AdaBoost Gabor Fisher Classifier for Face Recognition

Shiguang Shan[1], Peng Yang[2], Xilin Chen[1], and Wen Gao[1,3]

[1] ICT-ISVISION JDL for Face Recognition, Institute of Computing Technology, Chinese Academy of Sciences, Beijing, 100080, China
{sgshan, xlchen, wgao}@jdl.ac.cn
http://www.jdl.ac.cn/project/faceId/index_en.htm
[2] Department of Computer Sciences at Rutgers, The State University of New Jersey, USA
peyang@eden.rutgers.edu
[3] School of Computer Science and Technology, Harbin Institute of Technology, 150001 Harbin, China

Abstract. This paper proposes the AdaBoost Gabor Fisher Classifier (AGFC) for robust face recognition, in which a chain AdaBoost learning method based on Bootstrap re-sampling is proposed and applied to face recognition with impressive recognition performance. Gabor features have been recognized as one of the most successful face representations, but it is too high dimensional for fast extraction and accurate classification. In AGFC, AdaBoost is exploited to select optimally the most informative Gabor features (hereinafter as AdaGabor features). The selected low-dimensional AdaGabor features are then classified by Fisher discriminant analysis for final face identification. Our experiments on two large-scale face databases, FERET and CAS-PEAL (with 5789 images of 1040 subjects), have shown that the proposed method can effectively reduce the dimensionality of Gabor features and greatly increase the recognition accuracy. In addition, our experimental results show its robustness to variations in facial expression and accessories.

1 Introduction

Automatic Face Recognition (AFR) research has been motivated by both its scientific values and wide potential applications in public security, law enforcement, and video surveillance. Relevant research activities have significantly increased, and much progress has been made during the past few years [1,2,3]. However, most current systems work well only under constrained conditions, even requiring the subjects highly cooperative. Therefore, the general problems in AFR remain unsolved, especially under the practical unconstrained conditions.

The performance of a face recognition system depends not only on the classifier, but also on the representation of the face patterns. Generally speaking, a good representation should have such characteristics as small within-class variation, large between-class variation, and being robust to transformations without changing the class label [4]. Furthermore, its extraction should not depend much on the manual operation. Intuitively, one should derive face representation from the 3D face shape and skin reflectance if we could recover the above intrinsic information from a given 2D face image. Unfortunately, it is an ill-posed problem in computer vision. Therefore, most current famous face recognition methods derive face representation

W. Zhao, S. Gong, and X. Tang (Eds.): AMFG 2005, LNCS 3723, pp. 278 – 291, 2005.

directly from the 2D face image matrix. The obvious disadvantages of 2D image representation lie in its sensitivity to the changes in the extrinsic imaging factors such as viewpoint and lighting.

Another popular strategy to represent face pattern exploits some transformations of the 2D image. Typical transformations include the Fourier transform [5], various wavelets, among which Gabor wavelets have been widely accepted by researchers in AFR community [6,7,8,9], mostly because the kernels of Gabor wavelet are similar to the 2D receptive field profiles of the mammalian cortical simple cells and exhibit desirable characteristics of spatial locality and orientation selectivity [10, 11]. Previous works on Gabor features have also demonstrated excellent performance. Typical methods include the Dynamic Link Architecture (DLA) [6], Elastic Graph Matching (EGM) [7], Gabor Wavelet Network (GWN) [8], and Gabor-Fisher Classifier (GFC) [9].

EGM represents a face as a labeled graph [7]. Each vertex of the graph corresponds to a predefined facial landmark with fixed high-level semantics, and labeled by the multi-scale, multi-orientation Gabor ***Jet*** computed from the image area centered at the vertex landmark. And the edge of the graph represents the connection between the two vertices landmarks and labeled by the distance between them. After the construction of the graph, identification can be achieved by the elastic matching between the reference graph and the probe one. By selecting facial landmarks carefully, elastic graph can well model the local facial features as well as their configuration. Therefore, it makes the most of the local features as well as the overall facial configuration. Nevertheless, the high complexity of graph construction and matching may have prevented its further application. In addition, imprecise landmarks localization may also influence its recognition performance.

