ColorPCA: Color Principal Feature Extraction Technique for Color Image Reconstruction and Recognition

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Abstract—This paper introduces an effective mechanism to extract informative principal features from the color images and proposes a color principal feature extraction technique referred to as ColorPCA. ColorPCA performs in the color image space, extracting the principal features directly from the color images. As a result, the color and local topological information of pixels at each level of the color images can be effectively preserved. In extracting the most representative features, a color image scatter matrix is constructed and its eigenvectors are employed for color principal feature extraction. ColorPCA has only one parameter (i.e., the reduced dimension) to estimate and the projection axes can be effectively obtained using eigen-decomposition. Extensive color image reconstruction and recognition over the benchmark problems verified the effectiveness of the presented ColorPCA. Results show that ColorPCA can effectively reconstruct the color images. Image recognition also demonstrates that ColorPCA can deliver promising results compared with other state-of-the-art 1D and 2D principal feature extraction algorithms.

Keywords—Image feature extraction; Color image recognition; Color image reconstruction; Eigen-decomposition

I. INTRODUCTION

Informative feature extraction of high-dimensional real image data for subsequent classification and recognition by applying dimensionality reduction has aroused increasing attention over past decades, since most real data contains high-dimensional attributes bearing lots of redundancies and correlations hiding important relationships. In addition, reducing the dimension of data can also significantly improve the classification accuracy and efficiency. Principal Component Analysis (PCA) [2] is the most popular dimensionality reduction technique, working in vector space and extracting the features directly from the one-dimensional (1D) vectors. That is, if PCA is used, images need to be transformed to the 1D vectors. But it should be noticed that this operation may lose certain important information [13], since images are intrinsically two-dimensional (2D) matrices or 2-order tensor [9][11][19]. To enable PCA to handle images directly, the 2D extension of PCA, termed 2DPCA [3], was recently proposed. 2DPCA extracts principal features from 2D images directly rather than the 1D vectors. Due to the natural representation of gray images by 2DPCA, the computational efficiency and image recognition accuracy over original PCA method are significantly improved [3].

Notice that the ultimate goal of designing efficient feature extraction algorithms and recognition technologies is to apply them in practical applications, e.g., face recognition system [7] [21], biological recognition system, and vehicle identification system [22][23], etc. But note that in the real world, colorful images can often be encountered. But unfortunately, virtually all previous principal component analysis methods, including PCA and 2DPCA, cannot bear such responsibilities, since they extract the features from gray images directly. Given a color image $P$, with height $m$ and width $n$, Figure 1 shows the work stages of PCA, 2DPCA and our methodology to be addressed. A color image has important color information in the pixels [4] [6]. That is, converting color images to gray images may lose certain important information, which may directly decrease the representation power of the algorithms. PCA concatenates the pixels and transforms gray images into the vector patterns, but this destroys the local topology structure of the pixels in gray images. To address this issue and handle color images directly, some tensor based methods, e.g., [10][12][15], were recently proposed. Yu et al. generalize PCA to the high-order tensor and the solution is obtained by the multilinear singular value decomposition [5], which is so time-consuming. Thomas et al. [10] consider the characteristics of a three-dimensional (3D) color tensor to generate a subspace via unfolding the 3D color tensor and then apply 2DPCA on the unfolded color tensor to extract features. Apparently, using this method for extracting the principal features is not straightforward.

![Figure 1: Effective work stages of PCA, 2DPCA and our method.](image)

