Estimation of spectral reflectance of object surfaces with the consideration of perceptual color space

Hui-Liang Shen

Department of Information and Electronic Engineering, Zhejiang University, Hangzhou 310027, China

John H. Xin

Institute of Textiles and Clothing, The Hong Kong Polytechnic University, Hong Kong, China

Received July 10, 2006; revised August 15, 2006; accepted August 16, 2006;
posted August 21, 2006 (Doc. ID 72806); published December 13, 2006

Due to the nonlinear transform from spectral reflectance to CIELAB values, the solution obtained by minimizing reflectance error in traditional spectral characterization methods will not be optimal when evaluated by colorimetric error. We propose a reflectance estimation method with consideration of perceptual color space. It combines two approaches, i.e., colorimetric-based spectral calculation and weighted spectral calculation. The experimental results show that the proposed method performs better than previous methods in terms of color difference with very slight degradation in spectral accuracy.

OCIS codes: 330.1710, 330.1730.

In many applications such as industrial color quality control and art painting archiving, there is an increasing need to estimate the spectral reflectance of object surfaces using a digital camera or a color scanner. Shi and Healey[1] presented a spectral characterization method to recover reflectance from scanner responses based on the linear reflectance model (LRM) and showed that it outperformed the traditional polynomial transform.[2] Dicarlo and Wandell[3] found that the statistical distribution of spectral reflectance had an important influence on estimation accuracy. Inspired by that finding, Shen and Xin recently proposed two methods, namely, adaptive estimation[4] (AE) and optimized adaptive estimation (OAE),[5] for reflectance recovery by training sample selection and weighting. However, due to the color matching functions and the nonlinear transform between CIEXYZ values and CIELAB values, the minimization of reflectance error of previous methods does not guarantee an optimal solution in terms of color difference. This may be one of the reasons why the color accuracy of colorimetric characterization is sometimes better than that of spectral characterization.[6]

In this Letter, we propose a method for the accurate estimation of spectral reflectance from the responses of a color scanner with the consideration of approximately perceptually uniform color space CIELAB. To reduce errors in reflectance estimation, two approaches, namely, colorimetric-based spectral calculation and weighted spectral calculation, are involved in this method.

We suppose that the visible spectrum, from 400 to 700 nm, is equally sampled in N wavelengths. For an ideal three-channel color scanner, its 3×1 response vector $\mathbf{u}$ is simply the product of the $3\times N$ matrix $\mathbf{M}_s$ of spectral responsivity (including spectral radiance of the illuminant and spectral sensitivity of sensors) and the $N\times 1$ vector $\mathbf{r}$ of spectral reflectance, i.e., $\mathbf{u}=\mathbf{M}_s\mathbf{r}$. For a common scanner however, its 3×1 actual response vector $\boldsymbol{\rho}$ may carry some influence from a nonlinear optoelectronic conversion function (OECF) $F_{\mathrm{OECF}}(\cdot)$ and a 3×1 response bias vector $\mathbf{f}$ caused by dark current. Hence the imaging process is formulated as[4]

$$\boldsymbol{\rho}=F_{\mathrm{OECF}}(\mathbf{v})=F_{\mathrm{OECF}}(\mathbf{M}_s\mathbf{r}+\mathbf{f})=F_{\mathrm{OECF}}(\mathbf{u}+\mathbf{f}), \quad (1)$$

where $\mathbf{v}=\mathbf{M}_s\mathbf{r}+\mathbf{f}$. As $F_{\mathrm{OECF}}(\cdot)$ can be obtained using the actual responses and mean reflectance (or luminance) of gray-scale patches,[4] the crucial equation reads

$$\mathbf{v}=[\mathbf{M}_s \quad \mathbf{f}]\begin{bmatrix}\mathbf{r}\\ 1\end{bmatrix}, \quad (2)$$

from which $\mathbf{M}_s$ and $\mathbf{f}$ can be determined using the More–Penrose pseudoinverse

$$[\mathbf{M}_s \quad \mathbf{f}]=\mathbf{V}\begin{bmatrix}\mathbf{R}\\ \mathbf{1}\end{bmatrix}^{+}, \quad (3)$$

where $\mathbf{R}$ is the matrix of reflectance vector $\mathbf{r}$, $\mathbf{1}$ is a row vector of ones, and $\mathbf{V}$ is the matrix of response vector $\mathbf{v}$. In the following, we will use $\mathbf{u}$ for spectral reflectance estimation, without regarding the bias $\mathbf{f}$.

Colorimetric-based spectral calculation: Let $\mathbf{M}_c$ be the $3\times N$ matrix of color-matching functions, the corresponding 3×1 CIEXYZ vector is calculated as $\mathbf{a}=\mathbf{M}_c\mathbf{r}$. It can be converted into its CIELAB counterpart $\mathbf{t}=F_{\mathrm{LAB}}(\mathbf{a})$ by using a transform function $F_{\mathrm{LAB}}(\cdot)$.

