Estimation of Optoelectronic Conversion Functions of Imaging Devices Without Using Gray Samples

Hui-Liang Shen,[1*] John H. Xin,[2*] Dong-Xiao Yang,[1] Dong-Wu Lou[1]

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

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

Received 9 February 2007; revised 7 April 2007; accepted 25 April 2007

Abstract: In the colorimetric or spectral characterization of imaging devices such as digital cameras and scanners, the optoelectronic conversion functions (OECFs) are traditionally obtained from standard gray samples. However, these gray samples are sometimes unavailable when conducting color characterization. We propose an efficient method for recovering OECFs by using nongray samples, based on the finite-dimensional modeling of spectral reflectance and the second-order polynomial fitting of OECFs. Experimental results indicate that the accuracy of the estimated OECFs are close to those obtained from gray samples, with the correlation coefficients R^2 larger than 0.995. The proposed method should be useful in colorimetric and spectral characterization of imaging devices by using custom-made color samples in textile or other industries, when standard gray samples are not available and not easily made. © 2008 Wiley Periodicals, Inc. Col Res Appl, 33, 135 – 141, 2008; Published online in Wiley InterScience (www.interscience.wiley.com). DOI 10.1002/col.20386

Key words: color imaging; OECF; color characterization; input devices; linear model; color measurement

INTRODUCTION

Nowadays, digital imaging devices such as scanner and digital camera are widely used in visualization, communication, and reproduction. To obtain the faithful color information in these processes, the imaging devices need to be color characterized. Colorimetric characterization transforms the device responses (usually red, green, and blue) into colorimetric tristimulus values,[1–5] while spectral characterization converts them into spectral reflectance.[5–7] Some recent works show that the accuracy of color characterization can be improved by appropriate selection of training samples.[4–6] When compared with spectral characterization, the main disadvantage of colorimetric characterization is that it can only obtain tristimulus values under a certain illuminant. Recently, Cheung *et al*. found that colorimetric characterization outperformed spectral characterization in terms of color difference error.[7]

As the responses of the imaging device are generally nonlinear to scene radiance, the optoelectronic conversion functions (OECFs)[8] should be obtained or recovered before color characterization. It is noted that the OECFs are more important for spectral characterization than for colorimetric characterization, as the former always works in linear reflectance space,[5–7] while the latter can incorporate this nonlinear property inside.[1,4] In the literature of color science, there are some techniques to obtain the OECFs. For example, the ISO 14524 standard[8] introduces a method by using a gray scale test pattern, and it has been employed in the ISO 17321 standard[2] for the color characterization of digital cameras. Martinez-Verdu *et al*. obtained the OECFs using a simulated spectrally neutral gray scale test pattern illuminated by an equal-energy illuminant, which is equivalent to changing lens aperture or exposure time.[3] Recently, Cheung *et al*. proposed a spectral-sensitivity-based technique to estimate the OECFs, and found it performed better than the luminance- and mean-reflectance-based techniques.[9] It is worthwhile

*Correspondence to: Hui-Liang Shen (e-mail: shenhl@zju.edu.cn) and John H. Xin (e-mail: tcxinjh@inet.pdyu.edu.hk).

Contract grant sponsor: NSF, China; Contract grant number: 60602027. Contract grant sponsor: HKRITA; Contract grant number: ITP/009/07TP.

to noted that, in the literature of computer vision, some techniques have been introduced to estimate the radiometric response functions (a similar term for OECFs) of camera from multiple images or even a single image.[10–12] In those techniques, the scene reflectance values are assumed unknown, which is different to color characterization discussed in this study.

In color characterization, standard color targets such as GretagMacBeth ColorChecker hart (MCC) and GretagMacBeth ColorChecker DC (CDC) are always employed. There are six gray patches on MCC and 13 unduplicated gray patches on CDC, whose spectral reflectance curves are very flat in the visible spectrum range. With these gray samples or other carefully designed neutral gray scale patterns, the OECF can be easily obtained. However, these standard gray samples may sometimes not be available when conducting color characterization. For example, in some industrial applications, imaging devices need to be characterized using custom-made color targets, but it is often quite difficult and also time-consuming to make such gray samples with dyestuffs or inks. In these applications, it is also not feasible to produce a series of different neutral illumination levels.

This study proposes a method to recover OECFs accurately by using only nongray samples, based on which color characterization of imaging device can be conducted when standard gray samples are not available. The recovery of the OECFs is mainly based on two techniques: finite-dimensional modeling of spectral reflectance[13,14] and high-order polynomial fitting of the OECFs.[3,12,15] In this study, the OECF estimation is based on color scanner, but it is also applicable to digital cameras. In the scope of OECF estimation and color characterization, the only difference between scanner and digital camera is that the former works under a fixed illuminant, while the later can work under a wide range of illuminants.

