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Improved Inverse Characterization of Multicolorant Printer Using Colorant Correlation

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Abstract. *Inverse characterization in a printing device is the process to find control values of colorants to print out any input stimulus values (CIEXYZ, CIELAB, etc.). In a CMY-type printer, the control values can be simply estimated through the interpolation process using a lookup table with a one-to-one relation between the control values and the stimulus values. In a multicolorant printer with extra colorants like red (orange), blue, and green, however, since it has one to many correspondences between CIELAB values and control values, an appropriate control value must be selected from many candidate control values which have negligible color differences from input stimulus value. Selecting a control value without any restriction tends to induce interpolation errors because it does not consider the relation between neighbor control values. In this article, we propose an improved inverse characterization method for multicolorant printer to reduce interpolation errors using the correlation between distributions of control values. We first sampled the CIELAB values regularly in CIELAB space in order to find the appropriate control values for each CIELAB value, since a color stimulus can be represented by several control values of colorants in a multicolorant printer. To find control values for the sampled CIELAB values, the colorant space is sampled and the CIELAB values for all combinations of control values were estimated using the Cellular Yule Nielsen Neugebauer spectral model. The control value whose estimated CIELAB value was close to a sampled CIELAB value was extracted as a candidate for the appropriate control value of the sampled CIELAB value. Subsequently, the most appropriate candidate was selected by considering global and local correlation. For this purpose, we selected all control values for the sampled CIELAB values so that all the selected control values had higher similarity than the predefined threshold in the distribution of colorant amount for global selection step. In addition, in the local selection step, regarding the sampled CIELAB values for which we could not select a control value via this global selection step, the control value was reselected by comparing similarities between the neighbor selected control values and candidates in CIELAB space. Then, accurate CIELAB values of the selected control values were measured and stored in the lookup table. To evaluate the proposed inverse characterization method, a CMYKGO printer was utilized. The proposed method effectively reduced the color difference in the interpolation process. Moreover, the gamut was extended partially and the continuous tone could be represented more smoothly than by conventional methods.* © *2007 Society for Imaging Science and Technology.*
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INTRODUCTION

It is not easy to get good photoimages by using a general CMY ink jet printer, as compared with other output devices, such as CRTs, LCD, and projectors. Thus, the black colorant has been added to CMY colorants to increase the density for the dark region[1] and the color printer with the diluted colorants, like light cyan and light magenta, appear to reduce graininess.[2,3] These colorants, however, cannot effectively extend the gamut because the gamut of a printer, with a subtractive color system, is limited by colorants. Since colorants must be mixed to represent red, green, and blue regions, color saturation is also decreased. Recently, extra colorants (red, orange, green, and blue) have been used for gamut extension.[4,5] The saturation could be then increased and the gamut could be extended by replacing the mixed colorants with just a single additional colorant for a small region of the whole gamut. If the additional colorants, however, are just used to represent the original color of the colorant, the efficiency of the additional colorant is reduced because the combinations of colorants, including additional colorants, could represent various colors. Nevertheless, all combinations of additional colorants cannot be used because these combinations have redundancy in the inverse printer characterization process.[6,7]

The inverse printer characterization estimates the relation between the input control value of colorants and the output color stimulus. Hence, the relation should be unique to represent colors accurately.[8] Thus, in general, the sampled control values are printed and their color stimulus values are measured and stored in the lookup table (LUT). The control value for the input color can be simply estimated by tetrahedral interpolation based on the LUT. In a multicolorant printer, however, several control values can result in the same stimulus value because CMY colorants are independent components in the color system and additional colorants are dependent on the CMY colorants. Therefore, this general method, by measuring the sampled control value, cannot be used on account of redundancy.

In the conventional method, to prevent the redundancy problem beforehand, the number of colorants used to represent a color must be limited in advance. Namely, a special colorant set, for example CYG, MYR, CMB, and CMY, is decided and lookup tables for each colorant set are generated by measuring sample patches from each colorant set. After selecting the lookup table for the input color, the CMYKGO value for the input RGB or CIELAB value is estimated via a combination of three colorants.[9,10] This stra-

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tegy can avoid the redundancy problem by limiting the colorants; however, the idea of using other combinations of three more colorants should be abandoned and it led to reduce the gamut. In another approach, first, the lookup table for a characterization is generated by measuring sample patches from just CMY colorants. The input color, however, is mapped to the gamut of the CMYKGO printer. If the input color does not belong to the CMY color gamut, but if it belongs to the gamut composed with the additional colorants, the additional colorants are substituted for the CMY colorants at a special rate.[11,12] This method can be easily applied to extend the conventional method to the characterization method of the multicolorant printer. Since the rate is ambiguous, however, although the rate can be decided from training, the accuracy of this method is questionable and the gamut is reduced by the limited usage of colorants. As a consequence, the restricted usage of colorants in avoiding the redundancy problem reduces the whole color gamut.

To maintain color gamut using all colorant combinations we propose an inverse characterization method using correlation factors without gamut partioning. The use of all control values would make the CIELAB values redundant. Thus, we chose an appropriate control value for a CIELAB value and used the correlation factor as criteria for the selection. The correlation factor describes the similarity between the colorant distributions of control values. Similarity between near control values in the CIELAB space cannot be guaranteed because these control values are randomly distributed in CIELAB space. Thus, if the control values, which are closed in CIELAB space with a different distribution of colorants, are selected as components of LUT for inverse characterization, a color difference might occur in the interpolation process. Therefore, we chose control values considering the correlation factor. In addition, we fixed CIELAB values by composing the LUT. This is because control values could not be decided. Thus, the CIELAB space is divided by the regular lattice and the CIELAB value of each lattice becomes a component of the LUT. Then, the performance of the interpolation process can be improved because the distribution of the nodes for the LUT is more regular in CIELAB space, than in the conventional method which uses nodes generated by sampling the control value of the colorants space. The proposed method is as follows. First, the color stimulus values of all control values are estimated by the cellular Yule-Nielsen spectral Neugebauer model.[14] The proper combination set is selected through global and local selection methods. Finally, the selected combinations are measured and stored in a lookup table. Figure 1 presents a flowchart of the proposed method.

