

Development of CIEL*a*b*-CMYK color conversion system by Neural Network

Jong-pill Kim, Eu-Hwan Lee, Suk-chul Ahn*

Dept. of Graphic Arts Information, Pukyong National University

*Dept. of Electronics Engineering, Pusan National University

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신경망에 의한 CIEL*a*b*-CMYK 색변환 시스템 개발

김 종 필, 이 을 환*, 안 석 출

부경대학교 인쇄정보공학과 *부산대학교 전자공학과

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Abstract

현재, 디지털 하드카피에 있어서 색변환방법으로 신경망에 의한 비선형변환 방법은 많은 연구가 되어지고 있으며, 색변환 시스템으로서의 유용성이 확인되고 있다. 그러나, 학습용 패치의 제작시 여러 가지 프린트 왜곡에 의해서 톤 재현 범위가 좁아지게 되고, 전체적으로 불균일한 학습용 패치가 얻어지게 된다. 그러므로 신경망 학습의 허용오차 범위가 줄어들게 되어 CIEL*a*b*에서 CMYK로의 정확한 색변환이 어렵게 되고, 재현된 결과물이 원고 화상과 큰 색차를 가지게 된다.

본 논문에서는 이러한 문제점들을 해결하기 위해 시지각특성에 기반을 둔 프린터의 톤 재현 범위 확장법을 이용하여 신경망의 학습용 패치를 제작하여 CIEL*a*b*에서 CMYK로의 비선형 색변환 방법을 제안하고, 제안한 방법의 유용성을 확인하고자 하였다.

1. Introduction

Color transformation between color coordinates has become increasingly important since the advent of desktop publishing systems. In recent years, various color transformation methods from device-independent to device-dependent coordinates are proposed for color hardcopy system.

The polynomial regression method and the interpolation method by the look-up table(LUT)

have been used as color coordinates transformation. The polynomial regression method has higher error in color reproduction. The interpolation method by LUT performs accurate color reproduction, but it requires a large memory to store data. Recently, non-linear color transformation using neural networks has been proposed.^{1,2,3)} The neural network is adequate for modelling the non-linearity for CIEL*a*b* to CMY color conversion.

In the previous paper, the authors presented a color transformation method from CIEL*a*b* to CMY space by the neural network for the inkjet printer.^{1,3)} However, the range of tone reproduction of printed color patches for LUT design is reduced due to the effect of the dot gain. In the case that the color patches with the reduced tone range are used as the learning data of the neural network, the similar colors among the printed patches make it difficult to be the non-linear mapping from CIEL*a*b* to CMY color space.

In this paper, we describe a method of extending the range of tone reproduction based on equi-visual perception characteristic in order to reduce color difference between the original image and the reproduced image. Also, the proposed method is applied in CMYK printer with the four primary inks.

2. Theory

2.1 Equi-visual perception characteristic

Color is divided into psychophysical color and perceived color. Psychophysical color is represented as colorimetric value such as tristimulus values. It is based on a psychological impression. Object color is perceived differently according to the surface of object and environment. CIE(Commission Internationale de l'Eclairage) color system is representative of psychophysical color. Perceived color is described as color appearance values such as hue, value and chroma. Munsel color system is representative of perceived color.

Color systems used widely are XYZ color system, and CIELAB and CIELUV color system which are uniform perceptual color space. The color conversion from XYZ to L* a* b* is expressed as the following equation (1).

$$\begin{aligned} L^* &= 116(Y/Y_n)^{1/3} - 16 \\ a^* &= 500\{(X/X_n)^{1/3} - (Y/Y_n)^{1/3}\} \\ b^* &= 200\{(X/Y_n)^{1/3} - (Z/Z_n)^{1/3}\} \end{aligned} \quad (1)$$

Where X_n , Y_n , and Z_n are the tristimulus values of the reference white, and the value of Y_n is normalized as 100.

