Face recognition based on illumination adaptive LDA

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***Abstract*—The variation of facial appearance due to the illumination degrades face recognition systems considerably, which is well known as one of the bottlenecks in face recognition. However, the variations of each subject which are due to the changes of illumination are extremely similar to each other. We offline collect many face classes each of which has many images under different lighting conditions, a common within-class scatter matrix describing the within-class illumination variations of all the face classes can be gotten. Based on this, illumination adaptive linear discriminant analysis (IALDA) is proposed to solve illumination variation problems in face recognition when each face class has only one training sample under the standard lighting conditions. In the IALDA method, the illumination direction of an input face image is firstly estimated. Then the corresponding LDA feature, which is robust to the variations between the images under the estimated lighting conditions and the standard lighting conditions, is extracted. Experiments on the face databases demonstrate the effectiveness of the proposed method.**

Keywords-linear discriminant analysis; illumination variation; illumination adaptive linear discriminant analysis (IALDA); face recognition

I. INTRODUCTION

The significant impact of lighting variation on the performance of face recognition systems is well-known nowadays, and there are research efforts to design face recognition algorithms that are robust to illumination changes [1]. Many approaches have been proposed in the last years for solving the variable illumination problem in face recognition [2, 3, 4, 5]. These approaches can be roughly classified into four main categories: Extraction of illumination invariant features; Transformation of images with variable illuminations to a canonical representation; Modeling the illumination variations; Utilization of some 3D face models. Although the ability of algorithms to recognize faces across illumination changes has made important progress in the last years, FRVT 2006 results show that illumination still has an important effect on the recognition process.

In this paper, adaptive linear discriminant analysis (IALDA) is proposed. The basic principle of the proposed method is described as follows: Firstly, We offline collect the images of many subjects under the different lighting conditions to train illumination direction classifier and varieties of LDA projection matrices. Then the illumination direction of a test sample is estimated by illumination direction classifier. Thirdly, we extract the corresponding LDA feature which is robust to the illumination variation between images under the standard lighting conditions and the estimated lighting conditions.

II. BASIC IDEA OF THE PROPOSED METHOD (IALDA)

For better understanding the difficulty of the illumination problem in face recognition, the distribution of samples of many subjects under different lighting conditions is to be studied firstly.

Getting 20 distinct persons from Extended YaleB face database each of which has three frontal images taken under 3 different lighting conditions ((azimuth, elevation): (0, 0), (-60, 20), (60, -20)), we do principle component analysis (PCA) with them.

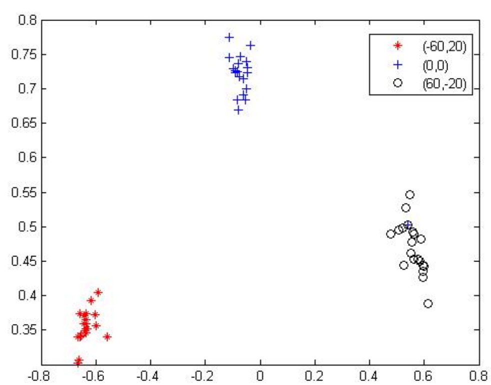

Figure 1. Feature extraction based on PCA

It can be seen from Figure 1 that the images under the same lighting conditions from different persons gather in one cluster, while the images under different lighting conditions from the same class have relatively big differences. That is to say, the changes induced by illumination are larger than the differences between individuals, which caused systems based directly on comparing images to misclassify input images [6].

The linear discriminant analysis (LDA) is a powerful method for face recognition. And it yields an effective representation that linearly transforms the original data space into a low-dimensional feature space where the data is as well separated as possible. However, the within-class scatter matrix (SW) becomes singular in face recognition and the

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classical LDA cannot be solved which is the undersampled problem of LDA (also known as small sample size problem). Especially when each face class has only one training sample, it can not be utilized for the recognition. However, face recognition has a very important characteristic [7]: human faces are very similar objects with similar geometrical shape and configuration. Therefore, the variations of each specific person's face images, due to changes of pose, illumination, expression, age and so on, are rather similar to each other. In other words, the SWs of different subject are rather similar to each other. Therefore, by offline collecting many subjects each of which contains many images under different lighting conditions, a common SW describing the within-class illumination variations of all the subjects can be trained. And with this common SW, LDA can be used to extract illumination robust discriminant features for the face recognition when each face class has only one frontal training sample under the standard lighting conditions [6].

