A Novel Hybrid Apporach Based on Normalized Color Spaces and 2DPCA for Color Face Recognition

Shangyou Chen
Beijing Municipal Key Lab of Multimedia and Intelligent Software Technology
Beijing University of Technology
Beijing, China
sychen@emails.bjut.edu.cn

Yanfeng Sun, Baocai Yin, Caifang Song
Beijing Municipal Key Lab of Multimedia and Intelligent Software Technology
Beijing University of Technology
Beijing, China
yfsun@bjut.edu.cn, yinbc@bjut.edu.cn

***Abstract*—Recently, in a task of face recognition, some researchers proposed a novel method called color space normalization (CSN) which can enhance the discriminating power of color spaces for color face recognition. This method can significantly reduce the correlation between the three color components RGB and thus can enhance the discriminating power of the concatenated color component RGB. This offers an intrinsic (or internal) reason for why the CSN techniques can improve the face recognition performance. The three color component images of normalized color spaces are concatenated into one pattern vector, then PCA+FLD is performed on the concatenated pattern vector. But the concatenated pattern vector based on PCA destroyed the overall structure of each pixel in image. Some local structure information may be ignored. While 2DPCA preserves the overall structure information well and eliminates the small sample problem on a certain extent. Therefore, in this paper, color space normalization was combined with 2DPCA for color face recognition. This CSN based 2DPCA was performed and compared with PCA, 2DPCA for color face recognition. Numerous experiments show that the proposed approach has better recognition performance than other traditional PCA-based methods for color face recognition.**

Keywords-Color space normalization, color mode, matrix-representation model, 2DPCA, color face recognition .

I. INTRODUCTION

Most of the algorithms for face recognition employed principal component analysis (PCA) or PCA-based approaches. Although great success has been obtained, some issues remain to be further investigated. First, the number of training samples is far smaller than the sample dimension. PCA is prone to be over-fitted to the training set samples; Secondly, the recognition rate of PCA-based method is low, this can not satisfy practical requirements. To address these issues, some researches have been addressed based on grayscale image, such as two-dimensional principal component analysis (2DPCA)[1], modular principal component analysis (Modular PCA)[2] . Yang et al. [3] propose a color space normalization and perform PCA+FLD [4] on the concatenated pattern vector of the normalized color spaces for color face recognition. Although this method can enhance the discriminating power of color space and improve face recognition rate, it need to be transformed into a vector prior to feature extraction. Since the traditional PCA method does not eliminate PCA's small sample size problem at all and can destroy local structure information due to concatenate the three color component images into one pattern vector directly. Three color components of each pixel in color face image are an organic body and there are strong correlations between them. However, most of the current recognition work utilizes the information of the three color channels respectively, which would destroy the structure of color information of the face image. This paper presents a novel color face representation model, a matrix-representation model, for recognition task. The matrix-representation model encodes three color space component of the face image directly in the format of a matrix. Pixel in color face image is defined as the basic unit for the representation. Property of the pixel in the image, i.e. values of the three color space components are defined as the basic component of the representation model. 2DPCA is then employed to compute the color-Eigenfaces for feature extraction. The RGB color space is fundamental and commonly used color space. Other color spaces can be calculated from the RGB color space derived by means of either linear or nonlinear transformations. For the color spaces such as RGB, the three color components are strongly correlated. As a result, the discriminative information from the three color component images is highly redundant. The proposed CSN techniques, which are capable of converting weak color spaces into powerful ones, provide us more flexibility for color space selection for specific pattern recognition tasks. So we make use of 2DPCA and normalized color space of RGB by CSN. 2DPCA not only avoids small sample size problem of PCA, but also preserves local geometric structures in the image Due to the important effect of CSN technique which can greatly reduce the correlation of the three color component images and thus can significantly enhance the discriminating power of color spaces for face recognition. Therefore, this paper proposes a novel hybrid approach based on normalized color spaces and 2DPCA. Experimental results show the efficiency of the improved strategy in face recognition performance.

