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Two-dimensional color uncorrelated discriminant analysis for face recognition

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ABSTRACT

This paper presents a novel color face recognition method called two-dimensional color uncorrelated discriminant analysis (2DCUDA), which can extract two-dimensional color uncorrelated features and simultaneously retain the face spatial structure information. The 2DCUDA method seeks to explore color uncorrelated discriminant properties of the color face images and eliminate the correlations between color-based features. The novelties of this paper are twofold. First, this paper develops a new color-based feature for face recognition, which can provide substantial mutual complementation information and improve the recognition performance. Second, theoretical analysis guarantees the uncorrelated property of the obtained color-based features. Comparative experiments on AR and FRGC-2 color face databases have been conducted to investigate the effectiveness of the proposed algorithm. Experimental results show that the proposed algorithm performs better than other color face recognition methods and the two-dimensional color uncorrelated discriminant features are more effective for low-resolution image compared with conventional gray-based features. Finally, we explain why the proposed algorithm can improve the recognition performance compared with other color face recognition methods.

1. Introduction

Face recognition has become a very active research in the field of pattern recognition and computer vision due to the wide range of applications including biometric identification, public securities and face indexing in multimedia contents, etc. [1]. In the last few decades, large amounts of methods for face recognition were brought forward [2–13]. Principal component analysis (PCA) [2] was a classical data representation technique widely used in the areas of pattern recognition and computer vision. Linear discriminant analysis (LDA) [3] could find the Fisher optimal discriminant vector. Furthermore, two-dimensional principal component analysis (2DPCA) [4] was proposed for face recognition, which could extract the spatial structure information of a gray image. Li and Yuan extended this idea using discriminant information and proposed the two-dimensional linear discriminant analysis (2DLDA) [5] for feature extraction. From the view of local feature extraction, Lei et al. [6] proposed a discriminant analysis method based on Gabor tensor representation. Derived from a nonparametric estimate of Renyi's quadratic entropy, He et al. [7] proposed a robust discriminant analysis method based on maximum entropy criterion. Moreover, Chai et al. [8] put forward a novel texture descriptor, called Gabor Ordinal Measures (GOM), for face representation and recognition. However, all these methods are used to deal with gray face images rather than color face images.

Some past researches suggested that the color information appeared to confer no significant advantage beyond the gray information for face recognition [11]. Recent research efforts, however, revealed that the color could provide useful and important information for face recognition [14–37,44,47].

The previous works in color-based face recognition have successfully demonstrated the importance of color information to improve face recognition performance, but these color-based features are still correlated, which leads to redundancy information between color-based features. The key problem of color image recognition is to effectively utilize the complementary information and eliminate redundancy information between the color components [35–37]. Therefore, reducing the correlation should contribute to enhance the complementation and further

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improve the recognition performance. The experimental results in [26] showed that the proposed Color Space Normalization (CSN) technique could greatly reduce the correlation between the three color components. They concluded that the reduced correlation made the discriminant information contained in the three color component images as mutually complementary as possible. The aforementioned studies [22–27] also reduced the correlation between three color components of the original images to some extent. However, these methods were not directly focused on feature extraction and the correlation between features was not completely eliminated. Jin et al. [38] and Jing [45] proposed an uncorrelated linear discriminant method (ULDA) to remove the statistical correlation between extracted features by making the acquired projective vectors mutually uncorrelated in statistics. 2DLDA [5] could directly extract 2D features from gray image matrices. However, both of them [5,38] cannot be directly used for color image matrices that are usually represented by three data sets. Man et al. [46] proposed a statistically orthogonal analysis method (SOA) to obtain statistically orthogonal color-based features, but SOA lost color face spatial structure information. Therefore, color uncorrelated discriminant properties of the original images have not been systematically explored in the current color face recognition investigations.

The aim of this paper is to fill this blank by presenting the effective color face recognition framework based on extracting two-dimensional color uncorrelated discriminant features. The main contribution of our paper is fourfold.

(1) This paper proposes a novel two-dimensional color uncorrelated discriminant analysis algorithm. The proposed algorithm calculates the projection matrix of three color components based on Fisher criterion [39], which can enhance the complementation and remove the correlation between 2D discriminant features extracted from three color image matrices.
(2) This paper provides the theoretical foundations of the proposed method and proves the uncorrelated property between color-based discriminant features in theory. This makes it sure that the discriminant features from three color image matrices will be uncorrelated.
(3) Comparative experimental results on the AR color face database [40] and color face recognition grand challenge database (FRGC 2.0) show that the proposed method achieves better face recognition performance and less training time than other color face recognition approaches.
(4) Moreover, the experimental results also demonstrate that two-dimensional color uncorrelated discriminant features are robust against variation of facial expression, time etc. and highly effective for low-resolution images, as compared with gray-based features. Furthermore, we clearly explain why the proposed algorithm can improve the recognition performance compared with other color face recognition methods from the property of the color component correlation.

The rest of this paper is organized as follows. In Section 2, we review the related work. In Section 3, we describe the proposed color face recognition method using two-dimensional color uncorrelated discriminant analysis, and provide the realization algorithm of the proposed method. In Section 4, we present comparative experiments on the AR and FRGC-2 public color image databases to evaluate the effectiveness of the proposed algorithm and explain why the proposed algorithm can improve color face recognition performance. Finally, conclusions are offered in Section 5.

2. Related work

Our starting point aims to seek an effective method for color face recognition from the view of uncorrelated features and discriminant analysis. First of all, we present an overview of the relevant work, i.e., two-dimensional linear discriminant analysis (2DLDA) [5], uncorrelated linear discriminant method (ULDA) [38] and color face recognition methods [14–32].

2.1. Two-dimensional linear discriminant analysis (2DLDA)

The aim of 2DLDA [5] is to seek 2D features from image matrices based on Fisher's linear discriminant analysis [3]. Let $\mathbf{A_j}$ denote a gray image of size $m \times n$, and x denote an n-dimensional column vector. $\mathbf{A_j}$ is projected onto x by the following linear transformation:

$$y_j = \mathbf{A_j}x, \quad \boldsymbol{j} = 1,2,\ldots,\boldsymbol{M} \tag{1}$$

Thus, an m-dimensional projected vector y_j, i.e., the feature vector of image, is obtained.

Suppose there are C pattern classes in the training set, and M denotes the size of the training set. The jth training image is denoted by an $m \times n$ matrix $\mathbf{A_j}(j = 1,2,\ldots,M)$, and the mean image of all training samples is denoted by $\overline{\mathbf{A}}$ and $\overline{\mathbf{A}_i}$ $(i = 1,2,\ldots,C)$ denoted the mean image of class C_i and N_i is the number of samples in class C_i.

The projection of 2DLDA is obtained from solving the following optimization problem:

$$x_{opt} = \underset{x}{\operatorname{argmax}} \frac{x^T S_B x}{x^T S_W x} \tag{2}$$

$$\mathbf{S_B} = \frac{1}{M}\sum_{i=1}^{C} N_i(\overline{\mathbf{A_i}} - \overline{\mathbf{A}})^T(\overline{\mathbf{A_i}} - \overline{\mathbf{A}}) \tag{3}$$

$$\mathbf{S_W} = \frac{1}{M}\sum_{i}^{C}\sum_{\mathbf{A_k} \in C_i} (\mathbf{A_k} - \overline{\mathbf{A_i}})^T(\mathbf{A_k} - \overline{\mathbf{A_i}}) \tag{4}$$

where $\mathbf{S_B}$ denotes between-class image scatter matrix and $\mathbf{S_W}$ denotes within-class image scatter matrix. In real world applications, $\mathbf{S_W}$ is always nonsingular [5], and the solutions of the above optimization problem are to solve the generalized eigenvalue problem [2]. The optimal projection vectors are exactly the generalized eigenvectors corresponding to the first d larger generalized eigenvalues of the generalized eigenequation [42,43]:

$$\mathbf{S_B} x_{opt} = \lambda \mathbf{S_W} x_{opt} \tag{5}$$

2.2. Uncorrelated linear discriminant method (ULDA)

ULDA [38] aims to compute a group of optimal discriminant vectors which can satisfy both the Fisher criterion and the following statistical uncorrelated constraints:

$$x_i^T \mathbf{S_t} x_j = 0, \ \forall i \neq j, \ \ i,j = 1,\ldots,d \tag{6}$$

where $x_\imath$ and x_j are the optimal discriminant vectors, d is the number of discriminant vectors, and $\mathbf{S_t}$ is the total scatter matrix. According to the ULDA algorithm, the first optimal x_1 is obtained by maximizing the Fisher criterion function [3]. Then, the ith optimal discriminant vector $x_\imath(i \geq 2)$ is the eigenvector corresponding to the maximal eigenvalue of the equation

$$\mathbf{PS_b} x_i = \lambda \mathbf{S_t} x_i \tag{7}$$

where $\mathbf{P} = \mathbf{I} - \mathbf{S_t}\mathbf{D^T}(\mathbf{D}\mathbf{S_t}\mathbf{D^T})^{-\mathbf{1}}\mathbf{D}$, $\mathbf{D} = [x_1,\ldots,x_{i-1}]^T$,$\mathbf{I}$ denotes the identity matrix, and $\mathbf{S_b}$ and $\mathbf{S_t}$ are the between-class scatter matrix and total scatter matrix, respectively.

