The Study of Entrance Guard & Check on Work Attendance System Based on Face Recognition

Lang Liying, Hong Yue
Hebei University of Engineering, Handan, Hebei province, 056038, P.R. China
langliying@126.com, hongyue925@163.com

Abstract

In this paper, the core algorithm is studied, which aiming at developing a robust and practical entrance guard & check on work attendance system based on face recognition, and this system is applied to the logistics management industry. Firstly, this algorithm divides the image into block images, which are also called sub-images. Then the well-known Fisher method is directly employed to the selecting sub-images obtained from the previous step, and the new lower dimensionality patterns that replace the original patterns are obtained. Finally the recognition results are obtained by the general minimum distance classifier. The ORL face image database is made use of to simulate and the results shows that this method presented in this paper is obviously superior to the traditional Fisher method. And when the training sample is only one, the recognition rate of 90.83 percent is achieved. It is indicate that M-FLDA can not only accelerate recognition speed by reducing dimensionality but also reduce the memory capacity. Finally, the preliminary study of solving facial pose changes is presented.

1. Introduction

Entering the 21st century, logistics management industry is developing at a speed that can not be conceived before; it has become indispensable in people's daily life. Because of the people involved in the logistics management industry are of different conditions, safer and more reliable safety precaution system is necessary. The entrance control system has become a very important part in the Security System, which can not only control entranceways of buildings, but also help the Close Circuit Television System in a safe working environment, personnel management and administration. In some developed countries, the entrance control system is developing at a much higher rapid speed than other security products. This paper studies an algorithm which is aiming at developing a robust and practical entrance guard & check on work attendance system based on face recognition, and trying to apply this system to the logistics management industry.

Face recognition technology is an important branch of Biometrics and it is also the study focus of Pattern Recognition and Computer Vision, which interest is mainly motivated by the broad range of potential applications for systems that are able to recognize the face they contain, such as surveillance, personal identification, access control, conference, and human computer interface. Now many approaches to face recognition problem have been devised over the years, from the early geometry based methods to statistics based methods. Fisher linear discriminating analysis (FLDA) method has been recognized as one of the most popular and classical ways, but it often encountered "small sample" in the application. Although linear techniques have been fully developed, they are still inadequate to describe the complexity of real face images because of the illumination, facial expression and pose variation. Hence it's necessary that how to take effectively extracting characteristics and reduce dimensions.

In this paper, based on Fisher criterion, a new criterion based on the modular image is presented, which is called Modular Fisher linear discriminating analysis (M-FLDA). First, the original images are segmented into four different regions, which are also called sub-images. Then the famous FLDA method is directly used to the sub-images obtained from the previous step, which the new criterion evaluated the quality of an image by encouraging inner region smoothness and inter-region contrast. It has not only played a role of dimensionality reduction but also increased the number of the sub-chart training sample to 2 indexes, which handle the problem of small sample into large sample and reduce the complexity of the issue. To test M-FLDA and to evaluate its

978-0-7695-3308-7/08 $25.00 © 2008 IEEE
DOI 10.1109/ICCSIT.2008.15

performance, a series of experiments are performed in the ORL human face image databases. The experimental results indicate that the performance of M-FLDA is obviously superior to the FLDA method in recognition. The memory capacity is reduced and the recognition rates are 90.83 percent and 82, respectively.

2. Algorithm theoretical model

2.1. Classical FLDA

Suppose that there are m known pattern classes $\omega_1, \omega_2, \cdots, \omega_m$, model X is the n-dimensional vector, based on the given training image samples (image matrices), the image within-class scatter matrix S_w and the image between-class scatter matrix S_b are definition, respectively, it shows that the S_b and S_w set non-negative matrix.

The generalized Fisher criterion can be defined by

$$F(\varphi) = \frac{\varphi^T S_b \varphi}{\varphi^T S_w \varphi} \quad (1)$$

φ is n-dimensional vector.