THE PROPOSED METHOD

Formulation of Imaging Process

Theoretically, for an ideal three-channel imaging device, i.e., color scanner, the 3×1 response vector $\mathbf{u}$ of an object surface can be formulated as

$$\mathbf{u} = \mathbf{M}\mathbf{r} + \mathbf{n}, \tag{1}$$

where the $3 \times N$ ($N = 31$) matrix $\mathbf{M}$ denotes spectral responsivity of the scanner, the $N \times 1$ vector $\mathbf{r}$ denotes spectral reflectance, and the 3×1 vector $\mathbf{n}$ denotes zero-mean imaging noise. The response u of a certain channel (for example, red) can be calculated as

$$u = \mathbf{m}^{\mathrm{T}}\mathbf{r}, \tag{2}$$

where the superscript T denotes transpose, and the $1 \times N$ vector $\mathbf{m}^{\mathrm{T}}$ represents a row vector of matrix $\mathbf{M}$. For simplicity in denotation and without loss of generality, the channel number is not explicitly expressed in Eq. (2) and the following discussion when no confusion is caused. It is also noted that the noise term is omitted in Eq. (2) and hereafter, as it only indicates the noise in the imaging process but is not involved in the following calculations unless otherwise especially mentioned.

Equations (1) and (2) assume that the responses of scanner are proportional to the intensity of light entering the sensor. However, for a traditional scanner, its actual response ρ of a channel may be subject to an input–output nonlinearity that can be represented by an OECF $F(\cdot)$ as the following[6]:

$$\rho = F(u) = F\left(\mathbf{m}^{\mathrm{T}}\mathbf{r}\right). \tag{3}$$

In the following discussion, ρ is referred as actual response and u is referred as linear response. It is noted that the OECFs of three channels are always different to each other. As ρ is actually known, the OECF is usually represented in its inverse counterpart $F^{-1}(\cdot)$

$$u = F^{-1}(\rho) = \sum_{i=1}^{N} m_i r_i, \tag{4}$$

where m_i and r_i are the ith element of vector $\mathbf{m}$ and $\mathbf{r}$, respectively.

For gray sample, its reflectance along the visible spectrum range is a constant, i.e., $r_i = r_0$. Hence, Eq. (4) can be written as

$$u = F^{-1}(\rho) = r_0 \sum_{i=1}^{N} m_i. \tag{5}$$

As $\mathbf{m}$ is fixed for an imaging system, the OECF can be simply obtained using a series of r_0 and ρ of gray samples. For nongray samples, however, this simple relationship does not hold. Therefore, it is necessary to propose a new OECF estimation method so that color characterization can be consequently conducted when gray samples are not available.

Recovery of Inverse OECF Using Nongray Samples

The inverse OECF is usually a monotonically increasing function, and can be represented using polynomial fitting[15]:

$$u = F^{-1}(\rho) = \sum_{k=0}^{K} c_k \rho^k. \tag{6}$$

where K is the order of polynomial terms.

In addition, as the reflectance of natural object is smooth in the visible spectrum range, $\mathbf{r}$ can be approximately represented using J ($\leq N$) basis functions[13]:

$$\mathbf{r} = \sum_{j=1}^{J} \alpha_j \mathbf{b}_j, \tag{7}$$

where $\mathbf{b}_j$ denotes the jth basis function, and α_j denotes its corresponding weighting. $\mathbf{b}_j$ can be calculated from the spectral reflectance space using principle component analysis.[13,14]

Substituting Eqs. (6) and (7) into (2) yields

$$u = \sum_{j=1}^{J} \alpha_j (\mathbf{m}^T \mathbf{b}_j) = \sum_{k=0}^{K} c_k \rho^k = c_0 + \sum_{k=1}^{K} c_k \rho^k. \quad (8)$$

It is noted that, as ρ is in the range of 0 and 255, c_0 is usually the largest one among c_k ($k = 0 \ldots K$). By dividing each side with c_0, followed by necessary arrangement, we get

$$\sum_{k=1}^{K} \left(\frac{c_k}{c_0}\right) \rho^k - \sum_{j=1}^{J} \left(\frac{\mathbf{m}^T \mathbf{b}_j}{c_0}\right) \alpha_j = -1. \quad (9)$$

Using vector-matrix notation, Eq. (9) becomes

$$\boldsymbol{\rho}^T \mathbf{c} - \boldsymbol{\alpha}^T \mathbf{d} = -1, \quad (10)$$

where

$$\boldsymbol{\rho} = \left[\rho, \ldots, \rho^K\right]^T, \quad (11)$$

$$\mathbf{c} = \left[\frac{c_1}{c_0}, \ldots, \frac{c_K}{c_0}\right]^T, \quad (12)$$

$$\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \ldots, \alpha_J]^T, \quad (13)$$

$$\mathbf{d} = \left[\frac{\mathbf{m}^T \mathbf{b}_1}{c_0}, \frac{\mathbf{m}^T \mathbf{b}_2}{c_0}, \ldots, \frac{\mathbf{m}^T \mathbf{b}_J}{c_0}\right]^T \quad (14)$$