The rest of this paper is organized as follows. In next Section, we will introduce a novel hybrid approach based on normalized color spaces and 2DPCA for color face recognition approach. In Section 3 expounds the experimental results and analysis of the face recognition on FERET face databases. Conclusion is drawn in Section 4.

II. A NOVEL HYBRID APPROACH BASE ON NORMALIZED COLOR SPACES AND 2DPCA

A. Color space normalization: concept and technique

Yang et al. [3] find out that the transformation matrices of powerful color spaces all share a common characteristic: the sums of the elements in the second and third rows of the transformation matrix are both zero. They present the concept of color space normalization (CSN) and develop two CSN techniques. These CSN techniques normalize any color space possesses the same property as the powerful color spaces do, i.e., the sums of the elements in the second and third rows of the transformation matrix are both zero. The proposed two CSN techniques are demonstrated to be very effective: the normalized RGB are powerful color spaces for face recognition.

To achieve the goal that the sums of the elements in the second and the third rows of the color space transformation matrix are zero, the within-color-component normalization technique works by directly removing the means of the second and the third row vectors, respectively.

The within-color-component normalization technique is named color space normalization Ⅰ(CSN-Ⅰ).

For example, the normalized RGB color space using CSN-Ⅰ is

$$\begin{bmatrix} \tilde{R}_{\mathrm{I}} \\ \tilde{G}_{\mathrm{I}} \\ \tilde{B}_{\mathrm{I}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ -1/3 & 2/3 & -1/3 \\ -1/3 & -1/3 & 2/3 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

To make the sums of the elements in the second and the third rows of the color space transformation matrix be zero, the across-color-component normalization technique works in the following way. The original three row vectors of the color space transformation matrix are first used to generate two zero-mean row vectors via a linear combination. A new color space transformation matrix is then obtained by replacing the second and third row vectors of the original transformation matrix with the generated two zero-mean row vectors.

For example, the normalized RGB color space using CSN-Ⅱ is

$$\begin{bmatrix} \tilde{R}_{\mathrm{II}} \\ \tilde{G}_{\mathrm{II}} \\ \tilde{B}_{\mathrm{II}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ -0.5774 & 0.7887 & -0.2113 \\ -0.5774 & -0.2113 & 0.7887 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{2}$$

Why can the CSN techniques improve recognition performance?

The CSN techniques can greatly reduce the correlation of the three color component images and thus can significantly enhance the discriminating power of color spaces.

TABLE 1 AVERAGE ABSOLUTE CORRELATION COEFFICIENT COMPARISON: BEFORE COLOR SPACE NORMALIZATION AND AFTER COLOR SPACE NORMALIZATION

Color Space	RGB
Before CSN	0.8109
After CSN−Ⅰ	0.5850
After CSN−Ⅱ	0.7775

The obtained average absolute correlation coefficients corresponding to color space mentioned before are shown in Table 1. From Table1, we can see that the average absolute correlation coefficients are decreased after color space normalization, no matter which CSN technique is used. These results indicate that the CSN techniques can greatly reduce the correlation between the three color components. The reduced correlation makes the discriminative information contained in the three color component images as mutually complementary as possible. Therefore, the concatenation of the three color component images can make use of the discriminative information from the three color components are strongly correlated. As a result, the discriminative information from the three color component images is highly redundant. The concatenation of these three color component images cannot help much for improving the recognition performance.

B. Color face recogntion based on 2DPCA

2DPCA[1] based color face recognition approach represents a $m \times n$ face image by a matrix. According to the theory of 2DPCA, eigenvectors are computed based on these matrices and color-Eigenfaces are computed by superimposing the eigenvectors upon the average color face image.

The matrix-representation model manipulates on the color information directly and represents the color face image in the format of a matrix.