2.3. Color face recognition methods

Prior research on color face recognition in [14] shows that color does play an important role in face recognition especially when shape cues were degraded. The work in [15] further demonstrates that color cues can significantly improve recognition performance and are less susceptible to resolution changes for recognition compared with gray-based features. Other research findings also show the usefulness of color for face recognition [16–21].

With the increasing demands of real-world face recognition, color images have been paid more and more attention because they can provide much more important or useful information for improving recognition accuracy compared with gray images [22–37]. In [22], the authors analyze the canonical correlations for color image and extract effective features for recognition. By fusing color, local spatial and global frequency features, the work in [23] provides a effective method to extract the complementary facial information for face recognition. Recently, Liu [24] presented a discriminant color feature method for face recognition. In [25], the authors developed a basic Color Image Discriminant (CID) model and its general version for color image recognition. The work in [26] shows that there is a common characteristic of a powerful color space for face recognition. In addition, based on the characteristics of powerful color space, this paper presents two color space normalization techniques (CSN). The work of Liu [27] proposes three new color representations, i.e., the so-called uncorrelated color space, the independent color space, and the discriminating color space. Recently, Wang et al. [28] proposed to represent a color image as a third-order tensor and presented the tensor discriminant color space model. And Choi et al. [29] present the color local texture features and develop two effective color local texture features. More recently, Wang et al. [31] further put forward a sparse tensor discriminant color space model which represents a color image as a third-order tensor. The work of Xu [32] presents a quaternion-based discriminant analysis method for color face recognition.

Though the previous works in color-based face recognition have successfully demonstrated the importance of color information to improve face recognition performance, these color-based features are still correlated, which leads to redundancy information between color-based features. Therefore, in this paper, we propose a two-dimensional color uncorrelated discriminant analysis (2DCUDA) for color face recognition, which can eliminate the correlations between the color-based features and simultaneously retain the face spatial structure information. The details are shown in the next section.

3. Two-dimensional color uncorrelated discriminant analysis (2DCUDA)

3.1. The idea of two-dimensional color uncorrelated discriminant analysis (2DCUDA)

2DLDA [5] can extract the 2D spatial features of gray images but it cannot reduce the correlation on raw data. ULDA [38] can eliminate the statistical correlation between the extracted features but lose the feature spatial in formations. Meanwhile, the computing cost of ULDA is expensive. Moreover, both 2DLDA and ULDA are not directly used to color face images.

If 2DLDA or ULDA is directly applied to three color component image sets, the discriminant features will be highly correlated and thus their performances will be degraded. Research results [14–29] suggest that the color can provide important information for face recognition. However, the data size of color images is three times that of gray images. Therefore, how to effectively exploit color information to enhance recognition performance while reducing correlation and redundancy becomes an important task in color image recognition.

Based on the aforementioned analysis and borrowing the idea of 2DLDA [5] and ULDA [38], we propose the 2DCUDA to obtain three mutually statistically uncorrelated two-dimensional discriminant features from the three color component image matrices in a serial manner, which can ensure complete uncorrelation between color-based discriminant features in theory. More details can be seen in Subsection 3.2. The framework of the proposed 2DCUDA is shown in Fig. 1

3.2. Theoretical foundation of the proposed algorithm (2DCUDA)

In this section, we describe the theoretical foundation of the proposed 2DCUDA algorithm and present the analytical solution.

Supposed there are M labeled color image samples $\mathbf{A_j^c}$ in the training set of each class, where $j=1,2,\dots,M, c=1,2,\dots,C$ and C denotes the number of classes, and M denotes the size of the training set.

Let $\mathbf{A_R},\mathbf{A_G},\mathbf{A_B}$ be $\mathbf{R},\mathbf{G},\mathbf{B}$ color component image sets of the color image samples and $\mathbf{S_{TR}},\mathbf{S_{TG}},\mathbf{S_{TB}}$ be the corresponding total image scatter matrices respectively, then the following formulates hold:

$$\mathbf{S_{TR}}=\mathbf{S_{BR}}+\mathbf{S_{WR}} \tag{8}$$

$$\mathbf{S_{TG}}=\mathbf{S_{BG}}+\mathbf{S_{WG}} \tag{9}$$

$$\mathbf{S_{TB}}=\mathbf{S_{BB}}+\mathbf{S_{WB}} \tag{10}$$

where $\mathbf{S_{BR}},\mathbf{S_{BG}},\mathbf{S_{BB}}$ denote between-class image scatter matrices of $\mathbf{A_R},\mathbf{A_G},\mathbf{A_B}$ and $\mathbf{S_{WR}},\mathbf{S_{WG}},\mathbf{S_{WB}}$ denote within-class image scatter matrices of $\mathbf{A_R},\mathbf{A_G},\mathbf{A_B}$ respectively. Let $\mathbf{X_R},\mathbf{X_G},\mathbf{X_B}$ represent the projection matrix consisting of projective vectors for $\mathbf{A_R},\mathbf{A_G},\mathbf{A_B}$ respectively. Based on the 2D Fisher criterion, the discriminant projection matrix $\mathbf{X_R}$ for $\mathbf{A_R}$ can be calculated by

$$\mathbf{X_R}=\arg\max_{\mathbf{X_R}}\frac{\mathbf{X_R^T}\mathbf{S_{BR}}\mathbf{X_R}}{\mathbf{X_R^T}\mathbf{S_{WR}}\mathbf{X_R}} \tag{11}$$

As is proved by 2DLDA [5], we can know that $\mathbf{X_R}$ is a matrix consisting of the eigenvectors corresponding to the nonzero eigenvalues of $\mathbf{S_{WR}^{-1}}\mathbf{S_{BR}}$.

Following the discriminant projection matrix $\mathbf{X_R}$, we attempt to find the discriminant projection matrix $\mathbf{X_G}$ for $\mathbf{A_G}$ in the principle of assuring complete uncorrelation between the discriminant features of $\mathbf{X_R}$ and $\mathbf{X_G}$. Guided by this principle, we design the algorithm to calculate $\mathbf{X_G}$ as follows.

Suppose two color component images $\mathbf{A_{jr}}\in\mathbf{A_R}$ and $\mathbf{A_{jg}}\in\mathbf{A_G}$, and let $\mathbf{Y_{jr}}=\mathbf{A_{jr}}\mathbf{X_R}$ and $\mathbf{Y_{jg}}=\mathbf{A_{jg}}\mathbf{X_G}$ separately denote the projected features of $\mathbf{A_{jr}}$ and $\mathbf{A_{jg}}$. The covariance between $\mathbf{Y_{jr}}$ and $\mathbf{Y_{jg}}$ is

$$\begin{aligned}Cov(\mathbf{Y_{jr}},\mathbf{Y_{jg}})&=E[\mathbf{Y_{jr}}-E(\mathbf{Y_{jr}})][\mathbf{Y_{jg}}-E(\mathbf{Y_{jg}})]^{\mathbf{T}}\\&=\mathbf{X_G^T}E[\mathbf{A_{jg}}-E(\mathbf{A_{jg}})]^{\mathbf{T}}[\mathbf{A_{jr}}-E(\mathbf{A_{jr}})]\mathbf{X_R}\\&=\mathbf{X_G^T}(\sqrt{\mathbf{S_{TG}}})^{\mathbf{T}}\sqrt{\mathbf{S_{TR}}}\mathbf{X_R}\end{aligned} \tag{12}$$

where M denotes the size of the training set, $\overline{\mathbf{A_R}}$ denotes the mean image of $\mathbf{R}$ color component image sets, $\overline{\mathbf{A_G}}$ denotes the mean image of $\mathbf{G}$ color component image sets, $\sqrt{\mathbf{S_{TR}}}=E[\mathbf{A_{jr}}-E(\mathbf{A_{jr}})]$ and $\sqrt{\mathbf{S_{TG}}}=E[\mathbf{A_{jg}}-E(\mathbf{A_{jg}})]$. The auto variances of $\mathbf{Y_{jr}}$ and $\mathbf{Y_{jg}}$ are defined as

$$Var(\mathbf{Y_{jr}},\mathbf{Y_{jr}})=E[\mathbf{Y_{jr}}-E(\mathbf{Y_{jr}})][\mathbf{Y_{jr}}-E(\mathbf{Y_{jr}})]^T \quad =\mathbf{X_G^T}\mathbf{S_{TG}}\mathbf{X_G} \tag{13}$$

and

$$Var(\mathbf{Y_{jg}},\mathbf{Y_{jg}})=E[\mathbf{Y_{jg}}-E(\mathbf{Y_{jg}})][\mathbf{Y_{jg}}-E(\mathbf{Y_{jg}})]^T \quad =\mathbf{X_G^T}\mathbf{S_{TG}}\mathbf{X_G} \tag{14}$$

