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Spectral Encoding/Decoding Using LabRGB

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Abstract. *Spectral encoding/decoding methods using unique base functions and physically meaningful values were explored. Three new methods such as, TrW6 consisting of six unique trigonometric functions, Lab2 consisting of two CIELAB functions, and LabRGB consisting of CIELAB and RGB, were derived and compared against the traditional eigenvectors method. It was found that TrW6 and LabRGB showed almost the same accuracy as the traditional eigenvector method. By using LabRGB, color characteristics can be estimated by only looking at its encoding values and we do not have to exchange base functions beforehand for exchanging a different population of object colors. LabRGB can be applied not only to spectral imaging but also to traditional trichromatic imaging world, so its use can extend beyond spectral uses. © 2008 Society for Imaging Science and Technology.*
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INTRODUCTION

Spectral encoding/decoding using eigenvectors is a well-known method since a long time ago. For example, spectral distribution can be written as a linear combination of six eigenvectors, such as

$$\rho(\lambda) = \sum_{i=1}^{6} w_i \cdot e_i(\lambda), \tag{1}$$

where λ is wavelength, $\rho(\lambda)$ is spectral reflectance of an object color, $e_i(\lambda)$ is ith eigenvector and w_i is a weighting factor of the ith eigenvector.

In the present study, six eigenvectors from $e_1(\lambda)$ through $e_6(\lambda)$ were obtained first by principal component analysis applied to a population of object colors as described below.

(a) Generating 1000 object colors using the pseudo-object color generating method.[1]
(b) Calculating eigenvectors by principal component analysis.
(c) Verifying estimation error.

An example of eigenvectors is shown in Figure 1.

The pseudo-object color generating method is a convenient method to generate spectral reflectance of pseudo-object colors with an assumption of less than 3% variations from the average reflectance of neighboring samples on an object's reflectance spectrum for 10 nm step data.

First, spectral reflectance estimation was made on an object color by multiple regression analysis using Eq. (1) with known eigenvectors and unknown weighting factors (called *W*6). Figure 2 shows spectral reflectance estimation for one color from the Macbeth color chart and Figure 3 shows the standard deviation of reflectance estimation as a function of wavelength for 1000 pseudo-object colors.

An encoding/decoding method above using eigenvectors has the lowest estimation error. On the other hand, eigenvectors cannot be defined uniquely, because they de-

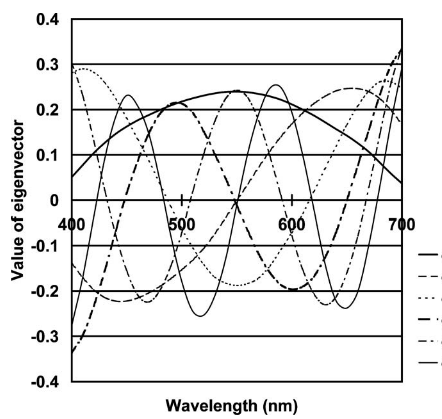

Figure 1. Example of eigenvectors.

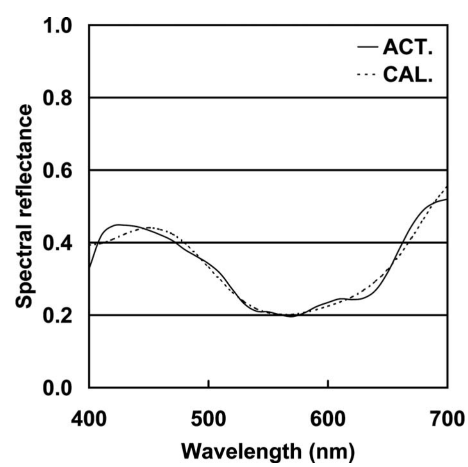

Figure 2. Spectral reflectance estimation using W6.

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pend on a sample selection from a larger population. Also, values used in the encoding/decoding method using eigenvectors have no physical meaning. So it is difficult to directly estimate either a shape of spectral reflectance, or color characteristics of an original object color. It is therefore not easy to verify an encoding/decoding process. Furthermore, this strategy cannot be applied to current trichromatic imaging systems directly.