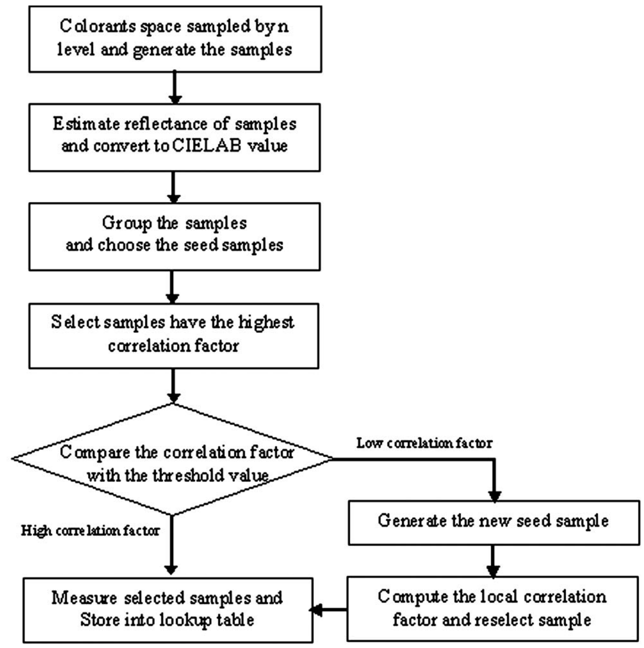


Figure 1. Flowchart of the proposed characterization method.

ESTIMATING THE REFLECTANCE VIA THE CELLULAR YULE-NIELSEN SPECTRAL NEUGEBAUER MODEL

In inverse characterization based on measurement, the colorant space of a device is regularly sampled and the sampled combinations of colorants are measured and stored in a lookup table. For example, in the CMY printer, each CMY colorant is sampled by six levels, then 216 samples are generated. These are measured and relations between CMY colorant amounts and the measured color stimulus are stored in a lookup table. Thus, the number of colorants determines the number of colorant combinations in a lookup table. The addition of colorants increases the number of colorant combinations exponentially. If extra colorants are added to the printer, considerable colorant combinations can be measured, although all combinations are not needed due to the redundancy problem. Thus, to reduce these efforts, a printer model is used to estimate color stimulus values. This printer model needs just a few measurements, but its results are less accurate than those of the characterization method which uses a lookup table. It dose not matter, however, because the estimated color stimulus values are measured at the end of the process. The number of selected colorant combinations is only a few compared to the number of samples for all combinations. To estimate the reflectance of colorant combinations, the cellular Yule-Nielsen spectral Neugebauer model is used.[14] In general, the Yule-Nielsen Neugebauer model is used to estimate the reflectance of the printed paper by ink jet printer, as it is described by Eq. (1),

$$R_\lambda = \left(\sum_i F_i R_{\lambda,i}^{1/n} \right)^n, \tag{1}$$

where $R_{\lambda,i}^{1/n}$ is the reflectance of the Neugebauer primary colorants, R_λ is the estimated reflectance, i designates the number of each element in the set of colorant combinations for the binary printer, n represents the effects of halftone screen frequency as the Yule-Nielsen factor, and F_i is the relative area coverage of the ith Neugebauer primary colorant. Regarding the CMY printer, the relative area coverage is described by Eq. (2),

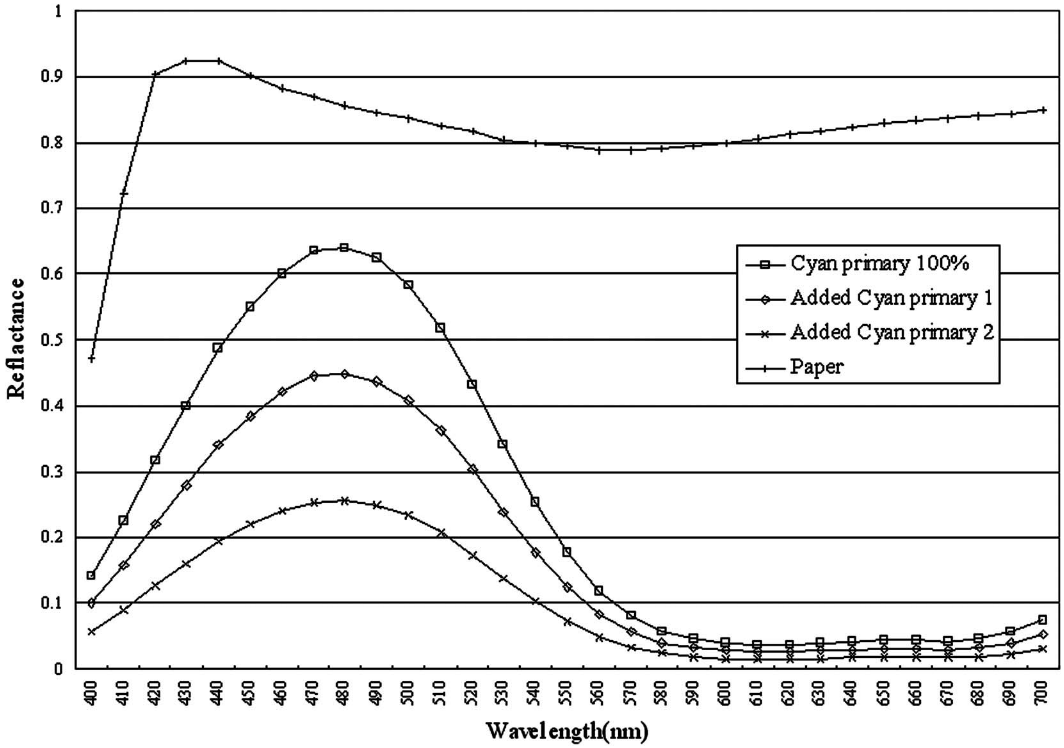


Figure 2. Fractioned reflectances for cyan.

$$F_i = \{(1-c)(1-m)(1-y), c(1-m)(1-y), m(1-c) \times (1-y), y(1-c)(1-m), cm(1-y), cy(1-m), my(1-c), cmy\}, \tag{2}$$

where c, m, y represent fractional area coverage which corresponds to digital inputs. Reflectance is estimated by the summation of Neugebauer primary reflectances which are obtained via the combination of two states, 0% and 100% area coverage for each colorant. In the cellular Yule-Nielsen spectral Neugebauer model, however, the two states between 0% and 100% area coverage are added to increase the accuracy of the estimation model. Figure 2 shows the fractioned reflectance values for cyan. Two reflectances are added to the reflectance of cyan for 100% area coverage and paper reflectance. Thus, by comparing the area coverage for the input digital value and the area coverages for a primary reflectance, the closest primary is selected to estimate the reflectance for the input digital value. In addition, the ink blot problem is considered in the model. It is restricted to the amount of colorant that can be used on paper. Thus, all combination of colorants cannot be used; in addition, there are some primaries that cannot be printed by ink blots. To solve these problems, the threshold of the total colorant amount is decided for an ink blot, and combinations which cause ink blots are excluded.