One straightforward way to exploit Gabor features for AFR is proposed by Liu [9]. In Liu's method, Gabor features of multi-scale and multi-orientation for each pixel in the normalized face images (with the eyes aligned) are firstly computed and concatenated to form a high-dimensional Gabor features, which is then uniformly down-sampled to a low-dimensional feature vector, and further reduced dimension by Principle Component Analysis (PCA), and discriminated by enhanced Fisher Discriminant Analysis for final face identification [9]. This method is simple and does not need to localize more facial landmarks except the two eyes. Liu has experimentally shown the excellent performance of such a method. However, the uniform down-sampling procedure would not only reduce the dimension of the high-dimension dense Gabor features, but also reject a great number of informative Gabor features and reserve many redundant ones, which would do harm to the final classification.

Aiming at the above-mentioned problem of GFC, this paper proposes to optimally select informative Gabor features to keep from losing discriminant Gabor features and introducing redundant ones by the simple down-sampling procedure. We originally apply AdaBoost to face recognition as a feature selection tool to reduce the dimension of Gabor features. The Gabor features selected by AdaBoost are further processed by Fisher discriminant as the final classifier. Our experiments on two large-scale face databases, FERET and CAS-PEAL, have shown that the proposed AGFC method can efficiently reduce the dimension of the original Gabor features, and the final recognition performance has also been improved.

2 Related Works

2.1 Gabor Features

Gabor wavelets model quite well the receptive field profiles of cortical simple cells, and they can capture salient visual properties such as spatial localization, orientation selectivity, and spatial frequency characteristic. Gabor filters extract both the overall and the subtle spatial frequency features in some local image area with multiple scales and multiple orientations, magnifying like a microscope all the features implied in the changing of gray-level intensity. Therefore, 2D Gabor filters enhance the low-level image features such as the peaks, valleys, and ridges. So, the eyes, the nose and the mouth, as well as the other salient local features like naevi, dimples, and scars, are enhanced as key features for the following discrimination of different faces. The Gabor wavelet representation also facilitates recognition without correspondence (hence, little need for manual annotations) because it captures the local structure corresponding to spatial frequency (scale), spatial localization, and orientation [9]. As a result, the Gabor wavelet representation of face images is robust to mis-alignment to some degree as Shan et al report in [12].

Lades et al. pioneered the use of Gabor wavelets for face recognition using the DLA framework, which is then expanded to EGM by Wiskott et al. [7]. The commonly used Gabor filters in face recognition area is defined as followings [6, 7, 9, 11]:

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

where u and v define the orientation and scale of the Gabor kernels, $z = (x, y)$, $\|\cdot\|$ denotes the norm operator, and the wave vector $k_{u,v}$ is defined as follows:

$$k_{u,v} = k_v e^{i\phi_u}, \quad (2)$$

where $k_v = k_{\max} / f^v$ and $\phi_u = \pi u / 8$ with $k_{\max}$ be the maximum frequency, and f be the spacing factor between kernels in the frequency domain. In face recognition area, researchers commonly use 40 Gabor wavelets with five scales $v \in \{0,1,2,3,4\}$ and eight orientations $u \in \{0, \cdots, 7\}$ and with $\sigma = 2\pi$, $k_{\max} = \frac{\pi}{2}$, and $f = \sqrt{2}$.

Convolving the image with these 40 Gabor kernels can then generate the Gabor features. Thus, for each pixel position in the face image, 40 complex values can be calculated. Note that, because the phase information of the transform is time-varying, generally, only its magnitudes are used to form the final face representation. Evidently, this will result in a feature with a dimension of 40 times of the original face images size, which is too high dimensional in pixel-wise dense sampling case. Therefore, GFC down-sampled the Gabor features, while in this paper learning method is used to select the most informative ones.

2.2 Adaptive Boosting (AdaBoost)

Boosting has been proposed to improve the accuracy of any given learning algorithm. In Boosting one generally creates a classifier with accuracy on the training set greater than an average performance, and then adds new component classifiers to form an ensemble whose joint decision rule has arbitrarily high accuracy on the training set [4]. In such a case, we say that the classification performance has been "boosted". In overview, the technique train successive component classifiers with a subset of the entire training data that is "most informative" given the current set of component classifiers [4].

AdaBoost (Adaptive Boosting) is a typical instance of Boosting learning. In AdaBoost, each training pattern is assigned a weight that determines its probability of being selected for some individual component classifier. Generally, one initializes the weights across the training set to be uniform. In the learning process, if a training pattern has been accurately classified, then its chance of being used again in a subsequent component classifier is decreased; conversely, if the pattern is not accurately classified, then its chance of being used again is increased [4]. In each iteration, one draws a training set at random according to the weights, and then trains a component classifier C_k on the patterns selected. Next one increases weights of those training patterns misclassified by C_k and decrease weights of the patterns correctly classified by C_k. Patterns chosen according to this new weights are used to train the next classifier, C_{k+1}, and the process is iterated to a predefined error rate or enough component classifiers have been constructed [4]. In this way, AdaBoost focuses on the informative or "difficult" patterns. The final classifier is a linear combination of the component classifiers. According to the idea, Freund and Schapire first proposed the concrete algorithms of Adaboost [13].

