The Middle Sample Based on Color Face Identification

Feature Extraction and Automatic Identification

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Abstract

Currently face recognition has made some success, algorithms are constantly being improved, this paper puts forward the sample was based on the middle sample what will consider existing deviation from the samples and it will affect samples, the average face recognition rate dropped to sample, therefore consider removing part of samples of the sample among affect outcomes. Combined with colored face feature identified and automatic identification, the improved algorithm will be applied to color facial identification. Finally, extensive experiments performed on the international and universal AR standard color face database verify the effectiveness of the proposed method.

Keywords:middle samples, color face recognition, discriminating characteristics, feature extraction, automatic identification

1. Introduction

In recent years, as a research subject with theoretical and application value, face recognition has being attached importance and attention to researchers. By this, varieties of recognition methods, one of which is Principal Component Analysis [1-4] (PCA), have emerged one after another. The traditional PCA method follows the following basic processing: by the K-L [5-8] transformation, we can extract the major ingredient of human face to establish Eigen-face space, then project test images into this Eigen-face space to get a group of projection coefficients, finally identify through comparing the projection coefficients with that of every face image. However, in the algorithm we calculate the sample mean, according to which we can get the deviation matrix and then get the general

scatter-difference[9], but because of the deviation of some samples, the sample mean is not so accurate, thereby the general scatter-difference is affected, and the recognition rate is decreased finally. To deal with this problem, this paper puts forward a method based on middle sample, which is also applied to gray-scale face image. It turns out the recognition rate is increased when color information is adopted comparing to that of recognition which just concern gray-scale image, therefore, more and more researchers begin to use the color information of face image to improve the performance of face recognition algorithm. But the basic idea of color face recognition is transforming color face image into gray-scale face image, then color face recognition is based on gray-scale image. So face recognition algorithm based on gray-scale image is still pervasive. This report applies the improved method to the identification of color face [10-11].

Starting from original color algebraic feature of images, analyzing the characteristics of the formation of color face image, the paper introduces how to extract principal component feature from the three components R, G, B of color face image and analyzed it [12-13], then experiments are tested by adopting the improved PCA. What's more, all of the results were validated through the international AR standard color face database.

2. Fisher linear discriminant analysis

2.1. Basic ideal of FLDA

PCA is the optimal orthogonal transformation, of which the basic idea is to get the direction projection of maximum general scatter-difference by covariance matrix of sample. The advantage of PCA lies that it eliminated the correlation between the various components of sample vector.

Eigen-face subspace it generates has the best representation of characteristics, but it didn't utilize category information of the training sample efficiently, therefore PCA is not the optimal at the sense of classification and identification. Fisher Linear Discriminant Analysis (FLDA) has compensated for the shortcoming. The basic idea of FLDA is to get a projection space in which the ratio of dispersion of between-class and within-class is the maximum, namely reaching between-class dispersion maximum and within-class minimum. It means to make the distance between different classes as large as possible, and the distance within class as small as possible. In figure 1, hollow circles and solid circle represent the two different types of samples; the figure represents the distribution of the two types of samples in two different projection directions W_1 and W_2 after projection. As shown in figure.1, projection got in direction W_1 can separate the two types of samples well, however, part of projection in direction W_2 overlaps together, it is difficult to separate the two types of samples. Thereby, whether to quest optimum projection direction is important.

Figure.1 sample projection distribution (a) meeting the requirement of Fisher criterion (b) not meeting the requirement of Fisher criterion

The classical linear discriminant analysis takes the fisher linear discriminant function, so that linear discriminant analysis is also called Fisher Linear Discriminant Analysis. The basis ideal of Fisher criterion lies in getting the optimum projection direction, on which the overlap of projections of the two types of samples is the minimum, so as to achieve the best classification results. Fisher criterion was first proposed by R.A. in 1936, and was applied to face recognition by Swets and Weng in 1996.

2.2. Principles of FLDA and algorithm

Training sample set of face image $\{x_1, x_2, \dots, x_N\}$,

x_i is n -dimensional vector. Training samples are divided into K classes, recorded as $C_1, C_2, \dots, C_K$, and there are N_i training samples in class C_i . Then mean vector of all samples is defined as:

$$m = \frac{1}{N} \sum_{i=1}^N x_i \quad (1)$$

Mean vector of class C_i is defined as:

$$m_i = \frac{1}{N_i} \sum_{x_i \in C_i} x_i \quad (2)$$

The between-class scatter matrix is defined as:

$$S_b = \frac{1}{N} \sum_{i=1}^K N_i (m_i - m)(m_i - m)^T \quad (3)$$

The within-class scatter matrix is defined as:

$$S_w = \frac{1}{N} \sum_{i=1}^K \sum_{x_i \in C_i} (x_i - m_i)(x_i - m_i)^T \quad (4)$$

The total scatter matrix is defined as:

$$S_t = S_b + S_w = \frac{1}{N} \sum_{i=1}^N (x_i - m)(x_i - m)^T \quad (5)$$

Obviously, S_t is the covariance matrix of all samples.

