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Updating a CMYK Printer Model Using a Sparse Data Set[1]

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Abstract. *Two distinct approaches for updating a CMYK printer model in response to systematic changes in print device behavior are presented. In the first method, a corrective model is constructed from a sparse set of newly acquired characterization data and used in addition to the initial printer model. A number of corrective models are investigated, including linear, quadratic, and artificial neural network models. The second method involves directly updating the parameters within the printer model. The updated model parameters are obtained using both the original characterization data and a set of newly acquired data. Both methods are evaluated in a set of experiments in which either the paper stock or the cyan toner cartridge is changed. The corrective model approach is found to be the most effective. The most successful corrective models removed between 76% and 100% of the systematic error. © 2006 Society for Imaging Science and Technology.*
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INTRODUCTION

In this study, we consider the accuracy of printer models that link device-dependent CMYK values to device-independent CIELAB values.[1] The accuracy of a printer model is generally highest directly following a thorough device characterization, and is diminished due to subsequent changes in device behavior. Calibration techniques are typically applied to a printing system in an attempt to maintain device characteristics at a consistent level. If a printer model becomes unacceptably inaccurate, a full device recharacterization may be performed to bring the system back to peak performance.

A wide variety of factors can affect the accuracy of a printer model, resulting in both sudden changes in device properties and changes that occur over a period of time. The changing of consumables such as paper or colorants can produce sudden changes in device performance. Changes in environmental conditions, such as humidity or temperature, typically alter the behavior of a print device over a period of hours or days. Changes in the device itself, including electrophotographic drum characteristics and print head performance, also reduce the accuracy of a printer model, typically over a longer period of time. Differences between two individual printers of the same make and model can also be treated as a systematic shift. If a printer manufacturer has developed a printer model to capture the average behavior of a specific make and model of printer, the methods presented in this study offer a way of fine tuning this generic printer model for each individual device.

Building a complete printer model anew is relatively complex and expensive, involving the printing and measuring of a large set of color patches. The expense of building a printer model motivates the use of calibration techniques. For example, adjusting device settings with the goal of maintaining the optical density of individual colorants may prolong the accuracy of a device model. This approach, however, does not take into account interactions between colorants, and is not as accurate as rebuilding the printer model. Methods designed to maintain device characteristics are less expensive than building a new printer model, but building a new printer model is more accurate. Methods that are less complex also have the advantage of being more easily facilitated by the end user, as opposed to the system vendor.

We present methods for updating a previously characterized CMYK printer model using a sparse set of newly acquired characterization data.[2] The goal is to capture systematic shifts in device behavior with one of two distinct methods: the introduction of a corrective model used in conjunction with the existing printer model, and the recalculation of printer model parameters using an augmented characterization data set. These methods can be considered viable if they improve printer model accuracy and offer considerable savings in effort relative to a complete system recharacterization.

For the purpose of this study, we consider systematic error to be distinct from other errors in a printer model. Systematic error is considered to be the result of underlying changes in system behavior that occur some time after the print device has been characterized. These changes may result from any number of sources, such as a change of consumables or changes in environmental conditions that occur over time, as mentioned above. Errors not considered to be systematic include error in the original printer model, and random errors that contribute to the lack of repeatability of the printing system. It is a goal of this study to bring a

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printer model back to its original level of accuracy following a systematic shift in device behavior, in other words, to remove systematic errors.

Two sets of experiments were carried out to evaluate the proposed methods for updating a printer model. In the first set of experiments, the paper stock was changed following the characterization of a printer model, resulting in a reduction in colorimetric accuracy. The methods for updating a printer model were applied using a small set of data acquired after the change of paper stock. The improvement in colorimetric accuracy was then evaluated by comparing sets of test patches printed before and after the application of corrective methods. In the second set of experiments, a loss of printer model accuracy was induced by changing the cyan toner cartridge. The methods for updating a printer model were then applied and evaluated as in the first set of experiments. In the analysis of the proposed methods, particular attention was paid to the possibility of introducing new, localized errors as a result of incorrectly capturing systematic shifts in printer behavior.

PREVIOUS WORK

The subject of compensating for changes in print device characteristics with efficient characterization and calibration techniques is addressed by several studies in the literature. These studies all strive for an improvement in colorimetric accuracy, but differ in their balance of efficiency, accuracy, and control. Several of the calibration studies present techniques for on-line printer adjustment, and often restrict themselves to optical density measurements for speed and cost effectiveness. The approaches investigated in the present study were performed off-line, and utilized spectrophotometer data, which offer greater control and accuracy but are generally more expensive than optical density measurements. The present study focuses on the mathematics of updating an existing printer model with a sparse set of recharacterization data, as opposed to the development of an on-line calibration system. It is quite feasible, however, that the methods in the present study could be incorporated with related methods in the literature.

Compared to research present in the literature, the work completed in this study is most closely related to that of Balasubramanian and Maltz.[3] Balasubramanian and Maltz hypothesized that a local linear transform can adequately capture the difference between actual printer behavior and a printer model. They created local, matrix-based correction models to capture printer model error, printer drift, and look-up table (LUT) approximation error. The coefficients for the correction matrices were determined by weighted regression in such a way that they could vary considerably over the printer color space. The corrective models in the present study take a number of forms, and are constant over the printer gamut. Balasubramanian and Maltz tested their method by attempting to improve the accuracy of a LUT-based color management system for a Xerox®5760 xerographic printer. They were successful in reducing the average model error from 4.85 ΔE^*_{ab} to just over 2.62 ΔE^*_{ab} for a set of 500 test patches.

Wu presented a method for calibration that combines one-dimensional and three-dimensional approaches.[4] He addressed differences in the output of two individual printers of the same model, and of a single printer at two different times. He differentiated between luminance changes, which he addressed with a one-dimensional linearization method, and chrominance changes, which he addressed by updating specific regions in the three-dimensional LUT used by the color management system. In relation to the present study, the LUT update method employed by Wu is similar to a full recharacterization of the print device, but is limited to a carefully chosen section of the gamut. Wu focused on specific gamut regions, such as the neutral axis and skin tone regions, and recharacterized the print device only in those areas.

Bala et al. applied two-dimensional transforms for device calibration.[5] They sought to overcome the limitations inherent in standard one-dimensional tone response correction methods with only a modest increase in computational expense. Their method first computes two intermediate values using the device space values provided by the characterization. The intermediate values are then used to determine the final device values from a two-dimensional LUT. In the context of their work, the methods presented in this study are full device-correction functions which offer greater control but are more computationally expensive than one-dimensional or two-dimensional calibration approaches.

