Estimation of Spectral Distribution of Scene Illumination from a Single Image with Chromatic Illuminant

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ABSTRACT

The current paper proposes an illuminant estimation algorithm that estimates the spectral power distribution of an incident light source using its chromaticity determined based on the perceived illumination and highlight method. The proposed algorithm is composed of three steps. First, the illuminant chromaticity of the global incident light is estimated using a hybrid method that combines the perceived illumination and highlight region. Second, the surface spectral reflectance is then recovered from the image after decoupling the global incident illuminant for each channel. The surface spectral reflectance calculation is limited to the maximum achromatic region (MAR), which is the most achromatic and brightest region in the image, and estimated using the principal component analysis (PCA) method along with a set of given Munsell samples. Third, the closest colors are selected from a spectral database composed of reflected-lights generated by the given Munsell samples and a set of illuminants. Finally, the illuminant of the image is calculated using the average spectral distributions of the reflected-lights selected for the MAR region and its average surface reflectance. Simulations were performed using artificial color-biased images and the results confirmed the accuracy of the estimates produced by the proposed method for various illuminants.

Keywords: Illuminant estimation, Maximum achromatic region, Principal component analysis, Perceived illumination, Highlight region

1. INTRODUCTION

The color of an object can be determined by the characteristics of the scene illuminant and surface. As such, if the illuminant color changes, the surface color will be perceived differently. The human visual system (HVS) is able to discount this change to some degree. However, this phenomenon, called color constancy, is not found in cameras, as it is a characteristic of human visual adaptation and cognitive procedures in the brain. As a result, since input devices, like cameras, can not recognize the same color with a change of illuminant, this produces a different result as regards human color recognition. Although the color constancy in the HVS has already been studied by many color-researchers, this decoupling process remains a very difficult problem to solve\cite{1,2}. In the case of color constancy based on a linear model\cite{4}, given an RGB-format image including N surfaces, 3N + 3 descriptors are required to decouple an illuminant and surfaces. However, a trichromatic camera system only has 3N quantum catch data\cite{3}.

Using a basic theory in conjunction with a unique recovery method for lights and surfaces, D’Zmura and colleagues presented a criterion for determining this unique recovery method according to the number of unknown lights and surfaces parameters based on the linear model of Maloney and Wandell\cite{1,4,5}. As such, they estimated the spectral reflectance of an illuminant using the multiplication formula that the spectral reflection from an object surface results from the multiplication of the body and surface reflection. D’Zmura and Iverson\cite{3,6,7} proposed general linear and bilinear models to extend Maloney-Wandell’s approach. They used a combination of multiple illuminants and multiple surfaces and the relationship between these two factors. Shafer\cite{8} proposed a dichromatic reflection model using the surface reflection and body reflection. Based on a vector addition of these weighted components, they represented the light reflection from an object surface. The spectral composition of a surface reflection is assumed to be the same as the illuminant spectrum. The chromaticity distribution of the pixel values for a highlight region makes line patterns from the surface to the illuminant chromaticity or vice versa. A point on such a line can be represented as the linear combination of a body and illuminant chromaticity vector. Petrov\cite{9} also

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measured the perceived illumination effect empirically. Tominaga\textsuperscript{10,11} gave described extensions of the sensor correlation method for illuminant classification and discussed several methods that improve the accuracy and scope of the algorithm. Finlayson\textsuperscript{12,13} correlate the information with the colors in a particular image to obtain a measure of the likelihood that each of the possible lights is the scene illuminant. Sapiro\textsuperscript{14} proposed the method based on ideas from the generalized probabilistic Hough transform, to estimate the illuminant and reflectance of natural images. Each image pixel votes for possible illuminants and the estimation is based on cumulative votes. The approach using gamut-mapping is to form the set of all possible (R, G, B) due to surfaces in the world under a known, “canonical” illuminant. This set is convex and it is represented by its convex hull\textsuperscript{15,16}. Trusell\textsuperscript{17} proposed probabilistic approach using the highest occurrence probability of illuminant and pre-information of object surface in given scenes.

