Face Recognition Based on Local Steerable Feature and Random Subspace LDA

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Abstract. Both local features and holistic features are critical for face recognition and have different contributions. In this paper, we first propose a novel local steerable feature extracted from the face image using steerable filter for face representation. Discriminant information provided by steerable filter is locally stable with respect to scale, noise and brightness changes and it is semi-invariant under common image deformations and distinctive enough to provide useful identity information. We then present a new null space method based on random subspace. Linear Discriminant Analysis (LDA) is a popular holistic feature extraction technique for face recognition. Null Space LDA (NLDA) and Fisherface are adopted to extract global feature in the steerable feature space. Based on random subspaces, multiple NLDA classifiers are constructed under the most suitable situation for the null space. NLDA takes full advantage of the null space, while Fisherface extracts the most discriminant information in the principal subspace. Fisherface classifiers are constructed from the same set of random subspaces for NLDA classifiers. In each random subspace, Fisherface and NLDA share a unique eigen-analysis. There is no redundancy between such two kinds of complementary classifiers. Finally, all of the classifiers are integrated using a fusion rule. Experimental results on different face data sets demonstrate the effectiveness of the proposed method.

1 Introduction

Face recognition has attracted much attention due to its potential values for applications as well as theoretical challenges. To be successful for face recognition, features for classification must be robust to typical image deformations, and highly distinctive to afford identity information [2]. Local features offer advantages with stability to local deformations, lighting variations and expression variations. A variety of local features have been successfully employed in face recognition including Haar-like features [6, 7], Gabor wavelet features [5] and Local Binary Pattern (LBP) features [8]. In this paper, we propose a novel local descriptor based on steerable feature which is robust and distinctive for face recognition. The feature is extracted from face image based on the responses of complex-valued steerable filters. The amplitude and zero-crossings of such filters provide useful information for texture analysis in face recognition. The

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major advantage of using steerable feature is the stability with respect to image deformations that typically exist in the face images of the same person, so that similar structure is generally available for classification.

The use of local, band-pass and linear filters is the focus of considerable research on early biological and computational visual processing [3]. Oriented filters are useful in many early vision and image processing tasks. One often needs to rotate the same filter to different angles under adaptive control, or to calculate the filter response at various orientations. Because the synthesis of the rotated filters is analytic and exact, steerable filters offer advantages for image analysis over ad hoc methods which combine oriented filters at different orientations. Physiological data suggest that the response of complex-valued steerable filter may model the basic binocular interaction of simple cells and complex-cell response [3]. Steerable filter has been successfully used for edge detection, shape-from-shading, feature detection, and stereo matching [1, 3, 4]. Steerable filter can capture the local structure corresponding to any orientation in one scale, while discriminative information in the scales-space of face image should be good to improve recognition performance. To further improve the accuracy, steerable filter is implemented with a Gaussian pyramid of face image. Steerable features from multiple scales and orientations are concatenated to an augmented feature vector to represent a face image. Such steerable features are over-complete and redundant. It is prohibitively time-consuming to perform classification in such a high dimensional feature space. Thus, we use AdaBoost method to select a small subset of the most efficient features.

Both holistic features and local features are critical for face recognition and have different contributions [10]. Linear Discriminant Analysis (LDA) is employed to extract holistic feature in the AdaBoosted steerable feature space. However, LDA often suffers from the small sample size problem when dealing with the high dimensional face data. Null Space LDA (NLDA) and Fisherface are two conventional approaches to address this problem. They can respectively extract the most discriminative information from the null space and the principal space. Further, Liu et al. [15] proposed the most suitable situation for the null space, under which all null space contributes to discriminative power. In this paper, we propose a new null space method based on random subspace. Random subspace is generated under this situation. In a random subspace, the NLDA classifier and the Fisherface classifier are constructed sharing a unique eigen-analysis. Finally, the two kinds of complementary classifiers are combined using a simple fusion rule.

