Topic：Programming Languages and Software Engineering

Dimensionality Reduction of Multi-spectral Images for Color Reproduction

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***Abstract*—A new nonlinear dimensionality reduction method for multi-spectral images was presented to solve the problem brought by high dimensionality of multi-spectral images during color reproduction. Firstly, according to the characteristics of human visual system, the CIE standard observer color matching functions were weighted to the source spectral reflectance and then a principal component analysis (PCA) method was used to the weighted spectrum. This effectively improved the colorimetric precision and color difference stability of dimensionality reduction. Then for the spectral reflectance loss caused by weighting color matching functions, a PCA method was imposed on the lost spectrum to compensate the lost spectral accuracy caused by the improvement of colorimetric precision. This effectively improved the spectral precision of dimensionality reduction. Finally the principal components obtained from the first two steps were combined to form the low-dimensional spectral data. Experiments show that the new method outperforms the existing methods in the colorimetric accuracy, spectral accuracy and color difference stability under different illuminant.**

***Index Terms*—spectral color management; spectral image dimensionality reduction; principal component analysis; multi-spectral image; spectral reflectance**

I. Introduction

Multi-spectral images are those whose pixel values are spectral reflectance of source scenes. They are mainly used for the accurate and consistent color reproduction of source scenes under different illuminant. Now they have been widely used in high-end imaging fields such as art archiving[1-2], tele-medicine[3-4], military target imaging.

Multi-spectral images are acquired by narrow-band sampling in the range of visible light, e.g. from 400nm to 700nm. This results in the high dimension of image data. When color management is applied to the multi-spectral images, high dimension of the images will lead to high computational complexity, large storage space and long computing time during color mapping, device color space transforming, color calibrating, and so on. Therefore, reducing the data dimension and then exerting color management to the low-dimension data become the key technology in multi-spectral image reproduction.

The dimensionality reduction methods for multi-spectral images are mainly direct principal component analysis (PCA)[5-6] and LabPQR space method[7-9]. Direct PCA is a linear method. It can achieve high accuracy in spectral matching. But it ignores the color characteristics of the images. Because the color of images is obtained by the joint action of the illuminant, observer and spectral reflectance of the source scene, and the spectral characteristics is independent to the human visual system, the method of PCA cannot achieve the good color matching results. LabPQR is a nonlinear dimension reduction method. The Lab part of LabPQR expresses the color that obtained under one specific illuminant. When the illuminant is changed, the Lab value cannot indicate the color of the image under the new illuminant. Therefore, the color matching result of LabPQR under one illuminant is satisfied, but it will become worse under other illuminants.

The paper presents a WSPCAplus method, which is a nonlinear method. Firstly, according to the characteristics of human visual system, a weighted spectral PCA (WSPCA) method is proposed. It effectively improves the colorimetric precision of dimensionality reduction. Then for the spectral reflectance loss caused by weighting color matching functions, a PCA method is imposed on the lost spectrum to compensate the lost spectral accuracy caused by the improvement of colorimetric precision. This effectively improves the spectral precision of dimensionality reduction. Finally the principal components obtained from the first two steps were combined to form the low-dimensional spectral data. WSPCA introduces the effect of the human visual system

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to the spectral stimulus of the objects and eliminates the effect of illuminant during the dimension reduction. It improves the colorimetric precision. Meanwhile, it can match the color well under various lights. By compensating the spectrum loss caused by WSPCA, WSPCAplus can improve the spectral accuracy. The new method can achieve good colorimetric and spectral accuracy and good color matching results under various lights, which maintains the color difference stability when changed illuminant. It effectively improves the dimension reduction accuracy of the multi-spectral images and improves the color reproduction results of the multispectral images.

