AN IMPROVED 2DLPP METHOD ON GABOR FEATURES FOR PALMPRINT RECOGNITION

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ABSTRACT

We propose an improved 2DLPP method on Gabor features (I2DLPPG) for palmprint recognition in this paper. 2DPCA is first utilized for dimensionality reduction of Gabor feature space maintaining most prominent 2D information. Thus similarity matrix corresponding to elements is easily constructed and the followed 2DLPP can be implemented directly in the reduced feature space. The proposed method preserving more intrinsic manifold structure of feature matrices yields higher recognition accuracy than the existing 2DLPP which treats the Gabor feature matrices as a whole. Meanwhile, fewer coefficients are extracted for image representation and recognition owing to 2DLPP and 2DPCA in the row and column directions simultaneously. Euclidean distance and the nearest classifier are finally used for classification. The recognition accuracy of the proposed I2DLPPG can reach 99.5% with 15×5 features. Experiments results demonstrate the effectiveness of our proposed method in both recognition accuracy and speed.

Index Terms— LPP, 2DLPP, 2DPCA , Gabor , recognition

1. INTRODUCTION

Locality Preserving Projection (LPP) is an effective appearance-based approach for biometric recognition appeared in recent researches. Although Principle Component Analysis (PCA) [2] and Linear Discriminant Analysis (LDA) [3] are prevailing methods for dimensionality reduction, Euclidean structure can only be observed [1]. LPP emphasizes the manifold structure modeled by a nearest-neighbor graph which preserves the local structure of the image space. He[1] first applied LPP to face recognition and Laplicianfaces obtains satisfying recognition results. LPP is implemented on 1D vectors converted from the original 2D image matrix. The vectors of all the training samples are spanned to a space matrix of considerately large dimension. PCA is implemented before LPP to avoid the singular matrix and remove the noise effect.

2D methods that handle image matrices directly instead of transforming the matrix into 1D vectors was by first proposed by Yang [4]. His 2DPCA is a popular technique widely used in many applications with more effective and accurate results. Similarly 2DLPP [5, 6] was proposed to handle image matrix directly. 2DLPP not only solves the problem of singularity matrix without the preprocessing of PCA but avoids the loss of some structural information existing in original 2D images. Thus a higher recognition rate can be obtained.

2DLPP can be concluded to solve a generalized eigenvalues problem [6]

$$XLX^T a = \lambda XDX^T a \tag{1}$$

Differ from LPP, S, D, L are matrix-based rather than vector-based. There are three problems deserving attention.

The first is concerned with similarity matrix S. Because 2DLPP treat the image matrix directly, S_{ij} is a value of images X_i and X_j of $m\times n$ pixels according to the distance between the two images, not within the images. The same similarity value is imposed on the image matrix contradicting with the purpose of LPP aiming at the intrinsic manifold structures, which will inevitably affect the recognition accuracy of 2DLPP. S_{ij} is more reasonably to be defined as a $n\times n$ matrix with elements determined by the k-nearest neighborhood according to the distance matrix of images X_i and X_j of within images. If the number of training samples is N, then the size of similarity matrix S is $N\times N\times n\times n$. D and L are of the same dimensionality. For example, if a training set composes of 200 128×128 images, the dimensions of S, D, L are $200\times200\times128\times128$. Feasible it may sound; the large scale of S, D, L makes implementation still beyond reach.

Large dimensionality of training sample space is another problem to be dealt with. If numbers of the training sample and the image size are large, XLX^T and XDX^T can not be worked out directly, modular matrix calculation of $2N^2$ multiplications and $2(N^2-1)$ accumulations are required, respectively.

The third problem is that 2DLPP requires more coefficients for image representation and recognition which commonly exists in 2D projections.

Inspired by $(2D)^2$PCA [7], which implement 2DPCA to reduce the space dimension in column and row direction simultaneously, 2DLPP can be implemented in the column direction after 2DPCA projection in row direction. 2DPCA can effectively reduce the space dimension as well as preserve most prominent 2D information. Thus similarity matrix corresponding to pixels rather than treating the image matrices as a whole is easily constructed and 2DLPP can be implemented directly without modular matrix calculation in the reduced feature space. The proposed method can preserve more intrinsic manifold structure of image matrices and yield fewer coefficients for the projection in two directions than the existing 2DLPP. Additionally, Gabor features of the images are more robust to the variations in illumination and rotation than the gray-level images. So an improved 2DLPP on Gabor features (I2DLPPG) is proposed in this paper. Fig.1 illustrates the implementation procedure

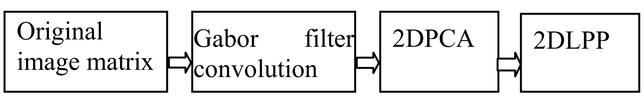


Fig.1. procedure of the improved 2DLPP on Gabor features

The rest of this paper is organized as follows: Section 2 introduces the proposed 2DLPPG algorithm. Section 3 reports our experiments and results analysis. Section 4 highlights the conclusions.

