Send Orders for Reprints to reprints@benthamscience.ae

The Open Automation and Control Systems Journal, 2015, *7*, 835-841 835

Open Access

Face Fusion Recognition Based on Bit-Plane Image

Xiaopu Ma[1,*], Changwang Liu[2] and Li Zhao[1]

[1]*School of Computer and Information Technology, Nanyang Normal University, Wolong Road 1638, Wolong District, 473061, Nanyang, Henan, China*

[2]*School of Software, Nanyang Normal University, Wolong Road 1638, Wolong District, 473061, Nanyang, Henan, China*

Abstract: Feature extraction is the main technology in the process of human face recognition system which is widely utilized as the mainstream approach in identity verification system. However, the traditional human face feature extraction algorithm of Eigenface has strict restraint on the light in the original human face image, posing as a hindrance in the practical application. Aiming at this problem, this paper proposes a novel method for human face feature extraction based on human face bit-plane image using Eigenface and Fisher's linear discriminant analysis at the same time. The constitution and characteristic of the fusion recognition method is analyzed and the experiments on performance study are proved the superiority of the new fusion recognition method.

Keywords: Bit-plane image, fisher's linear discriminant analysis, human face feature extraction, principle component analysis.

1. INTRODUCTION

With the rapid development of information system and distributed applications, how to detect and recognize one's identity effectively and automatically has become more and more importance in these systems. Now there are many methods have been proposed to solve this problem. Among of them the biological characteristic is the ideal source of information for identity verification because it has very strong stability and individual in-dependency. Especially the technique of human face recognition has become the most popular approach in identify verification at present and widely deployed as an alternative to traditional identify verification technology in enterprise security management and enterprise information application product. Perhaps the most distinctive and important feature of the human face recognition is the natural and direct to recognize one people in comparison with other biological characters [1].

The aim of human face recognition system can be easily described as follows: Given a certain static picture or dynamic video picture of scene, try to detect and recognize one or more persons in the picture or scene on the basis of the prearranged human face image database indicating relevant identity information. In the realm of computer vision, the process of human face recognition system consists of three components: one is face detection which detects the locations and sizes of human face image in the arbitrary digital pictures or dynamic video picture of scene, the other is feature extraction which transfers the original human face image data into a reduced representation set of features that can represent the main information of the original human face image data, and the third is face recognition which determines who is the right person in the static picture or dynamic video picture is according to the information that has already registered into the human face image database. Among of them feature extraction is the most significant parts that influences the correct recognition ratio of the human face recognition system [2]. Fig. (**1**) illustrates the structure of the representative face recognition system.

Feature extraction is a process which transfers the data from primary spaces into feature space in order to represent them in a lower dimensional space with less effective characters. Up to now, many methods of human face image feature extraction have been proposed, such as knowledge based methods, feature invariant approaches, template matching methods and appearance-based methods [3-5]. Among of them the most widely used method of Eigenface that is the most widely-used method of linear map based on PCA (Principle Component Analysis) has become the mainstream criterion to test the performance of various human face recognition system [6]. However the traditional algorithm of Eigenface and its transformation have strict restraints on the light and the veil in the original human face image, posing as a hindrance in the practical application.

As we know, the value of each pixel of gray human face image can be stored by eight binary bits in the computer system, hence we can obtain eight bit-plane images through decomposing the corresponding values of the eight binary bits pixel. That is a bit-plane of a human face gray image is a set of bits corresponding to a given bit position in each of the binary numbers representing the human face image. As for the each bit-plane image, most of the identification information are concentrated in the higher bit-plane image than the ordinary ones of the last general bit-plane image, hence, it can discard the interference information in the lower gen-

*Address correspondence to this author at the School of Computer and Information Technology, Nanyang Normal University, Wolong Road, Wolong District, 473061, Nanyang, Henan, China;
E-mail: mapxiao@nynu.edu.cn

