Estimation of Illuminant Chromaticity from Single Color Image Using Perceived Illumination and Highlight

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This article proposes a method for calculating the illuminant chromaticity of an image by combining the Perceived Illumination and Highlight approaches. Object color can be determined by the characteristic of scene illuminant and surface. In this article, perceived illumination effect is extended and with the highlight analysis, a hybrid approach is proposed to estimate the illuminant chromaticity. The perceived illumination approach provides a stable candidate range for the estimation of illuminant chromaticity however, the accuracy is slightly degraded depending on the image contents. The highlight approach does not depend on the image contents and provides an accurate solution of the scene illuminant chromaticity, however, it is difficult to determine the final solution among many cross-points. These two approaches are in effect mutually compensating. The solution from perceived illumination can be used as a starting point or as base information for the highlight approach to get the final solution.

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Introduction

Object color can be determined by the characteristic of scene illuminant and surface. If the illuminant color changes, the surface color will be perceived differently. The human visual system can discount this change to some degree. This phenomenon is called color constancy and cannot be found in a camera because it is a characteristic of human visual adaptation and cognitive procedures in the brain. Input devices like cameras, can not recognize the same color with the change of illuminant, thus giving a different result to human color recognition. There are many approaches to solve the color constancy problem[1–11] and these approaches estimate the spectral power distribution of illuminant and surface from captured image or color image by the human visual system. Input to these approaches can be regarded as spectral reflectance and tri-stimulus. Most image capturing devices give tri-stimulus values like RGB in camera.

In this article, the "Perceived Illumination" effect of A.P.Petrov[12] is extended and combined with a highlight analysis, a hybrid approach for estimating illuminant chromaticity is proposed. Perceived illumination effect is applied to the estimation of illuminant chromaticity and the concept of highlight analysis is the same as a conventional one.[9,13–14] In the proposed highlight approach, the selection method for the candidate highlight region is different from the conventional one. The perceived illumination effect is the phenomenon that there is some intensity level for the scene perceptually perceived as illuminant and some part of image can be recognized as illuminant and not the passive reflection from the surface. This part is called the "self-luminous" region and can be determined by the threshold value. In this article, this threshold is selected by the experiments regarding the perceived illumination effect and applied to the estimation of illuminant chromaticity. Illuminant chromaticity is the global color tone that can be recognized by a human observer for some scene or image and this tone depends on the characteristic of the illuminant itself. This tone is represented as the chromaticity coordinate or the color temperature. For the conventional averaging scheme,[10] this self-luminous region is included for the calculation and therefore, increases the estimation error. The proposed hybrid approach combines the stability of the perceived illumination approach and the accuracy of the highlight approach. The perceived illumination approach can provide a stable candidate range for estimating illuminant chromaticity, however, the accuracy is slightly degraded and depends on the image contents. In contrast, the highlight approach does not depend on the image content and provides an accurate solution for scene illuminant chromaticity, however, the drawback is in deciding on the final solution from many possible cross points. Accordingly, because the nature of these two approaches can be considered as mutually compensating, the solution from perceived illumination approach can be used as the starting point or base information for the highlight approach. The accuracy of the hybrid approach can be represented as the Euclidean distance between the estimated chromaticity coordinate and a reference chromaticity coordinate based on the measurement of the white patch of a Macbeth Color Checker on the scene.

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Conventional Estimation of Illuminant Chromaticity

There are two kinds of approaches for estimating scene illuminant from a color image. The representative approach using spectral reflectance is Maloney-Wandell's.[11] The spectral reflection from object surface comes from multiplication of body reflection and surface reflection. By analysis of this multiplication formula, they estimate spectral reflectance of illuminant. D'Zmura and Iverson[3–5] proposed the "General linear and Bilinear models" to extend Maloney–Wandell's approach. They presented necessary and sufficient conditions for the recovery, by linear and bilinear methods, of the spectral descriptors for lights and surfaces from an image with some surfaces viewed under different illuminants. The general idea is to write down the most general equations for the reconstruction when multiple objects are present in a scene that is viewed under multiple illuminants and, then, analyze the structure of these equations. They also showed conditions on the basis and sensitivity functions for unique reconstruction.[15] Checking this is reduced in their framework to investigating the dimension of the kernel of a matrix. These works provide a fundamental understanding of the role played by the different components in the image model, and give a theoretical analysis of the feasibility of the color constancy problem. If this technique is used for solving the color constancy problem, it is necessary to know a prior number of surfaces in the image, as well as the number of views. In addition, it is necessary to have the image segmented, that is, to distinguish between different objects and different illuminants.

Forsyth introduced the notion of canonical gamut into color constancy.[6] This is defined to be the "convex set of sensor responses obtained by imaging a maximal set of reflecting surfaces under a canonical illuminant". Only those mappings that take the image gamut within the canonical gamut are possible solutions to the color constancy and illuminant estimation problems.[16] The image gamut is just the convex hull of the sensor responses for the pixels in the image. This is due to the fact that any convex combination of sensor responses is also physically realizable. The canonical gamut is also a convex set. Any point in image gamut can be mapped into a point in canonical gamut by a diagonal matrix. Forsyth showed that the observed sensor responses constrain the set of mappings, and proposed a number of rules to select maps inside this set.