Accordingly several challenges have been made to the encoding/decoding method described above. A recently reported one is LabPQR.[2] LabPQR is a concept of encoding which has three dimensions (CIELAB[3]) to represent the colorimetric characteristics of a color under a specific illuminant and additional dimensions PQR to describe the metameric black spectrum of a spectral power distribution.[4] The intention of LabPQR is to convey physical values so that an encoding value can be used to estimate an original object color. Several variations of the PQR aspects of LabPQR have been described in the literature[2,5] including those based on a population of samples or those based on fundamental spectral stimuli.[4]

The present paper investigates and delivers an additional algorithm of the LabPQR concept to the real world and describes encoding/decoding methods which have unique, well-defined base functions, physically meaningful encoding values, and are capable of handling both spectral imaging and current trichromatic imaging equipment.

BASE FUNCTIONS USING TRIGONOMETRIC FUNCTION

There are several physically meaningful colorimetric values such as RGB and L*a*b. Among them, we use here the RGB values. Any base function set can be chosen as shown in Eq. (2). The first three base functions are designed roughly to represent RGB spectral distribution curve and the last three base functions cover higher frequency.

$$
\begin{aligned}
e_1(\lambda) &= \sin\left(\frac{1}{2}\pi\frac{\lambda-\lambda_{\min}}{\lambda_{\max}-\lambda_{\min}}\right)\\
e_2(\lambda) &= \cos\left(\frac{1}{2}\pi\frac{\lambda-\lambda_{\min}}{\lambda_{\max}-\lambda_{\min}}\right)\\
e_3(\lambda) &= \sin\left(\pi\frac{\lambda-\lambda_{\min}}{\lambda_{\max}-\lambda_{\min}}\right)\\
e_4(\lambda) &= \cos\left(\frac{3}{2}\pi\frac{\lambda-\lambda_{\min}}{\lambda_{\max}-\lambda_{\min}}\right)\\
e_5(\lambda) &= \sin\left(2\pi\frac{\lambda-\lambda_{\min}}{\lambda_{\max}-\lambda_{\min}}\right)\\
e_6(\lambda) &= \cos\left(\frac{5}{2}\pi\frac{\lambda}{\lambda_{\max}-\lambda_{\min}}\right)
\end{aligned} \tag{2}
$$

With this base function set, color characteristics can be estimated by weighting factors of the first three base functions. The shape of the trigonometric base functions is shown in Figure 4. Spectral reflectance estimation was made using an equation obtained by substituting Eq. (2) into Eq. (1) (called TrW6). Figure 5 shows spectral reflectance estimation for one color from the Macbeth color chart and Figure 6 shows the standard deviation of spectral reflectance estimation as a function of wavelength for 1000 pseudo-object colors. Overall standard deviation of 1000 pseudo-object colors was 0.0335 in W6 and 0.0365 in TrW6; the difference between those was only 0.3%, so that an almost equivalent accuracy could be obtained.

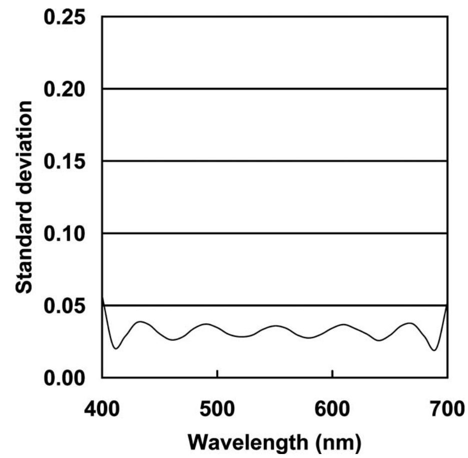

Figure 3. Standard deviation of spectral reflectance estimation using W6.

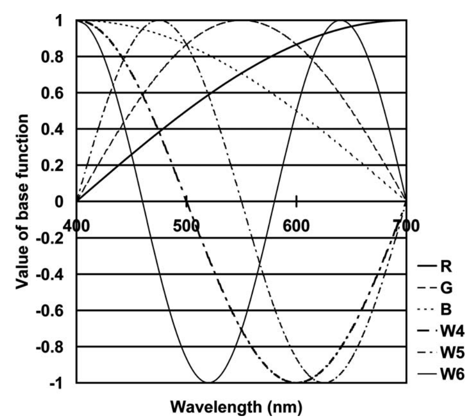

Figure 4. Eigenvectors using trigonometric function.

In Eq. (2), the frequency multiplier of the trigonometric function of $e_4(\lambda) \sim e_6(\lambda)$ was selected from all combinations of up to four by increments of one-half. As described later in this article, there were some other combinations of the frequency multiplier, which gave a standard deviation of spectral reflectance estimation better than TrW6 and surprisingly even better than W6 as well. The present selection was made on the basis of its simplicity, balance along the wavelength, and reasonable accuracy.