Chu et al. investigated a system for per-cartridge characterization that has several themes in common with our work.[6,7] They were motivated by observed variations between individual ink cartridge characteristics and those predicted by vendor supplied profiles. Their method involves taking a small number of measurements for individual cartridges at the manufacturing level and using these data to update an ICC profile at the time the cartridge is installed by the user. They sought an approach that does not require the end user to make measurements, and therefore restricted their updating characterization data to step wedges for individual cartridges. While their study investigated the feasibility of per cartridge characterization and the associated workflow, the present study focuses specifically on computational methods for updating a printer model with a sparse set of recharacterization data. In addition to the difference in general thrust of the work, an important difference lies in the choice of recharacterization set; Chu et al. used single colorant data, whereas the present study attempts to capture colorant interactions.

The need for improvement of an existing printer model is mentioned in other studies in the literature as well. Shiau and Williams, for example, considered a combined scanner-printer system.[8] They developed a method in which a corrective matrix is applied to the RGB values output by a scanner, prior to calculating the device independent values sent to the printing system. The topic of efficient calibration and characterization in general was studied by Haneishi et al., who investigated the number of measurements required for scanner characterization.[9] Emmel and Hersch mention the need to recharacterize quickly when the paper or ink cartridge of a printer is changed; they relate this to recharacterization by pointing out that a full system recharacterization can be achieved more efficiently if a small number of measurements are required to generate the full LUT.[10]

The error correction methods developed in this study may also be placed in the general context of model transfer. Model transfer refers to a model developed for one task being reused for related tasks.[11] In relation to general model transfer methods, the techniques developed in this study fall in the category of representational transfer. Representational transfer indicates that the adoption of the original model occurs at some time after the initial model creation. Furthermore, the methods developed here may be distinguished from general model transfer methods by their goal, which is to improve the generalization capability of an existing model based on a minimal recharacterization data set. It is also noted that the methods developed in this study are non-adaptive; that is, the correction methods are applied at a single point in time and do not adapt to changes in printer characteristics dynamically.

This study focuses on correcting an existing printer model in response to systematic changes in printer characteristics. The following sections outline two general approaches, the use of corrective models of various forms, and the recalculation of model parameters using a small number of new characterization data. These methods are validated experimentally, with results favoring methods using relatively simple corrective models.

METHODS

A printer model may be considered in terms of three functions, $F_L(C,M,Y,K)$, $F_a(C,M,Y,K)$, and $F_b(C,M,Y,K)$, which predict the L^*, a^*, and b^* values of printer output, respectively, based on the colorant dot fractions C, M, Y, and K. The error between the predicted CIELAB output values and the true CIELAB output values can be broken into two categories, systematic error ($E_{\text{systematic}}$) and printer model error ($E_{\text{printer model}}$). The systematic error is tied to underlying shifts in the characteristics of the print device, while printer model error reflects shortcomings in the printer model functions and the variability of output inherent in the physical system. The relationship between true output, predicted output, systematic error, and printer model error may be expressed as

$$L^*_{\text{true}} = F_{L_{\text{predicted}}} + E_{L_{\text{systematic}}} + E_{L_{\text{printer model}}},$$

$$a^*_{\text{true}} = F_{a_{\text{predicted}}} + E_{a_{\text{systematic}}} + E_{a_{\text{printer model}}},$$

$$b^*_{\text{true}} = F_{b_{\text{predicted}}} + E_{b_{\text{systematic}}} + E_{b_{\text{printer model}}}. \tag{1}$$

In general, the functions F_L, F_a, and F_b may be any nonlinear printer model functions that predict CIELAB output values based on CMYK dot fractions.

In the present study, the printer model is provided by the software program NeuralColor, as described in the Experimentation section. The NeuralColor system uses artificial neural networks (ANNs) to predict CIELAB output values based on CMYK dot fractions. Furthermore, NeuralColor contains optimization routines that allow for the inversion of the printer model. In this way, the printer model is utilized for conversion from CIELAB to CMYK. The experiments in this study were carried out by converting digital images stored in CIELAB format to CMYK and measuring the accuracy of the resulting prints.

Two strategies are applied in the current study to improve the predictive capabilities of the printer model functions F_L, F_a, and F_b by correcting for systematic errors. The primary goal of these methods is to reduce the overall error of the printer model using a sparse set of new characterization data. An additional and equally important goal is to avoid the introduction of new error in local regions of the printer gamut. A corrective approach that reduces average error but creates local artifacts in the output gamut is considered ineffective. Furthermore, emphasis is placed on the number of required characterization measurements; a corrective approach is useful only if it can be implemented at a significantly reduced cost relative to a full device recharacterization.

The first approach for compensating for systematic errors utilizes the corrective functions $\mathcal{F}_L$, $\mathcal{F}_a$, and $\mathcal{F}_b$, where

$$\mathcal{F}_L \approx -E_{L_{\text{systematic}}},$$

$$\mathcal{F}_a \approx -E_{a_{\text{systematic}}},$$

$$\mathcal{F}_b \approx -E_{b_{\text{systematic}}}. \tag{2}$$

The corrective models are used in conjunction with the printer model functions, resulting in a more accurate prediction of CIELAB output values

$$L_{\text{predicted}} + \mathcal{F}_L \approx L^*_{\text{true}} - E_{L_{\text{printer model}}},$$

$$a_{\text{predicted}} + \mathcal{F}_a \approx a^*_{\text{true}} - E_{a_{\text{printer model}}},$$

$$b_{\text{predicted}} + \mathcal{F}_b \approx b^*_{\text{true}} - E_{b_{\text{printer model}}}. \tag{3}$$

This approach is successful if the use of the corrective functions significantly improves the predictive capabilities of the printer model with less expense than a full device recharacterization.

The second approach involves updating the printer model functions F_L, F_a, and F_b in response to systematic shifts in device characteristics, resulting in an updated set of functions F'_L, F'_a, and F'_b. Unlike the corrective model approach, this strategy requires the modification of the parameters that define the printer model functions F_L, F_a, and F_b. The approach of updating parameters in the printer model is effective if the accuracy of the printer model can be improved based on the measurement of only a small number of new data values. The resulting system may be expressed as

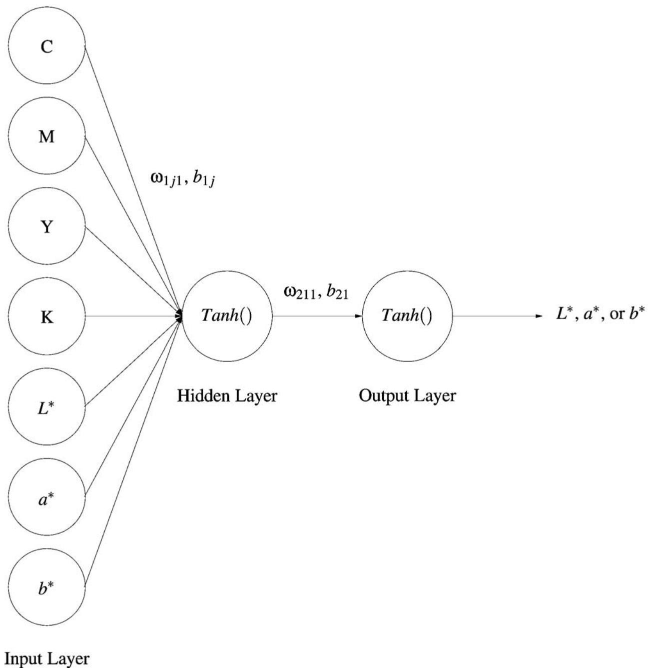


Figure 1. One-hidden-layer ANN with one hidden neuron.