Probabilistic approaches[17] use prior information about the world to estimate the largest possible illuminant and reflectance for a given scene. The basic idea is to use Bayes rule. Freeman and Brainard proposed that the priors for the illuminants and reflectance coefficients are drawn from standard illuminants and the Mulsell chips respectively. This estimation is similar to the design of the color gamut in Forsyth's approach, which is also established as prior information. One very important difference, previously noticed, is that all the members of the canonical gamut in Forsyth's scheme have equal probability, regardless of how often they appear in natural and if they appear in the image at all. With the illuminant constraint added by Finlayson, it is as if the area with non-zero probability is reduced, but a constant value is still assigned to it.

Sapiro[18] proposed a voting scheme for illuminant and surface reflectance vectors using Hough transform. The estimated illuminant corresponds to the local maximum in the parameter space and the solution can be found when there are multiple illuminants on the scene. The prior information for region segmentation is not necessary because of finding the local maximum point for the distribution. By analyzing several randomly selected surface reflectance using the probability of color signal and surface reflectance, multiple probable solutions can be found and through voting, the representative among them is selected as a solution. The use of a probability database is still a critical path to the performance. The approaches based on reflectance spectra have a problem of compatibility with conventional input devices which produce tristimulus outputs, such as RGB.

Land's Retinex theory[10] is the representative approach using tri-stimulus input and the average vector for three channels is assumed to be the illuminant chromaticity for the scene or image. The sum of local change for several paths in each color channel gives the illuminant chromaticity and the concept is equal to the global channel average mentioned above. Another approach using highlights is also proposed. Shafer[19] proposed "Dichromatic Reflection Model". There are two vector components as surface reflection and body reflection. By the vector addition of these weighted components, one can represent the light reflection from the object surface. The spectral composition of surface reflection is assumed to be the same as illuminant spectrum. The chromaticity distribution of pixel values for the highlight region makes the line patterns start from surface to illuminant chromaticity or vice versa. The point on the line can be represented as the linear combination of body and illuminant chromaticity vector. Klinker[9] proposed a method to separate the body reflection and surface reflection from image pixel values. In this scheme, chromaticity distribution of the highlight is used to estimate two reflections, however, segmented regions are needed for the estimation. Lee[13] proposed a method to estimate illuminant chromaticity by analyzing the region with chromaticity change, i.e., the highlight region in the image. The chromaticity distribution of the highlight region makes a line and if there are more than 2 lines, the cross point is assumed to be the illuminant chromaticity. It is difficult to find out the candidate highlight region and if there's only one highlight region in the image, the solution can not be found.

Proposed Estimation of Illuminant Chromaticity by Perceived Illumination

This article proposes a method for estimating scene illuminant chromaticity by selectively excluding the self-luminous region from an image, along with a process for extracting the chromaticity figures from an image. When a human being watches a scene, they are able to pick up a general color tone from the scene or image. For example, a reddish color tone can be sensed under an incandescent lamp, whereas a bluish tone will be seen under daylight for the same scene, and this feeling will differ from image to image. These different perceptions can be converted into figures in the form of chromaticity coordinates or transformed into 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 as active reflectors, like a lamp, an aperture on the wall, or a specular reflection of an arbitrary surface. These regions can be shown as a light radiation body or illuminant. Estimation results are expressed using chromaticity coordinates like CIE-xy or color temperature. If the color temperature format is preferred, a conversion process is needed from chromaticity coordinates to color temperatures. The flowchart of the proposed algorithm is shown in Fig. 1. Linear input (R_{Lij},G_{Lij},B_{Lij}) can be calculated as:

$$\begin{aligned} R_{Lij} &= R_{ij}^{(1/\gamma)}, \\ G_{Lij} &= G_{ij}^{(1/\gamma)}, \\ B_{Lij} &= B_{ij}^{(1/\gamma)}, \end{aligned} \tag{1}$$

by compensation of γ of input device, like a camera, where i and j represents the row and column of the image coordinates. R_{ij} represents ith row and jth column of red channel. Linearized input is converted to CIE XYZ coordinate system as:

$$\begin{bmatrix} X_{ij} \\ Y_{ij} \\ Z_{ij} \end{bmatrix} = \begin{bmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{bmatrix} \begin{bmatrix} R_{Lij} \\ G_{Lij} \\ B_{Lij} \end{bmatrix} \tag{2}$$

by using transform matrix M consists of m_{11}~m_{33}. This transform matrix can be calculated from device characteristics like a digital camera. The next step is calculating the global average of X_A, Y_A, and Z_A as:

$$\begin{aligned} X_A &= \frac{1}{(H \times W)} \sum_{i=0}^{H-1} \sum_{j=0}^{W-1} X_{ij}, \\ Y_A &= \frac{1}{(H \times W)} \sum_{i=0}^{H-1} \sum_{j=0}^{W-1} Y_{ij}, \\ Z_A &= \frac{1}{(H \times W)} \sum_{i=0}^{H-1} \sum_{j=0}^{W-1} Z_{ij}, \end{aligned} \tag{3}$$

where H is the number of rows in the image and W is the number of columns and X_{ij} is ith row and jth column of X frame. For the calculation of self-luminous threshold, estimation for the level of illuminant intensity (X_{IL},Y_{IL}, Z_{IL}) is needed and is calculated as:

$$\begin{aligned} X_{IL} &= f \times X_A, \\ Y_{IL} &= f \times Y_A, \\ Z_{IL} &= f \times Z_A, \end{aligned} \tag{4}$$

where f is derived from a visual test for self-luminous experiments. The self-luminous threshold (X_{Th},Y_{Th}, Z_{Th}) is calculated as:

$$\begin{aligned} X_{Th} &= k \times X_{IL}, \\ Y_{Th} &= k \times Y_{IL}, \\ Z_{Th} &= k \times Z_{IL}, \end{aligned} \tag{5}$$

by multiplying k and estimated illuminant intensity, where k is determined in the experiment of perceived illumination and its range is from 1.5 to 2.0. If there is a change in the self-luminous threshold compared to the previous one, if no change has occurred, the estimated illuminant chromaticity (I_x,I_y) can be calculated as:

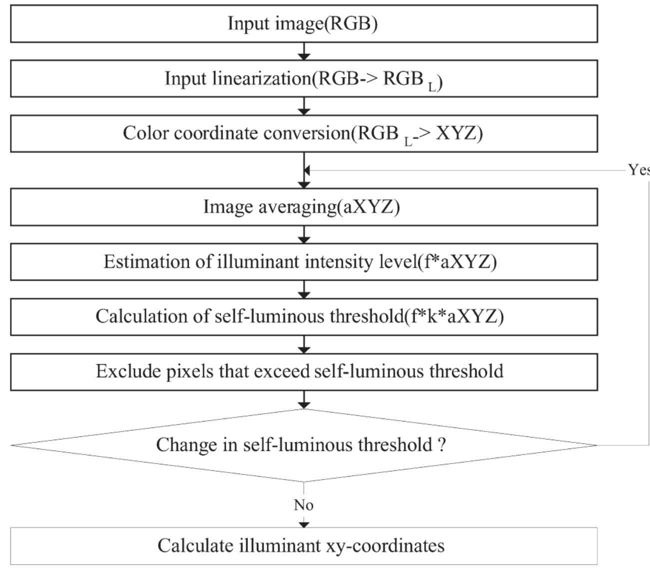


Figure 1. Flowchart of the proposed algorithm.

$$\begin{aligned} I_x &= \frac{X_{IL}}{X_{IL} + Y_{IL} + Z_{IL}}, \\ I_y &= \frac{Y_{IL}}{X_{IL} + Y_{IL} + Z_{IL}}, \end{aligned} \tag{6}$$

by normalization of estimated illuminant intensity. If there's change in the self-luminous threshold, illuminant intensity is estimated again by Eq. 4, and the self-luminous threshold is calculated. These two steps are repeated until there's no change in the self-luminous threshold. The number of repeat does not exceed 3 or 4 times in the experiment.

Proposed Estimation of Illuminant Chromaticity by Highlight Approach

The highlight approach is based on Shafer's dichromatic model[4] that consists 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 coordinates for each surface point create a line distribution. The direction of these lines is defined by the body and illuminant chromaticities, and their extentions cross 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 colored 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. This process can be summarized as follows. First, select the highlight candidate area from the input image R_{ij}, G_{ij}, and B_{ij} where i and j are the image coordinates for the row and column. The selection is based on the threshold I_{Th} obtained as a scaled value of the average of image intensity I_A as:

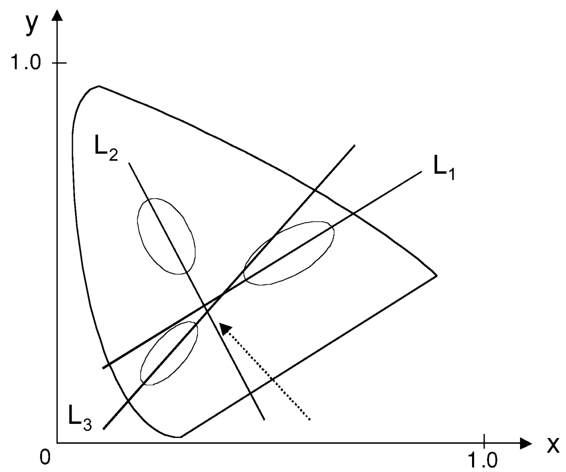


Figure 2. Estimation of illuminant chromaticity by highlight approach.