The purpose of projection is to reshape the underlying distribution of samples such that the obtained features are favorable of classification. Naturally, the desired effectiveness is that the within-class scatter is as small as possible, and the between-class scatter is as large as possible at the same time. It is easy to find a vector φ^* to maximize the Rayleigh quotient function $F(\varphi)$. After the projection of samples onto φ^*, the ratio of the between-class scatter to the within-class scatter is maximized. So, the vector φ^* is called the optimal mage projection direction. The optimization problem of (1) is equivalent to the following generalized eigenvalue problem,

$$S_b \varphi_i = \lambda S_w \varphi_i \quad (2)$$

It is also the characteristic vector of the matrix greater characteristic value λ_i, and this matrix has no more than c-1 the non-vanishing characteristic value.

2.2. M-FLDA

The FLDA method only applies to non-singular matrix scatter (reversible) situation on face recognition, but there is a large number of typical problems of small samples in practical applications, such as the within-class scatter matrix are often singular in face image recognition. The reason is that vector dimension of images which will be identified is always greater, and it is difficult to find sufficient number training samples to ensure the reversible of the within-class scatter matrix in the practical problems, then the Fisher algorithm is not necessarily the best identification performance. Therefore in the small sample situation, how to extract the Fisher most superior distinction characteristic became an admittedly difficult problem. The small sample refers that the sample number is smaller than the sample dimension, and r is used as its ratio. In common sense, when each kind of training sample number N is more than 10 times of sample dimension d (r=N/d=10), then, it can obtain better recognizing capability. The study, which is about the linear distinction analysis method in small sample situation, has aroused people's wide spread interests. And lots of methods have been proposed to solve such problems. Two alternatives can be summed up to solve this problem: □ directly increase the number of samples, such as increasing the mirror image of each image to the training centralism, doubling the number of training samples, however, the shortcoming about increasing the number of training samples is that it will lead to expenditure increase of the storage and computing (including training sample and testing sample); □ do not change the sample number, but reduce the sample dimension. The 1st method enhance r from N/d to r' =2N/d. The 2nd method makes r to increase from N/d to r'=2N/d=2r. Obviously, the 2nd method does not lead to the expenditure increases of storage and calculation, what's more it even decrease the expenditure. The method in this article belongs to the 2nd one.

Face recognition method proposed in this paper contains three important parts, image matrix block, feature extraction and determination criterion, the flow of process diagram is shown in Figure 1.

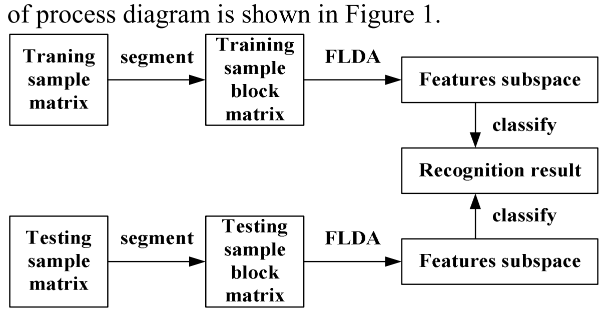

Figure 1 Face Recognition Process

Block of images is sub-block matrix of image, which converts the image matrix A from $m \times n$ to $p \times q$.

$$A = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1q} \\ A_{21} & A_{22} & \cdots & A_{2q} \\ \cdots & \cdots & \cdots & \cdots \\ A_{p1} & A_{p2} & \cdots & A_{pq} \end{bmatrix} \quad (3)$$

Among them, each sub-image A_{kl} is a $m_l \times n_l$ matrix, $pm_l = m,\ qn_l = n$. It must be pointed out that, during matrix block, the size of the sub-image ($m_l \times n_l$) and the number of the original image blocks should meet $m_l n_l \leq Npq$, ($N = \sum_{i=1}^{c} n_i$ the number of training sample) in order to ease the problems of small samples.

