A Method For Improved PCA in Face Recognition

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Abstract

Face recognition is an active subject in the fields of biometrics. Lots of achievements have been obtained in face recognition. Principal Components Analysis (PCA) is a basic method widely used in face feature extraction and recognition. In this paper, combined with the characteristics of PCA, an improved method based on normalization of within-class average face image is presented, which has the advantages of enlarging classification distance between different-class samples. Firstly, within-class average faces of training samples are computed to normalize training samples. Then the eigenface space can be gained. In order to be compared under the same conditions, the average face of all the training samples is used to normalize all the samples. Finally, training and testing samples are projected into the eigenface space to get their features respectively, and NND (Nearest Neighbor Distance) rule is utilized in classification. Experiments were done on ORL (Olivetti Research Laboratory) face database. Results show that 98% of correct recognition rate can be acquired and a better efficiency can be achieved by the improved PCA method. Therefore, it is valid in face recognition.

Keyword: PCA, Face Recognition, Biometric Feature Recognition

I. Introduction

Biometrical feature recognition techniques develop rapidly these days, especially in identification authentication. More and more people pay attention to this area. Face recognition is an active subject in the fields of biometrics. Without invasion, it has become a method for biometrical feature recognition, which is accepted widely [1-5].

The process of face recognition mainly contains two steps. The first one is face detection and localization, in which faces have to be found in the input image and separated from the background. The second one is face feature extraction and recognition. Face feature extraction is very difficult because of variable situations such as expression, location, direction and light etc. Some methods are presented and feasible in face recognition [1-6], such as geometric feature-based analysis; eigenface-based analysis; neural network-based analysis; local feature analysis; elastic match method and so on. Eigenface-based analysis is a method about the features of the whole face appearance. These features extracted are related to the whole face or even to the whole sample set. They needn't mean anything definitely. When you classify these features, you can get satisfactory results. PCA (Principal Components Analysis) is such an effective method [2]. Traditional PCA method need be improved for its large amount of computation and low recognition rate.

In this paper, a PCA-based method is presented, in which within-class average faces are computed to normalize training samples in order to reduce the difference between same-class samples, while at the same time to augment the difference between different-class samples. Experimental results on ORL (Olivetti Research Laboratory) face database show that 98% of correct recognition rate can be reached [7].

II. Improved PCA

Original face image can be represented as a two-dimensional matrix. In some methods, this face image matrix must be converted into a high-dimensional vector. So it is very difficult to process and recognize the face image matrix directly. Thus the first step need reduce the dimensions of face matrix. It is necessary to obtain the main features to represent the whole face. PCA is designed to transform a high-dimensional image into a low-dimensional one. It is based on statistical features, and eigenvectors of covariance matrix from a set of face image samples are used to represent the whole face features approximately. By decorrelation of eigenvectors of image covariance matrix, a set of projected coordinate vectors, which are orthogonal each other, are obtained. These vectors form the transformation matrix, expressed by W, where $W \in R^{n\times m}$ and $m < n$. Therefore, the high-dimensional vector $x \in R^n$ can be transformed into a low-dimensional one $y \in R^m$, while the main features of vector x can be held. Combined with the characteristics of PCA, an improved PCA method is presented. The flowchart of the method is shown in Fig.1.