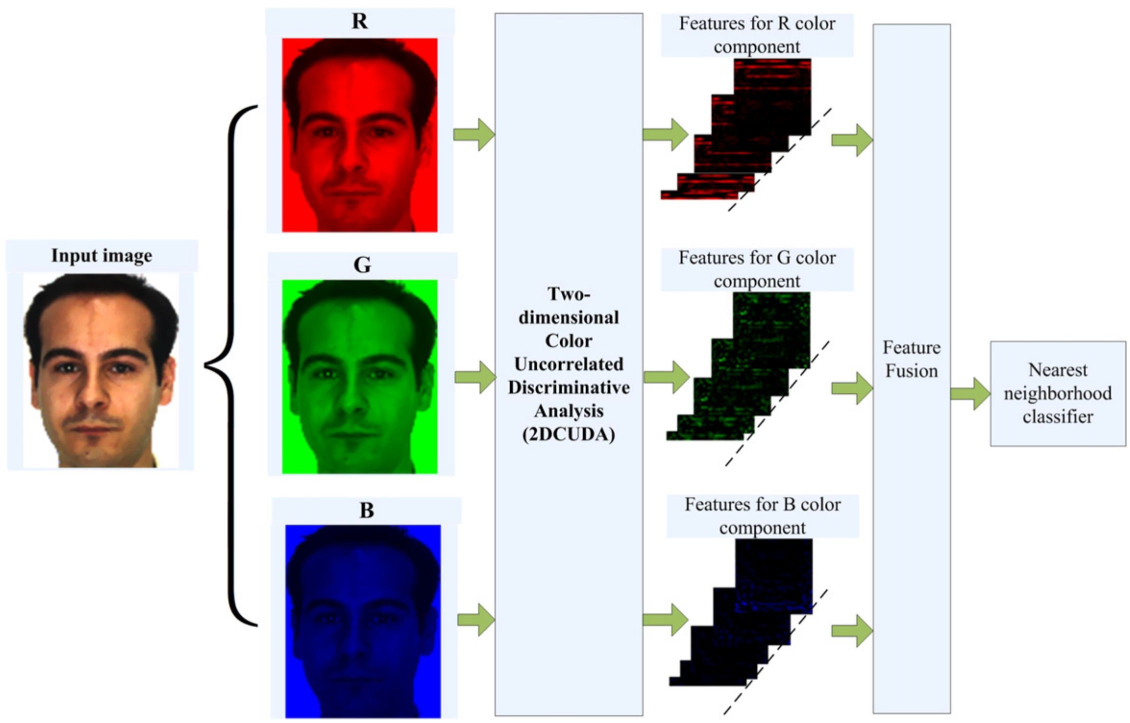

Fig. 1. The framework of the proposed 2DCUDA for color face.

The correlation between $\mathbf{Y_{jr}}$ and $\mathbf{Y_{jg}}$ can be defined as

$$Corr(\mathbf{Y_{jr}},\mathbf{Y_{jg}}) = \frac{Cov(\mathbf{Y_{jr}},\mathbf{Y_{jg}})}{\sqrt{Var(\mathbf{Y_{jg}},\mathbf{Y_{jg}})}\sqrt{Var(\mathbf{Y_{jr}},\mathbf{Y_{jr}})}} = \frac{\mathbf{X_G^T}(\sqrt{\mathbf{S_{TG}}})^\mathbf{T}\sqrt{\mathbf{S_{TR}}}\mathbf{X_R}}{\sqrt{\mathbf{X_R^T S_{TR} X_R}}\sqrt{\mathbf{X_G^T S_{TG} X_G}}} \tag{15}$$

The correlation of variables contains the statistical information of original samples, which is provided by $\mathbf{S_{TG}}$ and $\mathbf{S_{TR}}$. To remove the statistical correlation, we set $Corr(\mathbf{Y_{jr}},\mathbf{Y_{jg}})=0$, which is equivalent to $\mathbf{X_G^T}(\sqrt{\mathbf{S_{TG}}})^\mathbf{T}\sqrt{\mathbf{S_{TR}}}\mathbf{X_R}=0$. Note that $\mathbf{X_R}$ and $\mathbf{X_G}$ are statistically orthogonal if $Corr(\mathbf{Y_{jr}},\mathbf{Y_{jg}})=0$.

Then, we can obtain $\mathbf{X_G}$ by solving the following problem:

$$\mathbf{X_G} = \underset{\mathbf{X_G}}{\operatorname{argmax}} \frac{\mathbf{X_G^T S_{BG} X_G}}{\mathbf{X_G^T S_{WG} X_G}} \quad s.t.\ \mathbf{X_G^T}(\sqrt{\mathbf{S_{TG}}})^\mathbf{T}\sqrt{\mathbf{S_{TR}}}\mathbf{X_R}=0 \tag{16}$$

For solving Formula (16), we present a theorem as follows:

Theorem 1. The optimal solution $\mathbf{X_G}$ in model (16) can be achieved by solving the eigenequation

$$\mathbf{S_{WG}^{-1}}(\mathbf{I}-\mathbf{W}(\mathbf{W^T S_{WG}^{-1} W})^{-1}\mathbf{W^T S_{WG}^{-1}})\mathbf{S_{BG} X_G}=\lambda \mathbf{X_G} \tag{17}$$

where $\mathbf{W}=(\sqrt{\mathbf{S_{TG}}})^\mathbf{T}\sqrt{\mathbf{S_{TR}}}\mathbf{X_R}$, and $\mathbf{I}$ is an identity matrix.

Proof. Given $\mathbf{W}=(\sqrt{\mathbf{S_{TG}}})^\mathbf{T}\sqrt{\mathbf{S_{TR}}}\mathbf{X_R}$, the constraint can be rewritten as $\mathbf{X_G^T W}=0$. We construct the Lagrange function

$$L(\mathbf{X_G}) = \mathbf{X_G^T S_{BG} X_G} - \lambda(\mathbf{X_G^T S_{WG} X_G}\text{-}\mathbf{C_1}) - \mu(\mathbf{X_G^T W}\text{-}\mathbf{C_2}) \tag{18}$$

where λ and μ are the Lagrange multipliers, and $\mathbf{C_1}$ and $\mathbf{C_2}$ are two constant matrices. We set the derivative of $L(\mathbf{X_G})$ on $\mathbf{X_G}$ to be zero:

$$\frac{\partial L(\mathbf{X_G})}{\partial \mathbf{X_G}} = 2\mathbf{S_{BG} X_G} - 2\lambda \mathbf{S_{WG} X_G} - \mu \mathbf{W} = 0 \tag{19}$$

Left multiply $\mathbf{W^T S_{WG}^{-1}}$, then, we have

$$2\mathbf{W^T S_{WG}^{-1} S_{BG} X_G} - 2\lambda \mathbf{W^T S_{WG}^{-1} S_{WG} X_G} - \mu \mathbf{W^T S_{WG}^{-1} W} = 0$$
$$\Rightarrow 2\mathbf{W^T S_{WG}^{-1} S_{BG} X_G} - 2\lambda \mathbf{W^T X_G} - \mu \mathbf{W^T S_{WG}^{-1} W} = 0$$
$$\Rightarrow 2\mathbf{W^T S_{WG}^{-1} S_{BG} X_G} - 2\lambda * \mathbf{0} - \mu \mathbf{W^T S_{WG}^{-1} W} = 0$$
$$\Rightarrow 2\mathbf{W^T S_{WG}^{-1} S_{BG} X_G} - \mu \mathbf{W^T S_{WG}^{-1} W} = 0 \tag{20}$$

Thus μ could be expressed as

$$\mu = 2(\mathbf{W^T S_{WG}^{-1} W})^{-1}\mathbf{W^T S_{WG}^{-1} S_{BG} X_G} \tag{21}$$

Due to Eqs. (19)–(21), we have

$$\mathbf{S_{BG} X_G} - \lambda \mathbf{S_{WG} X_G} - \mathbf{W}(\mathbf{W^T S_{WG}^{-1} W})^{-1}\mathbf{W^T S_{WG}^{-1} S_{BG} X_G} = 0 \tag{22}$$

i.e.

$$\mathbf{S_{WG}^{-1}}(\mathbf{I}-\mathbf{W}(\mathbf{W^T S_{WG}^{-1} W})^{-1}\mathbf{W^T S_{WG}^{-1}})\mathbf{S_{BW} X_G}=\lambda \mathbf{X_G} \tag{23}$$

where $\mathbf{I}$ is an identity matrix; Eq. (23) is equivalent to Formula (17). Proof is over.

