Color Appearance Matching Based on Color Constancy Theory

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Abstract

A new color appearance matching based on color constancy theory is developed. In order to achieve color appearance matching between different color devices whose whites are quite different, the method recovers the hypothetical surface reflectances of objects and the hypothetical spectral power distribution of the illumination in a scene. The surface reflectances are changed according to illumination changes in the algorithm. It requires no complicated calculation and gives good color appearance matching. Experiments show the validity of the proposed method.

Introduction

With recent, rapid advances in color imaging, color matching between devices has become an increasingly important issue. In most CRT displays on the market the original white is set to bluish white (e.g. 9400K), while printers produce colors for the illumination D50 (i.e. 5000K). An appearance matching method needs to be able to accommodate such differences.

In most current color management frameworks, color transformation is based on colorimetric matching, which is conducted in terms of XYZ, $L^*a^*b^*$, or $L^*u^*v^*$ values. Even when these values are matched, however, the colors themselves may not appear to the human eye to be matched.

A number of different color appearance models have been proposed to replace colorimetric matching[1][2][3][4][5][6][7]. In these models, given tristimulus values for a stimulus and data about viewing environment, the brightness and colorfulness of the stimulus, which are absolute values in human color appearance, can be calculated by modeling color appearance phenomena, e.g. the Stevens effect and the Hunt effect. These models, however, consist of complicated equations to model color appearance phenomena and their computational costs may be high. When we consider color matching on personal computers, however, we doubt whether this is the best way to use these models.

We propose a new method for color appearance matching based on color constancy. In the method, instead of modeling color appearance phenomena, the hypothetical spectral power distribution of the illumination in a scene, obtained from white's chromaticity of the color device which reproduces the scene, is calculated. Second, the hypothetical surface reflectances of all objects in the scene are obtained. These hypothetical surface reflectances are used to calculate corresponding colors under different illumination. The computational cost is comparatively low. Experiments show that our model achieves better color appearance matching between different devices than other color appearance models.

Color Constancy

In Figure 1, the incident light $E(\lambda)$ is the product of the spectral power distribution $I(\lambda)$ of a light source and the surface reflectance $O(\lambda)$ of an object. Accordingly, if the illumination changes, the recognized color of the object should be changed. Human beings, however, can stably recognize the color of an object as the same color under different illuminations. The visual function, with which we can stably recognize an object color without being influenced by an illumination change, is called "color constancy".

Color Matching Algorithm

In order to approximate the color constancy on a computer, a number of methods have been proposed

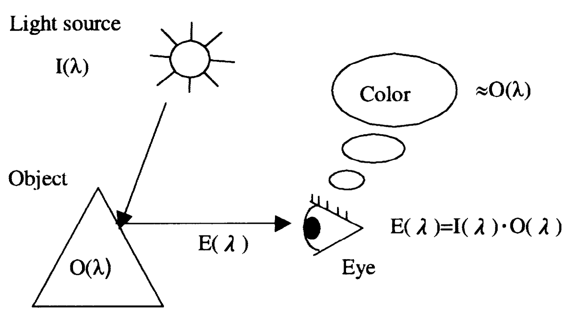

Fig.1 A Path of light

[8][9][10]. In the color constancy problem, the goal is to recover the spectral power distribution of the illumination and the surface reflectances of all objects in a scene from RGB values observed as an image.

RGB values for an object in a scene are expressed by

$$R = \int I(\lambda)O(\lambda)S_R(\lambda)d\lambda,$$
$$G = \int I(\lambda)O(\lambda)S_G(\lambda)d\lambda, \quad (1)$$
$$B = \int I(\lambda)O(\lambda)S_B(\lambda)d\lambda,$$

where $I(\lambda)$ is the spectral power distribution of the illumination in the scene, $O(\lambda)$ is the surface reflectance of the object, and $S_R(\lambda)$, $S_G(\lambda)$ and $S_B(\lambda)$ are the spectral sensitivities of sensors. Generally, the sensitivities of sensors are prior known in the color constancy problem. In order to solve $I(\lambda)$ and $O(\lambda)$ assumptions are needed in color constancy theory.

Computational theories of the color constancy are based on the assumption that the spectral properties of an object and its illumination can be recovered from the color of the light incident to the observer. It is mathematically impossible, however, to restore the spectral power distribution of the illumination and the surface reflectances of objects from RGB values in the image. In order to make the problem solvable, a finite dimensional linear model is used. The model assumes that most spectral properties of illuminations and objects usually show relatively smooth curves and the spectral properties can be represented with the weighted sum of a small number of basis functions. In fact, daylight can be represented well with the weighted sum of an average vector and the first two principal component vectors (CIE daylight illuminant).

