



# **Effects of surrounding stimulus properties on color constancy based on luminance balance**

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The visual system needs to discount the influence of an illuminant to achieve color constancy. Uchikawa *et al.* [J. Opt. Soc. Am. A29, A133 (2012)] showed that the luminance-balance change of surfaces in a scene contributes to illuminant estimation; however, its effect was substantially less than the chromaticity change. We conduct three experiments to reinforce the previous findings and investigate possible factors that can influence the effect of luminance balance. Experimental results replicate the previous finding; i.e., luminance balance makes a small, but significant, contribution to illuminant estimation. We find that stimulus dimensionality affects neither the degree of color constancy nor the effect of luminance balance. It is shown that luminance-balance-based estimation of an illuminant performs better for scenes with reddish or bluish surfaces. This suggests that the visual system exploits the optimal color distribution for illuminant estimation [J. Opt. Soc. Am. A 29, A133 (2012)]. © 2016 Optical Society of America

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# **1. INTRODUCTION**

When an illuminant changes, the chromaticity and luminance of a surface in a scene accordingly change. However, our perception of surface color does not change significantly. This visual property, which is known as color constancy, allows us to identify objects under different illuminants. To achieve color constancy, the visual system needs to discount the influence of the illuminant. However, such a subtraction is mathematically impossible because light entering our eyes is the product of the surface spectral reflectance and the illuminant spectral composition. Therefore, in some sense, the visual system needs to estimate the illuminant by exploiting various cues in the scene. Although there has been a substantial amount of research into color constancy, as recently summarized in review papers [1-3], its mechanism remains unclear.

Many potential algorithms have been proposed. One of the simplest solutions is retinal adaptation, known as von Kries adaptation [4]. A similar cone-based mechanism is Ives transformation [5], which considers cone signals globally across the retina, whereas von Kries adaptation acts locally. Although these low-level processes often provide sufficient cues for color constancy, the contributions of the higher-level visual process have also been reported [6]. Therefore, it is generally acknowledged that color constancy is not a specific level

process; several types of visual processes appear to underlie it in complex ways.

Another common approach to color constancy is to characterize the distribution of colors in a natural scene under various illuminants. Foster and Nascimento [7] pointed out that an illuminant change does not largely affect the spatial cone ratio; therefore, the visual system can use the invariant signal regardless of illuminant change, which might provide the basis of color constancy. Interestingly, unlike many other color constancy algorithms, this method allows the visual system to distinguish between the material change and the illuminant change without illuminant estimation.

It is known that brighter surfaces are better cues to estimate the illuminant than darker surfaces [8]. In its extreme form, a specular highlight would be particularly helpful because they directly convey an illuminant to the eye [9]. However, Fukuda and Uchikawa [10] found that colors appearing in the aperture-color mode do not significantly contribute to the degree of color constancy, suggesting that the visual system primarily exploits the colors in the surface-color appearance to estimate an illuminant.

In addition to these local cues interspersing in the scene, spatially global cues also seem to be reliable because the illuminant affects surfaces in a wide range of the scene. It is well known that simply taking a spatial average of scene chromaticity often provides a sufficient cue to estimate the illuminant under a constraint of the gray world hypothesis [11]. However, this method fails when the gray world hypothesis fails, and it is actually common that the scene is not gray [12]. As this acknowledged model implies, there has been a historical bias toward exploiting chromaticity to estimate the illuminant even though an illuminant change should also affect the luminance of surfaces in a scene.

One of the long-standing mysteries in the color constancy field has been how the visual system distinguishes a reddish scene under a neutral illuminant from a neutral scene under a reddish illuminant when both produce exactly same mean chromaticity. This problem was sharply focused on by Golz and MacLeod [13], who showed that surfaces with higher redness tend to have higher luminances under a reddish illuminant, resulting in a positive correlation between redness and luminance. They empirically showed that the visual system can exploit this correlation between luminance and redness to solve the ambiguity of mean chromaticity. The important implication shown by their study is that the luminance plays a significant role in illuminant estimation.

The optimal color, more precisely termed the optimal surface, has at most two abrupt spectral transitions between 0% and 100% reflectance, as shown in Fig. 1. The luminance of the optimal color is the maximum in colors with the same chromaticity. Therefore, the distribution of all optimal colors with different  $\lambda_1$  and  $\lambda_2$  visualizes a gamut of surface colors under a given illuminant (also known as the MacAdam's limit [14,15]). Figure 2(a) shows how this theoretical gamut changes relative to illuminant changes in the MacLeod-Boynton (MB) chromaticity diagram [17]. Each tiny dot indicates one optimal color. The peak of each distribution corresponds to the optimal color with 100% reflectance across all wavelengths (perfect reflecting diffuser), and thus indicates the white point of that illuminant. The cone-like shape of these optimal color distributions does not change dramatically across illuminants. However, their peaks are shifted toward the white point of each illuminant. This produces regions where optimal color distributions do not overlap. Thus, if a scene contains colors in the region where distributions do not overlap, it could provide a cue to estimate the illuminant. For instance, if a scene contains a saturated bright blue surface, the illuminant in the scene is unlikely to be reddish. A similar idea using the illuminant gamut has also been proposed [18].

To assess the feasibility of this notion, Fig. 2(b) shows the chromaticity versus luminance distributions of 574 natural



Fig. 1. Example of optimal color, which has at most two abrupt spectral transitions between 0% and 100% reflectance.



**Fig. 2.** (a) 3D representation of the optimal color distribution under three different illuminants and (b) 2D representation of optimal color distribution. 574 natural objects are plotted in (b). The luminance and chromaticity of optimal color were calculated by changing  $\lambda_1$  and  $\lambda_2$  in Fig. 1 in 4 nm steps under three illuminants (3000, 6500, and 20,000 K). We used Stockman and Sharpe cone fundamentals [16] for the calculation of cone responses.

objects [19] with optimal color distributions under three illuminants. Similar to optimal color distribution, the shape of the natural object distribution does not collapse when the illuminant changes; the natural object distribution is similar to the optimal color distribution. Therefore, the visual system might be able to internalize the shape of the optimal color distribution by exposure to the natural object distribution under various illuminants, such as those that occur in daily life.

In addition, a previous study has shown the relation between the luminous threshold and luminance of the optimal color, suggesting that the visual system knows this theoretical limit of the surface color [20]. If this is the case, the visual system would be able to estimate an illuminant by choosing the best-fit optimal color distribution for a given scene distribution (optimal color hypothesis).