II. Principal Component Analysis

Principal component analysis (PCA)[10] can project high-dimensional data to a low-dimensional space and keep the variance of the source data as large as possible. It can use few variables to express high-dimensional data and maintain the main information of these data. It is a common dimension reduction method. Given a set of high-dimensional vectors $\boldsymbol{S}$ and the variance of $\boldsymbol{S}$ $\boldsymbol{\Sigma}$, PCA solves the eigenvalue $(\lambda_1 \quad \lambda_2 \quad \dots \quad \lambda_k)$ and its eigenvector $(\boldsymbol{a_1} \quad \boldsymbol{a_2} \quad \dots \quad \boldsymbol{a_k})$ of $\boldsymbol{\Sigma}$, where $\lambda_1 \geq \lambda_2 \geq \dots \lambda_k > 0$ are all non-zero eigenvalue of $\boldsymbol{\Sigma}$, $k = rank(\Sigma)$. Then it combines the eigenvectors to forming a dimension reduction matrix $\boldsymbol{V} = (\boldsymbol{a_1} \quad \boldsymbol{a_2} \quad \dots \quad \boldsymbol{a_k})$ to complete dimension reduction:

$$\boldsymbol{C} = \boldsymbol{V}^T \boldsymbol{S} \tag{1}$$

$\boldsymbol{C} = (\boldsymbol{c_1} \quad \boldsymbol{c_2} \quad \dots \quad \boldsymbol{c_k})$ is the dimension reduced data, where $\boldsymbol{c_1}$ is called the first principal component. It can express the most important information of source data. $\boldsymbol{c_2}$ is called the second principal component. It can express the second important information of source data. Followed by analogy, $\boldsymbol{c_k}$ is the k-th principal component. So the high-dimensional data can be reconstructed from the low-dimensional data by the following equation,

$$\hat{\boldsymbol{S}} = \boldsymbol{VC} = \sum_{i=1}^{k} \boldsymbol{c_i a_i} \tag{2}$$

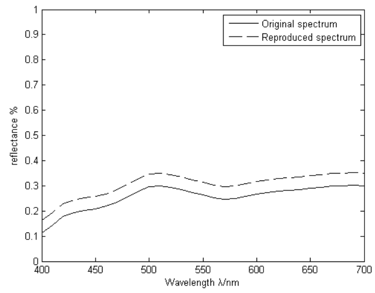
where, $\boldsymbol{c}_1\boldsymbol{a}_1$ is the largest approximation of the source data $\boldsymbol{S}$. $\boldsymbol{c}_2\boldsymbol{a}_2$ is the second largest approximation of $\boldsymbol{S}$. Followed by analogy, $\boldsymbol{c_k a_k}$ is the k-th largest approximation of $\boldsymbol{S}$. Using PCA to reducing the data dimension is essentially to make the reconstructed data from the low-dimensional data and the source data as close as possible, that is, the error ε of the two data should be as small as possible,

$$\varepsilon = \left\| \boldsymbol{S} - \hat{\boldsymbol{S}} \right\|_2^2 \tag{3}$$

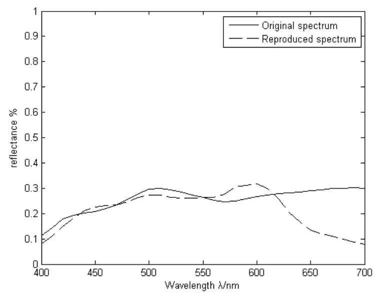
where $\| \bullet \|_2^2$ is the square of 2-norm.

III. Nonlinear Dimension Reduction of Multispectral Images for Color Reproduction

Dimension reduction of multispectral images endeavor to use few-dimensional data to represent high-dimensional spectral reflectance of the source image. It makes some information of the image be ignored. So the error is inevitable between the source spectral reflectance and the spectral reflectance reconstructed from the low-dimensional data. Because the spectral reflectance is independent of the color perception of the human visual system and the spectral reflectance space is non-uniform, the spectral error cannot reflect the color error of the low-dimensional image and the source image. Colorimetric error can reflect the color difference of the images under one specific view environment (illuminant, observer). High colorimetric accuracy can ensure the color matching quality under single environment. However, when the view environment is changed, the color distortion will become serious. For example, for the spectra shown in Fig.1, the colorimetric and spectral error is shown in Table I.



