Color Correction Method Based on the Spectral Reflectance Estimation using a Neural Network

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Abstract

This paper describes a new correction method for the color shift due to the illuminant changes based on the estimation of the spectral reflectance by a neural network. Proposed method has been compared to two conventional methods and evaluated. Our evaluation results show that the method can achieve better accuracy than other methods.

Introduction

Illuminant affects an observed and recorded colors of object that is colors tend to be reddish or greenish under incandescent or fluorescent lighting. These color shifts due to the illuminant changes in the image would be unacceptable as the natural colors.

In recent years the color desktop publishing (DTP) system was in general used for creating a document or editing digital images for personal and/ or professional uses. A digital camera also can be used to take an image for such purposes. However the problem of the color shifts due to the illuminant changes will occur when an image is recorded under some other illuminant since the color DTP system is typically calibrated for only one illuminant such as daylight illuminant D50. Thus it is required to perform a correction of the color shifts prior to printing an image so that it makes a color matching to the image recorded under daylight illuminant.

This paper presents a new correction method of the color shift due to the illuminant changes based on the estimation of the spectral reflectance using a transformation from CMY value by a three layered neural network. Two conventional methods for correcting the color shift will be briefly reviewed. Then a new color correction method will be compared to these conventional color correction methods for evaluation.

Color Correction Methods

The color shifts due to the illuminant changes can be represented as a difference between the tristimulus value under different illuminants since colors are colorimetrically defined by a tristimulus value using spectral reflectance, spectral distribution of the illuminant and color matching function. In other words when the tristimulus values under observation illuminant $\boldsymbol{L}$ and daylight illuminant $\boldsymbol{L_o}$ can be calculated by $\boldsymbol{t} = \boldsymbol{M^T L R}$ and $\boldsymbol{c} = \boldsymbol{M^T L_o R}$, the color shifts correspond to the difference between $\boldsymbol{t}$ and $\boldsymbol{c}$. Where $\boldsymbol{M}$ is $3 \times N$ Matrix which is comprised by XYZ color matching function (N is the number of its sampling point). N-element row vector $\boldsymbol{R}$ and $N \times N$ diagonal Matrix $\boldsymbol{L}$ represent the spectral reflectance and spectral distribution of the illuminant respectively. Figure 1 shows such color shifts due to the illuminant changes between daylight and observation illuminant (e.g. incandescent or fluorescent illuminant) and an aspect of the color correction. Then, if the spectral reflectance can be estimated from the tristimulus value under observation illuminant it is possible to acquire the tristimulus value under daylight illuminant by the calculation indicated by a dotted line in Figure 1. However this estimation is difficult mathematically because there exist huge number of spectral reflectance (metameric color) which can give the same tristimulus value. Therefore to obtain the tristimulus value of the daylight illuminant by this estimation it is necessary to put possible spectral reflectances somehow under constraint.

White Point Mapping (WPM) is a sort of method which is used in conventional video system, digital color imaging system and other recording systems. This method assumes that the same color shift due to the illuminant changes occurs in each colors, and use the reference white for determining the quantity of the correction. That is colors are corrected by the same quantity of the correction as the reference white.

However this would produce significant correction errors in each colors except for the vicinity of the white point because illuminant changes give rise to the various color shifts in each colors. On the contrary Vrhel and Trussell[1] have proposed Principal Components (PCS) method based on the estimation of the spectral reflectances by a finite dimensional linear model with a small number of principal components. Here. we will describe these two methods and our method for correcting the color shifts due to the illuminant changes.

