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Prediction of Incomplete Chromatic Adaptation Under Illuminant A from Images

Shoji Tominaga▲, Takahiko Horiuchi▲, Shiori Nakajima, and Mariko Yano
Graduate School of Advanced Integration Science, Chiba University, Japan
E-mail: shoji@faculty.chiba-u.jp

Abstract. *The authors propose a method of image rendering to predict the incomplete chromatic-adaptation effect for paintings. A simple model of incomplete chromatic adaptation is developed to predict the appearance of the paintings under the illumination of an incandescent light source and to produce the full color image on a display device. The authors extend the von Kries framework to incomplete chromatic adaptation. An index parameter representing the degree of incomplete chromatic adaptation is defined based on the color temperature of the black-body radiators. First, the optimum value of the index parameter is determined by visual experiments on memory matching using real paintings and color patches, so that the color image produced on the display is matched to the original appearance of objects in a real scene. This approach is shown to have better performance in comparison with the traditional CIECAM02. Next, an algorithm is presented to estimate the index parameter of the incomplete adaptation index based on the image data of colorimetric rendering for a target painting. It is found that the index parameter can be estimated using only three features extracted from the color image. The color images rendered with the estimated parameter are used to predict the incomplete chromatic-adaptation effect for the original painting under the incandescent light source. The feasibility of the proposed method is confirmed based on a series of experiments using a variety of paintings.* © *2014 Society for Imaging Science and Technology.*
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Figure 1. Appearance of an art painting observed under incandescent lights.

INTRODUCTION

Image rendering technologies are required for the production of the realistic appearance of objects in a scene under a variety of viewing environments. In spectral image rendering, spectral information such as the spectral-power distribution of illumination and the surface-spectral reflectance of objects is used to imitate the appearance of the objects based on light reflection within the visible wavelength range in a natural scene. The color signals from the objects to the visual system are computed and the rendered color images are normally produced on a display device.

It should be noted that in this situation colorimetric image rendering is not good enough to reproduce the correct appearance of the objects. We have to consider the perceptual effect of the chromatic adaptation on the objects observed under a particular illumination environment. For example, most art paintings are hung on indoor walls, and often illuminated by incandescent light, as shown in Figure 1. The adaptation effect makes the object color appearance less reddish. Since it is the most important color-appearance phenomenon of human vision, the case of complete adaptation has been considered to realize color constancy in color image rendering in the past.[1] Recently, images with general chromatic-adaptation effects have been required for realistic image rendering and image quality improvement.[2–5]

On the other hand, chromatic-adaptation and color-appearance models have important traditional contributions in the field of color science. Traditional color-appearance models[6–8] have been developed based on visual experimental data using uniform single color patches. These models consist of complicated equations with too many parameters to specify the viewing conditions. We have to determine every pixel value of a full color image with a complex color content to render the image with the adaptation effect. A simpler and more direct model should be considered in this case. A color-appearance model, called iCAM06, was proposed to be applicable to image rendering.[3–5,9] It is noted that in these previous models the factor representing

▲ IS&T Members.

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the degree of incomplete adaptation was determined as a function of only the adaptation luminance.[6,10] However, it is natural to consider that the adaptation degree depends on the color content and color composition of the target painting. For instance, the adaptation degree for a white painting or a bluish painting can be higher than for a reddish painting, even in a constant luminance level. Knowledge of a relationship between the adaptation degree and the color composition is useful for realistic image rendering.

This article proposes a method of image rendering to predict the incomplete chromatic-adaptation effect for paintings. We briefly describe the basic procedure for colorimetric image rendering based on the spectral data of surface reflectances and illuminant distributions. A simple model of incomplete chromatic adaptation is then developed to predict the appearance of objects under the illumination of an incandescent light source and to produce the full color image on a display device. We extend the von Kries framework[11] to incomplete chromatic adaptation. An index parameter representing the degree of incomplete chromatic adaptation is defined based on the color temperature of the black-body radiators. This index parameter d ranges from $d = 0$ for no adaptation at illuminant A to $d = 1.0$ for complete adaptation at illuminant D65. The optimum parameter value is determined by visual experiments of memory matching using real paintings, so that the color image produced on the display is matched to the original appearance of objects in a real scene. This new approach is shown to have better performance in comparison with the traditional CIECAM02.[6]

Next, we present an algorithm to estimate the index parameter d of the incomplete adaptation index based on the image data of the colorimetric rendering for a target painting. Many features are extracted from the color image to investigate the influence on incomplete adaptation. As a result, the index parameter can be estimated using only three features extracted from the image. The color images rendered with the estimated parameter can be used to predict the incomplete chromatic-adaptation effect for the original painting under the incandescent light source. The feasibility of the proposed method is confirmed based on a series of experiments using a variety of paintings including water paintings, oil paintings, printed postcards, single color patches, and color charts.

