Gabor-Kernel Fisher Analysis for Face Recognition

Baochang Zhang

Department of Computer Science and Engineering,Harbin Institute of Technology, Harbin,150001,China
Bczhang@jdl.ac.cn

Abstract. Kernel based methods have been of wide concern in the field of machine learning. This paper proposes a novel Gabor-Kernel Fisher analysis method (G-EKFM) for face recognition, which applies Enhanced Kernel Fisher Model (EKFM) on Gaborfaces derived from Gabor wavelet representation of face images. We show that the EKFM outperforms the Generalized Kernel Fisher Analysis (GKFD) model. The performance of G-EKFM is evaluated on a subset of FERET database and CAS-PEAL database by comparing with various face recognition schemes, such as Eigenface, GKFA, Image-based EKFM, Gabor-based GKFA, and so on.

Keywords: Gabor, Kernel Fisher, Face Recognition

1 Introduction

Principle Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are two classical techniques for linear feature extraction. Although LDA is conceptually simple and has been used in many applications, it has some limitations: it requires at least one of scatter matrices to be nonsingular and it can not easily capture a nonlinearly clustered structure. In recent years, the nonlinear feature extraction methods, such as Kernel Principal Component Analysis (KPCA) and Kernel Fisher Discriminant Analysis (KFD) have been of wide concern. KPCA was originally developed by Scholkopf [1], and KFD was subsequently proposed by Mika [2] and Baudat [3]. However, the KFD always faces the difficulty in its application. The reason is that KFD is trained by using mapped training samples, which make within-class covariance matrix singular. Moreover, when the input space is mapped to a feature space through a kernel function, the dimension of the feature often becomes larger than that of the sample space, and as a result, the scatter matrices become singular. In order to solve this problem, we proposed Enhanced Kernel Fisher Model (EKFM), which never faces the difficulty of calculation of the inverse of the within-class.

In this paper, we apply the proposed scheme to face recognition issue, which is one of hot points in the field of pattern recognition. A good face recognition methodology should consider representation as well as classification issues, and a good representation method should require minimum manual annotations[4,5,7]. The Gabor wavelets, whose kernels are similar to the 2D receptive field profiles of the mammalian cortical simple cells, exhibit desirable characteristics of spatial locality and orientation selectivity[6]. The Gabor wavelet representation facilitates recognition without correspondence,because it captures the local structure corresponding to spatial frequency (scale), spatial localization, and orientation selectivity [6,7], which is augmented into Gaborfaces by concatenating various scales and orientations [7,8]. Here, we will give the brief organization of this paper. In part 2, the Gaborface feature is briefly introduced, which focuses on the representation of face image. In part 3, G-EKFM is proposed by using the Enhance Kernel Fisher Model. In part 4, we will give some experiment results on CAS-PEAL and FERET Databases. In the last part, we will make some conclusions about the experiments results.

2 Gabor Wavelet Representation

Gabor wavelet model quite well the receptive field profiles of cortical simple cells. Lades et al.[9] pioneered the use of Gabor wavelet for face recognition using the Dynamic Link Architecture framework. Wiskott et al.[10] developed a Gabor wavelet based elastic bunch graph matching method to label and recognize human faces. M.J.Lyons [11] had shown through experiments that the Gabor wavelet representation is optimal for classifying facial actions.

2.1 Gabor Wavelet

Daugman pioneered the using of the 2D Gabor wavelet representation in computer vision in 1980's [6]. The Gabor wavelet representation allows description of spatial frequency structure in the image while preserving information about spatial relations [6,8,11]. A complex-valued 2D Gabor function is a plane wave restricted by a Gaussian envelope:

$$\psi_{u,v}(z) = \frac{||k_{u,v}||^2}{\sigma^2} * \exp(-||k_{u,v}||^2 * ||z||^2 \setminus (2*\sigma^2)) * [\exp(ik_{u,v}z) - \exp(-\delta^2)] \quad (1)$$

Here 5 frequencies and 8 orientations are used, Fig.1 shows the 40 Gabor Kernels in Eq.1 used by us.