(a) 0.05 spectral difference



(b) metamerism in D65

Figure 1. Spectral curves with different precision characteristics

TABLE I.
COMPARISON OF SPECTRAL AND COLORIMETRIC PRESISION

Spectrum	Colorimetric error (ΔE_{ab},D65,2° observer)	Colorimetric error (ΔE_{ab},A,2° observer)	Spectral error (E_{RMS})	Metamerism index (MI_{ab},D65,A,2° observer)
Fig.1(a)	4.5232	4.4553	0.0500	1.5770
Fig.1(b)	0.0002	4.1451	0.1076	4.7093

From Table I. we can see that colorimetric and spectral accuracy reflect the different characteristics of color matching. When the spectral accuracy is high, the metamerism index is low. This means that color perceptual difference of the reproduced color and source color is small (the change of color error of the spectra in Fig.1 (a) is small when illuminant changed from D65 to A). While the high colorimetric accuracy means that the color perception difference is small under one specific light (The colorimetric error of the spectra in Fig.1 (b) is small under illuminant D65. When the illuminant replaced by illuminant A, the colorimetric error increases significantly.) This means that only pursuing good spectral matching cannot produce the good color reproduction results for multispectral images. Whereas only pursuing high colorimetric accuracy under single specific illuminant tends to produce large color distortion when the illuminant is changed. Therefore, when reducing the data dimension of spectral reflectance, not only the spectral error between the spectra reconstructed from the low-dimensional data and the source spectral data is as small as possible, but also the colorimetric error is under various light. Only by this way, the data obtained by dimension reduction can express the source spectral information well. Thereby the accuracy and consistent color reproduction of multispectral images under various illuminants can be achieved.

A. Weighted spectral PCA (WSPCA)

Given a spectral reflectance r of one pixel in an image, the tristimulus value of this pixel under a specific light is

$$\boldsymbol{t}(\boldsymbol{r}) = \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} \boldsymbol{e}^T \boldsymbol{D}_{\bar{x}} \\ \boldsymbol{e}^T \boldsymbol{D}_{\bar{y}} \\ \boldsymbol{e}^T \boldsymbol{D}_{\bar{z}} \end{bmatrix} \boldsymbol{r} = \boldsymbol{e}^T \begin{bmatrix} \boldsymbol{D}_{\bar{x}} \\ \boldsymbol{D}_{\bar{y}} \\ \boldsymbol{D}_{\bar{z}} \end{bmatrix} \boldsymbol{r} \tag{4}$$

where $\boldsymbol{D}_{\bar{x}} = diag(\bar{\boldsymbol{x}}), \boldsymbol{D}_{\bar{y}} = diag(\bar{\boldsymbol{y}}), \boldsymbol{D}_{\bar{z}} = diag(\bar{\boldsymbol{z}})$, $\bar{\boldsymbol{x}}$, $\bar{\boldsymbol{y}}$, $\bar{\boldsymbol{z}}$ is the standard observer color matching function defined by International Commission on Illumination (CIE). It is used to express the color vision characteristics of the person with the normal color vision [11]. Its dimension is same as the dimension of spectra. $diag(\bullet)$ is to generate a diagonal matrix according to a vector. $\boldsymbol{e}$ is spectral power distribution of a given illuminant. From (4) we can see that the colorimetric value of a pixel is closely related the illuminant. When the light is changed, the deviation of colorimetric value between the high-dimensional spectral reflectance reconstructed from the low-dimension data and the source spectral reflectance will be big. So if the effect of light on color matching can be excluded and only the response of the standard observer to spectral reflected stimulus is inspected, and makes this response reach the best matching, spectral stimulus will achieve the better color matching under various lights. Based on this idea, the paper presents weighted spectral PCA (WSPCA) method. Given ε is the deviation of the response of standard observer to the reconstructed spectral reflectance and the source spectral reflectance,

