zhang D, Kamel M (2009). A survey of palmprint recognition. *Patt. Recog.*, 42(7): 1408-1418.
- Leng L, Zhang JS, Khan MK, Chen X, Alghathbar K (2010). Dynamic Weighted Discrimination Power Analysis: a Novel Approach for Face and Palmprint Recognition in DCT Domain. *Int. J. Phys. Sci.*, 5(17): 2543-2554.
- Lu GM, Zhang D, Wang KQ (2003). Palmprint recognition using Eigenpalms features. *Patt. Recog. Lett.*, 24(9-10): 1463-1467.
- Manisha PD, Madhuri AJ, Neena G (2009). Texture based palmprint identification using DCT features. In Proceedings of seventh International Conference on Advanced in Pattern Recognition, Kolkata, Indian, pp. 221-224.
- Murat E, Murat A (2008). Palmprint recognition by applying Wavelet-based kernel PCA. *J. Comput. Sci. Technol.*, 23(5): 851-861.
- The PolyU Palmprint Database (2004). The Hong Kong Polytechnic University, <http://www.comp.polyu.edu.hk/~biometrics/>.
- Wang JG, Yau WY (2008). A. Suwandy and E. Sung. Person recognition by fusing palmprint and palm vein images based on Laplacianpalm representation. *Patt. Recog.*, 41(5): 1514-1527.
- Wong WK, Zhao HT (2011). Supervised optimal locality preserving projection. *Patt. Recog.* (In press).
- Wu XQ, Zhang D, Wang KQ (2003). Fisherpalms based palmprint recognition. *Patt. Recog. Lett.*, 24(15): 2829-2838.
- You XG, Du L, Cheung YM, Chen QH (2010). A blind watermarking scheme using new nontensor product Wavelet filter banks. *IEEE Trans. Image. Process.*, 19(2): 3271-3284.
- Yu WW, Teng XL, Liu CQ (2006). Face recognition using discriminant locality preserving projections. *Image and Vision Computing*, 24(3): 239-248.
- Yue F, Zuo WM, Zhang D, Wang KQ (2009). Orientation selection using modified FCM for competitive code-based palmprint recognition. *Patt. Recog.*, 42(11): 2841-2849.
- Zhang D, Kong WK, You J, Wong M (2003). Online palmprint identification. *IEEE Trans. Patt. Anal. Mach. Intell.*, 25(9): 1041-1050.
- Zheng ZL, Yang F, Tan WN (2007). Gabor feature-based face recognition using supervised locality preserving projection. *Signal Process.* 87(10): 2473-2483.