

# Spectral-based color separation method for a multi-ink printer

Binyu Wang (王彬宇)<sup>1,2</sup>, Haisong Xu (徐海松)<sup>1\*</sup>, M. Ronnier Luo<sup>2</sup>, and Jinyi Guo (郭晋一)<sup>1,2</sup>

<sup>1</sup>State Key Laboratory of Modern Optical Instrumentation, Zhejiang University, Hangzhou 310027, China

<sup>2</sup>Department of Colour Science, University of Leeds, Leeds, LS2 9JT, UK

\*Corresponding author: chsxu@zju.edu.cn

Received November 12, 2010; accepted December 17, 2010; posted online April 28, 2011

A spectral-based 8-ink characterization model is developed to accurately predict the recipe for a multi-ink printer. The 8-ink color separation method is a union of five 3-ink and six 4-ink combinations based on the cellular Yule-Nielsen spectral Neugebauer model with a recipe selection strategy. The performance levels of the forward and backward models are evaluated for individual ink combinations using printed testing samples. Furthermore, the spectral-based method performs better compared with the XYZ-based approach. On the basis of the backward model performance, a novel fast recipe selection strategy is proposed and estimated.

OCIS codes: 330.1690, 300.6550, 330.1710, 330.1715.

doi: 10.3788/COL201109.063301.

In printer systems, two major approaches are used, i.e., the analytical and generic methods, to derive a characterization model. The analytical method is based on modeling physical phenomena, such as Kubelka-Munk theory and Neugebauer equations. The parameters of the model are usually obtained from a relatively small number of samples, while the accuracy depends on the extent to which the model describes the actual behavior of the device; some of these models are difficult to invert. The generic method requires a large set of training data to build the model, as in three-dimensional (3D) look-up table with interpolation<sup>[1]</sup>. Because the spectral data contain all color information compared with tristimulus values, the spectral-based approach achieves higher accuracy and lower illuminant metamerism than does the XYZ-based method at the expense of more calculations. Typical 4-ink color printers have small color gamut and limited degrees of freedom; thus, the use of more inks not only increases color gamut and the number of degrees of freedom, but also improves accuracy<sup>[2,3]</sup>.

In this letter, the cellular Yule-Nielsen spectral Neugebauer (CYNSN)<sup>[2,4]</sup> model is implemented to characterize a HP Designjet Z3200ps 44-inch photo printer, which uses 12 inks<sup>[5]</sup>. For simplicity, 8 inks are used in the experiment, including grey (Gy), photo black (K), light cyan (C), magenta (M), yellow (Y), chromatic red (R), green (Gn), and blue (B). The 8-ink color separation algorithm is a union of five 3-ink and six 4-ink sets based on the CYNSN model<sup>[6]</sup> with a recipe selection strategy, containing the ink combinations of CMY, RMY, CGnY, CMB, RGnB, CMYK, RMYK, CGnYK, CMBK, RGnBK, and CMYGy. A large number of training and testing hardcopy samples were prepared and measured, and then the performance levels of the forward and backward models were individually evaluated. In addition, the spectral-based method was compared with the XYZ-based approach in terms of color difference, reflectance root mean square<sup>[7]</sup> (RRMS) error, and metamerism index (MI). Finally, a novel fast recipe selection strategy with high accuracy is proposed for the printer.

In 1937, Neugebauer developed a method for modeling

CMY halftone printing<sup>[4]</sup>. It was based on improving the Murray-Davies<sup>[2]</sup> model and can be extended to use more inks. Afterward, two main improvements<sup>[2]</sup> were presented. One is the Yule-Nielsen  $n$ -factor describing the light scattering. The classical CMY Neugebauer model modified by the Yule-Nielsen effect is expressed as

$$R(\lambda) = \left\{ \sum_{i=1}^8 w_i [R_i(\lambda)]^{1/n} \right\}^n, \quad (1)$$

where  $R_i(\lambda)$  is the reflectance of the  $i$ th primaries ( $i = 1, 2, \dots, 8$ ) at wavelength  $\lambda$ ,  $w_i$  denotes the weighting coefficient for the  $i$ th primary defined by the Demichel equation<sup>[8]</sup>,  $n$ -factor is usually determined by optimization, and the typical value of  $n$ -factor ranges from 1 to 4. The other improvement is called the cellular Neugebauer model. Firstly, the entire color space (e.g. CMY, CMYK) is divided into smaller sub-spaces called cells, and then the classical Neugebauer model is applied in the selected cell dependent on the input ink amounts. Combining these two improvements with the classical Neugebauer model forms the CYNSN model, in which predicting accuracy dramatically increases.

