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Uncorrelated multi-set feature learning for color face recognition

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ABSTRACT

Most existing color face feature extraction methods need to perform color space transformation, and they reduce correlation of color components on the data level that has no direct connection with classification. Some methods extract features from R, G and B components serially with orthogonal constraints on the feature level, yet the serial extraction manner might make discriminabilities of features derived from three components distinctly different. Multi-set feature learning can jointly learn features from multiple sets of data effectively. In this paper, we propose two novel color face recognition approaches, namely multi-set statistical uncorrelated projection analysis (MSUPA) and multi-set discriminating uncorrelated projection analysis (MDUPA), which extract discriminant features from three color components together and simultaneously reduce the global statistical and global discriminating feature-level correlation between color components in a multi-set manner, respectively. Experiments on multiple public color face databases demonstrate that the proposed approaches outperform several related state-of-the-arts.

1. Introduction

Face image recognition is an important research topic [1–4]. Recently, color face images have attracted lots of research interest since they can afford more recognizing information than grayscale images [5–8]. The key of color face image recognition technique is how to utilize the color image information and extract effective features for classification [9–12]. Generally, current color face feature extraction methods can be categorized into following three types.

The first type of methods selects an existing color space (or existing color component) or transforms the conventional RGB color space to a new space, and then extracts features [13–19]. For example, Liu [20] 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 [21] to extract features. Yang and Liu [22] presented an extended general color image discriminant (EGCID) algorithm that produces three new color components. Yang et al. [23] constructed a discriminant color space with double-zero-sum characteristic (DCS-DZS). Choi et al. [24] 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 comes from current color spaces like RGB, YC_bC_r and YIQ. Liu [25] presented a method for effective use of color information and a new similarity measure. In this method, a new color model is obtained, which takes advantage of the subtraction of primary colors. And discriminant analysis is used to extract features from the compact color image representation. Sun et al. [26] presented a color image correlation similarity discriminant (CICSD) model, which involves two sets of variables: the color component combination coefficients for color face image presentation and the projection basis vectors for color face recognition. Xiang et al. [27] devised a color two-dimensional principal component analysis method to combine the spatial and color information.

The second type of methods transforms RGB space to the tensor color space and simultaneously extracts features [28]. Wang et al. [29] 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) [30] transforms the eigenvalue problem to a series of regression problems, and obtains one spare color space transformation matrix and two sparse discriminant projective matrices by solving regression problems. Huang et al. [31]

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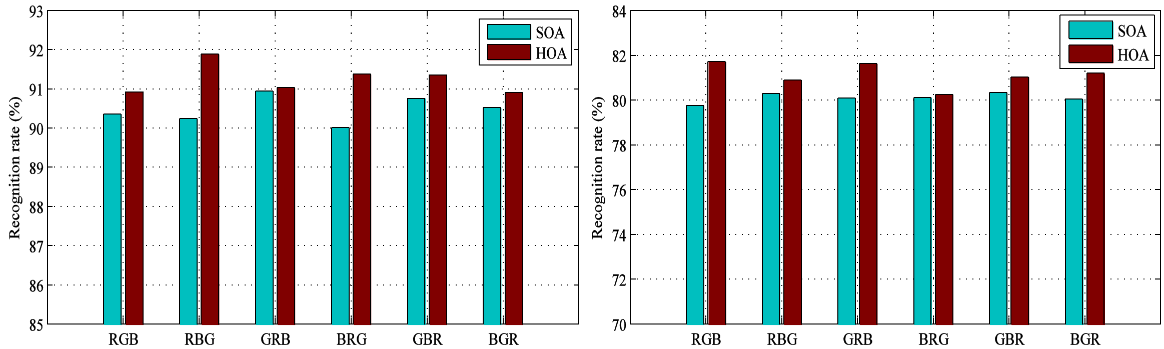

(a) On AR color face database.

(b) On FRGC color face database.

Fig. 1. Recognition rates of six orders of SOA and HOA on AR and FRGC databases. (a) On AR color face database. (b) On FRGC color face database (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

formalized a color face image sample as a high-order tensor to preserve its inherent structure, and presented a subspace learning method named sparse tensor canonical correlation analysis (STCCA) for color face recognition.

