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Dual multi-kernel discriminant analysis for color face recognition

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ABSTRACT

With the increasing use of color images in the fields of pattern recognition, computer vision and machine learning, color face recognition technique becomes important, whose key problem is how to make full use of the color information and extract effective discriminating features. In this paper, we propose a novel nonlinear feature extraction approach for color face recognition, named dual multi-kernel discriminant analysis (DMDA), where we design a kernel selection strategy to select the optimal kernel mapping function for each color component of face images, further design a color space selection strategy to choose the most suitable space, then separately map different color components of face images into different high-dimensional kernel spaces, and finally perform multi-kernel learning and discriminant analysis not only within each component but also between different components. Experimental results in the public face recognition grand challenge (FRGC) version 2 and labeled faces in the wilds (LFW) databases illustrate that our approach outperforms several representative color face recognition methods.

1. Introduction

Color images have been widely used all over the world, and particularly they are increasingly used in the fields of pattern recognition, computer vision and machine learning, because they can offer more identifiable information than grayscale images [1–3]. Currently, the RGB color space is the most commonly used color space, and other color spaces are generally converted from the RGB space via a linear or nonlinear transformation. Fig. 1 shows a color face image and its color component images in RGB, HSV and YC_bC_r color spaces. It is obvious that all color component images have similar facial contours and chiaroscuro to the color image, although they look evidently different and the contours in some color component images are fuzzy. This difference generated by colors can provide more useful information for recognition tasks. Therefore, the key problem of color face recognition technique is how to make full use of the color information and extract effective discriminating features [4–6].

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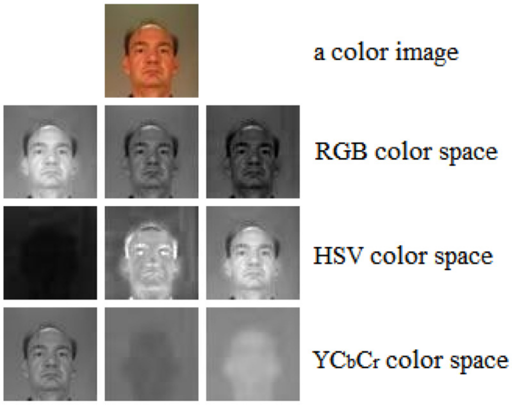

Fig. 1. A color face image and its color component images in RGB, HSV and YC_bC_r color spaces, where the color face image in the first row comes from the public face recognition grand challenge (FRGC) version 2 database [29], the left, center and right images in the second row separately are the R, G and B component images, the images in third row are the H, S and V component images in turn, and the images in fourth row are the Y, C_b and C_r component images in sequence.

Some color face recognition methods have been presented to solve this problem, which can be divided into following two categories.

(1) Most of color face recognition methods extract features from color images by using the linear transformation or linear projection techniques. For examples, Choi et al. [7] presented a boosting color-component feature selection framework to seek the best set of color-component features from diverse color spaces (or models). Wang et al. represented a color image as a third-order tensor and constructed a tensor discriminant color space (TDCS) model [8] to produce a discriminant color space while extracting features. In next year, the TDCS model was extended to sparse TDCS [9], which achieves a sparse color space transformation matrix and two sparse discriminant projection matrices. Shin et al. [10] applied sparse representations to multiple color components of face images, and employed score-level fusion to merge the complementary residuals obtained from different color component images. Liu [11] designed a method to obtain a compact color image representation and extract features via discriminant analysis. Zhao et al. [12] developed a two-dimensional color uncorrelated discriminant analysis method, which serially extracts discriminating features of R, G and B components and meanwhile makes the obtained projection transformations mutually statistically orthogonal. Huang et al. [13] formalized a color image as a third-order tensor, and then presented a sparse tensor canonical correlation analysis method for feature extraction. Wu [14] used the quaternion to represent a color pixel, and applied the locality preserving projection method to the quaternion vectors of color images to extract features. Sun et al. [15] combined the R, G and B color components of a face image into one monochromic image, and developed a color image correlation similarity discriminant model to extract features. Liu presented within-component and between-component discriminant analysis [16] and color-feature dual discriminating correlation analysis [17] methods, which apply discriminant analysis to enhance the class separability not only within each color component but also between different components. Xiang et al. [18] designed a color two-dimensional principal component analysis method to combine the spatial and color information for color face recognition. Lu et al. [19] presented a color component fusion method using jointly dimension reduction algorithms to select more features from reliable and discriminative components. Zou et al. [20] developed two representation-based classification methods, which model each color image as a quaternionic signal to preserve the color structures of face images. Wu et al. [21] designed two uncorrelated multi-set feature learning methods to extract discriminant features from three color components and reduce the global statistical and discriminating feature-level correlation between components in a multi-set manner.
(2) A few color face recognition methods extract nonlinear features from color images. For instance, Z. Liu and C. Liu designed a discrete cosine features method [22], which fuses the complementary features derived from discrete cosine transform of color component images in YIQ space. And then they developed a robust face recognition method using color information [23], where three image encoding methods are designed for nonlinear feature extraction in a RC_rQ space, and the weighted sum rule is employed to fuse the similarity matrices generated using the features of R, C_r and Q component images. Lajevardi and Wu [24] built a tensor perceptual color framework for facial expression recognition, which unfolds the color components of face images to 2-D tensors and applies Log-Gabor filters to extract features. Choi et al. [25] presented two color local texture feature methods to exploit the discriminating information achieved from the spatiochromatic texture patterns of different color components within a certain local face region. Elbouz et al. [26] designed a two-level correlation method. In the first level, the face image is decomposed using the RGB or HSV space, and three color components are separately processed and merge through correlations; in the second level, the color-based contour information is converted into a signature, and then the signatures are fused to fabricate one correlator. Taigman et al. [27] developed a nine-layer deep neural network named DeepFace, which is trained on a very large labeled dataset of