Equation (10) can also be written as

$$\boldsymbol{\rho}_\alpha^T \mathbf{c}_d = -1 \quad (15)$$

where

$$\boldsymbol{\rho}_\alpha = \left[\boldsymbol{\rho}^T, \boldsymbol{\alpha}^T\right]^T, \quad (16)$$

$$\mathbf{c}_d = \left[\mathbf{c}^T, -\mathbf{d}^T\right]^T. \quad (17)$$

$\boldsymbol{\rho}_\alpha$ and $\mathbf{c}_d$ are both $(K + J) \times 1$ vectors. If Q ($Q \geq K + J$) training color samples are employed, Eq. (15) can be represented in its matrix form:

$$\boldsymbol{\Lambda}_\alpha \mathbf{c}_d = -\mathbf{I} \quad (18)$$

where $\boldsymbol{\Lambda}_\alpha$ is the $Q \times (K + J)$ matrix of vector $\boldsymbol{\rho}_\alpha^T$, and $\mathbf{I} = [1,1, \ldots ,1]^T$. Then the coefficient $\mathbf{c}_d$ can be solved:

$$\mathbf{c}_d = -\boldsymbol{\Lambda}_\alpha^+ \mathbf{I}. \quad (19)$$

where the superscript + denotes pseudo-inverse.

In this manner, $\mathbf{c}_d$, or equivalently, $\mathbf{c}$ and $\mathbf{d}$, are obtained by minimizing the root-mean-square (rms) errors of Q training samples, but the obtained polynomial coefficient $\mathbf{c}$ is usually not optimal under the OECF fitting meaning as we desired. To refine the estimate of $\mathbf{c}$, we first assume $\mathbf{d}$ is free of error, and calculate the linear response û using the estimated $\mathbf{d}$,

$$\hat{u} = \boldsymbol{\alpha}^T \mathbf{d}, \quad (20)$$

From Eqs. (8) and (20), it is noticed that û is actually the estimate of u/c_0, not u. However, it should be noted that the scaling factor c_0 will not affect the accuracy of color characterization. Actually, its effect will be cancelled through the normalization of linear response$u$ when constructing the inverse OECF. û can be represented by polynomial fitting:

$$\hat{u} = \left[1, \rho, \ldots, \rho^K\right] \begin{bmatrix} \hat{c}_0 \\ \hat{c}_1 \\ \vdots \\ \hat{c}_K \end{bmatrix} = \tilde{\boldsymbol{\rho}}^T \hat{\mathbf{c}}. \quad (21)$$

Then $\hat{\mathbf{c}}$ can be reestimated as

$$\hat{\mathbf{c}} = \left[\tilde{\boldsymbol{\rho}}^T\right]^+ [\hat{u}], \quad (22)$$

where $\left[\tilde{\boldsymbol{\rho}}^T\right]$, is the $Q \times (K + 1)$ matrix of vector $\tilde{\boldsymbol{\rho}}^T$, and $[\hat{u}]$ is the $Q \times 1$ vector of $\hat{u}$. The investigation indicates that the $\hat{\mathbf{c}}$ estimated from Eq. (22) is actually more accurate than the $\mathbf{c}$ (component vector of $\mathbf{c}_d$) estimated from Eq. (19), in terms of correlation coefficient R^2 with gray samples.

In addition, the estimation of $\hat{\mathbf{c}}$ can be further refined using the following procedure:

– Initialize ĉ according to Eq. (22)
– Iterate the followings for L times
  - $[\hat{u}] \leftarrow \left[\tilde{\boldsymbol{\rho}}^T\right] \hat{\mathbf{c}}$ /* û from polynomial fitting, Eq. (21) */
  - $\mathbf{d} \leftarrow \left[\boldsymbol{\alpha}^T\right]^+ [\hat{u}]$ /* calculate eigen-terms according to Eq. (20) */
  - $[\hat{u}] \leftarrow [\boldsymbol{\alpha}^T]^+ \mathbf{d}$ /* û from finite-dimensional model ing, Eq. (20) */
  - $\hat{\mathbf{c}} \leftarrow \left[\tilde{\boldsymbol{\rho}}^T\right]^+ [\hat{u}]$ /* coefficients from polynomial fitting, Eq. (22) */
– End Iteration

After the recovery of $\hat{\mathbf{c}}$, the OECFs can then be represented by polynomial fitting. The accuracy of the estimated OECFs can be evaluated by their correlation coefficients with gray samples. Further more, its performance of the proposed method can also be evaluated by the color errors of colorimetric and spectral characterization. It should be noted that the absolute accuracy of color characterization is not our concerns in this study, and hence we can just use simple color characterization techniques.