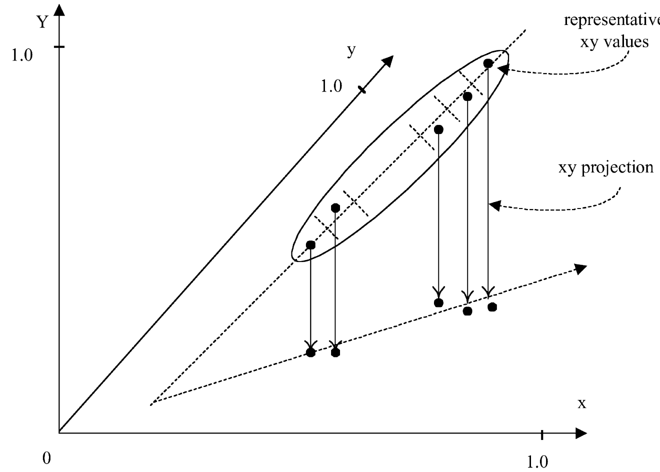


Figure 3. Proposed extraction of line parameters using intensity sorting.

$$
\begin{aligned}
I_{ij} &= 0.3 \times R_{ij} + 0.6 \times G_{ij} + 0.1 \times B_{ij}, \\
I_A &= \frac{1}{(H \times W)} \sum_{i=0}^{H-1} \sum_{j=0}^{W-1} I_{ij}, \\
I_{Th} &= 2.7 \times I_A,
\end{aligned}
\tag{7}
$$

where I_{ij} is the intensity at ith row, jth column by the weighted sum of each red, green and blue frame and H is the image height and W is the width of the image. The scale factor 2.7 is determined by experiments empirically. In this experiment, intensity threshold is set to variable because the average will be different for each image and absolute threshold value is not useful in most cases.

The line parameters like the slope and offset for the selected candidate area are calculated to get the cross point for these candidate line clusters. The conventional approach takes such parameters from fitting the shape of the distribution for a cluster from 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. The estimation of illuminant chromaticity for highlight approach is shown in Fig. 2. In the figure, three lines L_1, L_2 and L_3 can be obtained from the three independent highlight candidates of image. The cross point of these three lines are the estimated illuminant chromaticity.

In the proposed approach, line parameters are calculated reasonably by considering the intensity transition pattern of each distribution of clusters, rather than just the shape of distribution. Then, the chromaticity coordinate xy_{ij} and intensity Y_{ij} for each selected area are calculated, respectively. Next, sort the xy_{ij}–Y_{ij} pairs in ascending order of intensity Y_{ij}. The moving average of xy_{ij} for the sorted pairs are selected and several representative points are sampled from the sets of pairs by 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 was set to 20. The locus of the representative xy_{ij}s makes a line and also gives line parameters. This scheme is shown in Fig. 3 and Fig. 4. The next step is to calculate the cross-points $c(x,y)$ for the lines selected above and the representative cross-point from many cross-