**Fig. 3.** Key idea for experiments to test the optimal color hypothesis. On the left, each surface is within the optimal color distribution of 6500 K. However, on the right, a reddish surface exceeds the limit of 6500 K due to the luminance-balance change; thus, the visual system could estimate a reddish illuminant based on the optimal color hypothesis (see text for details).

Uchikawa et al. [21] conducted experiments to test this hypothesis (Fig. 3). On the left, three optimal surfaces are placed under a 6500 K illuminant. Thus, they are within the optimal color distribution of 6500 K. However, when the luminance balance of scene surfaces changes, some surfaces may exceed the optimal color distribution of 6500 K as shown on the right. If that occurs, the visual system needs to pick the best-fit color temperature so that all surfaces are within the limit of surface colors. In addition to this luminance shift condition with constant chromaticity across illuminants, Uchikawa et al. [21] also investigated the chromaticity shift condition with constant luminance across illuminants and the luminance and chromaticity shift condition. The results showed that the optimal color hypothesis sufficiently worked for a chromaticity shift and both luminance and chromaticity shift conditions. More importantly, they found that a luminance-balance change by itself could contribute to illuminant estimation.

Although the importance of luminance balance for estimating an illuminant was demonstrated, its effect was significantly smaller than that of a chromatic shift; thus, the results partially supported the hypothesis. In addition, only two observers participated in their experiments; therefore, the results might be observer-dependent. The present study conducted three experiments to reinforce the previous findings. The goal of the experiments was to identify the possible reason for the small luminance shift effect and extend its feasibility for different situations.

Since the experiments reported by Uchikawa *et al.* [21] employed 2D hexagons as surrounding stimuli, it is possible that the observers could not separate a surface and an illuminant sufficiently. In fact, some studies have reported the effect of the scene or stimulus dimensionality on color constancy [22]. Therefore, in Experiment 1, we tested the effect of stimulus dimensionality on luminance-balance-based illuminant estimation. However, the results showed little effect.

In Experiment 2, we assumed that the relatively smaller luminance shift effects might come from the small number of colors (six) used for surrounding stimuli. In terms of the optimal color hypothesis, a greater number of surrounding colors might make the shape of the scene distribution clearer and, thus, help the visual system pick the best-fit optimal color distribution more accurately. To compare the effect of the number of surrounding colors, we used a 60-color condition and the original six-color condition. The result showed that a larger number of surrounding colors enhances the effect of chromaticity shift but not luminance shift. In addition, the effect of luminance shift was still substantially smaller than that of chromatic shift.

As shown in Figs. 2(a) and 2(b), optimal color distributions are separated primarily at high redness or high blueness regions. Thus, optimal colors with high purity have largely different luminances under different illuminants. Consequently, we considered that the scene must contain high redness or high blueness surfaces to estimate reddish (3000 K) or bluish (20,000 K) illuminants based only on the luminance balance. Therefore, we assumed that a scene primarily consisting of reddish and bluish surfaces could enhance the effect of luminance balance, and employed a red-blue dominant scene, a green-yellow dominant scene, and a balanced scene in Experiment 3. As expected, the results showed that the effect of luminance balance is greater for the red-blue dominant scene than for the green-yellow dominant scene.

# 2. GENERAL METHODS

#### A. Apparatus

All experiments were conducted in a dark room. Stimuli were presented on a CRT monitor (Sony, GDM-520, 19 inches, 1600 × 1200 pixels) controlled by PC (Epson, MT7500) with 14-bit intensity resolution for each phosphor allowed by a ViSaGe (Cambridge Research System). The monitor was gamma-corrected using the Color-CAL colorimeter (Cambridge Research System) and spectrally calibrated with a spectral radiometer (PR-650, Photo Research Inc.). The observer was situated 114 cm from the CRT monitor, and viewed stimuli binocularly with his/her head supported by a chin rest.

#### **B. Stimuli**

Figure 4 shows an example of the experimental stimuli consisting of 61 hexagons (cubes were used for the 3D condition in Experiment 1). The center hexagon was used as a test field, and its chromaticity and luminance were adjustable. The others were employed as the surrounding stimuli. The methods used to manipulate the chromaticity and luminance of each hexagon are provided in the subsequent descriptions of each experiment.



**Fig. 4.** Example of the stimulus spatial configuration. The central hexagon was used as a test field, and its chromaticity and luminance were adjustable.

Hexagons were 2° diagonally, and the whole stimulus consequently subtended  $15.6^{\circ}$  by  $14.0^{\circ}$  (w × h).

#### C. Observers

Four observers participated in all experiments. Three male observers were 20-29 years of age, and one female observer (HH) was 30-39 years of age. All observers had normal color vision assessed by Ishihara Pseudoisochromatic Plate tests. TM was an author.

# **D.** Procedure

The observer was instructed to adjust both the chromaticity and luminance of the test field so that it appeared as a full-white paper under a test illuminant (paper-match criterion [23]) with a track ball and a keypad. The chromaticity adjustment was performed two-dimensionally on the MB chromaticity diagram. For all experiments, we defined the chromaticity and luminance of the test field selected as a full-white paper by the observer as an estimated illuminant chromaticity and intensity, respectively.

Prior to starting the first trial, the observer first adapted to an equal energy white light  $(33.0 \text{ cd/m}^2)$  that covered the full displayable area of the CRT monitor for 2 min. Both the initial chromaticity and luminance of the test field were chosen randomly from a possible range for each trial. After satisfactory adjustments without time limitations, the observer recorded their final choice. One block consisted of five successive repetitions without inter-trial interval. In the same block, the same surrounding stimuli but different spatial arrangements were presented. The observer readapted to the equal energy white for 30 s between blocks. One session comprised 18 blocks in Experiments 1 and 3 and 17 blocks in Experiment 2. The order of the conditions was fully randomized within a session. The observer performed four sessions resulting in 20 repetitions for each condition.

## 3. EXPERIMENT 1

#### A. Surrounding Stimuli

To examine the effect of stimulus dimensionality, we employed 60 hexagons for the 2D condition and 60 cubes for the 3D condition as surrounding stimuli, as shown in Fig. 5. A cube has the same chromaticity on all sides. The luminance of its topside was the same as that of the corresponding flat hexagon in the 2D condition, and its left and right sides had 60% and

20% luminance of the topside, respectively. These luminance values were chosen so that the resulting stimulus appeared as an illuminated cube. The observers confirmed these points in a pilot test.

We used three chromaticities and two luminance levels (bright and dim), resulting in the six colors. For the test illuminants, we employed 3000, 6500, and 20,000 K illuminants on the black body locus. Their intensity, which was defined as their luminance when they were reflected from the perfect reflecting diffuser, was 28.6  $cd/m^2$ .

