Maintaining an Accurate Printer Characterization

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Abstract

In this study, the problem of updating a printer characterization in response to systematic changes in print-device characteristics is addressed with two distinct approaches: the creation of corrective models used in conjunction with an existing device model, and the re-evaluation of regression-model parameters using an augmented characterization data set. Several types of corrective models are evaluated, including polynomial models and neural-network models. A significant reduction in error was realized by incorporating these techniques into the color-management program NeuralColor. The most successful of these methods was a quadratic polynomial correction model, which removed 90% of the error introduced by a change of paper stock, and all of the error introduced by a change in toner cartridge. A general conclusion is that simple corrective models exhibiting global control are preferred over more complex models which may introduce local errors.

Introduction

This study addresses the problem of updating a CMYK printer characterization in response to systematic changes in device characteristics. Printer characterization, along with calibration, is critical to the performance of a printing system. We consider characterization to be the generation of a function (or an approximation to a mathematical function) mapping a device-dependent CMYK color space to a device-independent color space, such as CIELAB. Implicit in the above statement is a belief that an inverse function between the device-independent space and CMYK space can be generated if the forward function exists. Thus, device characterization leads to a color correction model capable of converting device-independent data to device-dependent CMYK, as required for creating output on a four-color print device. We consider device calibration to refer to the process of maintaining consistent print-device characteristics following device characterization.

A thorough device characterization is a relatively expensive process, commonly involving the printing and measurement of a large number of color samples. Typically, colorimetric accuracy is highest immediately following device characterization, and is reduced due to changes in the print device. The resulting printing-system errors can be reduced by calibrating the system periodically or as necessary. This may involve, for example, attempting to maintain the optical density of the colorants at a consistent level. This approach does not consider ink interactions and is likely to be less accurate than a full system recharacterization. A trade-off exists between attempting to maintain consistent printer characteristics and performing a full device characterization; methods for maintaining printer characteristics are generally less expensive, but performing a full device characterization is more accurate. Additionally, accurate calibration requiring a limited number of measurements better facilitates printer calibration by the user as opposed to the print device vendor.

The characteristics of a print device may change due to a number of influences, such as changes in ambient humidity or ambient temperature, changes in toner or ink properties, changes in electrophotographic drum characteristics, changes in optical performance of printheads, or changes in paper characteristics. Changes in printer characteristics may occur suddenly, as when the paper stock is changed, or slowly, as when mechanical or electrical properties of the print device drift over time.

The goal of this work is to update a previously characterized four-color printing system in response to systematic changes in print-device characteristics. To be successful, methods must be efficient relative to a full system characterization. In addition, methods must reduce overall colorimetric error without introducing significant new error in any part of the gamut.

Two distinct approaches are used to update a printer characterization: the application of a corrective method used in conjunction with the original printer model, and the re-evaluation of printer-model parameters based on an augmented characterization data set. Both techniques are evaluated experimentally by changing the paper stock and cyan toner cartridge in a printing system, and attempting to update the printer characterization in response to these changes.

Previous work

Compared to research present in the literature, the work completed in this study is most closely related to that of Balasubramanian and Maltz [1]. 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 both systematic and random errors, such as printer drift, printer model error, or 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. Balasubramanian and Maltz tested their method by attempting to improve the accuracy of a LUT based color-management system for a Xerox 5760 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.

Despite the small number of studies addressing the improvement of an existing printer characterization, the need for such improvement is mentioned consistently in the literature. Shiau and Williams, for example, considered a combined scanner-printer system [2]. 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 [3]. Emmel and Hersch mention the need to recharacterize quickly when the paper or ink cartridge of a printer is changed [4]. They address characterization as it pertains to the creation of ICC profiles; they suggest using printer models that can be built with a relatively small number of colorimetric measurements to produce the full set of points in a LUT, as opposed to measuring all the data directly. 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.

This study focuses on correcting an existing printer characterization 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

The true output, y_{true}, of a multiple-input, single-output system may be expressed as

$$y_{\mathrm{true}} = y(\underline{x}) + \mathcal{E}_s + \mathcal{E}_r, \tag{1}$$

where $\underline{x}$ are model inputs, $y(\underline{x})$ is a model of the system output, $\mathcal{E}_s$ are systematic errors associated with the system, and $\mathcal{E}_r$ are random errors associated with the system.