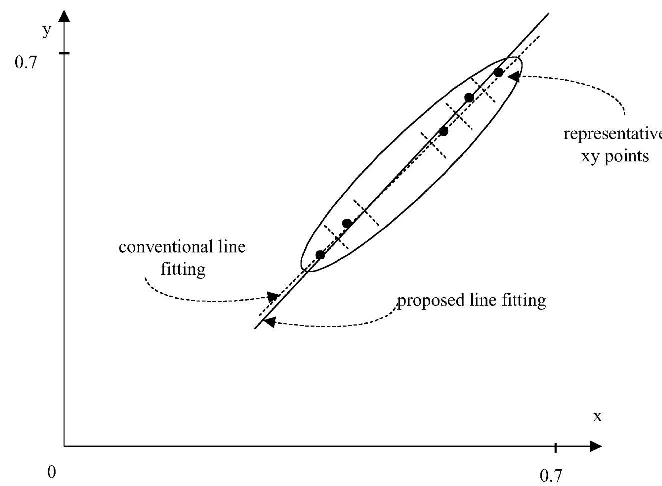
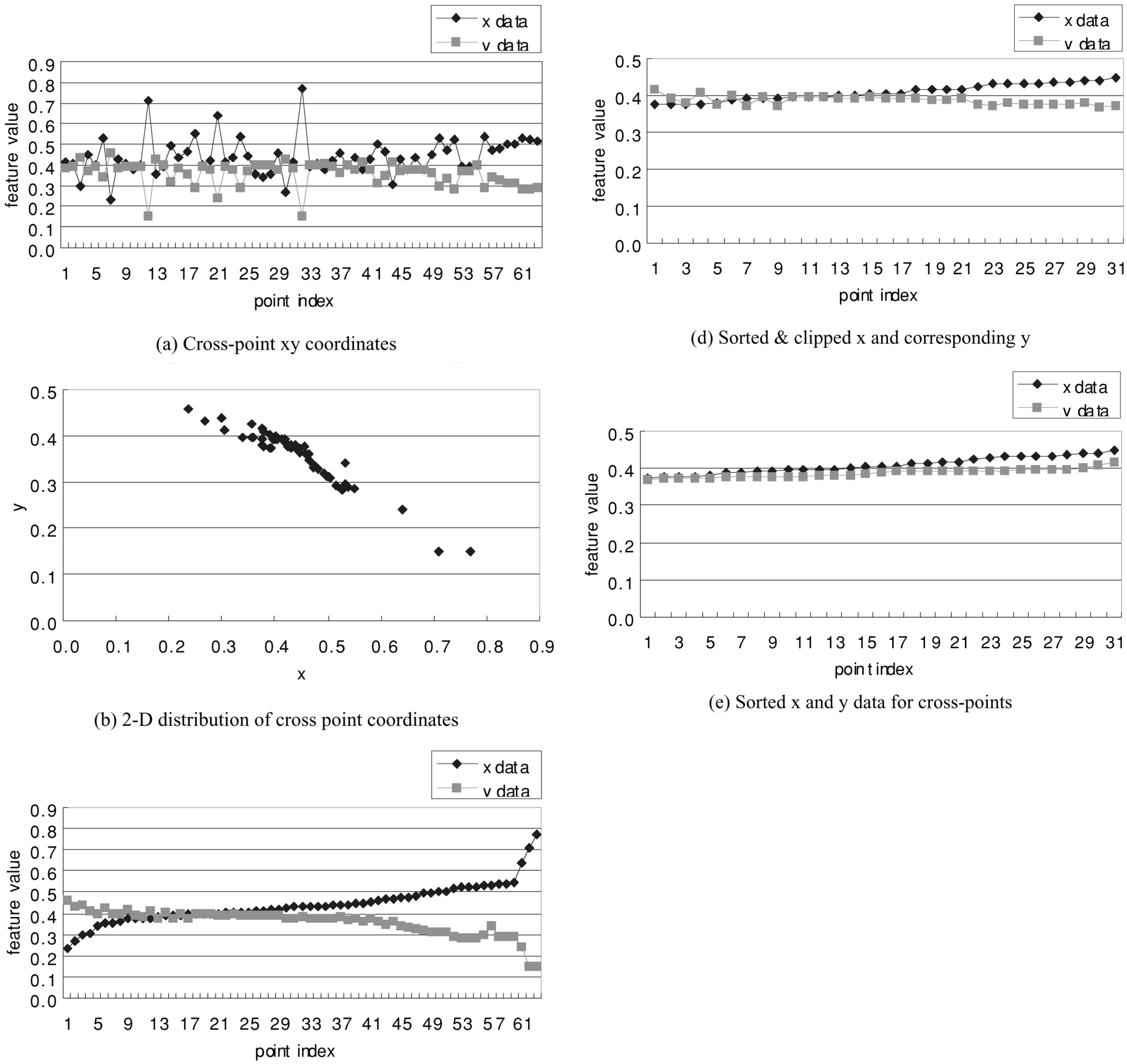


Figure 4. 2-D representation of proposed extraction of line parameters.

points. The conventional approach for selection uses histogram accumulation. If the valid digit for the coordinate figures is high, there is a problem in quantitizing the figures. The quantitization 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 use of sorting in the proposed approach preserves the accuracy while maintaining the concept of histogram accumulation. One cross-point consists of two components x and y, as shown in Fig. 5(a), and 5(b) is the 2-D distribution of xy data. At first, the set of cross-points is sorted in ascending order for x, as in Fig. 5(c). In this sorting process, the format of the cross-point $c(x,y)$ 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 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, select a neighborhood range that contains the center x value as a subset for the original coordinate set, as shown in Fig. 5(d). Apply the same subset sorting procedure for obtaining a y ref-



(a) Cross-point xy coordinates

(b) 2-D distribution of cross point coordinates

(c) Sorted data for x only

(d) Sorted & clipped x and corresponding y

(e) Sorted x and y data for cross-points

Figure 5. Selection of representative point among candidate points. (a) Cross-point *xy* coordinates; (b) 2-D distribution of cross point coordinates; (c) Sorted data for *x* only; (d) Sorted and clipped *x* and corresponding *y*; (e) Sorted *x* and *y* data for cross-points.

erence and center value for y as used above, see Fig. 5(e). The representative coordinates for the cross points can also be obtained using the above procedure. To select the representative coordinates, take the convex of the second derivative of a sorted curve, or the closest point to the convex available. This approach is more effective for a dense distribution than a conventional histogram approach when some level of accuracy is required. The representative chromaticity coordinate is regarded as the illuminant chromaticity.

Proposed Hybrid Method Using Perceived Illumination and Highlight

The proposed hybrid method can be used to estimate illuminant chromaticity and combines the advantages of stability from the perceived illumination approach and accuracy from the highlight approach. The perceived illumination approach can provide a stable candidate range for estimating illuminant chromaticity, however, the accuracy is slightly degraded and depends on the image content. In contrast, the highlight approach does not depend on the image content and provides an accurate solution for scene illuminant chromaticity, however, the drawback is in deciding on the final solution from many possible cross points. Accordingly, the nature of these two approaches can be considered as mutually compensating, as such, the solution from the perceived illumination approach can be used as the starting point or base information for the highlight approach. The proposed process is shown in Fig. 6.

