S2DLDP with its Application to Palmprint Recognition

Ligang Liu[1], Jianxin Zhang[1(✉)], and Yinghua Jiang[2]

[1] Key Lab of Advanced Design and Intelligent Computing, Ministry of Education, Dalian University, Dalian, People's Republic of China
zjx99326@163.com

[2] Information and Engineering College, Dalian University, Dalian, People's Republic of China

Abstract. In this paper, we introduce the sparse two-dimensional local discriminant projections (S2DLDP) algorithm into palmprint recognition, and give an exactly recognition performance evaluation of the S2DLDP algorithm on public PolyU palmprint database. S2DLDP algorithm applies the idea of sparse for 2DLDP, possessing advantages of high computational efficiency and recognition performance. We perform the algorithm using various non-zero elements and image sizes, and then compare it with LDA, LPP and DLPP algorithm. The optimal recognition rate obtained by S2DLDP is 99.5%, which is significantly higher than the other three methods. Experiment results illuminate the excellent effectiveness of the S2DLDP algorithm for palmprint recognition.

Keywords: S2DLDP · Sparse projection · Palmprint recognition

1 Introduction

Palmprint recognition is regarded as a potential biometric recognition technology. It has the advantages of low capture cost and high recognition accuracy, and can be widely applied to employees' attendance system, building security control, automatic teller machines and ID card [1–4].

Palmprint recognition mainly includes two key steps, i.e., feature extraction and classifier construction [4]. Generally, feature extraction algorithms have great influence to the recognition accuracy. Due to the characteristics of highly descriptive, low computational cost and well separability, the subspace-based feature extraction methods have been widely researched for palmprint recognition. The main idea of subspace recognition methods is to put the high dimensional matrix projection into a low dimensional space, thereby reducing the processing dimension and obtaining the recognition features. The subspace algorithms maintain the specific characteristic of the palmprint with lower dimensional vectors or matrices. Currently, the main subspace projection methods include principal component analysis (PCA), linear discriminant analysis (LDA), locality preserving projection (LPP) [5] and discriminant locality preserving projections (DLPP) [6], etc. Although PCA and LDA have been widely used in image processing field, they have some obvious disadvantages for recognition. PCA and LDA consider global statistical properties based on the training data, while ignore the local nature of

Y. Zhao et al. (Eds.): ICIG 2017, Part I, LNCS 10666, pp. 1–10, 2017.
https://doi.org/10.1007/978-3-319-71607-7_1

the sample data. For palmprint recognition, as the original sample data form is matrix, LDA and DLPP need to transform image matrix into a long vector form, which breaks the continuity properties of the image data in a certain degree. Also, this increases the time complexity due to the high dimension vector, and generates small sample problems. Therefore, some scholars propose some typical two-dimensional subspace methods, such as two-dimensional principal component analysis (2DPCA) [7], two-dimensional linear discriminant analysis (2DLDA) [8] two-dimensional locality preserving projections (2DLPP) [9] and two-dimensional discriminant locality preserving projections (2DDLPP) based on the comprehensive of sample class information.

However, at the point of the extracted features in a low-dimensional subspace, the greatest disadvantage of all methods mentioned above is that the learned projection axes are linear combination of all the original features. So, it is difficult to physically interpret the extracted features. In order to solve this problem, Zuo et al. [10] proposed sparse principle components analysis (SPCA) that uses the least angle regression [11, 12] and the Elastic Net [13]. Zhao et al. [14] proposed a spectral bounds framework for sparse subspace, and they also proposed sparse PCA and sparse LDA (SLDA). The sparse subspace algorithm has been widely studied. Though SPCA and SLDA can directly operate on the high dimensional vectors, they have two limitations. One limitation is time-consuming when the dimension of the features is very high. Another one is some manifold structural information embedded in the two-dimensional images may be lost. Recently, Lai et al. [15] introduced the idea of sparse into 2DDLPP and proposed a novel and effective image feature extraction method named sparse two-dimensional local discriminant projections (S2DLDP). The S2DLDP method shows well recognition performance for face recognition. This paper studies the application of S2DLDP methods in palmprint recognition.