The Yule-Nielsen spectral Neugebauer (YNSN) model is not analytically invertible; thus, its inversion is usually solved using iteration. A well-known method was proposed by Urban and Grigat, in which linear regression iteration was used<sup>[9]</sup>, based on which Li *et al.* introduced "QR" decomposition, further reducing computational costs<sup>[10]</sup>. Therefore, Li algorithm was employed in this letter.

Before conducting the backward YNSN model, determining the optimal cell is an indispensable step, within which the most accurate recipe can be predicted by the backward model. Urban *et al.* developed a cellular linear regression iteration algorithm, which dramatically decreased the number of cells tried but did not guarantee that the selected cell was the actual optimal cell<sup>[11]</sup>. Later, Guo *et al.* proposed a cell searching method, which ensured that the optimal cell was found at the

expense of a few more computations<sup>[12]</sup>. This approach was also adopted in this experiment.

A well-known terminology called ink saturation limit was used in the printing industry<sup>[3]</sup>. It represents the maximum amount of inks that can be absorbed by a substrate. If the total amount of inks deposited in one pixel exceeds the ink saturation limit, the pixel will most likely collapse. The pre-experiment showed that more than 4 inks deposited in a pixel with the maximum amount would generate disastrous effects on the substrate for the HP printer used in this letter. Furthermore, 5 or more inks in the CYNNSN model require many more calculations. Conversely, the reflectance generated by more than 4 inks can be approximated by a carefully chosen 3-ink or 4-ink combination. As a result, the 8-ink color separation in this experiment is a union of five 3-ink and six 4-ink combinations based on the CYNNSN model.

As mentioned above, 8 inks were used in this experiment, whose normalized reflectances (maximum ink amount, 100%), together with that of the substrate (HP Premium Instant-dry Satin Photo Paper with gloss level 30 at 60° measuring angle<sup>[13]</sup>), are illustrated in Fig. 1.

Considering the different color regions of 6 inks in CIE  $a^*b^*$  plane (see Fig. 2), five 3-ink combinations (CMY, RMY, CGnY, CMB, RGnB) were chosen, and then the five 4-ink combinations were derived from the corresponding 3-ink sets with ink K to enlarge their color gamut. Figure 1 shows that the reflectance of grey is much higher than that of photo black, whose reflectance is almost 0. Thus, CMYGY was chosen as well.

Each ink had 7 levels, including 0% (minimum) and 100% (maximum) ink amounts. Consequently, there were 343 ( $7 \times 7 \times 7$ ) and 2401 ( $7 \times 7 \times 7 \times 7$ ) training samples prepared for each 3-ink and 4-ink sets, respectively. In total, 14406 ( $2401 \times 6$ ) training samples were printed (4-ink sets involved the corresponding 3-ink sets when ink K was set as 0%). In terms of testing data, two sets were used for the forward and backward models. For the forward model, 1700 ( $100 \times 5 + 200 \times 6$ ) testing samples were generated, containing 100 and 200 samples for each 3-ink set and 4-ink set, respectively. A set of 324 ( $24 \times 5 + 34 \times 6$ ) ink combinations, including 24 and 34 samples for every 3-ink and 4-ink sets, respectively, were prepared to test the backward model performance. All these testing samples were randomly selected from all ink combinations and were independent of the training samples. Every testing data had two components, i.e., recipe and measured reflectance.

The GretagMacbeth Spectrolino spectrophotometer

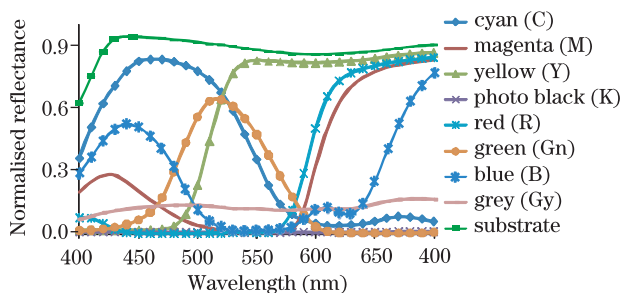


Fig. 1. (Color online) Normalized reflectances of the 8 primaries and substrate.