To test the optimal color hypothesis and investigate luminance and chromaticity contributions to illuminant estimation separately, we manipulated the luminance and chromaticity of each surface in three ways, as illustrated in Fig. 6. There are several ways to segregate the contribution of luminance shift and chromaticity shift, but we employed the following manipulations. Note that these were also used in a previous experiment [21].

In the (a) luminance shift condition, we first determined three MB chromaticities, which are R (0.824, 0.123), G (0.659, 0.181), and B (0.641, 2.70), so that we could use the display gamut as widely as possible, and its average corresponds to the equal energy white,  $W_E$  (0.708, 1.00). Then, the luminances of three bright colors were set to those of optimal colors under each test illuminant, while their chromaticities were kept constant across the test illuminants.

In the (b) chromaticity shift condition, we first defined the three optimal surfaces, which had R (0.759, 0.867), G (0.678, 0.700), and B (0.666, 1.78), under the 6500 K test illuminant. When those surfaces were placed under different test illuminants (3000 or 20,000 K), their chromaticity and luminance shifted. We employed only chromaticity shift for three surfaces under the corresponding test illuminants. In order to shift the chromaticity without luminance changes, we chose the lowest luminance value across the three test illuminants for each surface such that none of the surfaces exceeded the optimal color distribution under any of the illuminants.

In the (c) luminance and chromaticity shift condition, we again first defined the three optimal surfaces, which had R (0.733, 0.857), G (0.677, 0.705), and B (0.666, 1.79), under the 6500 K test illuminant. Then, to create 3000 and 20,000 K conditions, we placed those surfaces under each illuminant and employed the chromaticity and luminance shifts.



(a) 2-D condition

(b) 3-D condition

Fig. 5. (a) 2D and (b) 3D surrounding stimuli employed in Experiment 1. The manipulation of the shade is described in the main text.



Fig. 6. Simplified illustration of each shift condition. Hexagons and triangles show scene surfaces and optimal color distribution under three illuminants, respectively. Details are in the main text.



**Fig. 7.** Surrounding stimuli employed in Experiment 1. Each row and column indicates different color temperature and shift conditions, respectively.

These manipulations resulted in the surrounding stimuli shown in Fig. 7 (only the 2D condition is shown here). There were 18 conditions consisting of the combination among three shift conditions (luminance shift, chromaticity shift, and luminance and chromaticity shift), three test illuminants (3000, 6500, and 20,000 K), and two stimulus dimensionalities (2D and 3D). The same number of each of the six colors was arranged for the same eccentricity, and no two of the same colors were placed next to each other. Note that different spatial arrangements were used for each trial.

## **B.** Results and Discussion

The colored circles in Fig. 8 show the mean chromaticity settings across 20 responses for two observers, which corresponded to the estimated illuminant chromaticity. Orange, black, and blue represent 3000, 6500, and 20,000 K, respectively. The cross and plus symbols indicate the white point of each illuminant and the mean chromaticity of the surrounding stimuli, respectively. Note that there is only one plus symbol in the luminance shift condition because the mean chromaticities were the same across the test illuminants. We also calculated the mean cone response of the surrounding stimuli for each condition, and then converted those into MB chromaticity. These mean LMS are shown as diamonds. The error bar indicates ± S.D. across 20 repetitions. If the observer estimated test illuminants perfectly, each colored circle should superimpose the corresponding illuminant chromaticity.

In the luminance shift condition (top row panels), if the visual system fully relies on chromaticity to estimate an illuminant and does not exploit luminance at all, all settings should overlap because the chromaticity was kept constant across the test illuminants. For both 2D and 3D conditions, (a) observer HH and (b) TM indicated that the settings under the three test illuminants were somewhat close to each other. However, the



Fig. 8. Results of two observers in Experiment 1. Filled color circles show the mean setting across 20 repetitions. X, pluses, and diamonds indicate illuminant chromaticity, mean chromaticity, and mean LMS, respectively. The error bar indicates ± S.D. across 20 repetitions.

settings under 3000 and 20,000 K shifted slightly toward the white point of the corresponding illuminant.

For (a) observer HH, for both 2D and 3D conditions, multiple comparisons with Bonferroni's correction (significance level: 0.05) showed that the setting under 3000 K was separated significantly from the settings under 6500 and 20,000 K in the redness direction. It was also shown that the setting under 20,000 K was separated significantly from the settings under 3000 and 6500 K in the blueness direction in the 2D condition, but only from the setting under 3000 K in the 3D condition. For (b) observer TM, for both 2D and 3D conditions, settings under the three illuminants were separated significantly in both the redness and blueness directions. Therefore, although the amounts of shifts were substantially smaller than the physical shift of the illuminant chromaticity, these results confirm that the visual system seems to exploit the luminance balance to estimate an illuminant to some extent.

In the chromaticity shift condition (middle row panels) in the 2D condition for (a) observer HH, the settings under 6500 and 20,000 K were clustered closely, but the setting under 3000 K was distant from the settings under 6500 and 20,000 K. The 3D condition appears to show somewhat better estimations than the 2D condition. The (b) observer TM showed better estimations than those observed in the luminance shift condition in both 2D and 3D conditions. Therefore, as expected, the visual system was able to exploit chromaticity to estimate an illuminant even when the luminance did not change across the test illuminants.

In the luminance and chromaticity shift condition (bottom row panels), both observers' estimated points of the illuminants for 3000 and 20,000 K shifted more than the other two shift conditions for both the 2D and 3D conditions.

However, overall, the effect of stimulus dimensionality appears small or nearly absent. The other two observers also showed similar trends.

To quantify the relative amount of shift between the settings under 6500 and 3000 K or 20,000 K, we calculated a constancy index. However, to argue the amount of shift properly, it would be necessary to unify the scale of both axes in the MB chromaticity diagram. Thus, we divided both axes by the S.D. of the settings under 6500 K separately for each condition. Although the method to quantify the degree of color constancy remains controversial [1], we define it as Eq. (1) in the present study:

$$CI = a/b \tag{1}$$

In Eq. (1), a indicates the distance between the observer setting under 6500 K and either 3000 or 20,000 K, and b is the distance between the illuminant chromaticity points. Higher constancy index (CI) values indicate better color constancy.

Figure 9 shows the averaged constancy indices for all observers. The left and right bars indicate the 2D and 3D scene conditions. For both 3000 and 20,000 K, luminance and chromaticity shift conditions showed the highest CI, indicating that color constancy worked the best when the illuminant change occurred naturally. However, it was also clearly found that the luminance shift condition shows some amount of color constancy. Again, the effect of stimulus dimensionality seems negligible.