Furthermore, similar to $\mathbf{X_G}$, we can calculate the projection matrix $\mathbf{X_B}$. The projection matrix $\mathbf{X_B}$ is required to be statistically orthogonal to both $\mathbf{X_R}$ and $\mathbf{X_G}$. So, we calculate $\mathbf{X_B}$ by

$$\mathbf{X_B} = \underset{\mathbf{X_B}}{\operatorname{argmax}} \frac{\mathbf{X_B^T S_{BG} X_B}}{\mathbf{X_B^T S_{WG} X_B}}$$
$$s.t.\ \mathbf{X_B^T}(\sqrt{\mathbf{S_{TB}}})^\mathbf{T}\sqrt{\mathbf{S_{TR}}}\mathbf{X_R}=0$$
$$\mathbf{X_B^T}(\sqrt{\mathbf{S_{TB}}})^\mathbf{T}\sqrt{\mathbf{S_{TG}}}\mathbf{X_G}=0 \tag{24}$$

For solving Formula (24), we present a theorem as follows:

Theorem 2. $\mathbf{X_B}$ in Formula (24) can be achieved by solving the eigenequation

$$\mathbf{S_{WB}^{-1}}(\mathbf{I}-\mathbf{W}(\mathbf{W^T S_{WB}^{-1} W})^{-1}\mathbf{W^T S_{WB}^{-1}})\mathbf{S_{BB} X_B}=\lambda X_B, \tag{25}$$

where $\mathbf{W}=[(\sqrt{\mathbf{S_{TB}}})^\mathbf{T}\sqrt{\mathbf{S_{TR}}}\mathbf{X_R},(\sqrt{\mathbf{S_{TB}}})^\mathbf{T}\sqrt{\mathbf{S_{TG}}}\mathbf{X_G}]$, and $\mathbf{I}$ is an identity matrix. $\mathbf{X_B}$ is a matrix that consists of eigenvectors associated with nonzero eigenvalues of $\mathbf{S_{WB}^{-1}}(\mathbf{I}-\mathbf{W}(\mathbf{W^T S_{WB}^{-1} W})^{-1}\mathbf{W^T S_{WB}^{-1}})\mathbf{S_{BB}}$.

The proof of Theorem 2 is similar to the one in Theorem 1. So, it is omitted for saving space.

3.3. Classification method

After the transformation by 2DCUDA, three feature matrices of color components are obtained for each image. Moreover, a new overall dataset $\mathbf{Z}=1/3(\mathbf{A_R X_R}+\mathbf{A_G X_G}+\mathbf{A_B X_B})$ is drawn by three color components feature matrices. Then, a nearest neighbor classifier is used for classification. Here, the distance between two arbitrary feature matrices $\mathbf{Z_i}$ and $\mathbf{Z_j}$ is defined by $d(\mathbf{Z_i},\mathbf{Z_j})=\|\mathbf{Z_i}-\mathbf{Z_j}\|_2$, where $\|Z_i-Z_j\|_2$ denotes the Euclidean distance.

Suppose that the training samples after the transformation are $\mathbf{Z_1},\mathbf{Z_2},\ldots,\mathbf{Z_M}$, where M denotes the total number of training samples, and each of these samples is assigned a given class C_i. Given a test sample $\mathbf{Z}$, if $d(\mathbf{Z},\mathbf{Z}_l)=\min_j d(\mathbf{Z},\mathbf{Z_j})$ and $\mathbf{Z}_l\in C_i$ then the resulting decision is $\mathbf{Z}\in C_i$.

3.4. Image reconstruction

In 2DLDA, a face image can be reconstructed by using discriminant feature matrices or projection matrices. Similarly, 2DCUDA can be used to reconstruct a color face image in the following way.

$\mathbf{X_R},\mathbf{X_G},\mathbf{X_B}$ represent the projection matrixes for $\mathbf{A_R},\mathbf{A_G},\mathbf{A_B}$ respectively. After three color component image sets $\mathbf{A_R},\mathbf{A_G},\mathbf{A_B}$ are projected on this subspace, we can get the color 2D uncorrelated discriminant features $\mathbf{Y_R},\mathbf{Y_G},\mathbf{Y_B}$ respectively.

$$\mathbf{Y_R}=\mathbf{A_R X_R} \tag{26}$$

$$\mathbf{Y_G}=\mathbf{A_G X_G} \tag{27}$$

$$\mathbf{Y_B}=\mathbf{A_B X_B} \tag{28}$$

Since $\mathbf{X_R},\mathbf{X_G},\mathbf{X_B}$ are orthogonal matrices, from (24)–(26), it is easy to obtain the reconstructed color component images of $\mathbf{A_R},\mathbf{A_G},\mathbf{A_B}$.

$$\tilde{\mathbf{Y}}_\mathbf{R}=\mathbf{Y_R X_R^T} \tag{29}$$

$$\tilde{\mathbf{Y}}_\mathbf{G}=\mathbf{Y_G X_G^T} \tag{30}$$

$$\tilde{\mathbf{Y}}_\mathbf{B}=\mathbf{Y_B X_B^T} \tag{31}$$

Let $\tilde{\mathbf{A}}=[\tilde{\mathbf{Y}}_\mathbf{R},\tilde{\mathbf{Y}}_\mathbf{G},\tilde{\mathbf{Y}}_\mathbf{B}]$, then $\tilde{\mathbf{A}}$ is the reconstructed color face image of sample $\mathbf{A}$. In Fig. 2, some reconstructed images and the original image of one person were given. In Fig. 2, the variable d denotes the number of dimensions used to map and reconstruct the face image. It can be found that the reconstructed images are similar to the ones obtained by sample of the original image on the spacing horizontal scanning line. The reconstructed image $\tilde{A}$ is more and more like the original image A as the value of d increases. Compared with the 2DLDA method, the reconstructed image can provide more useful information, which is beneficial for face recognition.

3.5. Realization algorithm of 2DCUDA

As mentioned in the previous subsection, the proposed 2DCUDA in this paper aims to eliminate the correlations between color-based features and simultaneously retain the face spatial structure information. So, we extend color face recognition method from gray space to color space in the form of two-dimensional matrix, which helps obtain the face spatial structure information. Moreover, we proposed two theorems to ensure that the discriminant features are mutually statistically orthogonal. In summary, the proposed 2DCUDA can be realized as follows.

Algorithm of 2DCUDA

INPUT: a set of Mlabeled color image samples $\mathbf{A_j^c}$ in the training set, $j=1,2,\ldots,M, c=1,2,\ldots,C$. $\mathbf{A_R},\mathbf{A_G},\mathbf{A_B}$ respectively denote $\mathbf{R},\mathbf{G},\mathbf{B}$ color component image sets of the color image samples.

OUTPUT: a set of mutually orthogonal projection transforms $\mathbf{X_R},\mathbf{X_G},\mathbf{X_B}$ for $\mathbf{A_R},\mathbf{A_G},\mathbf{A_B}$

Algorithm:

Step 1: Compute between-class image scatter matrix, within-class image scatter matrix and total image scatter matrix for $\mathbf{A_R},\mathbf{A_G},\mathbf{A_B}$, i.e., $\mathbf{S_{BR}},\mathbf{S_{BG}},\mathbf{S_{BB}},\mathbf{S_{WR}},\mathbf{S_{WG}},\mathbf{S_{WB}},\mathbf{S_{TR}},\mathbf{S_{TG}},\mathbf{S_{TB}}$.

Step 2: Compute 2D projection matrix $\mathbf{X_R}$ for $\mathbf{A_R}$ by Formula (11).

Step3: Compute transitional matrix $\mathbf{W}$ by equation: $\mathbf{W}=(\sqrt{\mathbf{S_{TG}}})^\mathbf{T}\sqrt{\mathbf{S_{TR}}}\mathbf{X_R}$

Step4: Compute 2D projection matrix $\mathbf{X_G}$ for $\mathbf{A_G}$ by Formula (17).

Step5: Compute transitional matrix $\mathbf{W}$by equation: $\mathbf{W}=[(\sqrt{\mathbf{S_{TB}}})^\mathbf{T}\sqrt{\mathbf{S_{TR}}}\mathbf{X_R},(\sqrt{\mathbf{S_{TB}}})^\mathbf{T}\sqrt{\mathbf{S_{TG}}}\mathbf{X_G}]$

Step6: Compute 2D projection matrix $\mathbf{X_B}$ for $\mathbf{A_B}$ by Formula (25).

4. Experimental evaluation and analysis

In this section, we compare the classification performance of the proposed 2DCUDA with some representative color face recognition methods using AR and FRGC-2 color face image databases. In the experiments, we apply LDA [3] and fuzzy local maximal marginal embedding method (FLMME) [12] to color images, which are called color LDA (CLDA) and color FLMME

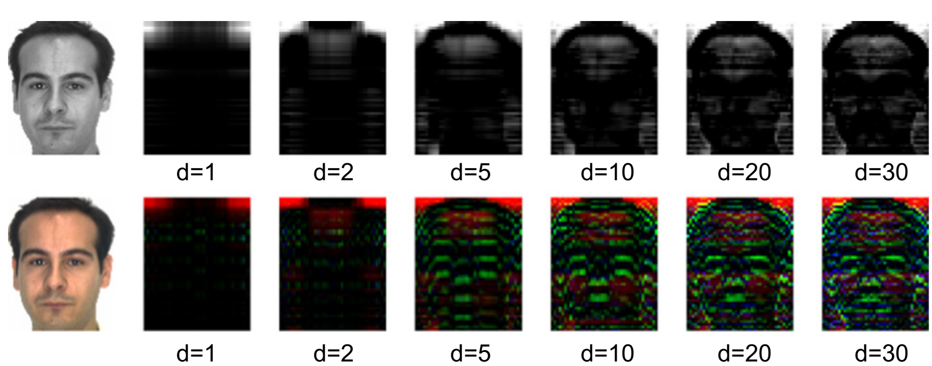

Fig. 2. Some reconstructed images of one person. The reconstructed images on the first row are extracted by the 2DLDA method. The reconstructed images on the second row are extracted by the proposed 2DCUDA.