In 2001, Viola and Jones proposed a modified AdaBoost algorithm and applied it to face detection successfully [14]. In Viola's AdaBoost, the component classifier (or so-called weak classifier) has been designed by one individual weak Haar-like feature. AdaBoost learning is adopted to combine these weak classifiers. Therefore, in some sense, in Viola's AdaBoost, weak classifier is somewhat equivalent to weak feature. For the specific face detection problem, Viola has designed a fast algorithm to exact a huge number of rectangle (Haar-like) features from a small candidate window region, a few of which are then selected and combined to form a strong classifier by AdaBoost learning. By far, AdaBoost-based face detection has been recognized as the most successful one for face detection task [15]. Viola has also applied the similar method to pedestrian detection and achieved similar success. By using AdaBoost for selecting Gabor features, this paper originally applies AdaBoost to face recognition successfully.

3 AdaBoost Gabor Fisher Classifier

The great success of AdaBoost on face detection has motivated our interest in applying AdaBoost to face recognition. Considering the success of Gabor features in face recognition area, we have previously proposed to design an AdaBoost classifier by using the Gabor representation as the original feature set [16]. Unlike our previous work in [16], this paper re-considers AdaBoost as a feature selection tool and Fisher Discriminant Analysis is exploited as the final classifier. To apply AdaBoost to multi-class AFR problem, the "dual difference class", i.e., intra-personal and extra-personal differences are introduced to convert the multi-class problem into a binary classification problem [17]. Given a training set, the two difference classes are first computed, and then AdaBoost is trained on them to select those most informative ones (named by AdaGabor features) from all the original high-dimensional pixel-wise dense Gabor features. The resulting AdaGabor features are then further reduced in dimensionality by PCA, and then fed into the Fisher Discriminant Analysis for final classification.

3.1 Intra-personal and Extra-personal Difference

To exploit AdaBoost for face recognition, we have to convert the multi-class problem to a binary one. Typical methods include one-to-one and one-to-rest, which need to construct *C(C-1)/2* and *C* classifiers respectively, where *C* is the number of persons to be recognized. Both of them are very complex, and inconvenience when we need to enroll new persons. To solve this problem, we have adopted the intra-personal and extra-personal difference method proposed by Moghaddam and Pentland [17]. Given two images in a training set coming from the same face, their feature vector difference would be put into the intra-personal difference class, otherwise, their difference will be labeled as an extra-personal difference. In this way, face recognition problem is re-formulated as a binary classification problem to determine which class the difference between the probe image and any gallery one belongs to. Therefore, AdaBoost can be applied straightforwardly to learn the separation super-surface.

3.2 Gabor Features Selection Using Chain AdaBoost Learning Based on Bootstrap Re-sampling

Inevitably, given a training set, the intra-personal/extra-personal difference method will result in the heavy unbalance between the amount of intra-personal (hereinafter as "positive") and extra-personal (hereinafter as "negative") difference samples. For instance, assume there are *m* persons with *k* samples for each person in the training set, the amount of intra-personal and extra-personal difference samples would be $N^+ = C_m^1 C_k^2 = mk(k-1)/2$ and $N^- = C_m^2 C_k^1 C_k^1 = k^2 m(m-1)/2$ respectively. So, their ratio is $R = N^- / N^+ = k(m-1)/(k-1)$. Let *m=500* and *k=5*, then N^+ and N^- will be *5,000* and *3,118,750* respectively with their ratio be *624*. Obviously, such huge amount of negative samples will lead to severe memory problem for the learning process. In addition, the heavy unbalance between the positive and negative samples will also influence the design of the final classifier. One simple way to deal with this problem is sampling part of the negative set randomly. However, random sampling would not necessarily guarantee inclusion of the most representative ones. To solve this problem, we further turn to the idea of bootstrap and propose a re-sampling strategy to construct a chain AdaBoost. The abstract procedure of the methods is described in Algorithm 1.