For the printing system studied in the present work, a system model $y(\underline{x})$ was created for each of the three CIELAB output values. These system models, f_L, f_a, and f_b, are each a function of the four colorant dot fractions C, M, Y, and K. The functions f_L, f_a, and f_b are the main components of the NeuralColor color-management system, as discussed in the Experimentation section.

Corrective Models

A corrective model $\mathcal{F}(\underline{\xi}) \approx -\mathcal{E}_s$ may be applied in addition to the system model expressed in Equation 1, giving

$$\begin{aligned} y_{\mathrm{true}} &= y(\underline{x}) + \mathcal{F}(\underline{\xi}) + \mathcal{E}_s + \mathcal{E}_r \\ &\approx y(\underline{x}) + \mathcal{E}_r. \end{aligned} \tag{2}$$

The corrective-model inputs $\underline{\xi}$ need not match the system inputs $\underline{x}$. The approach of adding a corrective model does not make any assumptions about the nature of the original system model $y(\underline{x})$. This strength allows corrective models to be applied to any type of color-management system.

There are several requirements for a useful corrective model: the model should accurately capture systematic errors, the model should be efficient to create, and the model should not introduce any new local or global errors into the system.

Several corrective models, ranging from from very simple to more complex, are examined in the present study. Specifically, linear corrective models, quadratic corrective models, and artificial-neural-network (ANN) corrective models were implemented. Parameters for the linear and quadratic models were calculated using linear regression. For the ANN models, nonlinear regression techniques were required.

The linear corrective models take the following general form,

$$\mathcal{F}(\underline{\xi}) = a_0 + a_1\xi_1 + a_2\xi_2 + \cdots + a_n\xi_n. \tag{3}$$

For a model with n inputs, a minimum of $n+1$ data are required to compute the coefficients a_i by regression. To allow more generality, the linear corrective models implemented in this study are a function of both the CMYK dot fractions, and the CIELAB values predicted by the original system models,

$$\mathcal{F}(C,M,Y,K,f_L,f_a,f_b) = a_0 + a_1C + a_2M + a_3Y + a_4K + a_5f_L + a_6f_a + a_7f_b. \quad (4)$$

Expanding the linear model to include the full set of quadratic terms yields

$$\begin{aligned}\mathcal{F}(C,M,Y,K,f_L,f_a,f_b) = {}& a_0 + a_1C + a_2M + a_3Y + a_4K + a_5f_L + a_6f_a \\ &+ a_7f_b + a_8C^2 + a_9M^2 + a_{10}Y^2 + a_{11}K^2 + a_{12}f_L^2 \\ &+ a_{13}f_a^2 + a_{14}f_b^2 + a_{15}CM + a_{16}CY + a_{17}CK \\ &+ a_{18}Cf_L + a_{19}Cf_a + a_{20}Cf_b + a_{21}MY + a_{22}MK \\ &+ a_{23}Mf_L + a_{24}Mf_a + a_{25}Mf_b + a_{26}YK + a_{27}Yf_L \\ &+ a_{28}Yf_a + a_{29}Yf_b + a_{30}Kf_L + a_{31}Kf_a + a_{32}Kf_b \\ &+ a_{33}f_Lf_a + a_{34}f_Lf_b + a_{35}f_af_b. \quad (5)\end{aligned}$$

The full quadratic model requires 36 new data points (over and above those used for original printer characterization) for computation of the model parameters. The mixed terms can be dropped from Equation 5, yielding a simplified quadratic model,

$$\begin{aligned}\mathcal{F}(C,M,Y,K,f_L,f_a,f_b) = {}& a_0 + a_1C + a_2M + a_3Y + a_4K + a_5f_L + a_6f_a \\ &+ a_7f_b + a_8C^2 + a_9M^2 + a_{10}Y^2 + a_{11}K^2 \\ &+ a_{12}f_L^2 + a_{13}f_a^2 + a_{14}f_b^2. \quad (6)\end{aligned}$$

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

ANN corrective models offer a more complex alternative to the polynomial regression models given in Equations (4), (5), and (6). They have the ability to model more complex systematic errors, but are also more susceptible to overfitting and introducing new error to the system. The ANN corrective models examined in this study are feed-forward networks with one hidden layer. They utilize hyperbolic tangent as the activation function. As with all regression models, the minimum number of data required for regression is equal to the number of unknown parameters in the system. The unknown parameters for ANNs are the weights and biases of the network. The number of weights in the ANNs used in this study is $N_{neurons}(N_{inputs} + N_{outputs})$, and the number of biases is $(N_{neurons} + N_{outputs})$. Because ANN outputs are nonlinear functions of the weights and biases, nonlinear regression is required to solve for model parameters.