**Fig. 9.** Averaged constancy indices across four observers in Experiment 1. Higher values indicate better color constancy. The error bar indicates  $\pm$  S.E. across four observers. The left and right bars indicate 2D and 3D conditions, respectively.

We conducted three-way repeated measures analysis of variance (ANOVA), with stimulus dimensionalities (2D and 3D), shift conditions (luminance shift, chromaticity shift, and luminance and chromaticity shift), and test illuminants (3000 and 20,000 K) as within-subject factors.

We found significant main effects of shift conditions (F(2, 6) = 16.72, p < 0.01), while the main effects of stimulus dimensionality and test illuminants were not significant (F(1, 3) = 0.0021, p > 0.1; F(1, 3) = 0.0155, p > 0.1). Note that there was no significant interaction. Multiple comparison by Bonferroni's correction (significance level: 0.05) revealed that the CI was significantly higher for the luminance and chromaticity shift condition than for the luminance shift and chromaticity shift conditions.

Interestingly, there was no significant difference between the luminance shift and chromaticity shift condition, suggesting that luminance shifts could have a similar contribution to chromaticity shifts for illuminant estimation. However, since we employed surrounding stimuli with higher purities for the luminance shift condition, as shown in Fig. 7, it seems difficult to conclude whether this is truly because luminance and chromaticity contribute equally to illuminant estimation. These different spectral purities across shift conditions were refined in Experiment 2.

Next, we discuss the illuminant intensity estimated by the observers. The bars in Fig. 10 show the average luminance settings across all observers. The error bars indicate  $\pm$ S.E. across observers. The green diamonds show the actual illuminant intensity, which was constant at 28.6 cd/m<sup>2</sup> across all conditions by design. The blue circles and red squares show the mean luminance and the highest luminance of the surrounding stimuli, respectively. Therefore, it was expected that the luminance settings would become equal to the green diamonds if the visual system estimated the illuminant intensity perfectly. On the other hand, if the estimation was made based on mean luminance or highest luminance, luminance settings should change across the conditions accordingly.

Figure 10 shows that the luminance settings appear substantially higher than the actual illuminant intensity. Although the mean luminance in the 3D condition was always less than that of the corresponding condition in the 2D condition, luminance settings were not largely different between the 2D and 3D



**Fig. 10.** Each bar shows the mean luminance settings across observers in Experiment 1. The error bar indicates  $\pm$ S.E. across observers. Green diamonds, red squares, and blue circles show the illuminant intensity (kept constant across all conditions), the highest luminance, and the mean luminance across surrounding stimuli, respectively.

conditions. This appears to rule out the possibility that the visual system uses mean luminance to estimate the illuminant intensity.

Three-way repeated measures ANOVA was performed, with the stimulus dimensionality (2D and 3D), the shift condition (luminance shift, chromaticity shift, and luminance and chromaticity shift), and the test illuminant (3000, 6500, and 20,000 K) as within-subject factors for the averaged luminance settings across the observers.

We found a significant main effect of the shift condition (F(2, 6) = 14.32, p < 0.01); however, the main effects of the other two factors were not significant. Note that no interactions were observed.

Multiple comparison with Bonferroni's correction (significance level: 0.05) revealed that the luminance setting was significantly higher for the luminance and chromaticity shift condition than for the luminance shift condition and chromaticity shift conditions.

Experiment 1 was intended to reveal whether the effect of the luminance-balance change could be enhanced by the 3D surrounding stimuli. However, the results showed no effect. Some previous studies argue the effect of 3D stimuli. Other studies have shown that color constancy improves by, for example, the binocular disparity [9], 3D stimuli [22,24], depth cue [25], and spatial structure [26].

However, similar to our results, some studies [27,28] have shown that scene dimensionality and complexity have limited influence on color constancy. In addition, in a recent review paper [1], it was pointed out that the degrees of color constancy are not systematically different between 2D and 3D scenes. Since the implications of the terms "2D" and "3D" differ from one study to another, it is difficult to make an exact comparison. However, at least for the present stimuli, stimulus dimensionality does not appear to affect the color constancy.

The results of Experiment 1 suggest that the relatively small effect of luminance shift observed in our previous study [21] was unlikely because the observers could not separate an illuminant from a surface due to stimulus dimensionality. Under the 3D condition, it is possible that the observers make a

judgment based solely on the chromaticity or luminance of the surfaces. In fact, in terms of the optimal color hypothesis, stimulus dimensionality should not matter because it does not affect the shape of chromaticity versus luminance distribution. Consequently, the best-fit optimal color distribution should not change. This might cause no difference between 2D and 3D conditions.

In Experiment 2, we examined whether this small effect of luminance balance might come from the small number (six) of surrounding colors because it might be easier to pick the best-fit optimal color distribution with a larger number of surrounding colors. Thus, in Experiment 2, to address this issue, we employed the 60 surrounding color condition with same shift conditions as in Experiment 1.

#### 4. EXPERIMENT 2

#### A. Surrounding Stimuli

To examine the effect of the number of surrounding colors, the 60-color condition was employed in addition to the six-color condition. We used flat hexagons for the surrounding stimuli, which is the same as that used for the 2D condition in Experiment 1.

We employed 30 or three chromaticities and two luminance levels (bright and dark) for the 60- and six-color conditions, respectively (Fig. 11). Three chromaticities of vertices were employed for the six-color condition. Dark colors always had 50% luminance of bright colors.

In Experiment 1, we used chromaticities with different purities across the shift conditions; however, we needed to equate those for a more accurate comparison. Thus, we first determined 30 chromaticities for all shift conditions, as shown in Fig. 11. These values were determined such that their average corresponded to the equal energy white and they did not exceed the display gamut when the test illuminant changed. Then, we simulated the illuminant change by three shifting manipulations, the same as in Experiment 1.

As a result of the manipulations, we obtained surrounding stimuli as shown in Fig. 12. Note that surrounding stimuli for



**Fig. 11.** Thirty chromaticities used in Experiment 2. The plus symbol indicates mean chromaticity (corresponds to the equal energy white). Three chromaticities of vertices were employed for the six-color condition.



**Fig. 12.** Surrounding stimuli employed in Experiment 2. Only the 60-color condition is shown.

6500 K were identical in the (a) luminance shift and (c) luminance and chromaticity shift conditions. However, the luminance of the surrounding stimuli of 6500 K in the (b) chromaticity shift condition slightly differed from these two shift conditions because they were set to the lowest luminance across the three test illuminants such that no surface exceeded the luminance of the optimal color under all test illuminants. As a result, there were 17 conditions in Experiment 2.