(CFLMME), respectively. For each color image sample, we concatenate the R, G and B components into a vector. Then, we extract features from the obtained vectors corresponding to color image samples. The AR color face database is used to explore the robustness of 2DCUDA with the variation over time and in expressions. The FRGC-2 color face image database is used to test the performance of 2DCUDA in the real-world environments and assess the impact of the color for degraded face images. The nearest neighborhood classifier with Euclidean distance is used in all experiments. We also provide the explanation on why the 2DCUDA method can improve the performance using the AR color face database as an example.

4.1. The AR and FRGC color face databases

The AR color face database [40] contains over 4000 color face images of 126 people (70 men and 56 women). In the experiments, we selected 120 people. Images are frontal view faces with different facial expressions and illumination conditions. The pictures were taken under strictly controlled conditions. No restrictions on wear (clothes, glasses, etc.), make-up, hair style, etc. were imposed to participants. Each individual participated in two sessions, separated by two weeks (14 days). The same pictures were taken in both sessions. The 14 images of each individual are selected and the occluded face images are excluded in our experiment. All images are down-sampled to 50×40 pixels. The sample images for one individual of the AR database are shown in Fig. 3. The images of Fig. 3(a)–(g) from the first session are used as the training set, and Fig. 3(n)–(t) from the second session as the testing set.

The FRGC-2 color face database [41] contains 12,776 training images, 16,028 controlled target images, and 8014 uncontrolled query images for the FRGC Experiment 4. The controlled images have good image quality, while the uncontrolled images display poor image quality, such as large illumination variations, low resolution of the face region, and possible blurring. It is these uncontrolled factors that pose the grand challenge to face recognition performance. In the experiments, we selected 100 people, each with 24 images. We cropped every image to the size of 60×60, and show images of one person from FRGC-2 in Fig. 4.

Fig. 3. Sample images for one person of the AR database.

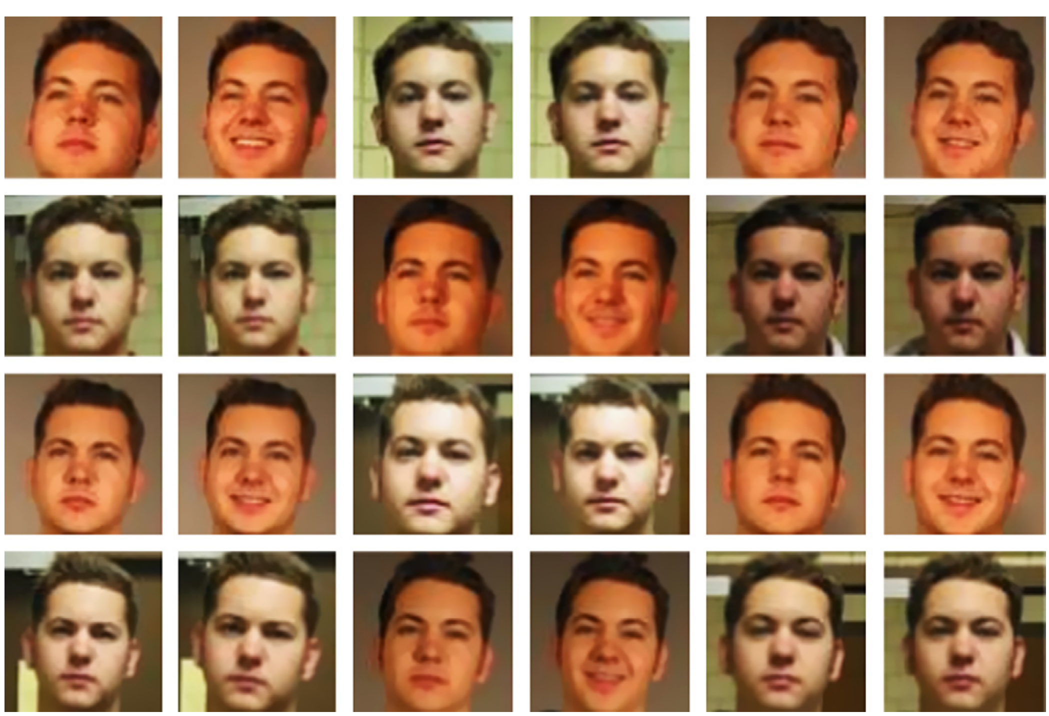

Fig. 4. Sample images for one person of the FRGC-2 database.

4.2. Experiments on the AR database

In this subsection, we first assess the performance of the proposed 2DCUDA under the variations over time. Then we design the experiment to evaluate the recognition performance of the proposed 2DCUDA under the variations in the facial expressions. Furthermore, we evaluate the computing efficiency of the proposed 2DCUDA in these experiments.

4.2.1. Comparative experiments under variations over time

In this experiment, the images from the first session (i.e., Fig. 3(a)–(g)) were used for training, and the images from the second session (i.e., Fig. 3(n)–(t)) were used for testing. Thus, the total number of training samples was 840. Since the two sessions were separated by an interval of two weeks, the aim of this experiment was to compare the performance of 2DCUDA and other methods under the conditions that the images change over time.

Fig. 5 shows the recognition rates vs. the variations of the dimensions (in Fig. 5, for one-dimensional methods, the dimension is equal to five times the numbers marked on the axes). The maximal recognition rates of each method are listed in Table 1. As can be seen from Table 1 and Fig. 5, 2DCUDA obtains the best recognition rates in the experiment under variations over time, which shows the effectiveness and robustness of the proposed 2DCUDA when there are variations over time. Why does 2DCUDA perform better than other methods in this experiment? From the view of feature correlations, the features extracted by CLDA and CFLMME are highly correlated. The CSN [26] and CICCA [22] methods can reduce the correlation between color-based features, but they cannot eliminate the correlation completely. The SOA [46] method obtains statistically orthogonal color-based features but loses color face spatial structure information (the problem of correlation between color features will be further analyzed in Section 4.4). However, the proposed 2DCUDA not only eliminates the correlations between color-based features but also simultaneously retains the face spatial structure information, which helps improve the color face recognition. In addition, the uncorrelation of the obtained color components can provide substantial mutual complementation features for face recognition. So, the performance of 2DCUDA is better than that of other methods in the experiment under variations over time.

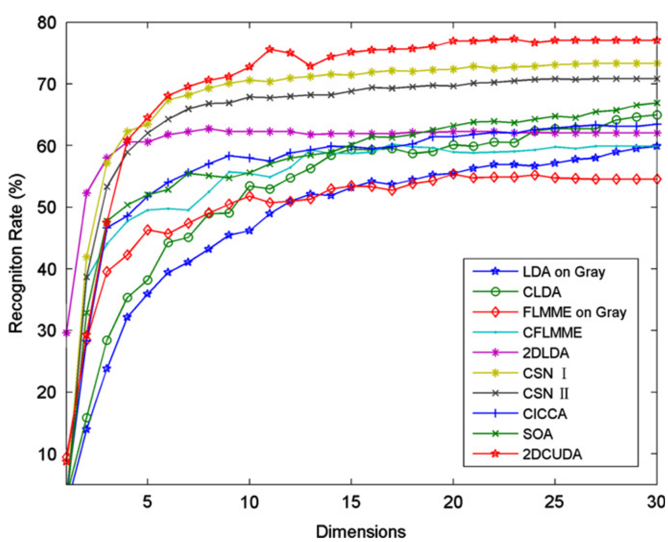

Fig. 5. The recognition rates (%) versus the dimension on the AR face database.

Table 1
The maximal recognition rates (%) and the corresponding dimensions on the AR database.

Method	LDA on gray	CLDA	FLMME on gray	CFLMME	2DLDA
Recognition rate	59.89	65.12	55.71	59.88	62.74
Dimension	117	115	134	120	50×16
Method	CSN-I	CSN-II	CICCA	SOA	**2DCUDA**
Recognition rate	73.33	70.83	63.45	66.90	**77.26**
Dimension	120	100	119	119	**50×24**

4.2.2. Comparative experiments under variations in facial expressions

In this experiment, the objective was to compare 2DCUDA and other methods under different facial expressions. We selected images (Fig. 3(a)–(d) and (n)–(q)), which involve variations in facial expressions. Fig. 3(a) and (n) was used for training and the others (i.e., Fig. 3(b)–(d) and (o)–(q)) were used for testing. Thus, the total number of training samples is 240. Table 2 lists the maximal recognition rates of each method and Fig. 6 shows the recognition rates vs. the variations of the dimensions (in Fig. 6, for one-dimensional methods, the dimensions are equal to five times the number of dimensions axes). Again, 2DCUDA performs better than the other methods, which demonstrates the robustness of the proposed 2DCUDA when there are variations in facial expressions. This is because of the fact that the proposed 2DCUDA can efficiently retain the face spatial structure and discriminant information during the procedure of eliminating the correlations between color-based features. Therefore, the proposed 2DCUDA can improve the performance in the experiment under variations in facial expressions compared with other methods.

