Component-based Cascade Linear Discriminant Analysis for Face Recognition

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Abstract. This paper presents a novel face recognition method based on cascade Linear Discriminant Analysis (LDA) of the component-based face representation. In the proposed method, a face image is represented as four components with overlap at the neighboring area rather than a whole face patch. Firstly, LDA is conducted on the principal components of each component individually to extract component discriminant features. Then, these features are further concatenated to undergo another LDA to extract the final face descriptor, which actually have assigned different weights to different component features. Our experiments on the FERET face database have illustrated the effectiveness of the proposed method compared with the traditional Fisherface method both for face recognition and verification.

1 Introduction

Over the past 20 years, numerous algorithms have been proposed for face recognition. See detailed surveys [1][2][3]. In the following we will give a brief overview of face recognition methods.

In the early researches, methods based on geometric feature and template matching used to be popular technologies, which were compared in 1992 by Brunelli and Poggio. Their conclusion showed that template matching based algorithms outperformed the geometric feature based ones [4]. Therefore, since the 1990s, methods based on appearance have been dominant researches. In these methods, each pixel in a face image is considered as a coordinate in a high-dimensional space and the classification is carried out in a low-dimensional feature space projected from the image space.

In this paper, we outline a new approach for face recognition named by component-based cascade LDA. Thus, we divide face recognition techniques into the global approach and the component-based approach as [5].

In the global approach, a feature vector that represents the whole face image is used as the input of a classifier. Several classifiers have been proposed in the literature: minimal distance classification in the eigenspace [6][7], Fisher's discriminant analysis

[8], and the neural network [9]. However, they are not robust against pose changes since global features are highly sensitive to translation and rotation of the face [5]. To avoid this problem, an alignment should be added before classifying the face [10][11].

In contrast with the global approaches, another way is classifying local facial components. [12] performs face recognition in independently matching templates of three facial regions. Elastic Bunch Graph Matching (EBGM)[13][14] is another typical instance, which is based on Gabor wavelet coefficients computed on the nodes of the elastic graph.

In this paper, we present a component-based face descriptor with cascade LDA for face recognition. First, we split a face image into four components and reduce the dimension of each of the four components by PCA plus LDA. Next, the four feature vectors obtained from PCA plus LDA are combined into one feature vector. At last, the new vector enters LDA as an input.

Following is the outline of the paper: Section 2 gives a brief overview of PCA and LDA algorithms. Section 3 describes the component-based approach. Section 4 explains the component-based Cascade LDA approach. Experimental results and conclusions are presented in Section 5 and 6, respectively.

2 PCA Plus LDA

2.1 PCA

Nowadays, a technique commonly used for dimensionality reduction in computer vision-particularly in face recognition-is principal components analysis (PCA) [7]. Let a set of N face images $\{\mathbf{x}_1, \mathbf{x}_2 \ldots, \mathbf{x}_N\}$ take values in an n-dimensional image space and let W represent the linear transformation that maps the original n-dimensional space onto a m-dimensional feature subspace where $m << n$. The new feature vectors $\mathbf{y}_i \in \Re^m$ are defined by the following linear transformation:

$$\mathbf{y}_i = W^T \mathbf{x}_i \quad i = 1, 2, \ldots, N \tag{1}$$

where $W \in \Re^{n \times m}$ is a matrix with orthonormal columns. The columns of W are the eigenvectors $\mathbf{e}_i$ obtained by solving the eigenstructure decomposition

$$\lambda_i \mathbf{e}_i = U \mathbf{e}_i \tag{2}$$

Where

$$U = \sum_{i=1}^{N} (\mathbf{x}_i - \boldsymbol{\mu})(\mathbf{x}_i - \boldsymbol{\mu})^T \tag{3}$$

is the covariance matrix and λ_i is the eigenvalue associated with the eigenvector $\mathbf{e}_i$. In PCA, the projection matrix W_{opt} is chosen to maximize the determinant of the total scatter matrix of the projected samples, i.e.,

$$W_{opt} = \arg\max \left| W^T U W \right| = \left[\mathbf{e}_1 \; \mathbf{e}_2 \ldots \mathbf{e}_m \right] \tag{4}$$

where $\{\mathbf{e}_i | i = 1, 2, \ldots, m\}$ is the set of n-dimensional eigenvectors of U corresponding to the m largest eigenvalues.

2.2 LDA

Linear Discriminant Analysis (LDA) [15] is a class specific method in the sense that it can represent data in form which is more useful for classification. Given a set of N images $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}$, assume each image belongs to one of the c classes $\{X_1, X_2, \ldots, X_c\}$, and LDA selects a linear transformation matrix $\mathbf{W}$ in such a way that the ratio of the between-class scatter and the within-class scatter is maximized.

