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Within-component and between-component discriminant analysis for color face recognition

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ABSTRACT

How to efficiently utilize the color image information and extract effective features is the key of color face recognition. In this paper, we first analyze the similarities between facial color component image samples and their influence on color face recognition. Then we propose a novel color face recognition approach named within-component and between-component discriminant analysis (WBDA), which realizes discriminant analysis not only within each color component but also between different components. Experimental results on the face recognition grand challenge (FRGC) version 2 database demonstrate that the proposed approach outperforms several representative color face recognition methods.
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1. Introduction

Color images are increasingly used in the field of pattern recognition, because they can afford more recognizing information than grayscale images [1–4]. The key of color face image recognition technique is how to efficiently utilize the color image information and extract effective features [5–7]. Current color face recognition methods can be categorized into following three categories.

(1) The methods choose another existing color space (or existing color component configuration) or transform the conventional RGB color space to a new space, and then extract features. For example, Liu [8] presented the uncorrelated color space (UCS), the independent color space (ICS) and the discriminating color space (DCS) to construct new color image representations, and then used the enhanced Fisher linear discriminant model (EFM) method [9] to extract features. Yang and Liu [10] presented an extended general color image discriminant (EGCID) algorithm that calculates three groups of combination coefficients to produce three new color components. Yang and Liu [11] constructed a discriminant color space with double-zero-sum characteristic (DCS-DZS). Yang et al. [12] presented two color space normalization techniques to enhance the discriminating power of color spaces. Choi et al. [13] put forward a boosting color component feature selection framework to find the best set of color component features from various color spaces (models). Lajevardi and Wu [14] developed a tensor perceptual color framework for facial expression recognition. Using this framework, the components of color images (in either RGB, YC_bC_r, CIELab or CIELuv space) are unfolded to 2-D tensors, from which the features are extracted by using Log-Gabor filters. Choi et al. [15] presented two color local texture feature methods to exploit the discriminative information derived from the spatiochromatic texture patterns of different color components within a certain local face region, where the color components come from current color spaces like RGB, YC_bC_r and YIQ. Liu [16] presented a method for effective use of color information and a new similarity measure. In this method, a new color model is first obtained, which takes advantage of the subtraction of primary colors. And discriminant analysis is used to extract features from the compact color image representation. These methods reduce the similarity between color components on the data level, which has no direct connection with recognition and still requires feature extraction.

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(2) The methods transform the RGB space to a tensor color space and simultaneously extract features. Wang et al. [17] represented a color image as a third-order tensor and presented the tensor discriminant color space (TDCS) model, which achieves a discriminant color space while extracting features. Sparse TDCS (STDCS) [18] transforms the eigenvalue problem to a series of regression problems, and obtains one sparse color space transformation matrix and two sparse discriminant projective matrices by solving regression problems. Li et al. [19] presented a multilinear color tensor discriminant model, which utilizes tensor representation to preserve image structure and enhances discriminant capability via color space transformation. These methods also reduce the similarity between color components on the data level.
(3) The methods do not perform color space transformation. They serially extract discriminating features in order of R, G and B color components with imposing the uncorrelated constraints. Holistically orthogonal analysis (HOA) [20] and statistically orthogonal analysis (SOA) [21] in turn extract the features of R, G and B color components by using the Fisher criterion [22], and simultaneously reduce the correlation between features of different components by making the obtained three projective transformations mutually orthogonal and statistically orthogonal, respectively. These methods use unsupervised uncorrelated constraints, and thus reduce both the useful within-class correlation and the adverse between-class correlation between different color components. Besides, serial feature extraction manner might make the discriminant capabilities of features separately derived from R, G and B color components distinctly different.

Discriminant analysis is a widely used and effective feature extraction technique in the field of pattern recognition. Linear discriminant analysis (LDA) [22] employs the Fisher criterion to calculate the projective vectors by maximizing the between-class scatter of features and simultaneously minimizing the within-class scatter of features, which is effective in extracting discriminative features and reducing dimensionality. Many methods have been developed to improve the performance of LDA, such as discriminant common vectors [23], incremental LDA [24], subclass discriminant analysis [25], perturbation LDA [26], and LDA based on L_1-norm maximization [27].

The RGB color space is a basic and widely used color space. Usually, the red (R), green (G) and blue (B) color components are highly similar, which leads to the difficulty of acquiring the complementary information between them. It is critical to utilize the complementary information between color components, reduce their redundancy and extract effective features. In this paper, we try to design more effective feature extraction approach for color face recognition. We summarize the contributions of our study as follows:

(i) We analyze the similarities between R, G and B components of color facial image samples and their influence on color face recognition.
(ii) We propose a novel within-component and between-component discriminant analysis (WBDA) approach for color face recognition. WBDA realizes discriminant analysis not only within each color component but also between different components. It makes the within-component and between-component sample feature points from the same class congregated, and those from different classes separated, which can enhance the within-component and between-component class separabilities, preserve the useful within-class similarity and reduce the adverse between-class similarity between color components on the feature level.

Experimental results on the face recognition grand challenge (FRGC) version 2 database [28] demonstrate that the proposed approach outperforms several representative color face recognition methods.

The rest of this paper is organized as follows. In Section 2, we introduce the representative color face recognition methods. In Section 3, we analyze the similarities between R, G and B facial color component image samples and their influence on color face recognition. In Section 4, we propose the WBDA approach. Experimental results are provided in Section 5 and conclusions are drawn in Section 6.

2. Representative color face recognition methods

2.1. Color space transformation methods

The ICS [8], EGCID [10] and DCS-DZS [11] methods learn a linear transformation $W \in R^{3\times 3}$ to transform the conventional RGB color space to a new space:

$$\begin{bmatrix} C_1(x,y) \\ C_2(x,y) \\ C_3(x,y) \end{bmatrix} = W \begin{bmatrix} R(x,y) \\ G(x,y) \\ B(x,y) \end{bmatrix}, \quad (1)$$

where $R(x,y)$, $G(x,y)$ and $B(x,y)$ separately denote the R, G and B pixel values of point (x,y) in a color image, and $C_1(x,y)$, $C_2(x,y)$ and $C_3(x,y)$ are the pixel values of three new color components.

In ICS, W is obtained by using the independent component analysis (ICA) [29,30] method. In EGCID, W is divided into three row vectors w_1, w_2 and w_3. w_1 is obtained by taking an iterative optimization method [10], and then w_2 and w_3 are calculated in a similar manner. These three row vectors are mutually L_w-orthogonal. In DCS-DZS, row vectors of W are also mutually w_1-orthogonal [11].

Suppose that there are K different color components coming from current color spaces, and S_i denotes the ith ($i = 1, \ldots, K$) color component image sample set. The color local binary pattern (CLBP) feature [15] for S_i can be defined as

$$x_i^{CLBP} = [(x_i^{U\_LBP})^T (x_{i,j}^{O\_LBP})^T \cdots (x_{i,K}^{O\_LBP})^T]^T, \text{ for } i \neq j. \quad (2)$$

Note that x_i^{CLBP} consists of one unichrome LBP feature $x_i^{U\_LBP}$ and $K-1$ opponent LBP features $x_{i,j}^{O\_LBP} \cdots x_{i,K}^{O\_LBP}$.

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