Optimized Discriminant Locality Preserving Projection of Gabor Feature for Biometric Recognition

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Abstract

Discriminant locality preserving projection(DLPP) can not obtain optimal discriminant vectors which utmostly optimize the objective of DLPP. This paper proposed a Gabor based optimized discriminant locality preserving projections (ODLPP) algorithm which can directly optimize discriminant locality preserving criterion on high-dimensional Gabor feature space via simultaneous diagonalization, without any dimensionality reduction preprocessing. The proposed method is applied to face and finger vein recognition problems and is compared with some other related Gabor based dimensionality reduction techniques. Experimental results conducted on the VALID face database and a subset of PKU finger vein database indicates the effectiveness of the proposed algorithm.

Keywords: *Optimized Discriminant Locality Preserving Projection, Gabor Feature, Finger Vein Recognition, Face Recognition*

1. Introduction

Discriminant locality preserving projection (DLPP) [1] encodes discriminant information into the objective of locality preserving projection and can obtain better classification performance than LPP. However, DLPP suffers from “small sample problem”. To conquer such weakness of DLPP, we proposed the optimized discriminant locality preserving (ODLPP) algorithm. The proposed ODLPP directly implemented the objective of DLPP in high-dimensional space without matrix inverse, which utmostly obtain the optimal discriminant vectors for DLPP without larger computation burden. Like DLPP algorithm, ODLPP can be used to biometric feature extraction. In this paper, considering the high performance of Gabor filter in face [2], iris [3], fingerprints[4] and palmprints [5] recognition, we utilize the multi-channel Gabor filters to extract the face and finger vein feature, where finger vein recognition is a newly proposed biometrics and gradually become a hot research field [6, 7, 8]. However, Gabor filters in different orientation and scales are not orthogonal, there may be some redundant information between Gabor features in different orientations and scales. To eliminate the redundant information, ODLPP was used to reduce the dimensionality of high-dimensional Gabor feature vector.

The rest of this paper is organized as follows: Section 2 introduces our algorithm in detail. Experimental results are given in Section 3. Section 4 highlights the conclusions.

2. Optimized Discriminant Locality Preserving Projection in Gabor Feature Space

2.1 Overview of Discriminant Locality Preserving Projection

Given a set of training Gabor feature set $T = \{x_1, \cdots, x_N\}$, where x_i denotes an n-dimensional Gabor feature column vector and N is the number of samples. Each Gabor feature vector x_i belongs to one of the C classes $\{X_1, X_2, \cdots X_C\}$, where $X_i = \{x_1^i, x_2^i, \cdots, x_{n_i}^i\}$, $(i = 1, 2, \cdots, C)$. DLPP tries to maximize an objective function as follows [1]:

$$\sum_{i,j=1}^{C} (m_i - m_j) B_{ij} (m_i - m_j)^T / (\sum_{c=1}^{C} \sum_{i,j=1}^{n_c} (y_i^c - y_j^c) W_{ij}^c (y_i^c - y_j^c)^T) \tag{3}$$

where n_c is the number of samples in the cth class, $y_i^c = A^T x_i^c$ represents the ith projected vector in the cth class, A is the mapping from x_i^c to y_i^c. Let m_i and m_j denotes the column vector of mean of the ith class and jth class, separately. $m_i = \frac{1}{n_i} \sum_{k=1}^{n_i} y_k^i$ and $m_j = \frac{1}{n_j} \sum_{k=1}^{n_j} y_k^j$, where n_i and n_j are the number of samples in the ith class and jth class, separately. $W_{ij}^{(c)}$ represents the elements of within-class weight matrix and $W_{ij}^{(c)} = \exp(-\|x_i^c - x_j^c\|^2 / \sigma^2)$, and B_{ij} represents the elements of between-class weight matrix and $B_{ij} = \exp(-\|m_i - m_j\|^2 / \sigma^2)$, where σ is an empirically determined parameter, x_i^c represents the ith vector in the cth class. Thus, the between-class weight matrix is

$$W = diag\{W^{(1)}, W^{(2)}, \cdots, W^{(C)}\} \tag{4}$$

where $W^{(i)} = [W_{jk}^{(i)}](j, k = 1, 2, \cdots, n_i)$. It is clear that both B and W are symmetric positive semi-definite matrices. The objective function (3) can be rewritten as

$$J(A) = A^T FHF^T A / (A^T XLX^T A) \tag{5}$$

where L and H are within-class Laplacian matrices and between-class Laplacian matrices, respectively. $L = D - W$,