The color difference, ΔL_{ab}^* is defined as equation (2)

$$\Delta E_{ab}^* = \{(\Delta L^*)^2 + (4a^*)^2 + (\Delta b^*)^2\}^{1/2} \quad (2)$$

Where ΔL^* , Δa^* , and Δb^* are the differences between L_1^* , a_1^* , b_1^* and L_i^* , a_i^* , b_i^* values.

We print the patches with constant input level using each C(Cyan), M(Magenta), and Y(Yellow) inks. Let us divide the printed patches into n equal-visual intervals. The difference of Equi-visual perception with n step is expressed as equation (3).

Equation (4) is written as a series of equation (3).

$$\Delta E = \frac{\Delta E_{max} - \Delta E_{min}}{n - 1} \quad (3)$$

$$\begin{aligned} \bar{E}_n &= \{E_1, E_1 + \Delta E, E_1 + 2\Delta E, \dots, E_1 + (n-1)\Delta E\} \\ &\{E_1, E_2, E_3, \dots, E_n\} \end{aligned} \quad (4)$$

Where ΔE_{max} and ΔE_{min} denote the maximum and the minimum of color difference between reference white and patch, respectively. In equation (4), E_1 is equal to ΔE_{min} and \bar{E}_n is equal to ΔE_{max} .

Fig.1 shows the relationship between a series of equi-visual perception E_{nk} and input digital level in color printing with C, M, and Y inks, where k represents color ink ($k=C, M, Y$). ΔE_{max} is the color difference between reference paper white and patch with 100% ink. ΔE_{min} becomes 0.

The calibrated value I_{out} for input digital level I_{inp} has equi-visual color difference with n step. So the relationship between the input value and the calibrated value becomes inverse.

$$\bar{I}_{inp} = \{I_{inp1}, I_{inp2}, I_{inp3}, \dots, I_{inp n}\} \quad (5)$$

$$\bar{I}_{out} = \{I_{out1}, I_{out2}, I_{out3}, \dots, I_{out n}\} \quad (6)$$

A series of the input level I_{inp} and the calibrated level I_{out} are described as equation (5) and (6).

The function for printer calibration, $f_k(I_{inp})$ is modelled as p th-order polynomial as shown in equation(7).

$$f_k(I_{inp}) = a_0 + a_1 I_{inp} + a_2 I_{inp}^2 + \dots + a_p I_{inp}^p \quad (7)$$

Where k represents color ink($k = C, M, Y$).

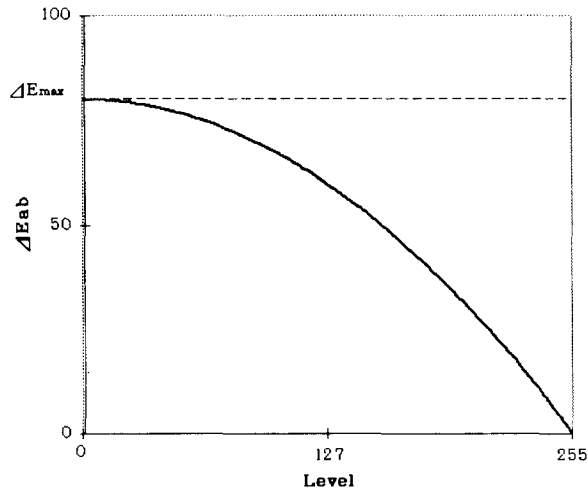


Fig.1. Color difference characteristic for digital level values.

2.2 Gray component generation

In high-end color printing and digital hardcopy, black(K) ink is added in CMY color inks in the purpose of the good reproduction in shadow area, the saving of color inks, and rapid dry of inks.

CMY inks and RGB colors have selective absorption ability, and black ink absorbs the light uniformly all over visible wavelength. Therefore, gray component represented by RGB colors is replaced as black ink.

Fig.2 shows gray component generation. Gray component generation is performed in RGB space because when the RGB color component is mixed, the color has gray component.

Equation (8) is the method for generating gray component.