$$\begin{aligned} \varepsilon &= \left\| \begin{bmatrix} \boldsymbol{D}_{\bar{x}} \\ \boldsymbol{D}_{\bar{y}} \\ \boldsymbol{D}_{\bar{z}} \end{bmatrix} \boldsymbol{r} - \begin{bmatrix} \boldsymbol{D}_{\bar{x}} \\ \boldsymbol{D}_{\bar{y}} \\ \boldsymbol{D}_{\bar{z}} \end{bmatrix} \hat{\boldsymbol{r}} \right\|_2^2 = \left\| \begin{bmatrix} \boldsymbol{D}_{\bar{x}} \\ \boldsymbol{D}_{\bar{y}} \\ \boldsymbol{D}_{\bar{z}} \end{bmatrix} (\boldsymbol{r} - \hat{\boldsymbol{r}}) \right\|_2^2 \\ &= (\boldsymbol{r} - \hat{\boldsymbol{r}})^T \begin{bmatrix} \boldsymbol{D}_{\bar{x}} & \boldsymbol{D}_{\bar{y}} & \boldsymbol{D}_{\bar{z}} \end{bmatrix} \begin{bmatrix} \boldsymbol{D}_{\bar{x}} \\ \boldsymbol{D}_{\bar{y}} \\ \boldsymbol{D}_{\bar{z}} \end{bmatrix} (\boldsymbol{r} - \hat{\boldsymbol{r}}) \\ &= (\boldsymbol{r} - \hat{\boldsymbol{r}})(\boldsymbol{D}_{\bar{x}}^2 + \boldsymbol{D}_{\bar{y}}^2 + \boldsymbol{D}_{\bar{z}}^2)(\boldsymbol{r} - \hat{\boldsymbol{r}}) \end{aligned} \tag{5}$$

where $\hat{\boldsymbol{r}}$ is the reconstructed spectral reflectance. Because $\boldsymbol{D}_{\bar{x}}$, $\boldsymbol{D}_{\bar{y}}$ and $\boldsymbol{D}_{\bar{z}}$ are all the diagonal matrix, define diagonal matrix $\boldsymbol{W}$,

$$\boldsymbol{W} = (\boldsymbol{D}_{\bar{x}}^2 + \boldsymbol{D}_{\bar{y}}^2 + \boldsymbol{D}_{\bar{z}}^2)^{1/2} \tag{6}$$

Then (5) is converted to

$$\varepsilon = (\boldsymbol{r} - \hat{\boldsymbol{r}})^T \boldsymbol{W}^2 (\boldsymbol{r} - \hat{\boldsymbol{r}}) = (\boldsymbol{r} - \hat{\boldsymbol{r}})^T \boldsymbol{W}^T \boldsymbol{W} (\boldsymbol{r} - \hat{\boldsymbol{r}}) \tag{7}$$

That is,

$$\varepsilon = \left\| \boldsymbol{W}(\boldsymbol{r} - \hat{\boldsymbol{r}}) \right\|_2^2 = \left\| \boldsymbol{W}\boldsymbol{r} - \boldsymbol{W}\hat{\boldsymbol{r}} \right\|_2^2 \tag{8}$$

Form (3) we know that if $\boldsymbol{S} = \boldsymbol{W}r$ is designated as the data which dimension to be reduced, the PCA method can be used to complete the dimension reduction of $\boldsymbol{Wr}$. By (2) the best approximation $\hat{\boldsymbol{S}} = \widehat{\boldsymbol{Wr}}$ of $\boldsymbol{Wr}$ can be obtained. Then the reconstructed spectral reflectance is

$$\hat{\boldsymbol{r}}_w = \boldsymbol{W}^{-1} \widehat{\boldsymbol{Wr}} \tag{9}$$

$\hat{\boldsymbol{r}}_w$ is the best approximation of the source reflectance $\boldsymbol{r}$ under the standard observer condition. Then the color matching of the spectra reconstructed from low-dimension data with the source spectra is better.

WSPCA introduces the characteristics of human visual system during spectral data dimension reduction. So compared with the traditional PCA method it can achieved better colorimetric matching. Meanwhile, it excludes the effect of the light and only inspects the response of the human visual system to the reflected spectrum. Therefore, when the light is changed, it can still obtain good color matching.