Feature extraction, feature selection and classification rule are some crucial issues for face recognition. Our algorithm handles them together. It can effectively solve the small sample size problem. Compared with existing LDA approaches, our method is more stable and efficient.

2 Local Steerable Feature

2.1 Steerable Filters

Steerable filter allows adaptive control over orientation. Steerable filter can be used for a variety of operations involving oriented filters. The oriented filter, rotated to an arbitrary angle, is formed as a linear combination of basis filters. Once the basis filter responses are known, the response of the filter steered (rotated) to an arbitrary angle can easily be found. A similar technique can be used to control the magnitude of the filters. Following Mathews and Michael [1], we consider templates of the form

$$h(x,y)=\sum_{k=1}^{M}\sum_{i=0}^{k}\alpha_{k,i}\frac{\partial^{k-i}}{\partial x^{k-i}}\frac{\partial^{i}}{\partial y^{i}}g(x,y)=\sum_{k=1}^{M}\sum_{i=0}^{k}\alpha_{k,i}g_{k,i}(x,y) \tag{1}$$

where $g(x,y)$ is an arbitrary isotropic window function and $g_{k,i}(x,y)$ is a basis filter. The filter $h(x,y)$ is steerable. Steerable filter is a class of filters in which a filter of arbitrary orientations is synthesized as a linear combination of a set of basis filters. In other words, the convolution of a 2D signal $f(x,y)$ with any rotated version of $h(x,y)$ can be expressed as

$$f(x,y)*h(x,y;\theta)=\sum_{k=1}^{M}\sum_{i=0}^{k}b_{k,i}(\theta)f_{k,i}(x,y) \tag{2}$$

where the functions $f_{k,i}(x,y)$ are filtered versions of the signal $f(x,y)$ and can be expressed as

$$f_{k,i}(x,y)=f(x,y)*g_{k,i}(x,y) \tag{3}$$

The orientation-dependent weights $b_{k,i}(\theta)$ are given by

$$b_{k,i}(\theta)=\sum_{j=0}^{k}\alpha_{k,j}\sum_{l,m\in S(k,j,i)}\binom{k-j}{l}\binom{j}{m}(-1)^{m}\cos(\theta)^{j+(l-m)}\sin(\theta)^{(k-j)+(l-m)} \tag{4}$$

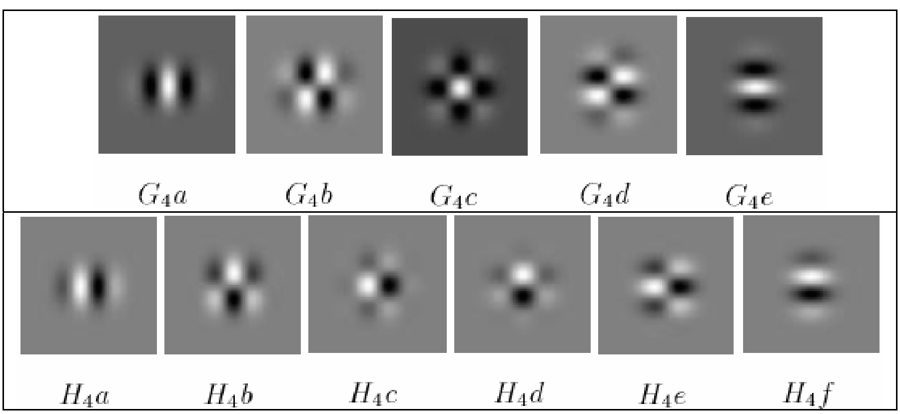

Fig. 1. X-Y separable basis filters for G4 and H4

where $S(k,i,j)$ is defined as

$$S(k,i,j) = \{l, m \mid 0 \le l \le k-i; 0 \le m \le i; k-(l+m) = j\} \tag{5}$$

Once the $f_{k,i}(x,y)$ are available, $f(x,y) * h(x,y;\theta)$ can be evaluated very efficiently via a weighted sum with its coefficients that are trigonometric polynomials of θ. We use X-Y separable basis filters G4/H4 to extract local steerable features from face images in our algorithm. These basis filters are showed in Figure 1. One important property of steerable filters is that they are X-Y separable [12]. This property allows efficient implement of G4/H4 filters and reduces the filters complexity from $O(N^2)$ to $O(2N)$. Another important property is that the coefficients are either symmetric or anti-symmetric which can be used to further save the computation cost [12].

