Gabor-based Discriminant Locality Preserving Projections for Face Recognition

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***Abstract*—In this paper, a novel face recognition method called Gabor-based Discriminant Locality Preserving Projections (Gabor-DLPP) is proposed. Locality Preserving Projections (LPP) is a recently proposed method for linear dimensionality reduction. Gabor-DLPP first gets the high-order statistic information by calculating the Gabor wavelet representation of face images. Based on LPP, Gabor-DLPP takes into account the between-class information, changes the objective function, and extracts the discriminant feature of face for recognition. We performed comparative experiments of various face recognition schemes, including PCA, Gabor-DLPP, LPP and LDA. Experimental results on AR and Yale database show the superior of the proposed method.**

Keywords—**Gabor feature; locality preserving projections; face recognition; feature extraction**

I. INTRODUCTION

Face recognition is one of the most successful applications of computer vision and pattern recognition. Therefore it attracts significant attention of world-wild researchers. In the past decades, numerous different face recognition methods have been developed[1]. Among them, the holistic methods is a hotspot which uses the whole face picture as the input of the recognition system and doesn't need priori knowledge and reference model[2]. The most prominent examples are Principal Component Analysis (PCA)[3] and Linear Discriminant Analysis (LDA)[4]. PCA, which is a classical method for data representation and compression, was first applied to face recognition as Eigenface by Turk et al. Linear Discriminant Analysis (LDA), which attempts to maximize inter-class distances and minimize intra-class distances simultaneously, was applied as a supervised method called Fisherface.

In recent years, it has been demonstrated that face images often reside on a nonlinear manifold[5, 6]. Some manifold learning techniques have been proposed, e.g. Locally Linear Embedding (LLE)[7], Isometric feature mapping (Isomap)[8], and Laplacian Eigenmap[9]. These methods have achieved impressive results on some nonlinear dimensional reduction applications[10]. However there are two difficulties when they were used in face recognition tasks. 1) These manifold learning methods yield maps that are defined only on the training samples and how to evaluate the maps on novel test samples remains unclear. 2) It is difficult to obtain a more effective discriminant subspace through manifold learning than through conventional dimensionality reduction approaches. He et al. proposed a new dimensionality reduction method named Locality Preserving Projections (LPP)[11] and applied it in face recognition area[12]. LPP is originally derived by the linear approximation of the Laplace Beltrami operator on compact Riemannian manifold. In view of difficulty 2), one potential reason is that high-order information of feature vectors hasn't been extracted. The other possible reason is many manifold learning methods emphasize on reconstruction of global coordinate system but pay less attention on discriminant information extraction.

In this paper, we proposed a novel face recognition method, called Gabor-based Discriminant Locality Preserving projections (Gabor-DLPP). First Gabor wavelets are used to extract high-order statistical information of face images and a set of Gabor features are obtained. Then we described a variant of LPP. Gabor-DLPP takes into account the between-class information and extract discriminant feature of face image. The proposed method was compared with Eigenface(PCA), Fisherface(LDA), Laplacianface(LPP) on the Yale and AR face databases. Experimental results indicated the promising performance of the proposed method.

II. GABOR FEATURE EXTRACTION

Some high-order statistics of face images are very important for face recognition. However general manifold learning methods may neglect these high-order statistics because they regard each pixel as one dimension. The characteristics of the Gabor wavelets, especially for frequency and orientation representations, are similar to those of the human visual system. And it has been found that Gabor wavelet representation gives better performance than other techniques for classifying facial actions[13-15].

The 2D Gabor wavelets can be defined as:

$$\psi_{u,v}(z) = \frac{\| k_{u,v} \|^2}{\sigma^2} e^{(-\|k_{u,v}\|^2 \|z\|^2 / 2\sigma^2)} [e^{ik_{u,v}z} - e^{-\sigma^2/2}] \tag{1}$$

$$k_{u,v} = k_v e^{i\phi_u} \tag{2}$$

Where u and v define the orientation and scale of the Gabor kernels, $z = (x, y)$, $\|\cdot\|$ denotes the operation of norm.

$k_v = k_{\max} / f^v$, $\phi_u = \pi u / 8$. $k_{\max}$ is the maximum frequency and f is the spacing factor between wavelets in the frequency domain. And we choose the following parameters: $\sigma = 2\pi$, $k_{\max} = \pi / 2$, $f = \sqrt{2}$, $u \in \{0, \cdots, 7\}$ and $v \in \{0, \cdots, 4\}$.

