Spectral characterization of a color scanner based on optimized adaptive estimation

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A scanner characterization method is proposed to estimate spectral reflectance from scanner responses by using an optimized adaptive estimation method. In contrast to our previous study [J. Opt. Soc. Am. A **21**, 1125 (2004)], this method considers the weighting of training samples. It is demonstrated that the color accuracy of this method is only slightly affected by the number of training samples and can provide more accurate reflectance estimation. © 2006 Optical Society of America

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1. INTRODUCTION

In applications of textiles and paint industries, it is often desired to estimate the color of a specimen under different viewing illuminants with the use of a single imaging device such as a color scanner. As the set of scanning filters is an important component for color accuracy, the design of filters and the figures of merit have been widely investigated by Trussell and co-workers.[1,2] For a certain commercial scanner, the filters are fixed and cannot be further modified. In this case, the problem can be posed as spectral characterization, which is to estimate the spectral reflectance from the scanner responses.[3–7] Recently, Shi and Healey[3] proposed a scanner characterization method based on the high-dimensional linear reflectance model (LRM), which is superior to the widely adopted polynomial-regression-based method.[4] However, the behavior of a real scanner usually departs from the LRM considerably, and hence the recovered spectral responsivity should not be explicitly used for accurate reflectance estimation. In addition, it is not reliable to estimate the reflectance by using just a single training sample. Considering these limitations, Shen and Xin[5] proposed a characterization method by adaptive estimation (AE) using a set of neighboring training samples. It was reported that this method outperformed the LRM-based method in terms of color difference error and reflectance error. Tsumura *et al.* also presented a method similar to AE and found that it can provide improved spectral reflectance estimation in comparison with the conventional method.[6] However, the AE method also has its limitation. The number of training samples has an obvious influence on color accuracy, and hence it is sometimes difficult in practical application to decide how many training samples are appropriate.

In this study, we propose a spectral characterization method, using an optimization technique to deal with this limitation. In contrast to our previous study,[5] this method considers the appropriate weighting of training samples, which takes into account the contributions of individual training samples in spectral estimation. It is reasonable to assume that the training samples closer to the target color should be more important.

2. REFLECTANCE ESTIMATION BY SCANNER CHARACTERIZATION

Vector space notation has been widely used to solve problems in color imaging systems. It is assumed that the visual spectrum 400–700 nm is equally sampled at N (N usually equals 31) wavelengths. For a three-channel color scanner, the device response can be formulated as[5,8]

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

where $\mathbf{v}$ is a 3×1 vector of device responses, $\mathbf{M}$ is the $3\times N$ matrix of spectral responsivity, $\mathbf{r}$ is a $N\times 1$ vector of spectral reflectance of the object, and $\mathbf{n}$ is the 3×1 constant bias vector. It should be noted that the spectral responsivity $\mathbf{M}$ combines all the effects of spectral transmittance of the filters, spectral sensitivity of the detectors, and the spectral radiance of the scanner illuminant. Equation (1) assumes that the scanner response is proportional to the intensity of the light entering the detector. For a common scanner, however, its responses are usually subject to an optoelectronic conversion function $F(\cdot)$[9,10]:

$$\boldsymbol{\rho} = F(\mathbf{v}) = F(\mathbf{M}\mathbf{r} + \mathbf{n}), \tag{2}$$

where $\boldsymbol{\rho}$ is the 3×1 vector of the actual nonlinear responses of the scanner.

The spectral responsivity $\mathbf{M}$ can be mathematically recovered by consideration of the physical constraints of smoothness, nonnegativity, and response accuracy.[5,11] The bias vector $\mathbf{n}$ in Eq. (1) can then be obtained. However, it is found that the recovered spectral responsivity is not very reliable and should not be explicitly used for scanner characterization. This is the major reason why the spectral characterization method based on the LRM fails to provide satisfactory color accuracy on an actual scanner.[5]

