Effects of Cone Response Function on Multispectral Data Compression

Qian Cao[1](✉), Xiaozhou Li[2], and Junfeng Li[3]

[1] Department of Printing and Packaging Engineering, Shanghai Publishing and Printing College, Shanghai, China
caoqian8889@163.com

[2] School of Light Industry Science and Engineering, Qilu University of Technology (Shandong Academy of Sciences), Jinan, Shandong, China

[3] School of Packaging and Printing Engineering, Henan University of Animal Husbandry and Economy, Zhengzhou, Henan, China

Abstract. This paper proposed a weighted principal component analysis method based on cone response function to reserve more color information. To verify the advantages of the proposed method, Munsell spectra were used as training samples to determine the conversion model between high-dimensional spectral space and low-dimensional space, Munsell, ISO SOCS spectra and two multispectral images were used as test samples. Compared with the principal component analysis method, the proposed method can significantly improve the colorimetric accuracy at the expense of a small amount of spectral accuracy. In addition, compared with the other three weighted principal component analysis methods based on cone response function, this method has a lot of improvement in colorimetric accuracy.

Keywords: Spectral Color Reproduction · Spectral Data Compression · Spectral Dimensionality Reduction · Cone Response Function

1 Introduction

In recent years, spectral color reproduction, which can reduce or even avoid the problem of "metamerism" in traditional color reproduction, has become a research hotspot in color science [1, 2]. However, using high-dimensional multispectral data directly will take up a lot of storage space, and the subsequent processing is complex. The common solution is to use multivariate statistical methods such as principal component analysis (PCA for short) [3] to reduce the dimension. However, PCA treats all wavelengths in the visible range equally, and the reconstructed spectrum is only a mathematical approximation of the original spectrum, which often leads to smaller spectral error and larger color difference. Some researchers have proposed weighted PCA to compress spectral data. Maloney [4] is the first scholar to use weighted PCA in the study of spectral data. He used the visual efficiency function v (λ) of the light spectrum of the bright vision as

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the weight function.He Songhua et al. [5] proposed two weight functions based on cone response function in 2015, which effectively improved the colorimetric accuracy of multispectral compression algorithm. Liu Shiwei et al. [6] proposed a weight function based on cone response functions in 2017. However, when the test samples are changed or other spectral images are used, the colorimetric error of the weighted PCA methods mentioned above is still very high.

2 Method

In 2015, He Songhua et al. [5] proposed two weight functions named W1 and W2 respectively, which can be expressed as Eqs. (1) and (2). Liu Shiwei et al. [6] proposed a weight function W3, as shown in Eq. (3).

$$\mathrm{W1} = (\mathrm{L}(\lambda) + \mathrm{M}(\lambda) + \mathrm{S}(\lambda)) \tag{1}$$

$$\mathrm{W2} = (\sqrt{\mathrm{L}(\lambda)^2 + \mathrm{M}(\lambda)^2 + \mathrm{S}(\lambda)^2}) \tag{2}$$

$$\mathrm{W3} = (\sqrt{\mathrm{L}(\lambda) + \mathrm{M}(\lambda) + \mathrm{S}(\lambda)}) \tag{3}$$

Among them, $\mathrm{L}(\lambda)\mathrm{M}(\lambda)$ and $\mathrm{S}(\lambda)$ denote three kinds of cone response functions, i.e., red sensitive, green sensitive and blue sensitive, respectively.

In order to minimize the colorimetric error, it is very meaningful to find an optimal combination of cone response functions. Therefore, we tried to use the sum of the square roots of three cone response functions as the weight function, and found that the weight function has significantly improved the colorimetric accuracy compared with the other weight functions. In this paper, a weight function W4 based on cone response function is proposed. Its expression is shown in Eq. (8).

$$\mathrm{W4} = (\sqrt{\mathrm{L}(\lambda)} + \sqrt{\mathrm{M}(\lambda)} + \sqrt{\mathrm{S}(\lambda)}) \tag{4}$$

3 Experiments and Process

3.1 Experimental Data

Munsell [7] and ISO SOCS [8] are used in this experiment as shown in Fig. 1. A multispectral hair image with a resolution of 512 × 512 pixels (named image-1) [9] and a multispectral landscape image with a resolution of 1024 × 1344 pixels [10] (named image-2) were also used as shown in Fig. 2.