This paper introduces a new color image principal feature extraction mechanism that can extract the informative features from color images directly. To the best of our knowledge, to date no related work on this topic was studied. We highlight the major contributions of this paper as follows. Technically, we propose a color image principal feature extraction method, termed ColorPCA, with the mathematical modeling, for color image representation and recognition. ColorPCA takes color images as inputs, extracting representative features from color images directly. ColorPCA can be considered as the colorized...
2DPCA. Specifically, ColorPCA clearly takes into account the color information of images and color information has been effectively incorporated into the formulation of image scatter matrix. By comparing ColorPCA with PCA and 2DPCA, the following properties can be found. (1) Similar to 2DPCA, the matrices to be eigen-decomposed are also of size $n \times n$, which is much smaller than $mn \times mn$ in the original PCA. That is, ColorPCA will be as computationally efficient as 2DPCA. (2) The color image scatter matrix of ColorPCA is shown to have full rank in most real cases, i.e., the eigenvalues of ColorPCA are all positive. The projection axes of ColorPCA can also be analytically computed by eigen-decomposition. (3) ColorPCA is linear making it particularly appealing in real applications. (4) ColorPCA delivers better results than PCA and 2DPCA for image representation, with no extra parameter involved. Note that this is desired in pattern recognition research, as optimal selection of model parameters is always difficult in reality.

The outline of the paper is as follows. We firstly introduce the important notations used in the paper in Section II. Then, we briefly review the ideas of PCA and 2DPCA algorithms in Section III. Subsequently, we propose the ColorPCA approach in Section IV. Section V describes the settings and test results. Finally, the conclusion is offered in Section VI.

II. NOTATIONS

<table>
<thead>
<tr>
<th>Notation</th>
<th>Descriptions</th>
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<tbody>
<tr>
<td>$m$</td>
<td>the height of gray or color images</td>
</tr>
<tr>
<td>$n$</td>
<td>the width of gray or color images</td>
</tr>
<tr>
<td>$L$</td>
<td>level or channel of images in color space</td>
</tr>
<tr>
<td>$P$</td>
<td>set of $m \times n \times L$ color images</td>
</tr>
<tr>
<td>$P_i$</td>
<td>the $i$-th color image of set $P$</td>
</tr>
<tr>
<td>$P_{ij}$</td>
<td>the $i$-th color image of class $l$ in $P$</td>
</tr>
<tr>
<td>$P_{ij}$</td>
<td>the $i$-th level of color image $P_i$</td>
</tr>
<tr>
<td>$P_{ij}$</td>
<td>the $i$-th level of color image $P_{ij}$</td>
</tr>
<tr>
<td>$\Psi$</td>
<td>transformation vector</td>
</tr>
<tr>
<td>$N$</td>
<td>the number of samples</td>
</tr>
<tr>
<td>$N_l$</td>
<td>the number of samples in class $l$</td>
</tr>
<tr>
<td>$H^{-1}$</td>
<td>the inverse of matrix $H$</td>
</tr>
<tr>
<td>$A$</td>
<td>set of $m \times n$ gray images</td>
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<tr>
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<td>the $i$-th gray image of set $A$</td>
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<tr>
<td>$A_{ij}$</td>
<td>the $i$-th gray image of class $l$</td>
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<tr>
<td>$X$</td>
<td>set of $mn$ by 1 vector patterns</td>
</tr>
<tr>
<td>$x_i$</td>
<td>the $i$-th vector pattern of set $X$</td>
</tr>
<tr>
<td>$x_{ij}$</td>
<td>the $i$-th vector pattern of class $l$</td>
</tr>
<tr>
<td>$H^T$</td>
<td>the transpose of vector or matrix $H$</td>
</tr>
<tr>
<td>$\nu(H)$</td>
<td>the matrix trace of matrix $H$</td>
</tr>
<tr>
<td>$T$</td>
<td>projection transformation</td>
</tr>
<tr>
<td>$d$</td>
<td>number of reduced dimensions</td>
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<tr>
<td>$Z$</td>
<td>low-dimensional representation</td>
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III. REVIEWS OF PCA AND 2DPCA

Let $x_i \in \mathbb{R}^q, i = 1, 2, \ldots, N$ be vectors of $N$ $q$-dimensional samples. PCA finds the maximum-variance direction of samples and projects the samples into $d$-dimensional reduced embedding space $(d \leq q)$. Let $\bar{M} = (1/N) \sum_{i=1}^{N} x_i$ be mean of all the samples and $S_{PCA}^{(ij)}$ be the total scatter (covariance) matrix, we have

$$S_{PCA}^{(ij)} = \frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{M})(x_i - \bar{M})^T.$$  \hspace{1cm} (1)