A. Adaptive Estimation Method

For completeness, the formulation of the AE method[5] is briefly summarized below. If $\mathbf{u}=\mathbf{v}-\mathbf{n}$, Eq. (1) becomes

$$\mathbf{u} = \mathbf{M}\mathbf{r}. \tag{3}$$

The estimation of reflectance is to find an $N \times 3$ matrix $\mathbf{W}$ that can transform the scanner response $\mathbf{u}$ into the predicted reflectance $\hat{\mathbf{r}}$,

$$\hat{\mathbf{r}} = \mathbf{W}\mathbf{u}, \tag{4}$$

such that the mean square error

$$J_0 = \frac{1}{L}\sum_{i=1}^{L} \|\hat{\mathbf{r}}_i - \mathbf{r}_i\|^2 = \frac{1}{L}\sum_{i=1}^{L} \|\mathbf{W}\mathbf{u}_i - \mathbf{r}_i\|^2 \tag{5}$$

is minimized. In Eq. (5), L is the number of training samples, and $\mathbf{r}_i$ and $\mathbf{u}_i$ represent the reflectance and response of the ith training sample, respectively. Let $\mathbf{R}$ be the $N \times L$ matrix combining $\mathbf{r}_i$, and let $\mathbf{U}$ be the $3 \times L$ matrix combining $\mathbf{u}_i$; then the matrix $\mathbf{W}$ in the AE method can be solved using the Wiener estimation as

$$\mathbf{W}_{\mathrm{AE}} = (\mathbf{R}\mathbf{U}^T)(\mathbf{U}\mathbf{U}^T)^{-1}. \tag{6}$$

In the AE method, the L samples with the smallest Euclidean distances in reflectance space (excluding the candidate $\mathbf{u}$ itself) are used for training. Alternatively, the training samples can also be selected in the low-dimensional response space to reduce calculations.[12]

B. Optimization Method

It must be noted that in the AE method, the L training samples $\mathbf{u}_i$ are equally treated in the calculation of $\mathbf{W}$, despite their distance with respect to the candidate $\mathbf{u}$. It is reasonable to assume that the training samples $\mathbf{u}_i$ nearer to candidate $\mathbf{u}$ are usually more reliable and thus should contribute more to the estimation of $\mathbf{W}$. In this sense, the contribution of $\mathbf{u}_i$ needs to be weighted as

$$\alpha_i = (2\pi)^{-3/2}|\boldsymbol{\Sigma}_{\mathbf{uu}}|^{-1/2} \exp\left[-\tfrac{1}{2}(\mathbf{u}_i - \mathbf{u})^T \boldsymbol{\Sigma}_{\mathbf{uu}}^{-1}(\mathbf{u}_i - \mathbf{u})\right], \tag{7}$$

where $\boldsymbol{\Sigma}_{\mathbf{uu}}$ is the covariance matrix of $\mathbf{u}_i$ defined as

$$\boldsymbol{\Sigma}_{\mathbf{uu}} = E\{(\mathbf{u}_i - \bar{\mathbf{u}})(\mathbf{u}_i - \bar{\mathbf{u}})^T\}, \tag{8}$$

where $E\{\cdot\}$ represents statistical expectation and $\bar{\mathbf{u}}$ is the mean of $\mathbf{u}_i$.

By incorporating the sample weighting, the mean square error between the actual and the predicted reflectance can be reformulated as

$$J_1 = \frac{1}{L}\sum_{i=1}^{L} \|\alpha_i\hat{\mathbf{r}}_i - \alpha_i\mathbf{r}_i\|^2. \tag{9}$$

Substituting Eq. (4) into Eq. (9) yields

$$J_1 = \frac{1}{L}\sum_{i=1}^{L} \|\mathbf{W}\alpha_i\mathbf{u}_i - \alpha_i\mathbf{r}_i\|^2 = \frac{1}{L}\sum_{i=1}^{L} \|\mathbf{W}\tilde{\mathbf{u}}_i - \tilde{\mathbf{r}}_i\|^2, \tag{10}$$

where $\tilde{\mathbf{u}}_i = \alpha_i\mathbf{u}_i$ and $\tilde{\mathbf{r}}_i = \alpha_i\mathbf{r}_i$.

Let $\tilde{\mathbf{R}}$ be the $N \times L$ matrix combining $\tilde{\mathbf{r}}_i$, and let $\tilde{\mathbf{U}}$ be the $3 \times L$ matrix combining $\tilde{\mathbf{u}}_i$; then matrix $\mathbf{W}$ can be easily solved as

$$\mathbf{W}_{\mathrm{opt}} = (\tilde{\mathbf{R}}\tilde{\mathbf{U}}^T)(\tilde{\mathbf{U}}\tilde{\mathbf{U}}^T)^{-1}. \tag{11}$$

By comparing Eqs. (6) and (11), we can find that the form of the solution $\mathbf{W}$ is similar in the AE and optimization methods.