Colorimetric characterization using the OECFs

The colorimetric characterization is conducted based on the widely adopted high-order polynomial regression.[1,4] Note not to confuse the term "polynomial regression" in colorimetric characterization with the term "polynomial fitting" in OECF estimation. Hong *et al*. found that 11 polynomial terms could produce satisfactory results in digital camera characterization,[1] while Cheung and Westland used 20 terms instead.[4] As there are only 18 nongray samples on MCC, we consider second-order polynomial terms should be appropriate in this study, and thus we obtain a 10×1 second-order response vector $\mathbf{a}$:

$$\mathbf{a} = \left[\hat{u}_1, \hat{u}_2, \hat{u}_3, \hat{u}_1^2, \hat{u}_2^2, \hat{u}_3^2, \hat{u}_1\hat{u}_2, \hat{u}_1\hat{u}_3, \hat{u}_2\hat{u}_3, 1\right]^T \quad (23)$$

where $\hat{u}_i$ represents the linear response of the ith channel obtained from OECF. If let the 3×1 vector of the tristimulus values be $\mathbf{x}$, then the purpose of colorimetric is to find a 3×10 transform matrix $\mathbf{H}$ between $\mathbf{x}$ and $\mathbf{a}$ such that

$$\mathbf{x} = \mathbf{Ha} \quad (24)$$

If Q color samples are employed, $\mathbf{H}$ can be calculated as

$$\mathbf{H} = [\mathbf{x}][\mathbf{a}]^{+} \tag{25}$$

where $[\mathbf{x}]$ is $3 \times Q$ matrix of vector $\mathbf{x}$, and $[\mathbf{a}]$ is the $10 \times Q$ matrix of vector $\mathbf{a}$. The accuracy of colorimetric characterization based on the estimated OECFs can be evaluated by the recently developed CIEDE2000 color difference[16] ΔE_{00} error under an illuminant such as D65.

Spectral Characterization Using the OECFs

The purpose of spectral characterization is to estimate a $N \times 3$ transform matrix $\mathbf{W}$ such that

$$\mathbf{r} = \mathbf{W}\hat{\mathbf{u}}, \tag{26}$$

where $\hat{\mathbf{u}} = [\hat{u}_1, \hat{u}_2, \hat{u}_3]^{\mathrm{T}}$. W can be calculated using pseudo-inverse as

$$\mathbf{W} = [\mathbf{r}][\hat{\mathbf{u}}]^{+}, \tag{27}$$

where $[\hat{\mathbf{u}}]$ is the $3 \times Q$ matrix of vector $\hat{\mathbf{u}}$, and $[\mathbf{r}]$ is the $N \times Q$ matrix of $\mathbf{r}$. It is noted that there are other spectral characterization technique available in the literature.[5,6] As the spectral characterization is only used to evaluate the accuracy of the estimated OECFs in this study, we simply choose the pseudo-inverse based one.

In addition to ΔE_{00} error, we can further use the spectral rms error

$$\mathrm{rms} = \left(\frac{(\mathbf{r} - \hat{\mathbf{r}})^{\mathrm{T}} (\mathbf{r} - \hat{\mathbf{r}})}{N} \right)^{1/2} \tag{28}$$

to evaluate the accuracy of the spectral characterization.

EXPERIMENTAL RESULTS AND DISCUSSION

In the experiment, the color targets MCC and CDC were employed. The spectral reflectance data and the tristimulus values of the color patches on MCC and CDC were measured by using a GretagMacBeth spectrophotometer model 7000A. For CDC, 172 color patches were used, excluding the duplicated darkest ones, the duplicated lightest ones, and the glossy ones. These 172 color samples were divided into one set containing 157 nongray colors, and one set that containing 13 gray colors. Similarly, the color patches on MCC were also divided into two sets, with one set containing 18 nongray colors and the other set containing 6 gray colors. The two sets containing nongray samples were used for the OECF estimation in the proposed method, as well as colorimetric and spectral characterization. The accuracy of the proposed method was evaluated by the correlation coefficients R^2 between the estimated OECFs and those obtained from gray samples. The color different error and spectral rms error of color characterizations are also used in the accuracy evaluation. It should be noted that the sets of nongray samples were not further divided into training and testing subsets as usual color characterization, since the purpose of this experiment is to evaluate whether the accuracy of the estimated OECF is adequate for color characterizations, but not the color characterization methods themselves.

The investigation found that second-order polynomial fitting to OECFs was adequate for the scanner used in this study. But it should be noted that for other imaging devices more higher-order polynomial fitting may be necessary.[12] In the experiment, it is also interesting to investigate whether the two parameters, i.e., the number J of basis functions and the iteration time L, have obvious influences on the accuracy of OECF estimation. The experimental evaluation was conducted on simulated data and real data, respectively.