Mathematically, the between-class scatter matrix and the within-class scatter matrix are defined by

$$\mathbf{S}_B = \sum_{i=1}^{c} N_i (\boldsymbol{\mu}_i - \boldsymbol{\mu})(\boldsymbol{\mu}_i - \boldsymbol{\mu})^T \tag{5}$$

and

$$\mathbf{S}_W = \sum_{i=1}^{c} \sum_{\mathbf{x}_k \in X_i} (\mathbf{x}_k - \boldsymbol{\mu}_i)(\mathbf{x}_k - \boldsymbol{\mu}_i)^T \tag{6}$$

respectively, where $\boldsymbol{\mu}_i$ denotes the mean image of class X_i and N_i denotes the number of images in class X_i. If $\mathbf{S}_W$ is nonsingular, LDA will find an orthonormal matrix $\mathbf{W}_{opt}$ maximizing the ratio of the determinant of the between-class scatter matrix to the determinant of the within-class scatter matrix. That is, the LDA projection matrix is represented by

$$\mathbf{W}_{opt} = \arg\max_{\mathbf{W}} \frac{\left| \mathbf{W}^T \mathbf{S}_B \mathbf{W} \right|}{\left| \mathbf{W}^T \mathbf{S}_W \mathbf{W} \right|} = \left[\mathbf{w}_1 \quad \mathbf{w}_2 \quad \cdots \quad \mathbf{w}_m \right] \tag{7}$$

The set of the solution $\{\mathbf{w}_i \mid i = 1,2,\ldots,m\}$ is that of the generalized eigenvectors of $\mathbf{S}_B$ and $\mathbf{S}_W$ corresponding to the m largest eigenvalues $\{\lambda_i \mid i = 1,2,\ldots,m\}$, i.e.,

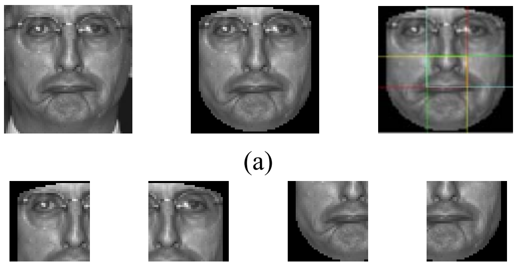
$$\mathbf{S}_B \mathbf{w}_i = \lambda_i \mathbf{S}_W \mathbf{w}_i, i = 1,2,\ldots,m \tag{8}$$

In order to overcome the singularity of $\mathbf{S}_W$, PCA reduces the vector dimension before applying LDA. Each LDA feature vector is represented by the vector projections

$$\mathbf{y}_k = \mathbf{W}_{opt}{}^T \mathbf{x}_k \,,\; k = 1,2,\ldots,N \,. \tag{9}$$

3 Component-Based Cascade LDA Face

Component-based face descriptors are less statistically complex than global image descriptors. The linear transformation like PCA/LDA in a component region becomes more suitable than that in the global image region. In addition, separated facial components overlap with neighboring components and the relationship is important to describe personal characteristics for face recognition [16].
Our method uses a component-based representation and we divide a face image into four overlapped components. An example of facial component division is shown in Figure.1.



(a)

(b)

Fig. 1. An example of facial component separation

LDA is applied to the facial components separately to learn the most class-distinguishable basis vectors in each local region and the feature vectors of these components are combined into a new vector, then LDA is applied to the new combined vector. The procedure of the component-based cascade LDA is shown in figure 2.

3.1 Face Description

Firstly, the PCA transformation matrices are extracted. Given a set of N images $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}$, each of the images is divided into four facial components according to the facial component separation definition. Each component patches are grouped and represented in a vector form; to the f th component, $\{\mathbf{x}_1{}^f, \ldots, \mathbf{x}_N{}^f\}$ $f = 1,2,\ldots,4$, the corresponding PCA matrix is U^f. The reduced vector of each component for the N face images is

$$\mathbf{y}_n^f = \left(U^f\right)^T \mathbf{x}_n^f,\ f = 1,2,\ldots,4;\ n = 1,2,\ldots,N \tag{10}$$

Secondly, LDA is applied to the set of the reduced vector of each component. For the f th facial component, the corresponding LDA matrix W^f is computed. Thus, the feature vectors obtained are computed by

$$\mathbf{z}_n^f = \left(W^f\right)^T \mathbf{y}_n^f,\ f = 1,2,\ldots,4;\ n = 1,2,\ldots,N. \tag{11}$$