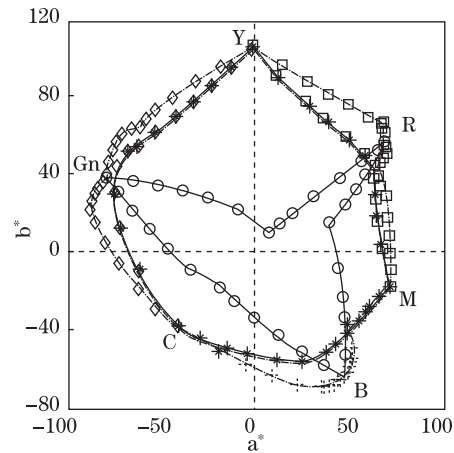


Fig. 2. Color gamut of 6 inks in CIE  $a^*b^*$  plane.

was used, with a geometry of 0/45, to measure all the training and testing samples in the spectral range from 400 to 700 nm at an interval of 10 nm. The CIEDE2000<sup>[14]</sup> color difference, denoted by  $\Delta E_{00}$ , was adopted to evaluate model performance under CIE D65 illuminant and 10° standard observer.

Figure 3 shows the procedures for evaluating the forward and backward model performances, in which the Yule-Nielsen  $n$ -factor was set to a typical value of 2.5.

The performance of the forward CYNNSN model for each ink set was evaluated in terms of mean, maximum, and standard deviation (Stdev) of  $\Delta E_{00}$ , together with the mean RRMS, as shown in Table 1. In general, the 3-ink sets work better than the corresponding 4-ink groups according to colorimetric accuracy, except for the RMY set, whose mean  $\Delta E_{00}$  (0.81) is similar to that of the RMYK set (0.65). Two factors are responsible for this phenomenon. One is that the measurement accuracy worsens with higher K levels, which results in darker colors. The other is that the training samples of 3-ink combinations appear more uniform compared with those of 4-ink groups. In other words, all the training samples of 4-ink combinations with high K levels appear dark, which indicates that all these training colors are located within a small volume in the CIELAB color space. In addition, the RGnB and RGnBK sets performs worst among all the 3-ink and 4-ink sets, possibly attributed to the absorption of two bands in the visual spectrum by RGB compared with one band for CMY. The accuracy of the CMYGY set is much better than that of the CMYK set

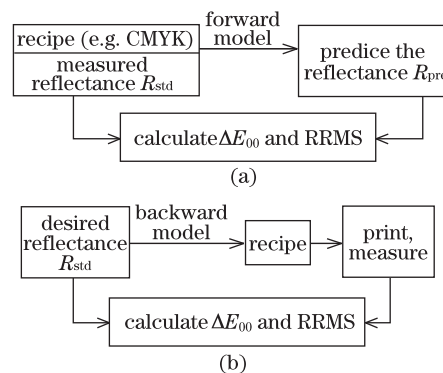


Fig. 3. Flowcharts for testing (a) forward and (b) backward model performances.

because the spectral reflectance of the Gy ink is much higher than that of the K ink (see Fig. 1). As a result, the training samples generated by the CMYGY combination appear lighter and more uniform compared with those generated by the CMYK set. As for RRMS values, all sets exhibit good performance with the mean RRMS being less than 0.005 (0.5%). However, the 3-ink sets perform slightly worse than the 4-ink sets because the spectral reflectance values of the testing samples for 4-ink sets are much lower than those of the 3-ink sets, and the darker color is less sensitive to reflectance variation.

As seen from the summary of the performance of the backward CYNNSN model for all the ink sets shown in Table 2, the CGnY set shows the best accuracy with a mean  $\Delta E_{00}$  of 0.55, followed by the CMYGY set, whereas the CMYK, RMYK, CGnYK, and CMBK sets perform poorly with a mean  $\Delta E_{00}$  around or over 2.00. The degree of spectral match is good for every ink set because all mean RRMS values are less than 0.02.

Taking the CMYK set as an example, the comparison between the spectral-based and XYZ-based cellular Yule-Nielsen Neugebauer (CYNN) model is shown in Table 3. MI, which is an important indicator for the reflectance differences between target and reproduction in case spectral data are unavailable, was also adopted to compare these two methods. The target and reproduction were compared under illuminant A and D65, F11 and D65, denoted as MIA65 and MI1165, respectively. Table 3 shows that both methods have similar forward model accuracies. As expected, for the backward conversion, the spectral-based CYNN model clearly outperforms the XYZ-based model, especially in MI because the CYNNSN method aims for a spectral match.