The rest of the paper is organized as follows: Sect. 2 describes the algorithm theory of S2DLDP. Section 3 presents the experimental results and gives some analysis of them. Section 4 offers our conclusions.

2 Palmprint Feature Extraction Based S2DLDP

Research results have proven that discriminative features play an important role in recognition and classification problems, and sparse-based feature extraction method can achieve better recognition performance [16]. In essence, the S2DLDP algorithm is 2DLDP form of sparse representation. This algorithm uses a direct sparse regression approach instead of the palm image matrix. It not only has high computational efficiency, but also can get more intuitive sparse projection matrix.

2.1 Two-Dimensional Discriminant Locality Preserving Projections (2DDLPP)

The main idea of 2DDLPP is projecting $m \times n$ image matrix A_i to the w by a linear transformation $y_i = A_i w$, and to get an m-dimensional column vector y_i, which is called the projection feature vector of image A_i. Given the projection vector P_{Φ}, sample array

$B_1, B_2, \ldots, B_M$ can be mapped to a set of d dimensional Euclidean space points $Z_1, Z_2, \ldots, Z_M$, where $Z_i^T = P_{\Phi}^T B_i, i = 1, \ldots, M$.

To resolve optimal projection vector P_{Φ}, we can turn 2DDLPP into the minimization of following function:

$$\sum_{i,j=1}^{M} \left\| Z_i - Z_j \right\|^2 W(i,j) \tag{1}$$

However, the issue can be transformed into a generalized eigenvalue problem:

$$P_{\Phi}^T S_L P_{\Phi} = \lambda P_{\Phi}^T S_L P_{\Phi} \Rightarrow S_L P_{\Phi} = \lambda S_D P_{\Phi} \tag{2}$$

S_D, S_W and S_L are respectively defined as:

$$S_D = \sum_{i=1}^{M} B_i B_i^T D_{ii}, S_w = \sum_{i,j=1}^{M} B_i B_j^T D_{ij}, S_L = S_D - S_W$$

S_L is the 2D Laplacian matrix. The larger value of D_{ii}, the more important of the position B_i, and the position of the projection results Z_i is more important. The optimal feature vectors $P_{\Phi_1}, \ldots, P_{\Phi d}$ should be the eigenvectors corresponding to a group of the smallest eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_d$ from the characteristic Eq. (2), and then we can get all features matrix of the sample to complete the feature extraction.

$$Z_i^T = \left[Z_i^{(1)}, \ldots, Z_i^{(d)}\right]^T = P^T B_i, i = 1, \ldots, M \tag{3}$$

2DDLPP avoids the singular value problem exists in DLPP to obtain the final matrix. Meanwhile, it possesses the characteristics of simple calculation, simple application and keeps the characteristics of nonlinear local retention from DLPP.

2.2 Sparse Two-Dimensional Local Discriminant Projections (S2DLDP)

Optimal projection from local feature extraction method, basing on image matrix, is often obtained by solving the eigenvalue equation. According to supervised learning representative model and unsupervised learning representative model, Lai [15] summarizes 2D projection learning framework as:

$$X^T \left(L_b \otimes I_{n1}\right) X\varphi = \lambda X^T \left(L_w \otimes I_{n1}\right) X\varphi \tag{4}$$

L_b and L_w represent image diagonal weighting matrices, and I_{n1} is an identity matrix of order n_1. The operator $\otimes$ is kronecker product of the matrices. Note that there are two obvious limitations in 2D projection learning framework. One is the high computational complexity due to the calculations of $X^T \left(L_b \otimes I_{n1}\right) X\varphi$ and $X^T \left(L_w \otimes I_{n1}\right) X\varphi$. Another is that learned projection axes are the linear combination of all the original features, which is difficult to semantically explain the extracted features. Therefore, the idea of sparsity is introduced.