The third type of methods does not perform color space transformation. They serially extract discriminating features in the order of R (red), G (green) and B (blue) components with imposing the unsupervised constraints. The holistically orthogonal analysis (HOA) method [32] borrows the idea of Foley-Sammon linear discriminant analysis (FSLDA) [33,34] that makes the achieved projective vectors from one sample set mutually orthogonal. HOA in turn extracts the features of R, G and B components by using the Fisher criterion, and simultaneously makes the achieved three projective transformations mutually orthogonal. Then it concatenates the extracted features from color components to do classification. Motivated by the uncorrelated linear discriminant analysis (ULDA) [35], statistically orthogonal analysis (SOA) [36] and two-dimensional color uncorrelated discriminant analysis (2DCUDA) [37] in turn extract discriminant features of R, G and B components and simultaneously make the achieved projective transformations mutually statistically orthogonal.

1.1. Motivation

Color images can provide more useful information than grayscale images, and therefore they play an important role in the field of face recognition. The RGB color space is a basic and widely used color space. Usually, there exists much correlation between R, G and B components. For color face recognition, it is critical to utilize the complementary information between color components, reduce their redundancy and extract effective features. Current color face recognition methods can be classified into three categories and have the following characteristics:

(1) The first type of methods selects existing color spaces or transforms RGB color space to another space and then extracts features. *They reduce the correlation between color components on the data level, which has no direct connection with classification as compared with the feature level***.**
(2) The second type of methods transforms RGB space to tensor color space and simultaneously extracts discriminant features. *They also reduce the correlation between color components on the data level.* Moreover, they are usually time-consuming when extracting features.
(3) The benefit of color space transform is that a favorable color space can be used for classification, where samples are more discriminative. However, the efforts are made on the data level, which has no direct connection with classification. The third type of methods (e.g., SOA and HOA) does not need to perform color space transform and serially extracts discriminant features from RGB components on the feature level with imposing the unsupervised constraints, which are orthogonal constraint and statistically uncorrelated constraint. *However, the serial feature extraction manner might make the discriminant capabilities of features separately derived from R, G and B color components distinctly different.* In addition, since these constraints are unsupervised, both the useful correlation between same-class samples and the adverse correlation between different-class samples from different color components are reduced. Specifically, there exist six orders to learn the projective transformations of R, G and B color components, i.e., the RGB, RBG, GRB, BRG, GBR, and BGR orders. To give a clear illustration of the influence of serial feature extraction order, we provide a figure here, i.e., Fig. 1, which shows the average recognition rates across 20 random runs of six orders of SOA and HOA on the AR [38] and FRGC [39] databases. Eight images per person are selected for training and the detailed experimental setting can be found in Section 7.2. It can be seen that different orders will lead to different recognition results, and the differences between the maximal and minimal recognition rates can even reach 0.92%(=90.94% −90.02%) for SOA and 0.98%(=91.89% −90.91%) for HOA on AR database; and 0.58%(=80.34% −79.76%) for SOA and 1.47%(=81.72% −80.25%) for HOA on FRGC database.

There exist two intuitive ideas to solve the calculation order problem of the third type of methods (e.g., SOA and HOA), that is designing a strategy to determine the best order or providing a solution to simultaneously extract discriminant features from three color components. The first idea may need large computational cost, while the second one may fully extract discriminant features from color components in an efficient manner. Recently, multi-set feature learning technique has attracted lots of research interest [40–42]. Multi-set feature learning refers to learning with multiple sets that reflect different characteristics or views of data. Multi-set subspace learning is an important research direction in this field. Canonical correlation analysis (CCA) [43] based and discriminant analysis based multi-set subspace learning are two representative techniques [44,45]. Color images can be regarded as a special case of multi-set data, and thus multi-set feature learning methods may be applied to color face recognition. However, CCA based multi-set methods tend to enhance the canonical correlation between multiple sets, and discriminant analysis based multi-set methods do not analyze the feature's correlation between different sets. Hence, these methods cannot be used directly to effectively reduce the redundancy between color components. It is necessary to design new multi-set feature learning method for color face recognition.