Supposing a normal $m \times n$ color face image, values of three color space components of the pixel in a face image are represented by normalized color space $(\tilde{R}, \tilde{G}, \tilde{B}) \in R^{1\times3}$. Here, pixel in the color face image is defined as the basic unit for the matrix-representation model. Let $x_{ij} = (\tilde{R}, \tilde{G}, \tilde{B}) \in R^{1\times3}$ denote the ith row and the jth column basic unit. Then a color face image can be represented in the following format:

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}_{m\times3n} \tag{3}$$

It is deserved to be noted that $u_{ij} \in R^{1\times3}$ can be utilized to represent any characteristic information of the ith row and the jth column pixel in the color face image. Where X is the $m \times 3n$ matrix.

2DPCA can work in either the row or column direction of the images. Here without loss of generality we continue based on the row direction of the images. Supposing X_j, a $m \times n$ random image matrix, is the jth sample in the database, and $\overline{X} = (\frac{1}{M})\sum_{j=1}^{M} X_j$ is the global mean matrix. Where X_j makes use of the above matrix-representation model. There is M training image samples in the database.

$$\text{Let } X_j = \begin{bmatrix} x_j^1 \\ x_j^2 \\ \vdots \\ x_j^m \end{bmatrix}, \ \overline{X} = \begin{bmatrix} \overline{x^1} \\ \overline{x^2} \\ \vdots \\ \overline{x^m} \end{bmatrix} \tag{4}$$

Where x_j^i and $\overline{x^i}$ are the ith row vector of X_j and $\overline{X}$, respectively. So the covariance matrix of 2DPCA can be obtained. It's easy to show that :

$$C^{2D} = \frac{1}{M}\sum_{j=1}^{M}\sum_{i=1}^{m}(x_j^i - \overline{x^i})^T (x_j^i - \overline{x^i}) \tag{5}$$

Where C^{2D} is called the image covariance matrix can directly be evaluated by using M training samples. The optimal projection axis W_{opt} is composed by the orthonormal eigenvector for the C^{2D} corresponding to the d largest eigenvalues.

C. Computing color-Eigenfaces by 2DPCA

Based on the matrix-representation model, color-Eigenfaces are computed by 2DPCA for feature extraction purpose. Computing color-Eigenfaces aims at constructing a color face subspace in which the variance of the projected data is maximized. The optimal projection directions consist into the projection matrix for feature extraction.

Let W_{opt} denote the optimal projection direction. According to the theory of 2DPCA, it is a unitary vector which is the eigenvector of covariance matrix. In practice, only one optimal projection direction is not enough. One need to compute a set of projection directions $e_1, e_2, \cdots, e_d$. Let $W_{opt} = [e_1, e_2, \cdots, e_d]$ denote the projection matrix for feature extraction. Where d denotes the number of eigenvectors which can be determined by the ratio of contribution of the eigenvectors of the eigenvalues. And $e_1, e_2, \cdots, e_d$ are the orthonormal eigenvectors of the covariance matrix corresponding to the top d largest eigenvalues. It should be noted that dimensionalty of each eigenvalues is the same as that of the color face image. One can obtain the color-Eigenfaces by superimposing the eigenvectors upon the average color face.

D. Nearest Neighborhood Classification

Having obtained feature matrix by 2DPCA, we need to define the distance measurement of the feature matrix. Let X_i and X_{test} denotes the ith face image and a test image respectively with $i = 1, 2, \cdots, N$, and Y_i and Y_{test} denote 2DPCA's feature matrixes of X_i and X_{test}. Then it follows

$$Y_i = W_{opt} X_i, \quad Y_{test} = W_{opt} X_{test}, \tag{6}$$

Where $Y_i = \left(y_i^{(1)}, \ y_i^{(2)}, \ \cdots, \ y_i^{(d)}\right)$. The distance between the feature matrices is defined as:

$$d(Y_i, Y_{test}) = \sum_{k=1}^{d}\left\| y_i^{(k)} - y_{test}^{(k)} \right\|_2 \quad i = 1, 2, \cdots, N \tag{7}$$

Where $\left\| y_i^{(k)} - y_{test}^{(k)} \right\|_2$ denotes Euclidean distance between $y_i^{(k)}$ and $y_{test}^{(k)}$.