Recalculating regression-model parameters

The alternative approach of updating an existing printer model based on a small set of newly acquired data may be applied to regression models. Newly-acquired data, combined with the original characterization data, form an augmented data set. An updated printer model is created by calculating new model parameters using this augmented data set. Weighting factors can be applied to the new data to control their influence. Conceptually, it is hoped that the underlying behavior of the system will be captured by the original characterization data, and the recharacterization data will provide a corrective effect in response to changes in the printing system.

The weighting of the new data must be carefully considered when retraining the regression models. If the new data are not weighted heavily enough, the retrained models will not differ significantly from the original models. If the new data are weighted too heavily, the system behavior captured by the original characterization data will be lost. There is also a potential for the introduction of new local errors when adding heavily-weighted data to the characterization set, as the regression models may develop undesirable local behavior in an attempt to fit the new data.

The color-management system used in this study, NeuralColor, is suitable for the approach of updating using a small set of new data. The regression models used by NeuralColor are ANNs that predict CIELAB values based on CMYK dot fractions.

Although ANN models were studied in the current work, the approach of recalculating model parameters can be applied to other types of color-management systems as well. Direct application of this method is suitable for any regression-based color-management system, such those using polynomial regression models [5, 6]. With the addition of several computational steps, the method of recalculating parameters with an augmented data set could be applied to a much wider range of color-management systems. In the case of a LUT-based system, for example, regressions model could be derived from the LUTs, updated using recharacterization data, and then used to create a new set of LUTs.

Experimentation

The methods outlined in the previous section were evaluated with a series of two experiments. In the first experiment, systematic error was introduced into a printing system by changing the paper stock. In the second experiment, error was introduced by changing the cyan toner cartridge. Experiments were carried out using a Tektronix Phaser 740 printer. The NeuralColor program was used as the color-management system, as described in the following section. Color measurements were made using a X-Rite Digital Swatchbook spectrophotometer.

NeuralColor

The program NeuralColor is a color-management system developed previously by the authors [7, 8, 9, 10]. NeuralColor is based on Pareto-optimal formulations that cast the color management problem in terms of competing objectives such as colorimetric accuracy, cost, and ink usage. The Pareto-optimal method requires the mapping functions $f_L(CMYK)$, $f_a(CMYK)$, and $f_b(CMYK)$ that predict CIELAB values based on CMYK inputs, and a numerical optimization routine capable of solving non-linear equality- and inequality-constrained optimization problems.

NeuralColor uses ANNs for the mapping functions f_L, f_a, and f_b. Each ANN is a function of C, M, Y, and K. The ANNs contain one hidden layer, with five, six, and seven neurons, respectively. Hyperbolic tangent is used as the activation function. The training data for the ANNs consist of 149 colors selected to capture printer behavior over the entire device gamut. For a listing of the 149-color characterization set, please refer to Littlewood, Drakopoulos, and Subbarayan [9]. The initial printer characterization in this study was determined by printing six copies of the 149-color characterization set. The data were averaged over the six measurements and used to train the ANNs f_L, f_a, and f_b.

For the purpose of the present study, NeuralColor may be viewed simply as a color-management system based on regression models. Since NeuralColor utilizes regression models, the approach of recalculating model parameters using an augmented data set may be applied directly.

Recharacterization data set

The choice of a recharacterization data set is important to ensure that a color-management system is updated accurately and efficiently. For the sake of efficiency, the data set should be as small as possible. Accuracy, however, tends to improve with an increase in the number of new measurements. Additionally, it is important that the recharacterization data be carefully located in the printer gamut, so as to accurately capture changes throughout the range of printable colors. Knowledge regarding the underlying changes in printer characteristics may be used to choose new measurement colors intelligently, perhaps focusing on an isolated part of the printer gamut if the changes are known to be local in nature.

