

Full Length Research Paper

Calculating cyan-magenta-yellow-black (CMYK) printer' gray component data based on polynomial modeling

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As gray color data is very important for printing quality, a method based on polynomial modeling is proposed to calculate the gray color data of different lightness. Firstly, the IT8.7/3 color target which defines input cyan-magenta-yellow-black (CMYK) signals is printed, and the corresponding CIELAB (Commission Internationale de l'Eclairage L*, a* and b*) values are obtained by a spectrophotometer with color sensors. Secondly, the polynomial regression method is used to determine the relationship between these two color spaces, in which the given CIELAB color's CMY value is calculated. At last, as the obtained cyan-magenta-yellow (CMY) gray color may contain Chroma information due to the computational error, a new color target is developed to find the real gray colors based on the relationship above, and the final relationship between CIE-L* and CMY are obtained. In the experiment, the average color error is 2.65ΔE, which is below the printing error threshold, hence the proposed algorithm for calculating gray color data can be used in printing process.

Key words: Gray balance, polynomial modeling, CIELAB (Commission Internationale de l'Eclairage L*, a* and b*) color, color sensors.

INTRODUCTION

The primary colors within subtractive imaging are cyan (C), magenta (M), yellow (Y). When combination of certain percentage of C, M, Y are printed, they produce color black (K). In printing or textile industry, cyan-magenta-yellow-black (CMYK) is often the primary color where K is used to replace a quantity of C, M and Y. There are many advantages with color K, such as the high color density, good color contrast, big gamut volume, low cost and so on.

When K color is used to replace certain amount of CMY, a black replacement algorithm is commonly used, which

determines the correspondence between K and combination of C, M, and Y. Now there are mainly two kinds of black replacement algorithms, GCR (gray component replacement) and UCR (under color removal) (Guo et al., 2011). It is very important to determine the relationship between the CMY and K, because the black ink has no Chroma, the issues turns into finding the same lightness between the K color and the combination of C, M and Y. In color science, the CIELAB space is independent of the color device, thus it is often used to connect the device color space. For CMYK printers,

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during the process of calculating gray color data, the CIE-L* can be selected to link the CMY and K, where the combination of C, M, Y colors and the K color correspond to CIE-L* value.

During the conversion between CIELAB and CMY colors, the color targets has to be used which includes many color patches (Fashandi et al., 2010). For example the IT8.7/3 target has 928 color patches, and ECI2002 has 1485 patches. In this paper, the former target is employed for gathering sample data; and then six gray colors with different CIELAB values are used for calculating CMY values; at last, taking into account the conversion errors, the calculated CMY values may present some Chroma after printing; a new gray color target is developed to modify the CMY values.

In general, the process of converting colors from CMY to CIELAB can be defined as characterization (Lee and Lee, 2013), while the contrary process is often called calibration (Yang et al., 2012); obviously the paper mainly interests the latter process. Now the commonly used calibration algorithms are 3D interpolation (Pekkucuksen and Altunbasak, 2013; Liu et al., 2013; Srivastava et al., 2010), polynomial regression (Hong et al., 2001; Nussbaum et al., 2011), neural network (Kang and Anderson, 1992; Hwang et al., 2013), Neugebauer equations (Morovic et al., 2012; Hebert and Hersch Roger, 2011), and so on. Taking into account the quantity of color patches, the precision and computing efficiency of the algorithms, polynomial regression modes is selected in this paper.

POLYNOMIAL REGRESSION MODEL

During the printer calibration process, the standard color target IT8.7/3 is firstly printed out. Among the 928 color patches most of them are not gray colors, hence it is hard to find the CMY patches which contain none Chroma information. Within the IT8.7/3 target, there are 216 CMY patches and each of their area coverage ranges within 0, 10, 20, 40, 70 and 100%; their CIELAB values can be measured by the spectrophotometer X-Rite 530 with color sensors. In experiment, the 216 color patches' CMY and CIELAB values form the training sample data. Then the relationship between CIELAB and CMY can be obtained by polynomial regression model.

In the process of calculating gray color data, the training sample data is generally less than regular color device calibration process. Because the polynomial regression model can obtain acceptable accuracy with less sample data, and it take less simulation time than neural network, it is used to calculate the gray color data.