$$L'_{\text{predicted}} \approx L^*_{\text{true}} - E_{L_{\text{printer model}}},$$

$$a'_{\text{predicted}} \approx a^*_{\text{true}} - E_{a_{\text{printer model}}},$$

$$b'_{\text{predicted}} \approx b^*_{\text{true}} - E_{b_{\text{printer model}}}. \tag{4}$$

Corrective Models

Four types of corrective models were applied to the NeuralColor system. The forms of the corrective models were selected to range from simple to more complex. Specifically, the corrective models were constructed using each of the following forms: linear, partial quadratic, full quadratic, and ANN.

An asset of the corrective model approach is that it does not depend on the form of the original printer model. This allows corrective models to be used with any type of color management system, including regression models, models based on ink mixing, and models based on LUTs. Furthermore, corrective models may be applied in situations where the original printer model is not accessible to the user, which may be the case when proprietary systems are in use.

Regression techniques are required to determine the coefficients in each of the corrective schemes. Linear regression can be used in the case of the linear, partial quadratic, and full quadratic corrective models. In the case of the ANN corrective models, nonlinear regression techniques must be applied to determine the model parameters.

The linear corrective models applied in this study take the following form:

$$\mathcal{F}_L(C,M,Y,K,F_L,F_a,F_b) = c_0^L + c_1^L C + c_2^L M + c_3^L Y + c_4^L K + c_5^L F_L + c_6^L F_a + c_7^L F_b,$$

$$\mathcal{F}_a(C,M,Y,K,F_L,F_a,F_b) = c_0^a + c_1^a C + c_2^a M + c_3^a Y + c_4^a K + c_5^a F_L + c_6^a F_a + c_7^a F_b,$$

$$\mathcal{F}_b(C,M,Y,K,F_L,F_a,F_b) = c_0^b + c_1^b C + c_2^b M + c_3^b Y + c_4^b K + c_b^L F_L + c_6^b F_a + c_7^b F_b. \tag{5}$$

Each of the corrective models is a function of the colorant dot fractions C, M, Y, and K, as well as the CIELAB values predicted by the original printer model (uncorrected model). This approach offers a great deal of generality and allows the corrective models to make use of the predictive capabilities of the original printer model.

Introducing the variable i to denote L, a, or b, Eqs. (5) may be written as a single expression

$$\mathcal{F}_i(C,M,Y,K,F_L,F_a,F_b) = c_0^i + c_1^i C + c_2^i M + c_3^i Y + c_4^i K + c_5^i F_L + c_6^i F_a + c_7^i F_b. \tag{6}$$

The coefficients in Eq. (6) can be determined using linear regression with a minimum of eight characterization data. (In general, a minimum of n data are required to determine the coefficients of an equation with n coefficients by linear regression.)

(a) Colors in the 18-color set. (b) Additional colors in the 36-color set.

Figure 2. The recharacterization data sets. (Available in color as Supplemental Material on the IS&T website, www.imaging.org)

Table I. Recharacterization data sets. CMYK dot fractions for the 18-color set are presented in the left column. The additional CMYK combinations used in the 36 color set are given in the right column.

C	M	Y	K	C	M	Y	K
1.0	0.0	0.0	0.0	0.3	0.0	0.0	0.0
0.0	1.0	0.0	0.0	0.0	0.3	0.0	0.0
0.0	0.0	1.0	0.0	0.0	0.0	0.3	0.0
0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.3
0.0	1.0	1.0	0.0	0.0	0.3	0.3	0.0
1.0	0.0	1.0	0.0	0.3	0.0	0.3	0.0
1.0	1.0	0.0	0.0	0.3	0.3	0.0	0.0
1.0	1.0	1.0	0.0	0.3	0.3	0.3	0.0
1.0	1.0	1.0	1.0	0.3	0.3	0.3	0.3
0.0	0.0	0.0	0.0	0.7	0.0	0.0	0.0
0.5	0.0	0.0	0.5	0.0	0.7	0.0	0.0
0.0	0.5	0.0	0.5	0.0	0.0	0.7	0.0
0.0	0.0	0.5	0.5	0.0	0.0	0.0	0.7
0.0	0.5	0.5	0.5	0.0	0.7	0.7	0.0
0.5	0.0	0.5	0.5	0.7	0.0	0.7	0.0
0.5	0.5	0.0	0.5	0.7	0.7	0.0	0.0
0.5	0.5	0.5	0.0	0.7	0.7	0.7	0.0
0.5	0.5	0.5	0.5	0.7	0.7	0.7	0.7

The full quadratic corrective models are of the following general form

$$\begin{aligned}\mathcal{F}_i(C,M,Y,K,F_L,F_a,F_b) &= c_0^i + c_1^iC + c_2^iM + c_3^iY + c_4^iK + c_5^iF_L \\ &\quad + c_6^iF_a + c_7^iF_b + c_8^iC^2 + c_9^iM^2 \\ &\quad + c_{10}^iY^2 + c_{11}^iK^2 + c_{12}^iF_L^2 + c_{13}^iF_a^2 \\ &\quad + c_{14}^iF_b^2 + c_{15}^iCM + c_{16}^iCY + c_{17}^iCK \\ &\quad + c_{18}^iCF_L + c_{19}^iCF_a + c_{20}^iCF_b \\ &\quad + c_{21}^iMY + c_{22}^iMK + c_{23}^iMF_L \\ &\quad + c_{24}^iMF_a + c_{25}^iMF_b + c_{26}^iYK \\ &\quad + c_{27}^iYF_L + c_{28}^iYF_a + c_{29}^iYF_b \\ &\quad + c_{30}^iKF_L + c_{31}^iKF_a + c_{32}^iKF_b \\ &\quad + c_{33}^iF_LF_a + c_{34}^iF_LF_b + c_{35}^iF_aF_b. \qquad (7)\end{aligned}$$

The full quadratic model requires 36 newly acquired characterization data for computation of the model parameters.