The reflectance of sample patches for the characterization lookup table is estimated using the measured reflectance of Neugebauer primaries. Then, reflectance is converted to the CIELAB value. First, the reflectance is converted to the CIEXYZ stimulus space[8]

$$X = k\sum_{\lambda} S_\lambda R_\lambda \bar{x}_\lambda \Delta\lambda, \quad Y = k\sum_{\lambda} S_\lambda R_\lambda \bar{y}_\lambda \Delta\lambda,$$

$$Z = k\sum_{\lambda} S_\lambda R_\lambda \bar{z}_\lambda \Delta\lambda, \quad k = \frac{100}{\sum_{\lambda} S_\lambda \bar{y}_\lambda \Delta\lambda}, \tag{3}$$

where S_λ is the D50 illuminant, $\bar{x}_\lambda, \bar{y}_\lambda, \bar{z}_\lambda$ are color-matching functions, R_λ is reflectance, and k is the normalization factor Y. The XYZ values are converted to CIELAB values[8]

$$L^* = 116\left[f\left(\frac{Y}{Y_n}\right) - \frac{16}{116}\right],$$

$$a^* = 500\left[f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right)\right],$$

$$b^* = 200\left[f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right)\right],$$

$$\text{where } f(s)\begin{cases} = s^{1/3} & s > 0.008856 \\ = 7.787s + 16/116 & \text{otherwise} \end{cases}, \tag{4}$$

where X_n, Y_n, and Z_n represent the maximum values of each function.

PRELIMINARY TO SELECTION

All sample patches are not used for the lookup table of characterization because the relation between a color stimulus

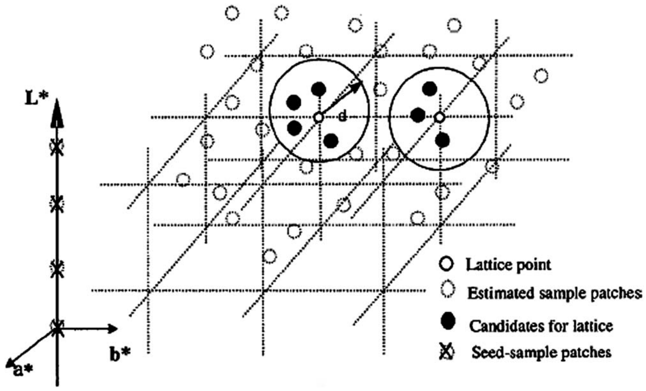


Figure 3. Grouping of samples and seed-sample patches.

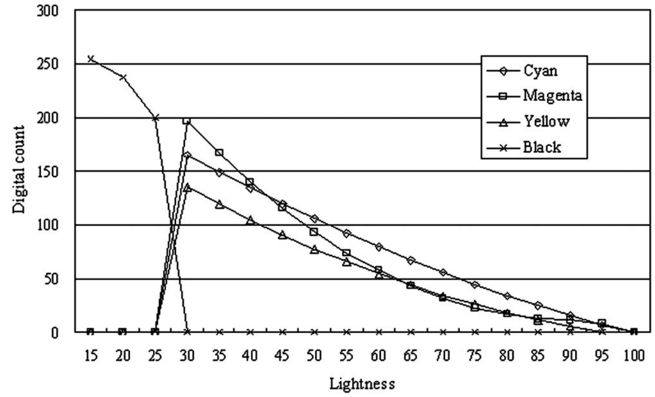


Figure 4. Result of gray-balanced calibration.

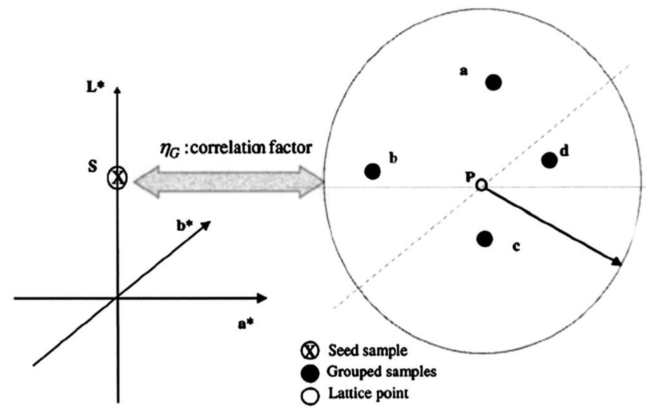


Figure 5. Sample selection using global correlation. (Available in color as supplemental material on the IS&T website, www.imaging.org)

and the combination of colorants must be unique in the inverse characterization process. Some samples should be selected and others should be removed in the lookup table to reduce the redundancy problem. In addition, if the samples in the lookup table are distributed uniformly in CIELAB space, the error can be reduced when the values between samples are estimated for the interpolation process. This is because the distribution of samples in CIELAB space is more regular than the samples of which the LUT is composed via the conventional method. Therefore, we divide CIELAB space into regular lattice points and one sample per lattice point is selected. Before selection, samples which are within regular Euclidian distance to a lattice are grouped and they become candidates for the lattice. This process simplifies selection by reducing the number of selectable samples for a lattice. Distance is determined by Eq. (5),

$$d = \sqrt{(L_l - L_s)^2 + (a_l - a_s)^2 + (b_l - b_s)^2} \tag{5}$$

where the Euclidean distance (d) indicates the linear distance between the lattice point and samples in CIELAB space, and it also represents the CIELAB color difference. After grouping, one sample among the grouped samples is selected for the lattice point by using a global selection method. Figure 3 shows the grouping process. The grouped black circles become candidates for the lattice in CIELAB space.

