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Printer spectral color characterization adjustment for change in substrates

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Abstract

Characterization data for printers is obtained by printing a test chart on the intended production substrate. In practice it is common for a different substrate to that used to obtain the characterization data to be used in proofing and in production, and this requires either reprinting and re-measuring the test chart or estimating new characterization data. Methods to do this exist for colorimetric characterization data, but with the increasing use of spectral data in the workflow, there is a need for a method that can be applied to spectral. reflectances. This paper proposes two different methods of adjusting printer spectral color characterization data for a change in substrates. In the first part, a Spectral Correction Technique was applied to spectral reflectance data obtained from different printers to predict a spectral color characterization data for an additional substrate. In the second part, the reference printing condition was used to adjust spectral color characterization data. The results were evaluated, and it was found that a good prediction is achieved with the use of machine learning.

Introduction

In the printing industry, a wide variety of substrates and their families have led to looking for alternative options for predicting color response in every substrate since the characterization process is time and resource-consuming. A number of sources have already investigated this problem, and some approaches have been widely adopted [1], [2]. Some characterization methods are based on spectral data [4], [5], [6], [7], [8]. Printer characterization methods may be solely numeric or may be based on the physical description of the printing process [1], [2], [10].

Beer's law and Neugebauer equations are classic examples of physically-based color prediction models; while others are based on an empirical approach [3], [9], using a relatively large number of color samples to which mathematical fitting techniques are applied. There is no straightforward solution to solving multi-substrate characterization problems - all the methods referred to above can be improved to get a more accurate characterization prediction. It is essential to obtain a reliable correction method that will be visually acceptable without additional measurements.

Two methods of spectral reflectance prediction

This work proposes and evaluates two printer spectral characterization adjustment methods for different substrates without additional printing and measuring. These are the Spectral Correction Technique and a Reference Printer-based method using machine learning. The latter method originated from [12] with a focus on prediction with data analysis.

Method 1: The Spectral Correction Technique

A correction method was developed [11] to adjust measured colorimetric data for differences in the backing material, and subsequently used to predict the measurements of a new substrate from reference printing conditions or to adjust printer characterization when the substrate colorimetry changed, primarily due to variation in the amount of optical brightening. Here we apply this approach in the spectral rather than colorimetric domain:

$$R_{pr}(\lambda) = \left(R_{ref}(\lambda) \times \left(1 + C(\lambda)\right)\right) - \left(R_{min} \times C(\lambda)\right) \quad (1)$$

$$C(\lambda) = \frac{R_{Wpr}(\lambda) - R_{Wref}(\lambda)}{R_{Wref}(\lambda) - R_{min}(\lambda)} \quad (2)$$

Where:

λ : [380,780] nm.

$R_{pr}(\lambda)$: The predicted spectral reflectance.

$R_{ref}(\lambda)$: The reference spectral reflectance.

$R_{min}(\lambda)$: The spectral reflectance of the patch where the inks are printed on top of each other with 100% coverage.

$R_{Wpr}(\lambda)$: The predicted spectral reflectance of white patch.

$R_{Wref}(\lambda)$: The reference spectral reflectance of white patch.

Method 2: Reference printing conditions

The idea for using reference conditions for adjusting printer characterization was taken from [14], where the predicted result is obtained as a vector difference between transforms P_1 and P_2 for differences in media and printer respectively (Figure 1).

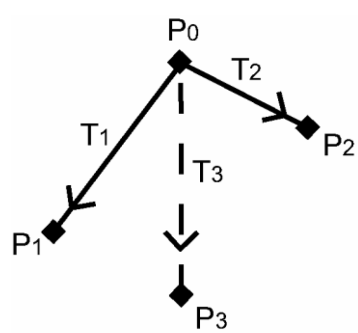

Figure 1. Transforms using reference printing condition.

A reference printer condition P_0 is defined by a set of colorimetric data and represents either by a model of this data or by a physical printer and media. The transforms T_1 and T_2 represent the transforms from this reference combination to a printer (printing condition P1 printed with same substrate and different printer) and substrate (printing condition P2, printed using the same printer and different substrate). The actual color transform T_3 is computed as the sum of the two vectors in CIELAB color space, but this will not apply in the same way in the spectral domain.