Simplified (reduced) quadratic models may be obtained by dropping the mixed terms from Eq. (7). The resulting models have the general form

$$\begin{aligned}\mathcal{F}_i(C,M,Y,K,F_L,F_a,F_b) &= c_0^i + c_1^iC + c_2^iM + c_3^iY + c_4^iK + c_5^iF_L \\ &\quad + c_6^iF_a + c_7^iF_b + c_8^iC^2 + c_9^iM^2 \\ &\quad + c_{10}^iY^2 + c_{11}^iK^2 + c_{12}^iF_L^2 + c_{13}^iF_a^2 \\ &\quad + c_{14}^iF_b^2. \qquad (8)\end{aligned}$$

Computation of the model parameters in this case requires 15 data.

The final form of corrective model investigated in the present study is ANN. ANN corrective models have a greater ability to capture more complex systematic errors than the polynomial-based models given by Eqs. (6)–(8). They are also, however, more susceptible to overfitting, and may exhibit less predictable behavior, possibly introducing new error into local regions of the gamut.

ANN corrective models utilized in this study are feed-forward networks with one hidden layer and one neuron in the hidden layer. They utilize hyperbolic tangent as the transfer function. The form of the ANN models is illustrated in Fig. 1.

Each of the seven inputs is multiplied by a weight w_{1j1} and summed with a bias b_{1j}. For example, the value that is passed from the cyan input neuron to the hidden-layer neuron is $w_{111}C+b_{11}$. The values passed from the input nodes are summed and passed into the hyperbolic tangent function in the hidden-layer neuron. The output from the hidden neuron is then multiplied by a weight w_{211} and summed with a bias b_{21}. This value is passed to the hyperbolic tangent function in the output layer; the resulting value is the ANN's output.

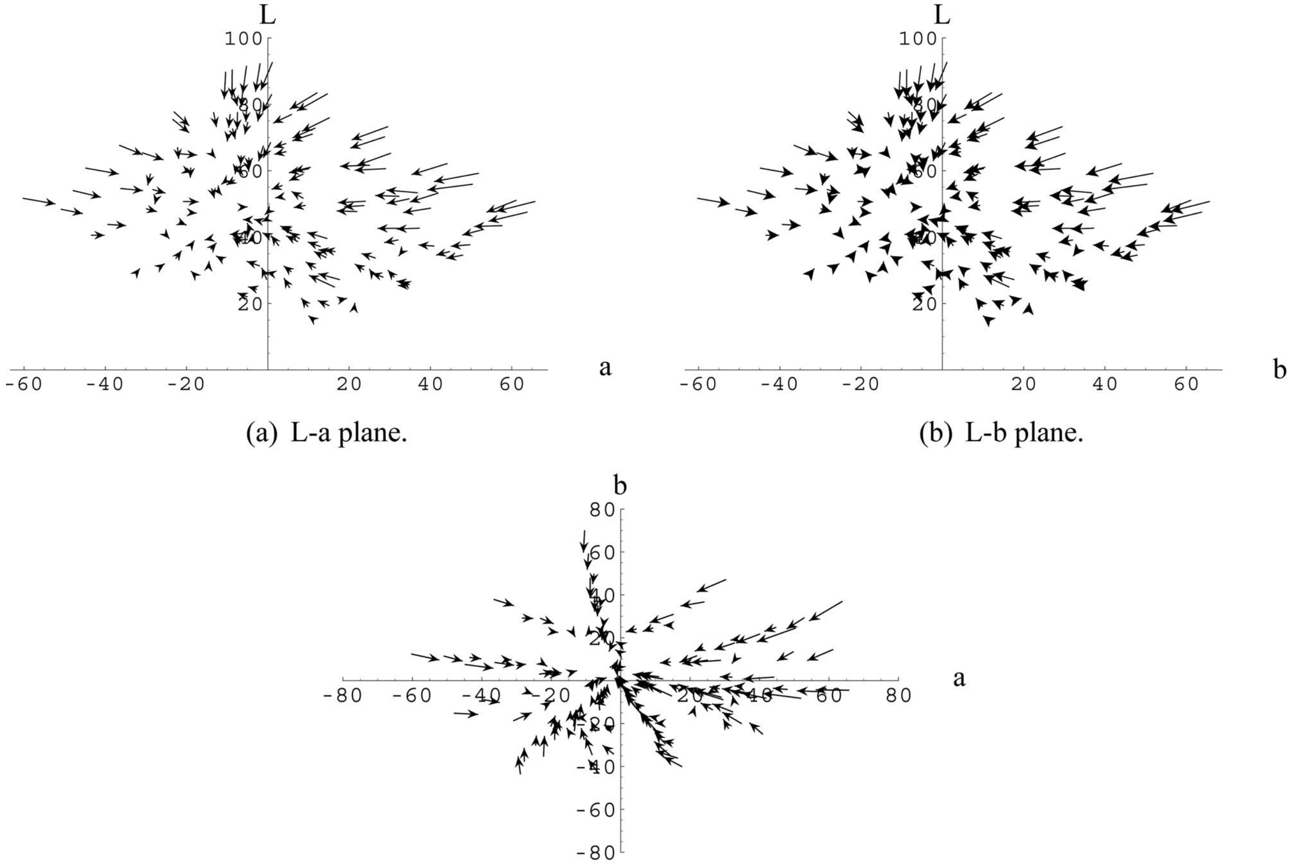
The model parameters for the system illustrated in Fig. 1 are the weights and biases of the ANN. The minimum number of data required to determine these parameters by regression is equal to the number of weights plus the number of biases. The number of weights in the feed-forward, one-hidden-layer ANNs used in this study is $N_{\text{neurons}}(N_{\text{inputs}}+N_{\text{outputs}})$, and the number of biases is $(N_{\text{neurons}}+N_{\text{outputs}})$. Since ANN outputs are nonlinear functions of the weights and biases, nonlinear regression is required to solve for the model parameters.

Recalculating Regression Model Parameters

A number of types of printer models may be altered directly by updating the printer model parameters using a revised set of characterization data. This approach differs significantly from the corrective model schemes, in which the original printer model remains unaltered.

In the present study, the parameters of a regression based printer model are recomputed using an augmented data set. The augmented data set is comprised of the original characterization data plus a set of newly acquired characterization data. A weighting scheme is applied to the newly acquired data to control their influence relative to the original characterization data. Conceptually, it is hoped that the updated printer model will capture the underlying behavior of the system, as captured by the original characterization data, as well as the systematic shifts in device behavior, as captured by the newly acquired characterization data.

The color management system used in the present study, NeuralColor, utilizes ANNs as transfer functions from C, M, Y, and K dot fractions to CIELAB values. This printer model is inverted using an optimization routine, allowing for conversion from CIELAB to CMYK. ANNs are a type of regression model, and are well suited for the approach of recomputing model parameters with an augmented data set. To apply this scheme, the weights and biases of ANN transfer functions are recomputed by nonlinear regression using a set of characterization data that includes both the original



(a) L-a plane.