Then, the projection matrix $T_{PCA}$ of PCA is obtained as

$$T_{PCA} = \arg \max_{T} \left[ \nu \left( (T^T)^T S_{PCA}^{(ij)} T \right) \right].$$  \hspace{1cm} (2)

Given a set of $m \times n$ gray images $A_i, i = 1, 2, \ldots, N$, 2DPCA seeks to obtain an $n$-dimensional column vector $Y$ to project images $A_i$ to $m$-dimensional principal component $Z$, by using transformation $Z = A_i Y$. Let $S_{2DPCA}^{(ij)}$ be the image covariance (scatter) matrix of 2DPCA and $A$ be the average image of all images, we can formulate the scatter matrix as

$$S_{2DPCA}^{(ij)} = \frac{1}{N} \sum_{i=1}^{N} (A_i - \bar{A})(A_i - \bar{A})^T.$$  \hspace{1cm} (3)

Then, the objective function of 2DPCA can be defined as

$$\max_{i \in \mathbb{R}^d} J_{2DPCA}(Y) = \max_{i \in \mathbb{R}^m} \nu \left( (Y^T)^T S_{2DPCA}^{(ij)} Y \right),$$ \hspace{1cm} (4)

where $I_{i \in \mathbb{R}^d}$ is an identity matrix in $\mathbb{R}^d$. So, the projection axes $\{Y_{ij}\}_{i=1}^d$ of 2DPCA can be obtained as the eigenvectors of $S_{2DPCA}^{(ij)}$ corresponding to the first $d$ largest eigenvalues.

IV. COLORPCA: COLOR PRINCIPAL IMAGE FEATURE EXTRACTION TECHNIQUE

Suppose the set $P$ has $N$ $m \times n \times L$ color images $P_i, i = 1, 2, \ldots, N$, ColorPCA finds an $n$-dimensional transformation vector $Y$ to project each color image $P_i$ into $m$-dimensional $Z$. Note that a color space, such as RGB [8] or HSV [8], is a mathematical representation of a set of colors. In this paper, the RGB space is considered if without special remarks. RGB space has three individual levels, i.e., Red $(R)$, Green $(G)$ and Blue $(B)$.

A. Objective Function and Algorithm

Different from PCA and 2DPCA, ColorPCA clearly considers color information of pixels and takes color images as inputs. In extracting informative features, ColorPCA represents the feature information in each level, i.e., $R$, $G$ and $B$, of the color images. Let $L = 1, 2, 3$ denote the $R$, $G$ and $B$ level of the RGB color space, respectively. Let $R_{COLORPCA}^{(ij)}$ be the image covariance matrix of projected images $P_i$ in the $L$-th level, $R_{COLORPCA}^{(ij)}$ can be characterized by $\nu \left( R_{COLORPCA}^{(ij)} \right)$, motivated by [3]. Based on this point, we can express $R_{COLORPCA}^{(ij)}$ as

$$R_{COLORPCA}^{(ij)} = E[(Z - E(Z))(Z - E(Z))^T] = E[(P_i^R - E(P_i^R))(P_i^R - E(P_i^R))^T]$$

$$= E\left[ \left( P_i^R-E(P_i^R) \right) Y_i \left( P_i^R-E(P_i^R) \right)^T \right]$$

where $E(\cdot)$ denotes the expected value operator or expectation operator. Then $\nu \left( R_{COLORPCA}^{(ij)} \right)$ can be described as
where $Z^*$ is the $k$-th represented feature vector by $Y$, and the $m \times d$ matrix $F^i = [Z^*_1, Z^*_2, \ldots, Z^*_d]$ of each level $L$ is called the feature matrix of $P^i_L$ in the $L$-th level of the color space. Thus feature matrices obtained from all three levels form $m \times 3d$ feature image $F = [F^{i_1}, F^{i_2}, F^{i_3}]$ of the color image $P$.