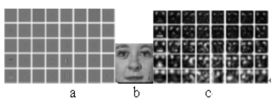

Fig. 1. a is the Real Part of 40 Gabor Kernels, b is the face image, c is Magnitude of Gaborfaces

2.2 Gaborfaces

Here, we will give a brief description about the Gaborfaces, the details of which are shown in [7,8]. In a given image, the convolution can be defined as

$$G_{u,v}(z) = I(z) * \psi_{u,v}(z) \tag{2}$$

where * denotes the convolution operator, and $G_{u,v}(z)$ is the convolution result corresponding to the Gabor kernel at scale u and orientation v, named by Gaborface (shown in Fig.1). In order to utilize different spatial frequencies, spatial localities, and orientation selectivity, we concatenate all these representation results and derive an augmented feature vector. Now, $G^N_{u,v}(z)$ is the normalized vector constructed from the Gabor feature vector (Gaborface), and then x^N is defined as following:

$$x^N = (G^N_{0,0}(z), G^N_{0,1}(z), .., G^N_{4,7}(z)) \tag{3}$$

The dimension of Gaborfaces is very high, In order to reduce the dimensionality, at the same time reserve the identification information, the Principal Component Analysis (PCA) method is used here.

$$\Sigma_x = E((x - E(x))(x - E(x))^T) \tag{4}$$

The PCA of a random vector x factorizes its covariance matrix , then get the transform matrix P , which is an orthogonal eigenvector matrix. An important property of PCA is its optimal signal reconstruction in the sense of minimum mean-square error when only subsets of principal components are used to represent the original signal. Following this property, an application of PCA is dimensionality reduction.

$$y^p = P^m x^N \tag{5}$$

The lower dimension vector y^p captures the most expressive features of the original data.

3 Gabor-Kernel Fisher Analysis

We describe in this part the Enhance Kernel Fisher Discriminant Model and Gabor feature based kernel Fisher analysis, which are main contributions of our paper.

3.1 Kernel Fisher Analysis

The idea of Kernel FDA is to yield a nonlinear discriminant analysis in the higher space. The input data is projected into an implicit feature space by nonlinear mapping,$\Phi : x \in R^N -> f \in F$, then seek to find a nonlinear transformation matrix, which can maximize the between-class scatter and minimize the within-class scatter in F[12, 13]. First, we define the dot product in F as following.

$$k(x, y) = \Phi(x).\Phi(y) \tag{6}$$

Between-class scatter matrix S_B and Within-class scatter matrix S_w are defined in the feature space F:

$$S_w = \sum_{i=1}^{C} p(\omega_i) E((\Phi(x) - u)(\Phi(x) - u)^T) \tag{7}$$

$$S_B = \sum_{i=1}^{C} p(\omega_i)(u_i - u)(u_i - u)^T \tag{8}$$

u_i Denotes the sample mean of class i and u denots mean of all the samples in F, $p(\omega_i)$ is the prior probability. To perform LDA in F, it is equal to maximize the following equation

$$J(w) = \frac{wS_Bw^T}{wS_ww^T} \tag{9}$$

Because any solution w must lie in the span of all the samples in F, there exists:

$$w = \sum_{i=1}^{n} \alpha_i \Phi(x_i) \tag{10}$$

Then maximizing Eq.9 is converted to maximize Eq.11

$$J(w) = \frac{wK_Bw^T}{wK_ww^T} \tag{11}$$

Details of K_B, K_w the can be seen in [3,12], Similar to LDA, this problem can be solved by finding the leading eigenvectors of $(K_w)^{-1}K_B$ showed in Liu[12] and Baudat(GDA)[3], which is the Generalized Kernel Fisher Discriminant(GKFD). In our paper, using the technique of pseudo inverse of the within-class covariance matrix, and the projection of a point x onto w in F given by:

$$w.\Phi(x) = \sum_{i=1}^{n} \alpha_i k(x_i, x) \tag{12}$$

3.2 Enhanced Kernel Fisher Model

We will propose the Enhanced Kernel Fisher (EKFM) model, which is more effective than the GKFD. Within-class covariance may be ill-conditioned, and so a regularized solution is obtained by substituting $K_w = K_w + \mu I, \mu$ is a regularization constant. The EKFM improves the generalization capability by decomposing its procedure into a simultaneous diagonalization of the two within- and between-class scatter matrices. The simultaneous diagonalization is stepwisely equivalent to two operations, and we can refer to [14, 15]. Especially in [15], Liu showed that the Enhanced Fisher Models achieved better performance than LDA. Our ideas partly originate from his methods. First we will whiten the within-class scatter matrix as following:

$$k_w \Xi = \Xi \ell, \Xi \Xi^T = I \tag{13}$$

where Ξ, ℓ are the eigenvector and the diagonal eigenvalue matrices of k_w .Ξ^*, ℓ^* are calculated by reserving min(l,c-1) eigenvectors and corresponding diagonal eigenvalue matrix,l is the length of input vector, and c is the number of classes. Then we proceed to compute the new between-class scatter matrix by using following method:

$$\ell^{*-1/2} \Xi^{*T} K_B \Xi^* \ell^{*-1/2} = \Xi_B \tag{14}$$

Diagonalizing now the new Between-class scatter matrix.