3.2 Experimental Process

The test samples were compressed to 6-dimensional space by compression algorithm, and then restored to 31 dimensional space. There are some errors between the original and the reconstructed spectra. The errors of original and reconstructed spectra are evaluated by spectral accuracy, colorimetric accuracy and mean value of color difference under different light sources.

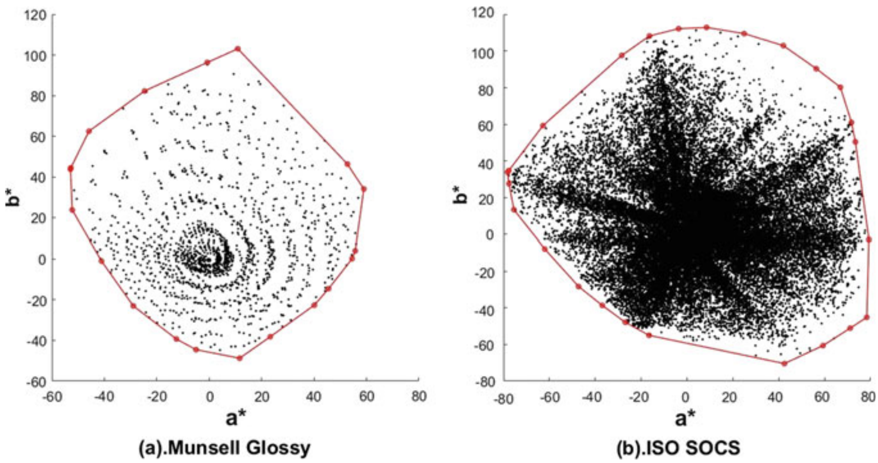

Fig. 1 Colorimetric coordinates a*b* (D50/2°): **a** Munsell Glossy, **b** ISO SOCS

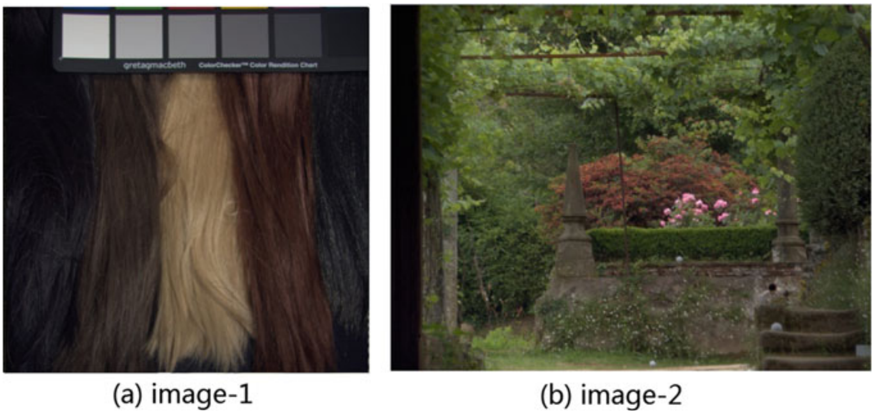

Fig. 2 Two multispectral images **a** image-1, **b** image-2

4 Results and Discussion

Munsell spectral data were used as training samples to determine principal components, Munsell glossy, ISO SOCS spectra and two multispectral images were used as test samples.

4.1 Spectral Accuracy

The root mean square errors (RMSE) [11] are employed to evaluate spectral accuracy between the original and reconstructed samples. The RMSE is expressed asequation (5).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(S(\lambda_i) - \hat{S}(\lambda_i)\right)^2} \tag{5}$$

Where $S(\lambda_i)$ and $\hat{S}(\lambda_i)$ are the original and reconstructed spectra, respectively, and n is the number of test samples.The average values of spectral errors between original and reconstructed spectra of Munsell and ISO SOCS of test samples are shown in Table 1, and those of multispectral images are shown in Table 2.

Table 1 Spectral accuracy (RMSE) of Munsell and ISO SOCS

	PCA	W1PCA	W2PCA	W3PCA	W4PCA
Munsell	0.0086	0.0145	0.0139	0.0116	0.0136
ISO SOCS	0.0132	0.0210	0.0207	0.0186	0.0203

Table 2 Spectral accuracy (RMSE) of multispectral images

	PCA	W1PCA	W2PCA	W3PCA	W4PCA
Image-1	0.0043	0.0056	0.0057	0.0045	0.0056
Image-2	0.0041	0.0048	0.0046	0.0045	0.0045

As shown in Table 1, when the test sample is Munsell, the order of spectral accuracy from good to poor is PCA, W3PCA, W4PCA, W2PCA, W1PCA; when the test samples are ISO SOCS, the multispectral hair image and themultispectral landscape image, the conclusion of spectral accuracy is similar.