Next, we have to determine seed samples which will be the reference for the correlation factors of the selection process. These seed samples can reduce the color artifact, such as color contours. This is because the overall region of the color gamut could be represented smoothly if the selected samples have a similar distribution of colorant. Thus, a reference is needed to compute the correlation factor so that the selected samples have a similar distribution of colorant. We use the gray-balanced calibration method to determine the reference. The human eye sight is particularly sensitive to color differences near neutral. Hence, after printer characterization, in the postprocess, gray-balanced calibration[8] is needed in the printer. Therefore, gray-balanced samples on the gray axis become reference samples. In this process, only cyan, magenta, yellow, and black are used. This is because only the combination of CMYK can represent gray and the usage of other colorants might change the color or grain. To apply the gray balance process, first, it is important to vary the control value of C and M for a fixed Y and find the combination which corresponds to gray, a^* and b^* are 0, and repeat for the other Y values. The black colorants are inserted into the low lightness region which the combination of CMY could not represent. This is because the black dot has a high level of visibility. Figure 4 shows the relation between lightness and the control count of colorants. In low lightness areas over 85, only black colorant is used. Then, we can obtain combinations which represent the gray tone. These correspond to the seed samples shown in Fig. 3. Each combination in Fig. 4 becomes a seed sample on the lightness axis of Fig. 3. Then, using these seed samples guarantees that the colorant distribution of the selected samples is leaned to CMYK colorants mostly.

GLOBAL SELECTION METHOD

To select samples which have a similar distribution of colorant to that of the seed sample, according to the same lightness, the global correlation factor must be computed. The colorants amount of sample is defined by vector **s**, as follows:

Table I. Computations of the global correlation factor.

Grouped samples	C	M	Y	K	G	O	Correlation factor (η)
a	30	20	10	2	4	20	0.48
b	42	25	20	1	3	16	0.58
c	10	38	52	2	2	7	0.82
d	18	57	42	1	4	8	0.98
Seed sample	2	50	30	1	5	10	1

$$\mathbf{s} = \{s_1, s_2, s_3, s_4, \ldots, s_n\}, \tag{6}$$

where n is the number of colorants and s_i is the digital count of each colorant. Its average, μ and standard deviation, σ, are computed by Eq. (7),

$$\mu = \frac{1}{n}\sum_{i=1}^{n} s_i, \quad \sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (s_i - \mu)^2}. \tag{7}$$

Finally, the correlation factor between seed sample, S_s, and grouped samples, S_g, is computed by Eq. (8),

$$\eta = \frac{\frac{1}{n}\sum_{i=1}^{n} (s_{i,s} - \mu_s)(s_{i,g} - \mu_g)}{\sigma_s \cdot \sigma_g}. \tag{8}$$

This factor indicates the similarity of distribution between samples. Thus, we select samples using this factor. Then, the selected samples have a similar distribution of colorant to that of the seed samples, and it means that CMY are weighed much weight in terms of the total colorant amount of the selected samples. As a result, we can reduce the color difference in the interpolation process. This is because the sample which has a high rate to CMY amount is selected. Thus, we compare grouped samples to the seed sample and compute the correlation factor. Figure 5 describes the global selection method. For example, if we want to select a sample for the lattice point, P, we use the printer with CMYKGO. There are four samples, a, b, c, and d, which are within regular distance. The seed sample, s, is on the same lightness level as that of lattice point, P, in CIELAB space. First, we compute the correlation factor between seed sample, s, and the grouped samples. The results are shown in Table I. The correlation factor of sample d is the highest, so we select sample d for lattice point P. This process is repeated for all lattice points in CIELAB space. Then, the selected sample will have a similar distribution of colorant to the seed sample. As a result, the inner samples of the printer gamut have a high rate to CMY. However, the other samples of the lattice point which are close to the region extended by additional colorants have a high rate to additional colorants. Therefore, this process is not enough to select samples because the correlation factor of selected samples may be much lower than the neighbor lattice point's. Thus, we need to apply the local selection method.

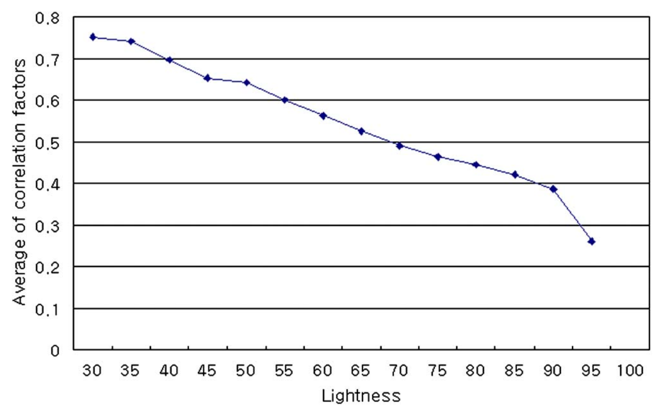


Figure 6. Averaged correlation factors for each lightness plane.