White-Point Mapping Method

WPM can be described as follows: if $\boldsymbol{C}_{wpm}$ is a three element vector produced from viewing $\boldsymbol{R}$ under daylight illuminant $\boldsymbol{L_o}$ then $\boldsymbol{t}$ can be matched to $\boldsymbol{C}_{wpm}$ by multiplying the correction matrix $\boldsymbol{D}$

$$C_{wpm} = Dt \tag{1}$$

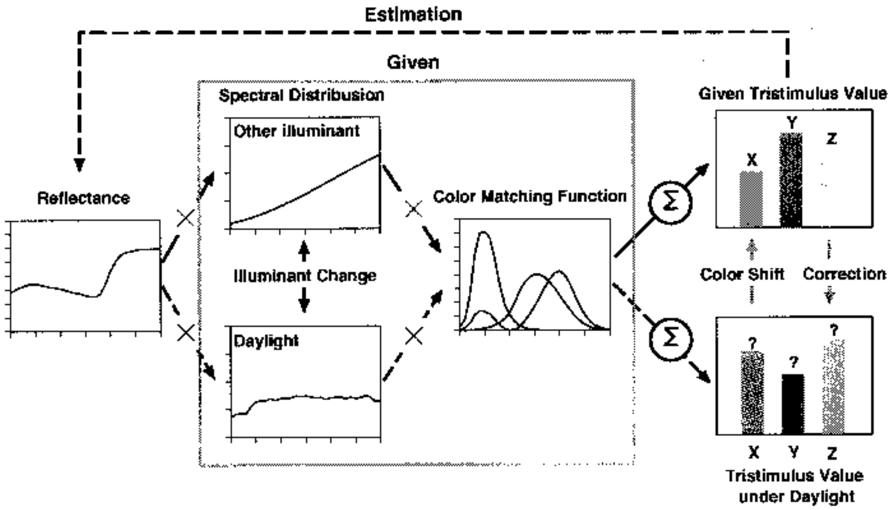


Figure 1. Scheme of the color correction for the color shifts due to the illuminant changes

Correction matrix $\boldsymbol{D}$ is given by:

$$D = \begin{bmatrix} \frac{X_w^{(0)}}{X_w} & 0 & 0 \\ 0 & \frac{Y_w^{(0)}}{Y_w} & 0 \\ 0 & 0 & \frac{Z_w^{(0)}}{Z_w} \end{bmatrix} \tag{2}$$

where $X_w^{(0)}$, $Y_w^{(0)}$, $Z_w^{(0)}$ and X_w Y_w, Z_w correspond to the tristimulus value of the reference white under daylight and observation illuminant.

Principal Components Method

A finite-dimensional linear model is used in PCS method to estimate the spectral reflectance of each color. It defined by:

$$\overline{R} = \overline{R} + \sum_{i=1}^{3} \psi_i \mu_i \tag{3}$$

where $\overline{\boldsymbol{R}}$ is a mean vector and ψ_i is the principal component associated with i-th principal component vector μ_i , respectively.

Then the tristimulus value can be calculated by using the above finite-dimensional linear model; Equation (3), which is:

$$\begin{aligned} t_{pca} &= M^T L \mu \psi + M^T L \overline{R} \\ &= M^T L \mu \psi + m_t \end{aligned}$$

where $\mu = [\mu_1, \mu_2, \mu_3]^T$ is a principal component vector matrix and $\boldsymbol{m}_t = \boldsymbol{M}^T \boldsymbol{L} \overline{\boldsymbol{R}}$ is a matrix of the tristimulus value for a mean vector. From this equation the principal component matrix $\psi = [\psi_1, \psi_2, \psi_3]^T$ is calculated by:

$$\psi = (M^T L \mu)^{-1} \left[t_{pca} - m_t \right] \tag{5}$$

Thus by using the finite-dimensional linear model the tristimulus value $\boldsymbol{C}_{vrh}$ under daylight illuminant corrected by principal components method is:

$$\begin{aligned} C_{vrh} &= M^T L_o \mu \left[M^T L \mu \right]^{-1} \left[t_{pca} - m_t \right] \\ &\quad + m_c \end{aligned} \tag{6}$$

For details of this correction method refer to the article of Vrhel and Trussell.[1]