4.2 Colorimetric Accuracy

The CIELAB color difference formula [12] recommended by the International Commission on illumination in 1976 is used to calculate the colorimetric accuracy.

$$\Delta E_{ab}^{*} = \sqrt{(L_2^{*} - L_1^{*})^2 + (a_2^{*} - a_1^{*})^2 + (b_2^{*} - b_1^{*})^2} \tag{6}$$

The average values of color difference between original and reconstructed spectra of Munsell and ISO SOCS are shown in Table 3. The average values of color difference between original and reconstructed spectra of multispectral images are shown in Table 4.

Table 3 Colorimetric accuracy of Munsell and ISO SOCS

	PCA	W1PCA	W2PCA	W3PCA	W4PCA
Munsell	0.8988	0.5563	0.6720	0.3607	0.2882
ISO SOCS	1.4675	0.9975	1.2937	0.8906	0.5582

Table 4 Colorimetric accuracy of multispectral images

	PCA	W1PCA	W2PCA	W3PCA	W4PCA
Image-1	0.9672	0.4533	0.5354	0.3678	0.2783
Image-2	1.3470	0.7527	0.7775	0.5026	0.2314

As shown in Table 3, when the test sample is Munsell, the colorimetric accuracy of weighted principal component analysis method is significantly better than that of principal component analysis method, and the order from good to poor is: W4PCA, W3PCA, W1PCA, W2PCA, PCA. When the test samples are ISO SOCS, multispectral hair image and multispectral landscape image, the conclusion of colorimetric accuracy is similar.

4.3 Colorimetric Error Under Various Illuminants

The main purpose of spectral color reproduction is to reduce or even avoid the phenomenon of "metamerism", so as to ensure that the original object and the replica have the same color sense under any observer and light source. In this paper, representative light sources D65, A, F2, and D50 were selected to evaluate the color difference of the original and reconstructed spectra. Table 5 shows the average values of color differences under the CIE standard illuminant D50, D65, A and F2 between the original and reconstructed reflectance spectra of Munsell. Table 6 shows the average values of color differences under the CIE standard illuminant D50, D65, A and F2 between the original and reconstructed reflectance spectra of ISO SOCS.

Table 5 Colorimetric accuracy between original and reconstructed spectra of Munsell under the CIE standard illuminant D50, D65, A and F2

	PCA	W1PCA	W2PCA	W3PCA	W4PCA
D50	0.8988	0.5563	0.6720	0.3607	0.2882
D65	0.9235	0.4572	0.5696	0.2911	0.2403
A	0.7771	0.7459	0.8312	0.4136	0.3870
F2	0.9054	0.3004	0.1889	0.2366	0.3013
Mean	0.8762	0.5150	0.5654	0.3255	0.3042

As shown in Table 5, the order of colorimetric accuracy between original and reconstructed spectra of Munsell under the CIE standard illuminant D50, D65, A and F2 is W4PCA, W3PCA, W1PCA, W2PCA, PCA.As shown in Table 6, the order of colorimetric accuracy between original and reconstructed spectra of ISO SOCS under the CIE standard illuminant D50,D65,A and F2 is W4PCA, W3PCA, W1PCA, W2PCA, PCA.

Table 6 Colorimetric accuracy between original and reconstructed spectra of ISO SOCS under the CIE standard illuminant D50, D65, A and F2

	PCA	W1PCA	W2PCA	W3PCA	W4PCA
D50	1.4675	0.9975	1.2937	0.8906	0.5582
D65	1.4717	0.8309	1.1260	0.7798	0.4988
A	1.3029	1.2721	1.5039	0.9066	0.6681
F2	1.4396	0.5823	0.4623	0.6401	0.6434
Mean	1.4204	0.9207	1.0965	0.8043	0.5921

5 Conclusions

Compared with the PCA method, this method can significantly improve the colorimetric accuracy at the expense of a small amount of spectral accuracy. In addition, compared with the other three weighted PCA methods based on cone response function, this method has a lot of improvement in colorimetric accuracy.

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