(b) L-b plane.

(c) a-b plane.

Figure 3. The 149 color characterization set before and after the change of paper stock.

data set and the (weighted) set of new characterization data. Examples of other color management systems that are well suited for the approach of recalculating model parameters using an augmented data set include any regression based printer model, such as the those using polynomials.[12,13] With the addition of several computational steps, this approach may be applied to a number of other types of color management systems. For example, in the case of LUT-based systems, a set of regression models could be derived from existing LUTs, updated using an augmented data set (possibly comprised of data in the LUTs as well as newly acquired data), and then used to build a set of updated LUTs.

There are several important issues to consider when applying weighting factors to the newly acquired data. If the new data are not weighted heavily enough, they will have little or no influence, resulting in updated printer models that are essentially unchanged from their original form. If a heavy weighting is applied, there is a danger that the updated printer models will not accurately capture the underlying behavior of the system (as captured by the original characterization data). There is also a danger of introducing new local error to the printer model. The presence of a small number of heavily weighted data points in the augmented data set has the potential to produce unwanted local characteristics in the resulting printer model functions.

EXPERIMENTATION

Two sets of experiments were carried out to evaluate the methods described in the preceding section. In each case, systematic error was introduced into the printing system, reducing the accuracy of the printer model. In the first set of experiments, a systematic shift in printer characteristics was introduced by changing the paper stock. In the second set of experiments, systematic error was introduced by changing the cyan toner cartridge. In both cases, the methods for updating the printer model using a sparse data set were applied in an attempt to eliminate the systematic error. All experiments were carried out using a Tektronix®Phaser®740 printer. Colorimetric measurements were made with a X-Rite® Digital Swatchbook® spectrophotometer with D65 illuminant and 2 deg. standard observer. The standard deviation of measured printer output was determined to be 1.145 ΔE^*_{ab} for this system.[14]

NeuralColor, a software package developed previously by the authors, was used as the color management system in this study.[14–17] NeuralColor utilizes ANNs for printer model functions. Three distinct ANNs that predict L^*, a^*, and b^*, respectively, based on CMYK dot fractions, were trained using a set of characterization data and embedded in the NeuralColor software. NeuralColor makes use of optimization

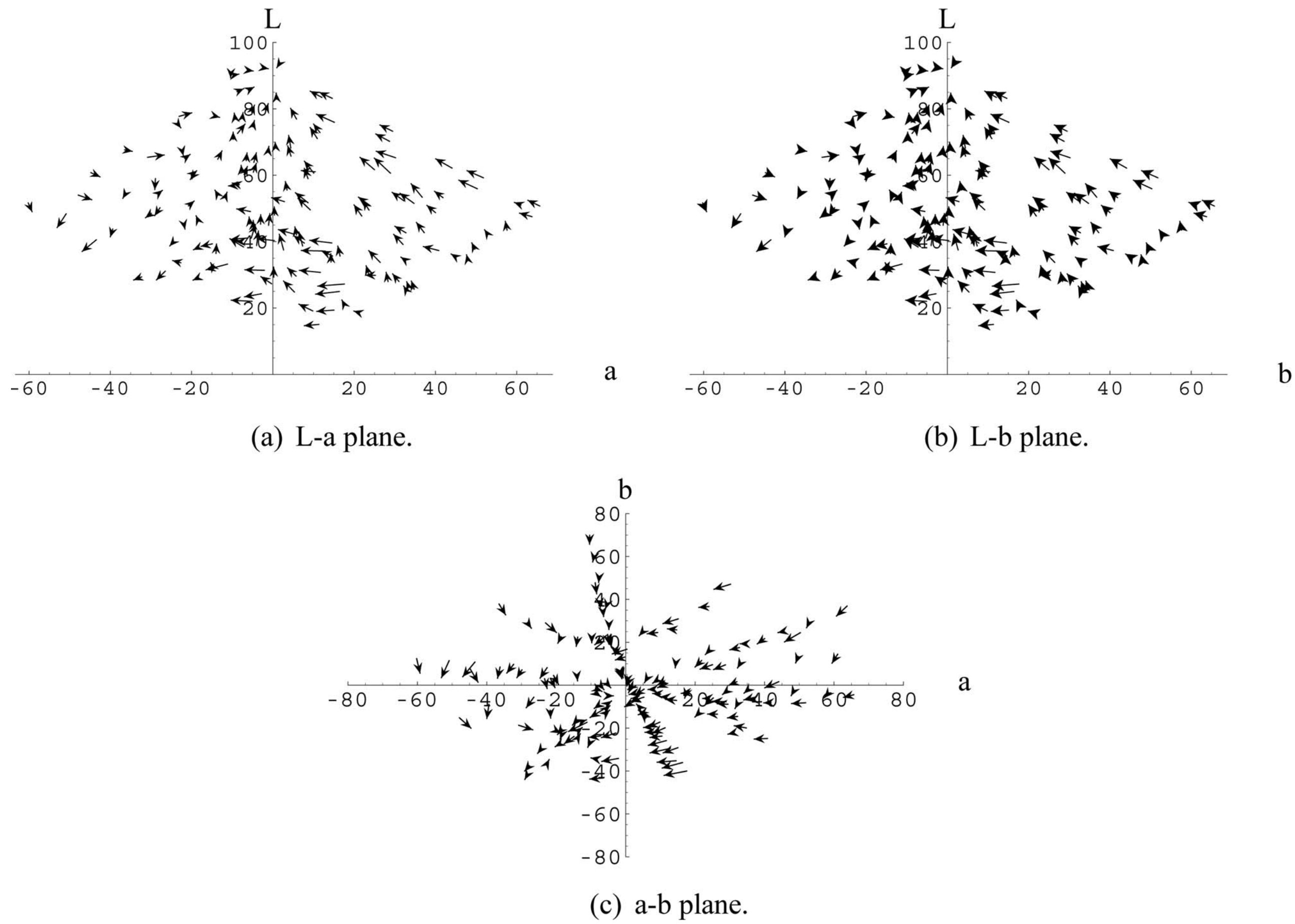


Figure 4. The 149 color characterization set before and after the change of cyan toner cartridge.

routines to compute CMYK dot fractions for a given set of CIELAB values. CMYK values may be calculated in accordance with a variety of printing objectives, including optimal colorimetric accuracy, reduced ink usage, and specific levels of gray component replacement. For the purpose of the present study, however, NeuralColor may be viewed simply as a printer model based on regression models. NeuralColor is suitable for application of both strategies for updating a printer model presented in the current work: the use of corrective models in conjunction with the original printer model, and the recalculation of printer model parameters based on a sparse set of new colorimetric measurements.