FLAD algorithm is to find the best projection direction W_{opt} , which is the orthogonal eigenvector when the ratio of scatter matrix between and within class is the maximum, Fisher criterion function is defined as:

$$J(W_{opt}) = \arg \max \frac{|W^T S_b W|}{|W^T S_w W|} \quad (6)$$

W_{opt} is the solution meets the following equation:

$$S_b W_i = \lambda_i S_w W_i, \quad i = 1, 2, \dots, m \quad (7)$$

It corresponds to eigenvector that corresponds to the first m larger eigenvalue λ_i of $\mathbf{S}_w^{-1}\mathbf{S}_b$.

However, we often encounter such a problem: scatter matrix within class is a singular, so that we can't get eigenvalue of $\mathbf{S}_w^{-1}\mathbf{S}_b$ directly. It is evoked that number of training samples is often less than the number of pixels of the samples. This is so-called small sample problem.

3. Our method

Because there are interference samples far away from all the samples, the article proposed a following new viewpoint: remove interference samples and seek middle sample, we can ensure that samples acquired not be influenced by some samples. Suppose there is a sample set $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N\}$, of which $\mathbf{x}_i$ is a dimensional vector, while training samples are divided into k classes, recorded as $C_1, C_2, \dots, C_k$, and there are M training samples in each class. As shown in figure.2, each column represents a sample. Firstly sorting all the samples in sample set $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N\}$ according to their pixel value, in other words, sorting pixel value in the red box of the figure to form a new sample set $\{\mathbf{x}_1', \mathbf{x}_2', \dots, \mathbf{x}_N'\}$, then we fetch the middle sample of the new sample set as mean vector $\bar{\mathbf{x}}_a$ of all the samples.

$$\begin{bmatrix} x_1(1) & x_2(1) & \cdots & x_N(1) \\ x_1(2) & x_2(2) & \cdots & x_N(2) \\ \cdots & \cdots & \cdots & \cdots \\ x_1(n) & x_2(n) & \cdots & x_N(n) \end{bmatrix}$$

Figure.2 Matrix representation of all samples

Under the new assumptions, new overall mean vector

$\bar{\mathbf{x}}^{ab}$ and mean vector of every class $\bar{\mathbf{x}}_i^{ab}$ are substituted to construct new scatter matrix by $\bar{\mathbf{x}}^{ab}$ and $\bar{\mathbf{x}}_i^{ab}$.

The new between-class scatter matrix is defined as:

$$\mathbf{S}_b^{ab} = \frac{1}{N} \sum_{i=1}^K N_i (\mathbf{x}_i^{ab} - \bar{\mathbf{x}}^{ab})(\mathbf{x}_i^{ab} - \bar{\mathbf{x}}^{ab})^T \quad (8)$$

The new within-class scatter matrix is defined as:

$$\mathbf{S}_w^{ab} = \frac{1}{N} \sum_{i=1}^K \sum_{\mathbf{x}_i \in C_i} (\mathbf{x}_i - \bar{\mathbf{x}}_i^{ab})(\mathbf{x}_i - \bar{\mathbf{x}}_i^{ab})^T \quad (9)$$

The total scatter matrix is defined as:

$$\mathbf{S}_t^{ab} = \mathbf{S}_b^{ab} + \mathbf{S}_w^{ab} = \frac{1}{N} \sum_{i=1}^N (\mathbf{x}_i - \bar{\mathbf{x}}^{ab})(\mathbf{x}_i - \bar{\mathbf{x}}^{ab})^T \quad (10)$$

Plug the obtained scatter matrix into Fisher criterion of the Eq.11 and maximum scatter difference discriminant criterion of the Eq.12

$$J(\mathbf{W}_{opt}) = \arg \max \frac{|\mathbf{W}^T \mathbf{S}_b \mathbf{W}|}{|\mathbf{W}^T \mathbf{S}_w \mathbf{W}|} \quad (11)$$

$$\begin{cases} J_s(\phi) = \phi^T \mathbf{S}_b \phi - \phi^T \mathbf{S}_w \phi = \phi^T (\mathbf{S}_b - \mathbf{S}_w) \phi \\ \phi^T \phi = 1 \end{cases} \quad (12)$$

We have to solve new projection direction for face identification feature extraction, measure similarity and classify to apply the new method to color facial identification.