#### **B.** Results and Discussion

In Experiment 2, we show only CIs because the chromaticity settings generally followed the patterns observed in Experiment 1. Figure 13 shows CIs for all conditions. The blue dashed line indicates the average CIs between the 2D and 3D conditions in Experiment 1 for comparison.

It was observed that color constancy worked in the luminance shift condition to some extent. However, CIs in the chromaticity shift condition and the luminance and chromaticity shift condition appeared to be higher than in the luminance shift condition. Importantly, the 60-color condition demonstrated higher CIs than the six-color condition for the chromaticity shift and luminance and chromaticity shift conditions, indicating that a greater number of surrounding colors improved estimation of the illuminant. However, for the luminance shift condition, the difference between the six and the 60-color conditions appears small.

CIs were analyzed by three-way repeated measures ANOVA, with the number of surrounding colors (six and 60), shift conditions (luminance shift, chromaticity shift, and luminance and chromaticity shift), and test illuminants (3000 and 20,000 K) as within-subject factors.

We found significant main effects of shift conditions (F(2, 6) = 26.50, p < 0.01) and the number of surrounding colors (F(1, 3) = 10.49, p < 0.05); however, the main effect of the test illuminants was not significant (F(1, 3) = 3.22, p > 0.1). In addition, interaction between the shift condition



**Fig. 13.** Averaged constancy indices across four observers in Experiment 2. Higher values indicate better color constancy. The error bar indicates ±S.E. across four observers. The blue dashed lines are the constancy index from Experiment 1 for comparison (2D and 3D conditions were averaged).

and the number of surrounding colors was marginally significant (F(2, 6) = 4.22, p < 0.1).

Further analysis of the simple main effect showed higher CI for the 60-color condition than the six-color condition in the chromaticity shift condition (F(1, 3) = 22.22, p < 0.05) and the luminance and chromaticity shift condition (F(1, 3) = 8.14, p < 0.1). However, there was no significant difference between the six- and the 60-color conditions in the luminance shift condition (F(1, 3) = 1.85, p > 0.1). In addition, there was a significant simple main effect of the shift conditions for both the six- and 60-color conditions (F(2, 6) = 17.21, p < 0.01 and F(2, 6) = 24.63, p < 0.01, respectively).

To specify which shift condition showed higher CI, we conducted further multiple comparisons by Bonferroni's correction (significance level: 0.05). It was revealed that, for both the sixand 60-color conditions, the CI was significantly higher in the chromaticity shift and the luminance and chromaticity shift conditions than in the luminance shift condition. There was also no significant difference between the chromaticity shift and the luminance and chromaticity shift condition. Therefore, the lack of difference between the luminance shift and the chromaticity shift observed in Experiment 1 was likely due to the difference in purity.

Figure 14 shows luminance settings for all conditions in Experiment 2. We conducted three-way repeated measures ANOVA, with the number of surrounding colors (six and 60), shift conditions (luminance shift, chromaticity shift, and luminance and chromaticity shift), and test illuminants (3000, 6500, and 20,000 K) as within-subject factors.

The results show that neither the main effects nor the interactions were significant, suggesting that the estimated illuminant intensities were relatively stable regardless of the condition.

The main finding in Experiment 2 is that increasing the number of surrounding colors helps the estimation of the illuminant in the chromaticity shift condition and the luminance and chromaticity shift condition, while that in the luminance shift condition was not affected. This suggests that these are mediated by different mechanisms.

As shown in the left panel of Fig. 2(b), the optimal color distribution of 3000 K is separated from the other two

60 colors



**Fig. 14.** Each bar shows the mean luminance settings across observers in Experiment 2. The error bar indicates  $\pm$ S.E. across observers. Green diamonds, red squares, and blue circles show the illuminant intensity (constant across all conditions), highest luminance, and mean luminance across surrounding stimuli, respectively.

6 colors

illuminants in the luminance direction primarily in the higher redness region. Similarly, as shown in the right panel of Fig. 2(b), the optimal color distribution of 20,000 K is primarily separated from other illuminants at the high blueness region. Therefore, if we need to estimate the illuminant with only luminance balance as required in the luminance shift condition, the scene would need to contain high redness or high blueness surfaces. In Experiment 2, both the six- and 60-color conditions contained at least some high reddish and bluish surfaces; thus, this might explain the lack of effect of the number of surrounding colors. In Experiment 2, we chose various chromaticities so that the averaged chromaticity corresponded to the equal energy white. However, if a scene predominantly consists of reddish and bluish surfaces, the effect of luminance shift could be enhanced.

To address this issue, we conducted a final experiment using chromatically biased surrounding stimuli to reveal the effect of chromatic bias on the luminance-balance-based estimation of the illuminant.

## 5. EXPERIMENT 3

Luminance setting [cd/m2]

#### A. Surrounding Stimuli

In Experiment 3, we employed only the luminance shift condition. To examine the effect of the chromatic bias of scene surfaces, we employed the balanced scene, the red-blue dominant scene, and the green-yellow dominant scene. The balanced scene had various chromaticities across the display gamut, and its average chromaticity corresponded to the equal energy white. The green-yellow dominant scene was intended to have a smaller effect of luminance balance than the other two conditions because it lacks surfaces with high redness and blueness.

We used three or 30 chromaticities and two luminance levels (bright and dark) for the 60- and six-color conditions, respectively (Fig. 15). Three chromaticities of vertices were employed for the six-color condition. The manipulation of the luminance shift was the same as in Experiments 1 and 2,



**Fig. 15.** Thirty chromaticities used for each scene in Experiment 3. The plus symbol indicates mean chromaticity. Three chromaticities of vertices were employed for the six-color condition.

and the test illuminants were also the same. Figure 16 shows the surrounding stimuli for the 60-color condition.

### **B.** Results and Discussion

Figure 17 shows the mean chromaticity settings across 20 repetitions. The cross and plus symbols indicate the illuminant chromaticity and the mean chromaticity of the surrounding stimuli, respectively. The mean LMS are shown as diamonds. The error bar indicates ± S.D. across 20 repetitions.

In the balanced condition (top row), both observers indicated that settings under 3000 and 20,000 K shifted toward the white point of each illuminant in both the six- and 60-color conditions, as demonstrated by the previous experiments. Similar trends were observed in the red–blue dominant scene (middle row), but the overall settings appeared to shift slightly toward the mean chromaticity in both the six- and 60-color conditions. The green–yellow dominant condition essentially agreed with these trends, but the distance between the settings under each illuminant appeared to be closer than the other two conditions for both observers.