For classifying the color images, similarly a training set of color images are prepared for training the learner and another set of color images are used for testing. If ColorPCA is used for color image feature extraction, each training or test image $P_{\text{train}}$ is projected to a feature matrix $F_{\text{train}}$. For two arbitrary feature matrices $F_i = [Z_{i1}, Z_{i2}, \ldots, Z_{id}]$ and $F_j = [Z_{j1}, Z_{j2}, \ldots, Z_{jd}]$, the distance between them is $d(F_i, F_j) = \sum_{k=1}^{d} |Z_{ik} - Z_{jk}|$. When $\rho$ color training images $\{P_{i1}, \ldots, P_{ic}\}$ and their labels $l_i \in \{1, 2, \ldots, c\}$ are available, we firstly compute the feature matrices of the training images, denoted by $\{F_{i1}, \ldots, F_{ic}\}$, according to class labels. A nearest-neighbor classifier can then be employed for pattern classification. For a new test image $P_{\text{test}}$, the feature matrix of $P_{\text{test}}$ is represented by $F_{\text{test}}$, and if $d(F_{\text{test}}, F_{il}) = \min d(F_{\text{test}}, F_{ij})$, where $i \in \{1, 2, \ldots, c\}$, then $P_{\text{test}}$ is classified to the $i$-th class.

D. Reconstructing Color Images with ColorPCA

Given a set of gray images of size $m \times n$, the projection matrix of PCA can be used for image reconstruction [1][16][17]. But the gray images have to be transformed to a set of $m$ by 1 column vectors. In contrast, 2DPCA aims at reconstructing the gray images with the learnt transforming basis vectors and the represented principal components directly [4]. Note that PCA and 2DPCA are unable to reconstruct the color images directly, while our ColorPCA can do. Next we show how to reconstruct the color image $P$ by our proposed ColorPCA.

Based on the projection axes $\{Y^*_i\}_{i=1}^c$ obtained by conducting eigen-decomposition of $S_{ij}^{(l)}$ for the $L$-th level image $P^i_L$, we are able to obtain the principal component vectors $Z_i^* = [P^{i_1}_L - \bar{P}^{i_1}], k = 1, 2, \ldots, d$, then $F^i = [P^{i_1}_L - \bar{P}^{i_1}], Y = [1, 2, 3, \ldots]$. It is noted that basis vectors $\{Y^*_i\}_{i=1}^c$ are orthogonal together, letting $\bar{P}$ be the reconstructed image of the $L$-th level image of $P$, i.e., $P^i_L$, of the color space, we can obtain

$$
\begin{align*}
\bar{P}^{i_1} & = \left[P^{i_1}_L - \bar{P}^{i_1}\right] \bar{Y}^T + \bar{P}^{i_1} = \sum_{k=1}^{d} \left[P^{i_1}_k - \bar{P}^{i_1}\right] \bar{Y}^T_k + \bar{P}^{i_1} \\
\bar{P}^{i_2} & = \left[P^{i_2}_L - \bar{P}^{i_2}\right] \bar{Y}^T + \bar{P}^{i_2} = \sum_{k=1}^{d} \left[P^{i_2}_k - \bar{P}^{i_2}\right] \bar{Y}^T_k + \bar{P}^{i_2} \\
\bar{P}^{i_3} & = \left[P^{i_3}_L - \bar{P}^{i_3}\right] \bar{Y}^T + \bar{P}^{i_3} = \sum_{k=1}^{d} \left[P^{i_3}_k - \bar{P}^{i_3}\right] \bar{Y}^T_k + \bar{P}^{i_3} 
\end{align*}
$$

where $m \times n$ matrix $\bar{Y}^*_i = [P^{i_1}_k - \bar{P}^{i_1}], k = 1, 2, \ldots, d$ is the reconstructed sub-image of $L$-level image. When each gray sub-image $\bar{V}^*_L, L = 1, 2, 3$ is obtained, we can colorize the sub-images by extending $\bar{V}^*_L, k = 1, 2, \ldots, d$ to all three levels. In other words, we are able to obtain the reconstructed color sub-image $\bar{V} = [\bar{V}^{i_1}, \bar{V}^{i_2}, \bar{V}^{i_3}]$ of $P$, with three levels. As a result, color image $P$ can be approximately reconstructed by adding up
the first $d$ color sub-images. Notice that the more number of color principal component vectors, $d$, is selected, the less information will be lost and thus the reconstructed color image is more accurate. More specifically, when $d = n$, that is without dimensionality reduction, the color images can be completely reconstructed with all color information preserved.