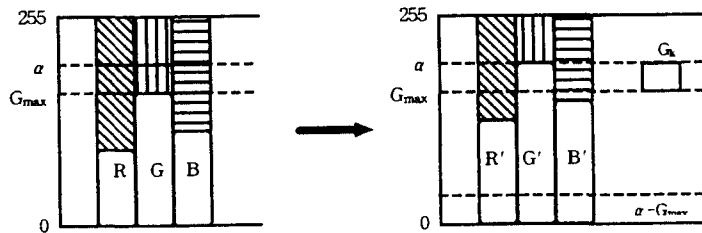


Fig.2. The method of gray component generation.

$$\begin{aligned}
 G_k &= \alpha - G_{max} \\
 R' &= R + G_k \\
 G' &= G + G_k \\
 B' &= B + G_k
 \end{aligned}$$

(8)

Where α is threshold value used in order not to generate gray component in highlight area. G_{max} is maximum value of gray component generation. The amount of $\alpha - G_{max}$ is gray component and G_k is added in each R, G, B component.

2.3 Neural network

Fig.3 shows the structure of neural network which consists of unit of multi-input and one output⁶⁾.

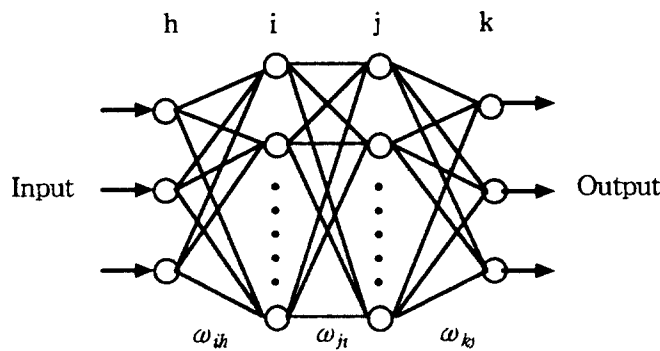


Fig.3. structure of neural network.

The input net_j of a unit in layer j is the sum of the weighted outputs from the prior layer. It is described as equation (9).

$$net_j + \sum w_{ij} o_i \tag{9}$$

Where o_i is the output of the a unit in layer i w_{ij} is the weight of connection from the a unit in layer i and the a unit layer j.

The output of unit j is defined as equation (10).

$$o_j = f(net_j) \tag{10}$$

The transfer function f is called an activation function and it is chosen to be "sigmoid" function as expressed in equation (11).

$$f(net_j) = \frac{1}{1 + e^{-net_j}} \tag{11}$$

Let the p-th target vector of XYZ values be defined as $tp \equiv [tp_1, tp_2, tp_3]$ and the corresponding output vector of the XYZ values from the neural network be defined as $op = [op_1, op_2, op_3]$.

The error between target t_p and the output o_p is expressed as equation (12) and the average error for all vectors is given by equation (13).

$$E_p = \frac{1}{2} \sum_k (t_{pk} - o_{pk})^2$$

$$E = \frac{1}{2p} \sum_p \sum_k (t_{pk} - o_{pk}) \quad (13)$$

The backpropagation algorithm is used to minimize the overall error of the neural network. The weights are changed using the following relationship.

$$\Delta w_{kj} = \eta \delta_k o_j \quad (14)$$

Where Δw_{kj} is the change value of a weight from a unit in layer k to a unit in layer j , η is a learning rate coefficient, δ_k is the backpropagation error for the a unit in layer k , and o_j is the output of a unit in layer j .

The error delta δ_k and delta δ_j are given by the following equations.

$$\delta_k = (t_k - o_k) o_k (1 - o_k)$$

$$\delta_j = (1 - o_j) \sum_k \delta_k w_{kj} \quad (15)$$

3. Experimentation

3.1 CIEL*a*b*-CMYK color conversion system by neural network

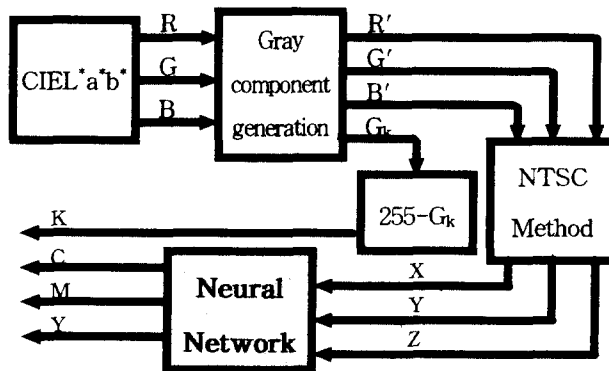


Fig.4 CIEL*a*b*-CMYK color conversion system by Neural Network.