OECF Evaluation Using Simulated Scanner Responses

The simulated nonlinear response of a channel (for example, red) is calculated based on the spectral responsivity $\mathbf{m}$ of the scanner and the spectral reflectance $\mathbf{r}$ of the color sample, followed by an OECF with exponential form and added Gaussian noise n:

$$\rho = F(u) + n = lu^{1/\gamma} + n = l\left(\mathbf{m}^{\mathrm{T}}\mathbf{r}\right)^{1/\gamma} + n \tag{29}$$

In this study, we let $\gamma = 1.8$ and $l = 22$, and ρ is kept in the range [0, 255]. It should be noted that, different to Eq. (1), the noise term n in Eq. (29) is in the nonlinear response space. The spectral responsivities of all three channels are shown in Fig. 1, which is similar to the ones recovered froma real scanner.[6] To evaluate the influence of noise n on the OECF recovery method, we used four simulated datasets of nonlinear responses ρ: without noise, Gaussian noise with standard deviation $\sigma = 1.0$, 2.0, and 3.0, respectively.

The distribution of average ΔE_{00} errors with respect to different basis function numbers J and different noise levels for the colorimetric and spectral characterizations are shown in Figs. 2 and 3, respectively. The calculations are

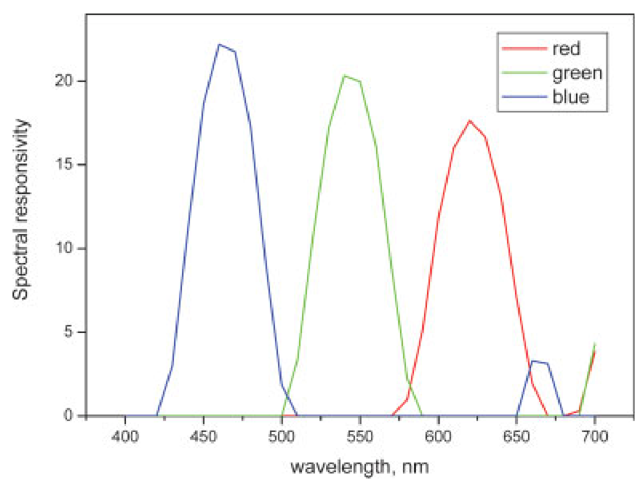

FIG. 1. The spectral responsivity of the scanner for simulating nonlinear responses. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

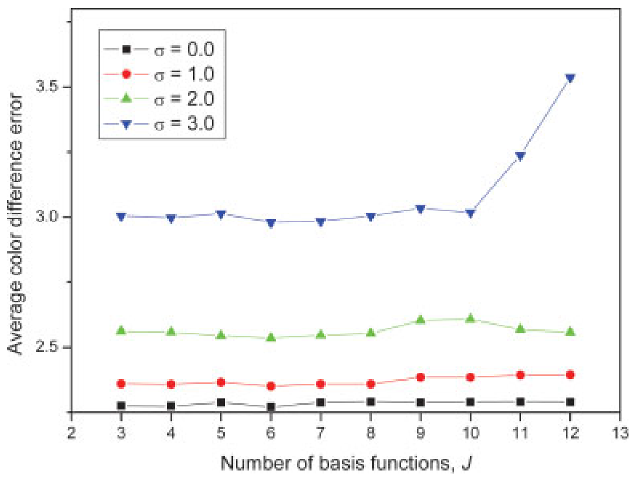

FIG. 2. Average ΔE_{00} errors of colorimetric characterization with respect to different numbers of basis functions J. The nonlinear responses ρ are simulated by using the scanner spectral responsivity and CDC spectral reflectance, added by different levels of Gaussian noises. Iteration number $L = 1$. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

based on CDC, and the iteration number $L = 1$. It is expected that, with the increasing of noise level, the color difference error becomes larger for both colorimetric and spectral characterizations. It is found from Fig. 2 that the color accuracy of colorimetric characterization keeps stable with respect to J when noise level $\sigma = 0.0$, 1.0, and 2.0. However, color difference errors become obviously larger when $\sigma = 3.0$ and $J > 10$. It is also found from Fig. 3 that the color difference errors of spectral characterization for small J values ($J \leq 4$) and large J values ($J \geq 9$) are usually larger than those of medium J values ($5 \leq J \leq 8$). This indicates that a small number of basis functions are usually not adequate to represent the spectral reflectance space, while the OECF estimation may be affected by noise when a large number of basis functions are used. This is not surprising as the high-order basis functions always contain high-frequency variations of reflectance, and thus the OECF estimation can be more easily affected by noise. In comparison, a small number of basis functions do not obviously degrade the accuracy of colorimetric characterization. The reason may be that the inaccuracy caused by insufficient basis functions can be compensated by the interaction terms and second-order terms in colorimetric characterization. In addition, the further color characterization on MCC found that ΔE_{00} distributions were rather fluctuant when noise level becomes heavier. The reason may be that as MCC contains only 18 nongray samples, the OECF estimation is more easily affected by noise.