To solve sparse problems, so far, researchers have put forward a lot of regression method for fitting data, which is representative of the Ridge regression, Lasso regression and Elastic Net regression. In this paper, we use Elastic Net regression to resolve the above equation. The two-dimensional representation of Elastic Net regression method is given:

$$\varphi = \arg\min_{\varphi} \left(\sum_{i=1}^{m} \sum_{h=1}^{n_1} (X_i(h,:) \times \varphi - y_i)^2 + a \sum_{j=1}^{n_2} \overline{\varphi}_j^2 + \beta \sum_{j=1}^{n_2} \left| \overline{\varphi}_j \right| \right) \tag{5}$$

Elastic net regression is widely used for feature extraction, which compounds Ridge regression and Lasso regression. It also introduces the l_1 norm and l_2 norm, and overcomes the limitations of Lasso regression. The selected features of elastic net regression, unaffected by sample restrictions on the number, effectively choose the characteristics of the groups [17–19]. In this paper, the S2DLDP algorithm is implemented in this way. After the algorithm introduces sparse limit, Lai [15] draws the following algorithm model framework:

$$\begin{cases} X^T \left(L_b \otimes I_{n1} \right) X\varphi = \lambda X^T \left(L_w \otimes I_{n1} \right) X\varphi \\ subject\ to\ Card(\varphi) \leq K \end{cases} \tag{6}$$

Among them, $Card(\varphi)$ is the number of non-zero elements contained in vectors φ, K is a positive integer not greater than the dimension of the image matrix.

3 The Experimental Results and Analysis

To test the application efficiency of S2DLDP in palmprint recognition, we perform the algorithm in PolyU palmprint database and give an exactly comparison with several typical subspace methods. PolyU palmprint database is the largest and most widely used palmprint database with the original palmprint image size of 384 * 284 pixels. Our experiment is tested on a subset of the PolyU database. The subset consists of 1000 images form 100 palms. We segment the region of interest (ROI) in these images, and then the image size is 128 * 128 pixels. In the experiment, we select the top four images of each person as the training image, and the remained six images as test set. In recognition phase, the Euclidean distance is employed to calculate the similarity between palmprint features (Fig. 1).

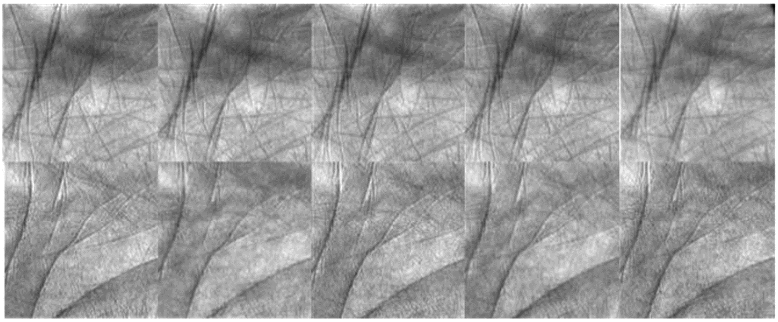

Fig. 1. Typical palmprint ROI images in PolyU database

3.1 The Non-zero Number Test Result

From Eq. 6 we can get that non-zero $Card(\varphi)$ in vector has the function of sparse restriction in image. The feature corresponding to the non-zero element is important, and influences the objective function. Based on this conclusion, to some extent, we discovery the features play a key role in the palmprint recognition. So it is not necessary to use the whole features, but only the key features. This has certain guidance in terms of the acquired characteristics. Therefore, studying the number of non-zero elements $Card(\varphi)$ under circumstances may achieve better recognition results.

At first, the eigen-palms learned by S2DLDP with $Card(\varphi)$ = 1:4:20 are shown in Fig. 2, where the eigen-palms are much clearer. This indicates that non-zero elements automatically form the palm profiles in the metrics of the S2DLDP algorithm. Thus S2DLDP can learn a set of semantic palm contours. This method not only gives a meaningful and intuitive explanation on the learned subspace, but also shows us the more discriminative feature subspace for palmprint recognition.