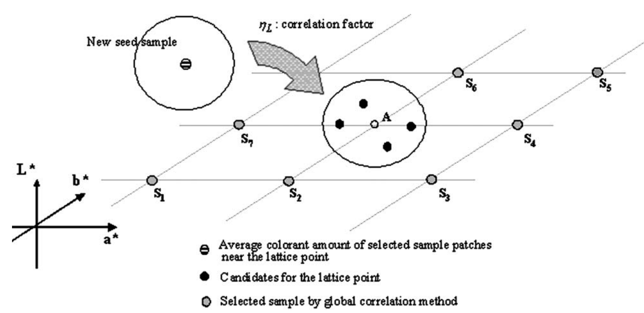
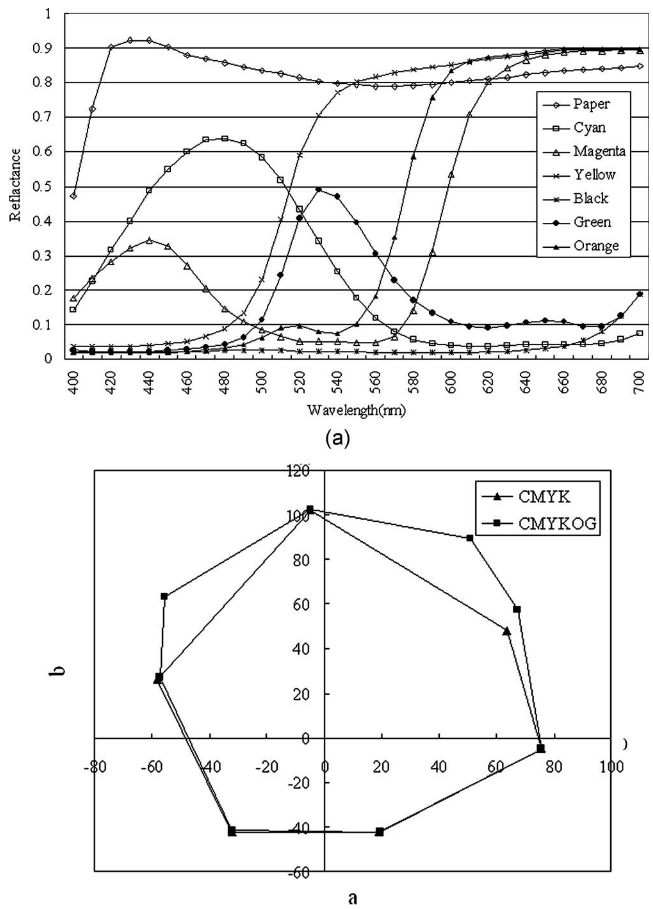


Figure 7. Sample selection using local correlation.

LOCAL SELECTION METHOD

If all samples which are grouped for a lattice point are different from the seed sample, and if the correlation factor is much lower than the neighbor's but the highest one is selected, we cannot depend on its similarity about seed point and the neighboring selected samples. Therefore, we need to apply the local selection method. First, we should decide whether to reselect each lattice point. To determine the threshold value for reselection, the global correlation factors are averaged on the same lightness plane by Eq. (9),



(a)

(b)

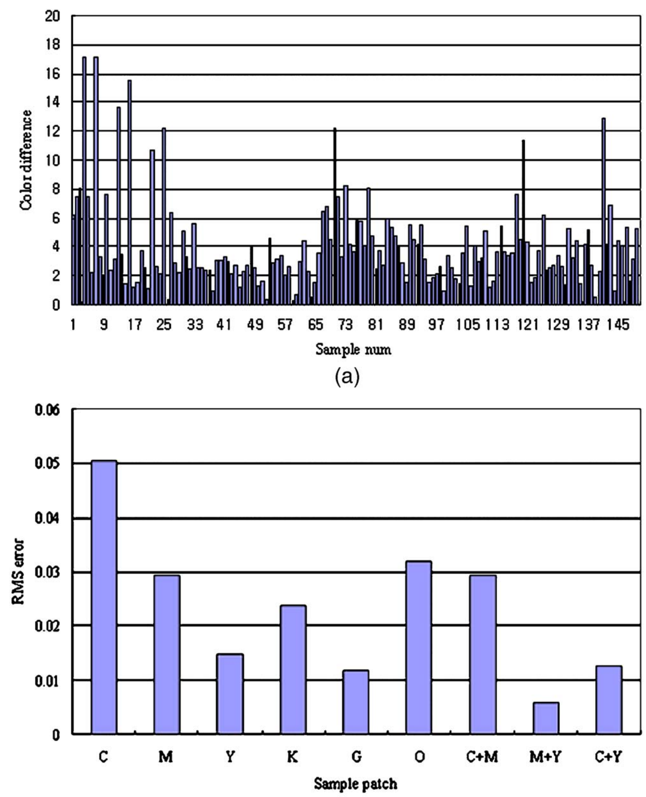
Figure 8. (a) Spectral reflectance and (b) colorimetric positions for six inks.

$$\eta_a = \frac{1}{m}\sum_{i=1}^{m} \eta_g, \tag{9}$$

where η_g is the global correlation factor on the same lightness plane and m is the number of global correlation factors. Figure 6 presents the results of averaging, η_a. The averaged correlation factor is decreased by an increase in lightness, indicating that the samples have an irregular distribution and that they are crowded into a low-lightness region. Thus, these values are used as the threshold value for each level of lightness. Next, we compare the global correlation factors with the averaged correlation values by the level of lightness. If the global correlation factor of the selected sample is less the confidence interval, 50%, the lattice is reselected by the local selection method. For example, Fig. 7 describes the local selection method. Assume that an arbitrary lattice point, A, has a lower global correlation factor than the neighboring lattice. First, a new seed sample for the lattice must be decided. The new seed sample is computed by Eq. (10),

$$\mathbf{s}_e = \frac{1}{n}(\mathbf{s}_1 + \mathbf{s}_2 + \mathbf{s}_3 + \cdots + \mathbf{s}_n), \tag{10}$$

where s_n is the selected sample vector around the lattice and n is the number of the vectors. In the local selection method,



(a)

(b)

Figure 9. Evaluation of the CYNSN model regarding estimated and measured results.

the sample is reselected which has a distribution similar to that of the selected samples of the neighboring lattice point. As in computing the global correlation factor, the local correlation factor is computed using Eqs. (7) and (8) with a new seed sample. The highest one is reselected. Consequently, the selected samples have a similar distribution of colorants, especially, between samples which are near to themselves.

