Chromatic Adaptation Model Based on Spectral Property Estimation and Its Color Matching Performance

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Abstract

This paper proposes a chromatic adaptation model based on spectral property estimation. In this model, the concept of color constancy in human vision is introduced into color matching. We performed detailed subjective experiments to evaluate the color matching performance of the model for natural color images between softcopy and hardcopy by comparing it with that of six other models. The results not only show the color matching performance of each model, but also demonstrate that our model enables better color matching than the six other models, as seen in a darkroom experiment involving color matching between two CRT monitors whose whites are quite different.

Introduction

Color matching between color imaging devices has become an increasingly important issue in practical applications. For example, if it were possible to confirm the exact color appearance which would be reproduced with a printer on a CRT monitor, it would help graphic designers etc to work more efficiently.

Various chromatic adaptation models and color appearance models have been proposed, and color matching methods based on these models would be able to solve the color matching problems in cross-media communications.[1-5]

In addition to the above-mentioned models, we also proposed a chromatic adaptation model, which is based on spectral property estimation.[6] In this model, hypothetical spectral properties of objects and the illumination in an image are recovered by introducing some assumptions on human color vision. The model applied to both incomplete and complete chromatic adaptation. We showed that our model produces good color matching for natural images between two CRT monitors whose whites are quite different (i.e. 9300K and D50) in a darkroom.

Since these models are very complicated, however, it is difficult to know which model produces good color matching performance in practical situations. Especially, good color matching performance between softcopy and hardcopy for color appearance models and chromatic adaptation models would be of great interest to those who want to use them.

We therefore performed detailed subjective experiments to fairly evaluate the color matching performance of our model for natural color images between softcopy, i.e. the white is 9300K, and hardcopy, i.e. the white is a white paper illuminated with D50 by comparing with it to that of six other models.

In this paper, we describe the subjective experiments we performed and show that our model will be useful for color matching between softcopy and hardcopy.

Color Matching Algorithm

The concept of color constancy in human vision is introduced into our model. We describe the background.

Various computational theories of color constancy have been proposed.[7-9] The methods to which these theories are applied are designed so that robots, not human beings, can identify an object under different illuminations by estimating spectral properties of the object and the illumination in a scene. That is, the goal of the methods is to realize a mechanism of complete color constancy in a computer system.

In psychophysical experiments on human color constancy, it is confirmed that there are two circumstances under which color constancy failed.[10] The first case is when the stimulus appeared not as a reflecting object surface but as a self-luminous object. No surrounding conditions cause this phenomenon. The second one is when the illumination is nearly monochromatic. On the other hand, a good degree of color constancy is achieved for 3400, 6000, and 30000K illuminants in the experiments.

In practical use of color management, however, the surrounding conditions and the illumination do not apply to these cases in which color constancy fails. That is, it can be considered that color constancy might be one of the ways to solve the color matching issue in cross-media communication.

We attempt to apply the basic concept of the color constancy in human vision to color matching by introducing the following assumptions.

Assumption 1

In human vision, surface reflectance of an object color in a scene is inferred under the recognition that white in a scene is perceived as its nearest CIE daylight illuminant.

Assumption 2

Most spectral properties of objects and illuminations show comparatively smooth curves. We can model them as the weighted sum of a small number of vectors.

Assumption 3

White in the image is equal to the illumination in the scene.

As to assumption 1, unfortunately the exact physiological mechanism of human color recognition has not been elucidated yet since it is extremely complex. We, however, feel that this assumption might be appropriate when we consider that human brains learn from experience that objects' colors look similar under different colors of daylight by recovering the fundamental surface reflectance of an object. That is, since it has only been one hundred years at most since artificial illumination methods such as fluorescent lamps were developed, daylight color is very important for us to recognize an object's color. In fact, the results obtained under a 6000K daylight color illuminant showed almost perfect color constancy in Kuriki's experiments.[10]

Assumption 2 and Assumption 3 are needed to make the color constancy problem solvable. It is well known that spectral properties of daylight and objects can be represented by the weighted sum of a small number of basis vectors.[11,12]

Since the detailed algorithm we propose is described in Ref. 6 it is mentioned only briefly here. The chromatic adaptation transform from an input color under an original condition to a corresponding color under a reference condition is described below.