Cheng\textsuperscript{18} assumed the inclusion of a white patch within a whole image for estimating the surface spectral reflectances and proposed the maximum tristimulus method. For surface properties, he assumed that specular reflections should not be taken into account and that surfaces are neither self-illuminating nor fluorescent. Whereas for illuminants, he assumed that the hue and saturation of an illuminant remain the same over the whole scene, the illuminant is not saturated, and that it must be bright enough. However, since most images do not include a white patch, cases where the above assumptions are satisfied are rare. Thus, Lee\textsuperscript{19} proposed gray world assumption (GWA) to estimate surface spectral reflectance. Yet, because GWA is used to search the MAR, it is sometimes impossible to find an illuminant in an image that does not satisfy GWA. In particular, this problem is especially serious when an image includes a specular region or self-luminous region. Therefore, to remove a specular region or self-luminous region, the proposed method estimates the chromaticity of an illuminant using the perceived illumination and highlight region and extracts the illuminant of an image based on the estimated illuminant chromaticity.

The proposed algorithm is composed of three steps as follows. The first step uses a hybrid method based on combining the perceived illumination and highlight region to estimate the chromaticity of the illuminant so as to eliminate the illuminant effect. The perceived illumination effect is where a certain intensity level in a scene is perceptually perceived as the illuminant, although other parts of the image are the actual illuminant, therefore, passive reflection from a surface should not be included when estimating the illuminant chromaticity. As such, a solution to perceived illumination is to use a reference point or base information related to the highlight approach where different color surfaces create lines and the intersection of these lines determines the illuminant chromaticity. After the influence of illumination in the input image is globally eliminated, the neutralized image is used to obtain the MAR. The second step then recovers the surface spectral reflectances from the image after the illuminant has been removed. The extracted surface spectral reflectances are limited to the MAR, which is the most chromatic and brightest region in the image\textsuperscript{20}. Next, the surface reflectances of the MAR are calculated using the PCA method\textsuperscript{21} along with a set of given Munsell samples. The third step selects a spectral distribution for the reflected lights of the MAR from a spectral database. Then the closest colors from the spectral database are selected. Finally, the illuminant of the image is calculated by dividing the average spectral distributions of the reflected lights of the MAR by its average surface reflectances. After estimating the spectral power distribution of the illuminant, the colors of an image with chromatic illuminants can be recovered by a matrix transformation.

2. ESTIMATION OF ILLUMINANT CHROMATICITY

2.1 Perceived Illumination Method

A perceived illumination method is proposed for estimating scene illuminant chromaticity to remove the illuminant effect in an image with a chromatic illuminant. The proposed method estimates the illuminant chromaticity by selectively excluding self-luminous regions, along with a process for extracting the chromaticity. When a human being watches a scene, they are able to pick up a general color tone from the scene or image. These perceptions can be converted into the form of chromaticity coordinates or a daylight locus on the chromaticity plane.

A self-luminous area indicates a region in a scene that is not perceived as a passive surface reflection. These regions can also be thought of as active reflectors, like a lamp, aperture on a wall, or specular reflection of an arbitrary surface. As such, these regions can appear as a light radiation body or illuminant. Estimation results are expressed using chromaticity coordinates. After linearized $R, G, B$ are computed, $R, G, B$ are converted into $X, Y, Z$ using a transform matrix. This transform matrix can be calculated from device characteristics. The next step is calculating the global average of $X_A, Y_A, Z_A$.
\[
X_A = \frac{1}{(M \times N)} \sum_{i=1}^{M} \sum_{j=1}^{N} X(i, j) \\
Y_A = \frac{1}{(M \times N)} \sum_{i=1}^{M} \sum_{j=1}^{N} Y(i, j) \\
Z_A = \frac{1}{(M \times N)} \sum_{i=1}^{M} \sum_{j=1}^{N} Z(i, j),
\]

where \(M\) is the number of rows in the image, \(N\) is the number of columns, and \(X(i,j)\) is the \(i\)th row and \(j\)th column of \(X\). The self-luminous thresholds \(X_{th}, Y_{th}, Z_{th}\) are calculated as

\[
X_{th} = f \times X_A \\
Y_{th} = f \times Y_A \\
Z_{th} = f \times Z_A,
\]

where \(f\) is derived from a visual test in self-luminous experiments. Then pixels exceeding the self-luminous threshold are excluded. If the self-luminous threshold is changed, pixels of the image are averaged again. If not, estimated chromaticity of the illuminant \(x_{\text{perceived}}, y_{\text{perceived}}\) can be calculated. These steps are repeated until there is no further change in the self-luminous threshold. Finally, the chromaticity of illuminant is estimated.