COLORIMETRIC IMAGE RENDERING

Let us consider the image rendering of two-dimensional flat or rough surfaces like paintings under uniform illumination. The realistic appearance of the target surface under various illumination colors is rendered using the surface-spectral reflectance at every pixel point, the spectral-power distribution of light, the surface shape information such as the surface normal, and a proper reflection model. A ray-tracing algorithm is adopted for image rendering by tracing the imaginary rays of light from a viewing point to the target surface in a natural scene. In spectral image rendering, the color image is not represented by RGB, but firstly by the CIE tristimulus values XYZ. The XYZ values at each pixel point are computed from the spectral radiance distribution (color signal) from the object surface by using the CIE color-matching functions.

In this article, all spectral distributions are expressed in 61-dimensional vectors by sampling the visible range [400, 700 nm] at equal intervals of 5 nm. We do not reduce the number of spectral sampling points in the color computations by approximating the spectral distributions with a small number of basis functions. The finely point-sampled spectral representation is necessary for precise color calculations under various types of illumination.[12] The color image is produced on a calibrated display device to evaluate the appearance of the object surface produced. In the stage of color image production, the XYZ values are first transformed into the display RGB values, and then corrected into practical RGB digital values by a lookup table of the tone curve.[13]

It is not easy to directly measure the surface properties of shape and reflectance at each pixel point of paintings. Tominaga and Tanaka[14] proposed a technology of digital archiving of art paintings, where the surface-spectral reflectance and the surface-normal vector were recovered using the multi-band image data captured for different directions of illumination. The Cook–Torrance model was used in the image rendering. In this article, the surface properties of paintings are acquired from the image data of the real paintings and the colorimetrically precise images are rendered based on the proposed technology. The surface-spectral reflectances of flat sample objects such as color patches are directly acquired using a spectrometer.

PREDICTION OF THE INCOMPLETE CHROMATIC-ADAPTATION EFFECT

When the above colorimetric image rendering procedure is used for realistic image rendering on a display device, the original appearance of the object surfaces observed under the lighting environment of a low color temperature such as an incandescent light source does not match the rendered image in the same illuminant conditions or in daylight illuminant such as illuminant D65.

The concept of incomplete chromatic adaptation for object colors is described as follows (see Refs. 7, 15 for details). Generally, the complete adaptation is an ideal state, and almost all the adaptation experiments show the characteristics of some incomplete chromatic adaptation. For example, the color appearance of a gray sample under incandescent light source adaptation does not coincide with that of the same gray sample under illuminant D65, but shows a little yellowish color. This corresponds to the characteristic of incomplete adaptation. The corresponding color is found at a position between the two chromaticity coordinates of the incandescent light source and illuminant D65. This is the corresponding color without achromatic perception.

In this study, we expand this concept to investigate the incomplete adaptation for samples with complex color contents like paintings. The effective adaptation chromaticity

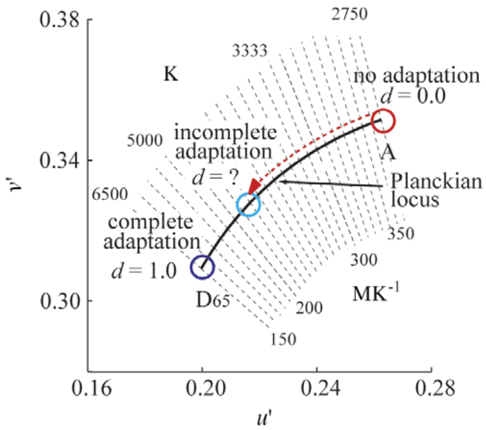

Figure 2. Model of the incomplete adaptation process on the Planckian locus in the (u', v') chromaticity plane.

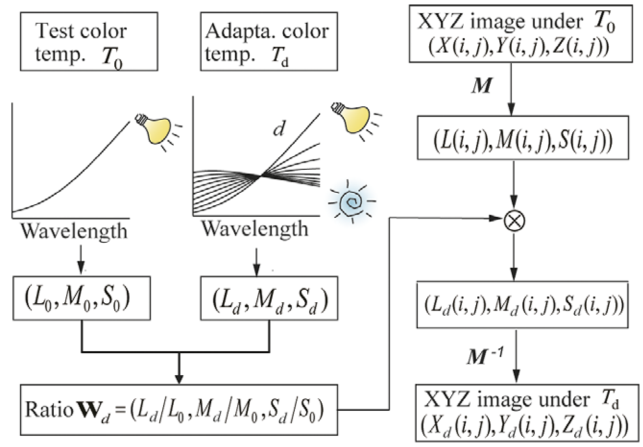

Figure 3. Rendering process of the incomplete adaptation images.

corresponding to the incomplete adaptation is estimated between the two illuminant chromaticity points. The degree of the incomplete adaptation is analyzed based on evaluation experiments using rendered images under different illuminant chromaticities.

