https://doi.org/10.2352/issn.2169-2629.2019.27.61

Illuminant Estimation Through Reverse Calibration of an Auto White-Balanced Image That Contains Displays

Abstract

This study proposes an illuminant estimation method that reproduces the original illuminant of a scene using a mobile display as a target. The original lighting environment of an auto white-balancing (AWB) photograph is obtained through reverse calibration, using the white point of a display in the photograph. This reproduces the photograph before AWB processed, and we can obtain the illuminant information using Gray World computation. The study consists of two sessions. In Session 1, we measured the display's white points under varying illuminants to prove that display colors show limited changes under any light conditions. Then, in Session 2, we generated the estimations and assessed the performance of display-based illuminant estimation by comparing the result with the optically measured values in the real situation. Overall, the proposed method is a satisfactory way to estimate the less chromatic illuminants under 6300 K that we experience as indoor light in our daily lives.

Introduction

Although we look at objects under a variety of illuminants, their colors stay relatively constant, relative to the illuminant changes. It is due to color constancy that attempts to perceive pure object colors are minimized, regardless of the effects of the illuminant on the object [1]. In digital image processors, such as digital cameras or image editing software, color constancy is usually achieved through automatic white balancing (AWB).

The majority of AWB algorithms follow a two-step process. The first step is illuminant estimation, which estimates or measures the illuminant at the time a picture was taken. Then, using the estimated illuminant information, a new image is generated, as if it had been taken under a standard illuminant.

Among various algorithms, White Patch and Gray World are widely known solutions [2]. The Gray World algorithm assumes that the average color of a scene is achromatic under a standard illuminant. More specifically, it estimates the illuminant of a scene on the basis of the chroma of the average color of the scene, and corrects the color by changing the average color into an achromatic one. The White Patch algorithm claims that the brightest point of a scene reveals the actual color of the illuminant [3]. Thus, it performs white balancing of an image by transforming the color of the brightest point into white [4].

Although these two methods offer robust and satisfactory AWB results for an overall scene, they confront a limitation in their ability to reproduce specific colors correctly [5]. To overcome this limitation, several studies have utilized a Macbeth Color Checker to ensure that the exact color values of 24 colors are known [6]. Once a picture was taken, together with the Macbeth Color Checker, it was much easier to estimate the original illuminant at the time the picture was taken and correct to perform white balancing.

However, in practice, it is hardly possible to routinely include a standard color checker within a scene of a photograph or a video, unless it is an experimental set-up. Moreover, these methods show a dramatic worsening in good performance when a picture is taken under chromatic illuminants, such as stage lighting [7]. In other words, as the illuminant moves even further away from being a standard illuminant, it becomes difficult to estimate the original illuminant on a given image. This seeks to identify any practically useful targets that can be used to estimate even chromatic illuminants using pictures of everyday life.

In this study, we propose a novel illuminant estimation method that deploys a mobile display as a target to estimate the illuminant of a scene. Because, unlike other object colors, a display is self-luminous, it always produces constant colors, regardless of the illuminant. In Figure 1, the white background in the smartphone display appears bluish, and this coloration may have occurred during the AWB process. If we return this bluish-white to a more neutral white, we may obtain a more yellowish or orangish figure. Consequently, we can refer to the hue characteristics of a display in a calibrated image to estimate the hue characteristics of the illuminant at the time the original picture was taken.

Figure 1 *The white background in the smartphone display appears bluish, and this may have occurred during the AWB process. If we return this bluish-white to neutral-white, we may obtain a more yellowish or orangish figure. (Picture by © Marc Mueller).*

Moreover, a mobile display is a much more practical and useful target than a standard color checker, due to its prevalence in our daily lives. By incorporating this characteristic of a mobile display into the AWB process, we aim to propose a practical way of reproducing the original illuminant of a scene, thereby widening the space for further processing.

This paper is structured as follows: first, it investigates the reliability of display as a target by measuring its color changes under various illuminants (Session 1); then it compares the performance of display-based illuminant estimation with the original photographs that have not undergone AWB (Session 2); last, paper discusses idea about applications of for the proposed method and identifies limitations and issues that demand further study.

