Discriminant Gaborfaces and Support Vector Machines Classifier for Face Recognition

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Abstract

Feature extraction, discriminant analysis, and classification rules are three crucial issues for face recognition. This paper presents method, named GaborfaceSVM, to handle three issues together. For feature extraction, we apply the Gabor wavelet transform to extract Gaborfaces. The proposed Modified Enhanced Fisher Discriminant model is used on Gaborfaces to reinforce discriminant power. During classification process, Support Vector Machines are used for robust decision in presence of wide facial and illumination variations. In experiments, the discriminant Gaborfaces incorporated with SVM classifier demonstrates better effectiveness and performance than other methods.

Keywords: Gabor Wavelet, Fisher Analysis, Face Recognition, Support Vector Machine

1. Introduction

Face recognition technology can be used in wide range of applications such as surveillance and security, telecommunication and digital libraries, human-computer intelligent interaction, and smart environments [1,2]. A good face recognition methodology should consider representation as well as classification issues, and a good representation method should require minimum manual annotations. 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. The biological relevance and computational properties of Gabor wavelets for image analysis have been described in [3]. The Gabor wavelet representation facilitates recognition without correspondence (hence, no need for manual annotations) because it captures the local structure corresponding to spatial frequency (scale), spatial localization, and orientation selectivity [4]. As a result, the Gabor wavelet representation of face images should be robust to variations due to illumination and facial expression changes

In general, feature extraction, discriminant analysis, classification rule are three basic elements in face recognition system. This paper introduces one method, which is hybrid method for face recognition. To encompass all the features produced by the different Gabor kernels one concatenates the resulting Gabor wavelet features to derive an augmented Gabor feature vector, named by Gaborfaces. After that, we apply Modified Enhanced Fisher Discriminant model (Modified EFM) to transform Gaborfaces to new feature space with higher separability and lower dimensionality. For the classification rule, we explored SVM classier to this problem. The feasibility of the new GaborfaceSVM method has been successfully tested on face recognition using a data set from the ORL database and FERET database. The effectiveness of the GaborfaceSVM method is shown by comparing with some popular face recognition schemes such as Kernel FDA [5], Fisher Discriminant Analysis (FDA) [6], and Eigenface method.

2. Discriminant Gaborface Features

Gabor wavelet model quite well the receptive field profiles of cortical simple cells. The Gabor wavelet representation, therefore, captures salient visual properties such as spatial localization, orientation selectivity, spatial frequency characteristic. Lades et al. [8] pioneered the use of Gabor wavelet for face recognition using the Dynamic Link Architecture framework. Wiskott et al.[9] developed a Gabor wavelet based elastic bunch graph matching method to label and recognize human faces. M.J. Lyons. [10] has recently 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 [3, 11]. The Gabor wavelet representation allows description of spatial frequency structure in the image while preserving information about spatial relations.

A complex-valued 2D Gabor function is a plane wave restricted by a Gaussian envelope:

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

$\vec{k}_j = \begin{pmatrix} k_{jx} \\ k_{jy} \end{pmatrix} = \begin{pmatrix} k_v \cos \phi_u \\ k_v \sin \phi_u \end{pmatrix}, k_v = 2^{-\frac{v+2}{2}\pi}$, Here 5 frequencies and 8 orientations are used, $\phi_u = u\frac{\pi}{8}, j = u + 8v, v = 0...4, u = 0...7$.

Figure 1 shows the 40 Gabor Kernels in Eq.1 used by us.