2.2 Steerable Feature

Steerable feature is a complex representation of local image data that is obtained through the use of steerable filters, tuned to a specific orientation θ. We use the steerable quadrature filter pairs G4/H4 as follows:

$$m(x,y;\theta) = G_4(\theta) * I(x,y) \tag{6}$$

$$n(x,y;\theta) = H_4(\theta) * I(x,y) \tag{7}$$

$$O(x,y;\theta) = m(x,y;\theta) + in(x,y;\theta) \tag{8}$$

where $I(x,y)$ is a 2D gray level face image. $G_4(\theta)$ is the fourth derivative of a Gaussian, and $H_4(\theta)$ is the approximation of Hilbert transform of $G_4(\theta)$. A complex polar representation can be written as

$$O(x,y;\theta) = \rho(x,y;\theta) e^{i\phi(x,y;\theta)} \tag{9}$$

where $\rho(x,y;\theta)$ and $\phi(x,y;\theta)$ are often called instantaneous amplitude and phase to emphasize their local nature. Since the magnitude part of complex response of the steerable filter provides a confidence measure for similarity between face images, it is used as local descriptor in our algorithm. Phase response of the steerable filter is also a good similarity measure, which we report in another paper.

The steerableface, representing one face image, is computed by convoluting it with steerable filters. Figure 2 shows the steerableface representation of a face image with magnitude part corresponding to four orientations $(0°, 45°, 90°, 135°)$ respectively, where $0°$ is vertical. We can see the synthesized texture orientation corresponding to the orientation of steerable filter from the steerableface. In other words, the

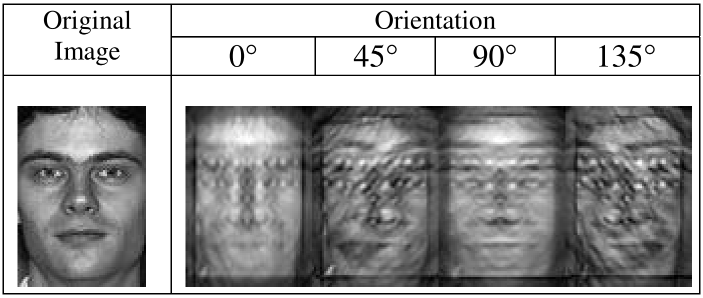

Fig. 2. X-Y separable basis filters for G4 and H4

steerableface of orientation $0°$ shows vertical texture and the steerableface of orientation $90°$ shows horizontal texture, while the steerablefaces of orientation $45°$ and $135°$ show oblique texture. In general, steerableface exhibits distinct spatial locality and orientation properties.

Steerable filter can capture the local structure corresponding to any orientation in a single scale, while recognition performance should benefit from discriminant information in the scales-space of face image. To further improve the accuracy, steerable filter is implemented in a Gaussian pyramid of face image. Gaussian pyramid is constructed by subsampling with a factor of 2 horizontally and vertically at each level. To avoid aliasing, which can happen as a result of down-sampling, we pass the input image through a low-pass anti-aliasing filter. In our algorithm, Gaussian FIR filter is used as an anti-aliasing filter in horizontal and vertical directions. Then each scale of the pyramid is decomposed using oriented quardrature-pair steerable filters G4/H4. Finally, to encompass different spatial frequencies, spatial localities, each face image is represented with an augmented steerable feature vector from multiple scales and orientations in our algorithm. However, such a steerable feature space is high dimensional and redundant. Actually, different facial regions in a face image have different levels of important and discriminant power for face recognition. AdaBoost method provides a simple yet effective stagewise learning approach for feature selection. Without loss of useful facial features, AdaBoost [11] is adopted to select a small number of features with the most discriminant power from a large pool.