Session 1. Display White Measurement

The purpose of this session is to examine whether a display's white chrominance is maintained or changed when illuminants vary. We photographed displays in an experimental room, where illuminants were manipulated by individually adjusting the intensity of the red (R), green (G), blue (B), and white (W) channels. The experimental room was colored either in white or light gray to best reflect the hue characteristics of the illuminant.

Illuminants

For the illuminants, we considered three categories: nuanced-white (9 kinds), chroma (12 kinds), and high-chroma (6 kinds). The illuminance level was fixed to approximately 800 lx throughout the experiments.

The first 9 illuminants were distinct nuanced-white illuminants that varied from 2,500 K to 18,000 K, which we tried to generate, according to the Planckian locus. The colorimetric values of each lighting condition were measured on the desk, using a Chroma Meter (Minolta CL 200A), as listed in Table 1; they are plotted as white-outlined dots in Figure 2.

Table 1. The 9 kinds of nuanced-white illuminants.

Illuminant category	CCT [K]	x	y
Nuanced-white (800 lux)	3035	0.436	0.406
	3911	0.379	0.360
	5087	0.345	0.385
	6266	0.317	0.336
	8708	0.283	0.313
	10291	0.270	0.301
	11498	0.261	0.297
	15116	0.254	0.271
	21351	0.245	0.253

Second, 12 kinds of chromatic illuminants were produced, covering a diverse hue range. Their dominant wavelength, relative to D65 white standard (6500K) and x-y coordinates, are presented in

Table 2; they are plotted as gray-outlined dots in Figure 2.

Table 2. The 12 kinds of chromatic illuminants.

Illuminant category	Dominant wavelength(nm)	x	y
Chroma (800 lux)	616.8	0.488	0.323
	573.1	0.413	0.463
	559.0	0.344	0.508
	529.8	0.230	0.576
	485.9	0.178	0.269
	478.8	0.164	0.186
	473.8	0.160	0.138
	466.6	0.156	0.083
	443.8	0.207	0.108
	445.0	0.206	0.108
	−563.3	0.251	0.127
	−550.6	0.316	0.174

In addition, 6 kinds of highly chromatic illuminants were added, and they were vivid enough to reach the primary colors of the Adobe RGB gamut. The details are listed in Table 3; they are plotted as black-outlined dots in Figure 2.

Table 3. The 6 kinds of highly chromatic illuminants.

Illuminant category	Dominant wavelength(nm)	x	y
High Chroma (800 lux)	619.7	0.602	0.314
	574.4	0.450	0.494
	530.6	0.195	0.695
	477.9	0.145	0.160
	464.3	0.140	0.043
	−563.3	0.239	0.091

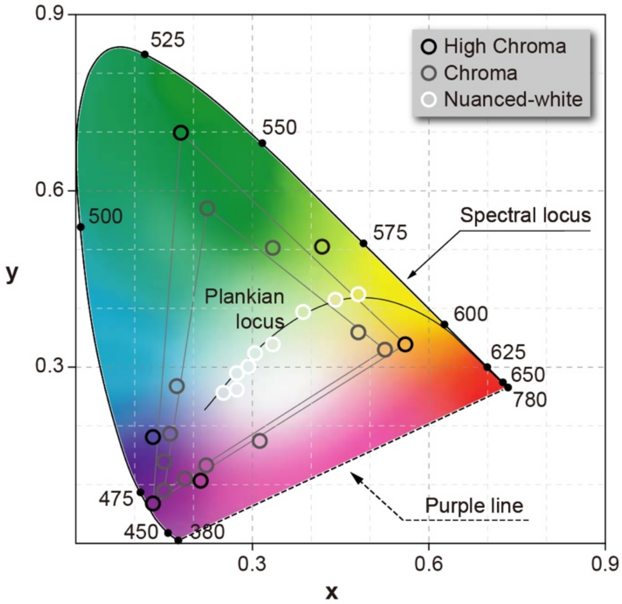

Figure 2 Plotting of 27 illuminants, which were used in experiments on the CIE 1931 XY color space. White-outlined dots were nuanced-white lightings, gray-outlined dots were chroma lightings, and black-outlined dots were high-chroma lightings.

