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Simple yet effective color principal and discriminant feature extraction for representing and recognizing color images

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A B S T R A C T

In this paper, we investigate the problem of extracting two-dimensional color principal and discriminant features for understanding color images. Specifically, two simple yet effective color image feature extraction criteria, called *Color Principal Component Analysis* (ColorPCA) and *Color Linear Discriminant Analysis* (ColorLDA), are proposed for color image analysis. The presented criteria can preserve color and topology information of pixels in images, and extract features directly from color images in an efficient manner by eigen-decomposing a single eigen-problem. In modeling the criteria, color image scatter matrices are defined. Like PCA, LDA and their two-dimensional (2D) extensions, our methods only need to choose the number of projection vectors. More importantly, the matrices to be eigen-decomposed in our criteria have the same size as 2DPCA and 2DLDA that are very efficient. To achieve an orthogonal projection matrix, trace ratio ColorLDA is also presented. We also present the alternative versions of our approaches for feature learning through mining row or column information of the images. Extensive simulations on benchmark datasets are conducted to evaluate our algorithms. The investigated cases demonstrate the effectiveness and efficiency of our techniques, compared with other most related state-of-the-art 1D and 2D criteria.

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1. Introduction

Mining informative features from high-dimensional real data by dimensionality reduction (DR) or feature learning has been arousing considerable attention in the context of image representation and understanding [36,41]. It is known that the process of feature learning can effectively remove unfavorable features and noise that may exist in given data, so the calculated compact expressions of high-dimensional data can greatly enhance the performance and scalability of classification algorithms. *Principal Component Analysis* (PCA) [1,2] and *Linear Discriminant Analysis* (LDA) [1] are two most well-known DR methods performed in the vector space, extracting principal and discriminant features directly from the vector patterns respectively. As a result, if PCA, LDA and their linearized extensions (such as [37,38]) are used for gray image feature extraction, we first need to transform the images into a set of one-dimensional (1D) vectors, which has been shown to be ineffective for image representation [11], since images are intrinsically two-dimensional (2D) matrices or 2-order tensors [3,4,11–13,21,23,30], and the vectorized representation of images may lose important topology information of pixels in images. To enhance the performance, 2D extensions of PCA and LDA, termed 2DPCA [3] and 2DLDA [4,32], were recently presented to extract representative features from gray images directly rather than converting images into the 1D vectors. Hence, eigen-decomposing the scatter matrices of the 2D versions will be far more efficient than their 1D counterparts.

It is worth noting that the growing amount of color images are rather common in our daily communication and Internet surfing. Although color images can reflect more important and useful information than gray-level images [25,34], they also contain redundant information (e.g., color and structure redundancy), and unfavorable features as the gray images. With this in mind, recent years have witnessed lots of efforts on the study of exploiting color information to improve the face recognition performance while reducing the redundancies of images, for instance [6,10,15,17,20,24,28,31,33,34,35,40], etc. It is noted that almost all existing color image feature extraction techniques can be roughly divided into two categories. The first category focuses on defining a new color space or improving the standard color space to enhance the image representation and analysis, for instance [6,20,28,35,40]. The other category aims at proposing novel color image feature extraction or feature learning algorithms in the standard color space for understanding and classifying images, such as [10,15,33,34].

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In this paper, we mainly aim at proposing novel color principal and discriminant image feature learning criteria, built on the existing 2DPCA and 2DLDA algorithms, in the second category for image understanding, resembling [10,15,33,34]. Note that the authors of [10,15] also aimed to solve the drawbacks of 2DPCA and 2DLDA, i.e., they cannot handle color images directly, by considering the properties of a three-dimensional (3D) color tensor and unfolding the 3D tensor to form a subspace onto which 2DPCA and 2DLDA are used to extract color based features for representation. Although the derived PCA and LDA Color Subspace criteria [10,15] can capture color information of images, the horizontal unfolding is however inefficient and even time-consuming when the width of given image is large. Jing et al. [34] also proposed a *Color Image Canonical Correlation Analysis* (CICCA) to extract canonical correlated features from the three color components and achieve an analytical solution. A similar criterion to CICCA is called *Two-Dimensional Color Uncorrelated Discriminant Analysis* (2DCUDA) [33] which was recently presented to extract color features and retain spatial structure information of images at the same time. But note that CICCA and 2DCUDA suffer from the same issue as the PCA and LDA Color Subspace criteria, i.e., inefficiency, since they handled the color components independently by optimizing three eigen-problems, which may be very time-consuming for large-scale images. In addition, CICCA transforms the color components further into vector patterns in each eigen-problem, so the topology structures of pixels may also be destroyed.

The main motivation of this study is to address the shortcomings of the above 2DPCA and 2DLDA based color image feature extraction algorithms by proposing more simple and efficient criteria to extract color principal and discriminant image features. Below, we highlight the major contributions of the work.