Model

We use illuminant D65 as the reference representing daylight, with a correlation color temperature of 6504 K, and illuminant A as the test, representing an incandescent light source with 2856 K. The adaptation process is considered as an incomplete adaptation along the color-temperature scale. Then, an incomplete adaptation index d ($0 \leq d \leq 1$), representing the degree of chromatic adaptation, is introduced on the color-temperature scale between the test illuminant A and the reference illuminant D65.

Figure 2 models the incomplete adaptation process in the (u', v') plane of the CIE 1976 UCS chromaticity diagram, where the Planckian locus (chromaticity locus of black-body radiators) is segmented in two ways, namely in equal color-temperature steps in kelvin (K) and equal reciprocal color-temperature steps in microreciprocal degrees (10^6 K^{-1}), called the reciprocal megakelvin (MK^{-1}). The degree of incomplete chromatic adaptation moves along the Planckian locus, in which $d = 0$ means no adaptation at $T = 2856$ K and $T' = 350\,(10^6$ K$^{-1})$ of A, and $d = 1.0$ means complete adaptation at $T = 6504$ K and $T' = 154\,(10^6$ K$^{-1})$ of D65. Note that the small intervals in reciprocal color temperature are more perceptually equal than the small intervals in color temperature. Let T'_0 and T'_R be the reciprocal temperatures of the test illuminant A and the reference illuminant D65, respectively. Then, the color temperature of adaptation illumination corresponding to the index d is modeled as

$$T_d = 10^6/((T'_R - T'_0)d + T'_0). \tag{1}$$

The spectral-power distribution corresponding to T_d is given by the formula[16]

$$E_d(\lambda) = c_1\lambda^{-5}\{\exp(c_2/\lambda T_d) - 1\}^{-1}, \tag{2}$$

where $c_1 = 3.7418 \times 10^{-16}$ W m^2 and $c_2 = 1.4388 \times 10^{-2}$ m K and λ is the wavelength (m). This distribution is used for calculation of the pixel values in spectral image rendering.

A proper value of the incomplete adaptation index d is determined in matching experiments between the real paintings under illuminant A and the color images on the calibrated display.

Rendering of the Incomplete Adaptation Images

There are two ways of rendering the incomplete adaptation images. A direct way is to produce the color images by using the spectral-power distributions of black-body radiators corresponding to the various degrees of incomplete adaptation. This is precise from a spectral rendering point of view. However, it is expensive from a computational point of view because the spectral computation requires multiplication of vectors at every pixel point. The other is an indirect way, which is regarded as an extended version of the von Kries model.[17] We compute the tristimulus values XYZ under illuminant A at every pixel point. These color values are mapped into the cone space to get relative cone responses (LMS) and then the cone signals' LMS are adjusted to the pixel values of an image under the incomplete adaptation illuminant with d. Finally, the LMS image is inversely transformed into the XYZ image. This computation is mainly based on the scalar multiplication at every pixel point. We examined the direct and indirect ways by using the X-Rite ColorChecker. The color images were produced with different values of the incomplete adaptation index d. We confirmed that the XYZ images produced were almost coincident between the two cases. The experiments in this article use the indirect way.

Figure 3 shows the rendering process for the incomplete adaptation images. First, we determine the gain coefficients w_L, w_M, and w_S for modeling chromatic adaptation, in which each of the three cone types has a separate gain coefficient. The gain coefficients are defined as the ratios of the LMS values for white under the adaptation illuminant to the responses under the test illuminant. The LMS values at different indices d in the range $0 \leq d \leq 1$ are calculated via the tristimulus values using the spectral-power distribution $E_d(\lambda)$ as

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \int_{400}^{700} E_d(\lambda) \begin{bmatrix} \bar{x}(\lambda) \\ \bar{y}(\lambda) \\ \bar{z}(\lambda) \end{bmatrix} d\lambda. \tag{3}$$

The gain coefficients are then calculated as

$$(w_L, w_M, w_S) = (L_d/L_0, M_d/M_0, S_d/S_0), \tag{4}$$

where (L_d, M_d, S_d) and (L_0, M_0, S_0) are the LMS values for white under the adaptation illuminant and the test illuminant, respectively. It is noted that the gain coefficients for different values of d are obtained separately from the image computation.