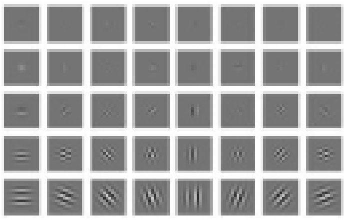

Figure 1. The Real Part of 40 Gabor Kernels used in this paper

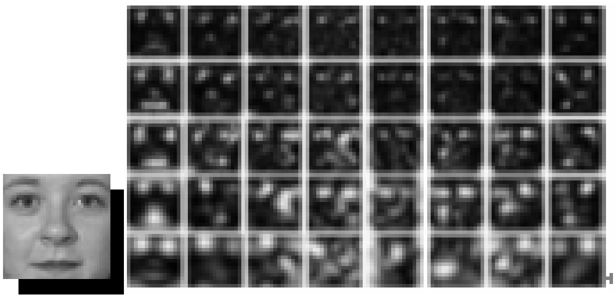

Figure 2. Left is the face image, Right is Magnitude of Gaborfaces

2.2 Gaborfaces

In a given image, the convolution can be defined as

$$G_{u,v}(z) = I(z) * \Psi_{u,v}(z) \quad (2)$$

Where $z = (x, y)$, * denotes the convolution operator, and $G_{u,v}(z)$ is the convolution result corresponding to the Gabor kernel at orientation $u = 0,...,7$ and scale $v = 0,...,4$, named by one Gaborface (showed in figure 2). Therefore, the set $S = \{G_{u,v} : u \in \{0,...7\}, v \in \{0,...4\}\}$ forms the Gabor wavelet representation of the image $I(z)$, applying the convolution thermo; we can derive each $G_{u,v}(z)$ from Eq.2 via the Fast Fourier Transform (FFT)

$$F\{G_{u,v}(z)\} = F\{I(z)\}F\{\psi_{u,v}(z)\} \quad (3)$$

$$G_{u,v}(z) = F^{-1}\{F\{G_{u,v}(z)\} = F\{I(z)\}F\{\psi_{u,v}(z)\}\} \quad (4)$$

Where F and F^{-1} denote the Fourier and inverse Fourier transform.

In order to encompass different spatial frequencies, spatial localities, and orientation selectivity, we concatenate all these representation results and derive an augmented feature vector χ . Before the concatenation, we first downsample each $G_{u,v}(z)$ by a factor ρ (Downsample size) to reduce the space dimension, and normalize it to zero mean and unit variance. We then construct a vector out of the $G_{u,v}(z)$ by concatenating its rows. Now, let $G^{\rho}{}_{u,v}(z)$ denote the normalized vector constructed from $G_{u,v}(z)$, the augmented Gabor feature vector (Gaborfaces) $X^{(\rho)}$ is then defined as follows:

$$X^{(\rho)} = (G^{\rho}{}_{0,0}(z), G^{\rho}{}_{0,1}(z)....G^{\rho}{}_{4,7}(z)) \quad (5)$$

The augmented Gabor feature vector thus encompasses all the elements of the Gabor wavelet representation set, $S = \{G_{u,v}(z) : \mu \in \{0,...,7\}, \nu \in \{0,...,4\}\}$, as important discriminating information. Chenjun Liu has shown its success of Gaborwavelet representation for face image [4].

2.3 Dimensionality Reduction and Discriminant Gaborface Analysis

The dimension of Gaborfaces is very high, $\chi^{\rho} \in R^N$, where N is dimension of the vector space. In order to reduce the dimensionality, at same time reserve the identification information, Principal component analysis, or PCA, is used to solve this problem.

Let $\sum_{X^p} = E\{[x^p - E(x)][[x^{(p)} - E(x^{(p)})]^t\}$ be the covariance matrix, the PCA of a random vector x^p factorizes its covariance matrix into following form:

$\sum_{X^p} = \Phi\Lambda\Phi^{Tt}$ With $\Phi \in R^{NxN}$ are an orthogonal eigenvector matrix and $\Lambda \in R^{NxN}$ a diagonal eigenvalue matrix.

An important property of PCA is its optimal signal reconstruction in the sense of minimum mean-square error when only a subset of principal components is used to represent the original signal. Following this property, an application of PCA is dimensionality reduction.

$$Y^{(p)} = P^t X^{(p)} \quad (6)$$

The dimension of $P \in R^{NxM}$ is $M(M < N)$. The lower dimension vector $Y^{(p)}$ capture the most expressive features of the original data $X^{(p)}$.

However, PCA is optimal and useful in coding schemes, does not focus on the recognition respect. To solve this problem, Fisher Linear Discrimination is alternative method. FLD is a popular discriminant criterion that measure the between-class scatter normalized by the within-class scatter. Now define between-class scatter matrix S_B and the within-class matrix S_W as

$$S_B = \frac{1}{C(C-1)}\sum_{i=1}^{C}\sum_{i=1}^{C}(u_i - u_j)(u_i - u_j)^T \quad (7)$$

$$S_W = \frac{1}{C(C-1)}\sum_{i=1}^{C}\sum_{i=1}^{C}(Y^p{}_j - u_i)(Y^p{}_j - u_i)^T \quad (8)$$