Alg.1 ***Chain AdaBoost Learning Based on Bootstrap Re-sampling of Negative Examples***

Input: $\{(\Delta_1, y_1),...,(\Delta_n, y_n)\}$ be the whole training set, with $\Delta_i \in D$ be the difference pattern, and $y_i \in Y = \{0,1\}$ its label ('1' denotes Intra-personal difference and '0' denotes extra-personal difference.)

Initialize: (1) All the positive exemplas form the positive training set S^+, which is remain unchanged during the whole learning procedure. (2) Randomly choose a predefined amount of negative exemplas to form the initial negative training set S_0^-. And assume $N^+ = \|S^+\|, N^- = \|S^-\|$. be the amount of positive and negative exemplas respectively. In our experiments, N^- is set to be 7 times of N^+.

For $l = 1,\cdots,L$

Begin

(1) Initialize the weights for each training exemplum.

$$w_{l,i} = \begin{cases} \dfrac{1}{2N^+} & y_i = -1 \\ \dfrac{1}{2N^-} & y_i = 0 \end{cases} \tag{3}$$

(2) Call AdaBoost procedure to learn the current level AdaBoost classifier C_l using the current training set:

$$C_l(\Delta) = sign(\sum_{t=1}^{T_l} \alpha_t h_t(\Delta) - \frac{1}{2}\sum_{t=1}^{T_l} \alpha_t) \tag{4}$$

where T_l is the number of weak classifiers learned in this level AdaBoost, which can be adjusted by controlling the learning accuracy, and $\alpha_t = \log \beta_t^{-1}$ be the combination weight of the *t*-th weak classifier in the AdaBoost. For the meaning of other symbols, please refer to the AdaBoost algorithm in [14] for details.

(3) Then, combine the C_l with the previous classifiers to form the lth strong classifier Hl:

$$\begin{aligned} H_l(\Delta) &= sign(H_{l-1}(\Delta) + C_l) \\ &= sign(\sum_{t=1}^{T} \alpha_t h_t(\Delta) - \frac{1}{2}\sum_{t=1}^{T} \alpha_t) \end{aligned} \tag{5}$$

where $T = \sum_{j=1}^{l} T_j$.

(4) Re-sampling the negative exemplas to form the next generation of negative training set:

a) Set S^- be a null set, $S^- = \phi$.

b) Randomly take out one negative exemplum, Δ_k, from the left negative training set. If Δ_k is classified incorrectly by the classifier,

$$H_l^{\xi_l}(\Delta_k) = sign(\sum_{t=1}^{T} \alpha_t h_t(\Delta_k) - \frac{1}{2}\xi_l \sum_{t=1}^{T} \alpha_t), \tag{6}$$

it is selected and added into the next generation negative exemplas set, $S^- = S^- \cup \{\Delta_k\}$. The classifier described by Equ.6 is a loose version of H_l, where $\xi_l < 1$ and increase gradually with the increase of *l*.

c) Repeat the above b-step until the size of S^- becomes the predefined number N^-.

End

So, finally H_L is the final classifier:

$$H_L(x) = sign(\sum_{t=1}^{T} \alpha_t h_t(x) - \frac{1}{2}\sum_{t=1}^{T} \alpha_t) \quad (7)$$

where $T = \sum_{j=1}^{L} T_j$, T_j is the number of weak classifier for the *j*th AdaBoost.

Though the above chain AdaBoost learning algorithm finally establishes a strong classifier discriminating the intra-personal and extra-personal difference that can be used for both face identification and verification, unfortunately, our experiments have shown that its performance for face recognition is not as satisfactory as expected. Therefore, in this paper, we have re-considered its usage as an excellent ***feature selection*** or ***dimension reduction*** tool to solve the high dimension problem when using Gabor features for face recognition. From the learning procedure, one can see that each weak classifier is constructed from one single Gabor feature using the simplest linear perceptron. This implies that the Gabor features selected to construct the weak classifiers should be the most informative ones. Therefore, in this sense, AdaBoost has selected a small quantity from all the Gabor features, i.e., AdaBoost has completed a feature selection or dimension reduction procedure. For convenience, we call the ***T*** Gabor features selected by the above-mentioned chain AdaBoost learning procedure ***AdaGabor*** features. These AdaGabor features are then further reduced in dimensionality by PCA and then fed into Fisher linear discriminant analysis for the final face identification.

3.3 FDA of AdaGabor Features

In face recognition research, Fisher Discriminant Analysis (FDA) has been recognized as one of the most successful methods [18]. In FDA, the original face representation is transformed to a new FDA subspace where the between-class scatter is maximized, while the within-class scatter is minimized by maximizing the Fisher separation criterion.