Regard the sub-image of all trainings image sample as the training image sample vector, and then execute it with the Fisher algorithm, the training sample A_{ij} image block $p \times q$ matrix representation is

$$A_{ij} = \begin{bmatrix} (\xi_{ij})_{11} & (\xi_{ij})_{12} & \cdots & (\xi_{ij})_{1q} \\ (\xi_{ij})_{21} & (\xi_{ij})_{22} & \cdots & (\xi_{ij})_{2q} \\ \cdots & \cdots & \cdots & \cdots \\ (\xi_{ij})_{p1} & (\xi_{ij})_{p2} & \cdots & (\xi_{ij})_{pq} \end{bmatrix} \quad (4)$$

The M-FLDA method is different from the former algorithm, and its within-class scatter matrix and the between-class scatter matrix is based on each training image sample, which is each training image sample has N= $p \times q$ kinds, and each training image sample has the within-class scatter matrix and the between-class scatter matrix, respectively.

Then the between-class scatter matrix of the training image sample A_{ij} is

$$(S_b)_{ij} = \sum_{n=1}^{N} (p(\omega_n))_{ij} ((m_n)_{ij} - (m_0)_{ij})((m_n)_{ij} - (m_0)_{ij})^T \quad (5)$$

The within-class scatter matrix of the training image sample A_{ij} is

$$(S_w)_{ij} = \sum_{n=1}^{N} (p(\omega_n))_{ij} E\{(x-(m_n)_{ij})(x-(m_n)_{ij})^T / \omega_n\} \quad (6)$$

Among which， $(p(\omega_n))_{ij}$ is priori probability of the nth kind of training image sample matrix A_{ij} , $(m_n)_{ij} = E(X/\omega_n)$ is average value vector of the nth kind of training image sample matrix $A_{ij}\ (n = 1, 2, \cdots, N), (m_0)_{ij} = E(X) = \sum_{n=1}^{N} (p(\omega_n))_{ij} (m_n)_{ij}$ is average value vector of overall training image sample matrix A_{ij} .

The duty after that is similar with Fisher algorithm, M-FLDA another innovation method concerning discovering the characteristic vector $\varphi_1, \varphi_2, \cdots, \varphi_r$, which are corresponding to $S_w^{-1} S_b$ first r maximum characteristic value, is that A_{ij} is separately projected on the training sample to these r characteristic vector, establishing a policy-making threshold value b_0 , training sample A_{ij} arrives the direction is φ_i projections is $G(x) = \varphi_i^T x\ (i = 1, 2, \cdots r)$, its policy-making function is $F(x) = sign(G(x) - b_0)$, according to policy-making rule $G(x) \gtrless b_0 \rightarrow x \in \begin{cases} \omega_1 \\ \omega_2 \end{cases}$ may cause sample A_{ij} according to the policy-making rule to divide into two matrices, To this analogy, A_{ij} may divide into $m = 2 \times r$ matrices. Respectively extracts these m matrix the average vector $\alpha_1, \alpha_2, \cdots \alpha_m$, Above again to testing sample B to carry on the characteristic to extract the process, extracts the testing sample finally m average vector $\beta_1, \beta_2, \cdots, \beta_m$.

Carry on the classification using the minimum range sorter, calculate $d_i = \|\alpha_i - \beta_i\|$, $(i = 1, 2, \cdots, r)$, if $d = \min(d_i) \leq d_0$, A_{ij} and B is the identical person, d_0 is the minimum range sorter threshold value.

3. Experimental results and discussions

In order to confirm the feasibility of M-FLDA method, the series experiments were carried out in the ORL database, which contains 40 persons' pictures, and each person has 10 pictures, there are 400 pictures in all. Each image is 92×112 with 256 gray levels per pixel. For some of the subjects, the images were taken at different times, varying lighting slightly, facial expressions (open/closed eyes, smiling/non-smiling) and facial details (glasses/no glasses). All the images are taken against a dark homogeneous background and the subjects are in up-right, frontal position (with tolerance for some side movement). Figure 2 shows the images of one person in ORL.