Displays in digital images

Due to the surface reflectance, the color of a display surface may change slightly, depending on the ambient light. We had to take this into consideration, because we assumed the color properties of a luminous surface to be constant. To determine the influence of ambient lighting on the luminous surface, we placed devices under varying illuminants and took pictures of all simultaneously. Four kinds of smartphones were used, manufactured by the major global brands, were used; the models were an iPhone 6, Galaxy S7, LG G5, and iPad 3, as illustrated in Figure 3. Each device displayed the Google search page. Under 27 kinds of illuminants, we fixed a camera position to take repeated pictures of the scene, as pictured in Figure 3. The iPhone 6S was tested, but not included in the analysis because that phone model operates the true-tone adjustment that varies the white points, depending on the hue characteristics of the ambient illuminant. We used a digital single-lens reflex camera, a Canon 100D, and all pictures were taken in the camera's manual mode. Subsequently, the pictures were recorded as RAW files to avoid automatic calibration, including AWB.

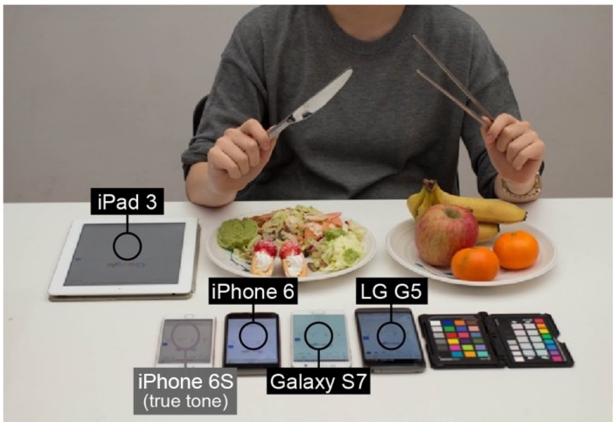

Figure 3 Pictures were taken under 27 illuminants, and each picture contained the four devices: iPad 3, iPhone 6, Galaxy S7, and LG G5. The Google search page was displayed on all devices. The iPhone 6S was not included in the analysis because that phone model operates the true-tone adjustment that varies the white points depending on the hue characteristics of the ambient illuminant.

After taking the 27 pictures, we measured how the Google search page was recorded within each picture. Using the pipette tool in Photoshop CC 2017, we selected the white background of the Google search page on each device (hereinafter, "white point"), and consequently, we collected 4 kinds of whites from every picture. In Table 4, we summarize the results, presenting the averaged R, G, B values of the white point of the devices pictured under the 27 kinds of illuminants. Obviously, the R, G, B values of white points were better maintained under the nuanced-white illuminants than those under the chromatic illuminants. Also, we observed that the standard deviation of blue ([B]) was often twice as big as that of R or G.

Table 4. Average red (R), green (G), blue (B) values and standard deviation of white points of the four devices pictured together under the 27 kinds of illuminants (N=18, 9 nuanced-white illuminants and 18 chromatic illuminants).

Device	Illuminants	
	9 kinds of Nuanced whites [R, G, B] ± SD	18 kinds of Chromatic lights [R, G, B] ± SD
iPhone 6	[137, 144, 162] ± [2, 4, 5.5]	[134, 142, 169] ± [6.3, 7, 9.3]
Galaxy S7	[135, 153, 148] ± [4.3, 2.9, 2.7]	[131, 151, 153] ± [4.9, 4.6, 11]
LG G5	[109, 118, 127] ± [5.4, 2.5, 5.2]	[104, 116, 142] ± [10, 8.5, 26]
iPad 3	[113, 111, 113] ± [7.9, 4.1, 16]	[100, 101, 142] ± [23, 23, 52]

Nevertheless, we regarded the color changes, caused by the surface reflection of the ambient illuminant, as marginal. Among the four devices, the iPhone 6 seemed to maintain the color of the luminous surface most successfully, while the iPad 3 did the worst job at this. This indicates that the iPhone 6 is a better target than the iPad 3, in the context of estimating original illuminants, based on the display images. Accordingly, in Session 2, we used the iPhone 6 and iPad 3 as the best and worst devices, respectively, among the four, expecting a range of performance of the display image, based on the reverse calibration, to estimate the initial illuminant.