### 2.2 Highlight Region Method

The highlight region method is based on Shafer’s dichromatic model\(^8\), which is composed of two different characteristic surfaces: matt and specular. The sum of these two reflections produces the reflected light from an arbitrary colored surface. The specular reflection is assumed to match the illuminant reflection. The chromaticity coordinate for each different surface point creates a line distribution. The direction of the line is defined by the body and illuminant chromaticity, and its extension crosses the illuminant chromaticity. This means that the surface reflection dilutes the saturation of the body reflection. The direction of the line usually starts from each individual body of chromaticity and ends at the direction of the illuminant chromaticity. Two different color surfaces create two lines and the cross-point of these two lines determines the illuminant chromaticity. If there are more lines, multiple cross-points will exist. In this case, the dominant cross-point is assumed to be the illuminant chromaticity. At first, the highlight candidate area is selected from the input image. The selection is based on the threshold \(I_{th}\) obtained as a scaled value of the average image intensity \(I_A\) as

\[
I = 2.7 \times R + 0.6 \times G + 0.1 \times B, \\
I_A = \frac{1}{(M \times N)} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} I(i, j), \\
I_{th} = 2.7 \times I_A,
\]

where \(I\) is the intensity based on the weighted sum of each red, green, and blue frame. The scale factor 2.7 is empirically determined by experiments. In the current study, the intensity threshold is set at variable, as since the average is different for each image, an absolute threshold value is not useful for most cases. The line parameters, including the slope and offset, for the selected candidate area are calculated to obtain the cross-point for the line clusters of the candidates. The conventional approach obtains such parameters from fitting the distribution shape of a cluster for each area in the chromaticity space. If a highlight candidate area is reasonably selected, the parameters will be useful, yet in some cases, it is very difficult to select a reasonable candidate area. Fig. 1 shows the highlight method used to estimate the illuminant chromaticity.

In the Fig. 1, the three lines \(L_1, L_2,\) and \(L_3\) are obtained from the three independent highlight candidates in the image. The cross-points of these three lines are the estimated illuminant chromaticity. In the proposed method, the line parameters are reasonably calculated by considering the intensity transition pattern of each distribution of clusters, rather than just the distribution shape. Then, the chromaticity coordinates \(x, y\) and intensity \(Y\) for each selected area are calculated, respectively. Next, the chromaticity coordinates \(x, y\) and intensity \(Y\) are sorted in an ascending order of intensity \(Y\). The moving average of the \(x\) and \(y\) chromaticity coordinates for the sorted pairs is selected and several representative points are sampled from the
sets of pairs using an equally divided sub-range from the whole intensity. Since the number of pixels for each candidate area is normally above 100, the size of the moving average window is set to 20. The locus of the representative $x$ and $y$ values makes a line and also gives the line parameters. The next step is to calculate the cross-points for the lines selected above and a representative cross-point from many cross-points. The conventional approach for selecting uses histogram accumulation. Yet, if the valid digit for the coordinate is high, there is a problem in quantizing. The quantization bin should be very fine for the sake of accuracy.

If a coarse bin is used, the accuracy will be substantially decreased. To solve this problem, the sorting method preserves the accuracy while maintaining the concept of histogram accumulation. One cross-point consists of two components, $x$ and $y$ shows the 2-D distribution of $x$ and $y$ data. At first, the set of cross-points is sorted in an ascending order for $x$. In this sorting process, the format of the cross-point should be preserved as a coordinate and the $x$ value is only used as a sorting reference. After sorting, a very smooth 3rd order curve can be achieved for the $x$ values, and the flat center part denotes the representative $x$ value for the set of cross-points. When fitting this 3rd curve, the convex of the second derivative is used as the center value. For this $x$ value, a neighborhood range is selected that contains the center $x$ value as a subset for the original coordinate set. The same subset sorting procedure is then applied to obtain a $y$ reference and center value for $y$. Representative coordinates for the cross-points can also be obtained using the above procedure. In this case, the convex of the second derivative of a sorted curve, or the closest point to the convex is used to select the representative coordinates. This is more effective for a dense distribution than a conventional histogram approach when some level of accuracy is required. After all, the representative chromaticity is regarded as the illuminant chromaticity.