Lab2

The next two encoding/decoding methods are to use two sets of CIELAB[3] values (called Lab2) and a combination of CIELAB and RGB (called LabRGB).

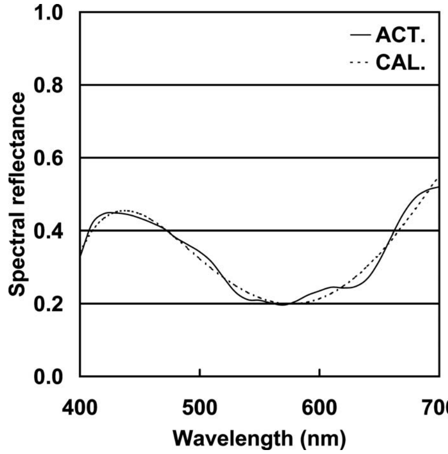

Figure 5. Spectral reflectance estimation using TrW6.

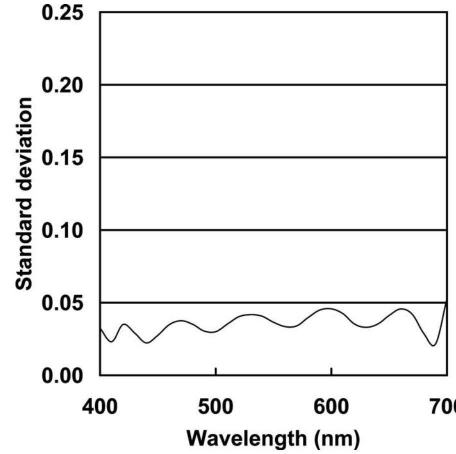

Figure 6. Standard deviation of spectral reflectance estimation using TrW6.

Lab2 uses two different sets of CIELAB values, corresponding to two illuminants such as D65 and A, for encoding values. So, encoding is done by calculating two different sets of CIELAB values from spectral reflectance of an object color. Decoding is then carried out using CIEXYZ[3] values X_{D65}, Y_{D65}, Z_{D65}, X_A, Y_A, Z_A calculated from the encoding values.

Equation (3) is obtained by substituting $\rho(\lambda)$ into the CIEXYZ formula using the right hand side of Eq. (1); $e_i(\lambda)$ can be either W6 eigenvectors or TrW6 base functions. Equation (3) contains 6 simultaneous equations with six unknown weighting factors $w_1 \sim w_6$, thus it forms six-dimensional first-order equations. In Eq. (3), $E_{65}(\lambda)$, $E_A(\lambda)$ are the spectral energy distributions of illuminant D65 and A, and $\bar{x}(\lambda)$, $\bar{y}(\lambda)$, $\bar{z}(\lambda)$ are the color matching functions.

$$
\begin{aligned}
X_{D65} &= \sum_{i=1}^{6} w_i \int e_i(\lambda) \cdot E_{65}(\lambda) \cdot \bar{x}(\lambda) d\lambda \\
Y_{D65} &= \sum_{i=1}^{6} w_i \int e_i(\lambda) \cdot E_{65}(\lambda) \cdot \bar{y}(\lambda) d\lambda \\
Z_{D65} &= \sum_{i=1}^{6} w_i \int e_i(\lambda) \cdot E_{65}(\lambda) \cdot \bar{z}(\lambda) d\lambda \\
X_A &= \sum_{i=1}^{6} w_i \int e_i(\lambda) \cdot E_A(\lambda) \cdot \bar{x}(\lambda) d\lambda \\
Y_A &= \sum_{i=1}^{6} w_i \int e_i(\lambda) \cdot E_A(\lambda) \cdot \bar{y}(\lambda) d\lambda \\
Z_A &= \sum_{i=1}^{6} w_i \int e_i(\lambda) \cdot E_A(\lambda) \cdot \bar{z}(\lambda) d\lambda
\end{aligned} \tag{3}
$$

By solving Eq. (3) for $w_1 \sim w_6$, and substitute to Eq. (1), the original object color can be readily obtained. With this method, the decoding was done, and Figure 7 shows a spectral reflectance estimation for one color from the Macbeth color chart and Figure 8 shows the standard deviation of spectral reflectance estimation as a function of wavelength for 1000 pseudo-object colors.