As $F_{\mathrm{LAB}}(\cdot)$ is nonlinear, it is difficult to minimize colorimetric error in CIELAB space directly.[7] Considering there is a cubic-root transform in $F_{\mathrm{LAB}}(\cdot)$, Hardeberg[8] precalculated the cubic root of response $\mathbf{u}$ before applying a polynomial transform. In this Letter, we generalize the cubic root into the qth root,

0146-9592/07/010096-3/$15.00

where q can be 3, 6, or 9, considering there are high-order polynomial terms in colorimetric characterization:

$$\mathbf{h} = F_{1/q}(u_1, u_2, u_3), \tag{4}$$

where $\mathbf{h}$ is the vector of polynomial terms, $F_{1/q}(\cdot)$ denotes the qth root calculation, and u_1, u_2, u_3 are the elements of vector $\mathbf{u}$. Table 1 shows the polynomial elements of vector $\mathbf{h}$ with typical 14 and 20 terms.

When all color samples are used for training, the global colorimetric transform matrix can be calculated as $\mathbf{W}_{GC} = \mathbf{T}_{GC}\mathbf{H}_{GC}^{+}$, where $\mathbf{H}_{GC}$ and $\mathbf{T}_{GC}$ are the matrices of vectors $\mathbf{h}_i$ and $\mathbf{t}_i$ of all available training samples, respectively. The predicted 3×1 CIELAB vector $\hat{\mathbf{t}}_{GC}$ of $\mathbf{h}$ becomes $\hat{\mathbf{t}}_{GC} = \mathbf{W}_{GC}\mathbf{h}$.

As the statistical distribution of training samples has an important influence on estimation accuracy,[3] we select K training samples (excluding the candidate for prediction itself) with minimal distances from the candidate color sample in terms of color differences $d_k = \|\hat{\mathbf{t}}_{GC} - \mathbf{t}_k\|$, $k \in \{1, 2, \ldots, K\}$ and calculate the local colorimetric transform matrix $\mathbf{W}_{LC} = \mathbf{T}_{LC}\mathbf{H}_{LC}^{+}$, where $\mathbf{H}_{LC}$ and $\mathbf{T}_{LC}$ are the matrices of vectors $\mathbf{h}_k$ $(k=1,2,\ldots,K)$ and $\mathbf{t}_k$ $(k=1,2,\ldots,K)$, respectively. It should be noted that the selection of training samples is conducted in approximately perceptually uniform color space, which is different from previous studies.[4,5] The predicted CIELAB vector can then be computed as $\hat{\mathbf{t}} = \mathbf{W}_{LC}\mathbf{h}$.

To recover spectral reflectance, we adopt Wiener estimation[9] by employing the matrix of color-matching functions $\mathbf{M}_c$:

$$\hat{\mathbf{r}}_c = \mathbf{K}_r\mathbf{M}_c^T(\mathbf{M}_c\mathbf{K}_r\mathbf{M}_c^T + \mathbf{K}_n)^{-1}\hat{\mathbf{a}}, \tag{5}$$

where $\hat{\mathbf{a}} = F_{LAB}^{-1}(\hat{\mathbf{t}})$, $\mathbf{K}_r$ denotes the covariance matrix of $[\mathbf{r}_k]$, and $\mathbf{K}_n$ denotes the covariance matrix of noise. Here, $\mathbf{K}_n = \mathbf{0}$ is assumed.

Weighted spectral calculation: It is reasonable to assume that the training samples closer to the candidate should contribute more in reflectance estimation.[5] In this Letter, considering that color accuracy is always evaluated in terms of color difference, we use a multivariate Gaussian distribution function to decide the weighting of reflectance and response in CIELAB space:

$$\mathbf{r}_{\alpha,k} = \alpha_k\mathbf{r}_k, \quad \mathbf{u}_{\alpha,k} = \alpha_k\mathbf{u}_k, \tag{6}$$

where

Table 1. Polynomial Elements of Vector h with 14 and 20 Terms

Terms	$\mathbf{h} = F_{1/q}(u_1, u_2, u_3)$
14	$[u_1^{1/q}, u_2^{1/q}, u_3^{1/q}, (u_1u_2)^{1/q}, (u_1u_3)^{1/q}, (u_2u_3)^{1/q}, u_1^{2/q}, u_2^{2/q}, u_3^{2/q}, u_1^{3/q}, u_2^{3/q}, u_3^{3/q}, (u_1u_2u_3)^{1/q}, 1]^T$
20	$[u_1^{1/q}, u_2^{1/q}, u_3^{1/q}, (u_1u_2)^{1/q}, (u_1u_3)^{1/q}, (u_2u_3)^{1/q}, u_1^{2/q}, u_2^{2/q}, u_3^{2/q}, u_1^{3/q}, u_2^{3/q}, u_3^{3/q}, (u_1u_2u_3)^{1/q}, (u_1^2u_2)^{1/q}, (u_1^2u_3)^{1/q}, (u_2^2u_1)^{1/q}, (u_2^2u_3)^{1/q}, (u_3^2u_1)^{1/q}, (u_3^2u_2)^{1/q}, 1]^T$