Suppose the training samples are $X_1, X_2, \cdots, X_N$,where N is the total number of the training samples. Each sample is assigned a given identity label ξ_k. Given a probe face sample x_{test} , if $D(X_{test}, X_l) = \min_{1 \le j \le N} d(X_{test}, X_j)$. and $x_l \in \xi_k$, then the resultant decision is $x_{test} \in \xi_k$.

III. Experimental Results and Analysis

In this section, we carry out a series of experiment on the FERET face database for evaluating the performance of 2DPCA and other PCA-based method. The FERET database contains a total of 11 338 facial images obtained from 994 subjects and has been widely used in the relative research work. In our test, we select randomly a subset of face images of 200 persons (74 women, 126 men) from FERET database. Each person has 2 front view images with the different expression (from two different sets 'fa' and 'fb' respectively). All face images are normalized to 64×64 pixels (Fig.1). The images from 'fa' are selected as training set, and the images from 'fb' are selected as testing set. Thus training set and testing set contain 200 samples respectively with different race, sex, age and facial expression.

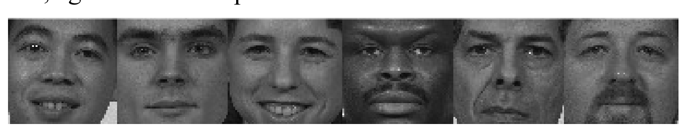

Fig.1. Normalized face images from the FERET database

In the following experiments, for a color space $C_1C_2C_3$, $C_1C_2C_3-N\mathrm{I}$ denotes its normalized version using $CSN-\mathrm{I}$, and $C_1C_2C_3-N\mathrm{II}$ denotes its normalized version using CSN-Ⅱ. For example, RGB-$N\mathrm{I}$ denotes the normalized RGB color space using $CSN-\mathrm{I}$, and RGB-$N\mathrm{II}$ denotes the normalized RGB color space using CSN-Ⅱ.

We now normalize the RGB color spaces using two CSN techniques and obtain two normalized color spaces: RGB-$N\mathrm{I}$, RGB-$N\mathrm{II}$. We apply the FERET database and evaluate the performance of the two normalized color spaces, Then we compare the recognition rate of PCA, 2DPCA based on CSNⅠ, CSNⅡ and grayscale. Nearest neighborhood classification with euclidean distance is used for PCA-based method distance measure. Table 2 shows the top recognition rate of eight methods.

TABLE 2 EXPERIMENTAL RESULTS USING THE FERET DATABASE

COLOR SPACE	PCA	2DPCA
RGB	91%	93%
RGB-NⅠ	94%	97%
RGB-NⅡ	95.5%	98%
GRAYSCALE	84.5%	90.5%

It can be seen from Table 2 that the recognition performance of 2DPCA is better than that of that of PCA. This paper uses the matrix-representation model to improve face recognition rate. We can see that the recognition rates is significantly improved after the color space normalization, no matter which CSN technique is applied. The matrix-representation model can be utilized efficiently to describe the color face image. The model can encode the three color space components information of the image simultaneously. And 2DPCA using this matrix–representation model can avoid high-dimensional vector space, where it is easy to evaluate the covariance matrix in 2DPCA due to its small size. 2DPCA's evident superiority is alleviating small sample size problem of PCA In addition, the transformation of matrix-to-vector may cause the loss of some useful structural information embedding in the original images. 2DPCA is well to overcome these problems. From the experiment result 2DPCA based on the matrix-representation model gets the good effect in the performance contest based on FERET Database.