Session 2. Illuminant Estimation Through Reverse Calibration

To estimate the original illuminant, we conducted a reverse calibration, using the white point of the display in an image as a target, especially when the image was taken with the AWB procedure. We attempted to examine the performance of this display-based illuminant estimation by comparing it with the original illuminant.

As with the images taken in Session 1, we employed the image data of iPhone 6 and iPad 3. As in Session 1, the images were recorded in the RAW format. We white balanced the RAW format images using the AWB option of Adobe Lightroom 5, as if the original images had been taken with AWB functions. Figure 4 presents an example of how an image taken in RAW mode is calibrated automatically, with the AWB option in Adobe Lightroom 5. In this way, we generated a total of 27 calibrated images.

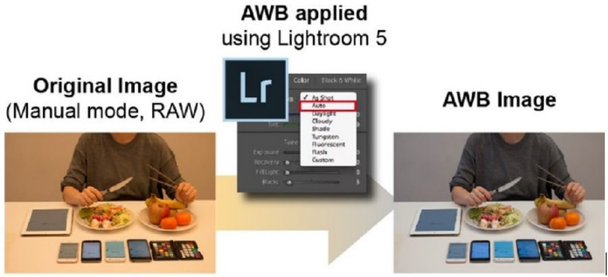

Figure 4 Pictures taken in a RAW mode (left) are transformed into an AWB applied image (right). Using Lightroom 5 Auto option for processing original image to auto white-balanced (AWB) image.

Then, we performed a reverse calibration, using the color of the display surfaces in AWB images. The reverse calibration consisted of the following steps: first, we picked white points of the display in an AWB image and labeled them as $R_{\text{after AWB}}$, $G_{\text{after AWB}}$, and $B_{\text{after AWB}}$; second, we referred to Table 4 to define R_{original}, G_{original}, and B_{original} and then calculated a gain matrix to transform the $RGB_{\text{after AWB}}$ into the RGB_{original}. The following formula (1) describes the procedure to calculate a 3 by 3 gain matrix.

$$\begin{bmatrix} R_{original} \\ G_{original} \\ B_{original} \end{bmatrix} = \begin{bmatrix} \frac{R_{gain}}{G_{gain}} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \frac{B_{gain}}{G_{gain}} \end{bmatrix} \times \begin{bmatrix} R_{afterAWB} \\ G_{afterAWB} \\ B_{afterAWB} \end{bmatrix} \quad (1)$$

Finally, we applied the gain matrix to calibrate the AWB image in reverse, and globally. Figure 5 presents an example of a reverse calibration, using the iPhone 6. The reversed image appears orangish, indicating that the picture actually was taken under a low correlated color temperature (CCT).

In this way, we obtained two sets of 27 reverse-calibrated images, based on the iPhone 6 and iPad 3. The computation was carried out using Matlab R2017. In Figure 6, RAW format images are compared with two reverse-calibrated images, based on the iPhone 6 and iPad 3 as the targets. Apparently, the reverse-calibrated images generally follow the hue characteristics of the RAW format images, along various illuminants, which indicates that the method is practically applicable.