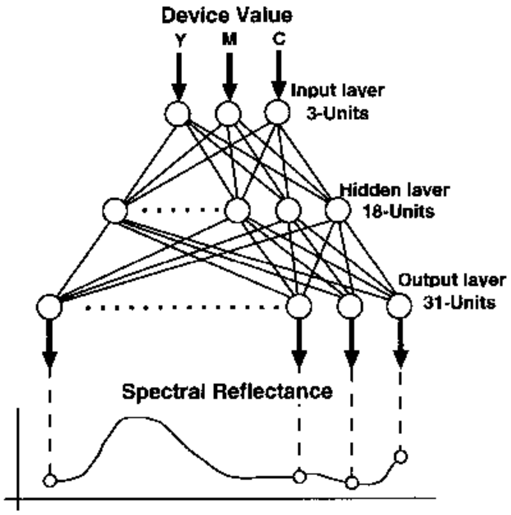


Figure 2. Structure of the neural network. It makes a transformation from CMY value to the spectral reflectance.

Proposal of the Color Correction Method using a Neural Network

A three layered neural network is used for the estimation of the spectral reflectance in proposed method instead of the finite-dimensional linear model. A structure of a neural network for estimating the spectral reflectance from CMY value is shown in Figure 2. A number of input and output units correspond to C, M, and Y value and a number of points of the spectral reflectance *(N* = 31). 18 units were used in a hidden layer. We can estimate the spectral reflectance using a neural network as shown in Figure 2. When the estimated spectral reflectance is represented as a nonlinear function of C M and Y: $\boldsymbol{R}(C,M.Y)$, the tristimulus value $\boldsymbol{t}_{NN}$ under the observation illuminant $\boldsymbol{L}$ is calculated from

$$C_{prop} = \boldsymbol{M}^T \boldsymbol{L}\boldsymbol{R}(C, M, Y) \tag{7}$$

where $\boldsymbol{R}$ *(C, M, Y)* is updated by the optimization process shown in Figure 3. In this process CMY value is adjusted so that the square error between original tristimulus value $\boldsymbol{t}$ and the calculated tristimulus value $\boldsymbol{t}_{NN}$ is minimized using nonlinear optimization process.

The tristimulus value $\boldsymbol{C}_{prop}$ corrected by the proposed method is defined as:

$$C_{prop} = \boldsymbol{M}^T \boldsymbol{L}_o \boldsymbol{R}_d (C, M, Y) \tag{8}$$

where $\boldsymbol{R}_d(C, M,Y)$ corresponds to the determined spectral reflectance by the optimization process.

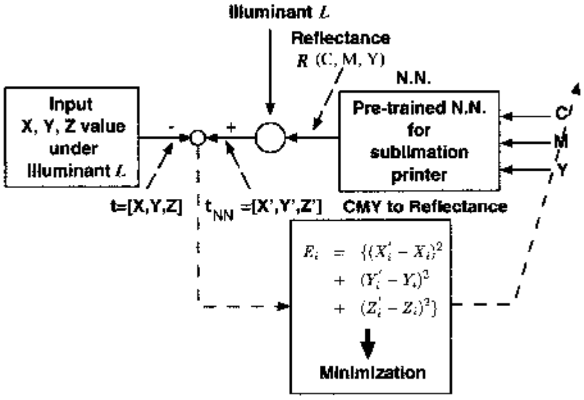


Figure 3. Color correction method using a neural network. The spectral reflectance is updated by nonlinear optimization process.

Evaluation of an Accuracy for Each Method

We printed 1331 color chips by dye-sublimation printer. As a training data set of the neural network and data of principal component analysis, 216 data were chosen from 1331 color chips. We also used the 125 color chips as a testing data set selected from 1115 unknown data. Both data sets equally include the chips with possible various kinds of hue chroma and lightness. For the reference white in WPM method the spectral reflectance of a paper of dye-sublimation printer was used. To evaluate each color correction method we calculated the tristimulus values $\boldsymbol{C}_{wpm}$, $\boldsymbol{C}_{vrh}$, and $\boldsymbol{C}_{prop}$ of the color chips for two cases: a fluorescent F3 illuminant and an incandescent A illuminant. These are compared to the tristimulus values obtained for actual spectral reflectances under daylight illuminant D50. Figure 4 indicates the spectral distribution of each illuminant are regulated by CIE. The distributions are normalized such that total energy is equal to 1.