Figure 18 shows averaged CIs across four observers for all conditions. We conducted three-way repeated measures ANOVA, with the number of surrounding colors (six and 60), chromatic biases (balanced, red–blue dominant, and green–yellow dominant), and test illuminants (3000 and 20,000 K) as within-subject factors.



**Fig. 16.** Surrounding stimuli employed in Experiment 3. Only the 60-color condition is shown.



**Fig. 17.** Results of two individual observers in Experiment 3. The filled color circles show mean observer setting across 20 repetitions. X, pluses, and diamonds indicate illuminant chromaticity, mean chromaticity, and mean LMS, respectively. The error bar indicates  $\pm$  S.D. across 20 repetitions.

We found significant main effects of chromatic biases (F(2, 6) = 6.65, p < 0.05); however, the main effects of the number of surrounding colors and test illuminants were not significant (F(1, 3) = 0.11, p > 0.1; F(1, 3) = 2.13, p > 0.1, respectively). In addition, there was no significant interaction.

To confirm which chromatic bias condition demonstrated significantly higher CI, we conducted multiple comparisons by Bonferroni's correction (significance level: 0.05). It was revealed that the CI was significantly higher in the red–blue dominant scene than in the green–yellow dominant scene. However, CIs were not significantly different between the balanced and the



Fig. 18. Constancy indices for all conditions in Experiment 3. Higher values indicate better color constancy. The error bar indicates  $\pm$ S.E. across four observers.

red-blue dominant scenes and between the balanced and the yellow-green dominant scenes. Thus, we found that the luminance-balance-based illuminant estimation works better in the red-blue dominant scene, suggesting that the effect of luminance balance depends on the chromaticities in the scene. In addition, the number of surrounding colors had no significant effect.

Figure 19 shows the luminance settings for all conditions in Experiment 3. We conducted three-way repeated measures



**Fig. 19.** Each bar shows the mean luminance settings across observers in Experiment 3. The error bar indicates  $\pm$ S.E. across observers. Green diamonds, red squares, and blue circles show the illuminant intensity (constant across all conditions), highest luminance, and mean luminance across surrounding stimuli, respectively.

ANOVA, with the number of surrounding colors (six and 60), chromatic biases (balanced, red–blue dominant, and yellow–green dominant), and test illuminants (3000 and 20,000 K) as within-subject factors.

No main effect was found to be significant. However, the interaction between the chromatic bias and the test illuminant was significant (F(4, 12) = 3.74, p < 0.05). Further analysis of the simple main effect revealed that the luminance settings among chromatic balance conditions were significantly different for the 20,000 K condition but not for the 3000 K condition. Multiple comparisons using Bonferroni's correction (significance level: 0.05) revealed that, in the 20,000 K condition, the luminance setting was significantly higher in the green-yellow dominant scene than in the red-blue dominant scene.

# 6. MODEL COMPARISON

Here, we compare the performance of the optimal color model with mean chromaticity, mean LMS, and luminance-redness correlation [13] models. Predictions from the proposed optimal color model corresponded to the chromaticities of the test illuminants. The spatial-average chromaticity of the surrounding stimuli was used as a prediction of the mean chromaticity model. Spatial-average cone signals of the surrounding stimuli were calculated first. We then converted those into MB chromaticity coordinates and used the resulting values for the prediction of the mean LMS model. Finally, for the luminance-redness correlation model, the prediction was calculated using an equation reported by Golz and MacLeod [13] (see theoretical analysis section). They also argued the luminance-blueness correlation [29]. However, we could not implement the model because an equation to predict blueness was not provided.

The comparisons were performed separately for redness and blueness directions, as shown in Fig. 20. The horizontal axis shows the redness or blueness predicted by the models. The vertical axis shows the actual settings averaged across four observers. If model prediction and observers' settings are exactly the same, each plot should be on the 45° dashed black line. However, note that the degree of color constancy is generally measured relatively. For example, as seen in Eq. (1), color constancy could be perfect even if the observer settings are not exactly on corresponding illuminant chromaticities and deviate from the black body locus. Such a deviation appears in Fig. 20 as an intercept of a regression line. Thus, we argue the accuracy of each model based only on how close a slope is to 1.0.

For comparison of Experiments (a) 1 and (b) 2, linear regression lines were fitted separately for six conditions in each shift condition. The red solid, green dashed, and blue dotted lines indicate luminance shift, chromaticity shift, and luminance and chromaticity shift conditions, respectively. For (c) Experiment 3, fittings were performed separately for six conditions in each chromatic bias. The black solid, magenta dashed, and lime dotted lines indicate the balanced, red–blue dominant, and green–yellow dominant conditions, respectively. Although each panel has many plots, each colored regression line and its slope at the top left would help illustrate the overall trend.



**Fig. 20.** Model comparison among optimal color, mean chromaticity, mean LMS, and luminance–redness correlation [13] models for all experiments. The horizontal and vertical axes show model prediction and actual observer settings, respectively. Slopes are shown at the top left in each panel in corresponding colors. Different colors indicate different shift conditions in Experiment (a) 1 or (b) 2 and different chromatic biases in (c) Experiment 3.

In (a) Experiment 1, for the chromaticity shift condition and luminance and chromaticity shift condition, performance is roughly similar for all models for both redness and blueness predictions. Therefore, once the chromaticity change is available to estimate an illuminant, each model can sufficiently predict the observer settings. However, for the luminance shift condition, the mean chromaticity model does not work because the chromaticities of all surfaces were constant across the test illuminants and, thus, incorrectly provided the same estimation for all test illuminants. In contrast, our optimal color model can perform prediction to some extent, and the mean LMS and luminance–redness correlation models worked sufficiently. A similar trend was observed in Experiment 2.

In (c) Experiment 3, we employed only the luminance shift condition; therefore, the mean chromaticity did not account for any of the results. Again, our model predicts the results to some extent. However, the mean LMS model also worked well, and the redness–luminance correlation model worked reliably, especially for the green–yellow dominant condition.

Overall, for most conditions, the mean LMS and luminance–redness correlation models showed good predictions. However, in our previous study [21], we tested a condition where the mean LMS values were equated across the test illuminants (Experiment 4). It turned out that, under such a condition, the observer's settings were shifted to the opposite direction from the illuminant chromaticity. Therefore, even if the mean LMS is a good predictor in the present study, it seems difficult to establish a basis for further discussion.