Table 2
The maximal recognition rates (%) and the corresponding dimensions on the AR database.

Method	LDA on gray	CLDA	FLMME on gray	CFLMME	2DLDA
Recognition rate	92.92	94.30	91.53	91.11	92.92
Dimension	119	119	80	100	50×10
Method	CSN-I	CSN-II	CICCA	SOA	**2DCUDA**
Recognition rate	93.19	95.14	70.97	93.19	**98.20**
Dimension	108	100	84	92	**50×14**

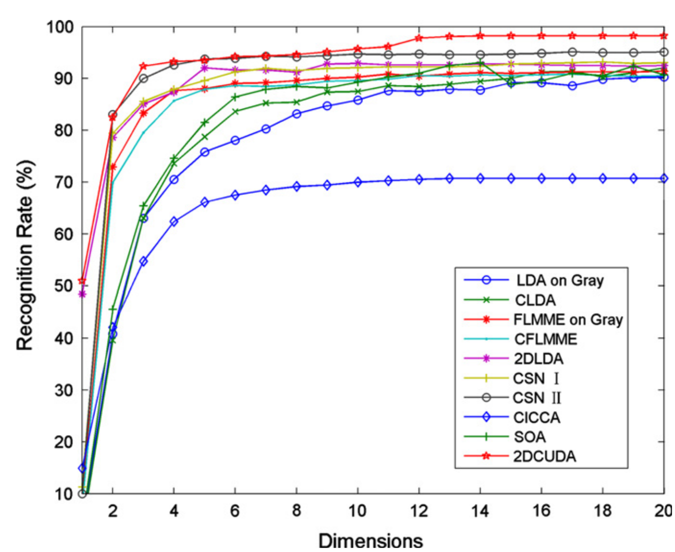

Fig. 6. The recognition rates (%) versus the dimension on the AR face database.

Training times for color face recognition methods are summarized in Table 3. The training time of 2DCUDA is more faster than SOA [46], CSN [26] and CICCA [22], mainly because the latter involves calculating the eigenvectors of an 840×840 matrix, whereas 2DCUDA calculates the eigenvectors of a 50×50 matrix.

Table 3
Comparison of training times on the AR color face database under the condition of variations over time, in facial expression.

Experiments		Recognition rate (%)	Training time (s)	Size of the matrix
Variations over time	CICCA	63.45	29.29	840×840
	SOA	66.90	27.49	840×840
	CSN	73.33	35.79	840×840
	2DCUDA	**77.26**	**1.49**	$\mathbf{50\times50}$
Facial expression	CICCA	70.97	25.17	240×240
	SOA	93.19	23.62	240×240
	CSN	93.19	14.02	240×240
	2DCUDA	**98.20**	**1.21**	$\mathbf{50\times50}$

Table 4
The maximal recognition rates (%) and the corresponding dimensions on the FRGC-2 database.

Method	LDA on gray	CLDA	FLMME on gray	CFLMME	2DLDA
Recognition rate	45	55.75	73.17	77.25	81.58
Dimension	99	97	156	140	60×5
Method	CSN-I	CSN-II	CICCA	SOA	**2DCUDA**
Recognition rate	84.67	85	79.25	69.58	**91.67**
Dimension	134	124	97	99	$\mathbf{60\times6}$

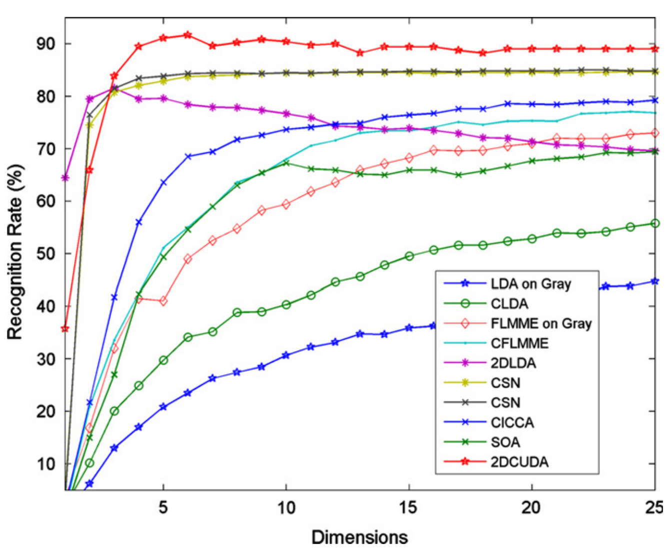

Fig. 7. The recognition rates (%) versus the dimension on the FRGC-2 face database.

4.3. Experiments on the FRGC-2 database

In this subsection, we first evaluate the performance of 2DCUDA compared with that of other methods on the FRGC-2 database. To assess the impact of color for degraded face images, we also show the comparisons on recognition rates between gray-based and color-based features with respect to six different face resolutions, i.e., 60×60, 50×50, 40×40, 30×30, 20×20 and 10×10 (pixels).

4.3.1. Comparative experiments

In this experiment, 12 images of each individual were selected and used for training, and the rest of the images were used for test. Table 4 lists the maximal recognition rates of each method and Fig. 7 shows the recognition rates vs. the variations of the dimensions (in Fig. 7, for one-dimensional methods, the dimensions are equal to five times the number of dimensions axes). Once more, the experimental results show that 2DCUDA performs better than the other methods. From Figs. 5–7, we can further observe that 2DCUDA performs better on FRGC-2 color face database than on AR color face database compared with the other gray-based methods. It is because of the fact that color cues play a more important role in uncontrolled image recognition than in controlled image recognition.

4.3.2. To assess the impact of color for degraded face images

The aim of this experiment is to assess the impact of the color for degraded face images. We design the comparative experiment on six different face resolutions. To acquire facial images with varying face resolutions, we carried out resizing over the original FRGC-2 dataset. Fig. 8 shows the examples of facial images with face resolution variations used in our experiment. As in the previous experiments, 12 images of each individual were selected and used for training, and the rest images are used for testing in our experiment on six different face resolutions.

Fig. 9 shows the recognition rates of different methods between the gray-based and color-based features with respect to six different face resolutions. As can be seen from Fig. 9, the differences in recognition performance from the gray-based feature (in the left side of Fig. 9) between face resolutions of 60×60, 50×50, 40×40, 30×30, 20×20 and 10×10 are relatively marginal compared to that of the color-based features (in the right side of Fig. 9). From the performance of color-based features, we can observe that color information improves the recognition rate compared with gray-based features over all face resolutions. In particular, the proposed 2DCULDA (color-based features) can significantly improve the performance in recognition accuracies from 81.58%, 76.75%, 78.08%, 78%, 74.08% and 67.5% for 60×60, 50×50, 40×40, 30×30, 20×20, 10×10 Gy face images (2DLDA) to 91.67%, 91.08%, 89.75%, 90.75%, 88.33% and 84.17%, respectively. So, we can conclude that color information can provide substantial mutual complementation features for face recognition especially in low resolutions. This conclusion is consistent with the ones in [14,15], i.e., the contribution of color cues becomes evident when shape cues are degraded.

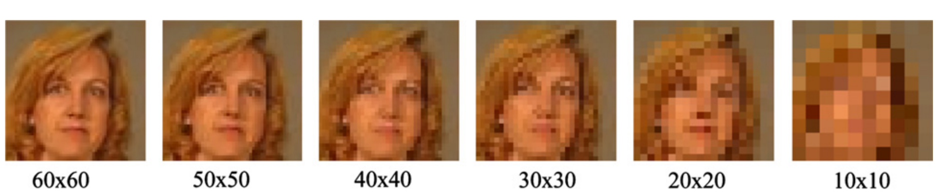

Fig. 8. Example of facial images from FRGC-2 according to six different face resolutions. A low-resolution observation below the original 60×60 pixels is interpolated using nearest-neighbor interpolation.