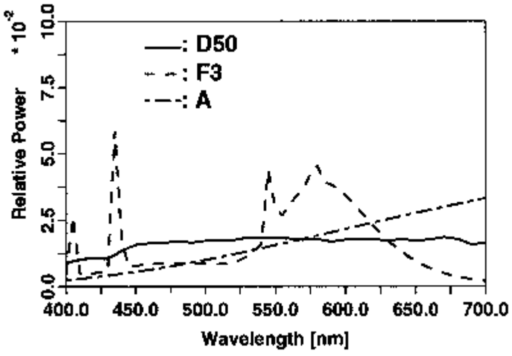


Figure 4.Spectral distribution of the illuminants. D50 A and F3 illuminants were used.

Figures 5 and 6 show an accuracy of each method for F3 and A illuminant, respectively. The upper side of each figure indicates that the errors of color correction are plotted on a*-b* plane of CIE L*a* b* uniform color space. Symbol • is the actual tristimulus value under D50 illuminants. The thin lines correspond to the color differences between estimated and actual tristimulus values. The lower side shows the histograms of these color differences for each method. Vertical lines in this figure represent the mean color differences.

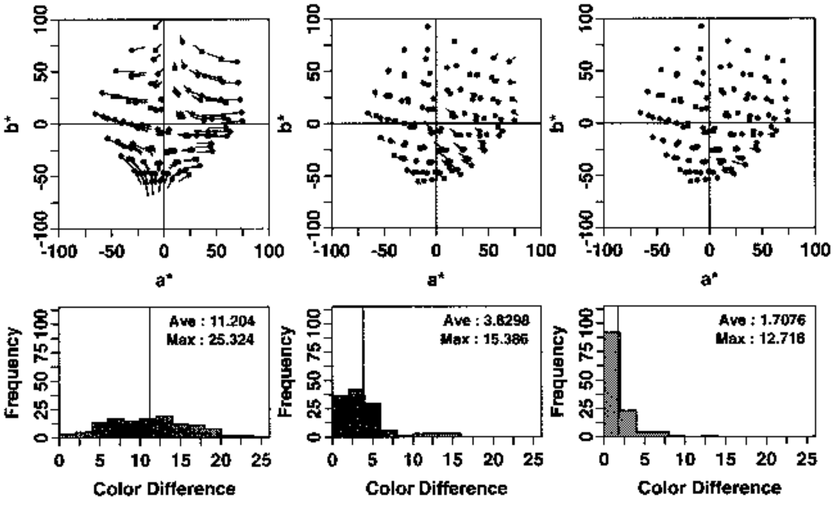
These results show that WPM can correct the reference white perfectly but produces significant errors in other colors under F3 illuminant and A illuminant. The mean and maximum color difference for both illuminants are considerably large: $\Delta E_{mean} = 11.204$, $\Delta E_{max} = 25.324$ under F3 illuminant and $\Delta E_{mean} = 9.7286$, $\Delta E_{max} = 20.768$ under A illuminant respectively. In contrast the principal components method performed a correction with relatively small errors not only for the reference white but also for chromatic colors. The mean and maximum color difference for both illuminants are also relatively small: $\Delta E_{mean} = 3.8705$. $\Delta E_{max} = 17.709$ under F3 illuminant and $\Delta E_{mean} = 3.8296$, $\Delta E_{max} = 15.386$ under A illuminant respectively. Furthermore the proposed method could perform better correction than the principal components method that is, $\Delta E_{mean} = 1.7076$, $\Delta E_{max} = 12.716$ under F3 illuminant and $\Delta E_{mean} = 1.4607$, $\Delta E_{max} = 11.679$ under A illuminant. This evaluation results of a proposed method indicate that the color correction errors would not be visually noticeable.