3 LDA-Based Methods

Steerable feature is a powerful descriptor for local facial structure, while both holistic features and local features are critical for recognition and have different contributions [10]. LDA is a popular holistic feature extraction technique for face recognition. LDA is used to extract global feature in the steerable feature space. There are many motivations for using features rather than pixels directly. The most common reason is that features can act to encode ad hoc domain knowledge which is difficult to learn using a finite quantity of training data [6].

Let n denote the dimension of the raw sample space and c is the number of classes. The between-class scatter matrix S_b and the within-class scatter S_w are defined as

$$S_b = \sum_{i=1}^{c} N_i (m_i - m)(m_i - m)^T = \Phi_b \Phi_b^T \tag{10}$$

$$S_w = \sum_{i=1}^{c} \sum_{k \in C_i} (x_k - m_i)(x_k - m_i)^T = \Phi_w \Phi_w^T \tag{11}$$

where N_i is the number of samples in class $C_i\left(i = 1,2,...,c\right)$, N is the number of all the samples, m_i is the mean of all the samples. The total scatter S_t, i.e. the covariance matrix of all the samples, is given by

$$S_t = S_b + S_w = \sum_{i=1}^{N} (x_i - m)(x_i - m)^T = \Phi_t \Phi_t^T \tag{12}$$

LDA determines a set of projection vectors maximizing S_b and minimizing S_w in the projective feature space. The optimal projection $W = [w_1, w_2, ..., w_{c-1}]$ satisfies

$$J(W) = \arg\max_{W} \frac{|W^T S_b W|}{|W^T S_w W|} \tag{13}$$

3.1 Fisherface

The optimal projection W can be calculated by the eigenvectors of $S_w^{-1} S_b$. But this method is numerically unstable because it involves the direct inversion of a likely high-dimensional matrix. The most frequently used LDA algorithm in practice is based on simultaneous diagonalization of S_w and S_b,

$$W^T S_w W = I, \qquad W^T S_b W = \Lambda \tag{14}$$

Most algorithms require S_w being non-singular because the algorithm need to diagonalize S_w at the first step. The above procedure will break down when S_w is singular. It surely happens when the number of training samples is smaller than the dimension of the sample vector, i.e. the small sample size problem. An available solution to the singularity problem is to perform PCA before LDA. However, this step greatly reduces the dimension of both S_w and S_b. It essentially removes null space from both S_w and S_b. So PCA projection potentially loses some significant discriminating information.

3.2 Null Space LDA

A more reasonable method called null space LDA was presented [14], where the optimal projection W should satisfy

$$W^T S_w W = 0, \qquad W^T S_b W = \Lambda \tag{15}$$

i.e. the optimal discriminant vectors must exist in the null space of S_w. In this case, the Fisher criteria in Eqs. (13) definitely reaches its maximum value. However, the computational complexity of extracting the null space of S_w is very high because of its high dimension.

3.3 Null Space LDA in Most Suitable Situation

In most cases,

$$rank(S_t) = \min\{n, \quad N-1\} \tag{16}$$

$$rank(S_w) = \min\{n, \quad N-c\} \tag{17}$$

$$rank(S_b) = \min\{n, \quad c-1\} \tag{18}$$

The dimension of null space of S_w is very large and not all null space contributions to the discriminative ability. Based on this observation, Liu et al [15] presented the most suitable situation for the null space. When n is equal to $N-1$, S_t is full-rank and the dimension of null space of S_t is zero. It follows that all null space of S_w contributes to the discriminative power. Under this situation, only one eigen-analysis is needed to perform on S_w

$$V^T S_w V = D_w \tag{19}$$

where $V^T V = I$, D_w is diagonal matrix sorted in increasing order. Discard those with eigenvalues sufficiently far from 0, and keep $c-1$ eigenvectors of S_w in most cases. Let Y be the first $c-1$ columns of V which spans the null space of S_w, and Z be the last $N-c$ columns of V which spans the principal space of S_w. We have

$$Y^T S_w Y = 0 \tag{20}$$

$$Z^T S_w Z \neq 0 \tag{21}$$

Y and Z span two orthogonal complementary subspaces. There is no redundancy in the context of discriminant information between the two subspaces since they are orthogonal complementary [18].