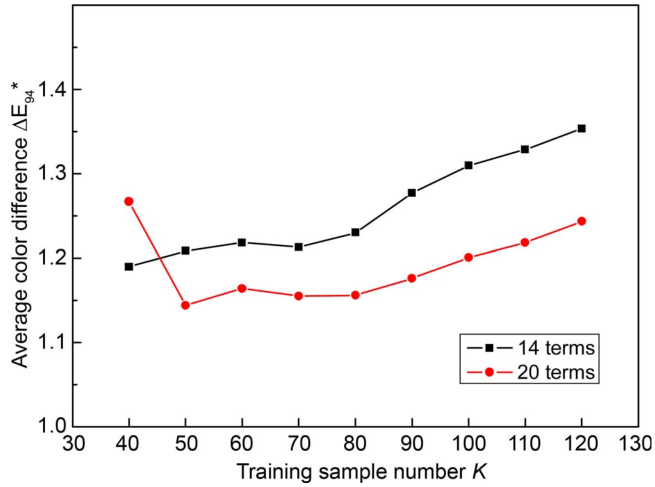

Fig. 1. (Color online) Distribution of average ΔE_{94}^* errors with respect to the number K of training samples when using target CDC under D65.

$$\alpha_k = (2\pi)^{-3/2}|\mathbf{K}_t|^{-1/2}\exp\left[-\frac{1}{2}(\mathbf{t}_k - \hat{\mathbf{t}})^T\mathbf{K}_t^{-1}(\mathbf{t}_k - \hat{\mathbf{t}})\right], \tag{7}$$

with $\mathbf{K}_t$ being the covariance matrix of $[\mathbf{t}_k]$. The local spectral transform matrix is calculated as $\mathbf{W}_{LS} = \mathbf{R}_{\alpha,LS}\mathbf{U}_{\alpha,LS}^{+}$, where $\mathbf{R}_{\alpha,LS}$ and $\mathbf{U}_{\alpha,LS}$ are the matrices of vectors $\mathbf{r}_{\alpha,k}$ $(k=1,2,\ldots,K)$ and $\mathbf{u}_{\alpha,k}$ $(k=1,2,\ldots,K)$, respectively. The reflectance then becomes

$$\hat{\mathbf{r}}_s = \mathbf{W}_{LS}\mathbf{u}. \tag{8}$$

Combined reflectance estimation: As these two calculations are independent, it is possible that the two recovered reflectances depart from the actual one in opposite directions at some wavelengths, and consequently, their combination may be able to improve reflectance estimation. We tried several combinations of these two reflectances including $\hat{\mathbf{r}} = (\hat{\mathbf{r}}_c\hat{\mathbf{r}}_s)^{1/2}$, $\hat{\mathbf{r}} = \frac{1}{3}[\hat{\mathbf{r}}_c + \hat{\mathbf{r}}_s + (\hat{\mathbf{r}}_c\hat{\mathbf{r}}_s)^{1/2}]$, $\hat{\mathbf{r}} = \beta\hat{\mathbf{r}}_c + (1-\beta)\hat{\mathbf{r}}_s$ where $\beta \in [0,1]$, and other forms. It was found that the simple average of $\hat{\mathbf{r}}_c$ and $\hat{\mathbf{r}}_s$ provides the most suitable final estimation:

$$\hat{\mathbf{r}} = \tfrac{1}{2}(\hat{\mathbf{r}}_c + \hat{\mathbf{r}}_s). \tag{9}$$

We evaluated the performance of the proposed method using a color scanner Epson GT-10000+. Three color targets, namely, GretagMacbeth ColorChecker DC (CDC), Kodak Gray Scale Q-14 (Q14), and Kodak Q60 photographic standard (IT8), were used. The images of these targets were scanned in at a resolution of 72 dots per inch. The reflectance data of the patches on CDC and Q14 were measured by the GretagMacbeth spectrophotometer 7000A, and those on IT8 were measured by the GretagMacbeth Spectroscan/Spectrolino spectrophotometer. The target Q14 was used for obtaining the OECF needed in Eq. (1), while CDC and IT8 were used for reflectance estimation. In total, 198 color patches (B1–B12,…,R1–R12, excluding the duplicated six most dark ones) in CQC and 144 color patches (A1–A12,…,