Using the backward CYNNSN model performance of each ink set as basis, we propose a novel fast recipe selection strategy (see Fig. 4). Considering the high accuracy of the CGnY set, it is selected as the first option for implementing the backward CYNNSN conversion for target reflectance  $R_{std}$  to generate the recipe  $c'gn'y'$ . Then,

the predicted reflectance  $R_{pre}$  is calculated from the recipe  $c'gn'y'$  using the corresponding forward CYNNSN model. Afterward, color difference  $\Delta E_{00}$  is calculated between  $R_{std}$  and  $R_{pre}$ . If  $\Delta E_{00}$  is less than the predefined threshold, which was set as 3 in this experiment, this recipe is accepted as the final recipe for  $R_{std}$ ; otherwise, it is refused and the second accurate CMYGY set is tested, and so on. The loop is not terminated until the required recipe is found. If no set satisfies the judgment condition (predicted  $\Delta E_{00} < 3$ ), the recipe with the smallest predicted  $\Delta E_{00}$  is chosen.

The spectral reflectances of the 324 samples for testing the backward model above were employed as the target to be reproduced using this recipe selection strategy, and the calculated final recipes were printed as the reproduction samples, whose assessment results are listed in Table 4.

Table 4 shows that the mean reproduction color difference  $\Delta E_{00}$  is 1.22, which is outstanding compared with that in other similar experiments<sup>[11]</sup>. The average RRMS, which is equal to 0.061, indicates the good spectral match between target and reproduction. Moreover, both the mean MIA65 and MI1165 values are at a reasonable level, around 2. For most target reflectances, testing two sets (CGnY and CMYGY) quickly reaches the final recipe. Despite this, the final recipe may not be the best choice for the desired reflectance, as in the final recipe from CMYGY for the desired reflectance from the RGB testing samples. One solution is to decrease the predefined threshold, so that the predicted  $\Delta E_{00}$  exceeds the threshold. However, this proposed recipe selection strategy achieves satisfactory performance at fast speeds. Two examples of the target and corresponding reproduction reflectances are illustrated in Fig. 5, and the curves reveal that the target and reproduction reflectances match quite well for the entire visual spectral range.

In conclusion, the 8-ink color separation algorithm is successfully established, as a union of five 3-ink and six 4-ink combinations based on the CYNNSN models with the proposed recipe selection strategy, to predict the recipe of the multi-ink printer. The average reproduction accuracy achieves 1.22 CIEDE2000 units, indicating that the developed method performs well. Meanwhile, the proposed algorithm provides a reasonable way to characterize multi-ink printers when the ink saturation limit is a problem. For the forward and backward model performances, the 3-ink sets generally worked better than the corresponding 4-ink sets because of the more uniform

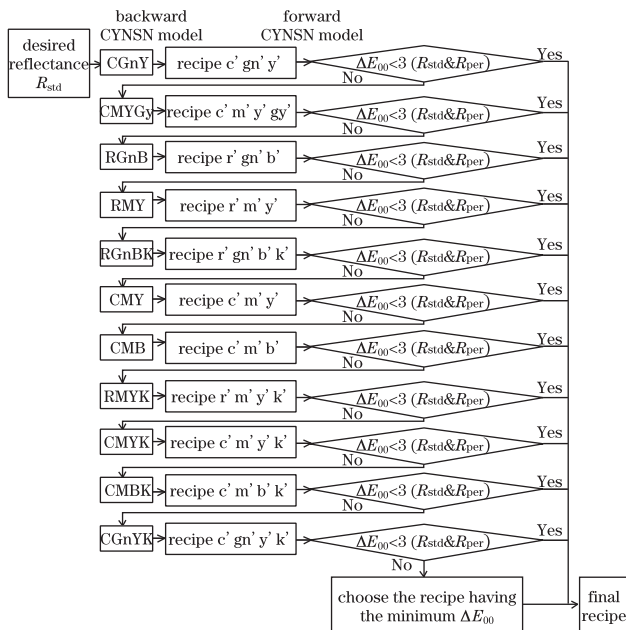


Fig. 4. Flowchart of recipe selection strategy.

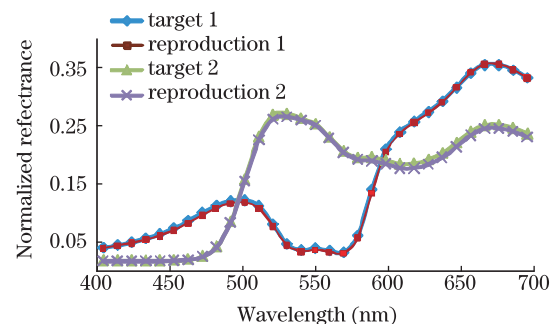


Fig. 5. Two examples of standard and corresponding reproduction reflectances.