4 Random Subspace LDA

4.1 Random Subspace NLDA

NLDA is always applicable to the small sample size problem. Any methods that can transform raw samples to $N-1$ dimensional data without adding or losing main information can exploit the full merit of NLDA. In [15], PCA projection and kernel mapping were used to accomplish this transformation. However, recall that PCA may lead to a loss of some significant discriminative information. On the other hand, kernel technique is time-consuming and it is also hard to select an optimal kernel function. In this paper, we propose a new NLDA method based on random subspace (RS-NLDA). A set of random subspaces with $N-1$ dimension are generated by random sampling among the AdaBoosted steerable features, and NLDA classifiers are constructed on the random subspaces. RS-NLDA contains the following steps:

At the training stage,

1) Apply AdaBoost to the training set to select sufficient steerable features.
2) Generate K random subspaces $\{R_i\}_{i=1}^{K}$. Each random subspace is constructed from $N-1$ steerable features.
3) K NLDA classifiers $\{C_i^N\}_{i=1}^{K}$ are constructed from the K random subspaces.

At the recognition state,

1) The steerable feature vector is projected to the K random subspaces and fed to the K NLDA classifiers in parallel.
2) The outputs of the K NLDA classifiers are fused to make the final decision.

RS-NLDA has several advantages over previous LDA methods. First, random subspace is used to reduce the feature vector dimension, rather than PCA projection or kernel mapping [15]. In this way, the central eigen-decomposition problem is made relatively smaller than traditional LDA approaches. Since eigen-analysis is the most time-consuming in the LDA training, we can save much computation cost.

Second, in our algorithm, random subspaces are completely independent. In comparison, the first 50 base vectors which are used to span the random subspace are identical in Wang and Tang's method [17]. As they mentioned, the random subspaces generated in such a way are not really independent.

Third, the random subspace dimension is determined empirically via extensive search experiments in [17]. By contrast, the optimal dimension of a random subspace is fixed theoretically given a training set.

Fourth, steerable features with AdaBoost selection ensure that the performance of random subspace is not too low. PCA is used to project the high dimension image data to the low dimension subspace prior to construct random subspaces in [17]. As mentioned above, this step arouses a loss of some useful discriminant information. In fact, face images span a nonlinear manifold in the image space [11]. With assumption of Gaussian distribution of original training data, PCA essentially changes the distribution of training samples in the projection subspace.

4.2 Random Subspace LDA

Though NLDA can make full use of the null space, it still discards important discriminative power in the principal subspace. The discriminating information retained by the two subspaces is mutually complementary. To further improve the recognition performance, we construct Fisherface classifiers from the same set of the random subspaces for NLDA classifiers (RS-Fisherface) and combine the two sets of complementary classifiers for final decision (RS-LDA). The main steps of RS-LDA are as follows:

At the training stage,

1) Apply AdaBoost to the training set to select sufficient steerable features.
2) Generate K random subspaces $\{R_i\}_{i=1}^{K}$. Each random subspace is constructed from $N-1$ steerable features.
3) K NLDA classifiers $\{C_i^N\}_{i=1}^{K}$ are constructed from the K random subspaces.
4) Based on the same K random subspaces $\{R_i\}_{i=1}^{K}$, K Fisherface classifiers $\{C_i^F\}_{i=1}^{K}$ are also constructed.

At the recognition state,

1) The steerable feature vector is projected to the K random subspaces and fed to the K NLDA classifiers and K Fisherface classifiers in parallel.
2) The outputs of the K NLDA classifiers and K Fisherface classifiers are integrated to make the final decision.