Table 2. Reflectance Estimation Accuracy of Different Methods when Using Target CDC

						Proposed		
			LRM	AE	OAE	Colorimetric-Based Spectral Calculation	Weighted Spectral Calculation	Combined
$\Delta E_{94}{}^{*}$	D65	Mean	3.08	1.65	1.52	1.24	1.24	1.14
		Maximum	13.3	7.46	7.19	5.88	6.49	6.17
	A	Mean	2.38	1.2	1.10	1.29	0.93	0.94
		Maximum	9.45	4.31	3.68	5.64	3.13	4.05
	F7	Mean	3.16	1.66	1.54	1.26	1.25	1.16
		Maximum	13.9	7.61	7.19	6.42	6.73	6.57
Spectral rms		Mean	0.033	0.019	0.017	0.027	0.015	0.019
		Maximum	0.117	0.094	0.099	0.149	0.078	0.105

[a]In the proposed method, $K=50$, $q=9$, and the term number is 20. In the AE and OAE methods, the training sample numbers are both 20.

L1–L12) in IT8 are used for reflectance estimation. In the experiment, the estimation error of each color patch is calculated with training samples selected in the same color target.

It is necessary to investigate the influences of individual factors on reflectance estimation accuracy. It is found that, for colorimetric-based spectral calculation (target CDC, 20 terms), the mean CIE 1994 color difference errors[10] $\Delta E_{94}{}^{*}$ under D65 with $q=1$, 3, 6, and 9 are 1.686, 1.249, 1.245, and 1.237, respectively. It is not surprising that $q=9$ produces the best estimation accuracy, as there are high-order terms and cross terms in the polynomial transform (Table 1). Figure 1 shows the mean $\Delta E_{94}{}^{*}$ errors under D65 for different combinations of polynomial terms and training sample numbers when $q=9$. Clearly, $K=50$ and the term number being 20 are appropriate. In addition to the $\Delta E_{94}{}^{*}$ error, the spectral rms error is also used for accuracy evaluation.

The performance of the proposed method is compared with those of the LRM-based,[1] AE,[4] and OAE[5] methods using targets CDC and IT8. Because of space limitations, only the results of CDC are given in Table 2. The mean $\Delta E_{94}{}^{*}$ error of the weighted spectral calculation is slightly larger than that of the OAE method for target IT8, and the improvement of the combined final estimation is ~ 0.1 $\Delta E_{94}{}^{*}$ unit. This is mainly due to the different numbers of training samples employed in the OAE and the weighted spectral calculation. For all other cases, the color accuracy of the proposed method is much better than the LRM, AE, and OAE methods in terms of the $\Delta E_{94}{}^{*}$ error at a significant level of $p<0.05$, while the spectral accuracy is close to those of the AE and OAE methods in terms of the spectral rms error. The combined final estimation of the proposed method is predominantly better than the colorimetric-based and weighted reflectance calculations in terms of the color difference error while in between them in terms of the spectral rms error. This is expected as the main objective of the proposed method is to minimize errors in CIELAB space.

In conclusion, a new method is proposed that recovers spectral reflectance from scanner responses with consideration of perceptual color space. This method performs better than previous methods in terms of color difference with very slight and even negligible degradation in spectral accuracy. The potential applications of the proposed method are art painting recording and industrial color quality control where high color accuracy is essential.

The authors thank the anonymous reviewers for comments and suggestions. H.-L. Shen's e-mail address is shenhl@zju.edu.cn.

References

1. M. Shi and G. Healey, J. Opt. Soc. Am. A **19**, 645 (2002).
2. G. W. Hong, M. R. Luo, and P. A. Rhodes, Color Res. Appl. **26**, 76 (2001).
3. J. M. Dicarlo and B. A. Wandell, J. Opt. Soc. Am. A **20**, 1261 (2003).
4. H. L. Shen and J. H. Xin, J. Opt. Soc. Am. A **21**, 1125 (2004).
5. H. L. Shen and J. H. Xin, J. Opt. Soc. Am. A **23**, 1566 (2006).
6. V. Cheung, S. Westland, C. Li, J. Hardeberg, and D. Connah, J. Opt. Soc. Am. A **22**, 1231 (2005).
7. M. Wolski, C. A. Bouman, J. P. Allebach, and E. Walowit, IEEE Trans. Image Process. **5**, 507 (1996).
8. J. Y. Hardeberg, "Acquisition and reproduction of color images: colorimetric and multispectral approaches," Ph.D. dissertation (Ecole Nationale Superieure des Telecommunications, 1999).
9. W. K. Pratt, *Digital Image Processing*, 2nd ed. (Wiley, 1991).
10. R. McDonald and K. J. Smith, J. Soc. Dyers Colour. **111**, 376 (1995).