In order to apply the color constancy to color matching in human vision, we propose the following assumptions.

Assumption 1

In human vision, the surface reflectance of an object in a scene is inferred under 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 particular set of a few vectors.

As to the first assumption, unfortunately, no one has yet physiologically elucidated the detailed mechanism of human color recognition. We feel, however, that the assumption should be appropriate when we consider that human brains learn from experience that objects' colors look similar under different colors of daylight by recovering their surface reflectances.

In order to make the color constancy problem solvable, we introduce another assumption below.

Assumption 3

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

By using Assumption 1 and the prediction equation for spectral power distribution of CIE daylight illuminant, the spectral power distribution of illumination in the scene can be calculated. The prediction equation for spectral power distribution of daylight illuminant at an arbitrary correlated color temperature T_{cp} is described below.

[Calculation Step]

1) Calculate the chromaticity of daylight illuminant at an arbitrary correlated color temperature T_{cp} by equations (2) through (4).

a) $4000 \le T_{cp} \le 7000$

$$x_p = -4.6070\frac{10^9}{T_{cp}^3} + 2.9678\frac{10^6}{T_{cp}^2} + 0.09911\frac{10^3}{T_{cp}} + 0.244063 \quad (2)$$

b) $7000 < T_{cp} \le 25000$

$$x_p = -2.0064\frac{10^9}{T_{cp}^3} + 1.9018\frac{10^6}{T_{cp}^2} + 0.24748\frac{10^3}{T_{cp}} + 0.237040 \quad (3)$$

$$y_p = -3.000x_p^2 + 2.870x_p - 0.275 \quad (4)$$

2) Recover a spectral power distribution of the daylight illuminant $I(\lambda)$ by

$$I(\lambda) = I_0(\lambda) + M_1 I_1(\lambda) + M_2 I_2(\lambda) \quad (5)$$

where M_1 and M_2 are coefficients represented as

$$M_1 = \frac{-1.3515 - 1.7703\,x_p + 5.9114\,y_p}{0.0241 + 0.2562\,x_p - 0.7341\,y_p}, \quad (6)$$

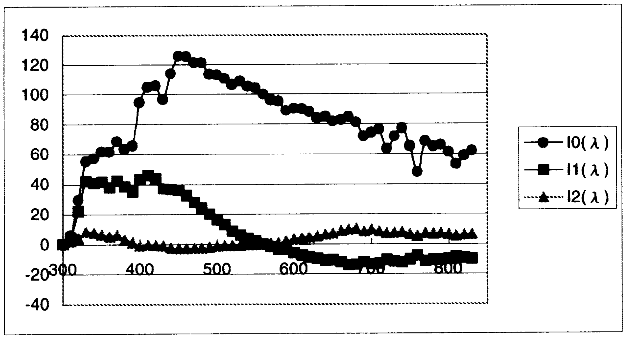

Fig. 2 Average and basis vectors for CIE daylight illuminant.

$$M_2 = \frac{0.3000 - 31.4424\,x_p + 30.0717\,y_p}{0.0241 + 0.2562\,x_p - 0.7341\,y_p}\,, \qquad (7)$$

where $I_i(\lambda)$s (i=0,1,2) are the average vector and basis vectors shown in Figure 2.

Spectral power distribution of daylight illuminant corresponding to a correlated color temperature of a color device's white can be recovered. If the color device's white lies within a color distribution of CIE daylight illuminant, the spectral power distribution can be recovered from the chromaticity of the white, not from the correlated color temperature.

We consider the spectral power distribution of daylight illuminant as a hypothetical spectral power distribution (HSPD) of illumination $I_f(\lambda)$ in the scene by using Assumption 3. Let us denote a surface reflectance of an object as a hypothetical surface reflectance (HSR) $O_f(\lambda)$. X, Y and Z values at each pixel in the image are given by Equation (8).

$$\begin{aligned} X &= \int I_f(\lambda) O_f(\lambda)\,\bar{x}(\lambda) d\lambda, \\ Y &= \int I_f(\lambda) O_f(\lambda)\,\bar{y}(\lambda) d\lambda, \\ Z &= \int I_f(\lambda) O_f(\lambda)\,\bar{z}(\lambda) d\lambda, \end{aligned} \qquad (8)$$

where $\bar{x}(\lambda)$, $\bar{y}(\lambda)$ and $\bar{z}(\lambda)$ are color matching functions which are known. Thus, Equation (8) is the observation equation for $O_f(\lambda)$.

