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Analysis of illumination correction error in camera color space

Minji Lee[12], and Byung-Uk Lee[1]
[1]Department of Electronics Engineering, Ewha Womans University, 52 Ewhayeodae-gil, Seodaemun-gu, Seoul 03760, Republic of Korea
[2]Current Affiliation: LG Electronics, 10 Magokjungang 10-ro, Gangseo-gu, Seoul 07796, Republic of Korea

Abstract

Achieving color constancy is an important step to support visual tasks. In general, a linear transformation using a 3×3 illuminant modeling matrix is applied in the RGB color space of a camera to achieve color balance. Most of the studies for color constancy adopt this linear model, but the relationship of illumination and the camera spectral sensitivity (CSS) is only partially understood. Therefore, in this paper, we analyze linear combination of the illumination spectrum and the CSS using hyperspectral data that have much more information than RGB. After estimating the illumination correction matrix we elucidate the accuracy dependence on illumination spectrum and the camera sensor response, which can be applied to CSS.

Index Terms *— Color constancy, illuminant estimation, camera spectral sensitivity*

1. INTRODUCTION AND RELEATED WORK

The human visual system can compensate for the effect of illumination, so that color of an object can be perceived consistently even though illumination changes. However, the image acquired through a camera, which captures physical signal intensity of the receiving light, is influenced by the illumination spectrum. Finding the actual reflectance of an object by compensating for the color of such illumination has been studied in the field of computational color constancy [1]. Implementation of color constancy can be divided into two stages: first, spectrum of the illumination is estimated, and then, color of the image is corrected based on the estimated lighting. For image correction, white balancing is generally applied using a 3×3 diagonal matrix [2]-[4]. White balance aims at recovering achromatic color from an image taken under unknown illumination. Since the method of correcting illumination using the diagonal matrix does not correct colors other than achromatic colors, there is a limitation in that it is not possible to achieve color correction for the entire color gamut presented in the image.

In order to improve the color correction performance of the diagonal matrix transformation model, narrowing the wavelength width of the sensitivity function of each RGB filter of the camera by a linear transformation is proposed [5]. In addition, there is a color correction method that realizes color consistency by estimating 9 elements of a 3×3 full matrix considering the correlation between RGB color channels, and is generally more effective than diagonal white balancing method [6][12].

However, despite the widespread use of this linear transformation model, most studies focus on how to implement the color constancy in the RGB color space; the underlying principles for color correction is not fully investigated yet. In contrast, Chong [7] proved that if the rank of the tensor of illumination, reflectance, and camera sensitivity function can be approximated to 3, the actual illumination can be expressed as a 3×3 illumination correction matrix without error. In another study, Cheng et al. [8] found that the accuracy of illumination estimation varies with illumination, and the diagonal matrix transformation under certain illumination conditions can estimate RGB illumination with small error. Cheng et al. also reported that this issue is related to intricate relationship between the illumination spectrum and CSS.

In this paper, hyperspectral data under actual illumination is analyzed, which enables an investigation beyond the limitations of 3D RGB color space. Through this work, we identify the reason for the observation in the Cheng's work [8], why diagonal model is as effective as the full matrix for some illumination spectrum. Unlike the Chong's mathematical analysis [7], which evaluates the illumination correction matrix on the assumption that the camera sensitivity function can have low rank, this paper assumes a general situation where a camera sensitivity function is given, and identify the reasons for the varying accuracy of RGB illumination estimates.

The structure of this paper is as follows. In Section 2, we describe existing models for estimating the illumination correction matrix in RGB color space using hyperspectral data. In Section 3, we analyze errors of a 3x3 RGB illumination estimation matrix. Finally, the conclusions and discussions of this study follow in Section 4.