V. SIMULATION RESULTS AND ANALYSIS

This section conducts simulations to examine our ColorPCA for color image reconstruction and representation. In this study, two benchmark (face and object) datasets are tested. The face database is used to test the color image reconstruction power of our ColorPCA. The object database is used for color image recognition. The performance of ColorPCA is compared with PCA and 2DPCA. All the used algorithms are implemented by MATLAB 7.1. For image recognition, one-nearest-neighbor (1NN) classifier with Euclidean metric is used because of its simplicity. Color image recognition process with our method is performed as follows. Partial color images of each class are selected to form a training set and the remaining are for testing. ColorPCA is then used to extract the informative features from the training set. The extracted features from the color images are then applied to train a 1NN classifier. After the learner is trained, test images are represented by the learned projection matrix. The learner is finally used to evaluate the recognition accuracies. We performed all simulations on a PC with Intel(R) Core(TM) i5 CPU 650 @3.20GHz 3.19 GHz 4G.

(a)

(b)

(c)

(d)

(e)

Figure 2: Partial reconstructed color sub-images are shown in inverted form of each level of the color space. (a) Original color face images, (b) $r=1$, (c) $r=2$, (d) $r=5$, (e) $r=10$.

A. Color Face Image Reconstruction

We first test ColorPCA for color face image reconstruction. In this study, the real Georgia Tech Face Database (GTFD) [7] is used. This database consists of color face images of 50 people taken at Center for Signal and Image Processing at Georgia Institute of Technology, and all persons are represented by 15 color JPEG images, thus the database has totally 750 color images. The average size of the face images is 150×150 pixels. The pictures show the frontal and/or tilted faces with different facial expressions, lighting conditions and scale. Figure 2(a) shows 10 samples. In this simulation, we resize all color faces to 64×64 and no other preprocessing is done. In order to learn the optimal projection axes, 6 color images from each person are selected for training. We select the 20 eigenvectors $\{y_i\}_{i=1}^{20}$ according to the 20 leading eigenvalues of the 64×64 matrix $S_{\text{ColorPCA}}^{(i)}$ to represent the color face images. For each axe $Y_{i}$, $k=1, 2, …, 20$, we can obtain the reconstructed color sub-image $Y'_i = [y_{i}^{1}, \ldots, y_{i}^{20}]$ of each color face, where $Y'_i = Z_i'Y_i$ is the reconstructed sub-image of the L-th level image of color face images and $Z_i'$ denotes the principal component vector represented by $Y_i$. We represent the color faces in Figure 2(a) and show the $r$-th reconstructed color sub-image of each color face image, where $r=1,2,5,10$. The reconstructed color sub-images of the color faces are shown in Figure 2(b), (c), (d) and (e). Note that we invert the gray-level value $\alpha$ of each pixel location in the reconstructed face sub-image at each level $L$ by replacing $\alpha$ with $255-\alpha$. Observing from results, we find the bigger the $r$ value, the less information or energy of the color images is contained. In particular, the first reconstructed sub-image represented using eigenvector according to the largest eigenvalue of $S_{\text{ColorPCA}}^{(1)}$ contains more information or energy hidden in the color face images.

![Figure 3: The illustration of the magnitude of the eigenvalues in decreasing order.](image)

We also report the magnitude of the eigenvalues of 2DPCA and ColorPCA in decreasing order in Figure 3. For 2DPCA, all the color faces will be transformed into gray images before feature extraction. We observe clearly that the magnitude of the eigenvalues of 2DPCA and ColorPCA decreases rapidly and then converges to smaller values close to zero. That is, the information of images will be concentrated on the first small number of principal components. Note that this observation keeps consistent with the results of Figure 2. It is noticed the image scatter matrix $S_{\text{2DPCA}}^{(i)}$ of 2DPCA has the same rank as ColorPCA, so eigenvalues of $S_{\text{2DPCA}}^{(i)}$ are also positive. But the eigenvalues of ColorPCA are consistently greater than that of 2DPCA before the reduced dimension $d=10$. In particular, the first two biggest eigenvalues computed using ColorPCA are significantly larger than that of 2DPCA. We also find that the difference between them reduces after $d=10$. 
By adding up the first $q$ reconstructed color face sub-images together, we can obtain the approximately reconstructed color faces of the original images. Figure 4 shows the reconstructed color face in Figure 2 (a) by adding the first $q = 2, 6, 10, 15, 20$ color sub-images together. It is clearly observed that the reconstructed color images become clearer when the number of added color sub-images is increased.