1. The hypothetical spectral power distribution (HSPD) of the illumination in a scene is calculated by using the prediction equation for the spectral power distribution of a daylight illuminant and the correlated color temperature or chromaticity of the white of a color device reproducing the scene.[13] HSPD under an original condition and that under a reference condition are, respectively, $I(\lambda)$ and $I(\lambda)'$.
2. The hypothetical surface reflectances (HSR) $O(\lambda)$ of all objects under an original condition are obtained by solving Equation (1) for $O(\lambda)$.

$$\begin{aligned} X &= \int I(\lambda)O(\lambda)\bar{x}(\lambda)d\lambda, \\ Y &= \int I(\lambda)O(\lambda)\bar{y}(\lambda)d\lambda, \\ Z &= \int I(\lambda)O(\lambda)\bar{z}(\lambda)d\lambda, \end{aligned} \tag{1}$$

where X, Y and Z are tristimulus values of an input color under an original condition and, $\bar{x}(\lambda)$, $\bar{y}(\lambda)$ and $\bar{z}(\lambda)$ are color matching functions. To solve Equation (1), HSR $O(\lambda)$ can be modeled as Equation (2) by introducing a finite dimensional linear model.

$$O(\lambda) = o_0(\lambda) + a_1o_1(\lambda) + a_2o_2(\lambda) + a_3o_3(\lambda), \tag{2}$$

where $o_0(\lambda)$ is the mean vector and $o_i(\lambda)$ s (i=1,2,3) are basis vectors. They are derived from a number of surface reflectances of objects and known parameters. The weighted coefficients a_i (i=1,2,3) are unknown parameters representing the color of an object.

An observation equation for HSR can be made by substituting Equation (2) for $O(\lambda)$ in Equation (1).

$$\begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix} = \begin{pmatrix} M(x,o_1) & M(x,o_2) & M(x,o_3) \\ M(y,o_1) & M(y,o_2) & M(y,o_3) \\ M(z,o_1) & M(z,o_2) & M(z,o_3) \end{pmatrix}^{-1} \begin{pmatrix} X - M(x,o_0) \\ Y - M(y,o_0) \\ Z - M(z,o_0) \end{pmatrix} \tag{3}$$

where $M(x,o_i)$ (i=0~3) represents an integral term $\int I(\lambda)o_i(\lambda)x(\lambda)d\lambda$. We can recover HSRs of all objects in the scene by calculating characteristic parameters a_i for all pixels in the image.

3. Two HSRs of the complete white are obtained, $O_w(\lambda)$ under an original condition and $O_w'(\lambda)$ under a reference condition. In order to obtain the HSR of the white $O_{wm}(\lambda)$ under a reference condition, which matches the color appearance of the white under an original condition, the mixture of an object's surface reflectances recovered under difference illuminations is introduced. We think that this would be a reasonable mechanism to describe incomplete chromatic adaptation in human color recognition. $O_{wm}(\lambda)$ can be calculated by using the equation below.

$$O_{wm}(\lambda) = MC \text{ x } O_w(\lambda) + (1 - MC) \text{ x } O_w'(\lambda). \tag{4}$$

where MC is the mixing coefficient ($0.0 \leq MC \leq 1.0$).