![Fig. 1. Estimation of illuminant chromaticity using highlight region.](image)

2.3 Hybrid Method Using Perceived Illumination and Highlight Region

The proposed hybrid method can be used to estimate the illuminant chromaticity by combining the advantages of stability from the perceived illumination and accuracy from the highlight. The perceived illumination can provide a stable candidate range to estimate the illuminant chromaticity, but the accuracy is slightly degraded and depends on the image content. In contrast, the highlight method does not depend on the image content and provides an accurate solution for scene illuminant chromaticity, although the drawback is to determine the final solution from many possible cross-points. Since the nature of these two approaches can be considered as mutually compensating, the solution from the perceived illumination can be used as a reference point or base information for the highlight method.

First, the $x$ and $y$ chromaticity coordinates are estimated from the perceived illumination and the same candidate regions are selected as for the highlight region. If there are no candidates for this region, the output is set to the $x$ and $y$ chromaticity coordinates using just the perceived illumination. Line parameters from representative points of each distribution are calculated and the three closest line distributions to the $x$ and $y$ chromaticity coordinates are selected. Among these cross-points, the three closest points are selected. From these three cross-points, the closest one to the $x$ and $y$ chromaticity coordinates based on the perceived illumination is determined as the illuminant chromaticity according to the hybrid method.
3. ESTIMATION OF SPECTRAL DISTRIBUTION OF ILLUMINATION

3.1 Estimation of surface spectral reflectance of MAR

The illuminant chromaticity was estimated using a hybrid method that combines the perceived illumination and highlight region. This estimated illuminant chromaticity is then used to remove effect of illumination in an image so as to identify the MAR. The proposed approach is based on the assumption that if there is a maximum surface reflectance, the maximum spectral power distribution of light reflected from surfaces with an illuminant \( E(\lambda) \) will be

\[
L_{\text{max}}(\lambda) = E(\lambda)R_{\text{max}}(\lambda).
\]

(6)

If an image is colorful, the maximum value of the spectral distribution of light reflected from the maximum surface reflectance can be assumed to be an estimation of \( L_{\text{max}}(\lambda) \). As a first step, \( L_{\text{max}}(\lambda) \) is obtained from the image. Thereafter, the estimation of the illuminant for an input image can be calculated using the equation below

\[
\hat{E}(\lambda) = \frac{\hat{L}_{\text{max}}(\lambda)}{R_{\text{max}}(\lambda)}.
\]

(7)

Basically, the current assumption for equations (6) and (7) is same as in the Cheng’s approach\(^{18}\). \( R_{\text{max}}(\lambda) \) is very important for obtaining an exact description of an illuminant, yet in Cheng’s approach, \( R_{\text{max}}(\lambda) \) is a fixed value deduced from the assumption that the lights reflected from \( R_{\text{max}}(\lambda) \) have a maximum tristimulus value, \( q = [111]^T \). Accordingly, \( R_{\text{max}}(\lambda) \) is calculated using a fixed spectral distribution of the reflected light with a constant weighting vector and fixed spectral distribution of D65. As a result, the \( R_{\text{max}}(\lambda) \) and estimated \( \hat{E}(\lambda) \) are not adaptive to an image. The estimated \( \hat{E}(\lambda) \) cannot be optimal for images that do not include ideal white. In the proposed method, the \( R_{\text{max}}(\lambda) \) and \( L_{\text{max}}(\lambda) \) of an image are simultaneously estimated from the same surface in the image. Therefore, the application of the proposed algorithm can extend to images that do not include ideal white because \( R_{\text{max}}(\lambda) \) is not required to become a constant spectral function or uniform spectral function.

To identify the MAR, the hybrid method using the perceived illumination and highlight outlined in previous section is applied to eliminate the influence of illumination before the MAR is identified. \( R', G', B' \) are computed using the \( x, y \) chromaticity coordinates estimated by the hybrid method. Above all, the \( X_{\text{hybrid}}, Y_{\text{hybrid}}, Z_{\text{hybrid}} \) tristimulus values for the illuminant are calculated as

\[
X_{\text{hybrid}} = k \times \frac{x_{\text{hybrid}} \times Y_{\text{hybrid}}}{Y_{\text{hybrid}}},
\]

\[
Z_{\text{hybrid}} = (1 - x_{\text{hybrid}} - y_{\text{hybrid}}) \times Y_{\text{hybrid}}
\]