![Figure 4: The reconstructed color face images by ColorPCA: (a) $q=2$, (b) $q=6$, (c) $q=10$, (d) $q=15$, (e) $q=20$.](image)

B. Color Scene and Object Image Recognition

In this simulation, the PHOS database publicly available from [http://utopia.dauth.gr/~dchrisos/pubs/database.html](http://utopia.dauth.gr/~dchrisos/pubs/database.html) is tested. PHOS is a benchmark color image database consisting of 8 scenes and 10 objects captured under different illuminations. Every scene or object has 10 color images, thus this database has totally 180 color images of $525 \times 342$ pixels each. We show typical color sample images in Figure 5(a). In this simulation, ColorPCA is also compared with PCA and 2DPCA. All color images are resized to images of $32 \times 32$ pixels because of the computational consideration.

![Figure 5: The reconstructed color object images by ColorPCA: (a) Original color object image, (b) $d=2$, (c) $d=7$, (d) $d=15$, (e) $d=20$.](image)

Color object image reconstruction

We first examine the ColorPCA algorithm for color scene and object image reconstruction. In this study, 6 color images per subject are used for learning the transforming axes and the rest are for testing. We select 20 eigenvectors $\{Y_{1}^{(1)}\}_{k=1}^{20}$ according to the first 20 leading eigenvalues of the $32 \times 32$ matrix $S_{ColorPca}^{(1)}$ to represent the images. We aim to reconstruct the color object images in Figure 5(a). After achieving the eigenvectors, the represented principal component vectors and the reconstructed color sub-images of the images can be obtained. By adding up the first $d$ sub-images together, we can obtain the approximate reconstruction of the color images. Figure 5(b), (c), (d) and (e) illustrate the reconstructed images. We see from Figure 5 that the color images can be effectively reconstructed by using our ColorPCA. Also, the more number of the sub-images is added together, the clearer the reconstructed color images are.

Image Recognition

This simulation tests PCA, 2DPCA and ColorPCA for color scene and object image recognition. For 2DPCA, color images are transformed into the corresponding gray images. The PCA method takes the vectorized representations of gray images as inputs for training and testing. We prepared four simulation settings over different training sample sizes. For each setting, we fix the training sample size and then vary the number of transforming axes. The one-nearest neighbor classifier is used for classification. For each case, the results are averaged over 20 random splits of training/test samples. We have described the recognition accuracy vs. number of transforming axes in Figure 6. Observing from Figure 6, we find that: (1) PCA is the worst compared with 2DPCA and ColorPCA. This can be explained by the fact that PCA extracts the features from the vectorized presentations of the images and the local topology structures of pixels in the image have been destroyed. (2) Our proposed ColorPCA method exhibits promising results that are better than those of 2DPCA, since our proposed ColorPCA is capable of extracting features directly from the color training images, exhibiting the natural representations of color object images with the color pixel information effectively preserved. And most importantly, ColorPCA requires fewer transforming axes for object image recognition than the 2DPCA algorithm to deliver higher accuracy in most cases.