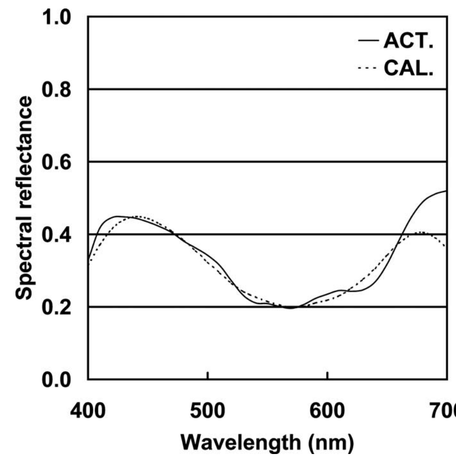

Figure 7. Spectral reflectance estimation using Lab2.

X_{D65}, Y_{D65}, Z_{D65}, X_A, Y_A, Z_A in Lab2 have a physical meaning, so that feature of an object color can be estimated without decoding into spectral reflectance curve. On the other hand, the standard deviation of spectral reflectance estimation is worse near the both ends of the wavelength scale. This is due to the low power in the x, y, z-bar equations at the low and high wavelength ends. So the colorimetric accuracy is quite independent of spectral accuracy there.

LabRGB

LabRGB uses a combination of CIELAB and RGB. Encoding is done by the following steps:

(a) Calculate CIEXYZ and CIELAB values of a spectral reflectance $\rho(\lambda)$;
(b) Substitute Eq. (2) into Eq. (1) and calculate six weighting factors $w_1 \sim w_6$ for six base functions in Eq. (2),

where CIELAB values, obtained by the above step (a), are used as the first three encoding values of LabRGB, while w_1, w_2, w_3, obtained by the above step (b), are the last three encoding values of LabRGB, which roughly represent the R, G, and B components, respectively.

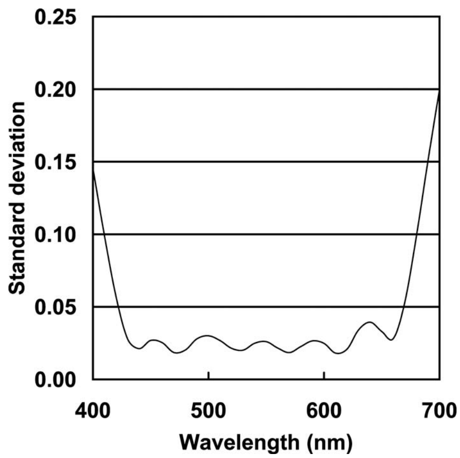

Figure 8. Standard deviation of spectral reflectance estimation using Lab2.

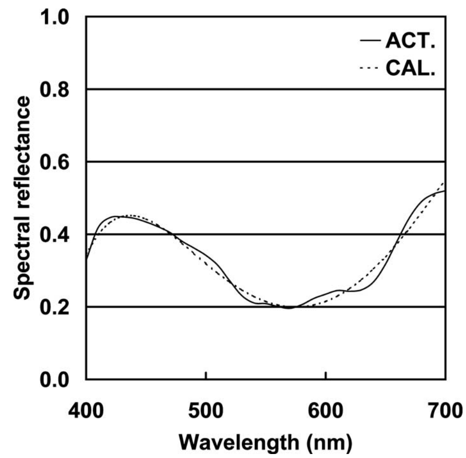

Figure 9. Spectral reflectance estimation using LabRGB.

Decoding is done by the following steps.

(a) Calculate original XYZ values using CIELAB, the first three encoding values of LabRGB. Also calculate an estimation of CIEXYZ values $\hat{X}\hat{Y}\hat{Z}$ using w_1, w_2, w_3, the last three encoding values of LabRGB, as

$$\begin{aligned}\hat{X} &= \sum_{i=1}^{3} w_i \int e_i(\lambda)\cdot E(\lambda)\cdot \bar{x}(\lambda)d\lambda \\ \hat{Y} &= \sum_{i=1}^{3} w_i \int e_i(\lambda)\cdot E(\lambda)\cdot \bar{y}(\lambda)d\lambda \\ \hat{Z} &= \sum_{i=1}^{3} w_i \int e_i(\lambda)\cdot E(\lambda)\cdot \bar{z}(\lambda)d\lambda\end{aligned} \tag{4}$$