Each of the three ANNs used by the NeuralColor system is a feed-forward ANN with one hidden layer. Hyperbolic tangent is used as the transfer function. The ANNs used by NeuralColor are structurally equivalent to the corrective model ANNs used in this study, and differ only by the number of neurons in the hidden layer. The corrective model ANNs are relatively simple, containing a single neuron in the hidden layer. The ANNs used in NeuralColor to predict L^*, a^*, and b^*, have five, six, and seven neurons in the hidden layer, respectively. The initial calibration of NeuralColor was carried out using a set of 149 characterization data. The data were obtained by printing six copies of the characterization set and averaging the results. Printing six copies of the characterization set correlates to a 95% confidence interval of $\pm 0.77\Delta E^*_{ab}$.[14] The CMYK values that make up the 149 color characterization set are listed Table IV.

Systematic error was introduced into the printing system in both sets of experiments carried out in this study. In the first set of experiments, this was achieved by changing the paper stock. A standard white Nekoosa®Bond by Georgia-Pacific® was used as the original paper stock, and was replaced with a multipurpose Xerox® paper that is light gray in color. In the second set of experiments, the cyan toner cartridge that was in use during the initial system characterization was replaced with an older cyan cartridge. Both the change of paper stock and the change of toner cartridge resulted in significant colorimetric error, and the corrective schemes were then applied in an attempt to reduce or eliminate this error. The corrective model approach and the approach of updating model parameters using a sparse data set were applied in separate experiments for both the change of paper stock and the change of cyan toner cartridge.

Seven distinct corrective models were applied in each set of experiments: (1) a linear corrective model (Eq. (6)) constructed using an 18 color recharacterization data set, (2) a

Table II. Results for experiments in which the paper stock was changed.

Baseline measurements	Overall ΔE^*_{ab}	MacBeth chart ΔE^*_{ab}	27 color test ΔE^*_{ab}	Max. ΔE^*_{ab}	Number improved
Orig. characterization, orig. paper	5.0	6.7	3.4	16.1	N/A
Orig. characterization, new paper	10.0	11.9	8.4	21.2	N/A
Corrective model					
Linear model (18 pt.)	5.6	8.3	3.3	21.3	47
Linear model (36 pt.)	5.6	8.0	3.4	20.5	47
Abridged quadratic model (18 pt.)	6.3	9.0	3.9	21.6	46
Abridged quadratic model (36 pt.)	5.5	7.9	3.3	21.1	48
Full quadratic model (36 pt.)	39.6	42.6	36.9	87.9	3
ANN model (18 pt.)	8.0	8.9	7.2	29.6	43
ANN model (36 pt.)	5.9	8.4	3.6	20.9	48
Updated printer model parameters					
18 color set included 5 times	7.2	10.3	4.5	20.9	43
18 color set included 20 times	7.4	10.0	5.1	21.2	43
36 color set included 5 times	6.6	9.4	4.1	22.1	45
36 color set included 20 times	6.6	8.9	4.6	22.5	39

linear corrective model constructed using a 36 color recharacterization data set, (3) an abridged quadratic model (Eq. (8)) constructed using an 18 color recharacterization data set, (4) an abridged quadratic model constructed using a 36 color recharacterization data set, (5) a full quadratic model (Eq. (7)) constructed using a 36 color recharacterization data set, (6) a one hidden neuron ANN model constructed using an 18 color recharacterization data set, and (7) a one hidden neuron ANN model constructed using a 36 color recharacterization data set. The 18 and 36 color recharacterization data sets are described in detail below.

The approach of updating printer model parameters using a sparse data set was applied using two different recharacterization data sets and two different weighting schemes. The two recharacterization data sets, described below, contain 18 and 36 colorimetric measurements, respectively. The newly acquired characterization measurements were combined with the original characterization data, forming an augmented data set. A weighting scheme was used to increase the influence of the newly acquired data relative to the original data. Weighting was achieved by including multiple entries of the newly acquired data in the augmented data set. Preliminary experiments showed that including five entries for each of the recharacterization data was sufficient to produce a change in the printer model parameters, and that including 20 entries for the newly acquired data produced a substantial change. In accordance with these initial findings, experiments were carried out using each of these weighting schemes and each of the recharacterization data sets, for a total of four cases.

Recharacterization Data Set

The methods outlined above for updating a printer model in response to systematic changes in the printing system require the measurement of a small recharacterization data set. For maximum efficiency, a minimal recharacterization set is desired. A minimal set is defined as the smallest set of new measurements with which a significant reduction in printer model error can be achieved.

The choice of the recharacterization data set is influenced by a number of objectives. To capture global shifts in printer characteristics, the data set should span the entire printer gamut as much as possible. If information is available regarding the nature of the systematic changes in printer behavior, importance may be placed on the specific region of the gamut most affected by the change in printer characteristics. Additionally, the type of corrective method applied to the printing system influences the choice of recharacterization data. Corrective models with a small number of model parameters, for example, require fewer recharacterization data than more complex corrective models.

Two different sets of recharacterization data were used in the evaluation of the proposed methods for updating a printer model. The first set contains 18 colors, and the second set contains 36 colors. Both data sets were designed to capture systematic changes throughout the entire printer gamut. The 18 color set is comprised of the eight chromatic primaries and secondaries of four color printing, overprints of the three subtractive primaries, overprints of all four colorants, and mixtures of the three chromatic colorants with black at 50% dot fraction. The 36 color recharacterization set contains the 18 color set, plus a number of additional CMYK combinations. The additional CMYK combinations are 30% and 70% dot fraction prints of the eight chromatic primaries and secondaries, the three subtractive primaries, and overprints of all four colorants. The recharacterization sets are shown in Fig. 2, and a listing of the CMYK dot fractions for each color in the two data sets is given in Table I.

Test Problem

The MacBeth ColorChecker Chart®, combined with a set of 27 additional colors, was used as the test print for this study. The test print contains a total of 51 patches: 24 patches from the MacBeth chart, and 27 additional in-gamut colors. The MacBeth chart is commonly used for evaluating color reproduction. The MacBeth chart, however, contains a number of

Table III. Results for experiments in which the cyan toner cartridge was changed.