**Table 1. Forward CYNSEN Model Performance for 11 Ink Sets**

Forward Model	Mean $\Delta E_{00}$	Max $\Delta E_{00}$	Stdev $\Delta E_{00}$	Mean RRMS
CMYK	1.04	2.71	0.43	0.0012
RMYK	0.65	2.65	0.63	0.0009
CGnYK	1.07	2.96	0.60	0.0019
CMBK	0.45	2.46	0.46	0.0008
RGnBK	1.28	2.94	0.58	0.0016
CMYGY	0.59	1.72	0.21	0.0013
CMY	0.62	1.34	0.26	0.0025
RMY	0.81	1.52	0.31	0.0027
CGnY	0.59	1.22	0.29	0.0042
CMB	0.41	1.28	0.21	0.0018
RGnB	1.02	2.75	0.60	0.0019

**Table 2. Backward CYNSEN Model Performance for 11 Ink Sets**

Backward Model	Mean $\Delta E_{00}$	Max $\Delta E_{00}$	Stdev $\Delta E_{00}$	Mean RRMS
CMYK	1.97	3.66	0.65	0.0072
RMYK	1.86	3.58	0.55	0.0096
CGnYK	2.91	4.82	0.76	0.0152
CMBK	2.07	3.78	0.48	0.0133
RGnBK	1.51	3.01	0.77	0.0051
CMYGY	0.83	1.10	0.16	0.0050
CMY	1.55	2.17	0.38	0.0114
RMY	1.38	2.08	0.36	0.0110
CGnY	0.55	1.35	0.23	0.0090
CMB	1.74	2.50	0.39	0.0177
RGnB	1.27	2.30	0.47	0.0051

**Table 3. Comparison between Spectral-Based and XYZ-Based Methods**

CMYK	Forward Model		Backward Model		
Mean Values	$\Delta E_{00}$	$\Delta E_{00}$	RRMS	MIA65	MI1165
Spectral-Based	1.04	1.97	0.0072	0.58	0.54
XYZ-Based	1.02	2.30	0.0082	1.49	2.19

**Table 4. Evaluation of Recipe Selection Strategy**

	$\Delta E_{00}$	RRMS	MIA65	MI1165
Mean	1.22	0.061	2.11	2.11
Max	7.25	2.236	11.13	12.82
Stdev	0.81	0.180	2.33	2.40

appearance of the 3-ink training samples. The colorimetric accuracy is enhanced and the MI considerably reduced for the spectral-based method compared with those in the XYZ-based approach. In future work, more efficient and accurate recipe selection strategies will be studied for different application purposes. Furthermore, the discontinuities between neighboring pixels should be considered when the color separation method is applied to the images.

## References

1. G. Sharma, *Digital Color imaging handbook* (CRC Press, New York, 2003). Chap. 5.
2. D. R. Wyble and R. S. Berns, *Col. Res. Appl.* **25**, 4 (2000).
3. D.-Y. Tzeng and R. S. Berns, in *Proceedings of CIC8* 342 (2000).
4. D. Wyble and A. Kraushaar, *Col. Res. Appl.* **30**, 322 (2005).
5. HP Corporation, "HP Designjet Z3200ps 44-in Photo Printer (Q6721A)-Product documentation", <http://h20195.www2.hp.com/v2/default.aspx?cc=us&lc=en&oid=3737567> (September 2008).
6. P. Urban, M. R. Rosen, and R. S. Berns, in *Proceedings of CGIV 2008* 548 (2008).
7. Y. Wang and H. Xu, *Chin. Opt. Lett.* **3**, 725 (2005).
8. J. Gerhardt and J. Y. Hardeberg, *Col. Res. Appl.* **33**, 494 (2008).
9. P. Urban and R. R. Grigat, *Col. Res. Appl.* **31**, 229 (2006).
10. C. Li and M. R. Luo, in *Proceedings of CIC16* 84 (2008).
11. P. Urban, M. R. Rosen, and R. S. Berns, in *Proceedings of CIC15* 178 (2007).
12. J. Guo, H. Xu, and M. R. Luo, *Chin. Opt. Lett.* **8**, 1106 (2010).
13. M. R. Luo, *Rev. Prog. Color* **32**, 28 (2002).
14. J. Ma, H. Xu, M. R. Luo, and G. Cui, *Chin. Opt. Lett.* **7**, 869 (2009).