Finally, the colorant amount of the selected samples is normalized to 255 and it is stored with the CIELAB value which corresponds to it in the lookup table. This lookup table has many nodes according to the number of selected samples. In the general CMY printer characterization process, CMY color space is sampled by 6 or 11 levels and sample patches are generated. Then CIELAB values for sample patches are acquired by measuring and the lookup table is generated with these. Thus, the final lookup table has 216 or 1331 nodes with sampling by 6 or 11 levels. In the proposed method, however, we used more than 1331 nodes and the number varies according to the volume of a printer gamut. Using this lookup table, it creates problems regarding space and time complexity in a real color reproduction process. Thus, to improve these points, a new lookup table is generated using the old one. For example, 1331 new nodes for the color signal (RGB or CIELAB) of the standard input or input device are generated. Next, values which are outside of the printer gamut are mapped into the printer gamut. The amount of colorant for each node is estimated by the old

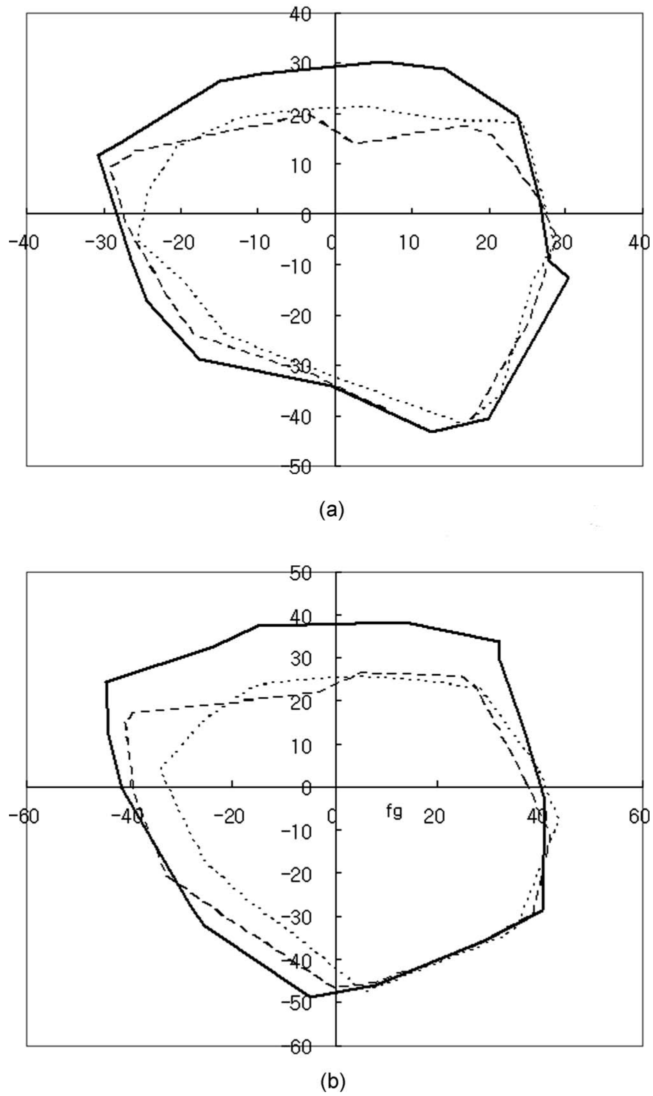


Figure 10. Gamut comparison among the proposed method (solid line), the method of substitution OG to CMY (dotted line), and the method of charactering each sub-gamut (dashed line) at lightness, (a) 35 and (b) 40.

lookup table in interpolation process, using the tetrahedral interpolation method.[8] As a result, we can reduce space and time complexity for a CMY printer.

EXPERIMENT AND RESULTS

The experiment was performed using an Epson Stylus Photo 700 which was retrofitted with orange and green colorant. Light cyan and light magenta were replaced by orange and green in the printer. As a result, the printer had cyan, magenta, yellow, black, orange, and green colorants. Figure 8 shows the spectral reflectance and colorimetric positions for the six inks. The Floyd–Steinberg error diffusion was applied to each independent channel for halftoning. To measure the reflectance of the sample patches for the estimation, a GretagMacbeth Spectrolino Spectrophotometer was used. Reflectance was measured between 400 and 700 nm in ten intervals under the D50 illuminant.

First, we decided on the cellular primary by optimizing the estimation of the Neugebauer printer model. The position of the cellular primary, which minimized the difference between the estimated and measured reflectance, was chosen for each colorant. Then, the reflectance of the cellular primary was measured; if the cellular primary could be printed without an ink blot. To define ink blot, we determined the total amount of ink that can be printed without an ink blot by printing ramp patches. As a result, the threshold for the ink blot phenomenon was 550 for a normalized digital value of colorants by 255. Then, we could print and measure 1241 primaries from 4096 (4^6) cellular primaries except for patches with an ink blot. The others with an ink blot were estimated by weighted linear regression with a uniformly distributed training sample set, 1241, in the colorant space. In Fig. 9, the cellular Yule-Nielsen spectral Neugebauer model was evaluated using 150 testing samples uniformly distributed in the colorant space. The color difference average was 3.83 ΔE^*_{ab} and the maximum was 17.16 ΔE^*_{ab}, as shown in Fig. 9(a). In addition, Fig. 9(b) indicates the rms errors of some samples and the averaged rms error is 0.023. As a result, it was determined that the performance of the cellular Yule Nielsen spectral Neugebauer model is not satisfied. There is no problem in using estimated CIELAB values on the proposed characterization method because they are measured after selection process.

Therefore, we sampled the colorant space according to the 12 levels for each colorant, CMYGO, and 248 832

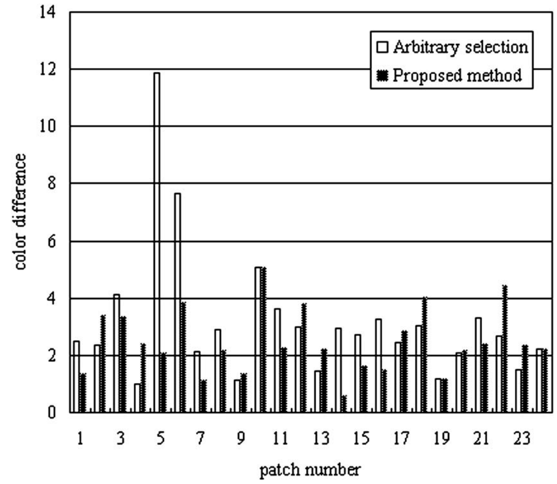


Figure 11. Evaluation of selection methods, the proposed method, and the arbitrary selection method.

Table II. Color difference, ΔE^*_{ab}, comparison; (a) using CMY colorants, (b) substituting OG to CMY, (c) characterizing each subgamut, and (d) proposed method.