When designing a Fisher classifier, one has to deal with the within-class scatter matrix carefully, because it may be singular. To avoid the singularity problem, PCA is conducted to further reduce the dimensionality of the AdaGabor features to be less than *N*-*C*, where *N* is the number of training examples, and *C* is the number of classes. The PCA transformed features are then fed into the final FDA for classification.

4 Experiments and Analysis

4.1 Description of the Testing Database

To evaluate the proposed method with some statistically salient comparisons, we choose the FERET and CAS-PEAL face database, both of which contain more than 1000 subjects with several face images for each subject.

FERET Face Database [2]

The Facial Recognition Technology (FERET) database was collected at George Mason University and at US Army Research Laboratory facilities as part of the FERET program, sponsored by the US Department of Defense Counterdrug Technology Development Program. The lists of images used in training, gallery and probe sets are distributed along with the database CD. Note that the FERET face database has strictly distinguished the testing set (composed of Gallery and Probe sets) from the training set. Table.1 shows the structure of the FERET face database we use to evaluate our method. We have tested our method on the largest probe set FB with 1195 images of different subject. Note that the training set we use is a near-frontal face subset of the standard FERET training set, in which only the near-frontal face images in the standard FERET training CD are included.

Table 1. Structure of the FERET face database used in our experimental evaluation

Database		#Persons	#Images	Note
Training Set		429	1002	All near-frontal faces in the standard FERET training set
Test Set	Gallery	1196	1196	Standard FERET gallery with Near-frontal faces
	FB Probes	1195	1195	Near-frontal faces with different expressions from those in Gallery.

CAS-PEAL-R1 Face Database [19]

CAS-PEAL face database is constructed by the Joint R&D Laboratory for Advanced Computer and Communication Technologies (JDL) of Chinese Academy of Sciences (CAS), under the support of the Chinese National Hi-Tech (863) Program. The CAS-PEAL face database contains 99,594 images of 1040 individuals (595 males and 445 females) with varying Pose, Expression, Accessory, and Lighting (PEAL). CAS has recently released part of the database named by CAS-PEAL-R1 face database, which consists of 30,900 images of 1040 Chinese and is divided into a frontal subset and a pose subset. In the release CAS-PEAL-R1 CD, the authors have also suggested a standard evaluation prototype, which has specified the images that compose the

Fig. 1. Frontal face examples in the CAS-PEAL-R1

training set, the gallery, and the probe sets. This paper has strictly followed the CAS-PEAL-R1 evaluation protocol as illustrated in Table 2. Some example images are shown in Figure 1.

Table 2. Structure of the CAS-PEAL-R1 face database used in our experimental evaluation

Datasets	Training set	Gallery	Probe sets (frontal)				
			Exp	Acc	Bac	Dis	Age
#Subject	300	1040	377	438	297	275	66
#Images	1,200	1040	1,570	2,285	553	275	66

Preprocessing

For both FERET and CAS-PEAL-R1 face database, the coordinates of the eyes in all the face images have been provided, which can be used as the ground-truth alignment. In our experiments, faces are normalized as shown in Fig.2. Faces are firstly cropped out, as Fig.2 (c), by placing the two eyes at fixed locations specified with *h, t, b* be 0.64, 0.43, and 1.85 respectively. A mask is then overlapped on the face region to eliminate the background and the hairstyle. Eventually, all faces are warped to the size of 64x64 as shown in Fig.2 (d) from their original form as in Fig.2 (b).

(a) (b) (c) (d)

Fig. 2. Face normalization method in our experiments

4.2 Analysis of the Selected AdaGabor Features

As we have analyzed, the AdaGabor features should be the most informative features discriminating different faces. To observe their characteristics intuitively, we conducted experiments on FERET training set to obtain 1000 AdaGabor features. Some of their statistics are given below.

The Most "Discriminant" Gabor Features

Figure 3 shows the leading 4 most "discriminant" AdaGabor feature obtained through the Chain AdaBoost learning procedure, in which their Gabor kernels are overlapped to a face image for intuitive understanding. From the figure, one can easily see the position, scale and orientation of the corresponding Gabor kernel. It seems that these four Gabor kernels have coarsely positioned at the two eyes, the nose, and the mouth. One may have expected the first two exactly coincide with the two eye centers, but the experimental results have conflict with this expectation. We suppose the precise alignment of the two eyes in the processing stage should answer for the phenomenon, since this may have greatly decreased the difference between eyes.