# 7. GENERAL DISCUSSION

Despite substantial psychophysical color constancy research, only a few studies have investigated the luminance contribution to color constancy. The present study was aimed at reinforcing a previous finding, i.e., luminance balance contributes to the estimation of an illuminant [21]. The luminance shift condition simulated the extreme situation in which the chromaticities of all surfaces in a scene happen to be exactly the same across the illuminants; thus, the visual system had to assess the illuminant based only on luminance balance. Although such a difficult situation never occurs in the real world, surprisingly, the visual system can resolve the ambiguity of chromaticity and estimate the illuminant to some extent. Needless to say, chromaticity-based models do not account for this ability of the visual system. These findings strongly confirm that the luminance balance of surfaces plays an important role in achieving color constancy.

In Experiment 1, we tested whether stimulus dimensionality could affect illuminant estimation. However, the results did not show any effect. There has been an implicit expectation that color constancy should improve for 3D stimuli because those appear more informative compared to 2D stimuli. While some studies have supported this idea, other studies did not show this effect. Therefore, whether 3D stimuli can improve color constancy remains controversial. However, in the present study, we used a shade to make hexagons appear as cubes, whereas other studies used various manipulations to create a 3D environment [9,21–26]. Therefore, the present results may have been due to the different stimuli manipulation method. It is possible that

the stimulus shape does not matter for the optimal color hypothesis; however, concrete conclusions require the testing of other shapes.

In Experiment 2, it was shown that chromatic variation enhances the effect of chromaticity shift. In contrast, chromatic variation does not appear to affect the luminance-balance effect. In terms of the optimal color hypothesis, low saturated colors are less helpful because they could be within more than one illuminant gamut. The six-color condition employed three chromaticities chosen from the vertices of the chromaticity triangle (Fig. 11) and thus contained the highest redness and blueness surfaces. This might be the reason why we could not obtain improvement by increasing the number of surrounding colors. The important implication from this result is that the visual system places greater weight on highly saturated colors as well as bright colors [8] when estimating an illuminant.

In Experiment 3, we investigated the luminance-balance effect in chromatically biased scenes. The results showed that observers made better estimations of illuminants for the red–blue dominant scene compared to the green–yellow dominant scene, suggesting that the accuracy of illuminant estimation based on luminance balance depends on the chromaticity in the scene. Although we specified a condition in which the luminance balance could work better, the degree of color constancy was still approximately 47% on average for the red–blue dominant condition, which is still generally less than the CI in the chromatic shift conditions. This result implies that the role of luminance in estimating an illuminant is limited to specify the direction of the illuminant color so that the visual system can maintain color constancy when a scene has chromatic ambiguity.

The observer's task employed in the present study allowed us to see the estimated illuminant chromaticity and intensity simultaneously. While the accuracy of the estimated chromaticity was dependent on the conditions, the observer demonstrated somewhat stable estimation of the illuminant intensity. However, the estimated intensity was substantially and consistently higher than the actual intensity of the test illuminant. This implies that, even though we employed optimal colors for surrounding stimuli, the visual system interpreted them as darker surfaces. This in turn suggests that the assumption of surfaces internalized in the visual system is less restricted than optimal colors. Note that the illuminant gamut extends in the luminance direction when its intensity increases. Therefore, in terms of the optimal color hypothesis, accurate estimation of illuminant intensity is required for a good estimation of illuminant chromaticity. For example, even if a scene contains a bright reddish surface, a bluish illuminant gamut could hold all surfaces in the scene when the visual system estimates the illuminant intensity at a high level. This might have caused the imperfect constancy observed in the present study. In the future, a broader investigation is required to assess the overall relationship between the estimations of intensity and color temperature.

There has been a long-standing argument about the method of measuring color constancy. Various methods have been proposed, such as asymmetric matching [23], achromatic adjustment [30], color naming [31], and classification between material change and illuminant change [32]. The present study employed achromatic adjustment based on the paper-match criterion rather than appearance match. It has often been reported that this operational color constancy shows a relatively high degree [23]. Nevertheless, CIs observed in luminance shift conditions were small. Thus, it would be difficult to extract the contribution of luminance in illuminant estimation using an appearance-based task.

The method of quantifying the degree of color constancy also remains controversial. In the present study, we employed a CI as Eq. (1), but this simple measure fails to reflect the data trend if shifts are in the opposite direction from the expected point. We found that one observer showed such opposite shifts under several conditions. However, the indices were nearly zero in those cases; thus, they did not affect the overall trends significantly.

Note that no model consistently provided satisfactory estimation for all conditions tested in the present study. This implies that the visual system does not rely on a specific algorithm to achieve color constancy. Although all models exploited the global statistics across the entire scene, many studies have agreed that multiple mechanisms underlie human color constancy, such as an adaptation, simultaneous contrast, and even familiarity or memory. Thus, the visual system could exploit the most reliable cue in a given situation, which might cause difficulty in specifying a consistently reliable model.

The neural mechanism for color constancy remains largely unclear. While there appears to be an important role in the retina, such as adaptation [33], color constancy could work without taking adaptation time [34]. Higher cortical mechanisms, such as V4, have also been identified [35–37]. Our proposed model essentially assumes the opponent level process, such as the mean chromaticity model. In our model comparison, we found that the mean LMS provided relatively reliable estimation for the most of the tested condition. The mean LMS model implies that illuminant estimation can be completed by simply taking the average of each class of cone signals before entering the opponent level process. However, it is possible that these are the average luminance-weighted chromaticities rather than actual cone signals.

The key idea of the proposed model stems from the expectation that the visual system internalizes possible references (optimal color distributions). In this notion, the given scene information is used to determine which internalized reference we should select to discount the influence of the illuminant properly. Thus, our model appears to oppose to frameworks that rely completely on external sources in a scene to set a reference, such as anchoring theory [38]. It is possible that the visual system uses both; however, in any case, we require a further investigation to reveal whether the visual system can utilize prior knowledge about the world.

One might suspect that it is more reasonable to assume that the visual system internalizes the shape of the natural scene distribution rather than the optimal color distribution because optimal colors do not exist in the real world. Although the present study cannot rule out this possibility, one way to assess the feasibility of the proposed method would be to identify how colors are distributed in the world. As shown in Fig. 2(b), the shape of optimal colors and natural object distribution are somewhat similar, implying that the visual system has access to the relative shape of the optimal color distribution. However, these natural objects were a limited number of samples, and it appears difficult to determine the actual surface gamut in the natural world. Pointer [39] has argued how large the gamut of real surfaces (known as Pointer's limit) would be, but this is also inconclusive. Another clue could be the mysterious relationship between the luminous threshold and the luminance of optimal color [20]. Since there is nothing connecting natural objects with the luminosity threshold, this seems to support what the visual system knows to be the theoretical limit of surface colors rather than the natural scene distribution.