B. WSPCAplus nonlinear dimension reduction method of multispectral image

From the previous section we know, during reducing the dimension of multispectral image, the response of human visual system to the reflected spectrum is introduced. So the image dimension reduced can match the source image well in color. However, the spectral matching is ignored. This leads to that the spectral precision is reduced. Therefore, in order to improve the spectral matching precision, it is necessary to compensate the loss spectrum. From (9) we know that $\hat{\boldsymbol{r}}_w$ is the reconstructed spectral by using WSPCA, then the loss spectrum is

$$\boldsymbol{r}_{lost} = \boldsymbol{r} - \hat{\boldsymbol{r}}_w \tag{10}$$

In order to compensate the loss spectrum, we define

$$\varepsilon = \left\| \boldsymbol{r}_{lost} - \hat{\boldsymbol{r}}_{lost} \right\|_2^2 \tag{11}$$

Then PCA method can be used to get the best approximation $\hat{\boldsymbol{r}}_{lost}$ of $\boldsymbol{r}_{lost}$. Using $\hat{\boldsymbol{r}}_{lost}$ to supplement $\hat{\boldsymbol{r}}_w$, the spectrum $\hat{\boldsymbol{r}}$ reconstructed from the low-dimensional data can be achieved, which is the best approximation to the source spectrum both in color and spectral field,

$$\hat{\boldsymbol{r}} = \hat{\boldsymbol{r}}_w + \hat{\boldsymbol{r}}_{lost} \tag{12}$$

According to the analysis in this section and previous section, if using WSPCA to reduce the dimension of weighted spectral data and using the first several principal components as the first several dimension data, the better colorimetric matching can be achieve. Then using PCA to reduce the dimension of loss spectrum in (10), and using the first several principal components as the last several dimension data to compensate the loss spectrum, the source spectrum information can be represented well by the low-dimensional data both in color and spectral field. The paper defines this method as WSPCAplus.

The algorithm of WSPCAplus can be described as follows,

i) According to CIE standard observer color matching functions, using (6) to obtain the weighted matrix $\boldsymbol{W}$.

ii) For the spectral reflectance of any pixel in the multispectral image, computing the stimulus $\boldsymbol{Wr}$ weighted by the human visual characteristics. Then using PCA to reduce the dimension of $\boldsymbol{Wr}$. According to the accuracy requirement, choosing the first few principal component and denoting them as $\boldsymbol{C}_{\boldsymbol{Wr}}$.

iii) Reconstructing spectral stimulus $\hat{\boldsymbol{Wr}}$ from $\boldsymbol{C}_{\boldsymbol{Wr}}$,and then using (9) to get spectrum $\hat{\boldsymbol{r}}_{\boldsymbol{w}}$ .By (10) to obtain the loss spectrum $\boldsymbol{r}_{\boldsymbol{lost}}$. Then using PCA to reduce the dimension of $\boldsymbol{r}_{\boldsymbol{lost}}$. According to the accuracy requirement reserving the first few principal components and denoting them as $\boldsymbol{C}_{\boldsymbol{rlost}}$.

iv) By combining the two set principal components obtained in steps ii) and iii), the dimension reduced data $\boldsymbol{C}$ is formed

v) For each pixel in the multispectral image, repeat the steps from ii) to iv), the nonlinear dimension reduction of the multispectral images can be achieved, which satisfying the requirement of colorimetric and spectral accuracy.

The process of reconstructing spectral reflectance from low-dimensional data $\boldsymbol{C}$ can be described as follows,

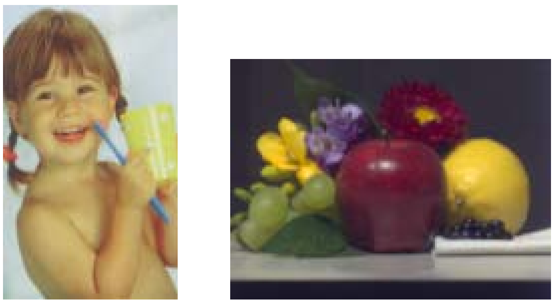
i) Extracting $\boldsymbol{C}_{\boldsymbol{Wr}}$ for low-dimensional data $\boldsymbol{C}$, using (2) to restore the human visual characteristics weighted stimulus $\hat{\boldsymbol{Wr}}$. Then using (9) to obtain a part of restored spectrum $\hat{\boldsymbol{r}}_{\boldsymbol{w}}$.

ii) Extracting $\boldsymbol{C}_{\boldsymbol{rlost}}$ from $\boldsymbol{C}$, using (2) to reconstruct the loss spectrum $\hat{\boldsymbol{r}}_{\boldsymbol{lost}}$.

iii) Using (12) to get the reconstructed spectral reflectance $\hat{\boldsymbol{r}}$ of the source spectral reflectance $\boldsymbol{r}$.