2. ESTIMATION OF RGB ILLUMINATION

2.1 Hyperspectral to RGB illumination modeling

We analyze existing methods of estimating the illumination correction matrix in the RGB color space with hyperspectral data, which enables an accurate description of color correction error. Under Lambertian reflectance image spectrum can be modeled as a multiplication of the spectral components of the illumination and the reflectance of the object. Let D represent a hyperspectral image with an m×n matrix, where m is the number of spectral bands and n is the number of pixels in the image. D can be expressed as a product of the reflectance R whose dimension is m×n and the illumination L which is an m× m diagonal matrix.

$$\mathbf{D_{m\times n}} = \mathbf{L_{m\times m}}\mathbf{R_{m\times n}} \quad (1)$$

RGB image is a projection of the hyperspectral data to the three-dimensional color space using the CSS $S = [s_r^T\ s_g^T\ s_b^T]^T$. The RGB image D_3 is 3×n matrix and the RGB reflectance R_3 is a 3×n matrix.

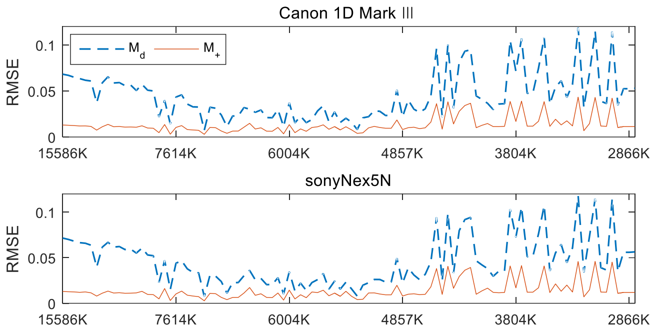

Figure 1. Residual error $\|\mathrm{MSR}-\mathrm{SLR}\|_F^2$ ***of*** $\mathrm{M_d}$ ***and*** $\mathrm{M_+}$ ***for SFU illuminants***

Then we have

$$\mathbf{D_3 = SD = SLR}$$

$$\text{`}\mathbf{R_3 = SR} \qquad (2)$$

Here, $\mathrm{D_3}$ denotes the RGB image acquired by the camera, while $\mathrm{R_3}$ represents the RGB image under ideal white illumination. Typical linear white balance algorithm approximates the lighting by a linear transformation using a 3×3 illumination matrix M in the RGB color space.

$$\mathbf{D_3 = SLR \cong MR_3 = MSR} \qquad (3)$$

Since the degree of freedom of M is 9 and the number of constraint is 3n, there is no illumination spectrum satisfying this over-determined problem [9]. Therefore, SLR and MSR do not match because there is no unique solution to project the illumination perfectly onto the three dimensional space.

2.2 Estimation of the illumination matrix

White balancing, which is commonly used in color constancy, calibrates color usually by a diagonal matrix. This method aims at adjusting the illumination vector on the white reference in the RGB color space of the camera to be aligned to the direction of R = G = B, which is an achromatic vector. Mathematically, this means that the scale of each color channel is independently adjusted by multiplying the diagonal element having the weights for each RGB illumination, while the correlation among RGB colors of illumination is ignored. Diagonal element $\mathrm{m_{di}}$ for each channel i= r, g, b of RGB illumination matrix $\mathrm{M_d}$ can be calculated using camera sensitivity function and illumination spectrum. Where $\mathrm{w_{m\times1}} = [1,\cdots,1]^\mathrm{T}$ is the m-dimensional ideal white illumination, and $\mathrm{l_{m\times1}} = \mathrm{diag(L)} = [\mathrm{l_1},\cdots,\mathrm{l_m}]^\mathrm{T}$ is an $\mathrm{m\times1}$ column vector consisting of the diagonal components of the illumination matrix. Then the diagonal element is:

$$m_{di} = \frac{s_i^T l}{s_i^T w}$$

$$\mathrm{M_d} = \begin{bmatrix} m_{dr} & 0 & 0 \\ 0 & m_{dg} & 0 \\ 0 & 0 & m_{db} \end{bmatrix} \qquad (4)$$

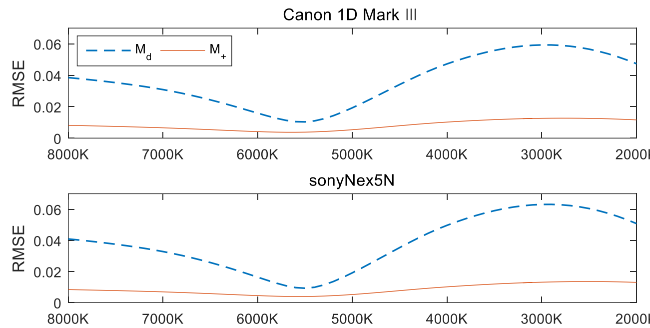

Figure 2. Residual error $\|MSR-SLR\|_F^2$ ***of*** M_d ***and*** M_+ ***for black-body radiation***