Color conversion from uniform color coordination CIEL*a*b* to printer signal CMYK means the transformation from device independent color coordinate to driving signal.

Fig.4 shows color reproduction system. Gray component is generated in RGB space and R' G' B' is transformed to XYZ space. XYZ is transformed to CMY by neural network. Gray component, GK is changed to K.

Neural network has two hidden layers with three input and three output. The optimal number of units for each hidden layer is determined by the experiment.

3.2 Design of color patches

Generally, ideal dots are square in digital printing. But this assumption does not hold for the most of printers. Printed dots are more closely round rather than square and the dot size is larger than ideal case. As a result, image distortion is generated and B/W image is significantly darker because of reduction of range of tone reproduction.

Image distortion has the effect on the operation of neural network. Although the permission error in the process of learning is small, reproduced color image has a large color difference.

To compensate image distortion, printer calibration based on equi-visual perception is performed and color patches are printed by calibrated printer based on equi-visual perception.

Color patches are designed with 10% step of CMY. The number of color patches is 1331 and color patches are printed using Jarvis, Judice, and Ninke error diffusion by PCL control of HP printer. The number of 216 patches among the color patches is used for learning and the number of 1115 patches is used for evaluating color difference between the original and the reproduced color by the neural network.

4. Results and Discussion

4.1 Determining the neural network structure

Fig.5 shows the learning error curves where the number of units in the hidden layer is changed from 11 to 30 in order to optimize the neural network. It is the result at 100000 iterative learning process.

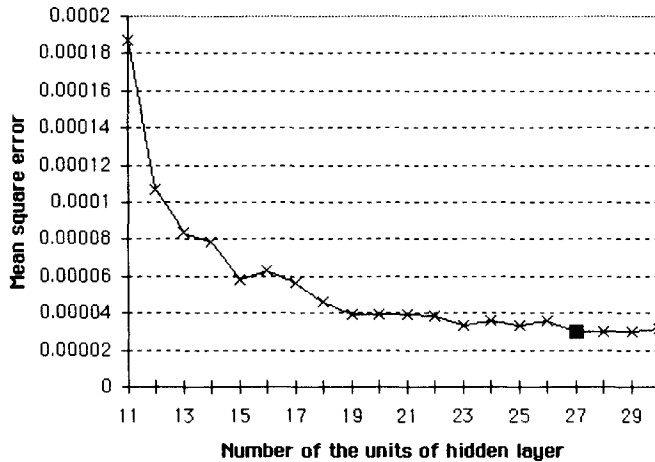


Fig.5. Mean square error according to different number of units in the hidden layer.

We observe that the learning error reach the minimums at 27 units although the number of units in the hidden layer is increasing. Thus the four-layer structure of 3-27-27-3 is chosen as the most effective system.

4.2 Evaluation of the neural network

Table 1. Color difference between the original color patches and the reproduced color patches by CMY inks

No.	ΔE_{ab}		No.	ΔE_{ab}		No.	ΔE_{ab}	
	conventional method	proposed method		conventional method	proposed method		conventional method	proposed method
1	1.80	1.34	7	6.59	1.53	13	6.14	1.50
2	8.08	3.11	8	7.90	0.92	14	4.19	5.38
3	3.11	4.57	9	3.16	3.17	15	4.54	10.97
4	3.95	1.71	10	5.29	0.80	16	8.92	2.62
5	7.02	1.58	11	9.15	1.65	Average		
6	3.32	4.22	12	1.74	7.06		5.58	3.27

Color patches produced on a printer were measured to evaluate the proposed neural network with equi-visual perception. Fig.6 shows the original color patches and the reproduced color patches by neural network. Fig.6 (a) shows the conventional printed color patches without printer calibration and Fig.6 (b) shows the printed color patches with printer calibration based on equi-visual perception characteristic. The patches of left side shown in Fig.6 (a) and Fig.6 (b) are original color patches and the patches of right side are patches reproduced by neural network.