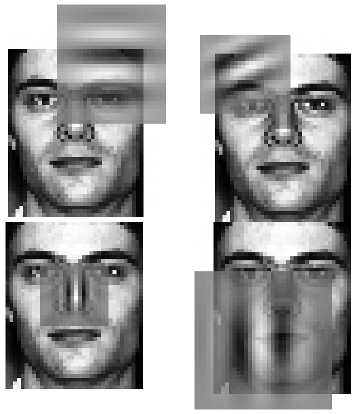

Fig. 3. The Four Leading AdaGabor features

Frequency analysis of the 40 Gabor kernels in the AdaGabor features

Figure 4 illustrates the frequency of the 40 Gabor kernels in the leading 1000 AdaGabor features. From the figure 4, we can safely conclude that different Gabor filters contribute to identification quite differently. At least for the FERET face database case, the No.1 (u=0, v=0), No.5 (u=4, v=0), and No.13 (u=4, v=1) Gabor kernels have contributed more when compared with the others.

Scale distribution and variation of the leading AdaGabor features

We also reviewed the distribution and variation of scales among the leading 100, 500, and 1000 AdaGabor features, as illustrated in Figure 5. Clearly, smaller scales contribute more to the accurate identification especially when we need to distinguish the subtle difference between faces, as we can see that the kernels with 0-scale are about 1/3 in the 1000 AdaGabor features. This is also coinciding with our basic intuition.

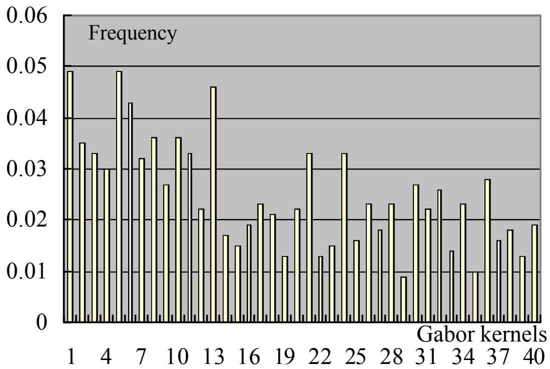

Fig. 4. Distribution of 40 Gabor kernels in the Leading AdaGabor features

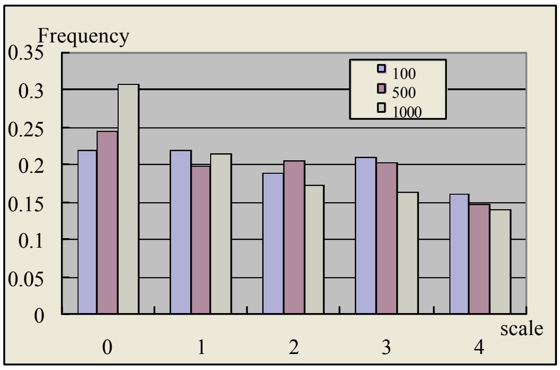

Fig. 5. The scale distribution and variation of the leading AdaGabor features

Orientation distribution and variation of the leading AdaGabor features
Different orientations also contribute differently to the classification. Figure 6 shows the distribution and variation of orientations among the leading 100, 500, and 1000 AdaGabor features. It seems that the orientation distribution is somewhat uniform. However, the vertical Gabor kernels (with *v=4*) have extracted stronger features, while those with 45 degree (*v=2* and *v=6*) are relatively weaker.

4.3 Methods for Comparison

We have implemented two algorithms, Fisherface and Liu's GFC, to compare with the proposed AGFC. In GFC, the down-sampling factor is 16, that is, the 16 Gabor Jets in a 4×4 rectangle are averaged to calculate one Jet. So, for the original normalized 64 pixels by 64 pixels face image, the dimension after down sampling is $15\times15\times40 = 9{,}000$. These 9000 Gabor features are then analyzed by PCA to further reduce its dimension to 500 for further Fisher discriminant analysis.