Characterization method	Average	Max	Standard deviation
(a) Using CMY colorants	10.27	27.85	7.37
(b) Substituting OG to CMY	11.90	28.10	7.75
(c) Characterizing each sub-gamut	9.98	30.61	8.18
(d) Proposed method	9.56	21.99	6.19

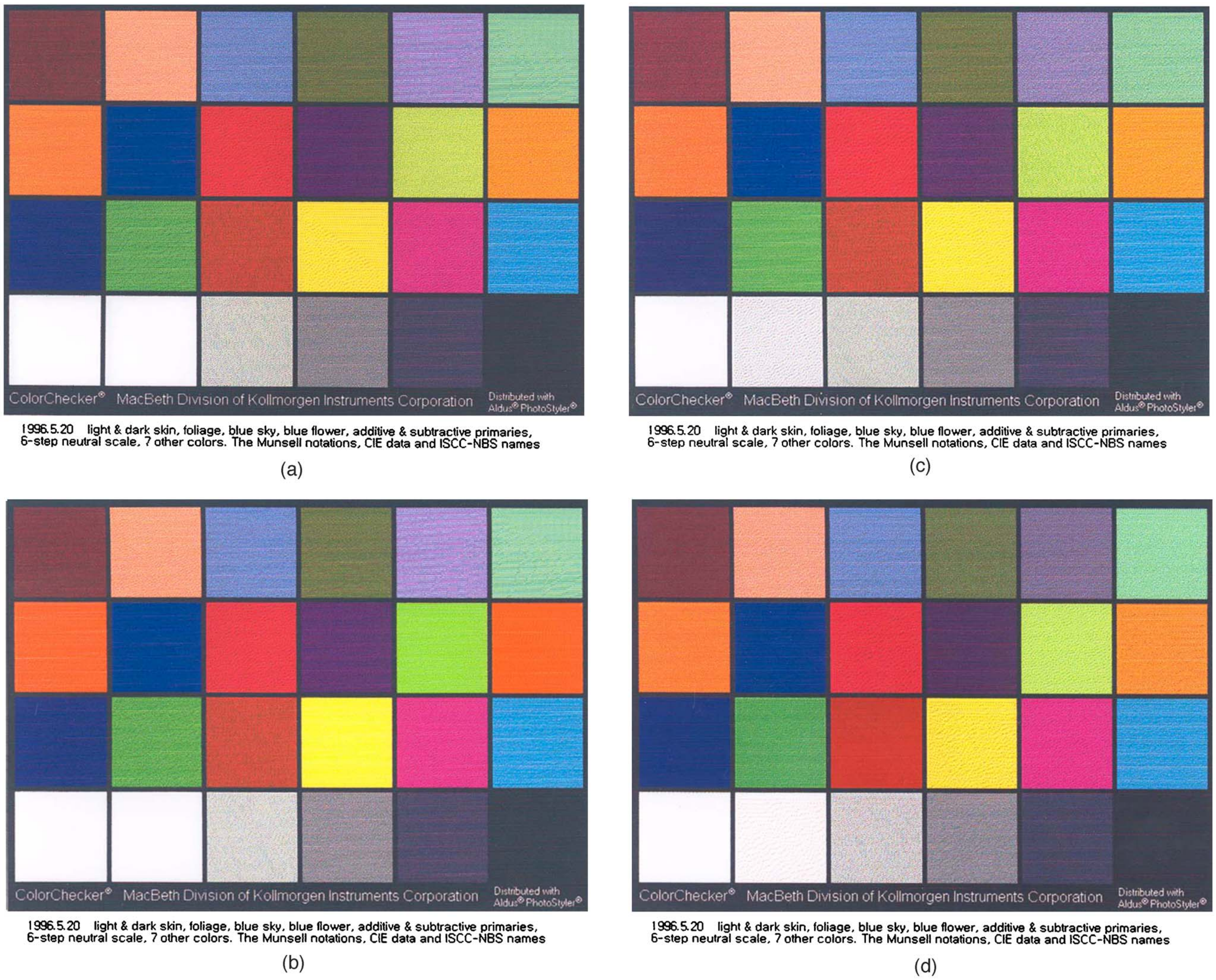


Figure 12. Printed Macbeth color checker with (a) using CMY colorants, (b) substituting OG to CMY, (c) characterizing each subgamut, and (d) the proposed method.

samples (12^5) were generated without black. Black dots are highly visible to human sight, especially when representing images, so the black colorant was used in low-lightness area by the gray component replacement method. The reflectance of the generated samples was estimated by the cellular Yule-Nielsen spectral Neugebauer model. These reflectance values are converted into CIELAB values by Eqs. (3) and (4). Using the global and local selection methods, we obtained 3368 samples from 248 862 samples for the lookup table. Then, these samples are printed and measured to obtain accurate CIELAB values for the selected samples. There are too many samples to apply to the real printer system. Thus, we use a new lookup table using the old lookup table. The 1331 new nodes for the color signal (RGB or CIELAB) of the standard input or input device are generated. Next, values which are outside of the printer gamut are mapped into the printer gamut by using SGCK gamut-mapping algorithms.[15,16] The amount of colorant for each node is estimated by using the tetrahedral interpolation method with the lookup table.[8] Consequently, a new lookup table could be obtained.

To evaluate the extension of the color gamut, we compared the gamut shaped by the proposed method with that obtained by conventional methods, substituting OG to CMY and characterizing each subgamut. In substituting OG to CMY, we generated a lookup table with sampled patches according to the 11 levels of the CMY colorants. For input colors outside of the gamut, using the closet combination of CMY colorants to the input color, orange colorant is substituted to parts of magenta and yellow and green is substituted to parts of cyan and yellow. In characterizing each subgamut, colorants are divided as CMY, CGY, and MYO. For each colorant set, lookup tables are generated by measuring the sampled patches by 11 levels. Then, the lookup table is selected for the input color, and the amount of colorants for the input color is estimated by tetrahedral interpolation method. As shown in Fig. 10, the gamut represented by the proposed method was extended further where lightness is 35 or 40, but the gamut is relatively unaffected at lightness over 50. Other methods, such as substituting OG to CMY and the method that characterizes each subgamut, could not be fully extended because they did not use all colorant combinations. Next, we used the Macbeth color checker to compare the