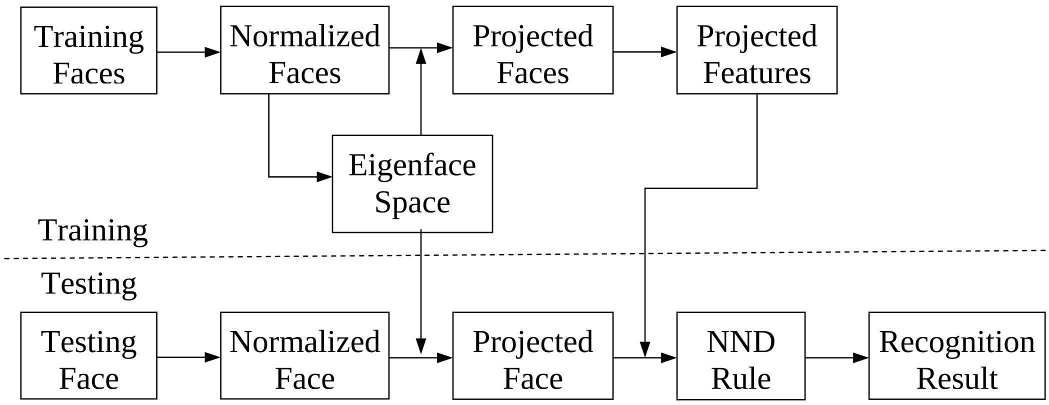

Fig. 1. Flowchart of improved PCA

In Fig.1, within-class average faces of training samples are computed firstly, and used to normalize the corresponding training samples. Then the eigenface space matrix can be gained. In order to be compared under the same circumstances, the average face of all the training samples is calculated to normalize all the samples. Finally, training and testing samples are projected into the eigenface space to get their features, and NND (Nearest Neighbor Distance) rule is utilized in classification. The method is discussed in detail as follows.

A. *Computation of Eigenvectors from Training Samples*

Suppose the dimension of training samples represented by n, and the class number of training samples by L. N_1, $N_2, \cdots, N_L$ denotes the number of training samples with different class respectively, and N denotes the total number of all the training samples. Sample set with class c is denoted by $X_c = \{x_1^c, x_2^c, \cdots, x_{Nc}^c\}$, where $x_i^c \in R^n$, and N_c expresses the number of class c. The set of all the training samples is shown by $X = \{X_1, X_2, \cdots, X_L\}$.

Within-class average face with class c is defined as

$$m_c = \frac{1}{N_c}\sum_{i=1}^{Nc} x_i^c \qquad c = 1,2,\cdots,L \tag{1}$$

Here, within-class average face is utilized to normalize all the training samples with class c. That is

$$v_i^c = x_i^c - m_c \qquad i = 1,2,\cdots,N_c,\ c = 1,2,\cdots,L \tag{2}$$

Then, the covariance matrix can be defined as

$$Q = \sum_{c=1}^{L}\sum_{i=1}^{N_c} v_i^c (v_i^c)^{\mathrm{T}} \tag{3}$$

where v_i^c expresses the normalized vector of training samples, and $Q \in R^{n\times n}$. The eigenvectors chosen correspond to the m largest eigenvalues of matrix Q, and are denoted by w_i, $i = 1,2,\cdots,m$. Thus eigenface space matrix W is formed, expressed by $W = [w_1\ w_2\ \cdots\ w_m]$, where $W \in R^{n\times m}$ and $m < n$.

B. *Projection of Training Samples into the Eigenface Space*

The same average face is required while training samples and testing samples are normalized, so that they can be compared under the same circumstances. The average face of all the training samples is defined as

$$m = \frac{1}{N}\sum_{c=1}^{L}\sum_{i=1}^{Nc} x_i^c \tag{4}$$

where x_i^c represents training samples with class c. Then training samples with this average face are normalized as

$$x_i^c \leftarrow x_i^c - m \qquad i = 1,2,\cdots,N_c,\ c = 1,2,\cdots,L \tag{5}$$

Each training sample with class c is projected into the eigenface space, and the projected features are obtained as follows

$$y_i^c = W^{\mathrm{T}} x_i^c \qquad i = 1,2,\cdots,N_c,\ c = 1,2,\cdots,L \tag{6}$$

where y_i^c expresses the projected features of training samples x_i^c, and $y_i^c \in R^m$.

C. *Projection of Testing Samples into the Eigenface Space*

Suppose a testing sample denoted by x_{test}, where $x_{test} \in R^n$. At first, this testing sample is normalized, and then projected into the eigenface space. Therefore, the projected features are acquired as follows

$$x_{test} \leftarrow x_{test} - m \tag{7}$$

$$y_{test} = W^{\mathrm{T}} x_{test} \tag{8}$$

where y_{test} expresses the projected features of testing sample x_{test}, and $y_{test} \in R^m$.