In the spectral domain, we assume that the difference between the spectral reflectance of the pair of substrates represents the difference in absorption between the two substrates. Therefore, that difference helps predict the ink printed on the substrates, indicating the chosen substrate's characterization.

$$f(P_1S_1, P_2S_1, \dots P_nS_m) = R_{nm}(\lambda) - R_{n_{ref}}(\lambda) \quad (3)$$

Where:

λ: [380,780] nm.

n: is number of printers.

m: is number of substrates.

$R_{nm}(\lambda)$: The predicted spectral reflectance for n-*th* printer and m-*th* substrate.

$R_{n_{ref}}(\lambda)$: The reference spectral reflectance of n-*th* printer.

Experimental

We used banner material and self-adhesive vinyl, papers, and three HP Latex printers with the same ink type in the evaluation.

We printed a 1485 patch test chart for every printer-media combination and measured it using M1 and M2 measurement conditions by Barbieri QB spectrophotometer.

To implement the Spectral Correction Technique, we used substrate pairs with similar b* to minimize the effect of different fluorescence levels in CIELAB color space for tristimulus correction. Then, we performed all the computations in the spectral domain and converted them to the colorimetric values to apply the color difference formula.

To implement the reference printing condition method, we used two approaches: a neural network with Keras and a multivariate polynomial regression.

For both methods, we organized the data differently with common preprocessing steps:

- The data were grouped based on the same reference printer. Then, for every data point of the group, we subtracted the spectral reflectance of the reference printer before prediction and added it after. Spectral reflectances were constrained to the range 0 - 1.
- We used printers and substrates as input variables and categorized them as a one-hot numeric array. One-hot encoding (OHE) step creates binary columns for the printer and substrate categories and returns a sparse matrix.
- The training dataset contained ten different combinations of substrate and printers with 41 wavelength intervals in the spectral domain. The test set includes four different combinations of printer and substrate and three references.

In the multivariate polynomial regression, we trained the model for every patch of printer-substrate combination and optimized it using cross-validation. As a result, we obtained 16335 different models with 42 polynomial coefficients for each model for all substrate and printer combinations in the training set using multivariate polynomial regression.

Considering that every printer, substrate, color patch, and wavelength of spectral reflectance are characteristics of our dataset, we treated those parameters as unique features for creating a neural network model. These models correlate those features to predict spectral reflectances. Then, we combined elements differently to get the desired output.

In the first case, we used printers, substrates, and color patch ID as input data to the neural network model to predict 41 wavelength values of spectral reflectance for every 1485 color samples.

In the second case, the data was organized in the same way as the polynomial regression: printers and substrates were used as input and spectral reflectance for all color samples with 60885 columns as output.

In the third considered case, knowing the printers, substrates, and wavelength intervals, we were trying to predict 1485 color samples for every wavelength and combination of printer and substrate. Then, finally, we made a model that correlates all possible parameters like printer, substrate, wavelength, and the sample ID to predict the spectral reflectance.

We tested different references for every scenario and evaluated their impact on the result.

Results

Method 1: The Spectral Correction Technique

The result shows in Table 1 that this technique works well for correcting spectral reflectances when the color of substrates changes. The correction works well for substrates with a maximum color difference of 12 ΔE_{2000}. After correction, we see that small color differences are still present. These residual differences suggest that substrates absorb the ink differently. In addition, the print and measurement systems add noise to the experiment.

Table 1: Prediction result with the Spectral Correction Technique

Printer name	Substrate Names Grouped by pairs	1485 color patches	ΔE_{2000}	
			Before correction	After correction
HP Latex 360	Antalis paper	Mean	3.07	0.36
	IGEPA	Max	9.82	0.78
HP Latex 560	MPI8726	Mean	2.9	0.25
	Antalis paper	Max	12.29	0.63
HP Latex 3100	MPI6021	Mean	4.06	0.19
	MPI1104	Max	11.48	0.88

Method 2: Reference printing conditions

We predicted spectral reflectances using reference printers and the multivariate polynomial model, and the neural network model. The results are shown in Table 2 and Table 3.