$u_i = \frac{1}{n_i}\sum_{j=1}^{n_i} Y^p{}_j$ Denote the sample mean of class i

To perform FDA in a set of samples, it is equal to maximize Equationg.9

$$J(W) = \frac{|w^T S_B w|}{|w^T S_W w|} \quad (9)$$

FLD derive a projection matrix w that maximizes the ratio $J(W)$. This ratio is maximized when w consists of the eigenvectors of the matrix $S_w^{-1}S_B$:

$$S_w^{-1}S_B W = W\Delta \quad (10)$$

Where w, Δ are the eigenvector and eigenvalue matrices of $S_w^{-1}S_B$ respectively.

2.4 Modified Enhanced Fisher Discriminant Model

In this part, we make some modification about the Enhanced Fisher Discriminant Model (EFM) [16]. The Modified Enhanced Fisher Discriminant Model improves the generalization capability of FLD by decomposing the FLD procedure into a simultaneous diagonalization of the two within- and between-class scatter matrices. The simultaneous diagonalization is stepwisely equivalent to two operations [4, 12, 13], First whiten the whiten-class scatter matrix:

$$S_w \Xi = \Xi\Gamma \text{ And } \Gamma^t\Gamma = \mathrm{I} \quad (11)$$

$$\Gamma^{-1/2}\Xi^t S_w \Xi\Gamma^{-1/2} = \mathrm{I} \quad (12)$$

Where Ξ, Γ are the eigenvector and the diagonal eigenvalue matrices of S_w, respectively .the eigenvalue spectrum of the within-class scattering matrix in the reduced PCA space can be derived by Eq.11.

Chenjun liu [16] chose a small set of features in the within-class space according to the eigenvalue spectrum of S_w. But we think the null space maybe contain discriminating information, so here we use all eigenvectors of within-class scattering matrix. Experiments show this method does work.

After the feature vector $Y^{(P)}$ is derived, diagonalize the within-class scatter matrix S_w using Eq.11 and Eq.12. Note that now Ξ and Γ are the eigenvector and the eigenvalue matrices corresponding to the feature vector $Y^{(P)}$. Then proceeds to compute the between-class scatter matrix as following:

$$\Gamma^{-1/2}\Xi^t S_b \Xi\Gamma^{-1/2} = \Xi_b \quad (13)$$

Diagonalize now the new between-class scatter matrix Ξ_b

$$\Xi_b\theta = \theta\gamma \text{ And } \theta^t\theta = I \quad (14)$$

Where θ, γ are the eigenvector and the diagonal eigenvalue matrices Ξ_b.

The overall transformation matrix is now defined as follows.

$$T = \Xi\Gamma^{-1/2}\theta \quad (15)$$

Here, we optimize the behavior of the trailing eigenvalues γ with the energy criteria; about 95% energy will be remained. Accordingly the reduced transformation matrix is represented as T'. In this paper, the reduced dimension is 80.

Then Discriminant Gaborfaces feature is calculated by eq.16

$$V^{(P)} = T'Y^{(p)} \quad (16)$$

3. Support Vector Machines Classifier

In this paper, Nonlinear SVMs are used as the face recognizer. SVM is a natural choice because of its robustness even in the absence of a rich set of training examples. The success of SVMs in face recognition [14, 15] provides us with further motivation to rely on SVMs as the recognizer. Since SVMs have originally been proposed for two-class classification, their basic scheme is extended to multi-class face recognition by adopting one-per-class decomposition. This work is done by constructing a SVM ω_r for each class r that first separates that class from all the other classes and then uses a max-selector, which is the simplest form of arbitrator to arbitrate between each SVM output in order to produce the final decision.

However, we should also deal with the problem that only one face image to single person in training set can't achieve good recognition result. In order to solve this problem, we use two simple techniques to derive multiple samples from single example face image. One is proper geometric transformation, such as translation, rotation in image plane, scale variance etc.. The other is proper gray-level transformation. Such simulative directional lighting, man-made lighting, etc.. Details of the method can be seen in [6], sample demonstration can be seen in figure3.

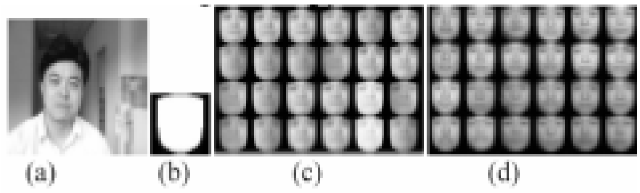

Figure3 Derive samples from single face image and normalization.