OECF Evaluation Using Real Data

In experiment using real data, color targets MCC and CDC were scanned by using an EPSON scanner model GT-10000+ at a resolution of 72 dots per inch. In the scanning process, all color adjustment functions of the scanner are disabled, except tone correction. In this experiment, the spectral responsivity $\mathbf{M}$ is not needed. Figure 3 shows the variation of color difference errors with respect to the number of basis functions J when $L = 2$. It was found that the influence of parameter J was very obvious to the color accuracy of MCC especially when $J = 7$, but was not so evident to CDC. The reason may be that CDC contains more color samples than MCC, and thus the OECF estimation is accordingly more robust. It is also found that the color accuracy of colorimetric characterization is higher than spectral characteri-

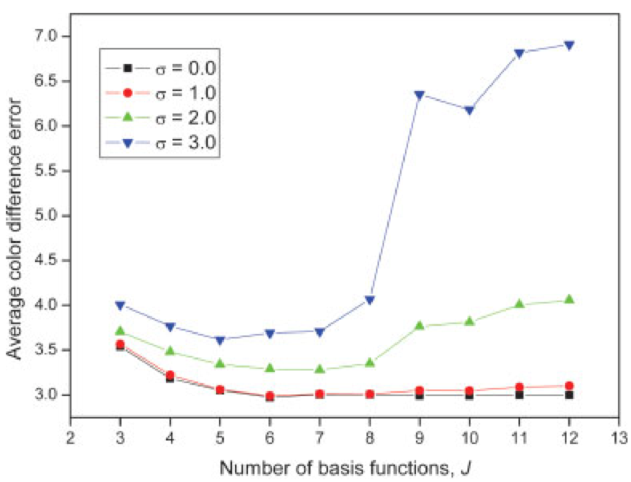

FIG. 3. Average ΔE_{00} errors of spectral characterization with respect to different numbers of basis functions J. The nonlinear responses ρ are simulated by using the scanner spectral responsivity and CDC spectral reflectance, added by different levels of Gaussian noises. Iteration number $L = 1$. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

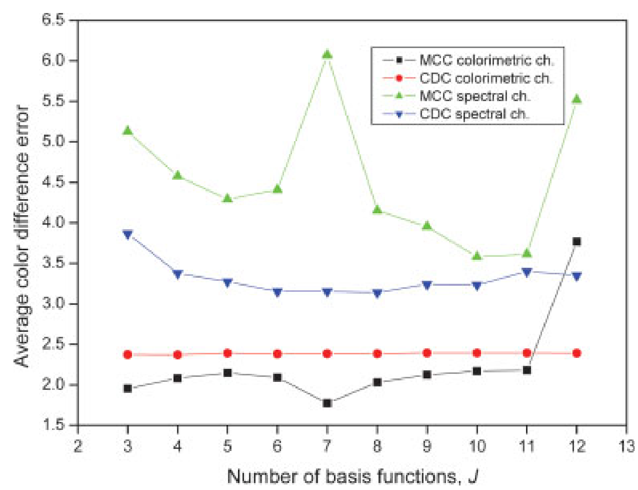

FIG. 4. Average ΔE_{00} errors of colorimetric and spectral characterizations with respect to different numbers of basis functions J. The actual responses ρ of MCC and CDC are used in calculation. Iteration number $L = 2$. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

TABLE I. Evaluation of the OECF estimation method in terms of correlation coefficient and by colorimetric characterization.

	Correlation coefficient R^2			Colorimetric characterization ΔE_{00} error		
	Red	Green	Blue	Mean	Std.	Max.
MCC						
Gray-based	–	–	–	2.13	1.75	5.96
Proposed						
$L = 0$	0.9988	0.9981	0.9666	2.03	1.68	6.12
$L = 1$	0.9980	0.9990	0.9954	2.11	1.71	5.95
$L = 2$	0.9973	0.9990	0.9995	2.14	1.73	5.85
$L = 3$	0.9969	0.9988	0.9998	2.16	1.76	5.81
CDC						
Gray-based	–	–	–	2.38	1.82	10.36
Proposed						
$L = 0$	0.9999	0.9998	0.9995	2.38	1.83	10.34
$L = 1$	0.9999	0.9998	0.9998	2.39	1.83	10.13
$L = 2$	0.9998	0.9997	0.9998	2.39	1.82	10.11
$L = 3$	0.9998	0.9997	0.9997	2.39	1.82	10.11

The correlation coefficients R^2 are calculated between the OECFs estimated from nongray samples and those obtained from gray samples. In the proposed method, the colorimetric characterization and OECF estimation are conducted on nongray samples. In the gray-based method, the OECFs are obtained from gray samples, while colorimetric characterization is conducted on nongray samples.

zation under the same conditions. This finding is in consistent to that by Cheung *et al.*[5] From Fig. 4, $J = 8$ is considered to be appropriate in both colorimetric and spectral characterization, for either MCC or CDC. Tables I and II show the influences of parameter L on OECF estimations and consequently on colorimetric and spectral characterizations, respectively. The correlation coefficients R^2 were calculated between the OECFs estimated from nongray samples and those obtained from gray samples. In Tables I and II, color characterization and OECF estimation are both conducted on nongray samples in the proposed method. While in the gray-based method, the OECFs are obtained from gray samples, but color characterization is also conducted on nongray samples.