(1) Technically, we propose two simple yet effective color principal and discriminant image feature extraction techniques, termed ColorPCA and ColorLDA, for color image understanding. ColorPCA and ColorLDA can represent the color images in a natural way, taking color images as inputs and extracting informative features from color images directly. Given a color image P_i of height m and width n, Fig. 1 gives the comparison of the mechanisms of one-dimensional PCA, LDA, two-dimensional PCA, LDA, and our color algorithms. Note that PCA, LDA, 2DPCA and 2DLDA cannot extract color features from color images directly. More specifically, 2DPCA and 2DLDA need to transform the color images to gray images prior to feature learning, while PCA and LDA concatenate the pixels and transform the gray images further into vector patterns for delivering the projection axes. But these operations will lose important color information and local topology information of pixels in images [11–13,21,23,30].

(2) ColorPCA and ColorLDA can be considered as the colorized model extensions of the 2DPCA and 2DLDA respectively, since our criteria clearly incorporate color information into the constructions of image scatter matrices so that the scatter matrices can reveal the intrinsic color information of pixels in images effectively. Besides, our criteria can avoid the statistical correlations of different color channels. The trace ratio criterion [43,44] based ColorLDA and the alternative versions of our approaches are also described.

(3) The proposed algorithms for color feature extraction are straightforward and efficient. Generally, ColorPCA and ColorLDA have the following properties, compared with other most related studies. First, the involved optimization for calculating the projection axes is simple and efficient, since our criteria are formulated as a single eigen-problem that can be analytically solved using eigen-decomposition. This property can make our criteria appealing than both CICCA and 2D CUDA for color image representation. Furthermore, the matrices to be eigen-decomposed in our techniques are also of size $n \times n$ that is the same as 2DPCA and 2DLDA, which is much smaller than that of size $mn \times mn$ in PCA and LDA, especially for large-scale images. Thus, the efficiency of ColorPCA and ColorLDA will be theoretically comparable with both 2DPCA and 2DLDA, which will be evaluated by simulations. In addition, the mechanisms of our criteria are different from the PCA and LDA color subspace methods [10,15]. Second, the constructed color image scatter matrices have full rank in most real problems, so ColorLDA can avoid the singularity problem in reality. Third, ColorPCA and ColorLDA are linear, which makes them appealing in the practical applications. More importantly, no extra tuning parameter is involved in modeling ColorPCA and ColorLDA, since estimating an optimal model parameter is never easy in practice.

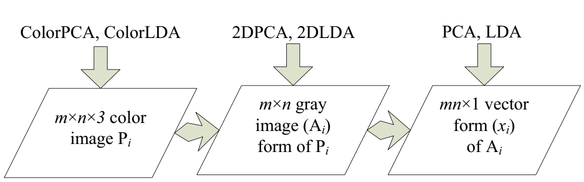

Fig. 1. Operational mechanisms of PCA, LDA, 2DPCA, 2DLDA and color techniques.

This paper is outlined as follows. In Section 2, we show important notations used in the paper. Section 3 briefly reviews the related work. In Section 4, we propose the color principal and discriminant image feature extraction criteria (i.e., ColorPCA and ColorLDA). The comparison with the other related works is also described. Section 5 describes the simulation settings and results. The paper is finally concluded in Section 6.

2. Notations

To facilitate the description, we present the important notations used in this present paper in Table 1.

3. Related work

In this section, we briefly review the formulations of PCA, LDA, 2DPCA, 2DLDA and some existing color image feature extraction algorithms, which are closely related to our proposed approaches.

3.1. PCA and 2DPCA Revisited

PCA is one most representative unsupervised dimensionality reduction technique. Let $x_i \in \mathbb{R}^q,\ i=1,2,\ldots,N$ denote N q-dimensional data vectors, PCA finds the maximum-variance direction of vectors and projects the samples into d-dimensional reduced embedding space $(d \le q)$. Let $\overline{M} = (1/N)\Sigma_{i=1}^{N} x_i$ denote the mean of all samples and let $S_{PCA}^{(t)} \in \mathbb{R}^{q \times q}$ represent the *total scatter* (*covariance*) *matrix*, we can have

$$S_{PCA}^{(t)} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{M})(x_i - \overline{M})^{\mathrm{T}}. \quad (1)$$

Then the optimal orthogonal projection transformation matrix $T_{PCA} \in \mathbb{R}^{q \times d}$ of PCA can be described as

$$T_{PCA} = \arg\max_{T \in \mathbb{R}^{q \times d}} [tr((T^{\mathrm{T}}T)^{-1} T^{\mathrm{T}} S_{PCA}^{(t)} T)]. \quad (2)$$

For a given set of $m \times n$ gray images $A_i,\ i=1,2,\ldots,N$, 2DPCA seeks a column vector $W_i \in \mathbb{R}^n$ to project each A_i into the principal

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