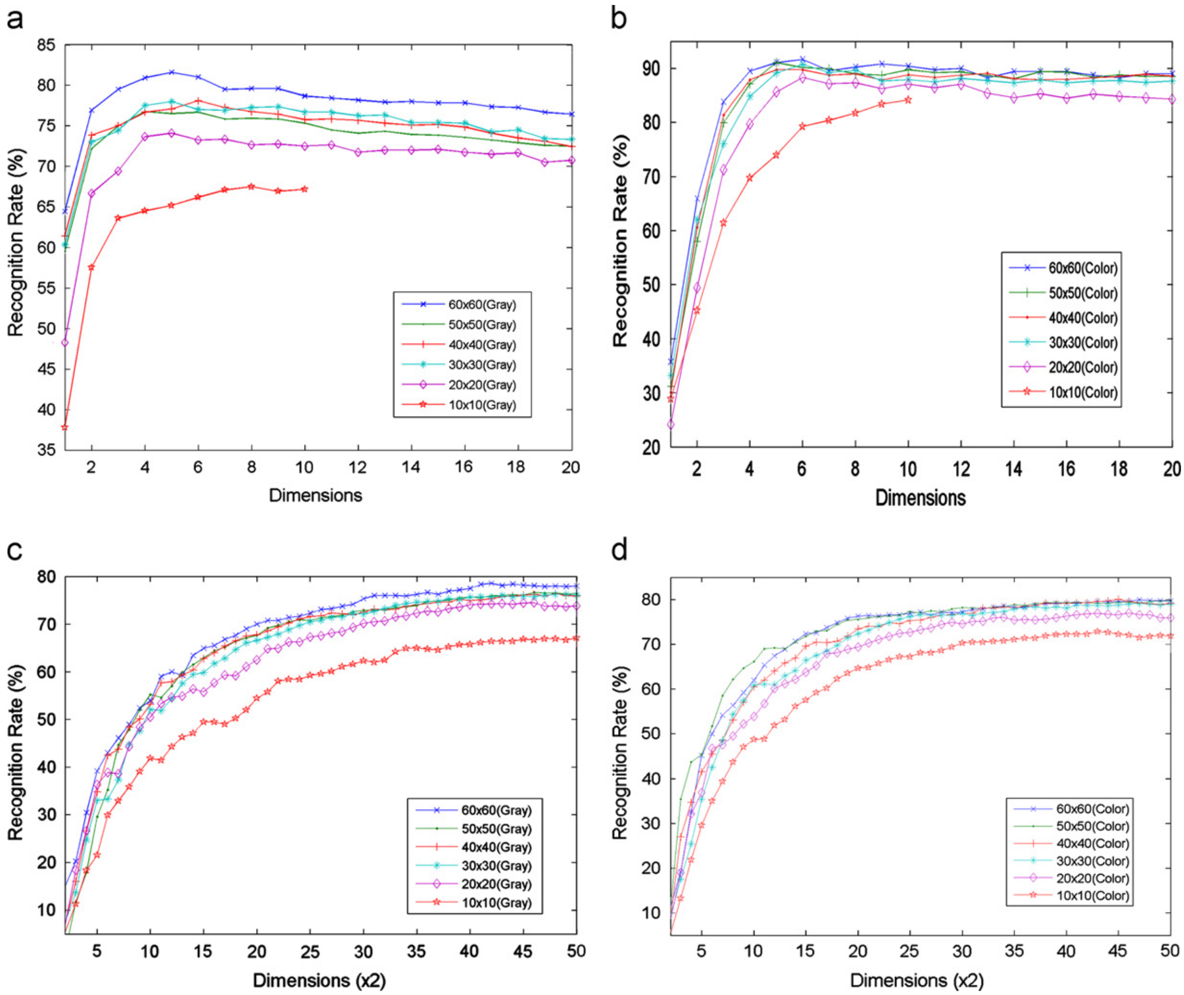

Fig. 9. Recognition rate comparison between gray-based and color-based features under the variation of face resolution. The graph on the left side resulted from gray-based feature, while those on the right side were generated from color-based feature for each face resolution. (a) 2DLDA, (b) 2DCULDA, (c) FLMME and (d) CFLMME.

Table 5
Average absolute correlation coefficient comparison.

Different features	Raw data	CLDA	CFLMME	CSN-I	CSN-II	CICCA	2DCUDA
Correlation coefficient	0.9019	0.7503	0.6230	0.5478	0.5678	0.2165	0

4.4. *Why can the 2DCUDA perform better for color face recognition?*

In this subsection, we try to interpret why the proposed 2DCUDA can improve the face recognition performance. We will show that the proposed 2DCUDA can completely reduce the correlation of the color-based discriminant feature for three color component images in the feature level. Here, we only show the analysis results on the AR database for conciseness, although similar results are achieved on the FRGC database.

Let $\mathbf{A}=(\mathbf{A_1},\mathbf{A_2},\mathbf{A_3})$ be the color component vector in the original RGB color space and $\mathbf{Y}=(\mathbf{Y_1},\mathbf{Y_2},\mathbf{Y_3})$ be the color-based features. The transformation from $\mathbf{A}$ to $\mathbf{Y}$ is given by $\mathbf{X}$, where $\mathbf{X}=(\mathbf{X_1},\mathbf{X_2},\mathbf{X_3})$ denotes the projection matrix for $\mathbf{A}=(\mathbf{A_1},\mathbf{A_2},\mathbf{A_3})$.

In color-based feature space, the correlation between the two color-based features $\mathbf{Y_i}=\mathbf{A_i}\mathbf{X_i}$ and $\mathbf{Y_j}=\mathbf{A_j}\mathbf{X_j}$ is

$$Cov(\mathbf{Y_i},\mathbf{Y_j})=E(\mathbf{Y_i}-E\mathbf{Y}_i)(\mathbf{Y_j}-E\mathbf{Y_j})=\mathbf{X}_j^T\{\mathrm{E}[\mathbf{A_j}-E(\mathbf{A_j})]^T[\mathbf{A_i}-E(\mathbf{A_i})]\}\mathbf{X}_i \tag{32}$$

Then, the correlation coefficient between $\mathbf{Y_i}$ and $\mathbf{Y_j}$ is

$$\rho(\mathbf{Y}_i,\mathbf{Y}_j)=\frac{\mathbf{X}_j^T\{\mathrm{E}[\mathbf{A_j}-E(\mathbf{A_j})]^T[\mathbf{A_i}-E(\mathbf{A_i})]\}\mathbf{X}_i}{\sqrt{\mathbf{X}_j^T\{\mathrm{E}[\mathbf{A}_j-E(\mathbf{A}_j)]^T[\mathbf{A}_j-E(\mathbf{A}_j)]\}\mathbf{X}_j}\sqrt{\mathbf{X}_i^T\{\mathrm{E}[\mathbf{A}_i-E(\mathbf{A}_i)]^T[\mathbf{A}_i-E(\mathbf{A}_i)]\}\mathbf{X}_i}} \tag{33}$$

Since the color space is usually three-dimensional, there are totally three correlation coefficients: $\rho(\mathbf{Y}_1,\mathbf{Y}_2),\rho(\mathbf{Y}_1,\mathbf{Y}_3),\rho(\mathbf{Y}_2,\mathbf{Y}_3)$. The average absolute correlation coefficient is defined as follows:

$$\rho=[\rho(\mathbf{Y}_1,\mathbf{Y}_2)+\rho(\mathbf{Y}_1,\mathbf{Y}_3)+\rho(\mathbf{Y}_2,\mathbf{Y}_3)]/3 \tag{34}$$

We use the above equation to measure the correlation of the three color-based discriminant features on RGB color spaces. The obtained average absolute correlation coefficients corresponding to different color-based features are presented in Table 5.

From Table 5, we can see that the average absolute correlation coefficient of raw data is 0.9019. After color-based feature extraction, the average absolute correlation coefficients are decreased from 0.7503 to 0. These results indicate that color-based features extraction methods can reduce the correlation between the three color components. In particular, the average absolute correlation coefficient of the proposed 2DCUDA is zero, which denotes the proposed 2DCUDA can completely eliminate the correlation on the original data. The reduced correlation makes color-based features contained in the three color component images as mutually complementary as possible. This offers an intrinsic reason for why the proposed 2DCUDA can improve the performance on color face recognition.

5. Conclusions

In this paper, we proposed a two-dimensional color uncorrelated discriminant analysis for face recognition. Experimental results on the AR and FRGC-2 color face databases show that 2DCUDA achieves better recognition performance (at least improve 3.07% and 6.67% in recognition rates on AR and FRGC face database, respectively) than other color face recognition methods. Experimental results also show that two-dimensional color uncorrelated discriminant features are robust against variation of facial expression, time compared with gray-based features. Moreover, training time of 2DCUDA is much less than those of other color face recognition methods, which indicates that 2DCUDA is more suitable for real-world color face recognition. Furthermore, experimental results explore that color information can provide useful complementation information for face recognition especially in low resolutions.

To address the problem of why the proposed 2DCUDA can improve the performance of color face recognition, we compute the correlation properties and show that color-based features can reduce the correlation between color component images. In particular, 2DCUDA can completely eliminate correlation between different color component images. The reduced correlation makes color-based features contained in the three color component images as mutually complementary as possible. This is a main reason why the proposed 2DCUDA can improve the performance of color face recognition.

Finally, it is should be pointed out that the focus of this paper is on improving the color face recognition from statistically uncorrelated view. Recently, some work [48,49] attempted to solve the problem of color face recognition from the view of human visual and obtained good experimental results. In the future, we plan to extract and combine more visual features to improve the color face recognition.