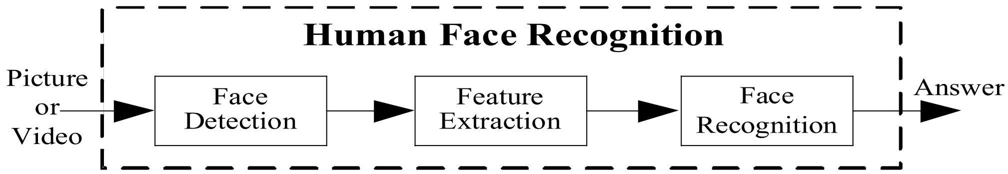


Fig. (1). The representative structure of face recognition system.

eral bit-plane image when we just consider the higher bit-planes image to extract the human face feature [7]. Furthermore, the Fisher's linear discriminant analysis method is not sensitive to illumination than Eigenface. Hence, in this paper, we will firstly test the human face recognition ratio based on the different human face bit-plane image, furthermore we will propose a new human face fusion recognition algorithm based on bit-plane image using Eigenface and Fisher's linear discriminant analysis at the same time to use the advantage of PCA and Fisher's linear discriminant analysis method.

The remainder of the paper is organized as follows. We discuss related work in Section 2. The limitations in existing Eigenface for human face feature extraction drive our motivation and Section 3 proposes our notation to recognize human face based on bit-plane image using Eigenface and Fisher's linear discriminant analysis. A summary of our experimental results on the real human face image database is discussed in Section 4. Finally, Section 5 provides some insight into our ongoing and future work.

2. RELATED WORK

PCA is used in all forms of analysis from neuroscience to computer graphics because it is a simple, nonparametric method of extracting relevant information from confusing data sets. Jian Yang et al. proposed a two-dimensional PCA (2DPCA) method in improving the accuracy of PCA algorithm which can successfully describe and reconstruct the human face image. However, the 2DPCA algorithm uses more coefficient than the traditional PCA algorithm that makes it is very difficult to achieve the desired effect because the storage space limited [8]. Another extension of PCA algorithm is modular PCA approach (MPCA) [9], the MPCA algorithm can achieve the expected target identification when facial pose or illumination changed because each piece of the original human face image is subdivided into smaller sub images before the algorithm execution. However, MPCA algorithm will spend more running time. In order to obtain high running speed, the new human face recognition algorithm using improved FFT based random on PSO and PCA techniques (FFTPCA) is proposed by Hamid [10] which can obtain higher recognition rate in the small calculations. However, in face recognition, PCA is sensitive to the facial variations, such as illumination, facial expression and pose. Furthermore, PCA is actually an unsupervised approach because it does not utilize the class label information. In contrast with PCA, the Fisher's Linear Discriminate (FLD) [11-13] algorithm will select the ratio of the between-class scatter and the within-class scatter is maximized. The FLD provides a better projection than PCA for pattern classification since it aims to find the most discriminate projection direction. Consequently, the classification results in the projected subspace may be superior to other methods. LDA suffers from Small Sample Size problem, which occurs when the number of training samples is smaller than the dimensionality of original feature space. In order to resolve this problem, some variants of LDA, such as regularization algorithms, maximum margin criterion, locality sensitive discriminant analysis and subspace algorithms, have been developed [14, 15]. Although FLD can solve the problem that the PCA method can't, it has other disadvantages than PCA method in the pictures that people don't located directly in the picture, however, the PCA algorithm has strict restraints on the light and the veil in the original human face image. To this aim, this paper proposes a new human face fusion recognition algorithm based on PCA and FLD using human face bit-plane image which can discard the interference information in a feasible way, furthermore, it also can take advantage of PCA and FLD optimization characteristic. The experimental results are tested to show the effectiveness of our findings.

3. FUSION RECOGNITION BASED ON BIT-PLANE IMAGE

3.1. Bit-Plane Image

Here we can use a $m \times n$ gray matrix A to describe the original human face image. The each element $A\{i,j\}$ is eight binary bits that can be described as $a_1, a_2, \ldots, a_8$, where $a_i \in \{0,1\}$. Thus we can get each bit-plane based on the original human face image as follows: if $A_{i,j} \geq 2^7$, then let $A_{i,j} = 128$ else let $A_{i,j} = 0$, thus we can get the first human face bit-plane image matrix A_1. Then restructure the residual gray human face image matrix as $A = A - A_1$, if $A_{i,j} \geq 2^6$, then let $A_{i,j} = 64$ else let $A_{i,j} = 0$, thus we can get the second human face bit-plane image matrix A_2, and so forth we can get all the remain human face bit-plane image matrix. An example of human face bit-planes image is shown in Fig. (**2**). It is possible to see that the higher order human face bit-plane image contains the set of the most significant information, and the lower order human face bit-plane image contain the least significant information.