4. In order to calculate the HSR for a color that is not white, we define an adjusting function for surface reflectance on wavelength in visible light. Let $rf_{ad}(\lambda)$ denote an adjusting function for surface reflectance.

$$rf_{ad}(\lambda) = \frac{O_{wm}(\lambda)}{O_w(\lambda)} \tag{5}$$

5. An HSR $O'(\lambda)$ under a reference condition corresponding to an HSR $O(\lambda)$ of an arbitrary input color under an original condition can be calculated by multiplying $O(\lambda)$ by $rf_{ad}(\lambda)$.

$$O'(\lambda) = O(\lambda) \text{ x } rf_{ad}(\lambda) \tag{6}$$

6. The tristimulus values of a color under a reference condition corresponding to an arbitrary input color under an original condition are obtained by Equation (7).

$$\begin{aligned} X' &= \int I'(\lambda)O'(\lambda)\bar{x}(\lambda)d\lambda, \\ Y' &= \int I'(\lambda)O'(\lambda)\bar{y}(\lambda)d\lambda, \\ Z' &= \int I'(\lambda)O'(\lambda)\bar{z}(\lambda)d\lambda, \end{aligned} \tag{7}$$

Experiments

We performed subjective evaluation experiments to investigate the validity of our model. Hereafter, we call our model the "SPEM (Spectral Property Estimation Model)" for convenience.

Referring to CIE guidelines[14] we set a printed image and a CRT monitor in the viewing booth in a dark room as illustrated in Figure 1. The printed image, which was printed by a dye sublimation printer (Victor TruePrint 3500PS) and illuminated with D50, was set in the left booth as a test stimulus. The reproduced image that was a reference stimulus was displayed on the right CRT monitor (NEC Multisync FE70), whose white was about 9300K, with no illumination.

To increase the reliability of the experiments, the original images were created carefully so that physical factors other than color appearance were discarded. To get color data based on measurement and avoid unnatural contours in the images as much as possible, half a million colors were created by using the linear interpolation based on the measured data of 2951 colors printed by the printer. To remove the problem of the gamut of the printer output being different from that of the CRT monitor, most colors in the original and reproduced images were determined so that they existed in both gamuts.

The comparison of the printer's gamut and the CRT monitor's one in CIELAB in Figure 2 demonstrates that these gamuts are different. From the figure, it can be said that the CRT monitor's gamut is generally bigger than that of the printer. The printer's gamut, however, protrudes from the monitor's one in the area from cyan to green. That is, colors reproduced by the printer include colors that the monitor cannot physically reproduce.

Four kinds of natural images were prepared as original images in the experiments because subjects could be influenced by the contents of the image. N1 (Portrait), N2 (Cafeteria), N3 (Fruit Basket), and N7 (Musician) in ISO/JIS-SCID were used for this evaluation.[15] These images were hemmed with a reference white.

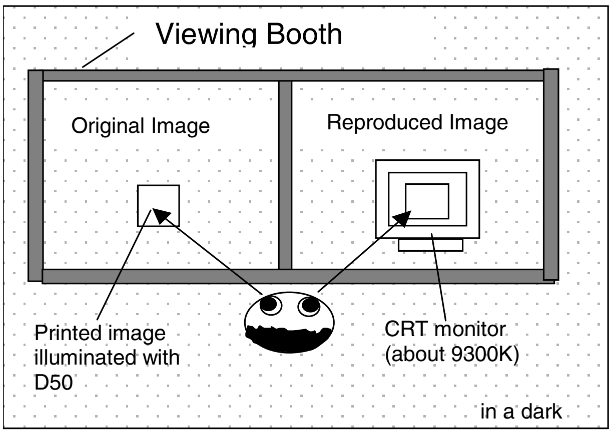

Figure 1. Viewing booth to evaluate color appearance matching.

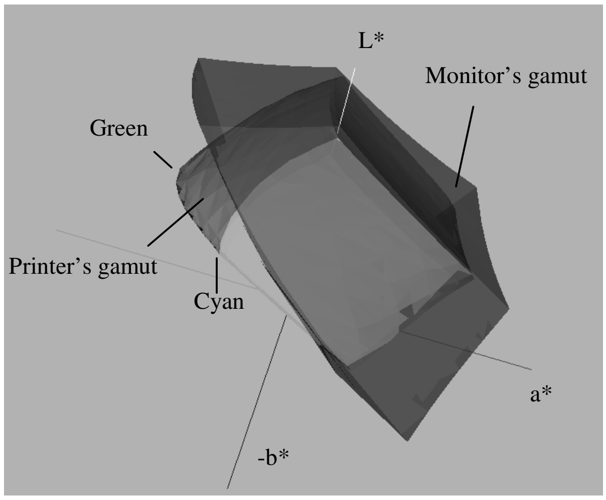

Figure 2. Comparison of the difference between printer's and CRT monitor's gamuts in CIELAB.