However, the total illumination variations are very complex, especially dealing with the large illumination variations. Therefore, the main steps of the proposed method are described as follows. Firstly, we offline collect images of many distinct persons, and each person have his/her frontal images taken under J different lighting directions. We take the illumination direction as class label to design illumination classifiers. Namely, the face images under the same lighting conditions from different persons are taken as one class. We define the j-th illumination variation as the variation between the images under the j-th lighting conditions and the corresponding images under the standard lighting conditions. Then, The illumination direction of an input face image is estimated by the illumination direction classifier, and let the estimated illumination direction be j. Thirdly, Let the j-th illumination variation be the within-class scatter matrix, and LDA is can be directly utilized to extract LDA projection matrix when each face class has only one image under the standard lighting conditions to be used as training set. Finally, the LDA projection matrix which is robust to the j-th illumination variation extracts discriminant features of the training set and the input face image, and the face recognition is accomplished by the nearest neighbor classifier. The framework of the proposed algorithm is illustrated in Figure 2.

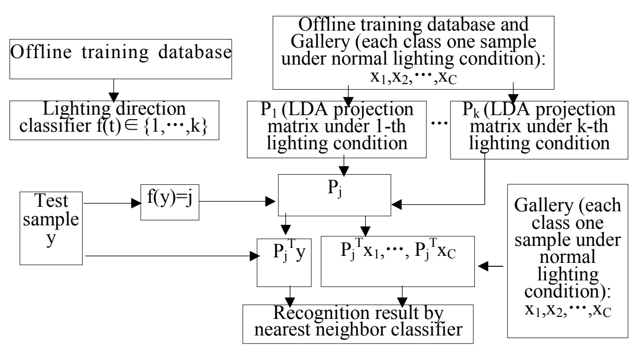

Figure 2. The framework of the IALDA algorithm

III. LIGHTING DIRECTION CLASSIFIER

We regard the illumination direction estimation as a general pattern classification problem. PCA is an unsupervised technique, and it finds a set of the most representative projection vectors such that the projected samples retain most information about original samples. That is, PCA is to project the data along the directions of maximal variances so that the reconstruction error can be minimized. Therefore, it doesn't fit classification problem greatly. We use the improved discriminant neighborhood embedding algorithm to estimate illumination direction.

A. Discriminant neighborhood embedding

Discriminant neighborhood embedding (DNE) [8] is a linear dimensionality reduction algorithm. It is powerful tool for pattern classification. Its basic principle of the algorithm is as follows. It assumes that multi-class data points in high-dimensional space tend to move due to local intra-class attraction or inter-class repulsion. Therefore, DNE extracts the optimal embedding vectors from the point of view of classification.

Given N points $X=[x_1,x_2,\cdots,x_N]$ in D dimensional space, dimension reduction is conducted such that these points are mapped to be new points $Y=[y_1,y_2,\cdots,y_N]$ in d dimensional space where $d << D$. The algorithmic procedure is formally stated below:

Constructing an adjacency graph (using the k nearest neighbors): An edge is put between nodes i and j if x_i is among k nearest-neighbors of x_j or x_j is among k nearest-neighbors of x_i.

Computing the weights: Suppose that c_i denotes the class label of x_i and *knn(i)* denotes the set of k nearest-neighbors of x_i, then the weight matrix W is defined as follows.

$$W_{ij}=\begin{cases}+1 & (x_i\in knn(j)\vee x_j\in knn(i))\wedge(c_i=c_j)\\ -1 & (x_i\in knn(j)\vee x_j\in knn(i))\wedge(c_i\neq c_j)\\ 0 & otherwise\end{cases} \quad (1)$$

A criterion is to minimize the following objective function

$$\arg\min_P \sum_{i,j}\left\|P^T x_i - P^T x_j\right\|^2 W_{ij},\ Subject\ to\ P^T P = I \quad (2)$$

Minimizing equation (2) is an attempt to minimize the expected distance among the samples of the same class and to maximize the total distance between different classes simultaneously.