(**a**) Original Face Image (**b**) Eight bit-planes face image

Fig. (2). An example of human face bit-planes image.

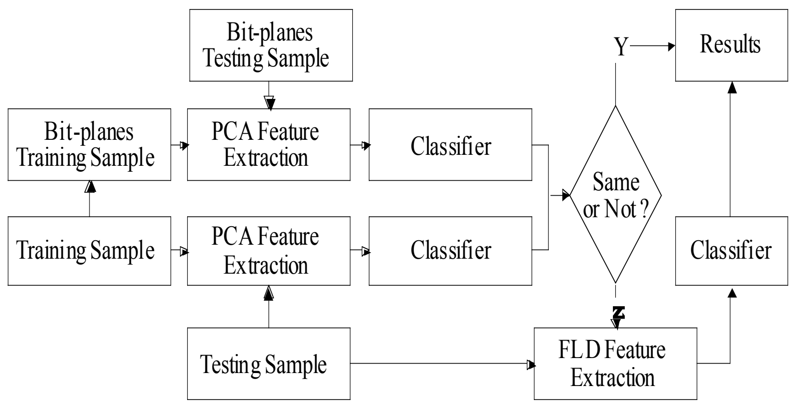


Fig. (3). The structure of the new human face fusion recognition system.

3.2. The Structure of Face Fusion Recognition System Based on Bit-Plane Image

In this section we will propose a new human face fusion recognition system based on bit-plane image using PCA and FLD algorithm at the same time in order to overcome the problem that lies in the PCA or FLD algorithm. Fig. (**3**) describes the structure of the new human face fusion recognition system.

The new human face fusion recognition system consists of three phase:

The first phase extracts the human face feature to recognize using PCA algorithm (PCA Feature Extraction) based on the original human face image (Training Sample);

The second phase extracts the human face feature to recognize using PCA algorithm based on the human face bit-plane image (Bit-Planes Training Sample);

After the first two stages, the new human face fusion recognition system will judge whether the human face recognition results are consistent or not (Same Or Not?), if the results are consistent, the human face recognition system outputs the first two stage's result as the final fusion recognition result (Results), else the third phase extracts the human face feature to recognize using FLD algorithm (FLD Feature Extraction) based on the original human face image. And the recognition system outputs the FLD recognition result as the final fusion recognition result.

In the new human face fusion recognition system, PCA feature extraction algorithm is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components.

Let the training set of human face image be $\{R_i \mid i = 1,2,...,K\}$ (where K is the number of training human face image). We can map the original human face image to a feature subspace face for recognition as follows:

1. The average human face image of the training human face image set is defined by

$$\Psi = \frac{1}{K}\sum_{i=1}^{K} R_i \tag{1}$$

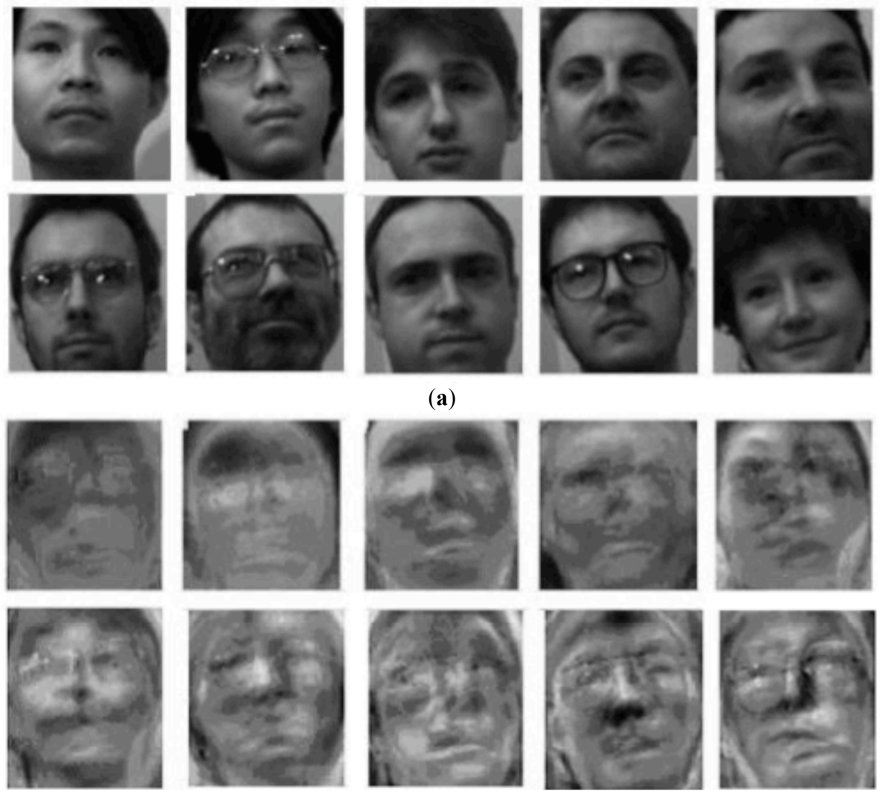
Each human face image differs from the average human face image is defined as

$$\varphi_i = R_i - \psi (i = 1,2,...K) \tag{2}$$

3. The co-variance matrix of the human face image is defined as

$$C = AA^T \quad A[\varphi_1, \varphi_2, ..., \varphi_K] \tag{3}$$

Hence, we can get the eigenvectors according to the co-variance matrix. Finally, we can map each human face image to a new vector based on the eigenvectors for recognition which can be described as



(**a**)

(**b**)

Fig. (4). An example of original human face and Eigenface image.

$$\Omega_k = U^T (R_k - \Psi) \tag{4}$$

(Where R_k is the original human face image, U^T is the eigenvectors transposed matrix). An example of Eigenface image is shown in Fig. (**4**), where (**a**) shows the example of original human face image and (**b**) shows the Eigenface for the original human face image.

In the new human face fusion recognition system, FLD is also a method used in statistics, pattern recognition and machine learning to find a linear combination of features which characterizes or separates two or more classes of objects or events based on linear discriminant analysis. The resulting combination will be used as classifier.

Let the training set of human face image be $\{X_i \mid i = 1,2,...,N\}$ (where N is the number of training human face image, the human face images of N_i belongs to the i^{th} class and $i = 1,...,C$, $N_1 + N_2 + ... + N_c = N$, each image has d pixel points). We can recognize the original human face image based on FLD algorithm as follows:

1. The average human face of each class is defined as

$$\mu_i = \frac{1}{N_i} \sum_{X \in Classi} X \quad (i = 1,2,...,C) \tag{5}$$

2. The average human face of all class is defined as

$$\mu = \frac{1}{N} \sum_{i=1}^{N} X_i \tag{6}$$

3. Then we can get the between-class scatter matrix and within-class scatter matrix as

$$S_B = \sum_{i=1}^{C} N_i (\mu_i - \mu)(\mu_i - \mu)^T \tag{7}$$

$$S_W = \sum_{i=1}^{C} \sum_{x_k \in x_i} (X_k - \mu_i)(X_k - \mu_i)^T \tag{8}$$

Finally, we can recognize the testing human face image according to the between-class scatter matrix and within-class scatter matrix based on the FLD algorithm.

4. EXPERIMENTAL RESULTS

In this section, we will implement the proposed fusion recognition system on an Intel(R) Core(TM) i5-2400 CPU @ 3.10 GHz machine with 4GB memory to evaluate how well our algorithm. The running platform is Windows 7. We will use the standard ORL human face image database to train and test our algorithm. In the ORL human face image database, there are 40 people and 10 images for each people, we will use the first five images as training samples and the other five images as test sample for each people to test the correct recognition rate.

Table 1. Average recognition rate under the various dimension of Eigenvectors using PCA algorithm.

Dimension	A	A_1	A_2	A_3	A_4
10	70%	40%	30%	20%	10%
20	80%	70%	90%	50%	30%

Table 2. Average recognition rate using FLD algorithm.