We can also estimate the full matrix $\mathrm{M_+}$ which minimizes the error between SLR and MSR. The least squares method using the Moore-Penrose pseudo inverse can estimate $\mathrm{M_+}$ which minimizes the Frobenius norm of the difference between two matrices:

$$\mathbf{\arg\min_{M_+} \|M_+SR - SLR\|_F^2} \qquad (5)$$

$$\mathbf{M_+ = SLRR^T\,S^T(SRR^TS^T)^{-1}} \qquad (6)$$

Please note that the illumination matrix $\mathrm{M_+}$ is influenced by the correlation of the reflectance RRT.

In this paper, hyperspectral data of 400 nm to 720 nm corresponding to the visible light range is sampled with 10 nm interval, therefore experiment is conducted using spectrum information of 33 bands. Since the image is expressed as a product of the reflectance and the illumination spectrum, all the hyperspectral data are normalized to the maximum value of 1 to facilitate the experiment and the result analysis. We use the reflectance of a 24-patch Macbeth chart, which is often used as reference measurements in color calibration. The camera sensitivity function for projecting hyperspectral data into the RGB color space uses the dataset measured by Jiang et al. [10]. The experiment of this work is based on Cheng et al. [8], which has 101 illuminant spectra measured in a variety of weather conditions [11], the illumination correction matrix M of the RGB color space is estimated for this hyperspectral data, and the RMSE between MSR and SLR is calculated to analyze the accuracy of illumination estimation.

The performance of the diagonal and full matrix model for illumination is compared as in [8]. Figure 1 is a graph comparing the accuracy of $\mathrm{M_d}$ and $\mathrm{M_+}$ estimated using SFU illuminants and two different camera sensitivity functions. Illumination spectrum is sorted according to the CCT (correlated color temperature) and CSS of Canon1D Mark III and Sony Nex5N was used. The horizontal axis of the graph shows the CCT of the SFU illuminants in the descending order of CCT as in [8], and the vertical axis represents the RMSE for each illumination. The result shows that the modeling RGB illumination using full matrix is better than the diagonal method for all the illuminants. This is because the diagonal matrix does not include correlation information between color channels. However, even in the case of $\mathrm{M_+}$, a perfect illumination modeling in the RGB space is not possible. The same phenomenon can be noticed again in Figure 2, which is the experimental result using black-body radiation spectrum instead of the actual illuminants. Mathematical interpretation is that the illumination spectrum has more degrees of freedom than 3 dimension. Experimental results show that the accuracy of illumination estimation is different depending on the illumination as confirmed by Cheng et al. [8]. They also report that diagonal matrix is close to full matrix near 6000K, and it is also evident in Figure 2: error for the diagonal compensation is close to that of the full matrix near 5800K. Yet the cause of this observation has not been elucidated in the previous research. In the next section, therefore, we examine the relationship between illumination spectrum and CSS that affect the accuracy of the illumination estimation in RGB space.

3. ANALYSIS ERROR IN ESTIMATION RGB ILLUMINATION

In this section, we analyze the cause of the accuracy variation of illumination estimation according to the illumination spectrum. The reason can be explained by reinterpreting the linear combination of the camera sensitivity function. The following equation (7) is an ideal condition that the 3x3 illumination correction matrix perfectly represents the actual illumination regardless of reflectance, where ⊙ denotes an element by element multiplication of two vectors of the same size.

$$\|\mathbf{SL}-\mathbf{MS}\|_F^2 = \mathbf{0}$$

$$\begin{bmatrix} s_r^T \odot l \\ s_g^T \odot l \\ s_b^T \odot l \end{bmatrix} = \begin{bmatrix} m_{11}s_r^T + m_{12}s_g^T + m_{13}s_b^T \\ m_{21}s_r^T + m_{22}s_g^T + m_{23}s_b^T \\ m_{31}s_r^T + m_{32}s_g^T + m_{33}s_b^T \end{bmatrix} \quad (7)$$