2. THE PROPOSED IMPROVED 2DLPP BASING ON GABOR FEATURES (I2DLPPG)

2. 1 Gabor feature extraction

2D Gabor has the following general form [9]:

$$G(x,y,\theta,u,\sigma)=\frac{1}{2\pi\sigma^2}\exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\}\exp\left\{2\pi i\left(ux\cos\theta+uy\sin\theta\right)\right\} \tag{2}$$

where $i=\sqrt{-1}$, u is the frequency of the sinusoidal wave, θ controls the orientation of the function, and σ is the standard deviation of the Gaussian envelope. D. Zhang and W.K. Kong [9] successfully applied Gabor filter to palmprint recognition. Generally the parameters of Gabor filters were set according to experience and a group of Gabor filters named Gabor filter bank of different scales and orientation are used for multiple features extraction in most biometric recognition [8].This will inevitably increase the cost of computation in time and speed. Thus Gabor features here are extracted only by a Gabor filter of θ =0, u=1.4656, σ =5.6179. The convolution of the Gabor filter and each image yield Gabor vectors X_i which are spanned to Gabor feature space $X=[X_1,X_2,...,X_N]$.

2. 2 2DPCA

Two dimensional PCA (2DPCA) directly treated the space matrix in row direction to yield an optimum projection [4]. The covariance matrix can be evaluated by

$$G=\frac{1}{N}\sum_{i=1}^{N}(X_i-\overline{X})^T(X_i-\overline{X}) \tag{3}$$

where average vector is

$$\overline{X}=\frac{1}{N}\sum_i X_i \tag{4}$$

The orthonormal eigenvectors of G corresponding to the d largest optimal value is proven to be optimal projection matrix

$$R_{opt}=[R_1,...,R_d] \tag{5}$$

The value of d can be determined by the ratio of the sum of chosen d largest eigenvalues to all which is normally no less than 93%. Project the Gabor feature space onto the row direction yielding

$$Z=XR \tag{6}$$

where $Z=[Z_1,Z_2,...,Z_N]$.

2.3 Improved 2DLPP

After 2DPCA projection in the row direction, the objective function of 2DLPP can be defined as [6]

$$\min\sum_{i,j}\left\|Y_i-Y_j\right\|^2 S_{ij} \tag{7}$$

Where Y_i is the n-dimensional representation of $m\times d$ ($d<<n$) matrix Z_i , and $\|\bullet\|$ means L_2 norm. Here S_{ij} can be defined according to distance matrix ($d\times d$) of Z_i and Z_j . S is a similarity matrix of $N\times N\times d\times d$. S_{ijkl} can be defined as $S_{ijkl}=1$ or $S_{ijkl}=\exp(\left\|Z_i-Z_j\right\|^2/t)$, if S_{ijkl} is among k minimum values of S_{ij}, which means the nearest pixels in distance matrix of Z_i or Z_j , otherwise $S_{ijkl}=0$. The transform matrix a can be obtained by solving the generalized eigenvalues problem

$$ZLZ^Ta=\lambda ZDZ^Ta \tag{8}$$

D is a diagonal matrix whose entries are column or row sums of S . $L=D-S$ is the Laplacian matrix. As the compressed space Z is $m\times N\times d$, XLX^T and XDX^T can be directly implemented without the modular matrix computation. The minimum eigenvectors $a_1,...,a_q$ of Eq. 8

corresponding to the q minimum eigenvalues formed the optimal projection matrix A_{opt}, i.e. $A_{opt} = [A_1, ..., A_q]$.