(8)

using the estimated illuminant chromaticity coordinates \( x_{\text{hybrid}}, y_{\text{hybrid}} \) where \( k \) is the coefficient, \( x_{\text{hybrid}}, y_{\text{hybrid}} \) are the chromaticity coordinates using the hybrid method, and \( X_{\text{hybrid}}, Y_{\text{hybrid}}, Z_{\text{hybrid}} \) are the tristimulus values according to the hybrid method. The \( R, G, B \) values in the input image are converted into \( X, Y, Z \) values using a transform matrix as follows

\[
\begin{bmatrix}
X_{\text{in}} \\
Y_{\text{in}} \\
Z_{\text{in}}
\end{bmatrix} = \begin{bmatrix}
0.430574 & 0.341550 & 0.178325 \\
0.222015 & 0.706655 & 0.071330 \\
0.020183 & 0.129553 & 0.939180
\end{bmatrix} \times \begin{bmatrix}
R_{\text{in}} \\
G_{\text{in}} \\
B_{\text{in}}
\end{bmatrix}
\]

(9)
where $X_n$, $Y_n$, $Z_n$ are the tristimulus values in the input image and $R_n$, $G_n$, $B_n$ are the $R$, $G$, $B$ values in the input image. The $X'$, $Y'$, $Z'$ values are computed using a matrix form as follows

$$
\begin{bmatrix}
X' \\
Y' \\
Z'
\end{bmatrix} =
\begin{bmatrix}
X_{D65} & 0 & 0 \\
X_{hybrid} & Y_{D65} & 0 \\
0 & Y_{hybrid} & Z_{D65} \\
0 & 0 & Z_{hybrid}
\end{bmatrix}
\begin{bmatrix}
inX \\
inY \\
inZ
\end{bmatrix}
$$

(10)

where $X_{D65}$, $Y_{D65}$, $Z_{D65}$ are the tristimulus values for the D65 illuminant, and $X'$, $Y'$, $Z'$ are the tristimulus values for an image after the illuminant has been removed. The tristimulus values for the D65 illuminant are $X_{D65} = 95.05, Y_{D65} = 100.0$, and $Z_{D65} = 108.88$. The $R'$, $G'$, $B'$ values are calculated as inverse matrix of equation (9). $R'$, $G'$, $B'$ are transformed into $Y_CR_CYBCR_C$ color space to find the MAR, as shown below

$$
Y = 0.299R' + 0.587G' + 0.114B'
$$

$$
C_b = 0.577(B' - Y)
$$

$$
C_r = 0.730(R' - Y).
$$

(11)

Then, the MAR is determined by selecting the minimum chromatic points in an image. The local chromatic component, $C(i,j)$, is the linear sum of $C_b$ and $C_r$ in a $7\times7$ block.

$$
C(i,j) = \sum_{i=1}^{9} \frac{C_b(i,j)^2 + C_r(i,j)^2}{
$$

(12)

The $7\times7$ block size was empirically determined to avoid the selection of impulse noise points in the MAR search. In addition, to select bright points, the range of the minimum chromatic points is limited to a region where the luminance channel, $Y$, is higher than 90% of that of the input image. After determining the MAR, the pixels of the central $3\times3$ block in the selected region are converted into XYZ values in order to apply the PCA method using the transform matrix in (12). To produce the principal components (basis functions) of the surface reflectance, 1269 chips from the Munsell Book of Color were exploited. The Munsell spectra were obtained from the Information Technology Dept., Lappeenranta Univ. of Tech. Thereafter, three basis functions of these spectra were generated by a PCA. Using the principal component vectors, the surface spectral reflectances of the object can be expressed as a linear combination as follows

$$
R(\lambda) \equiv \bar{R}(\lambda) + \sum_{i=1}^{3} \alpha_i \mathbf{u}_i = \bar{R}(\lambda) + [\mathbf{u}_1 \mathbf{u}_2 \mathbf{u}_3] \begin{bmatrix}
\alpha_1 \\
\alpha_2 \\
\alpha_3
\end{bmatrix},
$$