(b) Calculate w_4, w_5, w_6 from the original XYZ values and estimated $\hat{X}\hat{Y}\hat{Z}$ values using Eq. (5)

$$\begin{aligned}X-\hat{X} &= \sum_{i=4}^{6} w_i \int e_i(\lambda)\cdot E(\lambda)\cdot \bar{x}(\lambda)d\lambda \\ Y-\hat{Y} &= \sum_{i=4}^{6} w_i \int e_i(\lambda)\cdot E(\lambda)\cdot \bar{y}(\lambda)d\lambda \\ Z-\hat{Z} &= \sum_{i=4}^{6} w_i \int e_i(\lambda)\cdot E(\lambda)\cdot \bar{z}(\lambda)d\lambda\end{aligned} \tag{5}$$

(c) Substituting the resulting w_4, w_5, w_6 and known w_1, w_2, w_3 into Eq. (1).

With this method, decoding was carried out, and Figure 9 shows spectral reflectance estimation for one color from the Macbeth color chart. Figure 10 shows the standard deviation of spectral reflectance estimation as a function of wavelength for 1000 pseudo-object colors.

LabRGB consists of two classes of physical attributes, and its base functions TrW6 are unique trigonometric functions. Overall standard deviation of 1000 pseudo-object colors was 0.0389 in LabRGB, and the difference between W6

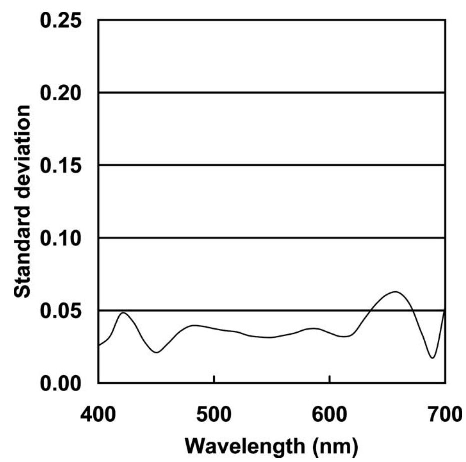

Figure 10. Standard deviation of spectral reflectance estimation using LabRGB.

and LabRGB was small (only 0.54%), similar to TrW6. Therefore almost equivalent accuracy could be obtained.

COMPARISON OF THE ENCODING/DECODING METHODS

Table I shows spectral estimation error of the four encoding/decoding methods described above with the three different populations of object colors. W6 base functions were calculated from 1000 pseudo-object colors, so W6 showed the best result for that population of object colors. Both TrW6 and LabRGB were better than W6 for 24 Macbeth colors and 49,776 SOCS colors.[6] It can be said that TrW6 and LabRGB performance is almost equivalent to W6 performance.

Figures 11 and 12 show the colorimetric estimation error of W6 and LabRGB using 1000 pseudo-object colors with the observation illuminant D65. Figures 13 and 14 show the same comparison with the observation illuminant D50. Figures 15 and 16 show the same comparison with the observation illuminant A. Summary of those comparisons is shown in Table II. Table III shows the same colorimetric estimation error comparisons as Table II except, in this case, using 49,776 SOCS colors. For Figures 12, 14, and 16, as well

Table I. Comparison of the spectral reflectance estimation overall standard deviation (ratio).

	Encoding/decoding methods			
Object colors	W6	TrW6	Lab2	LabRGB
24 Macbeth colors	0.0255	0.0206	0.0464	0.0222
1000 pseudo-object colors	0.0335	0.0365	0.0746	0.0389
49776 SOCS colors	0.0247	0.0216	0.0622	0.0226

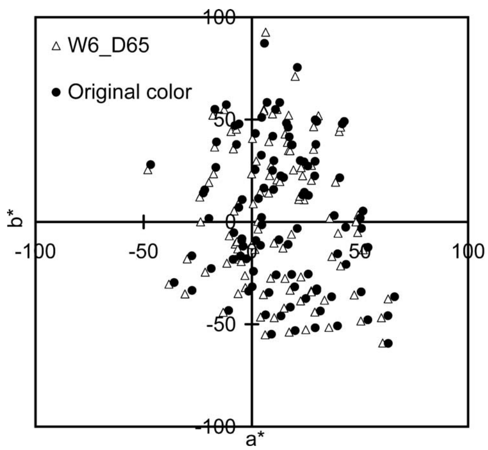

Figure 11. W6 colorimetric estimation error under illuminant D65.