At last, we combine the $\mathbf{z}_n^f$ s into a new vector $\mathbf{z}$, and LDA is applied to the new vector. The cascade LDA matrix is V, thus, the feature vector is computed by

$$\mathbf{s} = V^T \mathbf{z} \tag{12}$$

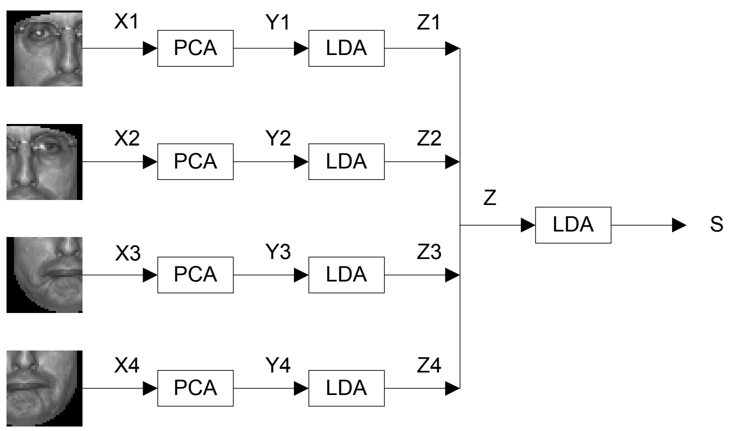


Fig. 2. The procedure of cascade LDA

4 Experimental Result

Identification and verification of a person's identity are two potential areas in application of face recognition systems. In identification, a system identifies an unknown face in an image. In verification, a system confirms the claimed identity of a face presented to it [17].

Thus, we have tested our face recognition algorithm in identification and verification respectively on the FERET test set which has been widely used to evaluate face recognition algorithms [18].

4.1 Experiments on FERET Face Database

There are 1002 images in the training set and all of the images come from parts of fa (regular facial expression) and fb (alternative facial expression) sets. The gallery consisted of images of 1,196 people with one image per person. In the probe category, there are 1195 images of FB.

All images are cropped and rectified according to the manually located eye positions supplied with the FERET data. We scale the images to 32 pixels height by 32 pixels width. To reduce the influence caused by different hairstyles and backgrounds, a mask is put on the face image. Figure 1(a) shows the cropped face image that is put on mask. Figure 1(b) shows an example of a face image in FERET set that is divided into four components.

The experimental results are presented in figure 3 and figure 4. The former shows the algorithm performance of the identification, and the latter shows the algorithm performance of the verification. In the figures, denotes our algorithm and denotes the conventional LDA algorithm.

In the verification problem, we achieve a 1.6% equal error rate while that of the conventional LDA is 2.0%. The equal error rate is the point at which the percentage of correct verifications equals one minus the percentage of false alarms [19]. In the recognition problem, where there are 1196 gallery images and 1195 probe images, we achieve a rank-1 recognition rate of 93.47% while that of the conventional LDA is 91.8%. The verification and the identification experimental results are shown in figure 3 and figure 4 respectively.

5 Conclusion

In this paper, we have presented a novel face recognition method based on cascade Linear Discriminant Analysis (LDA) of the component-based face representation. In our method, a face image is divided into four components with overlap at the neighboring area according to the facial organs. This is quite different from the traditional method such as Eigenface or Fisherface that process the whole face patch in one time. We first perform LDA on each component individually to extract component discriminant features. Then, these features are further concatenated to undergo another LDA to extract the final face descriptor. Actually, the final LDA procedure has assigned different weights to different component features. Our experiments on the FERET face database have illustrated the effectiveness of the proposed method compared with the traditional Fisherface method both for face recognition and verification. Our work has suggested that component-based face descriptor should be paid more attention.

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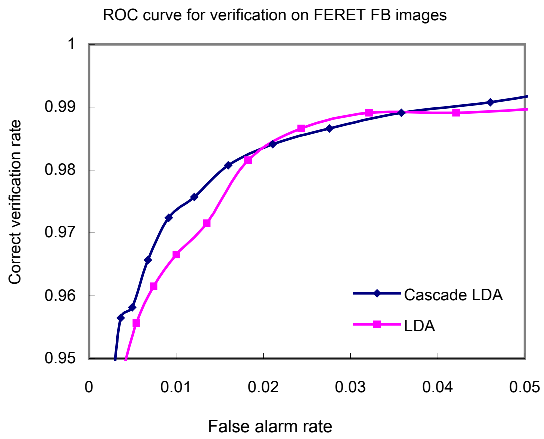

Fig. 3. ROC curve for verification task on FERET **FB** probe sets. The equal error rates are about 1.6% in Cascade LDA and 2% in LDA

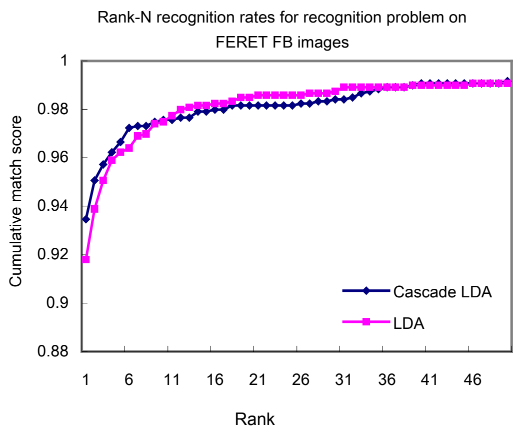

Fig. 4. Rank-N recognition rates for FERET **FB** images

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