Tables I and II show that increasing L will generallyproduce accurate OECF estimation. The only exception is in the colorimetric characterization on MCC, where the average color error increases from 2.03 to 2.16 when L increases from 0 to 3. Nevertheless, the color accuracy of the proposed method is still very close to that of the gray-based method. As a whole, it isconsidered that $L = 2$ is adequate and suitable for nongray sample based OECF estimation. For this reason, $L = 2$ is also used in Fig. 4. The correlation coefficients in all cases are larger than 0.995. Figure 5 plots the estimated three CDC OECFs using nongray samples and the actual ones from gray samples. It is obvious that these two kinds of OECFs are very close. On comparing with the results of previous works,[9] the proposed OECF estimation method is considered to be adequate and useful for colorimetric and spectral characterizations, especially when gray samples are not available.

CONCLUSION

A method for OECF estimation that does not require gray samples is proposed based on the finite-dimensional modeling of spectral reflectance and the second-order polynomial fitting of OECFs. The experimental results indicate that, to obtain accurate estimation of the OECFs, the number of basis functions need to be appropriately selected when there are not many training samples (such as the case of MCC). On the other hand, the influence of iteration number is not obvious. The correlation coefficients R^2 between the OECFs estimated from nongray samples and those directly obtained from gray samples are larger than 0.995. The performance of the OECF estimation method is further verified by the color accuracy of colorimetric and spectral characterizations.

TABLE II. Evaluation of the OECF estimation method in terms of correlation coefficient and by spectral characterization.

	Correlation coefficient R^2			Spectral characterization: ΔE_{00} error			Spectral characterization: Spectral rms error		
	Red	Green	Blue	Mean	Std.	Max.	Mean	Std.	Max.
MCC									
Gray-based	–	–	–	3.58	2.76	12.11	0.040	0.017	0.074
Proposed									
$L = 0$	0.9988	0.9981	0.9666	4.15	2.64	12.31	0.040	0.017	0.076
$L = 1$	0.9980	0.9990	0.9954	3.65	2.48	11.18	0.040	0.018	0.077
$L = 2$	0.9973	0.9990	0.9995	3.43	2.47	10.73	0.040	0.019	0.078
$L = 3$	0.9969	0.9988	0.9998	3.35	2.46	10.60	0.040	0.019	0.078
CDC									
Gray-based	–	–	–	3.05	1.81	12.09	0.033	0.021	0.147
Proposed									
$L = 0$	0.9999	0.9998	0.9995	3.13	1.88	12.58	0.033	0.022	0.150
$L = 1$	0.9999	0.9998	0.9998	3.05	1.78	12.49	0.033	0.022	0.150
$L = 2$	0.9998	0.9997	0.9998	3.03	1.77	12.39	0.033	0.022	0.150
$L = 3$	0.9998	0.9997	0.9997	3.02	1.76	12.32	0.033	0.022	0.150

The correlation coefficients R^2 are calculated between the OECFs estimated from nongray samples and those obtained from gray samples. In the proposed method, the spectral characterization and OECF estimation are conducted on nongray samples. In the gray-based method, the OECFs are obtained from gray samples, while spectral characterization is conducted on nongray samples.