3. EXPERIMENT AND DISCUSSION

Three color targets, namely, GretagMacBeth ColorChecker DC (CDC), Kodak Q60 photographic standard (IT8), and Kodak Gray Scale Q-14 (Q14), were used in the experiment. There are more than 200 color samples in the targets CDC and IT8. The majority of the samples of the target CDC are of diffuse material. The glossy ones (S1-T12) of CDC were excluded in the training sample database owing to the problem of material metamerism.[4,12] The dark samples of CDC were also not used because of low signal-to-noise ratio. The color target IT8 is of gloss film material, and all its color samples were used in the training sample database. The 20 neutral colors on Q14 were used to calculate the inverse optoelectronic conversion function in Eq. (2), but they do not serve as training samples. These three targets were scanned in, using the scanner Epson GT-10000+ at an appropriate resolution. During the scanning process, all the color adjustment functions of the scanner were disabled so that the raw color information could be obtained. The reflectance data were the same as those used in our previous study.[5] Considering the problems of material metamerism and different measurement instruments, the colors of CDC were not used as training samples for IT8 and vice versa.

In both the AE and the optimization methods, the selection of training samples is according to the Euclidean distance in the scanner response space:

$$d_i = \|\mathbf{u} - \mathbf{u}_i\|. \tag{12}$$

The L samples with smallest distances are used in Eqs. (6) and (11) for the estimation of $\mathbf{W}$. If the predicted spectral reflectance value is lower than 0 or larger than 1.0, it is simply clipped to 0 and 1.0, respectively. The color accuracy was evaluated in terms of color difference ΔE^*_{94} (Ref. 13) under four different illuminants (D65, A, F2, and F7) and rms error of reflectance:

$$\text{rms error} = \left[\frac{(\mathbf{r} - \hat{\mathbf{r}})^T(\mathbf{r} - \hat{\mathbf{r}})}{N}\right]^{1/2}. \tag{13}$$

For comparison of the AE and optimization methods, the ΔE^*_{94} under illuminant D65 with respect to different numbers of training samples L using the targets CDC and IT8 are given in Table 1. It is obvious that the optimization method performs better in terms of the mean, standard deviation (Std.), and maximum (Max.) of ΔE^*_{94}. For the optimization method, the color difference errors of CDC for L from 20 to 90 are all about 1.50, and those of IT8 range from 1.16 to 1.55. In comparison, the variations of color difference errors of the AE method are very large, with 1.65–2.30 for CDC and 1.59–2.97 for IT8. Therefore it is

Table 1. ΔE_{94}^{*} Error under Illuminant D65 with Respect to the Number of Training Samples L for the Optimization and AE Methods with targets CDC and IT8

	CDC						IT8					
	Optimization			AE			Optimization			AE		
L	Mean	Std.	Max.	Mean	Std.	Max.	Mean	Std.	Max.	Mean	Std.	Max.
10	2.00	3.16	25.52	1.89	2.54	24.42	1.17	0.77	4.37	1.35	0.90	5.15
15	1.76	2.19	16.27	1.75	1.81	15.90	1.15	0.77	4.60	1.53	1.15	7.34
20	1.52	1.41	7.19	1.65	1.36	7.46	1.16	0.84	6.14	1.59	1.22	7.52
25	1.48	1.37	6.81	1.66	1.38	8.19	1.16	0.82	6.13	1.68	1.30	7.95
30	1.47	1.36	7.64	1.78	1.40	8.30	1.16	0.81	6.11	1.75	1.36	8.03
35	1.47	1.34	7.77	1.84	1.40	8.71	1.18	0.80	5.97	1.83	1.37	8.21
40	1.46	1.33	7.46	1.91	1.42	8.88	1.21	0.85	5.75	1.92	1.41	8.67
45	1.46	1.30	6.54	1.97	1.46	9.37	1.24	0.88	5.44	2.07	1.46	9.06
50	1.46	1.29	6.57	2.03	1.47	8.80	1.26	0.92	5.28	2.22	1.54	10.10
55	1.47	1.29	6.59	2.06	1.52	8.84	1.29	0.96	5.73	2.36	1.60	10.43
60	1.47	1.29	6.55	2.07	1.53	8.93	1.31	0.99	6.15	2.48	1.66	9.75
65	1.47	1.29	6.65	2.13	1.54	9.34	1.33	1.02	6.34	2.58	1.75	9.99
70	1.47	1.28	6.63	2.16	1.54	9.86	1.35	1.04	6.66	2.70	1.94	11.67
75	1.48	1.27	6.66	2.22	1.53	9.96	1.40	1.11	7.15	2.75	1.98	12.70
80	1.49	1.29	6.72	2.22	1.52	9.63	1.44	1.15	7.44	2.82	2.01	11.66
85	1.49	1.28	6.81	2.25	1.53	9.61	1.49	1.20	7.57	2.94	2.01	10.72
90	1.50	1.28	6.89	2.30	1.52	9.62	1.55	1.25	7.74	2.97	1.98	10.15
95	1.52	1.28	7.05	2.35	1.54	10.38	1.61	1.28	7.78	3.05	2.10	11.07
100	1.53	1.29	7.29	2.39	1.56	10.40	1.80	1.41	8.33	3.33	2.21	11.05
105	1.56	1.30	7.50	2.42	1.57	10.61	1.87	1.47	8.55	3.42	2.26	11.10