$$D = diag\{D^{(1)}, D^{(2)}, \cdots, D^{(C)}\} \tag{6}$$

D_i is a diagonal matrix and $D_{kk}^{(i)} = \sum_j W_{kj}^{(i)}$; $H = E - B$, E is a diagonal matrix and $E_{ii} = \sum_j B_{ij}$. $F = [m_1, m_2, \cdots, m_C]$, $X = [x_1, x_2, \cdots, x_N]$. The transformation matrix $A = [a_1, a_2, \cdots, a_m]$ that maximizes the objective function (5) can be obtained by solving the generalized eigenvalues problem

$$FHF^T a_i = \lambda_i XLX^T a_i, \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m \tag{7}$$

Transformation A is constructed by the m leading eigenvector corresponding the m maximal eigenvalue of $(XLX^T)^{-1}(FHF^T)$.

2.2 Optimized Discriminant Locality Preserving Projection

However, as the dimension of sample is always larger than the number of sample, XLX^T is always singular and is nonreversible, PCA can be used as a preprocessing means. But PCA as a preprecessing means may lost some useful discriminant information which can be extracted by DLPP. DDLPP simultaneously diagonalize XLX^T and FHF^T to obtain the projection subpace without matrix inverse. This method has been used in the former research [10]. Four steps were included in our proposed DDLPP which are presented as follows:

Step 1. Diagonalization of FHF^T . To find a matrix $V \in R^{n \times n}$ such that $V^T(FHF^T)V = \Delta$, where $V^TV = I$ and Δ is a diagonal matrix whose elements are ordered in decreasing order. Matrix V is formed by the eigenvectors of FHF^T . Suppose the rank of FHF^T is P , there should exist P nonzero eigenvalues. Let Y be the P first columns of V ($Y \in R^{n \times P}$), then we can write $Y^T(FHF^T)Y = Dig_H > 0$, where Dig_H corresponds to the main $P \times P$ submatrix of matrix Δ and it is a positive definite diagonal matrix, without zero elements on its diagonal.

Step 2. Let Z be defined as $Z = YDig_H^{1/2}$ with $Z \in R^{n \times P}$. Clearly,

$$(YDig_H^{1/2})^T(FHF^T)(YDig_H^{1/2}) = I_P \tag{8}$$

then $Z^T(FHF^T)Z = I_P$. Matrix Z diagonalizes FHF^T and reduces its dimension from $n \times n$ to $P \times P$.

Step 3. Diagonalization of $Z^T(XLX^T)Z$. To find a matrix $U \in R^{P \times P}$ such that $U^TZ^T(XLX^T)ZU = Dig_L$ with $U^TU = I$. Again it is possible to find $Dig_L \in R^{P \times P}$ and U through an eigenvalue eigenvector analysis of matrix $Z^T(XLX^T)Z$. Notice that Dig_L can contain zero elements on its diagonal. Features vectors corresponding zero elements are the optimal vectors for DDLPP.

Step 4. Let A be defined as $A = U^TZ^T$, with $A \in R^{P \times n}$. It's clear that matrix A can simultaneously diagonalize FHF^T and XLX^T . A corresponds to the matrix formed by the eigenvectors associated with the P nonzero eigenvalues of $(XLX^T)^{-1}(FHF^T)$. A is also the solution of our proposed DDLPP.

In step 1, we should perform eigen-decomposition on FHF^T , but the dimension of FHF^T is very high, especially original images are transformed into the high-dimensional Gabor space. For example, when the size of original image on VALID database is 64×64, the dimension of its Gabor feature is 40960, the dimension of FHF^T is 40960×40960 which is hard for eigen-decomposition. Section 2.2.3 provides a convenient way to solve the problem.

2.3 Analysis of Eigenvalues-eigenvectors in High Dimensional Spaces

Obviously, after Gabor transformation, the size of matrix FHF^T is very high. Determining the eigenvectors and eigenvalues of matrix FHF^T is an intractable task for a typical image size. Therefore, we need to find an efficient method to calculate the eigenvectors and eigenvalues. It is well known that the following formula is satisfied for the matrix FHF^T :

$$(FHF^T)u_k = \lambda_k u_k \tag{9}$$

where u_k refers to the eigenvector of the matrix FHF^T , and λ_k is the correlative eigenvalue of matrix FHF^T .