(13)

where $\bar{R}(\lambda)$ is the average of the surface reflectances, $\mathbf{u}_i$ are the principal components, and $\alpha_i$ are the corresponding coefficients to $\mathbf{u}_i$. In equation (11), the 9 surface coefficients of the 9 selected pixels, i.e. the MAR of an image, can be calculated using equation (13) through equation as follows
where \( \bar{X}, \bar{Y}, \) and \( \bar{Z} \) are the tristimulus values for the averaged spectral of the 1269 Munsell samples and \( X_i, Y_i, \) and \( Z_i (i = 1, 2, 3) \) are the tristimulus values for the corresponding principal components. Accordingly, the surface coefficients \( \alpha_i (i = 1, 2, 3) \) are given by

\[
\begin{bmatrix}
\alpha_1 \\
\alpha_2 \\
\alpha_3
\end{bmatrix} = \begin{bmatrix} X_1 & X_2 & X_3 \\ Y_1 & Y_2 & Y_3 \\ Z_1 & Z_2 & Z_3 \end{bmatrix}^{-1} \begin{bmatrix}
X' \\
Y' \\
Z'
\end{bmatrix} - \begin{bmatrix} \bar{X} \\
\bar{Y} \\
\bar{Z}
\end{bmatrix}
\]  

(15)

Therefore, the 9 surface reflectances of the MAR can be estimated using above surface coefficients, the Munsell spectral mean, and the principal components as shown in equation (13).

### 3.2 Determination of spectral power distributions of reflected lights on MAR

The proposed approach for estimating the illuminants of a scene has two phases. First, the surface spectral reflectance of the MAR is estimated. Next, the spectral distribution of the reflected light of the MAR is determined. In the current study, 1269 samples from the Munsell Book of Color and 6 illuminants (A, C, D65, D50, green, yellow) were used to compose the set of reflected lights. The same 1269 Munsell spectra were used to build the principal components for the surface spectral reflectances and construct the spectral set of reflected lights. The Munsell spectra were multiplied by the 6 illuminants to generate a set of spectral power distributions of the reflected lights from 400 ~ 700 nm at 5-nm intervals. Hereafter, this set of spectra is referred to as the spectral database.

The colors of the MAR are then compared with the spectral database to find the closest spectral data. For a comparison in uniform color space, the 9 colors of the MAR and the spectral data in the spectral database can be transformed into \( L^*a^*b^* \) vectors as below:

\[
\begin{align*}
L^* &= 116 f(Y/Y_a) - 16 \\
a^* &= 500 \left[ f(X/X_a) - f(Y/Y_a) \right] \\
b^* &= 200 \left[ f(Y/Y_a) - f(Z/Z_a) \right] \\
f(\omega) &= \begin{cases} 
\omega^{1/3}, & \omega > 0.008856 \\
7.787\omega + 16/116, & \omega \leq 0.008856.
\end{cases}
\end{align*}
\]  

(16)

Then, the criterion for selecting the best matching spectra is as follows

\[
\Delta E_{ab} = \sqrt{(L_a^* - L_b^*)^2 + (a_a^* - a_b^*)^2 + (b_a^* - b_b^*)^2},
\]  

(17)

where \( L^* \) denotes the lightness of a MAR color in CIELAB color space and \( L_a^* \) means the lightness of a sample from the spectral database in the CIELAB metric. Using equation (17), 9 spectral distributions of the lights reflected from the MAR are selected from the spectral database. Finally, the selected spectral data are divided by the corresponding surface spectral reflectances of the MAR and averaged to estimate the spectral distribution of the illuminant.

### 4. EXPERIMENTAL RESULTS

The proposed method was simulated using artificial color-biased images. First, to produce artificial color-biased images, the RGB input images were converted into multi-spectral images using a linear model and the principal components. Here, it
was assumed that the scene illuminant of the original image was D65. Then, piecewise multiplication with known chromatic illuminants was used to produce the artificial color-biased images. A, C, D50, green, and yellow were utilized as the chromatic illuminants. Each chromatic illuminant had 61 samples and spanned 400 ~ 700 nm at 5 nm intervals. 1269 spectra were used as the spectral database.