Let $\boldsymbol{I}(z) = \boldsymbol{I}(x, y)$ be the gray-level face image, the convolution if image $\boldsymbol{I}$ and a Gabor kernel is defined as follows:

$$\boldsymbol{O}_{u,v}(z) = \boldsymbol{I}(z) * \psi_{u,v}(z) \tag{3}$$

In practice, applying the convolution theorem, it gives:

$$\boldsymbol{O}_{u,v}(z) = \mathfrak{F}^{-1}\{\mathfrak{F}\{\boldsymbol{O}_{u,v}(z)\}\} = \mathfrak{F}^{-1}\{\mathfrak{F}\{\boldsymbol{I}(z)\}\mathfrak{F}\{\psi_{u,v}(z)\}\} \tag{4}$$

Where $\mathfrak{F}$ and $\mathfrak{F}^{-1}$ denote the Fast Fourier Transform (FFT) and inverse Fast Fourier Transform (IFFT) respectively.

Considering computational cost, $\boldsymbol{O}_{u,v}(z)$ is down-sampled by a factor ρ to reduce the space dimension, and normalized to zero mean and unit variance. So far the Gabor wavelet representation of an image is:

$$\boldsymbol{x}^{(\rho)} = (\boldsymbol{O}_{0,0}^{(\rho)}, \boldsymbol{O}_{0,1}^{(\rho)}, \cdots, \boldsymbol{O}_{4,7}^{(\rho)}) \tag{5}$$

By concatenating the components of $\boldsymbol{x}^{(\rho)}$ into one dimension vector, we get the Gabor features of face image.

III. THE GABOR-DLPP ALGORITHM

After the step described in section II, we can extract the high-order statistical information of face images. However the dimension of Gabor feature vector is quite high because the algorithm considers five scales and eight orientations, and the “the course of dimensionality” will appear. In the following sections, we will introduce discriminant feature extraction techniques to reduce feature dimension.

A. *Outline of LPP*

More formally, let us consider a set of N sample images taking values in an D-dimensional image space $\boldsymbol{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_N\} \subset \mathbb{R}^D$. LPP seeks a mapping matrix $\boldsymbol{A}$ to project high dimensional data $\boldsymbol{X}$ into a low dimensional vector $\boldsymbol{Y} = \{\boldsymbol{y}_1, \boldsymbol{y}_2, \cdots, \boldsymbol{y}_N\}$ in which the local structure of $\boldsymbol{X}$ can be preserved, namely, $\boldsymbol{Y} = \boldsymbol{A}^T \boldsymbol{X}$, $\{\boldsymbol{y}_1, \cdots, \boldsymbol{y}_{\mathrm{N}}\} \subset \mathbb{R}^d, (d \ll D)$.

The objective function of LPP can be defined as:

$$\sum_{ij} \| \boldsymbol{y}_i - \boldsymbol{y}_j \|^2 \boldsymbol{W}_{ij} \tag{6}$$

where $\boldsymbol{W}$ is similarity measure matrix and is constructed through the nearest neighbor graph. If $\boldsymbol{x}_i$ is among the l nearest neighbors of $\boldsymbol{x}_j$ or $\boldsymbol{x}_j$ is among the l nearest neighbors of $\boldsymbol{x}_i$, then $\boldsymbol{W}_{ij} = e^{-\frac{\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2}{t}}$, otherwise $\boldsymbol{W}_{ij} = 0$. Finally, the minimization problem reduces to the following form:

$$\begin{aligned} \boldsymbol{A}_{opt} &= \arg\min_{\boldsymbol{A}} \sum_{ij} \| \boldsymbol{y}_i - \boldsymbol{y}_j \|^2 \boldsymbol{W}_{ij} \\ &= \arg\min_{\boldsymbol{A}} \sum_{ij} \| \boldsymbol{A}^T \boldsymbol{x}_i - \boldsymbol{A}^T \boldsymbol{x}_j \|^2 \boldsymbol{W}_{ij} \\ &= \arg\min_{\boldsymbol{A}} \boldsymbol{A}^T \boldsymbol{X}\boldsymbol{L}\boldsymbol{X}^T \boldsymbol{A} \end{aligned} \tag{7}$$

With the imposed constrain:

$$\boldsymbol{A}^T \boldsymbol{X}\boldsymbol{D}\boldsymbol{X}^T \boldsymbol{A} = 1 \tag{8}$$

Where $\boldsymbol{D}$ is a diagonal matrix; $\boldsymbol{D}_{ii} = \sum_j \boldsymbol{W}_{ji}$, $\boldsymbol{L} = \boldsymbol{D} - \boldsymbol{W}$ is the Laplacian matrix. The bigger the value $\boldsymbol{D}_{ii}$ is, the more “important” is $\boldsymbol{y}_i$.