As H is a symmetry and semi-definite matrix, H can be written as follow:

$$H = (\square\sqrt{\Lambda})(\square\sqrt{\Lambda})^T \tag{10}$$

where Λ is the eigenvalue matrix whose elements are nonnegative [11]. FHF^T can be rectified as

$$FHF^T = F(\square\sqrt{\Lambda})(F(\square\sqrt{\Lambda}))^T \tag{11}$$

The eigenvectors (v_k) and eigenvalues (a_k) of matrix $(F(\square\sqrt{\Lambda}))^T(F(\square\sqrt{\Lambda})) \in R^{C \times C}$ are much easier to calculate. Therefore, we have

$$(F(\square\sqrt{\Lambda}))^T(F(\square\sqrt{\Lambda}))v_k = a_k v_k \tag{12}$$

Then, we multiply each side of the Eq. (12) by $(F(\square\sqrt{\Lambda}))$,

$$(F(\square\sqrt{\Lambda}))(F(\square\sqrt{\Lambda}))^T((F(\square\sqrt{\Lambda})v_k) = a_k(F(\square\sqrt{\Lambda})v_k)$$
$$(F(\square\sqrt{\Lambda}\sqrt{\Lambda}\square^T)F^T)((F(\square\sqrt{\Lambda})v_k) = a_k(F(\square\sqrt{\Lambda})v_k)$$
$$FHF^T((F(\square\sqrt{\Lambda})v_k) = a_k(F(\square\sqrt{\Lambda})v_k) \quad (13)$$

Then, we can get the eigenvectors of matrix FHF^T, $u_k = F(\square\sqrt{\Lambda})v_k$.

3. Experimental Evaluation

In this section, we experimentally evaluate results and discussions on the proposed scheme for Gabor based face recognition and finger vein recognition on the VALID face database and the subset of PKU finger vein database, respectively. The system performance is compared with PCA, LDA, LPP, DLPP, orthogonal locality preserving projection (OLPP) [12], discriminant orthogonal locality preserving projection (ONPP) [13] and orthogonal neighbor preserving projection (ONPP) [14]. The parameters of Gabor filter are similar to literature [9]. To reduce calculation complexity, noise and avoid the "small sample problem", LDA, LPP, DLPP, OLPP, and ONPP all adopt PCA as a preprocessing method. In the following experiments, we apply Euclidean metric based nearest-neighbor classifier for simplicity. The neighborhood of each training sample in LPP, DLPP, OLPP, ONPP and ODLPP consist of its same class samples, which boosts the classification performance(for example, see also [12].).

3.1 Database

The PKU Finger Vein Database (V2) contains 4574 grayscale images corresponding to 431 different fingers, which were collected on the first semester of 08-09 school years [14]. In this paper, only a subset which contains 500 images of 51 subjects was used in our experiments. Figure 2 shows the preprocessing process of finger vein images. Some of samples of three subjects are shown in Figure 3. The sketch of enhanced finger vein images can be extracted using the same idea of Yu Chengbo's [15]. The VALID face database consists of 106 subjects (77 male, 29 female). Ten images are chosen for experiments. In our experiments, the facial areas were cropped into the final images for matching utilizing the supplied eyes position. Images of three persons are shown in Fig.4. The size of each cropped image in all experiments is 64×64 pixels, with 256 gray levels per pixel.