Fig. 2 and 3 illustrates the results for the artificial color-biased images with illuminant A and C. As shown in Fig. 2 and 3, the original image in RGB-format was biased by the chromatic illuminant A and C. The illuminant of the artificial color-biased image were then estimated using the proposed method, Cheng’s Maximum Tristimulus Value method, and Lee’s method, then the estimated scene illuminants for each image facilitated the recovery of a neutral image under D65. As previously mentioned, in the proposed method, \( R_{\text{max}}(\lambda) \) was adaptive according to the input image and did not need to be a constant spectral function or uniform surface spectral function. In addition, for images that did not satisfy GWA, the proposed method provided better results than Lee’s method. Since the proposed method used a hybrid method combining the perceived illumination and highlight region, it was also more adaptive than Cheng’s method using maximum tristimulus values or Lee’s method using GWA for the illuminant estimation. Table 1 shows the comparison of color difference for the test image of A, C, D50, green, and yellow. CIELAB \( \Delta E_{ab^*} \) was adapted to calculate the color difference. The color difference of the proposed method was much smaller than the Lee’s method and Cheng’s method.

**Table 1. The comparison of CIELAB color difference between Cheng, Lee, and the proposed method**

<table>
<thead>
<tr>
<th>illuminant</th>
<th>Cheng</th>
<th>Lee</th>
<th>Proposed method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inc A</td>
<td>0.020653</td>
<td>0.014803</td>
<td>0.005849</td>
</tr>
<tr>
<td>C</td>
<td>0.014306</td>
<td>0.007367</td>
<td>0.001266</td>
</tr>
<tr>
<td>Green</td>
<td>0.013214</td>
<td>0.009251</td>
<td>0.005659</td>
</tr>
<tr>
<td>Yellow</td>
<td>0.013359</td>
<td>0.008653</td>
<td>0.001512</td>
</tr>
</tbody>
</table>

However, the illuminant estimation for the red-biased image was somewhat incorrect in the long wavelength part even though the proposed method was better than both methods. This mismatch was analyzed by investigating the selected spectra in relation to the lights reflected from the MAR. In the case of illuminant A, the selected spectra from the spectral database were found to include a few reflected lights, illuminated by different lights. Accordingly, the slope in the long wavelength part did not follow the curve of the original illuminant. This phenomenon can be explained as follows. It is a problem related to the dimensional size of the selected minimum color spectra. When 61 dimensional spectral data were represented as the 3-dimensional data of CIELAB, a lot of information on the illuminant color can be lost. The size of the spectral database also influences the results. A small sample set for reflected lights can create large color differences between the colors of the spectral database. Therefore, if one or two colors, illuminated by different illuminants, are included in the selected spectra, this has a significant influence on the curve of the averaged spectra selected from the spectral database.

**5. CONCLUSION**

The current paper proposed an algorithm that can estimate the spectral power distribution of an incident light source using the chromaticity of the illuminant determined based on the perceived illumination and highlight method. A hybrid method combining the perceived illumination and highlight region is utilized to calculate the brightest surface from color-biased images in order to globally remove the effect of illuminants. The use of the hybrid method enables the influence of illumination to be eliminated in the input images for each channel. The neutralized image is then exploited to identify the MAR, and the surface spectral reflectances of the MAR are calculated using PCA. Next, the spectral distributions of the reflected lights, the closest ones to the colors of the corresponding MAR, are identified from the spectral database. Finally, color-biased images are recovered through dividing the spectral power distribution of the reflected lights by the surface spectral reflectance of the MAR. Experimental results confirmed that the proposed method could produce good estimations for various illuminants. However, since the results for the red-biased image were less accurate, further research is required to consider the saturation of the red channel in the image capture, along with the size of the spectral database. Given that an illuminant has a strong influence on determining the color appearance of an object, the estimation of the scene illuminant of...
an image in a spectral domain can be applied to a variety of applications, including a color appearance model.

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Fig. 2. Recovered images and spectral power distribution of estimated illuminants for illuminant A. (a) original image, (b) color-biased image using illuminant A, (c) recovered image using Cheng’s maximum-tristimulus value (MTV) method, (d) recovered image using Lee’s method, (e) recovered image using proposed method, and (f) spectral power distribution of estimated illuminants for illuminant A.
Fig. 3. Recovered images and spectral power distribution of estimated illuminants for illuminant C. (a) original image, (b) color-biased image using illuminant C, (c) recovered image using Cheng’s maximum-tristimulus value (MTV) method, (d) recovered image using Lee’s method, (e) recovered image using proposed method, and (f) spectral power distribution of estimated illuminants for illuminant C.