2.4 The improved 2DLPP on Gabor features (I2DLPPG)

The optimum projection matrix of 2DPCA $R_{opt} = [R_1, ..., R_d]$ and 2DLPP $A_{opt} = [A_1, ..., A_q]$ can be obtained from the above parts. Then project the $m \times n$ image X_i onto R and A simultaneously, yielding a $q \times d$ matrix Y_i

$$Y_i = A^T X_i R \tag{9}$$

Given a test image X_{test}, the feature matrix Y_{test} is

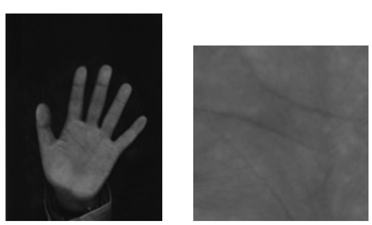
$$Y_{test} = A^T X_{test} R \tag{10}$$

Euclidean distance and the nearest classifier are applied for classification.

$$d(Y_{test}, Y_i) = \|Y_{test} - Y_i\| = \sqrt{\sum_{k=1}^{q \times d} (Y_{test} - Y_i)(Y_{test} - Y_i)^T} \tag{11}$$

3. EXPERIMENTS AND RESULTS

400 left hand images of 595 × 790 pixels of 75 dpi resolution were collected from 40 subjects by a digital scanner in our lab at an interval of three months. Subjects can spread their hands on a big scanner freely to capture images which contain tilting, rotation and variations. In our experiments, the central 128 × 128 pixels of each hand image extracted by the preprocessing method [10] constitute a palmprint database (see Fig.1). All the experiments are executed on the computer system of PIV 2.67GHz and 256MB RAM with Matlab 6.1. Fig.2 exemplifies some palmprint samples in the database.



(a) (b)

Fig.1 original image and experimental image (a) original hand image (b) palmprint image

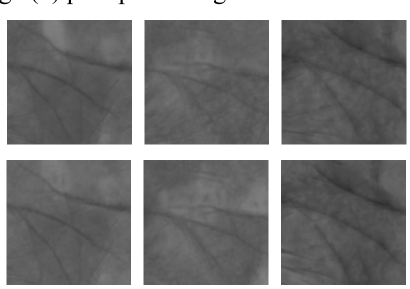


Fig.2 some examples in the palmprint database

To test the performance of the proposed method, PCA+LPP, 2DLPP and I2DLPP are executed on the original images and Gabor features obtained by Gabor convolution (see in part 2.1). The first five images per person are used for training and the rest five for testing set, i.e. both the training set and testing set contain 200 images. Table 1 presents the top recognition accuracy, final dimension and time for projection and recognition of the experiments. Improved 2DLPP outperforms better recognition accuracy than PCA+LPP and 2DLPP on both original images and Gabor features, validating the similarity matrix according to pixels is more effective than treating the matrices as a whole. Feature dimension of I2DLPP is much less than that of 2DLPP for the two-directional dimensionality reduction. The top recognition accuracy can reach 98% and 99.5% by the Improved 2DLPP method on original images(I2DLPPO) and Gabor features (I2DLPPG) with the corresponding feature dimension of 10×5 and 14×5, far below than 128×5 of 2DLPP. Fewer features coefficients shorten the time for projection and recognition to 1s with comparison 3.6560s of 2DLPP.

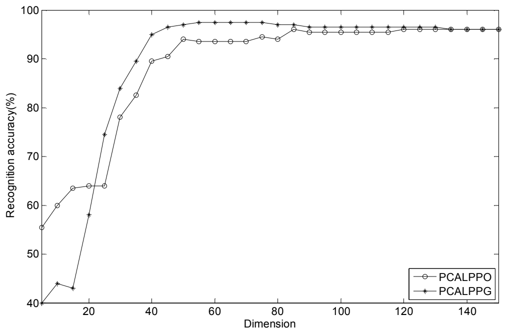
Table 1 Comparison of the top recognition accuracy, final dimension and time on original images and Gabor features

	Top recognition accuracy (%)	dimension	time(s)
PCALPPO	96.00	85	1.3430
2DLPPO	97.00	128×5	3.7030
I2DLPPO	**98.00**	**10×5**	**0.9840**
PCALPPG	97.50	55	1.2030
2DLPPG	98.00	128×5	3.6560
I2DLPPG	**99.50**	**15×5**	**1.0000**

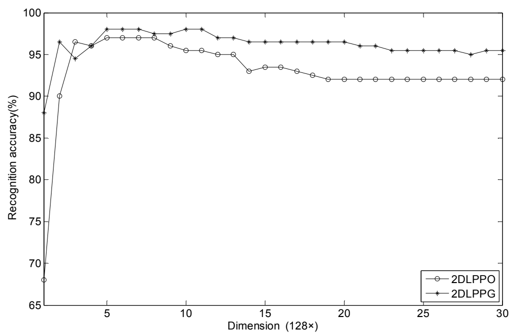
For further analysis, the recognition accuracy under different dimension is illustrated in Fig3. (a), (b), (c) correspond to PCA+LPP, 2DLPP, I2DLPP respectively. Gabor features obtain better recognition accuracy than original images by all the methods under different dimensions, which prove the robustness characteristic against variation of illusion and rotation in image representation and recognition. Especially, I2DLPPG has a stable better tendency in recognition accuracy when the dimension exceeds 40. The best results of different number of training samples on Gabor features are listed in Table 3. It can be seen that the proposed I2DLPPG performs best of the methods.