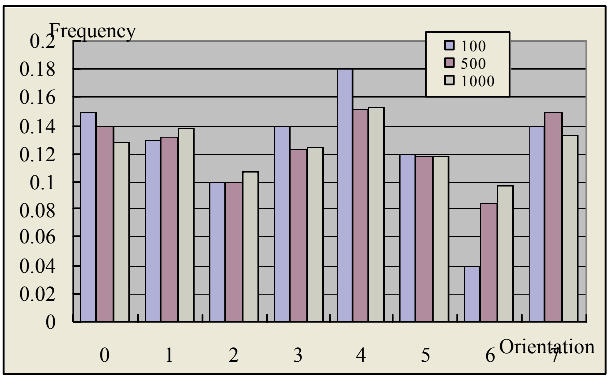

Fig. 6. The orientation distribution and variation of the leading AdaGabor features

4.4 Experimental Results

We then evaluate the proposed AGFC on FERET and CAS-PEAL-R1 face database, and compare its performance with that of the Fisherface and the GFC methods. The experimental results are illustrated in Table 3 and Table 4. In the experiments, 1884 and 2500 AdaGabor features are respectively selected for FERET and CAS-PEAL database by the AdaBoost procedure from the original 163,840 Gabor features. Note that to compare the three methods impartially, for each probe subset, all the possible dimensions for PCA and FDA (D_{pca} and D_{fda} in the table) are tested to find the optimal one. The D_{pca} and D_{fda} value in the Table 4 are the average for the 5 subsets.

From Table 3, one can see that our AGFC performs a little better than Fisherface and GFC from the recognition rate. This observation is more statistically salient on the CAS-PEAL-R1 face database as shown in Table 4. Especially for its "Expression" and "Accessory" cases, AGFC has achieved much higher recognition rate compared with Fisherface and GFC, which indicates that the AGFC is much more robust to the variations in facial expression and accessories.

Except its advantage in recognition accuracy compared with Fisherface and GFC, more importantly, our AGFC has greatly reduced the dimensionality of the original face features for classification. This will greatly facilitate the design of the classification as well as the real world face recognition systems, since we need not to compute all the Gabor features as GFC. So, a more fast and accurate face recognition system can be easily implemented using AGFC after the training stage.

Table 3. Performance Comparisons of Fisherface, GFC, and the AGFC on FERET face database fb subset

Methods	Dimensions			Recognition rate on FERET fb
	D_{ori}	D_{pca}	D_{fda}	
Fisherface	4096	300	210	94.4%
GFC	9000	500	250	96.3%
AGFC	1884	250	200	97.2%

Table 4. Performance Comparisons of Fisherface, GFC, and AGFC on the different subsets of CAS-PEAL-R1 face database

Methods	Dimension			Recognition rate on different CAS-PEAL Subsets (%)				
	D_{ori}	D_{pca}	D_{fda}	Exp	Acc	Bac	Age	Dis
Fisherface	4096	400	210	80.2	71.0	97.5	77.3	97.5
GFC	9000	500	250	92.9	85.1	98.9	93.9	100.0
AGFC	2500	250	200	98.2	87.5	99.6	97.0	99.3

5 Conclusion and Discussion

This paper has investigated the dimensionality reduction of high dimensional Gabor features and proposed a novel AdaBoost Gabor Fisher Classifier (AGFC) for robust face recognition by successfully applying the popular AdaBoost to face recognition as an effective feature selection tool to select the most informative Gabor features for discriminating different faces. In order to apply AdaBoost to multi-class problem, the intra-personal and extra-personal difference strategy is exploited to convert face recognition problem to a binary classification problem, then a chain AdaBoost learning algorithm is proposed based on Bootstrap re-sampling to make full use of the huge amount of extra-personal difference samples. Thus, thousands of informative AdaGabor features are selected for further Fisher discriminant analysis. In the experimental parts, we analyzed the distribution of the selected AdaGabor features, and compared the performance of the proposed AGFC with Fisherface and GFC on two large-scale face databases, FERET and CAS-PEAL-R1, which has impressively indicated the advantages of the AGFC.

(a) (b) (c)

Fig. 7. Intuitive difference between the EGM, the GFC, and the proposed AGFC

The intuitive difference in Gabor sampling of the EGM, the GFC, and the proposed AGFC is illustrated in Figure 7. In EGM, predefined facial landmarks with canonical positions can subsequently shift and adapt to the input face geometry, and all the 40 Gabor features (5 scales combing 8 orientations) are computed for each landmark. However, for GFC, after aligning the two eye centers, all the 40 Gabor filters are convoluted with the image at each vertex of a uniform grid. Evidently, both of them rely on the subjective selection of "informative" Gabor features. But in our AGFC method, the Gabor filters (in terms of its position, the orientation and the scale) to be exploited for identification are learned by the AdaBoost, which can be regarded as an objective standard.

Our future work would focus on the further investigation of the AdaGabor features. Also, we are trying other feature selection tools and comparing their performance with AdaBoost-based method.