With simple algebra knowledge, the matrix $\boldsymbol{A}$ is given by the minimum eigenvalues solution to the generalize eigenvalue problem:

$$\boldsymbol{X}\boldsymbol{L}\boldsymbol{X}^T \boldsymbol{A} = \lambda \boldsymbol{X}\boldsymbol{D}\boldsymbol{X}^T \boldsymbol{A} \tag{9}$$

B. *Outline of Gabor-DLPP*

As mentioned above, LPP is a linear approximation of Laplacian Eigenmap and is actually linear. LPP has specific mapping matrix and has the ability to solve the “out of the sample problem”. However LPP is belong to unsupervised learning technique, and it does not make full use of labels’ information. Here we propose a novel face recognition method which introduces between-class scatter constraint into the objective function of LPP and attempts to extract more discriminant information of face images.

After applying the Gabor filter, the Gabor feature of face images can be defined $\boldsymbol{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_N\} \subset R^D$. Let $\boldsymbol{x}_i$ belongs to one of C object classes $\{X_1, X_2, \cdots, X_C\}$. The objective function of Gabor-DLPP can be written as:

$$J = \frac{(\sum_{i,j=1}^{N} (\boldsymbol{y}_i - \boldsymbol{y}_j)(\boldsymbol{y}_i - \boldsymbol{y}_j)^T \boldsymbol{S}_{ij})}{(\sum_{i=1}^{C} n_i (\boldsymbol{u}_i - \boldsymbol{u})(\boldsymbol{u}_i - \boldsymbol{u})^T)} \tag{10}$$

where

$$\boldsymbol{S}_{ij} = \begin{cases} e^{-\frac{\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2}{t}} & \boldsymbol{x}_i \text{ and } \boldsymbol{x}_j \text{ belong to the same class} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

is the similarity matrix. $\boldsymbol{u} = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{y}_i$, $\boldsymbol{u}_i = \frac{1}{n_i}\sum_{\boldsymbol{y}_j \in X_i} \boldsymbol{y}_j$, n_i is the number of samples in the i^{th} class.

Considering the projection $\boldsymbol{Y} = \boldsymbol{A}^T \boldsymbol{X}$, the Eq.(10) can be written as:

$$\begin{aligned} J(\boldsymbol{A}) &= \frac{(\sum_{i,j=1}^{N} \| \boldsymbol{A}^T \boldsymbol{x}_i - \boldsymbol{A}^T \boldsymbol{x}_j \|^2 \boldsymbol{S}_{ij})}{(\sum_{i=1}^{C} n_i \| \frac{1}{n_i} \sum_{\boldsymbol{x}_k \in X_i} \boldsymbol{A}^T \boldsymbol{x}_k - \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{A}^T \boldsymbol{x}_i \|^2)} \\ &= \frac{tr(\boldsymbol{A}^T \boldsymbol{S}_{\boldsymbol{L}} \boldsymbol{A})}{tr(\boldsymbol{A}^T \boldsymbol{S}_{\boldsymbol{B}} \boldsymbol{A})} \end{aligned} \tag{12}$$

where $$S_B = \sum_{i=1}^{C} n_i \| \frac{1}{n_i} \sum_{x_k \in X_i} x_k - \frac{1}{N} \sum_{i=1}^{N} x_i \|^2 \quad (13)$$

is the between-class scatter matrix of original face image data x_i. The symbol "*tr*" denotes the operation of trace.

The projection matrix $A = [a_1, a_2, \cdots, a_d]$ that minimizes the objective function Eq. (12) can be obtained by solving the generalized eigenvalue problem:

$$S_L a_i = \lambda_i S_B a_i, \ \lambda_1 < \lambda_2 < \cdots < \lambda_d \quad (14)$$

IV. EXPERIMENTAL RESULTS

A. Database

The proposed face recognition method Gabor-DLPP was tested on two benchmark face databases: Yale database and AR database.