Table 2 Comparison of the top recognition accuracy (%) of different number of training samples

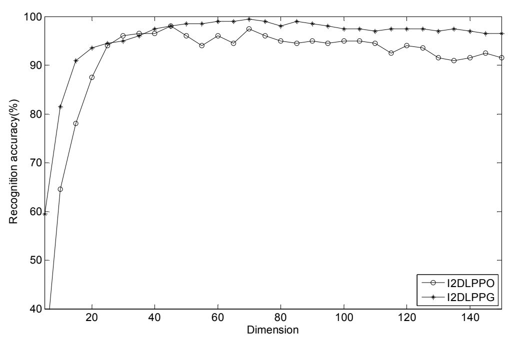
	2 Train	3 Train	4 Train	5 Train
PCALPPG	88.75	91.79	94.17	97.50
2DLPPG	89.69	93.57	96.67	98.00
I2DLPPG	**91.56**	**95.00**	**98.33**	**99.50**



(a)



(b)



(c)

Fig. 3 comparison of recognition accuracy on original images and Gabor features (a) PCA+LPP, (b) 2DLPP, (c) I2DLPP

4. CONCLUSION AND DISCUSSION

In this paper, an efficient palmprint representation method called improved 2DLPP on Gabor features (I2DLPPG) is proposed. 2DPCA is first utilized for dimensionality reduction of Gabor feature space maintaining most prominent 2D information. Thus similarity matrix corresponding to elements is easily constructed and the followed 2DLPP can be implemented directly in the reduced feature space. The proposed method preserving more intrinsic manifold structure of feature matrices yields higher recognition accuracy than the existing 2DLPP which treats the Gabor feature matrices as a whole. Meanwhile, fewer coefficients are extracted for image representation and recognition owing to 2DLPP and 2DPCA in the row and column directions simultaneously. Thus time for representation and recognition is greatly reduced. The best recognition accuracy of the proposed I2DLPPG can reach 99.5% with 15×5 features. Experiments results demonstrate the effectiveness of our proposed method in both recognition accuracy and speed.

5. ACKNOWLEDGEMENTS

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6. REFERENCES

[1] X. He, S.Yan, Y. Hu, P.Niyogi, and H. Zhang, “Face recognition using Laplicanfaces”, *IEEE Trans. Pattern Anal. Mach. Intell*. 27(3) ,pp.328-340, 2005.
[2] G. Lu, D. Zhang, and K. Wang, “Palmprint recognition using eigenpalms features”, *Pattern Recognition Lett*. 24(9), pp.1463-1467, 2003.
[3] X. Wu, D. Zhang, and K. Wang, “Fisherpalms based palmprint recognition”, *Pattern Recognition Lett*. 24 (15), pp. 2829-2838, 2003.
[4] J. Yang, D. Zhang, A. F. Frangi, and J.Y. Yang, “Two-dimensional PCA: a new approach to appearance-based face representation and recognition”, *IEEE Trans. Pattern Anal. Mach. Intell*. 26(1) ,pp.131-137, 2004.
[5] S. Chen, H. Zhao, M. Kong, B. Luo, 2DLPP: A two-dimensional extension of locality preserving projections, *Neurocomputing*, 70(4-6),pp912-921, 2007.
[6] D. Hu, G. Feng, and Z. Zhou, “Two-dimensional locality preserving projection (2DLPP) with its application to palmprint recognition”, *Pattern recognition*, 40(1), pp.339-342, 2007.
[7] D. Zhang, and Z. Zhou, “$(2D)^2$PCA: two-directional two-dimensional PCA for efficient face representation and recognition”, *Neurocomputing*, 69 (1-3) ,pp.224-231, 2005.
[8] C. Liu, “Gabor-Based kernel PCA with Fractional power polynomial models for face recognition”, *IEEE transaction on pattern analysis and machine intelligence*, 26(5), pp.572-581, 2004.
[9] D. Zhang, W. K. Kong, J. You, and M. Wong, “Online palmprint identification”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25 (9), pp.1041-1050, 2003.
[10] X. Pan, and Q. Ruan, “A Modified Preprocessing Method For Palmprint Recognition”, *Proceedings of the 8th International conference on Signal Processing (ICSP’06)*,2 , pp.1059-1062,2006.