Acknowledgements

This research is partially sponsored by Natural Science Foundation of China under contract No.60332010, "100 Talents Program" of CAS, ShangHai Municipal Sciences and Technology Committee (No.03DZ15013), and ISVISION Technologies Co., Ltd.

References

[1] R.Chellappa, C.L.Wilson, S.Sirohey, Human and Machine Recognition of faces: A survey, Proceedings of the IEEE, vol.83, no.5, 1995

[2] P.J.Phillips, H.Moon, etc. “The FERET Evaluation Methodology for Face-Recognition Algorithms,” IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol.22, No.10, pp1090-1104, 2000

[3] P.J.Philips, P.J.Grother, R.J.Micheals, D.M.Blackburn, E.Tabassi, and J.M.Bone, Face Recognition Vendor Test 2002: Evaluation report, Technical Report, NISTIR 6965, National Institute of Standards and Technology, 2003, http://www.frvt.org.

[4] R.O.Duda, P.E.Hart, D.G.Stork, Pattern Classification, Second Edition, John Wiley & Sons Inc. 2001

[5] J.Lai, P.C.Yuen, G.C.Feng, Face recognition using Holistic Fourier Invariant Features”, Pattern Recognition, 34(1), 95-109, 2001

[6] M.Lades, J.C.Vorbruggen, J.Buhmann, J.Lange, C.v.d.Malsburg, R.P.Wurtz, W.Konen, Distortion Invariant Object Recognition in the Dynamic Link Architecture, IEEE Trans. On Computers, 42(3), pp 300-311, 1993

[7] L.Wiskott, J.M.Fellous, N.Kruger, C.v.d.Malsburg, Face Recogniton by Elastic Bunch Graph Matching, IEEE Trans. On PAMI, Vol.19, No. 7, pp775-779, 1997

[8] V. Krueger. Gabor wavelet networks for object representation. . DAGM Symposium, Kiel, Germany, 9, 13-15, 2000.

[9] C.Liu and H.Wechsler: "Gabor Feature Based Classification Using the Enhanced Fisher Linear Discriminant Model for Face Recognition", IEEE Trans. Image Processing, vol. 11, no. 4, pp. 467-476, 2002.

[10] J.G. Daugman, “Uncertainty Relation for Resolution in Space, Spatial Frequency, and Orientation Optimized by Two-Dimensional Visual Cortical Filters,” J. Optical Soc. Amer., vol. 2, no. 7, pp. 1,160-1,169, 1985.

[11] T. S. Lee. Image Representation Using 2d Gabor Wavelets. IEEE Trans. Pattern Analysis and Machine Intelligence, 18(10):959--971, 1996

[12] S.Shan, W.Gao, Y.Chang, B.Cao, P.Yang, Review the Strength of Gabor features for face recognition from the angle of its robustness to mis-alignment, Proceedings of ICPR2004, vo1.I, pp338-341, 2004

[13] Y.Freund and R.E. Schapire. A decision-theoretic generalization of on-line learning and an application to boosting. J. Comput. Syst. Sci., 55(1):119--139, 1997

[14] Paul Viola, M.Jones, Rapid Object Detection using a Boosted Cascade of Simple, Proceedings of CVPR2001, vol.I, pp511-518, 2001

[15] S.Z.Li, ZhenQiu Zhang. "FloatBoost Learning and Statistical Face Detection". IEEE Transactions on Pattern Analysis and Machine Intelligence, Accepted, 2004.

[16] P.Yang, S.Shan, W.Gao, S.Z.Li, D.Zhang, Face Recognition Using Ada-Boosted Gabor Features, Proceeding of the 6th IEEE International Conference on Automatic Face and Gesture Recognition, pp356-361, Korea, May, 2004

[17] Baback Moghaddam, Tony Jebara, Alex Pentland, Bayesian Face Recognition, Pattern Recognition Vol.33 (2000), pp1771-1782, 2000

[18] P. N. Bellhumer, J. Hespanha, and D. Kriegman. Eigenfaces vs. fisherfaces: Recognition using class specific linear projection. IEEE Transactions on Pattern Analysis and Machine Intelligence, Special Issue on Face Recognition, 17(7): 711--720, 1997

[19] W.Gao, B.Cao, S.Shan, et al. The CAS-PEAL Larege-Scale Chinese Face Database and Evaluation Protocols, Technical Report JDL-TR-04-FR-001, Joint Research&Development Laboratory, CAS, 2004. http://www.jdl.ac.cn/peal/index.html