Though SCID images are supplied with CMYK data, the CMYK data cannot be used in the original images as it is, since physical factors other than color appearance should be removed from the original images. Original images and the reproduced images were created via the following steps.

(1) An appropriate color transformation from CMYK of SCID image to RGB in the device dependent color of the CRT monitor whose white was set to D50 was carried out. And the RGB values were converted to tristimulus values $X_0Y_0Z_0$ by linear transformation.
(2) For $X_0Y_0Z_0$ of (1), CMYK data and its tristimulus values XYZ under D50 were searched from an LUT that consists of half a million colors so that the color difference Eab is minimum. CMYK data was saved as the original image that was printed.
(3) For XYZ under D50 of (2), the corresponding colors X'Y'Z' under 9300K were calculated by using all color appearance models and chromatic adaptation models that we evaluated.
(4) For the corresponding colors X'Y'Z' of (3), R'G'B' values that were device dependent colors were calculated by using linear transformation.
(5) Gamut checking was carried out by judging whether R'G'B' values existed within the CRT monitor's gamut. When the number of pixels that were out of the gamut exceeded the threshold, saturation compression was performed to $X_0Y_0Z_0$ of (1) in CIELAB space.
(6) (2), (3), (4) and (5) were repeated until the reproduced image was obtained.

The procedures to create an original image and the reproduced image are summarized in Figure 3. When saturation compression of (5) was performed, the original image was updated.

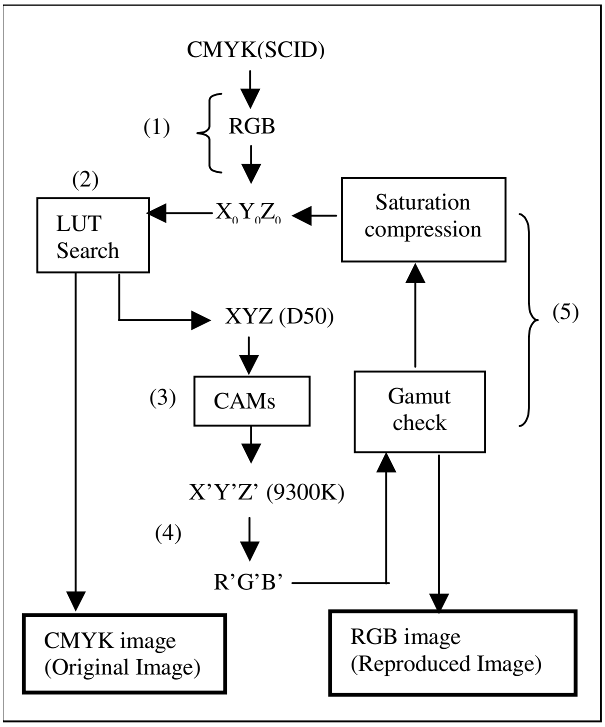

Figure 3. Procedures for the creation of an original image and a reproduced image

The white of a printed image had the same chromaticity as that of the white paper illuminated with D50, and that of a reproduced image was set to bluish white that was originally set to the CRT monitor. The chromaticity of the monitor's white was x= 0.2841 and y = 0.2944. Backgrounds of the original image and the reproduced image on the monitor were set to gray with a luminance factor of 0.2. Luminance level of the white of the original image was 94.59 cd/m^2 and that of CRT monitor's white was 94.06 cd/m^2.

In the left booth, a black wall with a hole was set between the original image and a subject so that light from the illumination did not directly reach the subject's left eye. The original image appeared not as a self-luminous object but as a reflecting object surface, since the subject could see a gray background around the original image. Viewing angles of the images are 9.54º (vertical) × 11.42º (horizontal) for Musician and Fruit Basket and the inverse for Portrait and Cafeteria.