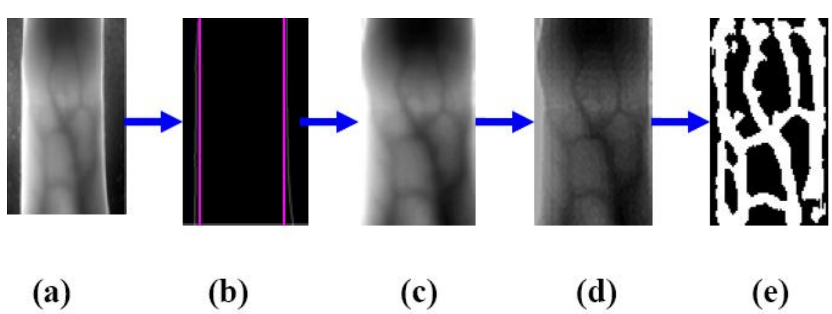


Figure 2. Preprocessing Process for Finger Vein Image

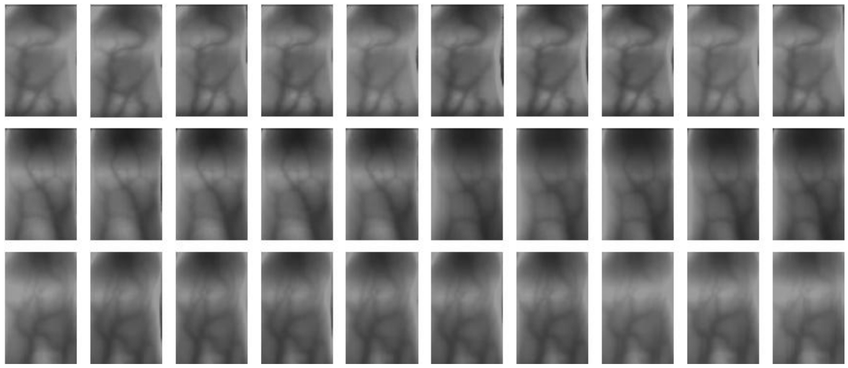


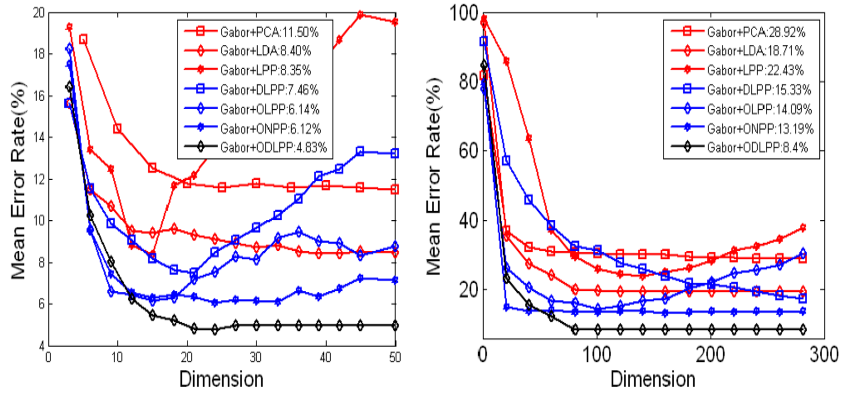
Figure 3. The Preprocessed Sample Images of Three Subjects from PKU Finger Vein Subset Database

Figure 4. The Preprocessed Sample Images of Three Subjects from VALID Face Database

3.2 Error Recognition Rate versus Feature Dimension

In this part, 2 training sample images of each subject from the finger vein database are randomly chosen to form the training set. The VALID training set are consisted of 5 random training sample images of each subject from VALID database. The rest of each database is considered to be the testing set. The PCA dimensionality of LDA, LPP, DLPP, OLPP, ONPP and ODLPP are all set to $N-C$, where N are the total number of training samples and C is the number of class. To compare the performance of various algorithms, the dimension of all algorithms on finger vein database and VALID database are all upper-bounded by 50 and 300, respectively.

We repeat the procedure 10 times and plot the mean error recognition rate versus feature dimension in Figure 5. In the two-step PCA+DLPP algorithm [1], PCA was used to reduce the dimension of the original data, which is actually to reduce the dimensions of FHF^T and XLX^T simultaneously. If dimension reduction was done simultaneously on XLX^T and FHF^T, the very important discriminant information in the null space of XLX^T will be lost. The mean minimal error recognition rate on VALID face database of PCA, LDA , LPP, DLPP, OLPP, ONPP and ODLPP are 28.92%, 18.71%, 22.43%, 15.33%,14.09%, 13.19% and 8.40%, respectively. The mean minimal error recognition rate on the subset of PKU finger vein database of PCA, LDA , LPP, DLPP, OLPP, ONPP and ODLPP are 11.50%, 8.40%, 8.35%,7.46%, 6.14%, 6.12% and 4.83%, respectively.



(a) (b)

Fig.5 Mean error recognition rate versus feature dimension on (a) finger vein database and (b)VALID face database

3.3 Error Recognition Rate with Different Number of Training Samples

In section 3.2, experimental results have shown our ODLPP outperforms other LPP based techniques. In this section, we evaluate the performances of these eight approaches with different numbers of training samples. We randomly choose the training samples and record the minimal error rate. We repeat the procedure 10 times and record the mean minimal error recognition rate and standard deviation. The dimension protocol is that of section 3.2. Experimental results have been shown on table 1. Experimental results on these databases show mean minimal error recognition rate of Gabor based ODLPP is lowest than the others with different number of training samples.