Next, we compute the XYZ values at each pixel (i, j) by using the distribution $E_0(\lambda)$ at T_0 to produce the XYZ image under illuminant A. These XYZ values are then mapped into the cone space to get relative cone responses (LMS) using a linear matrix multiplication[11]

$$\begin{bmatrix} L(i,j) \\ M(i,j) \\ S(i,j) \end{bmatrix} = \mathbf{M} \begin{bmatrix} X(i,j) \\ Y(i,j) \\ Z(i,j) \end{bmatrix}, \tag{5}$$

where

$$\mathbf{M} = \begin{bmatrix} 0.400,24 & 0.707,60 & -0.080,81 \\ -0.226,30 & 1.165,32 & 0.045,70 \\ 0 & 0 & 0.918,22 \end{bmatrix}.$$

Then, the cone signals corresponding to the pixel value of an image under the incomplete adaptation illuminant are described as

$$\begin{bmatrix} L_d(i,j) \\ M_d(i,j) \\ S_d(i,j) \end{bmatrix} = \mathbf{W}_d \begin{bmatrix} L(i,j) \\ M(i,j) \\ S(i,j) \end{bmatrix}, \tag{6}$$

where

$$\mathbf{W}_d = \begin{bmatrix} w_L & 0 & 0 \\ 0 & w_M & 0 \\ 0 & 0 & w_S \end{bmatrix}.$$

Finally, the LMS image is inversely transformed into the XYZ image. The entire process of color transformation is summarized as

$$\begin{bmatrix} X_d(i,j) \\ Y_d(i,j) \\ Z_d(i,j) \end{bmatrix} = \mathbf{M}^{-1}\mathbf{W}_d\mathbf{M} \begin{bmatrix} X(i,j) \\ Y(i,j) \\ Z(i,j) \end{bmatrix}. \tag{7}$$

The above formulation represents a simple transformation for the incomplete chromatic adaptation with separate gain coefficients. Note that, when d is equal to 1.0, this process reduces to the basic algorithm for complete chromatic adaptation.

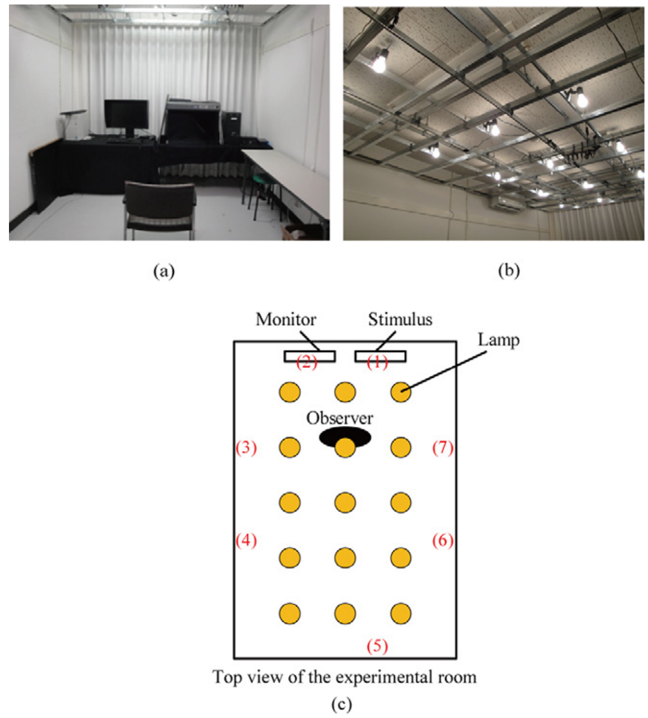

Figure 4. Situation of the experimental room. (a) Visual environment; (b) ceiling light sources; (c) top view of the experimental room.

Evaluation Experiment

Experimental Setup

In order to verify the validity of the proposed method for predicting incomplete adaptation, we performed a series of comparative evaluation experiments. Figure 4 shows two pictures of our experimental room. Real objects were put outside the light booth in Fig. 4(a). Therefore, in our experiments, the real objects were illuminated by ceiling lamps only. In order to realize a general exhibition environment for art paintings, we built the room with spatially uniform illumination. On the ceiling, as shown in Fig. 4(b), 15 incandescent lights of 100 W were equally arranged in a 3×5 array. Fig. 4(c) depicts the top view of the experimental room. The viewing distance from the observer to the horizontal line between the display and the stimulus (real object) was 150 cm. In order to confirm the uniformity of illumination, we measured the luminance and horizontal illuminance at seven locations, indicated as (1)–(7) in Fig. 4(c). Table I shows the measurement results. The color temperature was about 2850 K at each location. A good uniform illumination environment was realized in the room.