Table 2 describes the mean and best accuracies according to Figure 6. We also report the averaged running time, including training and testing phases, to compare the complexity of each algorithm. We have the following observations. (1) From the results, we see clearly that the performance superiority of the methods keeps consistent with the results exhibited in Figure 6. In particular, our proposed ColorPCA method obtains higher recognition accuracies than the other methods in most cases. (2) Considering the runtime performance, PCA is the slowest compared with other methodologies, since the matrices to be decomposed in PCA are of sizes $1024 \times 1024$ for this database. 2DPCA has the lowest computational complexity, because the matrices decomposed by 2DPCA are of sizes $32 \times 32$. Note that the matrices decomposed by ColorPCA are also sizes $32 \times 32$. Although ColorPCA aims at extracting the features from three levels of the color space to capture more useful information for recognition, the computational complexity of our proposed ColorPCA is always comparable with 2DPCA. It is important to notice that our proposed 2DPCA obtains higher accuracies than the 2DPCA algorithm in most cases.
and best results
the color images
We
tally 720 color images of 18 classes. The performance of
each color image set
rotat
our database to 90
work described in this paper has been partially supported by the National Natural Science Foundation of China (NSFC) under Grant No. 61033013.

Variations over different views
This study compares our presented ColorPCA for recognizing the color images under varying views. In this simulation, we create a new color image set through rotating each color image of the original image database to 90 degrees, 180 degrees and 270 degrees, respectively. After the images are rotated, their class labels are unchanged. As a result, each color image has four different views and the new sampled image set includes totally 720 color images of 18 classes. The performance of our ColorPCA is compared with PCA and 2DPCA. Four tests over different numbers of training images of each class are tested. We show the test results of the methods in Figure 7. The mean and best results according to Figure 7 are described in Table 3. The averaged running time of each method is also list in Table 3. We can obtain the following observations from Figure 7 and Table 3: (1) The performance of each method varies with the increasing number of training samples and transforming axes. Our ColorPCA algorithm can deliver better results than other techniques in most cases. (2) For runtime performance, PCA needs much more running time compared with other methods, since it performs in vector space directly. The computational complexity of our proposed ColorPCA method is comparable to that of 2DPCA in all cases.

Table 2: Performance comparison on the PHOS color image database.

<table>
<thead>
<tr>
<th>Method</th>
<th>Color PHOS (3 train)</th>
<th>Color PHOS (4 train)</th>
<th>Color PHOS (5 train)</th>
<th>Color PHOS (6 train)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Best</td>
<td>Time</td>
<td>Mean</td>
</tr>
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<td>PCA</td>
<td>0.3979</td>
<td>0.5024</td>
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<td>2DPCA</td>
<td>0.4568</td>
<td>0.5056</td>
<td>0.0233</td>
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<tr>
<td>ColorPCA</td>
<td>0.6221</td>
<td>0.7063</td>
<td>0.0577</td>
<td>0.6868</td>
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We in this paper have considered the color image principal feature extraction problem. We incorporate color information of the pixels into the modeling of the approach and propose a new and effective color principal feature extraction technique termed ColorPCA, for handling the color images. We examine ColorPCA by extensive simulations over benchmark databases. The color image reconstruction demonstrates the color image reconstruction power of the proposed ColorPCA method. For color image recognition, for all investigated cases, the overall performance of our ColorPCA outperforms PCA and 2DPCA. The presented color image principal feature extraction method evaluates the scatter matrix more accurately and are observed to be effective for color image representation and recognition, but the following three problems are still worth doing in future work. First, nonlinear structures are rather common in most real data, but it remains unclear how to extend our ColorPCA algorithm to nonlinear scenarios. Second, extending the idea of ColorPCA to take into account the manifold structures [14] [18] or discriminant information [20] of samples for locality preserving and discriminant color image representation and recognition. Third, determining optimal reduced dimensions for dimension reduction algorithms, including ColorPCA, still remains an open problem that requires further investigation.

ACKNOWLEDGEMENT

Figure 6: Recognition accuracy vs. number of transforming axes on the PHOS color image database.

Figure 7: Recognition accuracy vs. number of transforming axes on the PHOS color image database.
Table 3: Performance comparison of each algorithm on the PHOS color image database.

<table>
<thead>
<tr>
<th>Method</th>
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<th>Color PHOS (15 train)</th>
<th>Color PHOS (20 train)</th>
<th>Color PHOS (25 train)</th>
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<tr>
<td></td>
<td>Mean</td>
<td>Best</td>
<td>Time</td>
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REFERENCES