Within the polynomial regression method, the relationship between independent variable x and dependent variable $f(x)$ can be modeled as an n th degree polynomial as below.

$$f(x) = \alpha_0 + \alpha_1 x + \alpha_2 x^2 + \alpha_3 x^3 + \dots + \alpha_n x^n \quad (1)$$

where the coefficients α and the degree of x are selected reasonably, the complicated relationship between x and $f(x)$ can be described accurately. As the CMY and CIELAB color have three variables respectively, the three-variable polynomials of different degrees are used.

$$f(x, y, z) = \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^n a_{ijk} x^i y^j z^k \quad (2)$$

where $i+j+k \leq n$, a_{ijk} are the coefficients, x, y, z are the independent variables. For example, when the 2nd degree polynomial are selected, the given CIELAB color's corresponding CMY values can be expressed as:

$$\begin{aligned} C(L^*, a^*, b^*) &= \alpha_0 + \alpha_1 L^* + \alpha_2 a^* + \alpha_3 b^* + \alpha_4 L^* a^* \\ &+ \alpha_5 a^* b^* + \alpha_6 L^* b^* \\ M(L^*, a^*, b^*) &= \beta_0 + \beta_1 L^* + \beta_2 a^* + \beta_3 b^* + \beta_4 L^* a^* \\ &+ \beta_5 a^* b^* + \beta_6 L^* b^* \\ Y(L^*, a^*, b^*) &= \gamma_0 + \gamma_1 L^* + \gamma_2 a^* + \gamma_3 b^* + \gamma_4 L^* a^* \\ &+ \gamma_5 a^* b^* + \gamma_6 L^* b^* \end{aligned} \quad (3)$$

Therefore, when the coefficient α, β , and γ are determined, the CMY values can be calculated. The calculation of polynomial regression coefficients are usually based on the least squares method, which minimizes the variance of the unbiased estimators of the coefficients, under the conditions of the Gauss–Markov theorem. When enough samples are supplied, the coefficients of Equation 2 can be calculated as below:

$$U = (VV^T)^{-1}(VP) \quad (4)$$

where U is the coefficient matrix, P is the CMY sample data matrix, V is the CIELAB sample data matrix. If the sample matrix V 's size is $m \times n$, where m is the number of polynomial items, n is the number of sample points, to ensure U can be resolved, the requirement of $n > m$ must be satisfied.

EXPERIMENTAL RESULTS

In the experiment, the color target IT8.7/3 is printed out on a 120 g copper paper by the HP Indigo5500 printer, and the spectrometer X-Rite 530 is used to measure CIELAB values. Within the measured results for the sample data of 216 CMY colors, the maximal and minimal CIE-L* values are 94 and 21 respectively. Between these two lightness, another six CIELAB colors are selected to calculate the CMY values which form gray colors. By using the relationship between CMY and CIELAB calculated with polynomial modeling, the six gray colors' CMY and CIELAB values are obtained below.

As there are solving errors within the polynomial modeling, the directly calculated gray color data may be inconsistent with the actual gray data. For example, within the second gray color in Table 1, the calculated CMY is (70, 60, 59) for the CIELAB value (40, 0, 0), but when the CMY color is sent to the printer, the printed color' CIELAB value is (39, -1, 0). Therefore a new testing target similar to GrayFinder19 is developed according the color data in Table 1. As shown in Figure 1, six groups of low-Chroma patches are arranged, and the center patch's

Table 1. The preliminary calculated gray colors by polynomial modeling.

No.	CIELAB	CMY
1	(21,0,0)	(100, 100,100)
2	(40,0,0)	(70,60,59)
3	(50,0,0)	(60,50,48)
4	(60,0,0)	(50,40,38)
5	(65,0,0)	(42,32,31)
6	(75,0,0)	(30,22,20)
7	(85,0,0)	(20,12,11)
8	(94,0,0)	(0,0,0)

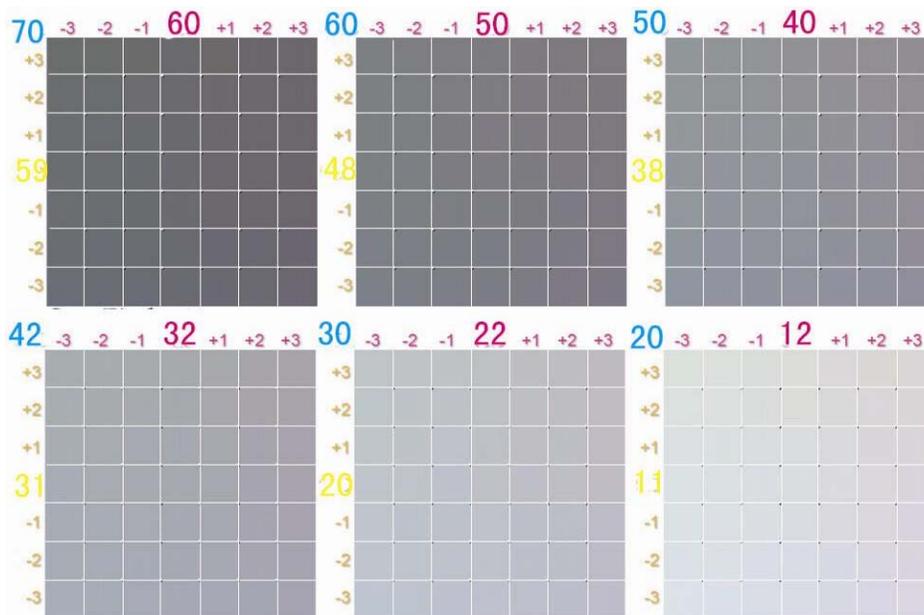


Figure 1. The gray target used for finding real gray colors.