The Yale face database (http://cvc.yale.edu/projects/yalefaces/yalefaces.html) was constructed at the Yale Center for Computational Vision and Control. It contains 165 grayscale images of 15 individuals. There are 11 images per subject, and these images demonstrate variations in lighting condition (center-light, left-light, right-light) and facial expression (happy, normal, sad, sleepy, surprised, and winking). All face images were cropped into 100*100 from original frames based on the location of the two eyes.

The AR face database (http://cobweb.ecn.purdue.edu/~aleix/aleix_face_DB.html) contains more than 134 people. The images were recorded twice at a 2-week interval. During each session, 13 conditions with varying facial expressions, illumination and occlusion were captured. The face portions of the images were cropped manually. All cropped images were aligned at the centers of eyes and normalized with resolution 64*72. In our experiments, only one session's images were used.

Figure 1 shows the sample images of Yale face database and AR face database.

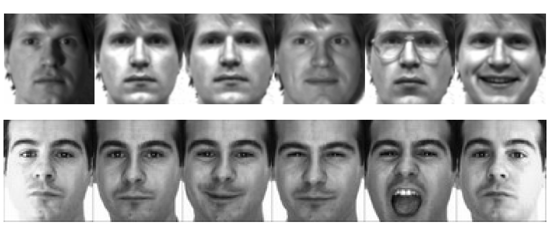

Figure 1. Sample face images of Yale face database and AR face database.

B. Experimental Results

For Yale face database, we focus on observing the recognition rates under different number training samples. We randomly selected $l(=2,3,4,5,6,7)$ images from each person for training, while the rest of the images of each person were selected for testing.

Gabor-DLPP was compared with Eigenface (PCA), Fisherface (LDA), and Laplacianface (LPP). The nearest neighbor classifier is employed for classification. We repeated the experiments 20 times in Yale face database, and the average accuracies were taken as their final recognition rates. The results were shown in Table I.

For Eigenface, we calculated the eigenvectors accounting for 95%. For Fisherface and Laplacianface, PCA process was accepted to remove the null subspace and avoid singular matrices. It can be seen that our Gabor-DLPP has the better performance than the other three methods expect when 2 training samples are selected from each person. The reason of this exception is maybe training samples are too less to support the face subspace.

TABLE I. RECOGNITION RATES COMPARISON ON YALE DATABASE

Method	Recognition rates with different number training samples/%					
	2 Train	3 Train	4 Train	5 Train	6 Train	7 Train
Eigenface(PCA)	66.3	71.3	74.7	75.4	75.7	76.2
Fisherface(LDA)	77.9	88.2	92.2	94.4	95.8	96.7
Laplacianface(LPP)	80.5	88.3	92.9	94.6	95.9	96.8
Gabor-DLPP	78.5	89.0	94.1	94.9	96.1	97.5

We also tested the performance on AR face database. From the AR face database, 4 images per person were select to construct the training set, and the test set was composed of the rest of the images. Thus the training set had 536 training samples and the testing set had 402 test samples. The best recognition rates and corresponding feature dimensionality are listed in Table II.

TABLE II. BEST RECOGNITION RATE AND CORRESPONDING DIMENSIONALITIES IN AR FACE DATABASE

Methods	Feature dimensionality	Recognition rate/%
Eigenface(PCA)	94	49.75
Fisherface(LDA)	40	93.06
Laplacianface(LPP)	40	93.58
Gabor-DLPP	50	94.43

The good performance of Gabor-DLPP owns to two factors. On the one hand, Gabor-DLPP uses specific Gabor wavelet to obtain high-order statistic feature of face images which is important for face recognition. On the other hand, Gabor-DLPP is belong to supervised learning algorithms and can extract more discriminant information for classification.

V. CONCLUSION

This paper proposes a new face recognition method called Gabor Discriminant Locality Preserving Projections. Gabor-DLPP includes two main stages: First, Gabor wavelet feature extraction process is implemented. Second, a supervised version of LPP algorithm is proposed to reduce dimensionality and extract discriminant features. Experimental results on Yale and AR face database show that

Gabor-DLPP has more discriminative power than Eigenface, Fisherface and Laplacianface.

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