Table 1. Mean Minimal Error Recognition Rate (%) and Standard Deviation on the Finger Vein And Valid Database

	Finger Vein Database			Valid Database			
#/class	1	2	3	2	4	6	8
Gabor+PCA	14.8±2.3	11.50±2.5	7.2±2.6	35.4±2.8	32.4±2.7	21.2±2.1	18.1±3.2
Gabor+LDA	9.5±2.1	8.40±2.4	6.6±1.8	28.7±2.2	26.5±3.1	14.1±2.7	12.6±2.3
Gabor+LPP	9.4±2.5	8.35±2.3	7.7±2.2	29.5±3.2	27.4±2.5	18.2±3.4	15.8±2.2
Gabor+DLPP	8.6±2.4	7.46±1.7	5.4±2.5	18.3±1.7	17.1±2.2	14.6±2.3	12.5±1.9
Gabor+OLPP	9.2±2.5	6.14±1.7	6.5±2.3	17.6±2.3	15.7±2.1	13.8±2.3	12.5±2.1
Gabor+ONPP	8.6±2.3	6.12±3.1	5.7±2.1	16.7±1.8	14.5±2.1	12.7±1.9	11.5±2.3
Gabor+ODLPP	6.2±2.5	4.83±2.3	3.2±2.7	11.2±1.7	10.3±2.1	7.5±2.4	6.8±2.1

4. Conclusion

In this paper, an efficient dimensionality reduction technique called ODLPP is proposed. ODLPP directly optimizes discriminant locality preserving criterion on the Gabor feature space via simultaneous diagonalization without any dimensionality reduction preprocessing. Experiments and simulations show superior performance of our proposed technique on feature extraction and classification.

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References

[1] W. W. Yu, X. L. Teng and C. Q. Liu, "Face recognition using discriminant locality preserving projections", Image Vision Comput, vol. 24, pp. 239–248, **(2006)**.

[2] Z. Jie, Q. Ji and G. Nagy, "A Comparative Study of Local Matching Approach for Face Recognition", IEEE Trans. on Image Processing, Vol. 16, No. 10, pp. 2617-2628, **(2007)**.

[3] L. Ma, T. Tan, Y. Wang and D. Zhang, "Personal Identification Based on Iris Texture Analysis", IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 25, No. 12, pp. 1519-1533, **(2003)**.

[4] A. Jain, Y. Chen and M. Demirkus, "Pores and Ridges: High-Resolution Fingerprint Matching Using Level 3 Features", IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 29, No. 1, pp. 15-27, **(2007)**.

[5] M. Laadjel, A. Bouridane, F. Kurugollu and S. Boussakta, "Palmprint Recognition Using Fisher-Gabor Feature Extraction", Int'l Conf. on Acoustics, Speech and Signal Processing, pp. 1709-1712, **(2008)**.

[6] Jian-Da Wu and Siou-Huan Ye, "Driver identification using finger-vein patterns with Radon transform and neural network", Expert Systems with Applications, vol. 36, pp. 5793-5799, **(2009)**.

[7] Jian-Da Wu, Chiung-Tsiung Liu, "Finger-vein pattern identification using principal component analysis and the neural network technique", Expert Systems with Applications, DOI: 10.1016/j.eswa.2010.10.013.

[8] Zhi Liu, Yilong Yin, et al., "Finger vein recognition with manifold learning", Journal of Network and Computer Applications, vol. 33,pp. 275-282, **(2010)**.

[9] Tai Sing Lee."Image Representation Using 2D Gabor Wavelets". IEEE Transactions on analysis and intelligence. vol. 18, No. 10, **(1996)** October.

[10] J. Lu, K. N. Plataniotis and A. N. Venetsanopoulos, "Face Recognition Using Kernel Direct Discriminant Analysis Algorithms", IEEE Trans. Neural Networks, vol. 14, no. 1, pp. 117-126, **(2003)**.

[11] FANG Bao-rong, ZHOU Ji-dong and LI Yi-min, "The Theory of Matrix," Beijing: Tsinghua University Press, **(2006)**.

[12] D. Cai, X. He and J. Han, "Orthogonal Laplacianfaces for Face Recognition", IEEE Trans. Image Processing, vol. 15, no. 11, pp. 3608-3614, **(2006)**.

[13] Z. Liu, Y. Yin, et al., "Finger vein recognition with manifold learning", Journal of Network and Computer Applications, vol. 33,pp. 275-282, **(2010)**.

[14] PKU Finger Vein Database (V2), available:http://ai.pku.edu.cn/.

[15] Y. Chengbo, Q. Huafeng and Z. Lian "A Research on Extracting Low Quality Human Finger Vein Pattern Characteristics", the 2nd International Conference on Bioin formatics and Biomedical Engineering, pp. 1876-1879, **(2008)**.

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