$$(\Xi_B)\Theta = \Theta\gamma, \Theta\Theta^T = I \tag{15}$$

where Θ, γ are the eigenvector and the diagonal eigenvalue matrices of Ξ_B. The overall transformation matrix is now defined as follows.

$$\alpha = \Xi^* \ell^{*-1/2} \theta \tag{16}$$

Here,we can get w as the transform matrix by using the Eq.16, and the kernel feature is calculated by using Eq.17.

$$v = w.\Phi(x) = \sum_{i=1}^{n} \alpha_i k(x_i, x) \tag{17}$$

3.3 Similarity Measure for G-EKFM

When an image is presented to the proposed method, the augmented Gabor feature vector of the image is first calculated by using Eq.3 as detailed in section2.2 and the lower dimensional feature,y^p , is derived by using Eq.5. The dimensionality of the discrimant feature space is determined by the Enhanced Kernel Fisher method, as defined by Eq.18. The new feature vector,v, of the image is defined as following:

$$v = w.\Phi(y) = \sum_{i=1}^{n} \alpha_i k(y_i, y) \tag{18}$$

Given that v_1, v_2 are the extracted feature vectors corresponding to two face images x_1, x_2. The similarity rule is based on the cross correlation between corresponding vectors.

$$d(x_1, x_2) = \frac{v_1.v_2}{||v_1||.||v_2||} \tag{19}$$

Experiments are performed on two databases, CAS-PEAL and FERET databases. In our paper, the kernel function is polynomial used in the proposed EKFM method,$k(x, y) = (\frac{x.y}{c} + 1)^r$,r is a constant, which is related to the length of the input vector.

4 EXPERIMENT

In our experiments, the face image is cropped to size of 32X32 and overlapped with a mask to eliminate the background and hair. For all images concerned in the experiments, no preprocessing is exploited.

4.1 CAS-PEAL Database

The CAS-PEAL face database was constructed under the sponsors of National Hi-Tech Program and ISVISION. Currently, the CAS-PEAL face database contains 99,594 images of 1040 individuals with varying Pose, Expression, Accessory, and Lighting (PEAL). In this experiment, only one face image for each person was used as Gallery database. Details about this database are shown in http://jdl.ac.cn.

In this part, we will give some experiments results about the selection of parameter of the polynomial kernel function. Note that the first order polynomial is equivalent to the LDA method. Therefore, the kernel method is better then LDA approach. I-GKFD is the image based GKFD method, G-GKFD is the Gabor based GKFD method, and I-EKFM is the image based EKFM method. the expriment results are shown in Table.1 and Table.2.

Table 1. Experiments on selection of parameter for polynomial kernel function

	I-EKFM		G-EKFM	
	r = 1	r = 2	r = 1	r = 2
Accessory	53.4	62.8	72.2	72.9
Background	94.1	93.4	93.6	93.4
Distance	89.1	93.8	98.1	99.6
Expression	60.8	77	90.8	91.9
Lighting	15.1	14.1	14.4	17.6
Aging	69.7	77.3	90.9	92.4

Table 2. Experiments Results on the CAS-PEAL database(r = 2)

	Eigenface	I-GKFD	G-GKFD	I-EKFM	G-EKFM
Accessory	37.1	54	70.2	62.8	72.9
Background	80.4	96.1	90.2	93.4	93.4
Distance	74.1	93	99.6	93.8	99.6
Expression	53.6	72	89.8	77	91.9
Lighting	8	9	11	14.1	17.6
Aging	50	63.5	87.8	77.3	92.4

4.2 FERET Database

The proposed algorithm is also tested on a subset of the FERET face image database. This subset includes 1400 images of 200 individuals, and each individual has 7 images. It is composed of images named with two-character strings, "ba","bj","bk","be","bd","bf" and "bg". This subset involves variations in facial expression, illumination, and pose. The accurate rate in the Table.3 and Table.4 is the average one, where we divide 200 people into two subsets, one of which is used to train the EKFM model and the rest is used to test the proposed approach. Both subsets have 100 people, with 7 pictures for each one. In our experiments, only "ba" part was used as gallery database, others are probe databases. Thus, we can do two groups of experiments by using this kind of partition method of the FERET database. So the results are the average accurate rate of two groups of experiments.