Baseline measurements	Overall ΔE^*_{ab}	MacBeth chart ΔE^*_{ab}	27 color test ΔE^*_{ab}	$C>0.5$ ΔE^*_{ab}	$C<0.5$ ΔE^*_{ab}	Max. ΔE^*_{ab}	Number improved
Orig. characterization, orig. cartridges	5.0	6.7	3.4	5.6	4.6	16.1	N/A
Orig. characterization, new cyan cartridge	7.6	9.2	6.2	10.5	6.0	18.5	N/A
Corrective model							
Linear model (18 pt.)	5.6	7.1	4.3	6.7	5.0	18.0	40
Linear model (36 pt.)	5.2	6.9	3.6	5.8	4.9	17.1	40
Abridged quadratic model (18 pt.)	8.9	10.8	7.2	6.6	10.2	30.0	27
Abridged quadratic model (36 pt.)	4.6	6.8	2.5	4.6	4.5	18.6	40
Full quadratic model (36 pt.)	33.9	42.5	26.3	31.2	35.4	104.5	3
ANN model (18 pt.)	5.4	7.0	4.0	5.5	5.4	18.1	35
ANN model (36 pt.)	5.3	7.1	3.6	5.8	5.0	18.2	36
Updated printer model parameters							
18 color set included 5 times	7.5	11.5	3.9	6.6	7.9	45.7	39
18 color set included 20 times	5.9	8.2	3.8	5.3	6.2	23.6	35
36 color set included 5 times	6.0	7.6	4.5	8.3	4.7	17.6	38
36 color set included 20 times	8.8	10.2	7.6	8.1	9.2	35.0	31

colors that are outside the gamut of the printer used in this study. These colors cannot be reproduced with zero colorimetric error. The additional 27 colors are made up of nine patches at a lightness level of 20 with a^* and b^* values set to all combinations of -10, 0, and 10, nine patches at a lightness level of 50 with a^* and b^* set to all combinations of -20, 0, and 20, and nine patches at a lightness level of 80 with a^* and b^* set to all combinations of -10, 0, and 10.

A number of metrics were used to evaluate the test results. In all cases, colorimetric error was calculated as the ΔE^*_{ab} between the CIELAB input values and the measured CIELAB output values. Overall error, error for the patches in the MacBeth chart, and error for the additional 27 patches were tabulated separately. The largest error across all 51 patches was also listed, as well as the number of patches for which colorimetric accuracy was improved. Individual experiments were averaged over three trials.

Introducing Systematic Error

Significant changes in printing system behavior resulted from both the change of paper stock and the change of cyan toner cartridge. The change in system behavior that resulted from the change in paper is illustrated in Fig. 3. Figure 3 was created by reprinting and measuring the 149 color set used for the original system characterization. The change of paper produced a general shift toward the neutral axis and a decrease of lightness for colors in the high-lightness portion of the gamut. This type of shift was expected due to the darker white point of the replacement paper stock. The average colorimetric error increased from 5.0 ΔE^*_{ab} to 10.0 ΔE^*_{ab} as a result of the change of paper.

Figure 4 illustrates the change in printer behavior that resulted from the change of cyan toner cartridge. The general shift in this case was toward the cyan portion of the printer gamut. In the case of the change of toner cartridge, the average colorimetric error increased from 5.0 ΔE^*_{ab} to 7.6 ΔE^*_{ab}.

RESULTS

Change of Paper Experiments

Results for the experiments in which the paper stock was changed are presented in Table II. In most cases, the corrective models gave excellent results. The full quadratic model and the ANN model based on 18 new characterization data were not successful. With the exception of these two cases, the corrective models removed between 80% and 90% of the error introduced by the change of paper stock.

The unsuccessful corrective models were both susceptible to overfitting. In the case of the full quadratic model, the number of characterization data was exactly equal to the number of parameters in the model. As a result of overfitting, the full quadratic model had a maximum error of 87.9 ΔE^*_{ab}, and improved only three patches. The ANN model based on 18 colors also exhibited behavior that is characteristic of overfitting. In this case, the corrective model im-

Table IV. The 149 color characterization data set.