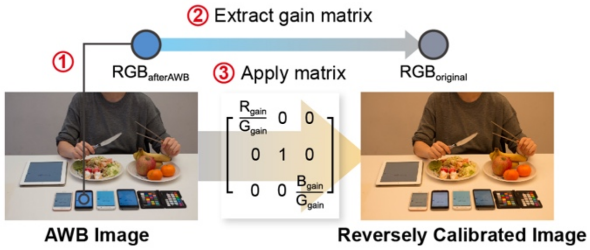

Figure 5 *Reverse calibration process. ① Pick distorted white point on AWB image. ② Calculate gain matrix based on distorted white point and original white point. ③ Transfer whole pixels in AWB image with the gain matrix calculated in step 2.*

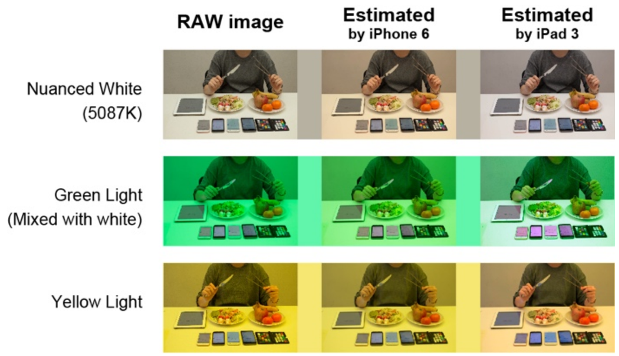

Figure 6 *Pictures recorded in RAW format (left) presented with reversely calibrated images. For the reverse calibration, display surfaces of the iPhone 6 (center) and iPad 3 (right) were used as the targets.*

Discussion

As shown in Figure 6, the method facilitated a satisfactory performance of estimating of the illuminant. In this study, we examined the performance of estimating the levels of illuminant more objectively. Also, we tried to compare the performance of reverse-calibrated images with that of RAW images. To obtain the information about the illuminant, based on a picture, we adopted the Gray World theory and applied the algorithm to both RAW and reverse-calibrated images. The computation was conducted using Matlab R2017. Consequently, the estimated illuminants from both images were compared with the actual illuminants, as measured with a Chroma Meter (Minolta CL 200A).

Table 5 compares the CCTs of estimated illuminants with regard to the 9 nuanced-white illuminants. In general, the estimated illuminants yielded lower CCTs than measured values, and this discrepancy widens as the measured CCT increases. A consideration of the differences between measured and estimated CCTs reveals that, on average, the values of such differences are 2691 K, 4541 K, and 3783 K, as presented in Table 5. However, given the CCT range we experience in daily life, it is possible to scale down the observation range to 6266 K. In that case, the differences are far lower, showing 813 K, 1626 K, and 364 K, respectively, thereby demonstrating that the method is a plausible choice in the event that a RAW-formatted image is unavailable. Moreover, in contrast to our negative speculation about using the iPad 3, due to its unstable surface reflection (see Table 4), the reverse calibration based on the image of the iPad 3 display seems to perform quite accurately, particularly when the illuminant is below 6000 K.

Table 5. The CCT of estimated illuminants from a RAW image and a reversely calibrated image based on the iPhone 6 and iPad 3.

Illuminant category	CCT of illuminants [K]			
	Measured	Estimated from RAW images	Estimated from reverse-calibrated images	
			iPhone 6	iPad3
Nuanced -white (800 lux)	3035	2199	1913	2964
	3911	2926	2094	3563
	5087	3846	2898	4381
	6266	6075	4889	5935
	8708	6977	5611	6386
	10291	8229	6138	7009
	11498	8880	6520	6807
	15116	9790	6886	7094
	21351	12123	7444	7080
Average difference from the measured CCT (all range)		2691	4541	3783
Average difference from the measured CCT (~6266 K)		813	1626	364

In the case of the chromatic illuminants, we identified the estimated illuminants' dominant wavelength, relative to D65 white standard (6500K). Table 6 demonstrates the comparative performances of the reverse calibration, based on the display images.

Table 6. The dominant wavelength of each illuminant estimation for 12 chromatic and 6 highly chromatic illuminants. Gray shaded cells indicate substantially large errors.