Table 2. Gray colors by reprinting and measuring.

No.	CIELAB	CMY
1	(21, 0, 0)	(100, 100, 100)
2	(39, 0, 0)	(70, 61, 59)
3	(49, 0, 0)	(60, 52, 49)
4	(61, 0, 0)	(50, 39, 37)
5	(65, 0, 0)	(42, 31, 31)
6	(74, 0, 0)	(30, 21, 20)
7	(86, 0, 0)	(20, 11, 10)
8	(94, 0, 0)	(0, 0, 0)

CMY value is from the data of Table 1. Taking the first group for example, the center patch's CMY is (70, 60, 59), and all the patches' C values remains unchanged, while the left patches' M values are 60-1, 60-2, 60-3

respectively, the right patches' M values are 60+1, 60+2, 60+3; similarly the upper patches' Y value are 59+1, 59+2, 59+3, and the underneath patches' Y are 59-1, 59-2, 59-3.

When the gray target is printed out and measured, the real gray colors can be found with CIE-a* =0 and CIE-b*=0. Finally, the real gray colors' CIE-L* and CMY are obtained in Table 2.

With this gray color data above, the relationship between CIE-L* and CMY are determined, and any given lightness gray color' CMY can be simulated. The fourth-degree polynomial is used to calculate the CMY values (Figure 2).

$$\begin{aligned}
 C(L^*) &= \alpha_0 + \alpha_1 L^* + \alpha_2 L^{*2} + \alpha_3 L^{*3} + \alpha_4 L^{*4} \\
 M(L^*) &= \beta_0 + \beta_1 L^* + \beta_2 L^{*2} + \beta_3 L^{*3} + \beta_4 L^{*4} \\
 Y(L^*) &= \gamma_0 + \gamma_1 L^* + \gamma_2 L^{*2} + \gamma_3 L^{*3} + \gamma_4 L^{*4}
 \end{aligned}
 \tag{5}$$

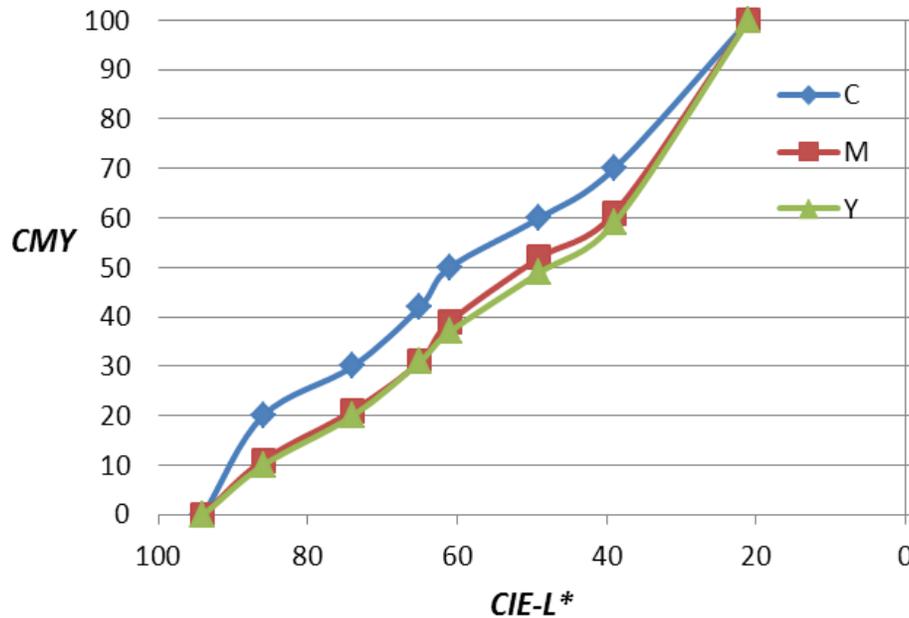


Figure 2. The gray color data curves.

From Equation 5, the gray data curve for lightness L^* from 21 to 94 are described from the scattered data below.