Because the HSR of an object is originally a continuous function of the wavelength λ in visible light, it is impossible to solve it analytically from Equation (8). However, based on Assumption 2, it is possible to model the HSR with a small set of parameters:

$$O_f(\lambda) = o_0(\lambda) + a_1 o_1(\lambda) + a_2 o_2(\lambda) + a_3 o_3(\lambda) \qquad (9)$$

where $o_0(\lambda)$ is an average vector and $o_i(\lambda)$s (i=1,2,3) are the first three principal component vectors obtained from a large number of object colors by principal component analysis and known parameters. The weighted coefficients a_i (i=1,2,3) are unknown parameters presenting the color of an object.

An observation equation can be made by substituting Equation (9) for $O_f(\lambda)$ in Equation (8). In this equation, we can compute each of the integral terms in advance since basis vectors for surface reflectance, the HSPD of illumination $I_f(\lambda)$, and human color matching functions are known. The equation becomes a set of three simultaneous linear equations with three unknown parameters a_i. We call parameter a_i a characteristic parameter.

$$\begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix} = \begin{pmatrix} M(x,o_1) & M(x,o_2) & M(x,o_3) \\ M(y,o_1) & M(y,o_2) & M(y,o_3) \\ M(z,o_1) & M(z,o_2) & M(z,o_3) \end{pmatrix}^{-1} \begin{pmatrix} X - M(x,o_0) \\ Y - M(y,o_0) \\ Z - M(z,o_0) \end{pmatrix} \qquad (10)$$

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

One goal in the color matching problem is to obtain a color (X', Y', Z') on a target color device that corresponds to an input color on a source color device. The tristimulus values (X', Y', Z') under an arbitrary illumination $I_f'(\lambda)$ can be calculated by substituting $I_f'(\lambda)$ for $I_f(\lambda)$ in Equation (8).

$$\begin{aligned} X' &= \int I_f'(\lambda) O_f(\lambda)\,\bar{x}(\lambda) d\lambda \\ Y' &= \int I_f'(\lambda) O_f(\lambda)\,\bar{y}(\lambda) d\lambda \\ Z' &= \int I_f'(\lambda) O_f(\lambda)\,\bar{z}(\lambda) d\lambda \end{aligned} \qquad (11)$$

Advanced algorithm

The basic algorithm for color matching based on color constancy theory was described. The algorithm can be applied in cases where complete chromatic adaptation is effective. The human color recognition mechanism is very complex, however, and is subject to many color appearance phenomena. For example, it often fails to adapt to a white displayed on a monitor in a dark room. Most color appearance models allow for these color appearance phenomena by predicting absolute values on color appearance we perceive in our brains. Let us consider the case where we transform an input color of an object under Illumination 1 to a corresponding color under Illumination 2. In color appearance models, color appearance values of the input color are calculated and then the corresponding color is obtained from the color appearance values by the inverse transformation.

We developed a new method to achieve good color appearance matching between color devices whose correlated color temperatures of white are quite different, e.g. 9400K and 5000K. Our method calculates a color corresponding to an input color in a way different from color appearance models. As for a complete white under Illumination 1, HSR of the complete white $O_{wf}(\lambda)$ is recovered as white from the tristimulus value (X_w, Y_w, Z_w) of the white and HSPD of Illumination 1. On the other hand, HSR of the complete white $O_{wf}'(\lambda)$ is recovered as not white from the tristimulus value (X_w, Y_w, Z_w) and HSPD of Illumination 2. That is, $O_{wf}(\lambda)$ is different from $O_{wf}'(\lambda)$. We assume that a human would predict HSR of a white under Illumination 2 which would match a white under Illumination 1, that is, a mixture of $O_{wf}(\lambda)$ and $O_{wf}'(\lambda)$.

Assumption 4

In human color recognition processing, object colors are estimated to be a mixture of surface reflectance recovered under Illumination 1 and that recovered under Illumination 2.

Given a complete white as an input color under Illumination 1, the tristimulus values (X_w, Y_w, Z_w) are consistent with those of Illumination 1. HSR of the white $O_{wf}(\lambda)$ under Illumination 1 can be obtained from HSPD of Illumination 1 $I_{f1}(\lambda)$ and tristimulus values (X_w, Y_w, Z_w) by using the basic algorithm.