A	A_1	A_2	A_3	A_4
85%	67.5%	72.5%	70%	60%

Table **1** shows the average correct recognition rate under the various dimension of eigenvectors using PCA algorithm based on the original human image and bit-plane respectively. From the table we can see that, when the dimension of eigenvectors is low, there is a low accuracy. As the dimension of eigenvectors increases, the accuracy of the results will increase. We can also see that, the accuracy of the algorithm is quite good based on the second human face bit-plane image A_2 which can get approximately to 90% when the dimension of eigenvectors is 20. This is reasonable because the PCA algorithm based on the human face bit-plane image can discard the interference information compared with the PCA algorithm based on the original human face image.

Table **2** shows the average correct recognition rate using FLD algorithm based on the original human image and bit-plane respectively. From the table we can see that, the accuracy of the second human face bit-planes image is the highest among the accuracy of all the others human face bit-planes image. However, it is lower than the accuracy based on the original human face image. This is reasonable because the FLD algorithm can discard the interference information.

According to these testing result, we design the new face feature extraction algorithm based on human face bit-plane image fusion. In which, if the results are consistent using PCA algorithm based on the original human face image and human face bit-plane image respectively, the algorithm will output the recognition result as the final recognition result, else the system will output the FLD recognition result as the final recognition result. The results are shown in Table **3**.

In Table **3**, Class No. means which class the original human face image belongs to (the total class is 40, each people belongs to one class), OC No. means which class the original human face image belongs to using PCA algorithm based on the original human face, BC No. means which class the original human face image belongs to using PCA algorithm based on the second bit-plane image, M No. means which class the original human face image belongs to from the first two stages, if the results of the first two stages are inconsistent, the result is *, FLD No. means which class the original human face image belongs to using FLD algorithm when the first two stages results are inconsistent, if the results of the first two stages are consistent, the FLD algorithm cannot work, Final No. means which the final class the original human face image belongs to.

As can be seen from the table, the error recognition human face image class are < 1, 3, 11, 16, 25, 38, 40 > using PCA under the original human face images, that is the recognition rate is 82.5%, the error recognition human face image class are < 3, 4, 16, 25, 28, 40 > using PCA under the second human face bit-plane image, that is the recognition rate is 85%, the error recognition human face image class are < 1, 22, 25, 28, 34, 40 > using FLD under the original human face images, that is the recognition rate is 85%, however the error recognition human face image class are < 1, 25, 28, 40 > using our proposed algorithm, that is the recognition rate is 90%. Hence it can be shown that the new feature extraction algorithm based on bit-plane image using Eigenface and Fisher's linear discriminant analysis at the same time can improve the correct recognition ratio than PCA or FLD.

CONCLUSION

Human face recognition has become the norm in many application. Hence how to improve the recognition performance has become a challenging task before all the benefits of human face recognition can be realized. In this paper, we present a new recognition system to recognize the human face based on the bit-plane image fusion which draws and combines together PCA and FLD optimization characteristic in order to obtain higher recognition rate,

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

ACKNOWLEDGEMENTS

This work is supported by the Joint Fund for National Natural Science Foundation of China and Henan Province for Fostering Talents under grants U1304619 and Innovation Fund of Nanyang Normal University under grants ZX2013013. We thank the anonymous reviewers for their helpful comments.

Table 3. Recognition results under different recognition technologies.

Class NO.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
OC No.	18	2	26	4	5	6	7	8
BC No.	1	2	38	25	5	6	7	8
M No.	*	2	*	*	5	6	7	8
FLD No.	13	2	3	4	5	6	7	8
Final No.	13	2	3	4	5	6	7	8
Class NO.	9	10	11	12	13	14	15	16
OC No.	9	10	19	12	13	14	15	1
BC No.	9	10	11	12	13	14	15	7
M No.	9	10	*	12	13	14	15	*
FLD No.	9	10	11	12	13	14	15	16
Final No.	9	10	11	12	13	14	15	16
Class NO.	17	18	19	20	21	22	23	24
OC No.	17	18	19	20	21	22	23	24
BC No.	17	18	19	20	21	22	23	24
M No.	17	18	19	20	21	22	23	24
FLD No.	17	18	19	20	21	4	23	24
Final No.	17	18	19	20	21	22	23	24
Class NO.	25	26	27	28	29	30	31	32
OC No.	5	26	27	28	29	30	31	32
BC No.	13	26	27	16	29	30	31	32
M No.	*	26	27	*	29	30	31	32
FLD No.	4	26	27	4	29	30	31	32
Final No.	4	26	27	4	29	30	31	32
Class NO.	33	34	35	36	37	38	39	40
OC No.	33	34	35	36	37	23	39	5
BC No.	33	34	35	36	37	38	39	5
M No.	33	34	35	36	37	*	39	5
FLD No.	33	31	35	36	37	38	39	5
Final No.	33	34	35	36	37	38	39	5