Computing the Projections:

$$\begin{aligned}Q(P) &= \sum_{i,j}\left\|P^T x_i - P^T x_j\right\|^2 W_{ij}\\ &= \sum_{i,j} x_i^T PP^T x_i W_{ij} + x_j^T PP^T x_j W_{ij} - x_i^T PP^T x_j W_{ij} - x_j^T PP^T x_i W_{ij}\\ &= 2\sum_i x_i^T PP^T x_i S_{ij} - 2\sum_{i,j} x_i^T PP^T x_i W_{ij} \quad (3)\end{aligned}$$

$$= 2Tr(P^T XSX^T P - P^T XWX^T P)$$
$$= 2Tr(P^T X(S-W)X^T P)$$

where $Tr(\cdot)$ is the trace of the matrix, S is a diagonal matrix whose entries are column (or row, since W is symmetric) sums of W.

Solve the following generalized eigenvector problem:

$$P^T X(S-W)X^T = \lambda P^T \quad (4)$$

Let the column vectors $p_1, p_2, \cdots p_d$ be the solutions of equation (4), ordered according to their eigenvalues $\lambda_1, \lambda_2, \cdots \lambda_d$. Thus, the embedding is as follows:

$$x_i \rightarrow y_i = P^T x_i \quad (5)$$

B. The improved DNE

The fist step and the third step of the improved DNE are the same as those of original DNE. Our main contribution lies in second step. Namely, we modify the weight matrix W.

$$W_{ij} = \begin{cases} m \ (m \geq 1) & (x_i \in knn(j) \vee x_j \in knn(i)) \wedge (c_i = c_j) \\ n \ (n \leq -1) & (x_i \in knn(j) \vee x_j \in knn(i)) \wedge (c_i \neq c_j) \\ 0 & otherwise \end{cases} \quad (6)$$

The improved W will make intra-class more compact and inter-class more separate. Therefore, the improved DNE is more suitable for pattern classification. In this paper, let m be 1.9, n be -0.1.

IV. LDA PROJECTION MATRIX

In this section, we introduce how to get the LDA project matrix P_j which is robust to the variation between the images under the j-th lighting conditions and the corresponding images under the standard lighting conditions.

Let all the images of the offline training data under the standard lighting conditions be denoted by $Y_0 \in R^{D \times N}$, and all the images under other lighting conditions be denoted by Y ($Y = [Y_1, \cdots, Y_k]$), where k (k=1,⋯,44) is the number of the lighting conditions, $Y_j \in R^{D \times N}$, N is the number of the images under the j-th lighting conditions.

Given a gallery dataset $x = [x_1, \cdots, x_C]$ in which each face class has only one training sample, where C is the number of the classes. For LDA projection matrix P_j (j=1,⋯, 44) the between-class scatter matrix S_B and the within-class scatter matrix S_W are defined by:

$$S_B = \sum_{i=1}^{C} (x_i - \mu) \cdot (x_i - \mu)^T,$$
$$S_W = \frac{C}{N} \sum_{i=1}^{N} (Y_j(:,i) - Y_0(:,i)) \cdot (Y_j(:,i) - Y_0(:,i))^T \quad (7)$$

where μ is the mean vector of all samples in gallery x.

The projection matrix P_j can be obtained by maximizing the ratio $\det|S_B| / \det|S_W|$.

V. EXPERIMENTS

In this section, we used the Extended Yale Face Database B [9] and CMU PIE face database [10] for experiments. The Extended YaleB database contains images of 38 distinct persons. Each individual has his/her frontal images taken under 45 different lighting directions, and there are 1710 images, where all the images of the first 28 persons is denoted by Face Database B1, all the images of the last 10 persons is denoted by Face Database B2. The CMU PIE face database contains 68 subjects with 41, 368 face images as a whole. We fixed the pose and expression, and we got 21 images under different lighting conditions for each subject. Face Database B2 is selected as offline training set which is utilized to train lighting direction classifier and varieties of LDA projection matrices. Face Database B1 and CMU PIE face database are selected as the test set. The size of all the face images is 48×42 pixels.

A. Illumination direction estimation

In order to compare the DNE method and the improved DNE method for illumination direction estimation of the face images, we take the illumination direction as class label, and all the images of the first 10 persons from Extended YaleB face database are taken as a test set, all the images of the last 28 persons are acted as training set. In addition, we also adopt Principal Component Analysis (PCA) method to fulfill the illumination direction estimation. Table I shows the recognition results.

TABLE I. THE ACCURACY OF THE ILLUMINATION DIRECTION ESTIMATION FOR VARIOUS METHODS

Method	Training samples/class	Test samples/class	Accuracy
PCA	28	10	74%
DNE	28	10	78.89%
The improved DNE	28	10	85.11%

It can be known from the Table I that the accuracy of the improved method is higher than that of the DNE method, and the accuracy of the PCA is significantly lower than that of the DNE method and the improved DNE.