Wang and Tang [17] used two different random sampling schemes to improve traditional LDA approaches: sampling feature vectors for Fisherface (random subspace) and sampling training samples for NLDA (bagging). It is clear that Fisherface and NLDA classifiers generated in such a way are not really orthogonal complementary. Our scheme is more reasonable and efficient.

5 Experiments on XM2VTS Database

We first conduct experiments on the XM2VTS face database [13]. There are 295 people, and each person has four frontal face images taken in four different sessions. In our experiments, two face images of each class are selected for training set, and the other two are for gallery and probe respectively. We adopt the recognition test protocol used in FERET [9]. In the following experiments, all the images are scaled to 96×64. Except histogram equalization used for reducing the influence of some extreme illumination, no other pre-processing is performed. Steerable features are extracted from preprocessed face images. The number of steerable features of each sample is 32256 containing four orientations with three scales $(1, 1/4, 1/16)$:

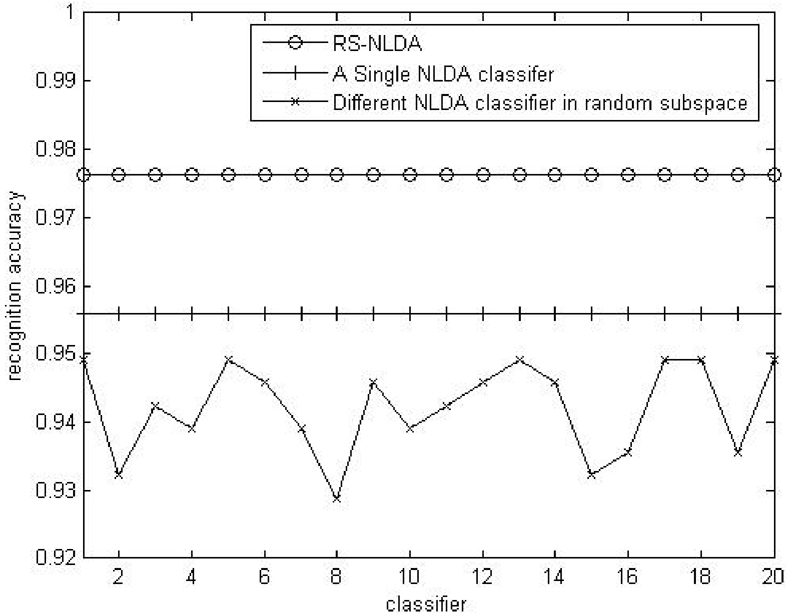

Fig. 4. Recognition accuracy of RS-NLDA on the AdaBoosted steerable feature space