IV. EXPERIMENTS

In order to validate the algorithm, two multispectral images and IT8.7/3 standard print color target are chosen in the experiments. The spectral reflectance of both the images and the target are sampled in 400nm to 700nm at 10nm intervals. The dimension of the reflectance data are 31. The RGB images synthesized from the multi-spectral images are shown in Fig.2. Fig.2(a) is a typical skin image and Fig.2(b) is s scene picture with high color saturation.



(a) Young-girl (b) Fruits-and-flowers

Figure 2. RGB images synthesized from multi-spectral images.

To validate the algorithm under various illuminants, the CIE standard illuminant A, D65, D50 and F2 are used in the experiments as the typical validation illuminants. The difference of the spectral power distribution of these standard illuminants is significant. The spectral power distribution of these four illuminants is shown in Fig.3. The CIE 1931 2° standard observer color matching function is shown in Fig.4.

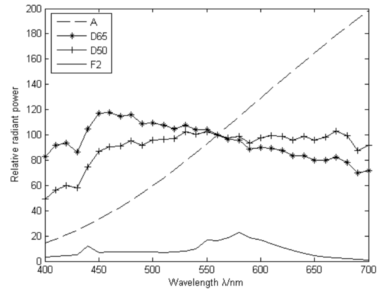


Figure 3. Sprectral power distribution of CIE A, D65, D50, F2.

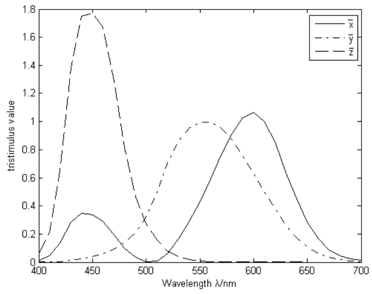


Figure 4. CIE 1931 Standard observer CMF.

The classical PCA, WSPCA, LabPQR and WSPCAplus are simulated in the experiments based on the two test images and IT8.7/3 standard color target. Because the image color management needs to be accomplished real-time, real-time using PCA to each multi-spectral image will reduce the efficiency of color management. In practical applications, a set of samples are always chosen as the base training samples, which are used to obtain dimension reduction transformation matrix and eigen-space. Then the transformation matrix is used directly to complete the dimension reduction and reconstruction of the multi-spectral images. The IT8.7/3 target contains rich color. Although its color gamut is relatively small, it can represent color better compared with using a single multi-spectral image. Therefore, in the experiment in this paper, the IT8.7/3 target is chosen as the base training samples for all the four dimension reduction method. Using these samples and by using PCA, the dimension reduction eigenvector matrix of source spectra, of weighted spectra and of loss spectra are obtained respectively.

The evaluation for the four methods is done from spectral and colorimetric precision. The standard colorimetric metric ΔE_{ab} [11] of uniform color space CIELAB is used for color error evaluation. The root-mean-square error equation E_{RMS} [12] is used for spectral error evaluation. Table II shows the comparison results of the direct PCA method and WSPCA when chosen the first six principal components. From Table II we know, compared with using PCA to the source spectral data directly, the colorimetric accuracy is improved obviously. Moreover, under different light, the colorimetric accuracy has better stability. But the better color matching results is at the price of spectral accuracy. WSPCAplus is to compensate the loss spectrum caused by WSPCA. Table III shows the comparison result of LabPQR and WSPCAplus. Because LabPQR reduces the data dimension to 6, WSPCAplus uses the form of 3 dimension plus 3 dimension, that is, the part of low-dimension data by WSPCA is 3 dimension and the part of loss spectrum low-dimension data is 3 dimension. So the dimension of final results is 6. In the experiment, LabPQR uses CIE A as the illuminant to calculate the Lab value.