The display device used in our experiment was a liquid crystal display (LCD) (EIZO ColorEdge CG221), which had a size of 22.2″ (56 cm) and a resolution of 1920×1200 pixels. The white point of the display was set to D65. It reproduced about 98% of the Adobe RGB color space. We measured the input–output relationship of the display at the standard setting of Adobe RGB. We then constructed a color lookup table (CLUT) in order to correct the display nonlinearity and to produce accurate color images. Figure 5 shows the set of

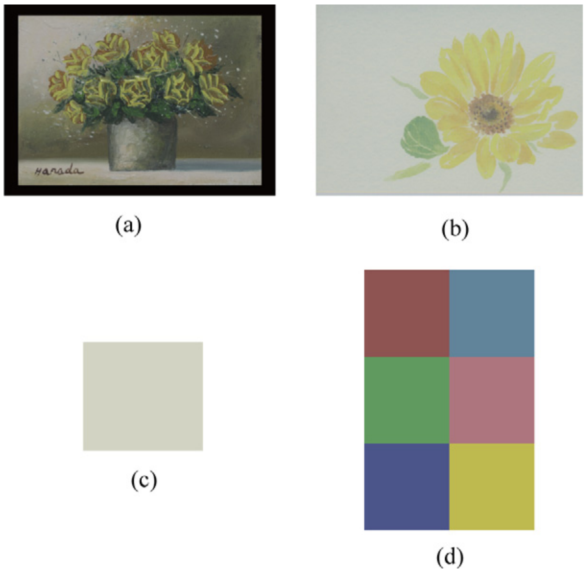

Figure 5. Set of four test stimuli used in the evaluation experiment. (a) Oil painting; (b) printed postcard; (c) single color patch; (d) multiple color chart.

four test stimuli used in this experiment, which consisted of an oil painting, a printed postcard, a white patch, and a color chart. The horizontal size was 10 cm to 17 cm. The luminance was set to match with the reflected light from a white reference at the position of the objects. The size of the displayed images was set to agree with the real objects. The background around the displayed images was black.

The experiment was conducted with nine participants, who were undergraduate students and graduate students at Chiba University. All subjects were color naive and had normal color vision. Each subject was guided into the experimental room and seated on the chair in front of the display and the stimulus. No training tasks were provided. The subject was given 3 min to adapt to the illumination environment. During the adaptation, the subject spent his/her time carrying out natural acts such as reading a magazine.

In the first step of evaluation, a stimulus was shown to the subject for 3 min. The background was a black cloth for the oil painting and the printed postcard, and an N5 gray paper for the color patch and the color chart. The subject memorized the color of the stimulus for 3 min. After turning off all the lamps and covering the stimulus with a black cloth, the rendered image using the proposed rendering algorithm with the adaptation index set to $d = 0$ was displayed on the monitor. The subject could switch the rendered image from $d = 0$ to $d = 1.0$ in 0.1 intervals using a keyboard. The subject judged whether the displayed color image was matched to the stimulus memorized. The reason why we adopted the memory-matching procedure is that the chromatic-adaptation state of the subject must be reset so that the evaluation procedure will not be influenced by real objects when evaluating the displayed images. By selecting the best matched image based on the memory-matching procedure,

Table I. Luminance and illuminance values at seven positions in the experimental room.

	Luminance (cd/m^2)	Illuminance (lx)
(1)	108.5	370
(2)	109.3	360
(3)	111.7	370
(4)	113.0	360
(5)	104.8	350
(6)	113.5	390
(7)	104.6	370
Ave.	109.3	367.1

the optimum parameter value of the incomplete adaptation index d was determined. No time restriction was set.

Then, the subject was given 3 min to adapt to the illumination environment, and the same stimulus was shown for 3 min. After turning off all lamps and covering the stimulus, two rendered images were displayed on the monitor side by side. One was the selected image with the optimum adaptation index d, and the other image was the rendered image by the traditional CIECAM02 model. The transformation algorithm of CIECAM02 includes many parameters for setting viewing conditions. We measured our viewing conditions and set the parameters as follows: $(X_w, Y_w, Z_w) = (104.1, 94.47, 31.97)$, $L_A = 18.89$, $Y_b = 18.89$, and Dim surround ($C = 0.59, N_C = 0.9$, $F = 0.9$). According to Ref. 6, the absolute luminance for the white was used to compute L_A by dividing by 5. The background luminance Y_b was estimated by the luminance of the samples' surfaces. The subject was asked to select one of the two rendered images, which was better matched to the memorized stimulus. No time restriction was set.

The above procedure was repeated for the four stimuli in Fig. 5.