The equation shows that there might exist an RGB illumination correction matrix without error when the illumination spectrum weighted by a basis vector s_i^T of the camera sensitivity function can be represented by a linear combination of camera spectral sensitivity vectors. The discrepancy is proportional to the error of RGB illumination estimation. In order to analyze the cause of the difference in accuracy of illumination correction using the above equation, we use M estimated in the previous section. In addition, the camera sensitivity function of Canon1D Mark III is used. Figure 3 shows the Frobenius norm of the difference between SL and MS for SFU illuminations and black-body radiation, respectively. The curves in Figure 3 is similar to those of Figures 1 and 2: Figures 1 and 2 show the color correction RMSE of color patches while Figure 3 represents the error for illumination modeling in camera RGB color space.

In order to analyze the difference between SL and MS in more detail, we compare two illuminants with similar CCT but with a large difference in RGB illumination estimation error. The illumination spectra selected for the experiment are the 68 and 69 illumination spectra indexed in descending order of CCT in the SFU dataset, with the CCT 4279K and 4216K, respectively. The illumination spectrum 68 shows higher accuracy of RGB illumination estimation than the illumination 69.

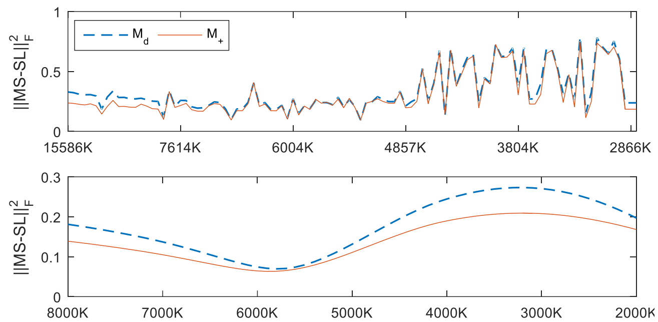

Figure 3.** $\|SL-MS\|_F^2$ **of SFU illuminants (top) and Blackbody radiation spectrum (bottom)

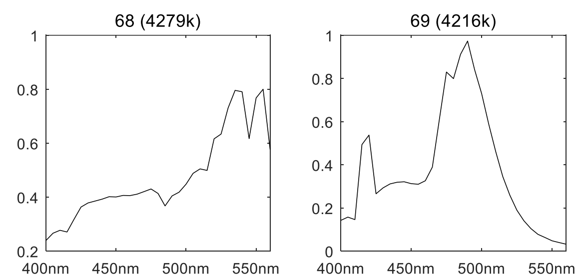

Figure 4. Two illumination spectra of similar CCT but with large difference in RGB modeling error

Table 1. Illumination estimation error using SFU illumination spectrum 68 and 69

Illuminant number	68	69
$\|\mathbf{SL}-\mathbf{MS}\|_F^2$	0.0124	0.0638

Figure 5(a) and (b) shows the SL and MS values for illumination spectrum 68 and 69, and their values are shown for each RGB components. The graph shows that the illumination 68 spectrum is better represented by the linear combination of camera

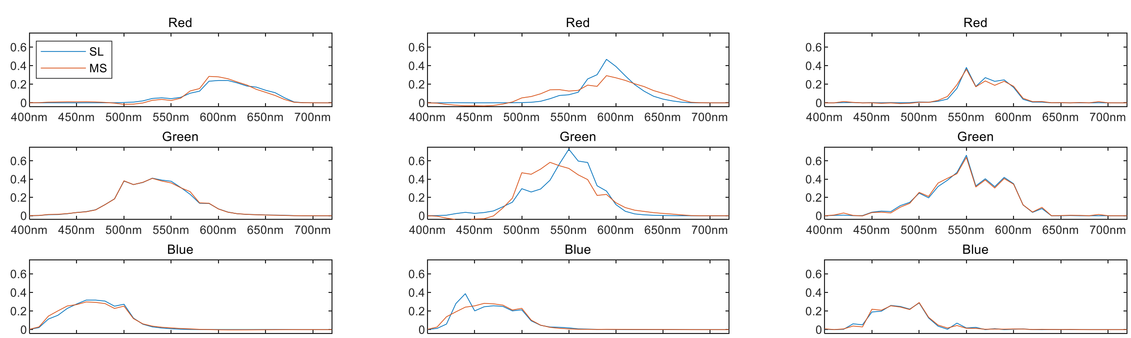

Figure 5. RGB components of SL and MS using SFU illumination spectrum (a) illumination 68, (b) illumination 69, (c) illumination 69 after optimizing the camera spectral sensitivity