The SPEM needs basis vectors for the HSPD of the illumination, the HSR of objects and the mixing coefficient *MC*. We used the same parameters as those used in Ref. 6.

Gamma correction for the CRT monitor was conducted by using an ICC profile[16] and an imaging software with a color management function that we developed. We confirmed that the average color difference (Eab) between an ideal image and an image displayed was less than 1.

We examined the following seven models:
1) von Kries
2) CIELAB
3) LLAB[1]
4) RLAB[2]
5) Nayatani97[4]
6) CIECAM97s[5]
7) SPEM (our model)

Ten subjects, who had normal color vision, evaluated the superiority or inferiority in the color matching of images reproduced by these models. The viewing condition was nearly successive-haploscopic viewing because subjects could not simultaneously see two images from the parallax.[17]

We followed the paired comparison method to determine the order of the models' performance for color appearance matching. We made reproduced images by using the above-referenced seven models and displayed two images randomly selected from these seven images on the right monitor. These two images were not simultaneously but alternately displayed on the monitor when subjects clicked their PC mouse.

From the two images displayed on the right monitor, subjects were instructed to select the one which was closer in color appearance to the original image set in the left booth. They were also requested to evaluate whole regions and colors in images and not to concentrate on specific regions or colors. The experiments were repeated twice to improve the accuracy of the data obtained.

Interval scales (Z-scales) were calculated from the evaluation results for the ten subjects by using Thurstone's law.[18] Figure 4 shows the results of the evaluation experiments.

From the figure, it can be seen that SPEM, RLAB, and CIECAM97s, which take account of incomplete chromatic adaptation, produce good results between softcopy (i.e. the white is about 9300K) and hardcopy (i.e. the white is a white paper illuminated with D50). The color appearance matching performance, ranked in order from high to low, is SPEM, RLAB, CIECAM97s, Nayatani, von Kries, CIELAB and LLAB.

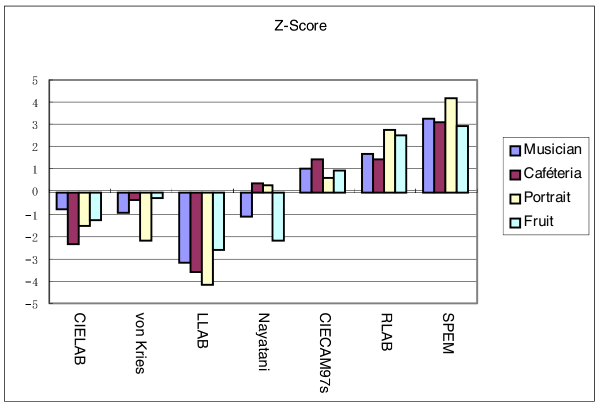

Figure 4. Result for color matching between printed images and images displayed on a CRT-monitor.

Conclusion

This paper has described our SPEM, which not only recovers the hypothetical surface reflectance of an object and the hypothetical spectral power distribution of illumination in a scene, but also adjusts the hypothetical surface reflectance according to changes in illumination.

Subjective experiments have been performed to evaluate the SPEM color matching performance between softcopy and hardcopy by comparing it with that of six other models. To increase the reliability of the experiments, the evaluation images we used were created carefully so that physical factors other than color appearance, such as the difference in device gamuts, color errors etc, were discarded.

The experimental results obtained demonstrated that our model produced better color matching than the six other models, as seen in color matching between two CRT monitors whose whites are quite different.

Since our model requires no complicated calculations and provides good color matching, we believe that it will prove to be especially useful for color management systems.

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Biography

Masato Tsukada received the BS degree and MS degree in computer science from Tsukuba University, Japan in 1989 and 1991, respectively. He joined NEC Corporation as a research scientist in 1991. He was awarded the best paper award by The Institute of Image Electronics Engineers of Japan (IIEEJ) in 1998. His research interests include color reproduction, color image processing, and pattern recognition.