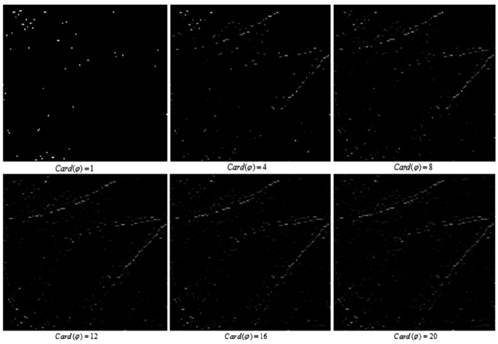

Fig. 2. Eigen-palm using various $Card(\varphi)$

$Card(\varphi)$ = 4:8:40 are taken to experiment, and we calculate the recognition rate under various $Card(\varphi)$. Then, we draw recognition rate in different experiments plotted in the same figure for comparison in Fig. 3, where the horizontal axes d, varying from 1 to 50 with one step, denotes the various dimension of features.

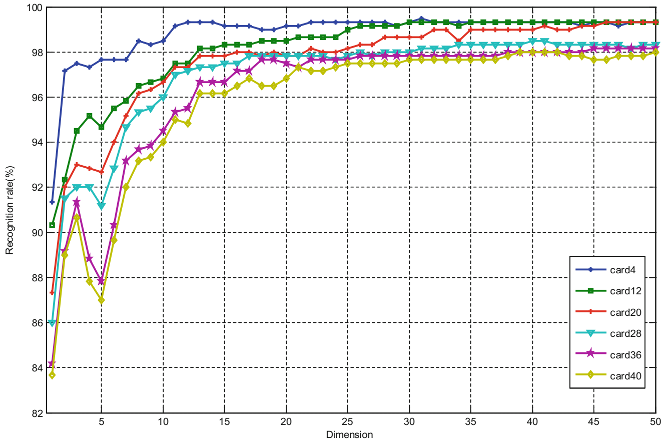

Fig. 3. Comparative palmprint recognition rate with various $Card(\varphi)$

In Fig. 3, recognition result gradually deteriorates with the increase of value $Card(\varphi)$. To achieve better recognition results, the number of non-zero should take a smaller value, and we set the value with 4. Note that when the number of non-zero elements is more, the effectiveness to enhance identify is not obvious. This experiment indicates that the sparse-palms with a large $Card(\varphi)$ are not necessary to obtain higher recognition rates. The above two figures show us an insightful understanding of the appearance-based 2D palm image representation and recognition.

3.2 The Image Size Test Result

After repeated experiments, the S2DLDP algorithm achieves optimal performance with $Card(\varphi) = 4$ and nearest neighbor number $k = 1$. Therefore, under the above conditions, we evaluate the effectiveness of recognition rate using various sub-image sizes of 32×32, 64×64, 128×128 pixels, respectively. Then, some different eigen-palms are given in Fig. 4 and comparison results are illustrated in Fig. 5, in which we take $d = 1{:}\ 1{:}\ 100$ as horizontal axes.

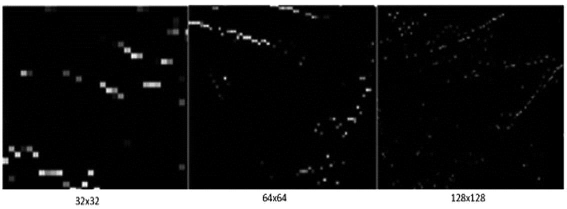

Fig. 4. Comparative eigen-palms based on different sub image size

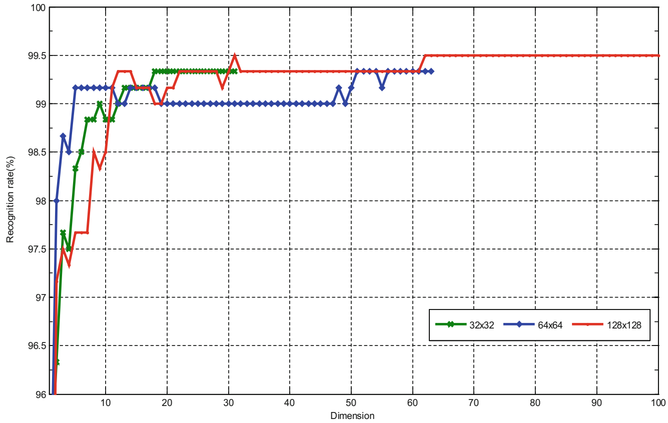

Fig. 5. Comparative recognition rate result based on different sub-image size

In Fig. 5, the recognition rate under different sub image size shows a trend of growth with the increase of the dimension size image characteristics, and gradually stabilizes. Meanwhile, curve clearly shows that S2DLDP algorithm achieves better recognition rate in dealing with a larger image, and the recognition rate can reach 99.5%. What is more, when image size is 32×32 pixel, recognition rate has no obvious descend, as the change of dimension.