Color face identification feature extraction and automatic identification is to find "feature space"

U_R, U_G, U_B of three color spaces by steps to create eigenface space based on principal component method, next, project the color image, any face image after centralization can be projected into eigenface subspace and get a group of coordinate coefficients:

$$\tilde{x}^i = U^T \bar{x}^i \quad (13)$$

Projections of three color spaces of color image can be expressed as follows:

R component:

$$\tilde{x}_R^i = U_R^T \bar{x}_R^i \quad (14)$$

G component:

$$\tilde{x}_G^i = U_G^T \bar{x}_G^i \quad (15)$$

B component:

$$\tilde{x}_B^i = U_B^T \bar{x}_B^i \quad (16)$$

Finally, input the selected discriminating characteristics into classifier for classification, the most classic classifier is the nearest neighbor classifier or minimum distance classifier.

4. Experimental results and analysis

In order to verify the validity of the proposed algorithm, the experimental is based on a large AR face image database. The database is made up of 26 face images per person which were taken in different periods, light, gesture, facial expressions and occlusion conditions from 120 persons. The 26 images were taken in two periods, the former 13 images were taken in one period, and the latter 13 images were taken in another period, there is a difference of 14 days before and after. The experiment only investigated unobstructed images; take images from the former 60 persons as the sample set. The experiment used standardized face images with a resolution of 50×40. Images shown in figure.31 are 14 color images of someone after standardization.

Figure.3 14 images of AR face image database

The experiment adopts linear discriminant analysis to establish within-class scatter matrix and between-class scatter matrix. As a result, the dimensions will be high, and obviously such a high number of dimensions are unrealistic to run on computers. Therefore the experiment first reduced the dimensionality of sample's three RGB components by principal component analysis, then used Fisher criterion and maximum scatter difference criterion for linear discriminant analysis. As shown in table.1 and table.2, they extracted feature on projection axis 50-59, they are comparison table of recognition rate and comparison table of time used using the nearest neighbor classifier and minimum distance classifier.

Table.1 Comparison table of recognition rate using two kind of classifier by two improved discriminant analysis methods which use $\bar{x}_a$

Number of projection axes	Improved Fisher criterion		Improved maximum scatter difference criterion	
	MD	1NN	MD	1NN
50	85.0%	86.5%	85.5%	86.5%
51	85.5%	87.0%	85.5%	87.5%
52	86.5%	88.5%	85.0%	89.0%
53	86.5%	88.0%	85.0%	88.5%
54	88.5%	88.0%	85.0%	88.5%
55	88.5%	89.0%	85.0%	89.0%
56	88.5%	89.0%	85.5%	89.0%
57	89.0%	89.5%	86.0%	89.0%
58	89.0%	90.0%	86.0%	89.0%
59	89.5%	91.5%	85.5%	89.0%

Table.2 Comparison table of recognition rate from two kind of classifier after two improved discriminant analysis methods by utilizing $\bar{x}_b$

NO. projection axes	Improved Fisher criterion		Improved maximum scatter difference criterion	
	MD	1NN	MD	1NN
50	86.0%	86.5%	86.5%	86.5%
51	86.0%	87.5%	86.5%	87.0%
52	87.5%	89.0%	88.0%	89.5%
53	87.5%	88.0%	88.0%	88.5%
54	88.5%	88.5%	88.0%	88.0%
55	89.5%	90.0%	89.0%	89.5%
56	89.5%	90.5%	89.5%	90.0%
57	89.0%	91.5%	90.0%	91.0%
58	90.0%	92.0%	90.0%	91.0%
59	90.5%	91.5%	91.5%	90.0%

Table.3 comparison table of time used under optimal recognition rate when using the nearest neighbor classifier by two improved discriminant analysis methods

Identification criteria	Time for feature extraction(s)	Time for classification(s)	Total time(s)
Maximum scatter difference criterion (47)	143.57	3.34	146.91
Fisher criterion (49)	177.43	3.46	180.89

Note: Numbers in brackets is the number of select projection axis

As shown in table1.and table.2, the recognition rate has been increased through Fisher criterion and improved maximum scatter difference criterion improved in the first and second program especially the second program duo to the two programs removed the effect of some interference samples. As shown in table.3, because of the addition of average sample problems, time for feature extraction is significantly increased, especially in the second program.

5. Conclusion

The paper puts forward a kind of face recognition based on the middle sample, which gets the average of some samples rather than gets average of all samples. This method excludes the influence of the interference samples on experiments and increased the recognition rate significantly. As researches nowadays are mainly based on

the gray-scale ones, this article applies improved methods to color face identification. Color face recognition is to transfer the color images into gray images, then use the extraction idea of the latter. Finally, through combination of the experiment and the new ideas, we find that the method is feasible.

In the end, large numbers of experiments based on international general AR standard color face database have adequately proved the validation of the method for processing color face image identification.

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