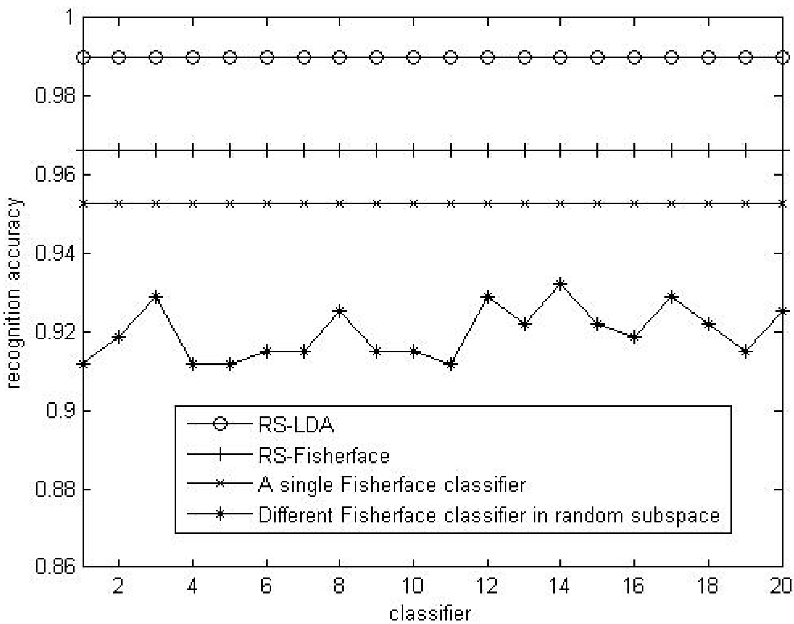

Fig. 5. Recognition accuracy of RS-LDA on the AdaBoosted steerable feature space

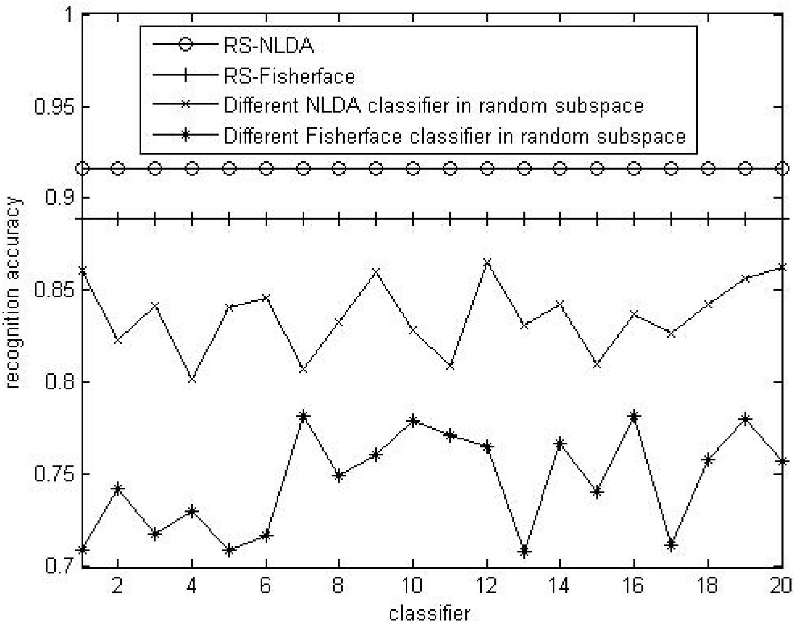

Fig. 6. Recognition accuracy of RS-LDA on the raw steerable feature space

$96 \times 64 \times 4 \times (1+1/4+1/16) = 32256$. In this paper, we use sum rule to combine multiple weak classifiers. More complex combination algorithms may further improve the algorithm performance.

5.1 Random Subspace NLDA

We first compare RS-NLDA with traditional NLDA. AdaBoost is adopted to select the most discriminative steerable features in advance. Since there are 590 face images of 295 classes in the training set, the optimal dimension of random subspace should be 589. In all, 1178 steerable features are selected via AdaBoost learning. A single NLDA classifier is constructed based on selected features and achieves a recognition rate of 95.93%. Then we randomly select 589 features among the selected features to generate a random subspace. The procedure is repeated for 20 times, and 20 NLDA classifiers are constructed. The result of RS-NLDA combining 20 NLDA classifiers is shown in Figure 4. The accuracy of individual NLDA classifier is between 92.88% and 94.92%. Using sum rule, the accuracy of RS-NLDA achieves 97.63%. This shows that NLDA classifiers constructed from different random subspaces are complementary of each other. Moreover, random subspace is indeed an efficient technique to enforce weak classifiers.

5.2 Random Subspace LDA

We then construct Fisherface classifiers from the same set of random subspaces for NLDA classifiers. A single Fisherface classifier is constructed based on selected steerable features and achieved a recognition rate of 95.25%. The accuracy of each individual Fisherface classifier varies from 91.53% to 92.88%. The recognition rate of RS-Fisherface is 96.61% using sum rule. The accuracy of individual Fisherface classifier is lower than that of each NLDA classifier on the same random subspace. This indicates that the null space of S_w encodes the more significant discriminative information than the principal subspace. Finally, all the NLDA and Fisherface classifiers are integrated to achieve a higher recognition accuracy of 98.98%. Figure5 reports the performance of RS-LDA. Figure 6 depicts the recognition accuracy of RS-NLDA and RS-Fisherface directly random sampling on the raw steerable feature space, rather than on the AdaBoosted steerable feature subspace. It shows that the improved method has a superior performance.