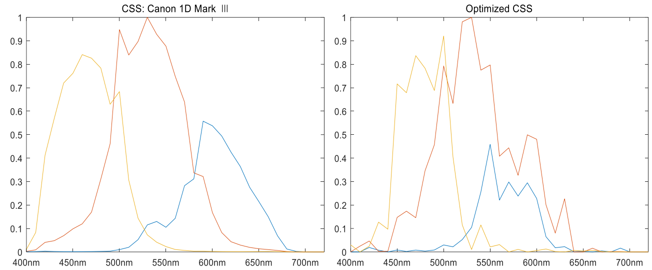

Figure 6. (a) The CSS of Canon 1D Mark III and (b) optimized CSS for illumination 69

sensitivity functions and the illumination than the illumination 69 and that the difference between SL and MS affects the accuracy of the illumination estimation. This example shows that the accuracy of a 3x3 illumination matrix depends on equation (7) rather than the CCT as implied in [8]. CSS should be designed to model human color perception after linear transformation [13], however, we can observe the effect of the CSS in color correction by finding an optimal solution for (7) for a given illumination. An optimized CSS which minimizes color correction error can be found, i.e.,

$$\mathbf{S}^{*} = \arg\min_{\mathbf{S}} \|\mathbf{SL} - \mathbf{MS}\|_F^2 + \lambda \|\mathbf{S} - \mathbf{S_0}\| \qquad (8)$$

where $\mathbf{S_0}$ is the original camera CSS. A reasonable solution is obtained for illumination 69 when λ= 0.1. Then the color correction error is reduced from 0.0638 to 0.0098. The updated plot of S*L and MS* is shown in Fig 5(c), which shows a remarkable match of MS and SL for the given illumination after optimization. The optimized CSS is shown in Fig. 6(b). This experiment demonstrates that CSS can be optimized to facilitate color correction under a given illumination. But it is more important for a CSS to model human color perception than achieving accurate color correction.

4. CONCLUSION

The contribution of this work is an understanding of the error for illumination correction matrix in the RGB color space using hyperspectral illumination. It has been reported that the accuracy of RGB illumination estimation varies depending on the CCT of the illumination, the reflectance, and the camera sensitivity function. We estimated the full and diagonal matrices for illumination correction that minimized the Frobenius norm between the camera image projecting the hyperspectral image into the camera RGB color space and the illumination compensated image obtained by multiplying the RGB reflectance by the three-dimensional projection of the hyperspectral illumination. Experimental results reconfirms that the full matrix is a better representation of the hyperspectral illumination for RGB illumination modeling.

In addition, we present a new interpretation of the illumination spectrum in camera sensor color space. For an ideal color correction in RGB space, illumination spectrum weighted by the CSS should be represented as a linear combination of camera sensitivity functions. By designing CSS that satisfy this linear relationship for a highly probable illumination spectrum, we can improve the color constancy performance in the RGB color space. This study is meaningful as a fundamental study to improve the accuracy of illumination correction in RGB color space.

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Author Biography

Minji Lee received her BS in Electronic and Electrical Engineering from the University Ewha Womans University (2015) and her MS in image processing from the University Ewha Womans University (2017). She works in the SW Research and Development Division at LG Electronics.

Byung-Uk Lee received the B.S. degree in electronic engineering from Seoul National University, Seoul, Korea, the M.S. degree in electrical science from Korea Advanced Institute of Science and Technology, Seoul, Korea, and the Ph.D. degree in electrical engineering from Stanford University, Stanford, CA. He joined the Department of Electronics Engineering, Ewha Womans University, Seoul, Korea, in 1995, where he is currently a Professor. His research interests include image processing, and medical signal processing.