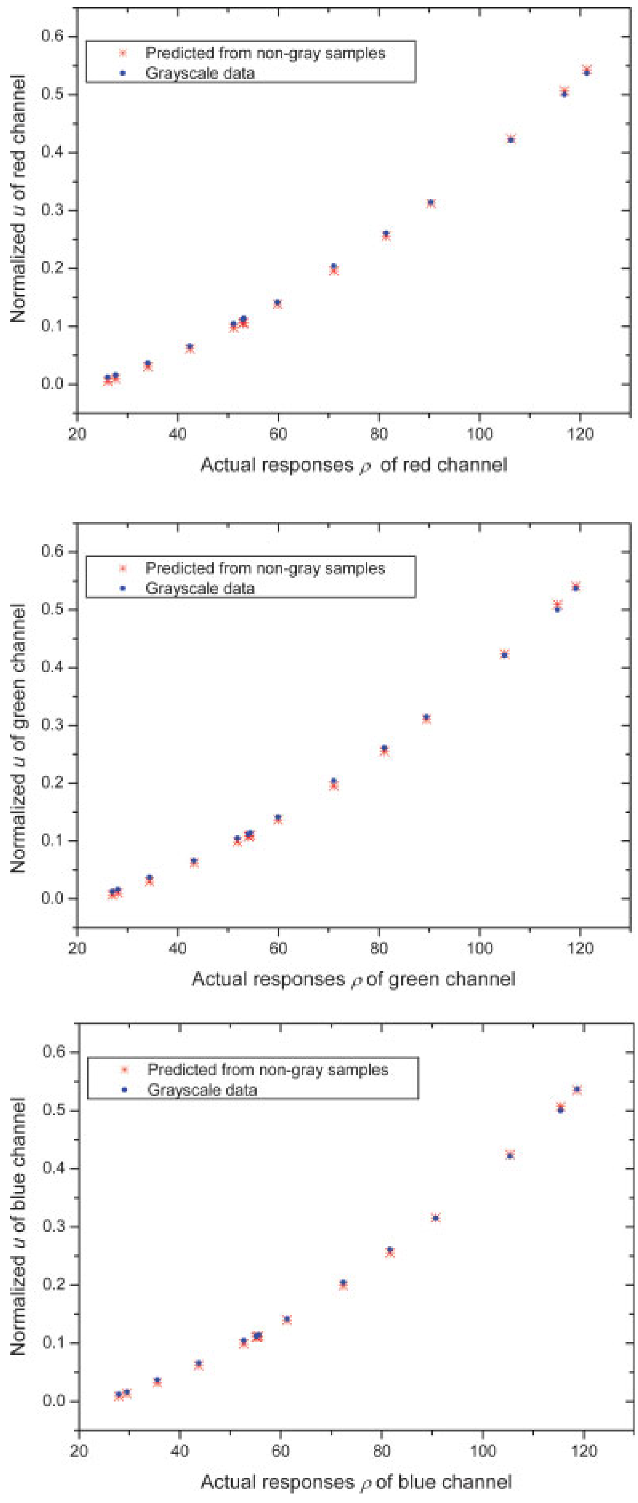

FIG. 5. The OECFs from gray samples and the OECFs estimated using nongray samples in red, green, and blue channels when iteration number $L = 2$ and basis function number $J = 8$. The circles represent the normalized average reflectance of gray samples, and the asterisks represent the normalized linear response $\hat{u}$ predicted from estimated OECFs. The color target is CDC. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

The proposed method is very necessary in color imaging and industrial colorquality evaluation when standard gray scale samples are not available. For example, in the textile industry, color scanner is sometimes employed to acquire images with high color fidelity. This can be ensured through color characterization by using some color textile fabrics. However, it is always difficult to collect or dye aseries of fabrics with flat spectral reflectance. The proposed method provides a promising solution for accurate colorimetric and spectral characterization of color scanner in this case.

It should benoted that a linear imaging model between the OECF-based linear response and spectral reflectance is assumed in this study. However, some scanners and digital cameras may employ nonlinear color adjustments in additional to tone correction. If applicable, these color adjustment functions should be disabled before estimating the OECFs from nongray samples. Otherwise, standard gray samples must be used to obtain the OECFs instead.

1. Hong GW, Luo MR, Rhodes PA. A study of digital camera colorimetric characterization based on polynomial modeling. Color Res Appl 2001;26:76–84.
2. ISO 17321 WD4, Colour characterisation of digital still cameras (DSCs) using colour targets and spectral illumination. 1999.
3. Martinez-Verdu F, Pujol J, Capilla P. Characterization of a digital camera as an absolute tristimulus colorimeter. J Imaging Sci Technol 2003;47:279–295.
4. Cheung V, Westland S. Methods for optimal color selection. J Imaging Sci Technol 2006;50:481–488.
5. Cheung V, Westland S, Li C, Hardeberg J, Connah D. Characterization of trichromatic color cameras by using a new multispectral imaging technique. J Opt Soc Am A 2005;22:1231–1240.
6. Shen HL, Xin JH. Spectral characterization of a color scanner by adaptive estimation. J Opt Soc Am A 2004;21:1125–1130.
7. Hardeberg JY. Acquisition and reproduction of color images: Colorimetric and multispectral approaches, Ph.D. dissertation. France: Ecole Nationale Superieure des Telecommunications; 1999.
8. ISO 14524, Photography—electronic still picture cameras—methods for measuring opto-electronic conversion functions (OECFs). 1999.
9. Cheung V, Westland S, Thomson M. Accurate estimation of the nonlinearity of input/output responses for color cameras. Color Res Appl 2004;29:406–421.
10. Grossberg MD, Nayar SK. Modeling the space of camera response functions. IEEE Trans Pattern Anal Mach Intell 2004;26:1272–1282.
11. Lin S, Gu G, Yamazaki S, Shum HY. Radiometric calibration from a single image. Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Washington, DC, USA, 2004. p 938–945.
12. Mitsunaga T, Nayar SK. Radiometric self calibration. Proceedings of the 1999 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Fort Collins, CO, USA, 1999. p 374–380.
13. Maloney L. Evaluation of linear models of surface spectral reflectance with small numbers of parameters. J Opt Soc Am A 1986;3:1673–1683.
14. Tzeng DY, Berns RS. A review of principle components analysis and its applications to color technology. Color Res Appl 2005;30:84–98.
15. Westland S, Ripamonti C. Computational Color Science: Using MATLAB. Chichester, UK: Wiley; 2004.
16. Luo MR, Cui G, Rigg B. The development of the CIE 2000 colour-difference formula: CIEDE 2000. Color Res Appl 2001;26:340–350.