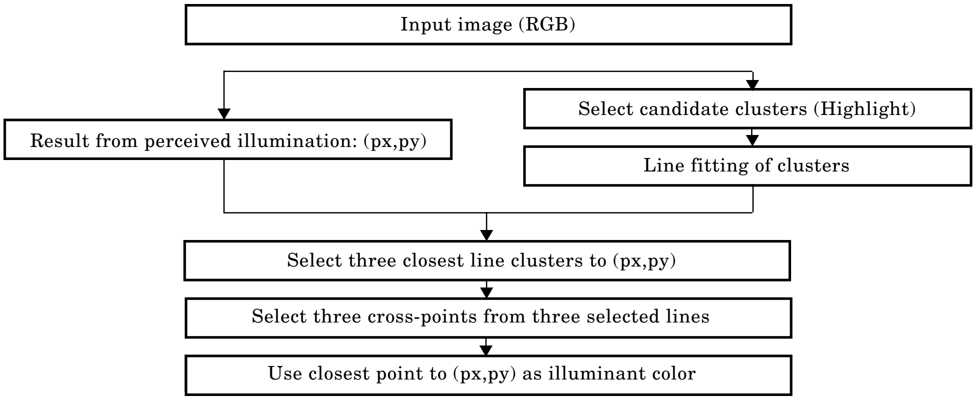


Figure 6. Flowchart of proposed hybrid approach.

First, calculate the result from the perceived illumination approach as (p_x,p_y) and select the same candidate regions as with the highlight approach. If there is no candidate for this region, output is set to (p_x,p_y). Line parameters from representative points of each distribution are calculated and the three closest line distributions to (p_x,p_y) are selected. Among these cross-points, the three closest points to (p_x,p_y) as $(cp_{x1},\mathrm{cp}_{y1})$, (cp_{x2},cp_{y2}), and (cp_{x3},cp_{y3}) are selected. From three cross-points, the closest one to (p_x,p_y) is determined as illuminant chromaticity as the output of the hybrid approach.

Experimental Results

The most popular method for making a chromaticity reference is to measure the white patch. In this article, two types of white were used as follows: the first was by inserting a Macbeth Color Checker into the scene to capture and measure the white patch. This is a good method since it is an actual and correct reference value. In most cases, a local illumination field is non-uniform with changes in the position of the scene, that is, there are different whites for the same scene. For example, in an outdoor scene, one section of the same surface can be under shadow, whereas another part is directly lit. As a result, the white measurement for these two cases will be different. The measurements in Table I show this variation in the white chromaticity relative to a change of surroundings. Three states were used, under shadow (S), directly light (D), and the effect of cloud (C). A Minolta CS-100 chroma-meter was used and maximum difference in the chromaticity was 0.04. The measurements show a variation in the white chromaticity with a change in the local illumination characteristics. Accordingly, it is very difficult to select a representative reference white, with the change of local illumination. In this article, a dominant white chromaticity for a scene was selected, that is, for outdoor images the measurement for direct light was used as the reference. For indoor images, fluorescent and halogen lamps were used as the illuminants therefore, since the local variations in the illumination field were not as big compared to the outdoor images, the selection of the representative white was simple. Another way to select a representative white is to insert a white patch in the image and then analyze the RGB values for this white area. Although this method is simple, it is not so reliable because of the problem of device calibration and color correction. Therefore, in this article, the reference white is based on measured data.

TABLE I. Measured Data for Reference White Patch

no.	*Y*	*x*	*y*	condition	clock
1	199.0	0.320	0.340	S	08:30
2	959.0	0.348	0.362	D	08:30
3	351.0	0.340	0.356	S	11:50
4	514.0	0.322	0.345	S	11:50
5	302.0	0.328	0.347	S	11:50
6	909.0	0.330	0.352	C	11:50
7	1540.0	0.340	0.356	D	11:50
8	1120.0	0.349	0.363	D	11:50
9	1690.0	0.343	0.357	D	11:50
10	650.0	0.295	0.318	S	15:30
11	1080.0	0.340	0.357	D	15:30

Two kinds of error metric were used in this article. One applied Euclidean distance to the chromaticity space and the other used the difference in the color temperature. When applying the distance metric to chromaticity space, the distance itself is an important measure and can be expressed in another format as follows:

i) simple Euclidean distance: Δxy

ii) $\Delta xy/xy_{ref}$: xy_{ref} is the vector magnitude of the reference chromaticity for the image.

iii) $\Delta xy/xy_{ref65}$: xy_{ref65} is the vector magnitude of the reference chromaticity for 6500K.