Table 3. Experiments on selection of parameter for polynomial kernel function

Methods	r = 1	r = 2
I-EKFM	76.2	85.1
G-EKFM	87	90.5

Table 4. Experiment Results on FERET database(r = 2)

Eigenface	I-GKFD	G-GKFD	I-EKFM	G-EKFM
37.1	81	83.3	85.1	90.5

5 Conclusions and Future Work

We have introduced in this paper Gabor feature based Kernel Fisher Analysis method for face recognition. The Enhance Kernel Fisher model achieves better performance than the GKFD method, and the experiments are performed on the FERET and CAS-PEAL databases. The Gabor transformed face images yield features that display scale, locality, and orientation selectivity. The effectiveness of the method is shown in terms of both absolute performance indices and comparative performance against various approaches such as Eigenface, EKFM, Generalized Kernel Fisher Analysis method, and Gabor based GKFD and son on. The excellent performance shown by the method is the direct result of coupling an augmented Gabor feature vector with the EKFM method .

Our next goal is to further search for an optimal and sparse code resulting from the Gabor wavelet representation of face images, for example, AdaBoost method, before forming the augmented Gabor feature vector and applying the G-EKFM method for classification. Another possibility is that we can try to use the support vector machines to train the classifier and aim to get more generalized classifier.

6 Acknowledgements

This research is partially supported by National Hi-Tech Program of China (No.2001AA114190 and No. 2002AA118010), National Nature Science Foundation of China (No. 60332010), and ISVISION Technologies Co. Ltd. Specially, many thanks for the advice from Dr. Shiguang Shan.

References

1. B.Scholkopf, A.Smola, K.R.Muller, Nonlinear component analysis as a kernel eigenvalue problem, Neural Computation 10(5) (1998) 1299-1319.
2. S.Mika, G.Ratsch, J.Weston, B.Scholkopf, K.R.Muller, Fisher discriminant analysis with kernels IEEE International Workshop on Neural Networks for Signal Processing, Bol.IX, Madison, USA, August, 1999, pp.41-48.
3. G.Baudat, F.Anouar, Generalized discriminant analysis using a kernel approach, Neural Computation 12(10) (2000) 2385-2404.
4. R.Chellappa, C.L.Wilson, and S.Sirohey, "Human and machine recognition of faces: A survey," Proc. IEEE, vol. 83, no. 5, 1995.
5. J.G.Daugman, "Face and gesture recognition: Overview," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 675-676, 1997.
6. J.G.Daugman, "Two-dimensional spectral analysis of cortical receptive field profiles," Vision Research, vol. 20, pp. 847-856, 1980.
7. Chengjun Liu and Harry Wechsler,"Gabor Feature Based Classification Using the Enhanced Fisher Linear Discriminant Model for Face Recognition" IEEE Trans. Image Processing vol.11 no.4 2002.
8. Baochang Zhang, Wen Gao, Shiguang Shan, Yang Peng. Discriminant Gaborfaces and Support Vector Machines Classifier for Face Recognition. Asian Conference on Computer Vision. ACCV2004, Jeju Island, Korea, Jan.27-30, 2004, pp37-42.
9. M.Lades, J.C.Vorbruggen, J.Buhmann, J.Lange, C.von der Malsburg, Wurtz R.P., and W.Konen, "Distortion invariant object recognition in the dynamic link architecture," IEEE Trans. Computers, vol. 42, 1993.
10. L.Wiskott, J.M.Fellous, N.Kruger, and C.von der Malsburg, "Face recognition by elastic bunch graph matching," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, 1997.
11. M.J.Lyons, J.Budynek, A.Plante, and S.Akamatsu, "Classifying facial attributes using a 2-d gabor wavelet representation and discriminant analysis," in Proc. the fourth IEEE international conference on automatic face and gesture recognition, 2000.
12. Qingshan Liu, Rui Huang,"Face Recognition Using Kernel Based Fisher Discriminant Analysis" FGR2002.
13. K.Fukunaga, Introduction to Statistical Pattern Recognition, Academic Press, second edition, 1991.
14. Chenjun liu, Harry Wechsler, Enhanced Fisher Linear Discriminant Models for face Recognition, 14th International Conference on Pattern Recognition, ICPR'98.