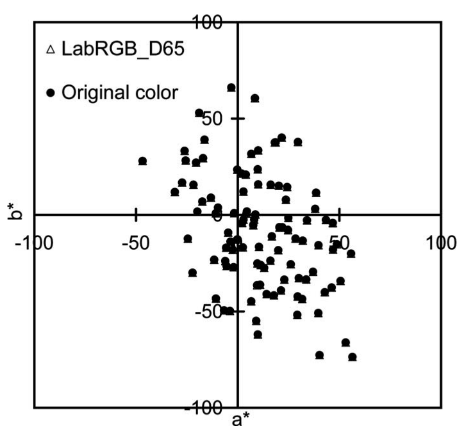

Figure 12. LabRGB colorimetric estimation error under iiluminant D65.

as Tables II and III, illuminant D65 was used in LabRGB encoding/decoding calculation, so the combination of LabRGB and observation illuminant D65 shows minimum colorimetric estimation error (almost zero). Furthermore, LabRGB also worked better than W6 with observation illuminant D50 and A, because W6 minimizes spectral estimation error, and LabRGB minimizes colorimetric estimation error.

MINIMIZING COLORIMETRIC ESTIMATION ERROR

According to Table III, the colorimetric estimation error in LabRGB is about $\Delta Eab = 1.8$ from observation illuminant A

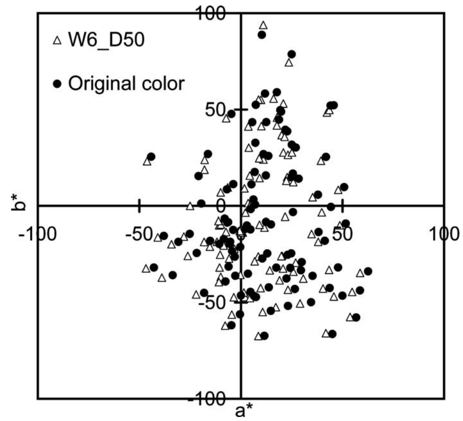

Figure 13. W6 colorimetric estimation error under illuminant D50.

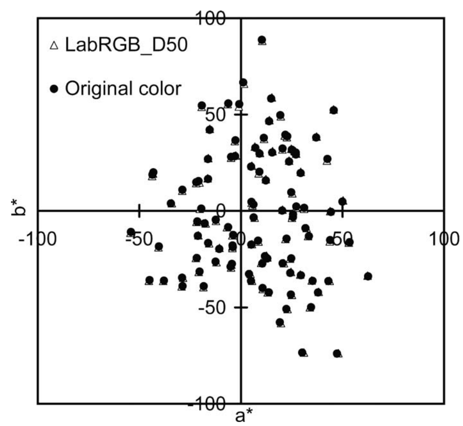

Figure 14. LabRGB colorimetric estimation error under illuminant D50.

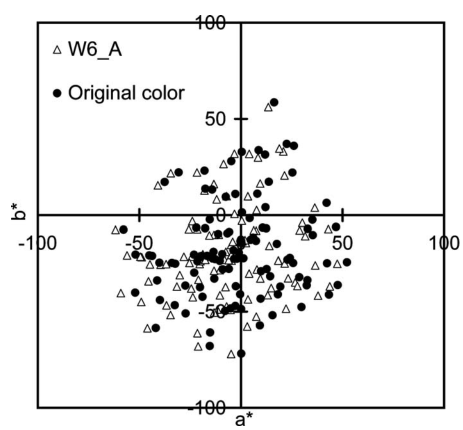

Figure 15. W6 colorimetric estimation error under Illuminant A.

to D65, which is about 3600 K in color temperature range. So, colorimetric estimation error of less than one in ΔEab unit can be achieved over the same observation color temperature range by selecting illuminant color temperature of LabRGB encoding/decoding calculation to disperse colorimetric estimation error.

Table IV shows the standard deviation of colorimetric estimation error using 49,776 SOCS colors. Five different illuminants were used in LabRGB encoding/decoding calcu-

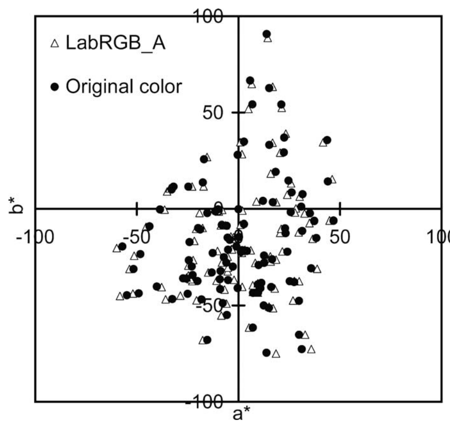

Figure 16. LabRGB colorimetric estimation error under Illuminant A.