〈Table 1〉 shows color difference, ΔE_{ab} between the original color patches and the reproduced color patches. The average color difference between the original color patches and reproduced patches by the neural network without equi-visual perception is 5.58. In the case of using equi-visual perception, the average color difference is reduced to 3.27.

4.3 Application

Fig.7 shows the printed image of the portraits. Fig.7 (a) is printed image using linear color transformation($C=1-R$, $M=1-G$ and $Y=1-B$) and Fig.7 (b) is a portrait without equi-visual perception by CIEL*a*b*-CMY color conversion system. Fig.7 (c) shows a portrait with equi-visual perception by CIEL*a*b*-CMY color conversion system. Fig.7 (d) is a portrait with equi-visual perception by CIEL*a*b*-CMYK color conversion system.

Table 2. The quality scales of subjective estimation

Single estimation		Comparative estimation	
Quality scale	Valuation marks	Quality scale	Valuation marks
Excellent	5	The same	5
Good	4	Slightly different	4
Fair	3	Different	3
Poor	2	Definitely different	2
Bad	1	Very different	1

Table 3. The results of subjective estimation

Figure	Valuation marks	Quality scale
Fig.6 (a)	3.4	Different
Fig.6 (b)	4.4	Slightly different
Fig.7 (a)	1.2	Bad
Fig.7 (b)	3.8	Good
Fig.7 (c)	4.1	Good
Fig.7 (d)	4.8	Excellent

We perform the subjective estimation for the printed images. Fig.6 and Fig.7 are tested by 10 observers under D50 illuminant. <Table 2> shows the quality scales of subjective estimation and Table 3 shows the results of subjective estimation.

5. Conclusion

As the result of printer calibration using equi-visual perception characteristic and CIEL*a*b*-CMYK color conversion by the generation of gray component, We observe the following :

(1) The optimal number of units in each two hidden layers is 27 in the neural network with 216 learning data.

(2) Color difference of the method that use learning data as patches without equi-visual perception characteristic is about 5.58. In the case of using equi-visual perception characteristic, the color difference is about 3.27. The reduced value of the color difference is about 2.31.

(3) The result of subjective evaluation of the image printed by CMY inks is 4.1(Good). The result of the image generated by gray component and printed by CMYK inks is 4.8(Excellent). In case of CMYK inks, shadow area is represented in detail.

As above results, we observe that after printer calibration, CIEL*a*b*-CMYK color conversion of neural network by generation of gray component is a practical and an efficient transformation method.