For the purpose of testing the accuracy of the obtained gray color data, twenty testing patches were created to calculate the color errors. Firstly, twenty CIELAB gray colors were randomly selected between the maximal and minimal lightness ($CIE-a^*=0$ and $CIE-b^*=0$); secondly, for the given $CIE-L^*$ values, the corresponding CMYs are calculated according to the Equation 5; finally, these CMYs are printed out and measured with the new CIELAB values obtained. To test the errors, the two groups of CIELAB values are compared using the CIEDE76 color difference formula. For all testing colors, the average error is $2.65\Delta E$ with the maximal error $5.2\Delta E$. Because for most of the printing process, the average error threshold is $5\Delta E$, the experiment result in the paper is acceptable, which indicates polynomial regression modeling is suitable for gray color calculations.

Conclusions

The calculation of CMY gray color data is essential for color reproduction including scanning, proofing, and printing process. If the CMY gray color data is not accurate, the gray images will show some Chroma information in the highlights, mid-tones, or shadows. In this paper, a method of finding gray color data based on polynomial modeling is proposed, which can be used in UCR/GCR algorithms. In this experiment, 20 testing gray colors were used to calculate CMY values, and the result

shows the accuracy is acceptable.

Conflict of Interests

The author(s) have not declared any conflict of interests.

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REFERENCES

- Fashandi H, Amirshahi SH, Tehran MA (2010). Evaluation of Scanner Capability for Measuring the Color of Fabrics with Different Textures in Different Setups. *Fibers Polym.* 11(5):767-774. <http://dx.doi.org/10.1007/s12221-010-0767-4>
- Guo J, Xu H, Luo MR (2011). Spectral characterisation of colour printer based on a novel grey component replacement method. *Chin. Optics Lett.* 9(7):073301. <http://dx.doi.org/10.3788/COL201109.073301>
- Hebert M, Hersch RD (2011). Yule-Nielsen based recto-verso color halftone transmittance prediction model. *Appl. Optics.* 50(4):519-525. <http://dx.doi.org/10.1364/AO.50.000519>; PMID:21283243
- Hong GW, Luo MR, Rhodes PA (2001). A study of digital camera colorimetric characterization based on polynomial modeling. *Color Res. Appl.* 26(1):76-84. [http://dx.doi.org/10.1002/1520-6378\(200102\)26:1<76::AID-COL8>3.0.CO;2-3](http://dx.doi.org/10.1002/1520-6378(200102)26:1<76::AID-COL8>3.0.CO;2-3)
- Hwang C-L, Lu K-D, Pan Y-T (2013). Segmentation of Different Skin Colors with Different Lighting Conditions by Combining Graph Cuts Algorithm with Probability Neural Network Classification, and its

- Application. *Neural Process. Lett.* 37(1):89-109. <http://dx.doi.org/10.1007/s11063-012-9275-4>
- Kang HR, Anderson G (1992). Neural network application to color scanner and printer calibrations. *J. Electron. Imag.* 1(2):125-135. <http://dx.doi.org/10.1117/12.57526>
- Lee K-J, Lee B-W (2013). Estimation of rice growth and nitrogen nutrition status using color digital camera image analysis. *Eur. J. Agron.* 48:57-65. <http://dx.doi.org/10.1016/j.eja.2013.02.011>
- Liu Q, Wan X-X, Xu H-P (2013). Study on Ink Restriction of Ink-Jet Printing Based on Spectral Gamut Maximization. *Spectrosc. Spectral Anal.* 33(6):1636-1641.
- Morovic J, Morovic P, Arnabat J (2012). HANS: Controlling Ink-Jet Print Attributes Via Neugebauer Primary Area Coverages. *IEEE Trans. Image Process.* 21(2):688-696. <http://dx.doi.org/10.1109/TIP.2011.2164418>; PMID:21846605
- Nussbaum P, Hardeberg JY, Albrechtsen F (2011). Regression based characterization of color measurement instruments in printing applications. Conference on Color Imaging XVI - Displaying, Processing, Hardcopy, and Applications, Proceedings of SPIE. San Francisco, CA. 7866:78661R.
- Pekkucuksen I, Altunbasak Y (2013). Multiscale Gradients-Based Color Filter Array Interpolation. *IEEE Trans. Image Process.* 22(1):157-165. <http://dx.doi.org/10.1109/TIP.2012.2210726>; PMID:22868571
- Srivastava S, Delp EJ, Ha TH, Allebach J (2010). Color Management Using Optimal Three-Dimensional Look-Up Tables. *J. Imag. Sci. Technol.* 54(3):030402. <http://dx.doi.org/10.2352/J.ImagingSci.Technol.2010.54.3.030402>
- Yang F, Murakami Y, Yamaguchi M (2012). Digital color management in full-color holographic three-dimensional printer. *Appl. Optics.* 51(19):4343-4352. <http://dx.doi.org/10.1364/AO.51.004343>; PMID:22772106