For a given data set, the multivariate polynomial model showed slightly better results. With the help of an optimization algorithm, we found that the most accurate prediction is with a second order polynomial. However, we saw that the IGEPA substrate was not predicted accurately in every iteration using different references. Running the multivariate polynomial regression for a dataset measured without UV filter slightly improved the overall prediction result and significantly improved the prediction for the IGEPA substrate. Thus, using this approach the IGEPA substrate was no longer ab outlier within the M2 measurement conditions dataset.

For all predicted spectral reflectance, we saw a similar tendency in which colors were predicted less accurately. As a result, most of the patches with color difference $\Delta E_{2000} > 1$ are less chromatic tertiary colors and have CIELAB L* lightness in the range 70-80. Thus, we can conclude that light near-neutral colors have more variable results, or possibly that printers have less repeatability in low contones due to the variability in the ink drop size. Using the M2 data set (measured with UV-blocking filter) improves the prediction, although the same trend of poorly predicted lower chromatic light patches persists.

Table 2: Prediction result with polynomial regression

Printer / Substrate		ΔE_{2000} for 1485 patches	
		Mean	Max
HP Latex 360	MPI1104	1.13	5.14
	MNSO600	1.06	5.07
HP Latex 560	MPI8726	1.08	4.05
HP Latex 3100	IGEPA	2.71	11.94
	Antalis paper	1.68	7.66

In comparison, the ANN model implemented with Keras gave relatively good predictions based on reference conditions with a higher number of outliers. Table 3 shows the implementation results of ANN models, where the dataset was structured differently. In Result 1, the dataset was organized the same way as in the case of the multivariate polynomial regression model: printer and substrates are inputs variables, 60885 columns of spectral reflectance as output variables. In addition, we experimented with changing the number of layers, activation, and optimization functions. Among the optimization we tried were Adam [16], Adamax, SGD, and RMSprop [17] [18], and we found out that RMSprop gave the most accurate results. We tried the rectified linear (Relu), the exponential linear (Elu), hyperbolic tangent (Tanh), and exponential for the activation function. In the end, we discovered that Tanh in the first layer and Relu in 2nd layer gave the best result in the prediction. Apart from the input and output neuron layers, we added one additional hidden layer for the model to look for the optimum weights for every parameter. However, adding more layers did not lead to better results, although it increased the training time considerably.

We kept the number of neurons in the first layer equal to the input dimension 1494 and the number in the last layer the same as output dimensions: 41 was an intuitive choice that was found to work well.

Since we didn't have many samples for creating the ANN model, we manually ran k-fold cross-validation on the full dataset to find optimal parameters for the ANN model. Then, we validated it using the training set.

Table 3 shows Result 2 when the neural network model predicts 41 spectral reflectance numbers with a subtracted reference printer based on a given printer, substrate, and color sample ID. Unlike Result 1, Result 2 includes a sample ID as an independent feature. This data structure keeps the wavelength sampling together, so generic settings for the process of optimization and cross-validation can still be applied.

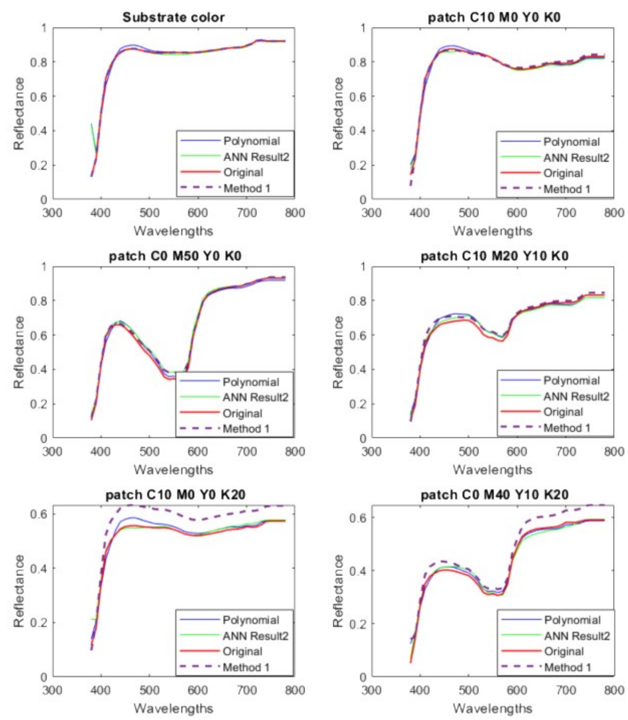

Figure 2. Predicted and original spectral reflectances for L560 MPI6021

Looking closely at all spectral reflectances predicted poorly with the ANN model, we saw a similar tendency as in the case with the multivariate polynomial model. Again, colors close to neutral CIE Lab axis with 75-85 L* gave the most inaccurate spectral reflectance prediction on a larger scale.