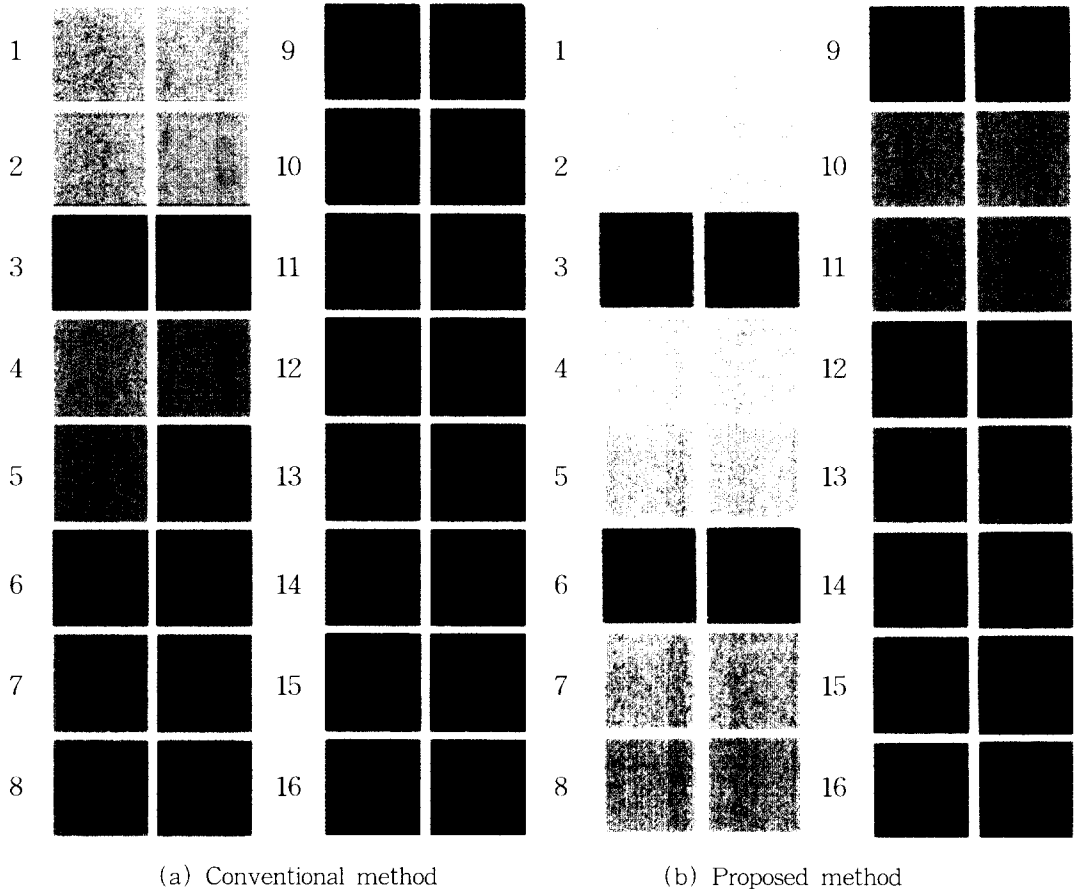


Fig.6 The original color patches and the reproduced color patches by neural network.

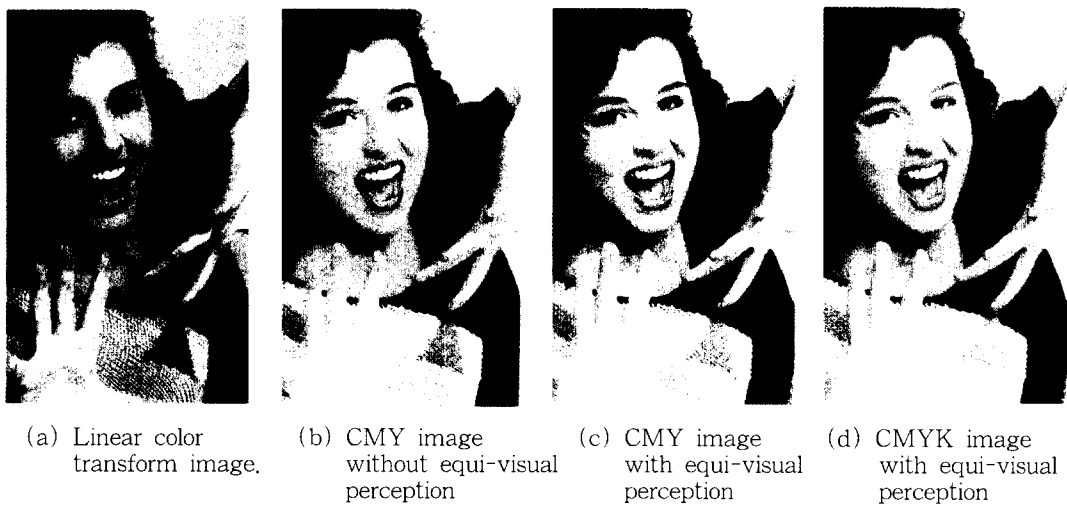


Fig.7 Comparison of portrait image.

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