Table II. Comparison of colorimetric estimation error (standard deviation of 1000 pseudo-object colors ΔEab).

Encoding/decoding methods	Observation illuminants D65	D50	A
W6	1.5540	1.8730	2.4700
LabRGB	0.0006	0.2906	1.1416

Table III. Comparison of the colorimetric estimation error (standard deviation of 49776 SOCS colors ΔEab).

Encoding/decoding methods	Observation illuminants D65	D50	A
W6	3.0773	3.3676	4.1670
LabRGB	0.0009	0.4757	1.7336

lation. Values of ΔEab are less than one for all observation illuminants in the LabRGB encoding/decoding calculation using 4000K black body radiation [underlined text indicates BBR (black body radiation, unless otherwise noted) 4000K in Table IV], while the sum of ΔEab is minimized in the LabRGB encoding/decoding calculation using illuminant D50 (underlined text, indicated as D50 in Table IV). D50 is better than BBR 4000K, because D50 is a well defined common illuminant, spectrally about equal energy distribution and it gives minimum of sum of ΔEab.

DISCUSSION

All three new spectral encoding/decoding methods, TrW6, Lab2 and LabRGB have the following common features:

(a) Device independent.
(b) Color characteristics can be estimated by only looking at its encoding values.
(c) Enabling use of same base function for different population of object colors.
(d) Can be applied to both spectral imaging and traditional trichromatic imaging.

The features (b), (c), and (d) are advantageous for the traditional orthogonal eigenvector method, and feature (a) is advantageous for LabPQR.

Each new spectral encoding/decoding method has the following different features:

(e) TrW6 and LabRGB worked surprisingly well for three different population of object colors in terms of spectral and colorimetric estimation accuracy.
(f) Encoding process in Lab2 is very easy, since it uses two sets of CIELAB as encoding values.
(g) LabRGB is better than TrW6 in terms of the above common feature (b).

LabRGB has an encoding/decoding illuminant dependency. If the encoding/decoding illuminant and the observation illuminant are the same, colorimetric error is always zero. Colorimetric estimation error is strongly related to color temperature difference between the encoding/decoding illuminant and the observation illuminant. A greater color temperature difference gives a greater colorimetric estimation error. So the choice of encoding/decoding illuminant is up to the application, but if one can only choose one to cover all ordinary and daily basis viewing conditions, D50 is the best as stated above. It should be noted that this choice does not affect the spectral estimation error.

Table IV. Comparison of the colorimetric estimation error (standard deviation of 49,776 SOCS colors ΔEab).

Illuminants used in LabRGB encoding/decoding calculation	Observation illuminants D65	D50	A	Sum of ΔEab
A	1.8429	1.4902	0.0010	3.3340
BBR 4000K	*0.8720*	*0.6652*	*0.9558*	*2.4930*
BBR 4500K	0.6693	0.6061	1.2160	2.4914
D50	0.4755	0.0008	1.3588	1.8351
D65	0.0009	0.4757	1.7336	2.2103

Table V. Comparison of the spectral reflectance estimation overall standard deviation (ratio).