Illuminant category	Dominant wavelength (nm)			
	Measured	Estimated from RAW images	Estimated from reverse-calibrated images	
			iPhone6	iPad3
Chroma (800 lux)	616.8	611.8	623.1	615.4
	573.1	587.7	594.5	539.5
	559.0	574.4	580.0	541.7
	529.8	561.1	567.6	549.6
	485.9	537.8	548.9	492.0
	478.8	485.2	487.1	492.0
	473.8	476.5	478.3	491.7
	466.6	495.0	475.7	500.1
	443.8	471.0	470.5	497.0
	445.0	465.0	-560.8	518.2
	−563.3	-562.8	-541.9	529.1
	−550.6	-550.4	-541.6	591.9
High Chroma (800 lux)	619.7	611.8	623.1	611.8
	574.4	587.7	594.5	587.7
	530.6	574.4	580.0	574.4
	477.9	561.1	567.6	561.1
	464.3	537.8	548.9	537.8
	−563.3	485.2	487.1	485.2

Overall, the estimated dominant wavelength squares well with the measured values, but the performance deteriorates quite seriously in the purple range, particularly when the illuminant is highly saturated. The cells shaded in gray indicate that the proposed method is not be practical to estimate both purplish and vividly bluish illuminants. This may be due mainly to the fact that the recording of B was more unstable, relative to R or G when illuminants vary (Table 4). The results indicate that the display surface is highly affected by illuminants' blue light changes and this negatively impacts the process of reverse calibration, which yields a lower-quality estimation.

Also, this study has limited application to display devices that do not change their white points. We were aware of the true-tone function, introduced by Apple upon the release of the iPhone 6S, and the fact that the true tone adjusts the white point of the display, according to the ambient lighting, to best serve color consistency. Recent empirical studies have suggested matching models between the white point of a display and chromatic characteristics of illuminants [8-10].

Nevertheless, at least for now, the proposed method is applicable to most everyday pictures. The method enables us to remotely estimate the local illuminant if a digital image with a display surface is available. We can easily investigate the local illuminant, using everyday pictures available in social media, because cameras usually proceed with AWB by default. In particular, as we determined on the basis of examination, the estimation is less correct when the method is applied to predict higher CCTs, of approximately 6000 K and above. However, the CCT of most indoor illuminants range from 2800 K to 6500 K, which means that the method can adequately cover the relevant CCT range in our everyday lives.

Conclusion

This study proposes a new way to estimate illuminants through reverse calibration of an AWB image, in which a display surface is contained. In Session 1, we observed the luminous surfaces of four devices, including three smartphones and one tablet PC, under 27 kinds of varying illuminants to make sure the hue characteristics of luminous surfaces appear constantly. In general, B values were less stable than R or G values, implying that the proposed method would perform more weakly when estimating higher CCTs or bluish illuminants. In Session 2, we conducted the reverse calibration and obtained the estimated illuminants. With regard to 9 kinds of nuanced-white illuminants, we applied the CCTs to measured and estimated illuminants, which revealed better estimation performance for the illuminants up to 6200 K. Also, with regard to 15 kinds of chromatic illuminants, we used the dominant wavelengths to determine the quality of the performance. The results showed that the method is more powerful for estimating the range between green and red than for the range between blue and purple. As an illuminant approached a primary color, the error increased. Nevertheless, the proposed method is capable of estimating the illuminant range that dominates in our daily lives, advocating its practical use to predict local illuminants where people use any display devices and take pictures with them.

References

Author Biography

Taesu Kim was born in Changwon, South Korea. He received aB.S. in Industrial Design from KAIST, Daejeon, South Korea, in 2018, where he is currently pursuing a Ph.D.. His current research interests include ambient color temperature for electronic devices and designing light and color in products.

Eunjin Kim received her Ph.D. in Industrial Design from KAIST. Throughout her Ph.D. studies, she has investigated techniques for affective and aesthetic color imaging and their practical usages in design practice. Based ontwhat she has learneds, she now works as a UX designer in NAVER Main & Search Studio.

Hyeon-Jeong Suk received her B.S. and M.S. in Industrial Design from KAIST in 1998 and 2000, respectively. In 2006, she received a doctoral degree in in Psychology from the University of Mannheim in Germany. Currently, she is an associate professor of Industrial Design at KAIST, leading a color laboratory (color.kaist.ac.kr). Dr. Suk is an Editor-in-Chief of Journal of Korea Society for Color Studies.