6 Experiments on FERET Database

The proposed method is also tested on the FERET FA/FB sets, which has been widely used to evaluate face recognition methods [9]. There are 1196 images in FA and 1195 images in FB. Each set contains at most one image per person and FA contains different facial expressions with FB. The FA images are used as gallery images and the FB images are used as probes. The training set is also from the training set of FERET database, which includes 1002 images of 429 subjects. The preprocessing procedure for face images is identical with the last experiment. The optimal dimension of each

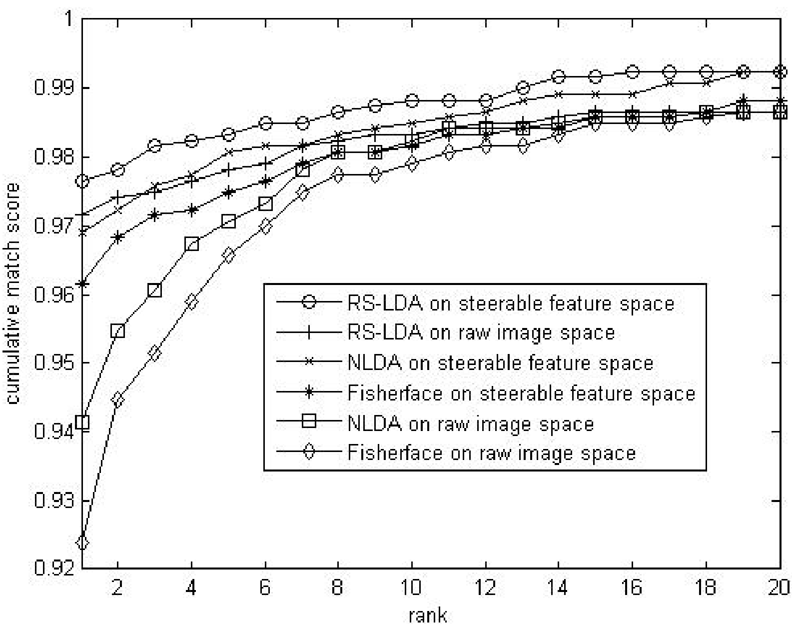

Fig. 7. Recognition accuracy of RS-LDA on the raw image space and the selected steerable feature space

random subspace is 1001. To investigate the effect of steerable feature on recognition performance, RS-LDA on the raw face image space is also performed. Totally, AdaBoost selected 2002 steerable features and original pixels respectively for constructing the random subspaces. We compare RS-LDA with NLDA and Fisherface. The rank curves of all the methods are shown in Figure 7. We achieve a high recognition rate of 97.66%. It can be observed that all of the methods based on steerable feature space outperform that on the raw image space. Steerable feature is a powerful local descriptor for face structure. On the other hand, both RS-NLDA and RS-Fisherface are superior to NLDA and Fisherface. It confirms that NLDA or Fisherface are not sufficient to discriminate the complex data consisting of many classes like human faces.

7 Conclusions

Local descriptor is popular in the field of face recognition. We propose a novel local steerable feature extracted from the face image using steerable filter. Furthermore, steerable filter is implemented in the scales-space to encode more discriminate information.

Subspace discriminant analysis involves two aspects: 1) Extract the most discriminative features from each subspace. 2) Exploit as much the complementary discriminative information as possible. In this paper, NLDA and Fisherface classifiers are constructed from the same set of random subspaces and integrated using a fusion rule. All the random subspaces are constructed under the most suitable situation for the null space. Our approach is simple, efficient and reasonable. Experimental results on multiple face databases show an encouraging recognition performance.

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