IV. CONCLUSIONS

In this paper, A novel hybrid normalized color spaces and 2DPCA is proposed firstly for the face image recognition. The main characteristics of this method are as follows: (1) We try to make use of CSN technique to normalize RGB color space in order to get the powerful ones. This normalized color space $\tilde{R}\tilde{G}\tilde{B}$ provide us more flexibility for color space selection for specific pattern recognition tasks. (2) We uses the above normalized color space $\tilde{R}\tilde{G}\tilde{B}$ to encode the color information of color face image and the matrix-representation model to describe the color image. The model defines the pixel in color face image as the basic unit, the color information of the pixel as the basic component, and then represents the color face image efficiently in the format of matrix. Based on th matrix-representation model of color face image, we use 2DPCA for feature extraction. (3)The experimental results on FERET face database show that the proposed method has better recognition performance than other PCA-based.

ACKNOWLEDGMENT

This work is supported by NSFC (No.60973057, 60825203, 60973056, U0935004), National Key Technology R&D Program (2007BAH13B01), Beijing Natural Science Foundation（4102009）.

REFERENCES

[1] J. Yang, D. Zhang, A.Frangi, and J.Yang. Two-dimensional pca: A new approach to appearance-based face representation and recognition. IEEE Trans. On Pattern Analysis and Machine Intelligence, 26(1):131-137,2004.

[2] R. Gottumukkal, V.K. Asari, An improved face recognition technique based on modular PCA approach, Pattern Recogn. Lett. 25 (4) (2004) 429–436.

[3] Chengjun Liu and Lei Zhang, Color space normalization: Enhancing the discriminating power of color spaces for face recognition, Pattern Recognition, doi:10.1016/j.patcog.2009.11.014.

[4] P.N. Belhumeur, J.P. Hespanha, D.J. Kriegman, Eigenfaces vs. fisherfaces: recognition using class specific linear projection, IEEE Trans. Pattern Anal. Machine Intell. 19 (7) (1997) 711–720J.

[5] J. Creed, A Abbott, Face Recognition by Hypercomplex Gabor Analysis, Proceedings of the 7th International Conference on Automatic Face and Gesture Recognition, 2006.

[6] Rajapakse M, Tan J, Rajapakse and J., Channel Encoding with NMF for Face Recognition. In: Proceedings of International Conference on Image Processing, Singapore: IEEE, 2004. 2007-2010.

[7] Chengzhang Wang, Baocai Yin, Xiaoming Bai and Yanfeng Sun, Face Recognition Based on 2DPCA. ICPR'08, Tampa, USA, Dec 7-11, 2008.

[8] Lang Fangnian, Zhou Jiliu, Yan Bin, Song Enbin and Zhong Fan, Obtain Method of Quaternion Matrix Orthogonal Eigenvector Set and Its Application in Face Recognition (In Chinese), 34（2）: 121-129, 2008.

[9] L. Torres, J. Y. Reutter and L. Lorente, The Importance of the Information in Face Recognition, Proceedings of International Conference on Systems, Man and Cybernatics, 3: 627-631, 1999.

[10] L. Torres, J. Y. Reutter and L. Lorente, The Importance of the Information in Face Recognition, Proceedings of International Conference on Systems, Man and Cybernatics, 3: 627-631, 1999.

[11] J. Yang, C. Liu, A General Discriminant Model for Face Recognition, IEEE 11th International Conference on Computer Vision, pp. 1-6, Oct. 2007.

[12] Li Wenliang and Quternion Matrix (In Chinese), Changsha: National University of Defense Technology Press, 2002.

[13] M. Safayani, M.T.Manzuri Shalmani, M. Khademi, Extended Two-Dimensional PCA for efficient face representation and recognition, ICCP 28-30 Aug. 2008, 295 – 298.

[14] S. Chen, Y. Zhu, Subpattern-based principle component analysis, Pattern Recognition 37 (2004) 1081-1083.

[15] K. Tan, S. Chen, Adaptively weighted sub-pattern PCA for face recognition, Neurocomputing 64 (2005) 505-511.