B. Illumination adaptive LDA (IALDA)

In the recognition experiment, for Face Database B1 and CMU PIE face database, only one face image of each person under the standard lighting conditions (azimuth=0, elevation=0) is used as training set, and the rest images of each person is acted as test set. The lighting direction of the test samples are firstly estimated by the improved DNE method, where Face Database B2 was used as a training set. Then the suggested method (IALDA) is adopted to fulfill recognition task. For comparison, we also adopt the traditional EigenFace method [11] and LDA method [12] for face recognition. The recognition results are respectively shown in Table II and Table III.

TABLE II. THE RECOGNITION RATE FOR VARIOUS METHODS ON FACE DATABASE B1

Method	Training samples/class	Test samples/class	Accuracy
PCA	1	44	57.2%
LDA	2	43	59.38%
LTV	1	44	96.43%
IALDA	1	44	85.52%

TABLE III. THE RECOGNITION RATE FOR VARIOUS METHODS ON CMU PIE FACE DATABASE

Method	Training samples/class	Test samples/class	Accuracy
PCA	1	20	64.56%
LDA	2	19	74.25%
LTV	1	20	100%
IALDA	1	20	98.9%

It can be concluded from Table II and Table III that the recognition accuracy of the suggested method (IALDA) is far higher than that of PCA method and LDA method. The recognition accuracy of the suggested method is lower than that the LTV algorithm [13]. However, The LTV algorithm has high time complexity. Therefore, the LTV method is not practically applicable. At the same time, this also indicates that the proposed IALDA method is robust for illumination variations.

VI. CONCLUSION

In this paper, we propose a novel illumination invariant face recognition method called illumination adaptive linear discriminant analysis (IALDA). Extensive experiments on publicly available databases verify the efficacy of the proposed method.

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REFERENCES

[1] A.U. Batur and M.H. Hayes, Segmented Linear Subspaces for Illumination-Robust Face Recognition. International Journal of Computer Vision, 2004, 57(1):49-66.

[2] Shashua, A., Riklin-Raviv, T. The Quotient Image: class based re-rendering and recognition with varying illuminations, IEEE Trans. Pattern Analysis and Machine Intelligence, 2001, Vol. 23, No. 2, 129-139.

[3] Shin, D., Lee H.-S., kim, D. Illumination-robust face recognition using ridge regressive bilinear models, Pattern Recognition Letters, 2008, vol. 29, 49–58.

[4] Xudong Xie, Kin-Man Lam. An efficient illumination normalization method for face recognition, Pattern Recognition Letters 2006, 27, 609-617.

[5] Shin, D., Lee H.-S., kim, D. Illumination-robust face recognition using ridge regressive bilinear models, Pattern Recognition Letters, 2008, vol. 29, 49–58.

[6] Zhenger Wang, Xiaoqing Ding, Chi Fang. Pose adaptive LDA based face recognition. ICPR 2008, 1:4.

[7] Pin liao and Li shen, Unified probabilistic models for face recognition from a single example image per person. Journal of Computer Science and Technology. 2004, Vol.19, No.3, pp.383-392 (in Chinese).

[8] Wei Zhang, Xiangyang Xue, Hong Lu, Yuefei Guo. Discriminant neighborhood embedding for classification. Pattern Recognition, 2006, vol.39, no.11, pp.2240-2243.

[9] A.Georghiades, D.Kriegman, and P.Belhumeur. From few to many: Illumination Cone models for face recognition under variable illumination and pose. IEEE Trans. Pattern Analysis and Machine Intelligence. 2001, 23(6):643-660.

[10] Sim, T. , Baker, S. , Bsat, M. The CMU Pose, Illumination, and Expression (PIE) Database of Human Faces, CMU-RI-TR-01-02, pages. 1-17, USA, 2002.

[11] Kirby M, Sirovich I. Application of the KL Procedure for the Characterization of Human Faces[M]. IEEE Trans. Pattern Analysis and Machine Intelligence, 1990, 12(1) : 103-108.

[12] P. Belhumeur, J. Hespanha and D. Kriegman, “Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 711-720, 1997.

[13] T. Chen, W. Yin, X.S. Zhou, D. Comaniciu, T.S. Huang, Total variation models for variable lighting face recognition, IEEE Trans. Pattern Anal. Mach. Intell. 28 (9) (2006) 1519--1524.