Two sets of recharacterization data were used in this study, one containing 18 colors, and one containing 36 colors. In both cases, an effort was made to capture changes over the entire printer gamut. The 18-color set was created using the eight chromatic primaries of four-color printing, as well as an overprint of the three subtractive primaries, an overprint of all four colorants, and mixtures of each primary with black at 50% dot fraction. The 18-color set is presented in Table 1. The 36-color set is a superset of the 18-color set, with additional colors comprised of the eight chromatic primaries, an overprint of the three subtractive primaries, and an overprint of all four colorants, each at 30% and 70% dot fractions. Table 2 gives the additional CMYK values used in the 36-color set.

Table 1: *The 18-color recharacterization set.*

C	M	Y	K
1.0	0.0	0.0	0.0
0.0	1.0	0.0	0.0
0.0	0.0	1.0	0.0
0.0	0.0	0.0	1.0
0.0	1.0	1.0	0.0
1.0	0.0	1.0	0.0
1.0	1.0	0.0	0.0
1.0	1.0	1.0	0.0
1.0	1.0	1.0	1.0
0.0	0.0	0.0	0.0
0.5	0.0	0.0	0.5
0.0	0.5	0.0	0.5
0.0	0.0	0.5	0.5
0.0	0.5	0.5	0.5
0.5	0.0	0.5	0.5
0.5	0.5	0.0	0.5
0.5	0.5	0.5	0.0
0.5	0.5	0.5	0.5

Table 2: *The additional 18 color patches in the 36-color recharacterization set.*

C	M	Y	K
0.3	0.0	0.0	0.0
0.0	0.3	0.0	0.0
0.0	0.0	0.3	0.0
0.0	0.0	0.0	0.3
0.0	0.3	0.3	0.0
0.3	0.0	0.3	0.0
0.3	0.3	0.0	0.0
0.3	0.3	0.3	0.0
0.3	0.3	0.3	0.3
0.7	0.0	0.0	0.0
0.0	0.7	0.0	0.0
0.0	0.0	0.7	0.0
0.0	0.0	0.0	0.7
0.0	0.7	0.7	0.0
0.7	0.0	0.7	0.0
0.7	0.7	0.0	0.0
0.7	0.7	0.7	0.0
0.7	0.7	0.7	0.7

Evaluation methodology

Two sets of experiments were carried out to evaluate the recharacterization methods. In the first set of experiments, systematic error was introduced into the printing system by changing the paper stock. A standard white Nekoosa Bond by Georgia-Pacific was used as the original paper stock, and was then replaced with a multipurpose Xerox paper that is light gray in color. In the second set of experiments, colorimetric error was introduced by substituting an older cyan cartridge for the cartridge used during the original characterization. Both changes resulted in significant colorimetric error, and the goal was then to update the system in response to these changes.

A total of seven different corrective models were applied in each set of experiments, as follows:

1. A linear polynomial model (Equation 4) based on the 18-color data set;
2. A linear polynomial model based on the 36-color data set;
3. An abridged quadratic model (Equation 6) based on the 18-color data set;
4. An abridged quadratic model based on the 36-color data set;
5. A full quadratic model (Equation 5) based on the 36-color data set;
6. A one-hidden-neuron ANN model based on the 18-color data set; and,
7. A one-hidden-neuron ANN model based on the 36-color data set.

To evaluate the method of adding newly acquired characterization data to an existing data set, both the 18- and 36-patch characterization sets were added to the original 149-color characterization set used to train the ANNs f_L, f_a, and f_b used by NeuralColor. Two weighting schemes were used in each case. Each of the two sets was added five times and twenty times, resulting in four cases overall:

1. The original 149-color set combined with the 18-color recharacterization set added five times (239 data total);
2. The original 149-color set combined with the 18-color recharacterization set added twenty times (509 data total);
3. The original 149-color set combined with the 36-color recharacterization set added five times (329 data total); and,
4. The original 149-color set combined with the 36-color recharacterization set added twenty times (869 data total).

Test problem

A test problem containing 51 patches was constructed to evaluate the recharacterization methods for a variety of in-gamut and out-of-gamut colors. The MacBeth ColorChecker Chart makes up the first 24 patches in the test print. It is important to note that the MacBeth ColorChecker Chart contains colors that are outside the gamut of the Tektronix Phaser 740 printer used in this study, and hence cannot be reproduced with zero colorimetric error. An additional 27 in-gamut colors spanning several lightness levels and a variety of hues in the CIELAB color space were included as well. Specifically, at lightness levels of both 20 and 80, nine patches were specified with a and b set equal to all combinations of -10, 0, and 10. At a lightness level of 50, nine patches were specified with a and b equal to all combinations of -20, 0, and 20.