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References

[1] A.K. Jain, A. Ross, S. Prabhaker, An introduction to biometric recognition, IEEE Trans. Circuits Syst. Video Technol. 14 (1) (2004) 4–20.
[2] M. Turk, A. Pentland, Eigenfaces for recognition, J. Cognitive Neurosci. 3 (1) (1991) 71–86.
[3] P.N. Belhumeur, J.P. Hespanha, D.J. Krigman, Eigenfaces vs. Fisherfaces: recognition using class specific linear projection, IEEE Trans. Pattern Anal. Mach. Intell. 19 (7) (1997) 711–720.
[4] J. Yang, D. Zhang, A.F. Frangi, J.Y. Yang, Two-dimensional PCA: a new approach to appearance-based face representation and recognition, IEEE Trans. Pattern Anal. Mach. Intell. 26 (1) (2004) 131–137.
[5] M. Li, B.Z. Yuan, 2D-LDA: a statistical linear discriminant analysis for image matrix, Pattern Recognition Lett. 26 (5) (2005) 527–532.
[6] Z. Lei, R. Chu, R. He, S. Liao, S. Li, Face recognition by discriminant analysis with Gabor tensor representation, Adv. Biom. 4642 (2007) 87–95.
[7] R. He, B.G. Hu, X.T. Yuan, Robust discriminant analysis based on nonparametric maximum entropy, Adv. Mach. Learn. 5828 (2009) 120–134.
[8] Z. Chai, R. He, Z. Sun, T. Tan. Histograms of Gabor ordinal measures for face representation and recognition, in: Proceedings of the IAPR International Conference on Biometrics (ICB), 2012, pp. 52–58.
[9] W.K. Yang, C.Y. Sun, L. Zhang., A multi-manifold discriminant analysis method for image feature extraction, Pattern Recognition 44 (8) (2011) 1649–1657.
[10] W.K. Yang, J.G. Wang, M.W. Ren, J.Y. Yang, Feature extraction based on Laplacian bidirectional maximum margin criterion, Pattern Recognition 42 (11) (2009) 2327–2334.
[11] R. Kemp, G. Pike, P. White, A. Musselman, Perception and recognition of normal and negative faces: the role of shape from shading and pigmentation cues, Perception 25 (1) (1996) 37–52.
[12] C.R. Zhao, Z.H. Lai, C.C. Liu, X.J. Gu, J.J. Qian, Fuzzy local maximal marginal embedding for feature extraction, Soft Comput. 16 (1) (2012) 77–87.
[13] D.Q. Miao, C. Gao, N. Zhang, Z.F. Zhang, Diverse reduct subspaces based co-training for partially labeled data, Int. J. Approximate Reasoning 52 (8) (2011) 1103–1117.
[14] A. Yip, P. Sinha, Role of color in face recognition, MIT Technical Reports, AIM-2001-035 CBCL-212, 2001.
[15] J.Y. Choi, Y.M. Ro, K.N. Plataniotis, Color face recognition for degraded face images, IEEE Trans. Syst., Man, Cybern. B: Cybern. 39 (5) (2009) 1217–1230.
[16] A. Diplaros, T. Gevers, I. Patras, Combining color and shape information for illumination-viewpoint invariant object recognition, IEEE Trans. Image Process. 15 (1) (2006) 1–11.
[17] G. Dong, M. Xie, Color clustering and learning for image segmentation based on neural networks, IEEE Trans. Neural Networks 16 (4) (2005) 925–936.
[18] H.Y. Lee, H.K. Lee, Y.H. Ha, Spatial color descriptor for image retrieval and video segmentation, IEEE Trans. Multimedia 5 (3) (2003) 358–367.
[19] A.W.M. Smeulders, M. Worring, S. Santini, A. Gupta, R. Jain, Content-based image retrieval at the end of the early years, IEEE Trans. Pattern Anal. Mach. Intell. 22 (12) (2000) 1349–1380.
[20] R.L. Hsu, M. Abdel-Mottaleb, A.K. Jain, Face detection in color images, IEEE Trans. Pattern Anal. Mach. Intell. 24 (5) (2002) 696–706.
[21] Y. Wu, T.S. Huang, Nonstationary color tracking for vision-based human–computer interaction, IEEE Trans. Neural Networks 13 (4) (2002) 948–960.
[22] X.Y. Jing, S. Li, C. Lan, D. Zhang, J.Y. Yang, Q. Liu, Color image canonical correlation analysis for face feature extraction and recognition, Signal Process. 91 (2011) 2132–2140.
[23] Z.M. Liu, C.J. Liu, Fusion of color, local spatial and global frequency information, Pattern Recognition 43 (2010) 2882–2890.
[24] C.J. Liu, Extracting discriminative color features for face recognition, Pattern Recognition Lett. 32 (2011) 1796–1804.
[25] J. Yang, C.J. Liu, Color image discriminant models and algorithms for face recognition, IEEE Trans. Neural Networks 19 (12) (2008) 2088–2098.
[26] J. Yang, C.J. Liu, L. Zhang, Color space normalization: enhancing the discriminating power of color spaces for face recognition, Pattern Recognition 43 (2010) 1454–1466.
[27] C.J. Liu, Learning the uncorrelated, independent, and discriminating color space for face recognition, IEEE Trans. Inf. Forensics Secur. 2 (3) (2008) 213–222.
[28] S.J. Wang, J. Yang, N. Zhang, s Zhou, Tensor discriminant color space for face recognition, IEEE Trans. Image Process. 20 (9) (2011) 2409–2501.
[29] J.Y. Choi, Y.M. Ro, K.N. Plataniotis, color local texture features for color face recognition, IEEE Trans. Image Process. 21 (3) (2012) 1366–1380.
[30] C.R. Zhao, C.C. Liu, Z.H. Lai, Multi-scale gist feature manifold for building recognition, Neurocomputing 74 (17) (2011) 2929–2940.
[31] S.J. Wang, J. Yang, M.F. Sun, X.J. Peng, M.M. Sun, C.G. Zhou, Sparse tensor discriminant color space for face verification, IEEE Trans. Neural Networks Learn. Syst. 23 (6) (2012) 876–888.
[32] Y. Xu, Quaternion-based discriminant analysis method for color face recognition, PLoS One 7 (8) (2012) e43493.
[33] J. Luo, D. Crandall, Color object detection using spatial-color joint probability functions, IEEE Trans. Image Process. 15 (6) (2006) 1443–1453.
[34] G. Hua, M.H. Yang, L.M. Erik, Y. Ma, M. Turk, D.J. Kregman, T.S. Huang, Introduction to the special section on the real-world face recognition, IEEE Trans. Pattern Anal. Mach. Intell. 33 (10) (2011) 1921–1923.
[35] G.D. Finlayson, S.D. Hordley, P.M. Hubel, Color by correlation: a simple, unifying framework for color constancy, IEEE Trans. Pattern Anal. Mach. Intell. 23 (11) (2001) 1209–1221.
[36] H. Stokman, T. Gevers, Selection and fusion of color models for image feature detection, IEEE Trans. Pattern Anal. Mach. Intell. 29 (3) (2007) 371–381.
[37] B.V. Funt, G.D. Finlayson, Color constant color indexing, IEEE Trans. Pattern Anal. Mach. Intell. 17 (5) (1995) 522–529.
[38] Z. Jin, J.Y. Yang, Z.S. Hu, Z. Lou, Face recognition based on the uncorrelated discriminant transformation, Pattern Recognition 34 (2001) 1405–1416.

[39] A.M. Martinez, A.C. Kak, PCA versus LDA, IEEE Trans. Pattern Anal. Mach. Intell. 32 (2) (2001) 228–233.
[40] A.M. Martinez, R. Benavente, The AR face database, CVC Technique Report 24, 1998.
[41] P.J. Phillips, P.J. Flynn, T. Scruggs, K.W. Bowyer, J. Chang, K. Hoffman, J. Marques, et al., Overview of the face recognition grand challenge, in: Proceedings of the International Conference on Computer Vision and Pattern Recognition, 2005, pp. 947–954.
[42] M.H. Wan, Z.H. Lai, J. Shao, Z. Jin, Two-dimensional local graph embedding discriminant analysis (2DLGEDA) with its application to face and palm biometrics, Neurocomputing 73 (2009) 193–203.
[43] Z.H. Lai, M.H. Wan, Z. Jin, J. Yang, Sparse two-dimensional local discriminant projections for feature extraction, Neurocomputing 74 (2011) 629–637.
[44] H.X. Duan, Y.H. Wu, A calibration method for paracatadioptric camera from sphere images, Pattern Recognition Lett. 33 (6) (2012) 667–684.
[45] X.Y. Jing, D. Zhang, Z. Jin, UODV: improved algorithm and generalized theory, Pattern Recognition 36 (11) (2003) 2593–2602.
[46] J.Y. Man, X.Y. Jing, Q. Liu, Y.F. Yao, K. Li, J.Y. Yang, Color face recognition based on statistically orthogonal analysis of projection transforms, Lect. Notes Comput. Sci. 7098 (2011) 58–65.
[47] S.J. Wang, C.G. Zhou, N. Zhang, X.J. Peng, Y.H. Chen, X.H. Liu, Face recognition using second order discriminant tensor subspace analysis, Neurocomputing 74 (12–13) (2011) 2142–2156.
[48] G. Hua, M.H. Yang, E. Learned-Miller, Y. Ma, M. Turk, D.J. Kriegman, T.S. Huang, Introduction to the special section on real-world face recognition, IEEE Trans. Pattern Anal. Mach. Intell. 30 (10) (2011) 1921–1924.
[49] N. Kumar, A. Berg, P.N. Belhumeur, S. Nayar, Describable visual attributes for face verification and image search, IEEE Trans. Pattern Anal. Mach. Intell. 33 (10) (2011) 1962–1977.

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