Table 2. Comparison of the Optimization (Opt), AE, and LRM-based Methods in Terms of ΔE_{94}^{*} Error and rms Error Using Target CDC[a]

	D65			A			F2			F7			rms Error		
Method	Mean	Std.	Max.	Mean	Std.	Max.	Mean	Std.	Max.	Mean	Std.	Max.	Mean	Std.	Max.
Opt.	1.52	1.41	7.19	1.10	0.82	3.68	1.48	1.17	5.92	1.54	1.39	7.19	0.017	0.015	0.099
AE	1.65	1.36	7.46	1.20	0.87	4.31	1.65	1.33	7.29	1.66	1.38	7.61	0.019	0.017	0.094
LRM	3.08	2.29	13.3	2.38	1.50	9.45	3.11	2.29	15.4	3.16	2.30	13.9	0.033	0.023	0.117

[a]For the optimization and AE methods, the number of training samples $L=20$.

Table 3. Comparison of the Optimization (Opt), AE, and LRM-based Methods in Terms of ΔE_{94}^{*} Error and rms Error Using Target IT8[a]

	D65			A			F2			F7			rms Error		
Method	Mean	Std.	Max.	Mean	Std.	Max.	Mean	Std.	Max.	Mean	Std.	Max.	Mean	Std.	Max.
Opt.	1.16	0.84	6.14	1.15	0.82	5.61	1.13	0.83	6.22	1.15	0.85	6.40	0.007	0.005	0.027
AE	1.59	1.21	7.52	1.46	0.98	6.02	1.51	1.03	5.99	1.58	1.21	7.44	0.008	0.006	0.028
LRM	3.32	2.21	13.8	3.04	1.93	10.6	2.97	1.80	10.0	3.24	2.12	13.6	0.014	0.008	0.067

[a]For the optimization and AE methods, the number of training samples $L=20$.

reasonable to conclude that the performance of the optimization method is less influenced by the number of training samples L and can thus provide more accurate estimation of reflectance. This advantage is important since in practical application, it is sometimes difficult to decide how many training samples are suitable.

The color difference errors under different illuminants and the reflectance rms errors of the optimization method, the AE method, and the LRM-based method are given in Tables 2 and 3. In these two tables, the number of training samples $L=20$, which is the most suitable value for the AE method. It is easy to find that the optimization method performs obviously better than the LRM-based method for both targets and the AE method for the IT8 target. Compared with the AE method for the target CDC, the optimization improves by about a 0.1

color difference unit when $L=20$. Despite the seemingly slight amplitude, the statistical t-test shows that the color difference errors of the optimization method are lower than those of the AE method at a significant level, $p < 0.05$.

4. CONCLUSION

This study proposes a method to estimate high-dimensional reflectance from low-dimensional device responses by using an optimization technique. In contrast to the previous adaptive estimations,[5] it incorporates the weighting of training samples. Experiment evaluation indicates that this method outperforms the adaptive estimation method and the linear-reflectance-model-based method in terms of both color difference error and reflectance rms error. In addition, as the color accuracy of the optimization method is less influenced by the number of training samples, it should be more practical for color correction applications.

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