3.3 The Comparative Test Result with LDA, LPP and DLPP

To further illustrate the effectiveness of the algorithm which is used to identify, experiment changes the number of training samples, using the top three and five palmprint images of each person as the training image, the remained images as the test images.

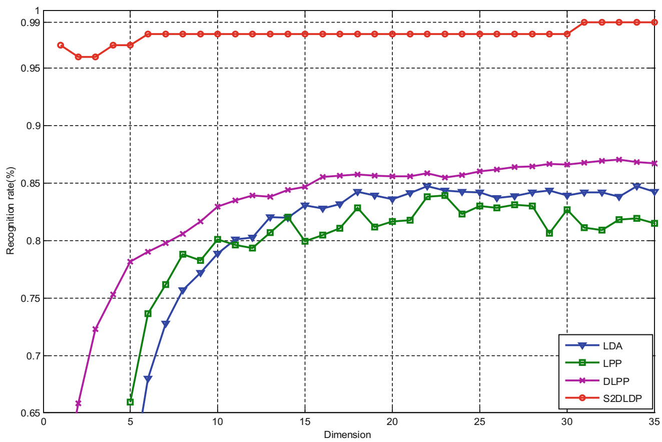

Fig. 6. The comparison of recognition rate for 3 training samples

For S2DLDP algorithm, the parameters do not change. In order to save computation time, all of the images are resized to 32 * 32 pixels. The comparative test results are given in Figs. 6 and 7 in which we take $d = 1: 1: 35$ as horizontal axes. The best recognition performance under corresponding feature dimension is shown in Table 1.

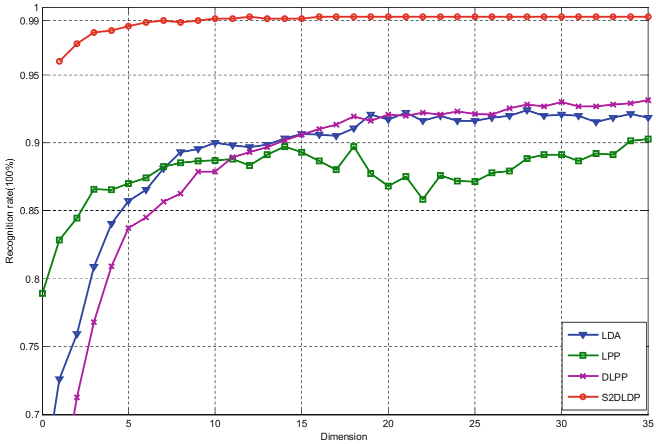

Fig. 7. The comparison result of recognition rate for 5 training samples

Table 1. The optimal recognition rate results with feature dimension of the four methods on the PolyU palmprint database

Methods	3 training samples		5 training samples	
	Recognition rate (%)	Dimension	Recognition rate (%)	Dimension
LDA	85%	22	92%	20
LPP	84%	23	90%	18
DLPP	87%	33	93%	30
S2DLDP	99%	31	99.5%	6

In Figs. 6 and 7, the recognition rates of S2DLDP are significantly higher than other methods. S2DLDP not only gives an intuitively semantic interpretation of the learned subspace, but also shows that palm profile subspace is more discriminative for palmprint recognition.

4 Conclusions

In this paper, the S2DLDP algorithm is introduced into palmprint recognition, and achieves the optimal recognition rate of 99.5%. The S2DLDP algorithm fully integrates the local separability, sample information and inherent attribute of two-dimensional images. To a certain extent, it reduces the complexity of calculation and improves the recognition rate. This algorithm provides intuitive, semantics, and interpretable palmprint feature space, and the palmprint features extracted have strong distinction. The experimental results show that the sparse projection in the process of feature extraction and dimensionality reduction realizes the function of feature selection, also proves its validity application for palmprint recognition.