Discussions

An accuracy of color correction obtained by the proposed method fairly improved as compared with principal components method. We consider that this is because the estimation accuracy of the spectral reflectance by neural network is better than that by finite-dimensional linear model. To examine how well a neural network can approximate the spectral reflectance we compared the estimation accuracy of a neural network with finite-dimensional linear model with three and four principal components vectors. In this evaluation 1115 spectral reflectance data (described in the previous section) were used. The mean squared error between original and estimated spectral reflectance were calculated by:

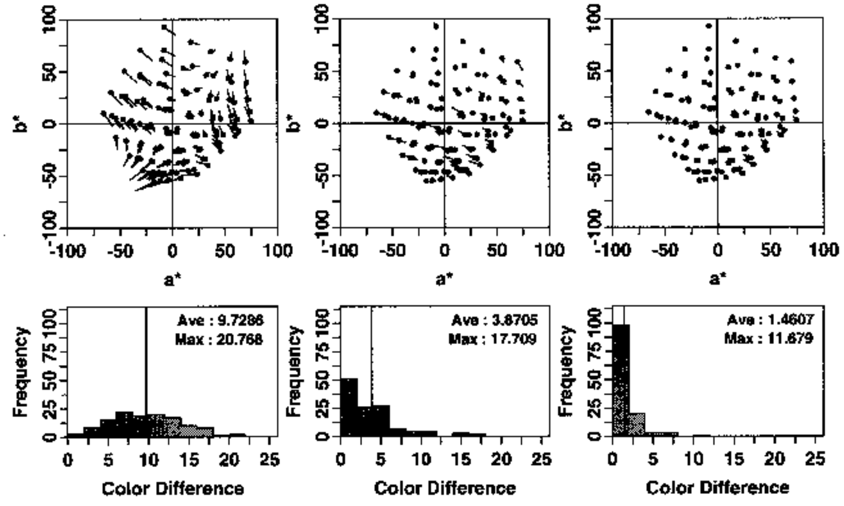
$$MSE = \frac{1}{NM}\sum_{i=1}^{M}\sum_{j=1}^{N}\{R_i(\lambda_j) - \tilde{R}_i(\lambda_j)\} \qquad (9)$$

where M is the number of spectral reflectance (M = 1115) $R_i(\lambda_j)$ and $\tilde{R}_i(\lambda_j)$ correspond to the original and the estimated spectral reflectance respectively. MSE of each model are specified in Table 1. We can see that a finite dimensional linear model can not achieve better approximation accuracy than a neural network even if four principal components are used.



(a) WPM **(b) Vrhel** **(c) Proposed**

Figure 5. Accuracy of each correction method for the color shift due to the F3 illuminant.



(a) WPM **(b) Vrhel** **(c) Proposed**

Figure 6. Accuracy of each correction method for the color shift due to the A illuminant.

Table 1. Comparison of the Estimation Accuracy of the Spectral Reflectance. Finite Linear Model with Three and Four Principal Components and Neural Network Model were Compared.

Method	3-terms	4-terms	N.N.
MSE	0.00123	0.000691	0.000364

Conclusions

A new method of color correction based on the estimation of the spectral reflectance by a neural network was described and compared to the standard method of the White Point Mapping and Principal Components method. These methods were tested on spectral reflectance of color chip reproduced by a dye sublimation printer under F3 and A illuminant. We found that the proposed method produced color errors less noticeable than white-point mapping method and principal components method. That is the mean and the maximum color difference was ΔE_{mean} = 1.7076 ΔE_{max}= 12.716 under F3 illuminant and ΔE_{mean} = 1.4607. ΔE_{max} 11.679 under A illuminant. respectively.

References

1. M. J. Vrhel and J. Trussell, “Color Correction using Principal Components”, *Color Res. and Appl.,* **17**, pp. 328-338, 1992.