TABLE II.
COMPARISON OF THE RESULTS BY PCA AND WSPCA

Test image	Method	mean/max colorimetric error (ΔE_{ab} , 2°observer)				mean/max spectral error (E_{RMS})
		A	D65	D50	F2	
IT8.7/3	PCA	0.5853/7.8056	0.8568/11.5825	0.8004/11.2224	0.9870/12.0852	0.0072/0.0383
	WSPCA	0.4976/4.3887	0.4903/4.4493	0.4615/ 4.0962	0.3726/3.6017	0.0139/0.0503
Fig.2(a)	PCA	0.5925/2.2773	0.8375/3.4580	0.7614/3.1599	0.8533/2.8517	0.0162/0.0473
	WSPCA	0.3574/1.3521	0.3214/1.1283	0.3716/1.1184	0.3402/1.3251	0.0189/0.0522
Fig.2(b)	PCA	3.9993/9.1049	5.6624/15.2915	5.2439/13.9949	5.0715/14.8918	0.0258/0.0947
	WSPCA	2.1376/10.4318	1.6375/6.8420	1.6849/7.9424	1.8763/6.8666	0.0412/0.1655

TABLE III.
COMPARISON OF THE RESULTS BY LABPQR AND WSPCAPLUS

Test image	Method	mean/max colorimetric error (ΔE_{ab} , 2° observer)				mean/max spectral error (E_{RMS})
		A	D65	D50	F2	
IT8.7/3	LabPQR	0/0	0.6159/ 3.0154	0.5651/ 2.8845	0.6253/ 4.6420	0.0069/ 0.0407
	WSPCAplus	0.3760/ 2.0205	0.4434/ 2.8992	0.4038/ 2.7847	0.3765/ 2.3317	0.0058/0.0371
Fig.2(a)	LabPQR	0/0	0.5884/ 1.9034	0.5450/ 1.7092	0.6250/ 1.5886	0.0154/ 0.0463
	WSPCAplus	0.3165/ 0.7373	0.3147/ 0.9296	0.3051/ 0.8372	0.3038/ 0.9742	0.0136/0.0396
Fig.2(b)	LabPQR	0/0	2.8760/ 6.7477	2.4816/ 5.4357	2.9378/ 7.8976	0.0259 / 0.0954
	WSPCAplus	1.4807/4.7995	1.3892/4.2774	1.2445/3.4349	1.5160/4.3141	0.0224/0.0793

From Table II and Table III we can see that the methods in Table III are better than those in Table II in spectral accuracy. LabPQR have the obvious advantage over direct PCA in terms of colorimetric accuracy. The colorimetric precision is also improved obviously by WSPCAplus compared with direct PCA and WSPCA. This means that nonlinear methods are better than linear dimension reduction methods for multi-spectral images. In Table III, under for typical illuminant, except the illuminant that used to compute the Lab, under it, the colorimetric error is 0, the colorimetric error increases obviously under other three illuminants. However, the change of the color error using WSPCAplus under four illuminants is unconspicuous. This means that the method has better color error stability when illuminant is changed. Thus it can be seen that WSPCAplus is advantage over the direct PCA and LabPQR in terms of colorimetric accuracy, spectral accuracy and stability under various illuminants.

V. CONCLUSION

A nonlinear dimension reduction method, WSPCAplus, is presented in this paper. Firstly, according to the response of human visual system to spectral reflected stimulus, a WSPCA method is proposed which using the human visual color matching function to weight the source spectra and then reducing the dimension of weighted spectral data. It improves the colorimetric accuracy of dimension reduction for multi-spectral image under various illuminants effectively. Then based on the WSPCA method, a WSPCAplus method is presented. By compensating the loss spectra caused by WSPCA, the method improves the spectral accuracy of dimension reduction for multi-spectral image effectively. Compared with the existing method, direct PCA and LabPQR, the new method improves the colorimetric precision, spectral precision and colorimetric error stability under various illuminants obviously.

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