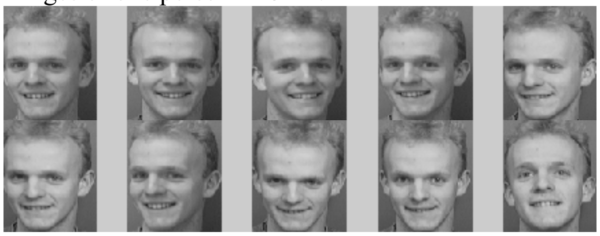

Figure 2 Ten images of one person in the ORL face database

In the M-FLDA method, each person's first picture was used as the training sample; the other nine were used as testing sample, which greatly reduced the memory capacity. Each picture was divided into four parts. But in the classics FLDA method, respectively, 2, 3, 4 and 5 pictures were taken as the training sample, and 8, 7, 6 and 5 pictures were used as the testing sample. The comparative results of the test with the classics FLDA method and the M-FLDA method was given in Table 1. The results indicated that the identification rate of M-FLDA method is obviously higher than the classics FLDA method, and the memory capacity of M-FLDA method is far smaller than the classics FLDA method.

Table 1 Comparison between experimental results

	NT	NTE	NTI	NTT	IR
FLDA	2	8	245	320	76.56%
	3	7	219	280	78.21%
	4	6	192	240	80%
	5	5	164	200	82%
M-FLDA	1	9	327	360	90.83%

NT-the number of training samples
NTE-the number of testing samples
NTI-the total number of correct identification
NTT-the total number of testing samples
IR-identification rate

In experiment, when the original image of facial expression changes was used for test sample, the recognition result was error, such as the image showed in Figure 3 on the left, compared to the right image, which is a more distortion in the forehead part.

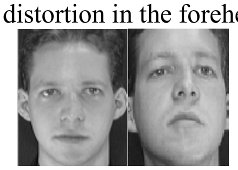

Figure 3 Two images in ORL database

In order to resolve the problem, we attempt to apply M-FLDA method after removing the distortion part, and the experiment indicated that it may obtain the correct identification result.

Therefore, through selecting suitable feature, it can enhance the recognition rate and speed for a more distortion image. But, there still needs the further study how to discriminant the priority of the sub-images in M-FLDA.

4. Conclusion

In this paper, the core algorithm is studied, which aiming at developing a robust and practical entrance guard & check on work attendance system based on face recognition. The method of M-FLDA for face recognition is presented, which is the directly sub-image matrix linear discrimination analysis method based on image segmentation. Compare to the classical FLDA method, the advantage of M-FLDA method is that the local discriminant features of the original image is efficiently extracted, and effectively alleviate small sample question, accelerate the speed of recognition, improve the accuracy of face recognition, and also help to reduce the memory capacity. The system makes working environment safer, personnel management and administration unitize, standardization.

Besides, the M-FLDA is that divided the primitive digital image, which conveniently use the method of the distinction analysis in a smaller image and make its process easier. M-FLDA is also effective in recognition the facial expression changes image. However, in order to accelerate the recognition speed under the unreduced the recognition rate, it also needs to study in future.

5. References

[1] G. J. Kaufman, Jr. and K. J. Breeding. "The automatic recognition of human faces from profile silhouettes". *IEEE Transaction on Syst., Man and Cybern.*, 1976, Vol. SMC-6,pp. 113-121.

[2] A.Lanitis,C.J.Taylor,T.F.Cootes. "An automatic face identification system using flexible appearance models". *Journal*, Image and Vision Computing, 1995,13(5):393-401.

[3] J Miao, B Yin,K Wang. "A Hierarchical Multiscale and Multiangle System for Human Face Detection in a Complex Background Using Gravity-Center Template". *Journal*, Pattern Recognition, 1999, 32(7): 1237–1248

[4] Jian Yang, Jing-yu Yang, Alejandro F. Frangi,. "Combined Fisherfaces framework". *Journal*, Image and Vision Computing, 21 (2003) 1037–1044

[5] Jeffery R. Price, Timothy F. Gee. "Face recognition using direct, weighted linear discriminant analysis and modular subspaces". *Journal*, Pattern Recognition, 38 (2005) 209–219

[6] Xiaoyang Tan, Jun Liu, Songcan Chen. "Sub-intrapersonal space analysis for face recognition". *Journal*, Neurocomputing, 69 (2006) 1796–1801.