Let us consider that the tristimulus values (X_w, Y_w, Z_w) of the white are reproduced as the same tristimulus values under Illumination 2. HSR of the white $O_{wf}'(\lambda)$ under Illumination 2 is recovered from HSPD of Illumination 2 $I_{f2}(\lambda)$ and tristimulus values (X_w, Y_w, Z_w).

Thus two HSRs of the complete white are obtained, $O_{wf}(\lambda)$ under Illumination 1 and $O_{wf}'(\lambda)$ under Illumination 2. In order to obtain HSR of the white $O_{wfm}(\lambda)$ under Illumination 2, which matches the color appearance of the white under Illumination 1, we introduce a mixing coefficient MC, where $0.0 \le MC \le 1.0$. $O_{wfm}(\lambda)$ can be calculated by the equation below.

$$O_{wfm}(\lambda) = MC \times O_{wf}(\lambda) + (1 - MC) \times O'_{wf}(\lambda) \qquad (12)$$

In this case, we hypothesize that human eyes completely adapt to Illumination 1 but their adaptation to Illumination 2 is incomplete. When MC is equal to 1.0, Equation (12) means the basic algorithm for complete chromatic adaptation.

In order to calculate 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.

$$rf_{ad}(\lambda) = \frac{O_{wfm}(\lambda)}{O_{wf}(\lambda)} , \qquad (13)$$

A HSR under Illumination 2 $O_f'(\lambda)$ corresponding to HSR $O_f(\lambda)$ of an arbitrary input color under Illumination 1 can be calculated by multiplying $O_f(\lambda)$ by $rf_{ad}(\lambda)$.

$$O_f'(\lambda) = O_f(\lambda) \times rf_{ad}(\lambda) \qquad (14)$$

Thus tristimulus values of a color under Illumination 2 corresponding to an arbitrary input color under Illumination 1 are obtained by Equation (15).

$$\begin{aligned} X' &= \int I_{f2}(\lambda) O_f'(\lambda)\, \bar{x}(\lambda) d\lambda \\ Y' &= \int I_{f2}(\lambda) O_f'(\lambda)\, \bar{y}(\lambda) d\lambda \\ Z' &= \int I_{f2}(\lambda) O_f'(\lambda)\, \bar{z}(\lambda) d\lambda \end{aligned} \qquad (15)$$

Experiments

We performed experiments to investigate the validity of our color appearance matching proposed in this paper. Hereafter, we call our color appearance matching method the "color constancy model" for convenience. We made a viewing booth and set two CRT monitors in the viewing booth in a dark room as illustrated in Figure 3. Viewing conditions followed the CIE guideline [12].

For several kinds of natural images, subjects evaluated the color appearance of the images displayed on two CRT monitors whose whites were quite different. Images displayed on the right monitor showed original color appearances. Images reproduced by several kinds of color appearance models or chromatic adaptation models were displayed on the left monitor. Subjects evaluated superiority or inferiority in color appearance matching of these images reproduced by these models with the original images displayed on the right monitor under a haploscopic viewing condition. Backgrounds of the images on monitors were set to gray with a luminance factor of 0.2.

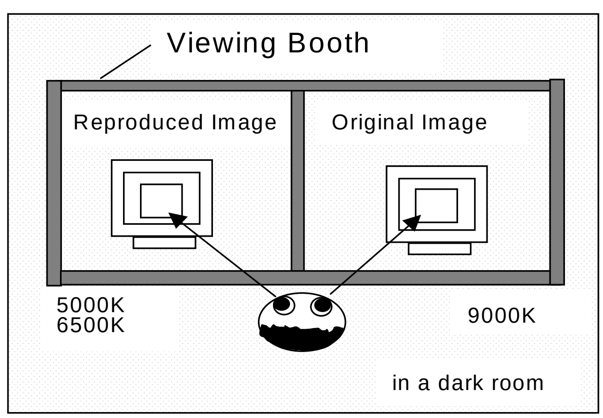

Fig. 3 Viewing booth for evaluation of color appearance models

White of the right monitor was adjusted to 9000K and that of the left monitor to the same chromaticities as D50 and D65. We examined the following seven models:

1) von Kries
2) CIE-L*a*b*
3) LLAB[1]
4) RLAB[2]
5) Nayatani97[4][5]
6) CIECAM97s[6]
7) Color constancy model (our model)

Four kinds of natural images were prepared because the evaluation result for only one image was influenced by the contents in the image. N7 (musician), N1 (portrait), N3 (fruit) and N6 (orchid) in ISO/JIS-SCID were used for evaluation. These images were appropriately converted to RGB images since these images were supplied as CMYK images. These images were hemmed with a reference white.