Evaluation Results

Table II shows the results of the evaluation experiments for the nine subjects and four stimuli, where the selected adaptation parameter value and the selected method are listed for each stimulus by each subject. According to the Grubbs–Smirnov rejection test, no outliers were detected from any of the stimuli. The optimum parameter of the incomplete adaptation index was around 0.6 on average. For all stimuli, the images rendered by the proposed method were chosen more often than those by CIECAM02, especially for the multiple color chart. Thus, the feasibility of the proposed method was confirmed.

PARAMETER ESTIMATION FOR THE INCOMPLETE ADAPTATION INDEX

Estimation Method

We consider a method for estimating the parameter d of the incomplete adaptation index based on the image data

Table II. Results of the evaluation experiments.

	Oil painting		Printed postcard		Single white patch		Multiple color chart	
Subject	*d*	Method	*d*	Method	*d*	Method	*d*	Method
A	0.9	CIECAM02	0.8	CIECAM02	0.8	CIECAM02	0.3	Proposed
B	0.7	Proposed	0.7	Proposed	0.7	Proposed	0.6	Proposed
C	0.6	Proposed	0.6	Proposed	0.5	Proposed	0.3	Proposed
D	0.5	CIECAM02	0.6	CIECAM02	0.5	Proposed	0.6	Proposed
E	0.7	Proposed	0.6	Proposed	0.7	Proposed	0.9	Proposed
F	0.9	CIECAM02	0.7	Proposed	0.7	CIECAM02	0.7	Proposed
G	0.5	Proposed	0.7	CIECAM02	0.9	Proposed	0.6	Proposed
H	0.4	Proposed	0.6	Proposed	0.3	Proposed	0.3	Proposed
I	0.7	CIECAM02	0.6	Proposed	0.7	Proposed	0.7	Proposed
Ave.	0.66		0.66		0.64		0.56	
Std.	0.17		0.07		0.18		0.21	

of colorimetric rendering for a target painting. We recall that our motivation in this study was to reproduce color images matched to the color appearance of paintings under an incandescent lighting environment such as a museum. Since the factors that influence the parameter d depend on the color composition of the image, we investigated the following eight features: (1) surface luminance, (2) the area of white pixels, (3) the ratio of the number of pixels with similar chromaticity to the illumination in the entire pixel number, (4) reciprocal correlated color temperature, (5) chromaticity a^*, (6) chromaticity b^*, (7) hue angle, and (8) the number of discernible colors.[18] In the preliminary experiment, we conducted a subjective evaluation of test images of paintings and color patches. The best features were selected by calculating correlation values between the subjective evaluation and each feature value. As a result we found that the three features of (3) the ratio of the number of pixels with similar chromaticity to the illumination in the entire pixel number, (5) chromaticity a^*, and (6) chromaticity b^* are the most essential factors in the incomplete adaptation index. Therefore, we use these three features to estimate the parameter d.

First, we determine the range of "similar chromaticity to illumination" on the CIE 1960 UCS diagram. The range is defined to have small difference in correlated color temperatures between the incandescent light source and the chromaticity coordinates of each pixel. It is noted that the color temperatures of typical light sources can be classified roughly at 1000 K intervals, such as incandescent (2800 K), warm white (3500 K), white (4200 K), and neutral white (5000 K). Therefore, we define the range within ±500 K as "similar chromaticity". Figure 6 shows the range with ±500 K from 2800 K on the (u', v') chromaticity diagram. Furthermore, the industrial standard (e.g., see Ref. 19) shows that the correlated color temperature is specified in the range of chromaticity coordinates that exist in less than 0.02 from the black-body radiation locus on the UCS diagram. We use this range as the second similarity measure. The orange area in Fig. 6 shows the range of "similar chromaticity" by combining the two measures on the (u', v') chromaticity diagram. Figure 7 shows an example of image areas with similar chromaticity to the incandescent light source. Fig. 7(a) shows the original image of a printed postcard under the incandescent light. The areas with magenta in Fig. 7(b) demonstrate the extracted areas that are close to the incandescent illuminant color.

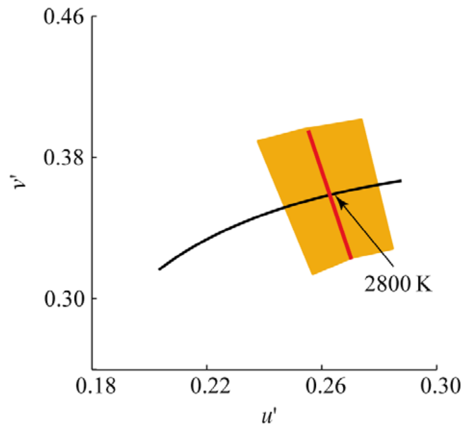

Figure 6. Area of "similar chromaticity" on the (u', v') chromaticity diagram.