Type i) is the most stable and absolute metric for error measure, however, the error magnitude of this value is very hard to understand. For example when Δxy = 0.03, it is difficult to directly perceive the error magnitude. Type ii) is a normalized version of type i) and represents the error percentage of distance compared to the vector magnitude of the reference chromaticity. Accordingly, it provides a basic ratio between the error distance and the target reference magnitude. The problem with type ii) is when the reference chromaticity vector differs from illuminant to illuminant, as the same error distance can be represented as a different ratio. To cope with this problem, the magnitude of the reference chromaticity needs to be fixed in order to provide the same ratio for different illuminants. In type iii), a reference chromaticity of 6500K (daylight) was used as the reference magnitude and used as a final error measure in all the experiments in this article. The other error metric method utilized the difference between the estimated color temperature and the reference temperature. The color temperature can be obtained from the chromatic-

TABLE II. Estimation Results for Perceived Illumination

illuminant	R_x	R_y	E_x	E_y	Δ*xy*	error [%]
HRZ	0.5030	0.4120	0.4634	0.3722	0.0561	12.325
INC	0.4590	0.4110	0.4435	0.4048	0.0167	3.665
CLW	0.3790	0.3910	0.3868	0.3982	0.0106	2.330
D50	0.3520	0.3680	0.3576	0.3702	0.0006	1.321
D65	0.3170	0.3450	0.3238	.03535	0.0109	2.390
D75	0.3020	0.3320	0.3087	0.3473	0.0167	3.667

error = Δxy/0.456*100 [%] (0.456: vector magnitude for 6500K)

TABLE III. Estimation Results for Highlight Approach

illuminant	R_x	R_y	E_x	E_y	Δ*xy*	error [%]
HRZ	0.5030	0.4120	0.5344	0.3757	0.0480	10.5367
INC	0.4590	0.4110	0.5117	0.4058	0.0530	11.6254
CLW	0.3790	0.3910	0.3969	0.4003	0.0202	4.4283
D50	0.3520	0.3680	0.3662	0.3568	0.0181	3.9703
D65	0.3170	0.3450	0.3237	0.3388	0.0091	2.0040
D75	0.3020	0.3320	0.3135	0.3347	0.0118	2.5933

error = Δ*xy*/0.456*100 [%] (0.456: vector magnitude for 6500K)

ity coordinates. This method is a well-known error metric in the public domain, however, the non-linearity required for the conversion of the chromaticity into a temperature also causes non-linearity in the error metric. As a result, the same difference in the chromaticity space can produce a different error with the color temperature. This situation particularly affects high color temperatures. In the proposed approach, a combination of type iii) and color temperature is used for the error calculation.

The input images were captured by a Kodak DC-420 digital camera under six different illuminants. All images included highlights and output was represented using an *xy* coordinate system. The six illuminants used were as follows: HRZ (Horizon), INC (Incandescent), CLW (Cool White), D50 (Daylight 5000K), D65 (Daylight 6500K), and D75 (Daylight 7500K).

The information for the reference data was obtained by shooting black and white patches from a Macbeth Color Checker under corresponding illuminants. The distance between the camera and the patch was approximately 1.2 m and the Macbeth Color Checker was placed at the bottom of a light booth. The parameter *f* was set to 2.0 and *k* was 1.5 for calculating the self-luminous threshold and the following criteria were used to check the validity of the pixels in the image.

- If the ratio between max(X,Y,Z) and min(X,Y,Z) is larger than 5.0, the corresponding pixel is rejected.
- If one of *X, Y*, or *Z* is less than 0.05, the corresponding pixel is rejected.

The next step is to make a linear pixel value using gamma compensation as follows:

$$R_{Lij} = 0.971 \times R_{ij}^{\,1.4924}, \quad G_{Lij} = 0.971 \times G_{ij}^{\,1.4924}, \quad B_{Lij} = 0.971 \times B_{ij}^{\,1.4924}, \tag{8}$$

After gamma correction, the pixel values were converted from RGB to XYZ as follows:

$$\begin{bmatrix} X_{ij} \\ Y_{ij} \\ Z_{ij} \end{bmatrix} = \begin{bmatrix} 1.0755 & 0.3833 & -0.1744 \\ 0.2668 & 1.1197 & -0.4178 \\ -1.7172 & -0.6965 & 6.1078 \end{bmatrix} \begin{bmatrix} R_{Lij} \\ G_{Lij} \\ B_{Lij} \end{bmatrix} \tag{9}$$

where input range of RGB is 0 ~ 1, upper limit of output is 1.127 for XYZ, and lower limit of output is 0.0 for XYZ. The result for MCC with canonical illuminants are shown in Table II where R_x and R_y is the reference white point and E_x and E_y is the estimated white point.

In this experiment, the same conditions as in the above perceived illumination case was applied and the results are shown in Table III. The estimation performance depended on the validity of the selected highlight candidate and the accuracy was lower than the perceived illumination approach. The average error percentage was about 5.8~5.9 % in (*x,y*) coordinate distance. In this experiment, six kinds of illuminants and a Kodak DCS-420 digital camera were used. The illuminants were from a Macbeth Light Booth and were the same as in the above experiments. The estimation performance was slightly lower compared to the perceived illumination case. However, this error difference is insignificant when compared with the instability and image content dependency of the perceived illumination approach.