Acknowledgments. The work is supported by the Natural Science Foundation of Liaoning Province (No. 201602035) and the High-level Talent Innovation Support Program of Dalian City (No. 2016RQ078).

References

1. Tamrakar, D., Khanna, P.: Noise and rotation invariant RDF descriptor for palmprint identification. Multimedia Tools Appl. **75**, 5777–5794 (2016)
2. Leng, L., Li, M., Kim, C., et al.: Dual-source discrimination power analysis for multi-instance contactless palmprint recognition. Multimedia Tools Appl. **76**, 333–354 (2017)
3. Guo, Z.H., Zhang, D., Zhang, L., et al.: Feature band selection for online multispectral palmprint recognition. IEEE Trans. Inf. Forensics Secur. **7**, 1094–1099 (2012)
4. Li, H., Zhang, J., Wang, L.: Robust palmprint identification based on directional representations and compressed sensing. Multimedia Tools Appl. **70**, 2331–2345 (2012)
5. Yang, J., Zhang, D., Yang, J.Y., et al.: Globally maximizing, locally minimizing: unsupervised discriminant projection with applications to face and palm biometrics. IEEE Trans. Pattern Anal. Mach. Intell. **29**, 650–664 (2004)
6. Zhong, F., Zhang, J., Li, D.: Discriminant locality preserving projections based on L1-norm maximization. IEEE Trans. Neural Networks Learn. Syst. **25**, 2065–2074 (2014)
7. Yang, J., Zhang, D., Frangi, A.F., et al.: Two-dimensional PCA: a new approach to appearance-based face representation and recognition. IEEE Trans. Pattern Anal. Mach. Intell. **26**, 131–137 (2004)
8. Li, M., Yuan, B.: 2D-LDA: a statistical linear discriminant analysis for image matrix. Pattern Recogn. Lett. **26**, 527–532 (2005)
9. Hu, D., Feng, G., Zhou, Z.: Two-dimensional locality preserving projections (2DLPP) with its application to palmprint recognition. Pattern Recogn. **40**, 339–342 (2008)
10. Zou, H., Hastie, T., Tibshirani, R.: Sparse principal component analysis. J. Comput. Graph. Stat. **15**, 265–286 (2006)
11. Gluhovsky, I.: Multinomial least angle regression. IEEE Trans. Neural Networks Learn. Syst. **23**, 169–174 (2012)
12. Hagiwara, K.: Least angle regression in orthogonal case. In: Loo, C.K., Yap, K.S., Wong, K.W., Teoh, A., Huang, K. (eds.) ICONIP 2014. LNCS, vol. 8835, pp. 540–547. Springer, Cham (2014). https://doi.org/10.1007/978-3-319-12640-1_65
13. Wang, L., Cheng, H.: Robust sparse PCA via weighted elastic net. Pattern Recogn. **321**, 88–95 (2012)
14. Zhao, Q., Meng, D., Xu, Z.: Robust sparse principal component analysis. Sci. Chin. Inf. Sci. **57**, 1–14 (2014)
15. Lai, Z., Wan, M., Jin, Z., et al.: Sparse two-dimensional local discriminant projections for feature extraction. Neurocomputing **74**, 629–637 (2011)
16. Wagner, A., Wright, J., Ganesh, A., et al.: Toward a practical face recognition system: robust alignment and illumination by sparse representation. IEEE Trans. Pattern Anal. Mach. Intell. **34**, 372–386 (2012)

17. Li, C.N., Shao, Y.H., Deng, N.Y.: Robust L1-norm two-dimensional linear discriminant analysis. Neural Netw. Official J. Int. Neural Netw. Soc. **65**, 92–104 (2015)
18. Wang, J., Lu, C., Wang, M., et al.: Robust face recognition via adaptive sparse representation. IEEE Trans. Cybern. **44**, 2368–2378 (2014)
19. Zhong, F., Zhang, J.: Linear discriminant analysis based on L1-norm maximization. IEEE Trans. Image Process. **22**, 3018–3027 (2013)