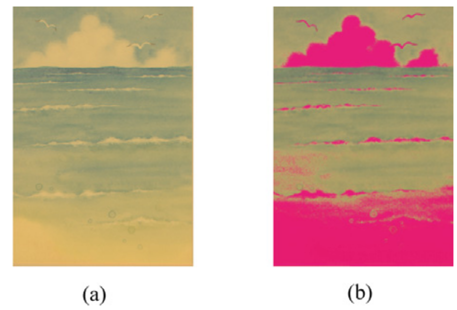

Figure 7. Example of image areas with similar chromaticity to the incandescent light. (a) Original image of a printed postcard; (b) extracted areas.

Second, concerning the chromaticity features, the feature values of chromaticities a^* and b^* are defined as the averages over the entire pixels of the target color image in the CIELAB color space.

We propose a linear model for the estimation of the parameter d from the above three features. The parameter d is simply modeled using the three features as

$$d = w_0 + w_1 p + w_2 a^* + w_3 b^*, \tag{8}$$

where p represents the ratio of the number of pixels with similar chromaticity to the illumination in the entire pixel number. The scalars $w_0, w_1, w_2,$ and w_3 are weighting coefficients to the features, where w_0 is a constant bias. These weighting coefficients are determined based on a multiple regression analysis using the evaluation experimental data. Let $d_1, d_2, \ldots, d_n$ be the parameter values obtained from the subjective visual evaluation for n paintings under the incandescent light, and let (p_i, a_i^*, b_i^*) $(i = 1, 2, \ldots, n)$ be the corresponding feature values obtained from the image data

Figure 8. Different types of paintings used to collect the learning data. (a) Printed postcards; (b) water painting; (c) oil paintings; (d) multiple color charts; (e) single color patches.

rendered under the same illumination. Then, the weights (w_0, w_1, w_2, w_3) are determined to minimize the squared error:

$$\underset{w_0, w_1, w_2, w_3}{\arg\min} \sum_{i=1}^{n} \{d_i - (w_0 + w_1 p_i + w_2 a_i^* + w_3 b_i^*)\}^2. \quad (9)$$

Estimation Results

To collect the learning data, we used 10 subjects with normal vision and 14 different types of painting, as shown in Figure 8, including water paintings, oil paintings, printed postcards, color charts, and single color patches. The reason for using the different media is that we want to evaluate whether the proposed method can be applied to objects with various material appearances. The parameter values of the incomplete adaptation index d for the respective paintings were determined by the subjective evaluation experiments according to the procedure shown

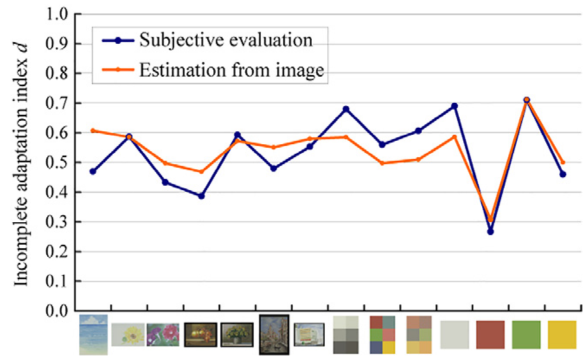

Figure 9. Results of the parameter estimation for the respective paintings match human subjective evaluation.

Table III. Weighting coefficients determined from the learning data.

w	w_1	w_2	w_3
0.5065	0.0808	0.0006	−0.0057

in experimental setup section. Table III shows the weighting coefficients determined from the least-squared-error fitting in (9), where a set of 140 learning data was obtained from the combination of 14 images and 10 subjects. We note that the estimated values of the weighting coefficients (w_1, w_2, w_3) are in the order $|w_1| > |w_3| > |w_2|$, where the estimates correspond roughly to the ratio of white areas, the green component, and the blue component in a color image.

Figure 9 shows the estimation results for d for the respective paintings by using the coefficients in Table III. The orange dots connected by the orange line represent the estimates of the parameter d obtained from the respective image data. The blue dots connected by the blue line in Fig. 9 represent the averages of the incomplete adaptation levels with which the 10 subjects responded to the respective paintings. The subjects were undergraduate students and graduate students at Chiba University with naive and normal color vision. The averaged error and maximum error were 0.06 and 0.14, respectively. The residual sum of squares was 0.07 for the 14 images, and the p-value of the estimated indices was $p < 0.001$. The reproduced color images within 0.15 of the estimated error were acceptable for the human subjects. In other words, the proposed parameter estimation falls within the range and matches human subjective evaluation. We also note that the index values of paintings with whitish or bluish compositions are higher than those of reddish paintings.