REFERENCES

[1] W.Y. Zhao, R. Chellappa, A. Rosenfeld, and P.J. Phillips, "Face recognition: a literature survey", *ACM Computing Surveys*, vol. 35, no. 4, pp. 399-458, 2003.

[2] C.S. Tsai, C.T. Shih, J.Y. Tsai and W.D. Lin, " Development of a face recognition system", *ICIC Express Letters*, vol. 8, no. 5, pp. 1289-1294, 2014.

[3] A.J.O. Toole, P.J. Phillips, and F. Jiang, "Face recognition algorithms surpass humans matching faces over changes in illumination", *IEEE Transaction on PAMI*, vol. 29, no. 9, pp. 1642-1646, 2007.

[4] J. Wright, A.Y. Yang, A. Ganesh, S.S. Sastry, and Y. Ma, "Robust face recognition *via* sparse representation", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 31, no. 2, pp. 210-227, 2009.

[5] T. Ahonen, A. Harid, and M. Pietik, “Face description with local binary patterns: application to face recognition”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 12, pp. 2037-2041, 2006.

[6] M. Turk, and A. Pentland, “ Face recognition using eigenfaces”, In: *Proceedings of the Compute Society Conference on Vision and Pattern Recognition*, pp. 586-591, 1991.

[7] W. Hui-yuan, L. Yan, and W. Zeng-feng, “Application of Image correction and bit-plane fusion in generalized pca based face recognition”, *Pattern Recognition Letters*, vol. 28, no. 16, pp. 2352-2358, 2007.

[8] J. Yongwon, and S.K. Hyung, “New speaker adaptation method using 2-D PCA”, *Signal Processing Letters*, vol. 17, no. 2, pp.193-196, 2010.

[9] J. Yang, and D. Zhang, “Two-dimensional PCA: a new approach to appearance-based face representation and recognition”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 26, no. 1, pp. 131-138, 2004.

[10] H.M. Hasan, W.A. AL-Jouhar, and M.A. Awan, “Face recognition using improved FFT based random by PSO and PCA techniques”, *International Journal of Image Processing*, vol. 6, no. 1, pp. 26-37, 2012.

[11] P.N. Baelhumeur, J.P. Hespanha, and D.J. Kriegman, “Eigenfaces *vs*. Fisherfaces: recognition using class specific linear projection”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 711-720, 1997.

[12] S. Shi-guang, Y. Peng, and C. Xin-lin, “AdaBoost gabor fisher classifier for face recognition”, In: *Proceedings of International Workshop Analysis and Modeling of Faces and Gestures*, pp. 278-291, 2005.

[13] Z. Wei-shi, J.H. Lai, and P.C. Yuen, “Perturbation LDA: learning the difference between the class empirical mean and its expectation”, *Pattern Recognition*, vol. 42, no. 5, pp. 764-779, 2009.

[14] W. Chen, X. Dai, T. Huang, and B. Pan, “A novel discriminant criterion based on feature fusion strategy for face recognition”, *Neurocomputing*, vol. 159, pp. 67-77, 2015. http://dx.doi.org/10.-10-16/j.neucom.2015.02.019.

[15] L.F. Chen, H.Y.M. Liao, and M.T. Ko, “A new LDA-based face recognition system which can solve the small sample size problem”, *Pattern Recognition*, vol. 33, no. 10, pp. 1713‑1726, 2000.

Received: December 13, 2014 Revised: March 04, 2015 Accepted: March 08, 2015