To measure the performance of the proposed hybrid method, three illuminants and 111 images were used. The illuminants were halogen, fluorescent, and daylight. The camera was a Kodak DC-260. The measured reference chromaticity of the illuminants were halogen (0.4650.411), fluorescent (0.390,0.414), and daylight (0.340,0.357). The number of images used was 33 (halogen), 42 (fluorescent), and 36 (daylight). The parameters for image calibration were gamma for 1.573 and conversion matrix from RGB to XYZ is as follows:

$$\begin{bmatrix} X_{ij} \\ Y_{ij} \\ Z_{ij} \end{bmatrix} = \begin{bmatrix} 0.514 & 0.359 & 0.016 \\ 0.247 & 0.704 & -0.078 \\ 0.012 & 0.081 & 0.606 \end{bmatrix} \begin{bmatrix} R_{ij} \\ G_{ij} \\ B_{ij} \end{bmatrix} + \begin{bmatrix} -0.002 \\ 0.001 \\ 0.013 \end{bmatrix}$$

TABLE IV. Results for Hybrid Method

illuminant	R_x	R_y	E_x	E_y	Δxy	error [%]
HRZ	0.5030	0.4120	0.4989	0.3640	0.0048	10.576
INC	0.4590	0.4110	0.4380	0.3880	0.0311	6.837
CLW	0.3790	0.3910	0.3993	0.4081	0.0265	5.827
D50	0.3520	0.3680	0.3634	0.3763	0.0141	3.096
D65	0.3170	0.3450	0.3283	0.3526	0.0136	2.989
D75	0.3020	0.3320	0.3542	0.3542	0.0222	4.874

error = Δxy/0.456*100 [%] (0.456: vector magnitude for 6500K)

TABLE V. Reliability of Hybrid Method(Δxy)

illuminant	hybrid method	perceived illumination	remarks
halogen	5.91	5.79	average error
fluorescent	6.01	6.01	percentage
daylight	6.61	6.72	(Δxy-percentage)
total	6.18	6.18	

TABLE VI. Reliability of Hybrid Method (Color Temperature)

illuminant	hybrid method	perceived illumination	remarks
halogen	146	194	average error
fluorescent	287	286	percentage
daylight	717	730	(Δxy-percentage)
total	384	403	

TABLE VII. Results of Hybrid Method (Outdoor: Δxy)

Error illuminant	Perceived illumination [%]				Hybrid method [%]			
	H	F	D	total	H	F	D	total
group 1	5.79	6.01	6.72	6.18	5.91	6.01	6.61	6.18
group 2	4.84	5.93	9.27	8.69	5.66	8.24	9.46	9.07
group 3	5.00	7.29	7.60	7.32	5.00	9.57	7.35	9.06

H: halogen, F: fluorescent, D: daylight

TABLE VIII. Results of Hybrid Method (Outdoor: Color Temperature)

Error illuminant	Perceived illumination [%]				Hybrid method [%]			
	H	F	D	total	H	F	D	total
group 1	194	286	730	403	146	287	717	384
group 2	142	315	1068	943	139	490	1071	957
group 3	175	402	866	493	175	523	843	583

H: halogen, F: fluorescent, D: daylight

TABLE IX. The Comparison Between Proposed and Conventional

Error illuminant	Perceived illumination [%]				Hybrid method [%]			
	H	F	D	total	H	F	D	total
group 1	170	535	971	568	146	287	717	384
group 2	309	584	1149	1043	139	490	1071	957
group 3	15	379	820	463	175	523	843	583

H: halogen, F: fluorescent, D: daylight

The input and conditions for the experiment were the same as in the indoor case above. The number of images used in the experiment was 360, and most were taken outdoors or other places. The input images were classified into 4 groups from group 1 to 4. The classification was based on the characteristic of the reference illuminant. Group 1 represented a physically measured reference, group 2 represented human perception without a physical measurement, group 3 represented complex illuminants without a dominant one, and group 4 represented an unknown reference that was difficult to guess. The test was applied to all groups, except for group 4. The result for the proposed algorithm is compared with conventional one as gray world assumption as shown in Table IX.

Conclusions

A method for estimation of illuminant chromaticity from single color image was proposed to estimate the chromaticity of scene illuminant. In this article, the perceived illumination approach is proposed to exclude high intensity regions in the image that is a problem in simple averaging algorithm. In the estimation of highlight approach, the selection of line clusters and extraction method of line for the candidate highlight region is proposed. These two approaches are in effect mutually compensating. Therefore, the proposed hybrid approach combines the stability of the perceived illumination type and the accuracy of the highlight type. The perceived illumination approach provides a stable candidate range for the estimation of illuminant chromaticity, however, the accuracy is slightly degraded depending on the image contents. The highlight approach does not depend on the image contents and provides an accurate solution of the scene illuminant chromaticity, however, it is difficult to determine the final solution among many cross-points.

The accuracy of the hybrid approach can be represented as the Euclidean distance between the estimated chromaticity coordinate and a reference. The proposed algorithm was compared to the conventional Retinex algorithm using gray world assumption, and gives better estimation of illuminant chormaticities.

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