Test results are tabulated as follows: overall error, error for the MacBeth chart, and error for the 27-color test print. The single largest error throughout the 51-patch test is also listed, as well as the number of test colors improved by the corrective method. Three copies of the test patches were printed in each experiment, and the measured CIELAB values were averaged over the three prints. ΔE^*_{ab} error values were determined by comparing the original CIELAB input values to the measured CIELAB values.

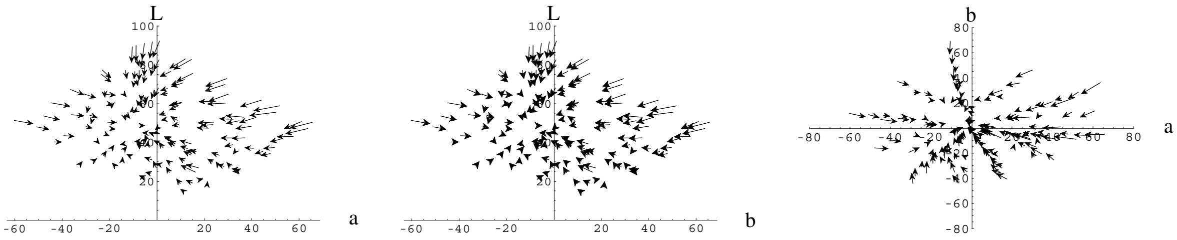
Results

Changes in printer characteristics resulting from the change in paper and the change in cyan toner cartridge are illustrated in Figures 1 and 2. These figures were created by reprinting the 149-color characterization set after changing the paper and toner, respectively. The new measurements of the 149-color characterization set were used only to create Figures 1 and 2; they were not used for updating the printer models. In the case of the change in paper stock, the general shift is toward the neutral axis with a decrease in lightness for colors in the high-lightness region. This is as expected, since the replacement paper has a much darker white point than the original paper. The change in paper stock increased average colorimetric error over the 149-color set from 5.0 ΔE^*_{ab} to 10.0 ΔE^*_{ab}. The general shift resulting from the change in cyan toner cartridge was toward the cyan portion of the gamut. The change in cyan toner cartridge increased average colorimetric error from 5.0 ΔE^*_{ab} to 7.6 ΔE^*_{ab}.

Change of paper

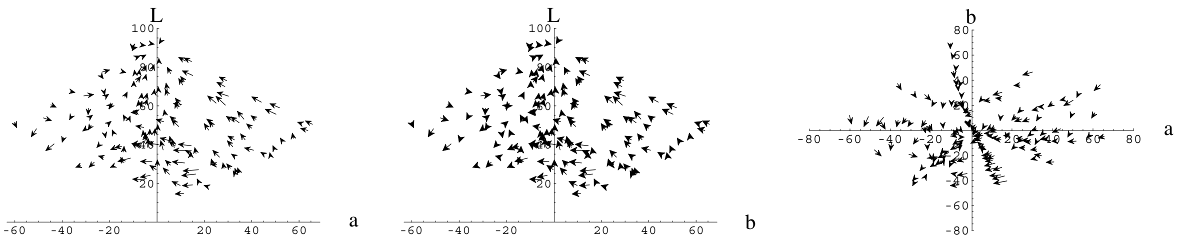
Corrective-model results for the change in paper stock are presented in Table 3. The corrective models gave excellent results, with the exception of the full quadratic model and the ANN model based on 18 colors. The successful corrective models removed between 80% and 90% of the error.

The full quadratic corrective model failed to reduce the average system error, had a maximum error of 87.9 ΔE^*_{ab}, and improved only three patches. In the case of the full



(a) L-a plane. (b) L-b plane. (c) a-b plane.

Figure 1: *Change in printer output resulting from the change of paper.*



(a) L-a plane. (b) L-b plane. (c) a-b plane.

Figure 2: *Change in printer output resulting from the change of cyan toner cartridge.*

quadratic model, the number of model parameters is exactly equal to the number of recharacterization data, resulting in an interpolation of the recharacterization data. This interpolation is highly susceptible to noise.