In order to verify the applicability of the estimated weighting coefficients, we prepared a set of test samples consisting of five images that were different from the learning samples, as shown in Figure 10. The five images were three oil paintings and two single color patches. The same coefficients as given in Table III were used for the estimation. Figure 11 shows the estimation results for the test sample images. The averaged error and maximum error were 0.08 and 0.12,

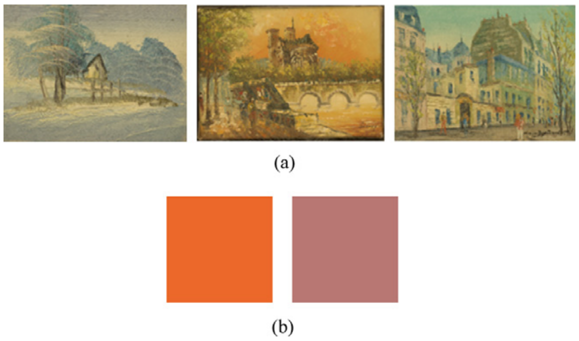

Figure 10. Five paintings used to test the applicability of the estimated weighting coefficients. (a) Oil paintings; (b) single color patches.

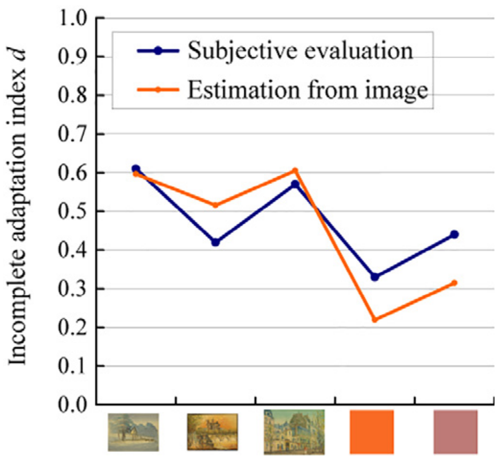

Figure 11. Parameter estimation results for the test samples match human subjective evaluation.

respectively. Thus it is shown that the proposed parameter estimation algorithm is applicable to the test paintings.

Comprehensive Evaluation

Figure 12 demonstrates five sets of painting images rendered by using different values of the index d. These are representatives of printed postcards, oil paintings, water paintings, single color patches, and color charts. In each set of images, the left image shows the original image of the painting illuminated by illuminant A, which was rendered by the parameter $d = 0$. The middle image shows the image rendered using the parameter value of d estimated by the proposed estimation algorithm. The right image shows the image rendered under illuminant D65, which was rendered by the parameter $d = 1.0$. We should note that the predicted images with the incomplete adaptation effect have different appearances from both the original image under illuminant A and the ideal image with the perfect adaptation effect. The validity of these rendered images was confirmed in the subjective visual evaluation.

CONCLUSION

In this article we have proposed a method of image rendering to predict the incompletechromatic-adaptation effect for paintings. First, a simple model of incomplete chromatic adaptation was developed to predict the appearance of the paintings under the illumination of an incandescent light and to produce the full color image on a display device. We extended the von Kries framework to incomplete chromatic adaptation. An index parameter d representing the degree of incomplete chromatic adaptation was defined based on the color temperature of the black-body radiators. This index parameter ranged from $d = 0$ for no adaptation at A to $d = 1.0$ for complete adaptation at D65. The optimum value of the index parameter d was determined by visual experiments of memory matching using real paintings and color patches, so that the color image produced on the display was matched to the original appearance of objects in a real scene. This approach was shown to have better performance in comparison with the traditional CIECAM02. Next, an algorithm was presented to estimate the index parameter d of the incomplete adaptation index based on the image data

Figure 12. Rendered images by different values of the index parameter. (Left) Original image under Illuminant A ($d = 0$). (Middle) Rendered image by the estimated parameter value of d. (Right) Rendered image under Illuminant D65 ($d = 1.0$). (a) Printed postcard; (b) oil painting; (c) water painting; (d) single color patch; (e) color chart.

of colorimetric rendering for a target painting. We found that the index parameter could be estimated using only three features extracted the image data, which were (1) the ratio of the number of pixels with similar chromaticity to the illumination in the entire pixel number, (2) chromaticity a^*, and (3) chromaticity b^*. The color images rendered with the estimated parameter could be used for predicting the incomplete chromatic-adaptation effect for the original painting under an incandescent light source.

Since art paintings in museums are often illuminated by incandescent lamps, the proposed incomplete adaptation method could have applications to digital archiving of art paintings such as cultural heritage recording and virtual museums.

In this article, no relationship was found between the color distribution and the estimation accuracy. Even if the color distribution and the spatial structure of the paintings might have influenced the performance of the model, the current technology does not allow us to analyze the influence. A detailed analysis using a large set of paintings and color patches remains as a future work.

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