No.	C	M	Y	K	No.	C	M	Y	K
1	1.0	0.0	0.0	0.0	76	1.0	1.0	0.0	0.7
2	0.0	1.0	0.0	0.0	77	1.0	0.0	1.0	0.7
3	0.0	0.0	1.0	0.0	78	0.0	1.0	1.0	0.7
4	1.0	1.0	0.0	0.0	79	0.2	0.0	0.0	0.7
5	1.0	0.0	1.0	0.0	80	0.0	0.2	0.0	0.7
6	0.0	1.0	1.0	0.0	81	0.0	0.0	0.2	0.7
7	0.2	0.0	0.0	0.0	82	0.2	0.2	0.0	0.7
8	0.0	0.2	0.0	0.0	83	0.2	0.0	0.2	0.7
9	0.0	0.0	0.2	0.0	84	0.0	0.2	0.2	0.7
10	0.2	0.2	0.0	0.0	85	0.4	0.0	0.0	0.7
11	0.2	0.0	0.2	0.0	86	0.0	0.4	0.0	0.7
12	0.0	0.2	0.2	0.0	87	0.0	0.0	0.4	0.7
13	0.4	0.0	0.0	0.0	88	0.4	0.4	0.0	0.7
14	0.0	0.4	0.0	0.0	89	0.4	0.0	0.4	0.7
15	0.0	0.0	0.4	0.0	90	0.0	0.4	0.4	0.7
16	0.4	0.4	0.0	0.0	91	0.7	0.0	0.0	0.7
17	0.4	0.0	0.4	0.0	92	0.0	0.7	0.0	0.7
18	0.0	0.4	0.4	0.0	93	0.0	0.0	0.7	0.7
19	0.7	0.0	0.0	0.0	94	0.7	0.7	0.0	0.7
20	0.0	0.7	0.0	0.0	95	0.7	0.0	0.7	0.7
21	0.0	0.0	0.7	0.0	96	0.0	0.7	0.7	0.7
22	0.7	0.7	0.0	0.0	97	0.0	0.0	0.0	0.0
23	0.7	0.0	0.7	0.0	98	0.0	0.0	0.0	0.2
24	0.0	0.7	0.7	0.0	99	0.0	0.0	0.0	0.4
25	1.0	0.0	0.0	0.2	100	0.0	0.0	0.0	0.7
26	0.0	1.0	0.0	0.2	101	0.0	0.0	0.0	1.0
27	0.0	0.0	1.0	0.2	102	0.5	0.5	0.5	0.0
28	1.0	1.0	0.0	0.2	103	1.0	0.5	0.5	0.0
29	1.0	0.0	1.0	0.2	104	0.5	0.5	1.0	0.0
30	0.0	1.0	1.0	0.2	105	0.5	1.0	0.5	0.0
31	0.2	0.0	0.0	0.2	106	1.0	0.5	0.0	0.0
32	0.0	0.2	0.0	0.2	107	1.0	0.0	0.5	0.0
33	0.0	0.0	0.2	0.2	108	0.5	0.0	1.0	0.0
34	0.2	0.2	0.0	0.2	109	0.0	0.5	1.0	0.0
35	0.2	0.0	0.2	0.2	110	0.0	1.0	0.5	0.0
36	0.0	0.2	0.2	0.2	111	0.5	1.0	0.0	0.0
37	0.4	0.0	0.0	0.2	112	0.5	0.5	0.5	0.3
38	0.0	0.4	0.0	0.2	113	1.0	0.5	0.5	0.3
39	0.0	0.0	0.4	0.2	114	0.5	0.5	1.0	0.3
40	0.4	0.4	0.0	0.2	115	0.5	1.0	0.5	0.3
41	0.4	0.0	0.4	0.2	116	1.0	0.5	0.0	0.3
42	0.0	0.4	0.4	0.2	117	1.0	0.0	0.5	0.3
43	0.7	0.0	0.0	0.2	118	0.5	0.0	1.0	0.3
44	0.0	0.7	0.0	0.2	119	0.0	0.5	1.0	0.3
45	0.0	0.0	0.7	0.2	120	0.0	1.0	0.5	0.3
46	0.7	0.7	0.0	0.2	121	0.5	1.0	0.0	0.3
47	0.7	0.0	0.7	0.2	122	0.5	0.5	0.5	0.7
48	0.0	0.7	0.7	0.2	123	1.0	0.5	0.5	0.7
49	1.0	0.0	0.0	0.4	124	0.5	0.5	1.0	0.7
50	0.0	1.0	0.0	0.4	125	0.5	1.0	0.5	0.7
51	0.0	0.0	1.0	0.4	126	1.0	0.5	0.0	0.7
52	1.0	1.0	0.0	0.4	127	1.0	0.0	0.5	0.7
53	1.0	0.0	1.0	0.4	128	0.5	0.0	1.0	0.7
54	0.0	1.0	1.0	0.4	129	0.0	0.5	1.0	0.7
55	0.2	0.0	0.0	0.4	130	0.0	1.0	0.5	0.7
56	0.0	0.2	0.0	0.4	131	0.5	1.0	0.0	0.7
57	0.0	0.0	0.2	0.4	132	0.3	0.7	0.0	0.0
58	0.2	0.2	0.0	0.4	133	0.7	0.3	0.0	0.0
59	0.2	0.0	0.2	0.4	134	0.3	0.0	0.7	0.0
60	0.0	0.2	0.2	0.4	135	0.7	0.0	0.3	0.0
61	0.4	0.0	0.0	0.4	136	0.0	0.3	0.7	0.0
62	0.0	0.4	0.0	0.4	137	0.0	0.7	0.3	0.0
63	0.0	0.0	0.4	0.4	138	0.3	0.7	0.0	0.5
64	0.4	0.4	0.0	0.4	139	0.7	0.3	0.0	0.5
65	0.4	0.0	0.4	0.4	140	0.3	0.0	0.7	0.5
66	0.0	0.4	0.4	0.4	141	0.7	0.0	0.3	0.5
67	0.7	0.0	0.0	0.4	142	0.0	0.3	0.7	0.5
68	0.0	0.7	0.0	0.4	143	0.0	0.7	0.3	0.5
69	0.0	0.0	0.7	0.4	144	0.3	0.7	0.2	0.0
70	0.7	0.7	0.0	0.4	145	0.7	0.3	0.2	0.0
71	0.7	0.0	0.7	0.4	146	0.3	0.2	0.7	0.0
72	0.0	0.7	0.7	0.4	147	0.7	0.2	0.3	0.0
73	1.0	0.0	0.0	0.7	148	0.2	0.3	0.7	0.0
74	0.0	1.0	0.0	0.7	149	0.2	0.7	0.3	0.0
75	0.0	0.0	1.0	0.7					

proved 43 out of 51 test colors, but introduced error in certain local regions of the gamut as can be seen by the increase in maximum error.

The approach of updating model parameters using an augmented data set resulted in an overall reduction of error in all cases. In addition, the updated printer models did not significantly increase the maximum error. The printer models updated with 36 colors outperformed the printer models updated with 18 colors. The weighting of the newly acquired characterization data did not have a significant impact on performance.

Change of Toner Cartridge Experiments

Results obtained for the experiments in which the cyan toner cartridge was switched are presented in Table III. Because of the obvious correlation between the cyan toner cartridge and the printer's behavior in the cyan portion of the gamut, Table III includes separate listings of the error for patches with a cyan dot fraction less than 0.5 and for patches with a cyan dot fraction of greater than 0.5. These separate listings isolate the corrective methods' effect on local portions of the gamut.

The corrective models were generally successful in removing the error introduced by changing the cyan toner cartridge. The linear corrective models and the ANN corrective models reduced the overall error by between 76% and 93% and did not increase the maximum error. The abridged quadratic model trained with 36 new data yielded results that were an improvement over the original printer model under the original conditions, indicating that 100% of the systematic error was removed. The full quadratic corrective model failed to improved colorimetric accuracy, and in fact greatly increased the error. As in the change of paper experiments, the full quadratic corrective model was highly susceptible to overfitting.

The approach of updating the printer model parameters using an augmented data set was, in general, not successful in removing the error introduced by the change of cyan toner cartridge. The case of including the 36 color recharacterization set five times reduced the error across all categories and did not increase the maximum error. The other schemes, however, did not significantly improve the average error and dramatically increased the maximum error.

CONCLUSIONS

The methods for updating a printer model using a sparse data set were generally successful in removing systematic error. The corrective model approach was the most successful. In particular, the linear, abridged quadratic, and ANN corrective models performed well by reducing overall colorimetric error without increasing the maximum error across the printer gamut.

A primary source of concern was the tendency of certain corrective models to exhibit overfitting. This behavior was apparent in the increase in maximum error in the experimental results. Overfitting appeared only in cases where the number of parameters in the corrective model was approximately equal to the number of newly acquired characterization data. In cases where the shift in printer characteristics is local in nature, the more complex corrective models have the potential to produce the best results. However, corrective models that can create localized artifacts are also susceptible to overfitting and to the introduction of new error in localized regions of the gamut. This result is undesirable, and therefore it is recommended that corrective models that create changes of a more global nature be applied. If more complex corrective models are utilized, a large number of recharacterization data relative to the number of parameters in the corrective model should be acquired.

The method of recalculating the parameters in a printer model using an augmented data set gave inconsistent results. This approach was often successful in reducing the overall error, but also exhibited a tendency to increase the maximum error across the printer gamut. This method was shown to have merit, but it was not as successful, in general, as the corrective model approach.

There are a number of possibilities for future work stemming from this study. The most successful of the methods, namely the linear and abridged quadratic corrective models, are a good choice for application in an industrial setting. Furthermore, an investigation of the qualitative effects of these methods on image reproduction is a natural extension of this work. This project focused on quantitative evaluation of colorimetric data across the printer gamut. A study of the qualitative effects of the corrective techniques on pictorial images, as determined by a group of observers, would offer more insight into the effectiveness of these methods.

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