D. *Classification of Testing Samples*

In this paper, Euclidean Norm is utilized to compute the distance difference between testing sample features y_{test} and training sample features y_i^c [6]. That is

$$\mathrm{d}(y_i^c, y_{test}) = \left\| y_i^c - y_{test} \right\|_2 = \left[\sum_{j=1}^{m} \left| y_{ij}^c - y_{test \cdot j} \right|^2 \right]^{1/2} \qquad i = 1,2,\cdots,N_c,\ c = 1,2,\cdots,L \tag{9}$$

where y_{ij}^c expresses the j-th projected element of the i-th training sample with class c, and $y_{test \cdot j}$ the j-th projected element of arbitrary testing sample. After all distance differences between the testing sample and training samples are computed by way of the method, the class of the testing sample is discriminated according to NND rule

$$\mathrm{d}(y_{i^*}^{c^*}, y_{test}) = \min_{1 \le c \le L} \min_{1 \le i \le N_c} \mathrm{d}(y_i^c, y_{test}) \tag{10}$$

Therefore, the testing sample y_{test} can be determined as class c^*.

III. Experimental Results and Analysis

In this paper, experiments are based on ORL face database, which can be used freely for academic research [7]. ORL face database contains 40 distinct persons, each person having ten different face images. There are 400 face images in total, with 256 gray degrees and the resolution of 112×92. These face images are attained in different situations, such as different time, different angles, different expression (closed eyes/open eyes, smile/surprise/angry/happy etc.) and different face details (glasses/no glasses, beard/no beard, different hair style etc.). Some images are shown in Fig.2.

Fig. 2. Some images from ORL face database

In order to increase the speed of computation, and reduce the dimension of face image, bilinear interpolation method is utilized to resize the image into 22×18. Bilinear interpolation is a method to calculate the value of interpolation points within a unit square according to the values of its four top points. The formula is represented as

$$f(x,y) = [f(1,0) - f(0,0)]x + [f(0,1) - f(0,0)]y + [f(1,1) + f(0,0) - f(0,1) - f(1,0)]xy + f(0,0) \quad (11)$$

where (x, y) denotes a point within a unit square, whose four top points are $(0,0)$ 、 $(0,1)$ 、 $(1,0)$ 、 $(1,1)$ respectively, and $f(x, y)$ 、 $f(0,0)$ 、 $f(0,1)$ 、 $f(1,0)$ 、 $f(1,1)$ represent the values of these points respectively. Then, the data is converted into

$$x_i^{'} \leftarrow (x_i - 128)/128 \qquad x_i^{'} \in [-1, 1] \quad (12)$$

Because the eigenvalues of covariance matrix Q decline very fast, the 100 most important eigenvectors corresponding to the 100 largest eigenvalues are selected to form the eigenface space matrix. The first 5 to 8 images from each person are used as training samples, and the rest 5 to 2 images as testing samples. In order to compare with the method presented in this paper, experiments were done by way of traditional PCA method at the same time [8]. Here, correct recognition rate (CRR) is defined as the number of samples recognized correctly divided by the number of all the samples, while running time (RT) denotes average processing time of the whole training and testing samples. All the experiments were based on the computer with Pentium II 400MHz, 192M RAM. Experimental results are demonstrated in Table 1.

From Table 1, we can see that correct recognition rate increases as the number of training samples rises. Compared with traditional PCA method, correct recognition rate is higher and running time is less. When the first 8 samples are used as training samples and the rest 2 samples are used as testing samples, correct recognition rate by improved PCA method reaches 98%.

Table 1. Correct recognition rate and running time with variable number of training samples

Training samples	5		6		7		8	
	CRR (%)	RT (ms)	CRR (%)	RT (ms)	CRR (%)	RT (ms)	CRR (%)	RT (ms)
Traditional PCA	89.5	3.83	93	3.7075	93.3	3.555	95	2.63
Improved PCA	93.3	3.8075	95	3.63	96.5	3.305	98	2.5025

IV. Conclusions and Future Work

Face recognition is an active subject in the fields of pattern recognition. There still exist some difficulties in practical applications. Thus it is necessary to improve traditional methods. PCA is based on the features of the whole face, these features may not mean anything, and they are only used as classification. In this paper, integrated with the advantages of PCA, an improved method based on the normalization of within-class average face image is presented. Compared with traditional PCA method, it is more reasonable to process samples with same class and different class. Therefore, a higher correct recognition rate can be acquired, and a better efficiency can be achieved. How to improve feature extraction method to make the classification more easily and more quickly is expected to research deeply in the future.

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