(a) Input image (b) Mask (c) Derive samples from single face image (d) Normalization faces

To construct SVMs classifier, feature vector $X^{(P)}$ is derived by Eq.5. Details of The augmented Gabor feature vector of the image is showed in section2.2. Then discriminant Gaborfaces feature is calculated by eq.16.

4. Experiment

Experiments are performed on two database, ORL database and FERET database. For SVM classifier, the polynomial kernel function, $k(x,y)=(x.y)^2$, is selected. As for the eigenvectors selection, we follows rule that ratio between the sum of the first s selected eigenvalues and the sum of all the eigenvalues is greater that 0.95, that is:

$$ratio = \frac{\sum_{i=1}^{s} \lambda_i}{\sum_{i=1}^{all} \lambda_i} \geq 0.95 \qquad (17)$$

Comparative performance is carried out against some popular face recognition schemes such as Kernel FDA, Kernel PCA, FDA, and Gabor wavelet method.

4.1 ORL Database

The ORL database used for evaluation face recognition algorithm displays across gender, age, and facial expression. The experiment involve 400 face images corresponding to 40 subjects such that each subject has ten images of 92X112 with 256 gray scale levels. First the centers of an image are manually detected, and then align the centers of the eyes to predefined location. Finally, the face is cropped to the size of 64X64 to extract the facial region, which is further normalized to zero mean and unit variance. As five images are randomly chosen for Gallery database, while the remaining image is used for probe database, the GaborfaceSVM has to cope with facial expression and rotation variability. GaborfaceSVM1 method uses Modified EFM. And GaborfaceSVM uses EFM. * represent that the data is from [5]

Methods	Gaborface SVM1	Gaborface SVM2	FDA	Eigenface
	99.4	97.2	96.3	85.7

Table1. Experiment Result on ORL database

4.2 FERET Database

The proposed algorithm was applied to problem of face recognition and tested on a subset of the FERET face image database. This subset includes 1400 images of images of 200 individuals (each individual has 7 images). It is composed of the images named with two-character strings: ”ba”,”bj”,”bk”,”be”,”bd”,”bf” and “bg”. These strings indicate the kind of imagery, see Table 1. this subset involves variation in facial expression, illumination, and pose. In our experiments, the facial portion of each original image was cropped based on the location of the eyes and then, the cropped image was resized to 64x64 pixels. Train database contains 100 person with the large indices. In this experiment, only “ba” part is used as gallery database, others are probe database.

Figure 4. Sample of Face Images in FERET database

Methods	Gaborface SVM1	Gaborface SVM2	FDA	Eigenface
	85.2	81.5	78.3	50.6

Table2. Experiment Result on FERET database

5. Conclusion and Future Work

We have introduced a Gaborfaces method in this paper, which is robust to variations in illumination and facial expression by augmenting the Gabor feature vector derived from the Gabor wavelet representation of face images and Modified Enhanced Fisher Discriminant model. The Gabor Wavelet transformed face images yield features that display scale, locality, and orientation selectivity .The feasibility of the new method has been successfully tested on face recognition using data set from the ORL frontal database, which is a standard testbed for face recognition technologies, and FERET database is also used to test this method. The effectiveness of the method is shown in terms of both absolute performance indices and comparative performance against some popular face recognition schemes such as Kernel FDA, FDA, and Eigenface methods.

The excellent performance shown by the method is the direct result of coupling Gaborfaces and Modified Enhanced Fisher Discriminant model with the SVM classifier. The effectiveness of Gabor wavelets has been shown so far to match and capture only the statistics of natural scenes, it is also quite possible that the same Gabor wavelets are also tuned for face processing tasks.

Our next goal is to further search for extracting the facial feature and weighting salient feature such as eyes, nose and mouth before forming the augmented Gabor feature vector and applying the SVMs classifier to finish classification task. Another possibility is to increase the ability of the classifier minimizing the empirical risk encountered during training and narrowing the confidence interval for reducing the guaranteed risk while testing on unseen data. Moreover, how to increase quality of face image is very important for all identification problems; surely, we have to make more try to solve it.

6. Acknowledgement

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