The corrective ANN model based on 18 colors also introduced error, as seen in the increased maximum error. Here, the corrective model improved 43 of the 51 test colors, but introduced error elsewhere, which is characteristic of overfitting.

Results obtained using an augmented data set to retrain the ANNs used by NeuralColor are given in Table 4. In each case, the newly trained ANNs yielded a lower overall error than the ANNs trained with the original characterization set and did not significantly increase the maximum error. The corrective ANNs trained with the 36-color set outperformed those trained with the 18-color set. In general, the number of times each data set was added did not have a significant impact on the results.

Change of toner cartridge

Results obtained for the application of corrective models to correct for the change in cyan toner cartridge are presented in Table 5. Table 5 includes two additional data columns, one giving the error for printed patches with a cyan dot fraction less than 0.5, and one giving the error for printed patches with a cyan dot fraction greater than 0.5. Both of the linear models and both of the ANN models succeeded in reducing the overall error by between 76% and 93% without a significant increase in maximum error. The abridged quadratic model actually outperformed the original characterization under the original conditions, indicating that all the systematic error was removed. As in the change-of-paper experiment, the full quadratic corrective model failed completely.

Results obtained using an augmented data set to retrain the ANNs used by NeuralColor in response to the change in cyan toner are given in Table 6. The retraining of ANNs with an augmented data set was less successful for the change in cyan toner than for the change in paper stock. ANNs trained with the 18-color set did not significantly improve the overall error, and dramatically increased the maximum error. The ANNs trained with the 36-color set had similar results; the overall error increased slightly and the maximum error increased dramatically. Only the ANNs trained with the 36-color set included five times reduced the error across all the error categories and did not introduce new error into the region of the printer gamut with a cyan dot fraction of less than 0.5.

Table 3: *Results for corrective models - change of paper.*

Approach	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
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

Table 4: *Results for regression model retraining - change of paper.*

Approach	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
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

Table 5: *Results for corrective models - change of cyan toner.*

Approach	Overall ΔE^*_{ab}	MacBeth Chart ΔE^*_{ab}	27-color Test ΔE^*_{ab}	$C > .5$ ΔE^*_{ab}	$C < .5$ 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
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

Table 6: *Results for regression model retraining - change of cyan toner.*

Approach	Overall ΔE^*_{ab}	MacBeth Chart ΔE^*_{ab}	27-color Test ΔE^*_{ab}	$C > .5$ ΔE^*_{ab}	$C < .5$ ΔE^*_{ab}	Max. ΔE^*_{ab}	Number Improved
Orig. characterization, orig. paper	5.0	6.7	3.4	5.6	4.6	16.1	N/A
Orig. characterization, new cartridge	7.6	9.2	6.2	10.5	6.0	18.5	N/A
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

Conclusions

This study validates corrective methods as a means to efficiently and accurately update an existing print-device characterization. The most successful of the methods employed are the linear, abridged quadratic, and one-hidden-neuron ANN corrective models, which reduced overall error for the change of paper and toner without introducing new error into the system.

Overfitting should be a major concern in the design of corrective methods. In this study, the errors introduced by the change of paper stock and the change of toner cartridge were approximately equal in magnitude to the error of the original printer model. This sets the stage for corrective methods to potentially overfit the model error, resulting in the unacceptable introduction of new error into the system. The balance between local and global control is crucial; methods that capture some local behavior can accurately model changes in the printing system, but if local behavior is too strong the corrective model may behave unpredictably in local regions. A corrective model that improves overall accuracy but introduces new local errors is a poor corrective method, and therefore it is recommended that simple corrective models exhibiting global control be selected. In addition, overfitting can be reduced by choosing a model with a small number of regression parameters relative to the size of the recharacterization set.

The ANN corrective models used in this study should be used cautiously. Their tendency to exhibit strong local behavior makes them prone to overfitting. If corrective ANNs are used, the number of hidden neurons should be kept small.

It is difficult to draw conclusions regarding the retraining of ANNs with an augmented data set. This approach was largely successful in reducing overall model error, but the maximum error across the entire printer gamut was often increased, and this detracts from the value of the method. As a general method, the approach of re-evaluating regression-model parameters may be valid, but additional studies are required in which this approach is applied to other types of regression models.

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Biography

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