The color constancy model needs basis vectors for HSR of objects. The basis vectors, shown in Fig. 4, were derived from 2763 surface reflectances of color patches printed by an NEC PC-PR810 dye sublimation printer with principal component analysis. In addition to the vectors experimentally used in this paper, there are many other basis vectors which could be used. Mixing coefficient MC was set equal to 0.6 in this experiment.

We followed the method of paired comparison to determine the order of the model's 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 left monitor. These two images were not simultaneously but alternately displayed by subjects' click operation on a mouse. From the two images displayed on the left monitor, subjects were instructed to select the image that was closer in color appearance to the original image displayed on the right monitor.

Interval scales were calculated from the evaluation results of ten subjects by using the law of Thurstone's comparison judgment[13]. First, a matrix with the elements of the probability P(i,j) which means that model-i is closer to the original image than model-j was made. Second, the elements P(i, j)s were converted into Z-scores Z(i, j)s by using a normal distribution diagram. This calculation was based on the assumption that human judgement on difference would show a normal distribution. The Z-score matrix consists of these Z-scores Z(i, j)s. Table 1 shows a sample of a Z-score matrix. Third, summations ΣZ(i, j)s in each column are calculated. Finally, the average of a ΣZ(i, j) is an interval scale for the model.

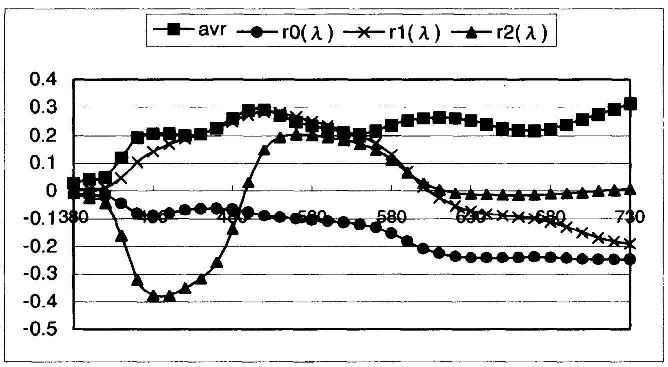

Fig.4. Basis vectors for surface reflectance.

Table 1. A sample Z-score matrix

j \ i	Model1	Model2	Model3	Model4	Model5
Model1	0.000	-1.282	0.524	0.253	-0.253
Model2	1.282	0.000	1.282	0.000	0.524
Model3	-0.524	-1.282	0.000	0.253	0.253
Model4	-0.253	0.000	-0.253	0.000	0.842
Model5	0.253	-0.524	-0.253	-0.842	0.000
ΣZ(i,j)	0.758	-3.088	1.300	-0.336	1.336
S_i=ΣZ(i,j) /5	0.152	-0.618	0.260	-0.067	0.273

The interval scores are significant in that they show the relative degree of difference in model performance, whereas probability values merely show the order of model performance. On the other hand, differences in interval scales correspond to differences in human perception. The interval scale shows a linear relationship between the difference in scales and human perceptions. That is, we can evaluate the model performance that is consistent with human perception by using a method of evaluation based on the interval scale.

Figures 5 and 6 show results of the evaluation experiment. We can see that the color constancy model, RLab, Nayatani and CIECAM97s, which take account of incomplete chromatic adaptation, produce good results for two monitors whose whites are quite different, i.e. 9000K-D50 and 9000K-D65, in a dark room. These results show that human color cognition has a tendency to fall into incomplete chromatic adaptation in the absence of information on illumination color.

In particular, our color constancy model made the highest scores for all images in the 9000K-D50 experiment. RLAB showed the next best performance. In the 9000K-D65 experiment, there is not much difference between the seven models; however, our color constancy model and RLAB produced comparatively good results.

Four kinds of natural images were selected in this evaluation experiment. The results obtained for N3 (fruits) are obviously different from those obtained for other images. LLAB and von Kries, which take account of complete chromatic adaptation, produced especially good