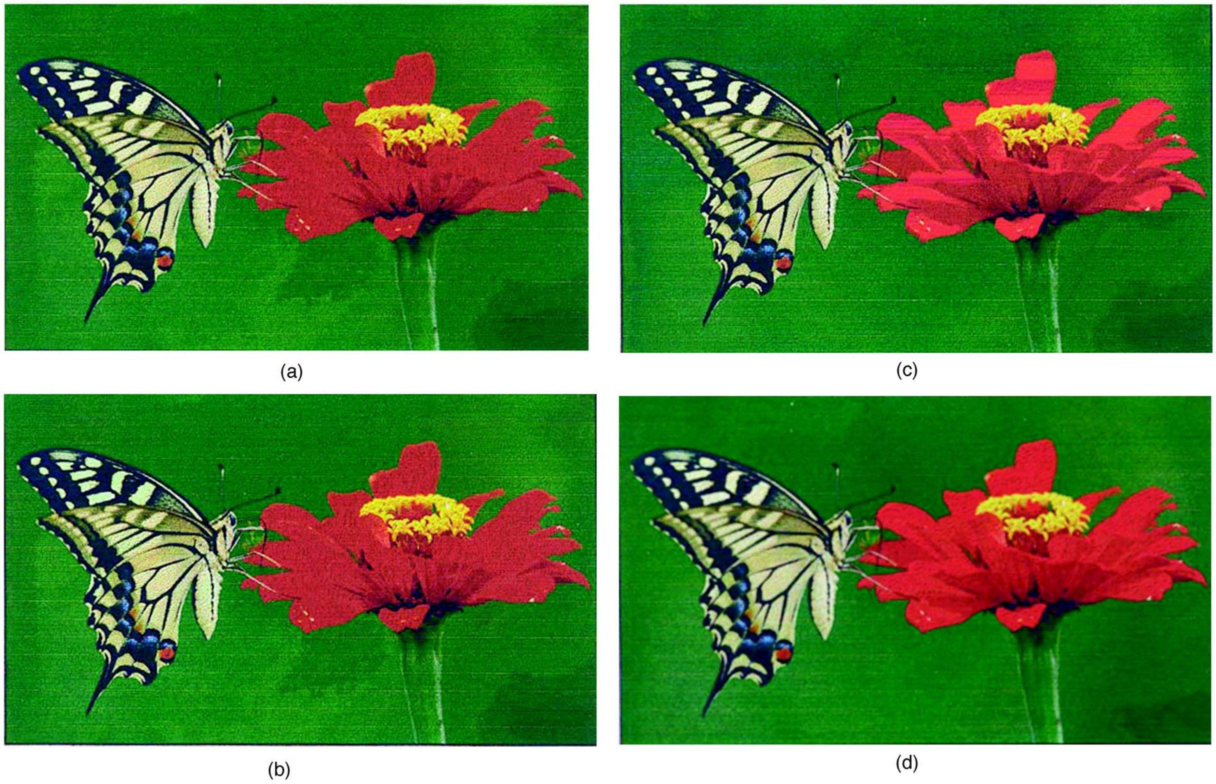


Figure 13. Printed flower and butterfly image with (a) using CMY colorants, (b) substituting OG to CMY, (c) characterizing each subgamut, and (d) the proposed method.

Figure 14. Printed parrot image with (a) using CMY colorants, (b) substituting OG to CMY, (c) characterizing each subgamut, and (d) the proposed method.

characterizations quantitatively. First, we evaluated the selection methods, proposed method, and arbitrary selection that choose the sample which is closed to the lattice point. In considering the color difference of the selection part from the total process, in order to compare the selection methods, we did not include differences in the gamut-mapping process. Figure 11 indicates the color difference of the two methods. The average color difference of the proposed method was 2.49 ΔE^*_{ab} and the arbitrary selection method was 3.17 ΔE^*_{ab}. In addition, the maximum differences were 5.05 ΔE^*_{ab} and 11.85 ΔE^*_{ab}, and the standard deviations were 1.14 and 2.33, respectively. As a result, the average color difference showed some improvement, but the proposed method showed greater improvement in terms of maximum difference and standard deviation. It was verified that if the colorant distribution between samples was similar to the neighboring samples, the interpolation error would be reduced and the characterization performance would be improved. Next, the proposed method was compared with conventional methods. This was done using CMY colorants, substituting OG to CMY, and characterizing each subgamut. The original image was obtained by the characterization model of a LCD monitor, Samsung SyncMaster 176T, and the image was mapped to the gamut of each method using the SGCK method.[15,16] The average color difference of the proposed method was less than that of the others. The lower maximum and standard deviation values were more stable in Table II. In the printed image Fig. 12, the other three methods, which use OG, are more colorful than those which only use CMY colorants. Compared with the proposed method, however, the method of substituting OG for CMY is over saturated in the orange patch which is caused by the rate of substitution. The method of characterizing each subgamut is under saturated in the orange, red, and green patches. In the proposed method, the red patch is more saturated than other red patches from conventional methods.

"Flower and butterfly" and "parrot" images are used to evaluate the methods as a real image. As shown in Fig. 13(b), OG was not fully substituted for CMY, so the petals were dark, and it similar to the results shown Fig. 13(a). The results shown in Fig. 13(c) were also less saturated, whereas in the results of Fig. 13(d), the proposed method, the petals were more reddish. This is because the proposed method used green colorant to represent the region. A green dot on a red background is less visible than a cyan dot. Therefore, the proposed method was able to represent subdivided gray levels in the dark and saturated regions. The results shown in Fig. 14(d) were also more saturated, not only in the reddish regions, the body of the parrot, but also in green regions, the leaves, when compared with other methods.

CONCLUSIONS

The use of additional colorants, exclusive of CMY, is needed to extend the narrow color gamut of a printer. The problem of redundancy by using additional colorants, however, restricts the representation of color in the inverse characterization process. In addition, the number of control values is too large to measure CIELAB values. Therefore, we proposed an inverse characterization method to solve the redundancy problem and to extend the gamut. The accuracy of the color reproduction process is improved by using a correlation factor between distributions of colorants for nodes in the lookup table. The whole gamut was extended by considering all combinations for sampled colorants space. Moreover, by using the forward characterization model in the inverse characterization process, this reduced measurements of color stimulus values for control values. Nonetheless, since the proposed method still involves the forward characterization method and the ink blot problem is not defined clearly, future research will attempt to minimize the forward characterization error and to define further the ink blot problem.

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