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## REFERENCES

- 1. D. H. Foster, "Color constancy," Vis. Res. 51, 674-700 (2011).
- H. E. Smithson, "Sensory, computational and cognitive components of human colour constancy," Philos. Trans. R. Soc. B 360, 1329–1346 (2005).
- A. Werner, "Spatial and temporal aspects of chromatic adaptation and their functional significance for colour constancy," Vis. Res. 104, 80–89 (2014).
- J. von Kries, "Influence of adaptation on the effects produced by luminous stimuli," in *Sources of Color Science*, D. L. MacAdam, ed. (MIT, 1905), pp. 120–126.
- H. E. Ives, "The relation between the color of the illuminant and the color of the illuminated object," Trans. Illuminant. Eng. Soc. 7, 62–72 (1912).
- M. Olkkonen, T. Hansen, and K. R. Gegenfurtner, "Color appearance of familiar objects: effects of object shape, texture, and illumination changes," J. Vis. 8(5), 13 (2008).
- D. H. Foster and S. M. C. Nascimento, "Relational colour constancy from invariant cone-excitation ratios," Proc. Biol. Sci. 257, 115–121 (1994).
- S. Tominaga, S. Ebisui, and B. A. Wandell, "Scene illuminant classification: brighter is better," J. Opt. Soc. Am. A 18, 55–64 (2001).
- J. N. Yang and S. K. Shevell, "Stereo disparity improves color constancy," Vis. Res. 42, 1979–1989 (2002).
- K. Fukuda and K. Uchikawa, "Color constancy in a scene with bright colors that do not have a fully natural surface appearance," J. Opt. Soc. Am. A 31, A239–A246 (2014).
- G. Buchsbaum, "A spatial processor model for object color perception," J. Franklin Institute **310**, 1–26 (1980).
- R. O. Brown, "The world is not gray," Invest. Ophthalmol. Vis. Sci. 35, 2165 (1994).
- J. Golz and D. I. A. MacLeod, "Influence of scene statistics on colour constancy," Nature 415, 637–640 (2002).
- D. Macadam, "The theory of the maximum visual efficiency of colored materials," J. Opt. Soc. Am. A 25, 249–252 (1935).
- D. Macadam, "Maximum visual efficiency of colored materials," J. Opt. Soc. Am. A 25, 361–367 (1935).
- A. Stockman and L. T. Sharpe, "Spectral sensitivities of the middleand long-wavelength sensitive cones derived from measurements in observers of known genotype," Vis. Res. 40, 1711–1737 (2000).
- D. I. A. MacLeod and R. M. Boynton, "Chromaticity diagram showing cone excitation by stimuli of equal luminance," J. Opt. Soc. Am. A 69, 1183–1186 (1979).
- D. A. Forsyth, "A novel algorithm for color constancy," Int. J. Comput. Vis. 5, 5–35 (1990).

- R. Brown, "Background and illuminants: the yin and yang of colour constancy," in *Colour Perception: Mind and the Physical World*, R. Mausfeld and D. Heyer, eds. (Oxford University, 2003), pp. 247–272.
- K. Uchikawa, K. Koida, T. Meguro, Y. Yamauchi, and I. Kuriki, "Brightness, not luminance, determines transition from the surface-color to the aperture-color mode for colored lights," J. Opt. Soc. Am. A 18, 737–746 (2001).
- K. Uchikawa, K. Fukuda, Y. Kitazawa, and D. I. A. MacLeod, "Estimating illuminant color based on luminance balance of surfaces," J. Opt. Soc. Am. A 29, A133–A143 (2012).
- M. Hedrich, M. Bloj, and A. I. Ruppetsberg, "Color constancy improves for real 3D objects," J. Vis. 9(4), 16 (2009).
- L. Arend and A. Reeves, "Simultaneous color constancy," J. Opt. Soc. Am. A 3, 1743–1751 (1986).
- B. Xiao, B. Hurst, L. MacIntyre, and D. H. Brainard, "The color constancy of three-dimensional objects," J. Vis. **12**(4), 6 (2012).
- A. Werner, "The influence of depth segmentation on colour constancy," Perception 35, 1171–1184 (2006).
- Y. Mizokami and H. Yaguchi, "Color constancy influenced by unnatural spatial structure," J. Opt. Soc. Am. A **31**, A179–A185 (2014).
- V. M. N. de Almeida, P. T. Fiadeiro, and S. M. C. Nascimento, "Effect of scene dimensionality on colour constancy with real three-dimensional scenes and objects," Perception **39**, 770–779 (2010).
- J. M. Kraft, S. I. Maloney, and D. H. Brainard, "Surface-illuminant ambiguity and color constancy: effects of scene complexity and depth cues," Perception 31, 247–263 (2002).

- D. I. A. MacLeod and J. Golz, "A computational analysis of colour constancy," in *Colour Perception: Mind and the Physical World*, R. Mausfeld and D. Heyer, eds. (Oxford University, 2003), pp. 205–246.
- D. H. Brainard, "Color constancy in the nearly natural image. 2. Achromatic loci," J. Opt. Soc. Am. A 15, 307–325 (1998).
- J. M. Troost and C. M. M. de Weert, "Naming versus matching in color constancy," Percept. Psychophys. 50, 591–602 (1991).
- B. J. Craven and D. H. Foster, "An operational approach to colour constancy," Vis. Res. 32, 1359–1366 (1992).
- H. E. Smithson and Q. Zaidi, "Colour constancy in context: roles for local adaptation and levels of reference," J. Vis. 4(9), 3 (2004).
- O. Rinner and K. R. Gegenfurtner, "Cone contributions to colour constancy," Perception 31, 733–746 (2002).
- M. Kusunoki, K. Moutoussis, and S. Zeki, "Effect of background colors on the tuning of color-selective cells in monkey area V4," J. Neurophys. 95, 3047–3059 (2006).
- V. Walsh, D. Carden, S. R. Butler, and J. J. Kulikowski, "The effects of V4 lesions on the visual abilities of macaques: hue discrimination and colour constancy," Behav. Brain. Res. 53, 51–62 (1993).
- H. M. Wild, S. R. Butler, D. Carden, and J. J. Kulikowski, "Primate cortical area V4 important for colour constancy but not wavelength discrimination," Nature **313**, 133–135 (1985).
- A. Gilchrist, C. Kossyfidis, F. Bonato, T. Agostini, J. Cataliotti, X. Li, B. Spehar, V. Annan, and E. Economou, "An anchoring theory of lightness perception," Psychol. Rev. **106**, 795–834 (1999).
- M. R. Pointer, "The gamut of real surface colours," Col. Res. Appl. 5, 145–155 (1980).