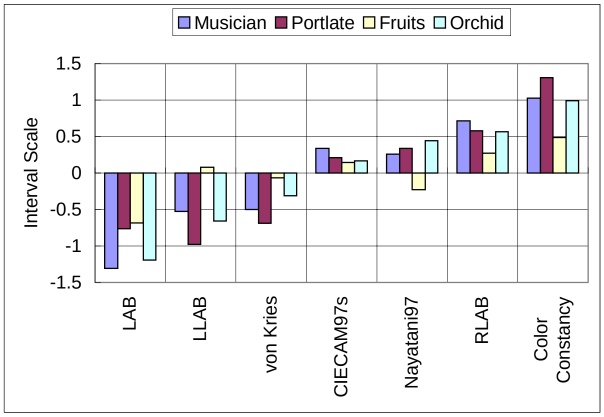

Fig.5. Result for 9000K V.S. D50

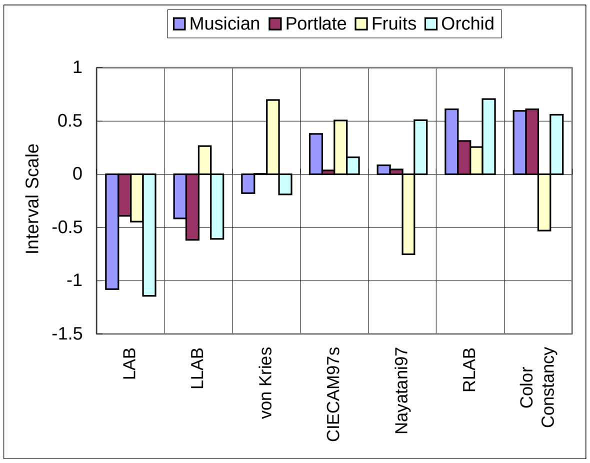

Fig.6. Result for 9000K V.S. D65

results for N3 in the 9000K-D65 experiment. It is commonly said that human chromatic adaptation from higher correlated color temperature to lower correlated color temperature can easily occur for warm colors. N3 mainly comprises warm colors, and subjects' color cognition for N3 in this experiment was apparently the result of complete chromatic adaptation.

Conclusion

In this paper, a new color appearance matching method based on the color constancy theory is proposed. It recovers hypothetical surface reflectance of an object and hypothetical spectral power distribution of illumination in the scene. Furthermore, it adjusts the hypothetical surface reflectance according to changes in illumination. Our model needs no complicated calculation and gives good color appearance matching.

We believe that the algorithm is especially suitable for use in color management systems. We are currently applying our model to color appearance matching between a monitor and a printer, and anticipate we will be able to report the results in the near future.

References

[1] Luo M.R. Lo M. C. and Kuo W. G. : "The LLAB(l:c) Colour Model", Color Res. Appl., 21,6, pp.412-429(1996).

[2] Fairchild M.D. : "Refinement of the RLAB Color Space", Color Res. Appl., 21, 5, pp.338-346(1996).

[3] Hunt R.W.G. : "An Improved Predictor of Colourfulness in a Model of Colour Vision", Color Res. Appl., 19, pp.23-26(1994).

[4] CIE TECHNICAL REPORT : "A Method of Predicting Corresponding Colours under Different Chromatic and Illuminance Adaptations", (CIE109-1994).

[5] Sobagaki H. and Nayatani Y. : "Field Trials of the CIE Chroma-Adaptation Transform", Color Res. and Appl., 23, pp.78-91(1998).

[6] Luo M.R. and Hunt R.W. : "The Structure of the CIE 1997 Colour Appearance Model (CIECAM97s)", Color Res. Appl., 23, 3, pp138-146 (1998).

[7] Katoh N. : "Practical Method for Appearance Match Between Soft Copy and Hard Copy", SPIE, Vol.2170, pp.170-181(1994).

[8] Maloney L.T. and Wandell B.A. : "Color Constancy: a method for recovering surface spectral reflectance", J. Opt. Soc. Am. A, 3, 1, pp.29-33(1986).

[9] Gershon R., Jepson A. D. and Tsotsos J.K. :"From R,G,B to Surface Reflectance : Computing Color Constancy Descriptors in Images", Proc. 10th Int. Joint Conf. on Artificial Intelligence, pp.755-758(1987).

[10] Tsukada M. and Ohta Y. :"An Approach to Color Constancy Using Multiple Images", Proc. IEEE 3rd Int. Conf. on Computer Vision, pp.385-389(1990).

[11] Handbook of Color Science 2nd ed., University of Tokyo Press, pp69-71(1998).

[12] "CIE Guideline for Coordinated Research on Evaluation of Colour Appearance Models for Reflection Print and Self-Luminous Display Image Comparisons", Color. Res. Appl., 19, pp.49-58, (1994).

[13] Ohkushi K., Nakayama T. and Fukuda T. :"Evaluation Techniques for Picture and Sound Qualities", Shoukoudou, pp34-47(1991).