sin 1	cos 2	sin 3	cos 4	sin 5	cos 6	Standard deviation
0.5	0.5	1.0	3.0	3.5	3.5	0.03327
0.5	0.5	1.0	2.5	3.0	3.5	0.03375
0.5	0.5	1.0	1.5	3.5	3.5	0.03378
0.5	0.5	1.0	1.5	3.0	3.5	0.03400
0.5	0.5	1.0	1.5	3.0	3.0	0.03412
0.5	0.5	1.0	2.5	3.0	3.0	0.03443
0.5	0.5	1.0	2.5	2.5	3.0	0.03445
0.5	0.5	1.0	1.5	2.5	3.0	0.03464
0.5	0.5	1.0	1.0	2.5	3.0	0.03485
0.5	0.5	1.0	1.5	3.0	5.0	0.03492
0.5	0.5	1.0	1.5	2.0	3.5	0.03497
0.5	0.5	1.0	2.5	3.5	3.5	0.03501
0.5	0.5	1.0	1.5	2.5	2.5	0.03513
0.5	0.5	1.0	2.5	2.5	3.5	0.03516
0.5	0.5	1.0	1.0	2.5	2.5	0.03520
0.5	0.5	1.0	3.0	3.0	3.5	0.03524
0.5	0.5	1.0	2.0	2.0	3.0	0.03537
0.5	0.5	1.0	1.0	2.0	2.5	0.03551
0.5	0.5	1.0	2.0	2.5	3.0	0.03552
0.5	0.5	1.0	3.0	4.0	4.0	0.03552
0.5	0.5	1.0	1.5	3.0	4.5	0.03578
0.5	0.5	1.0	2.0	2.0	3.5	0.03585
0.5	0.5	1.0	2.0	2.5	3.5	0.03587
0.5	0.5	1.0	1.5	2.0	3.0	0.03605
0.5	0.5	1.0	2.0	2.0	2.5	0.03609
0.5	0.5	1.0	1.5	1.5	3.0	0.03610
0.5	0.5	1.0	1.5	4.0	4.0	0.03610
0.5	0.5	1.0	1.5	2.0	2.0	0.03613
0.5	0.5	1.0	1.0	2.0	2.0	0.03624
0.5	*0.5*	*1.0*	*1.5*	*2.0*	*2.5*	*0.03648*
0.5	0.5	1.0	1.5	2.5	4.5	0.03653
0.5	0.5	1.0	1.5	3.5	4.0	0.03661
0.5	0.5	1.0	1.5	1.5	3.5	0.03662
0.5	0.5	1.0	1.5	1.5	5.0	0.03685
0.5	0.5	1.0	1.5	1.5	2.5	0.03690
0.5	0.5	1.0	1.0	1.5	1.5	0.03706

There are a lot of different choices in defining the shape of trigonometric functions in Eq. (2).

The shape of first three trigonometric functions was defined to represent the shape of R, G and B. The trigonometric functions have intrinsic flexibility, so one can define many combinations of trigonometric functions to get the same curve shape. For example, Figure 17 shows the two different trigonometric functions in Eq. (6) and Eq. (7), which look almost the same.

$$y = \sin(2x), \tag{6}$$

$$y = \frac{\sin(x) + (\cos(x) - 1)}{\sqrt{2} - 1}. \tag{7}$$

The shapes of last three trigonometric functions were defined by implementing multiple case studies of all the combinations. Part of the results were shown in Table V as

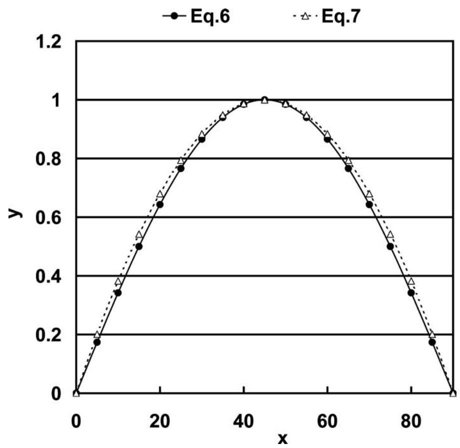

Figure 17. Comparison of trigonometric functions.

an incremental order of the standard deviation. There were many combinations which give lower standard deviation, calculated from 1000 pseudo-object colors, compared to the one in Eq. (2) (italic with underlined text in Table V). But the difference in the standard deviation is less than 0.5%, which is reasonably small. So, as stated above, the present selection was made by on the basis of its simplicity, balance along the wavelength range, and reasonable accuracy.

LabRGB involves multiple regression analysis for encoding and three-dimensional first-order equations for decoding. It is desirable to create a straightforward encoding/decoding calculation algorithm, which is not covered in this paper, to apply LabRGB to a real multispectral image.

CONCLUSION

Spectral encoding/decoding methods using unique base functions and physically meaningful values were explored.

It was found that the unique trigonometric functions TrW6 can be used as base functions without any or with negligible loss of accuracy. Lab2, consisting of two CIELAB values, had standard deviation of spectral reflectance estimations worse near the both ends of the wavelength, this was due to the lack of power in the x, y, z-bar equations at the ends. LabRGB consisting of CIELAB and RGB and showed almost the same performance as the traditional eigenvectors W6. By using LabRGB, we do not have to worry about a population of object colors each time, and we can send/receive encoding values without exchanging base functions beforehand. LabRGB consists of physically meaningful attributes, so that color characteristics can be estimated by only looking at its encoding values. LabRGB can be applied not only to spectral imaging but also to the traditional trichromatic imaging world, so its usage is unlimited. The future plan is to apply LabRGB to a multispectral imaging system and implement a performance evaluation.

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