Table 3: Prediction result with Keras neural network

Printer / Substrate	ΔE_{2000} for 1485 patches			
	Result 1		Result 2	
	Mean	Max	Mean	Max

HP Latex 360	MNSO600	1.31	18.34	1.3	13.11
HP Latex 560	MPI6021	1.66	15.90	1.58	15.10
	MPI8726	1.58	14.44	1.35	9.63
	IGEPA	2.08	25.85	2.5	28.67
HP Latex 3100	Antalis paper	1.48	19.11	2.29	18.82

In the experimental part, we implemented two other options for structuring the data for analysis. One of the options was to predict 1485 color samples for every wavelength interval and combination of printer and substrate. As a result, we faced difficulties keeping all 41 points of spectral reflectance for every color as a single array. Another option was considering printers, substrates, wavelengths nanometers, and color sample ID as input variables (unique features) and the value of spectral reflectance as output predicted variable. But we faced the same issues of manual preprocessing, when all wavelength nanometers per printer, substrate, and color patch need to be kept together in one of the sets for training, validation, and testing. These extra preprocessing and post-processing steps introduce a high risk of training-serving skew when the dataset is not segregated correctly beforehand.

We manually chose the different references and tested them for both machine learning models with reference conditions and their impact on the results obtained. And we found that certain reference conditions led to a better prediction result. For example, we found that a high level of optical brightening agents (OBAs) for reference printers gave rise to a less accurate prediction. We also tried to implement models without references or one fixed reference, and we obtained a significantly less accurate result.

Conclusion

We evaluated two methods for estimating spectral characterization data with a change in substrate. The spectral correction technique was found to give a more accurate result in comparison with the reference printer method.

However, spectral correction works in pairs using a single reference. Despite this, the technique is simple, easy to use, and quickly implemented for a relatively small dataset. Furthermore, unlike the reference printer method, the Spectral Correction Technique does not predict spectral reflectances from scratch. Instead, it corrects the spectral reflectances based on the spectral reflectance of white of another substrate, which makes reflectances closer to each other.

When implementing the reference printer method, we tried to predict the ink on the substrate by introducing the references and subtracting them from the spectral reflectances. This approach represents the differences in absorption between two substrates, and multivariate polynomial models and the ANN models could predict the absorption between substrates well. Nevertheless, the multivariate polynomial regression model gave a more accurate spectral reflectance prediction for a given dataset since it most accurately describes a small dataset. Thus, for the current dataset, characterization with instruments of deep learning would not be a solution.

However, the multivariate polynomial model becomes a computationally costly process for more complex datasets to add more features into the equation like Sample ID. Therefore, in the case of working with a very large amount of data, the neural network expects to get a more accurate prediction than a polynomial regression.

Also, we suggest further improvement of the result to adding more data in training set for the colors within CIELAB L* 70-85.

For further analysis, we propose creating a reference as a separate feature vector or absorption vector in the feature space for the work with extensive data. The reference feature vector will be computed on the preprocessing stage and treated as input data. In this case, it is essential to assign a reference dynamically without interfering manually. Furthermore, other features as measurement conditions should be added into the feature space and treat the data differently depending on if there is UV information in the spectral reflectance or not.

References

[1] M. Shaw, G. Sharma, R. Bala, and E.N. Dalal, ‘Color printer characterization adjustment for different substrates,’ Col Res Appl, 28, 454-467, 2003.

[2] M. Shaw, et al. "Minimal-effort characterization of color printers for additional substrates." Color and Imaging Conference. Vol. 2002. No. 1. Society for Imaging Science and Technology, 2002.

[3] R. Schettini, D. Bianucci, G. Mauri, S. Zuffi, An Empirical Approach for Spectral Color Printers Characterization, Proc. CGIV, 2004.

[4] D. R. Wyble, R. S. Berns, A Critical Review of Spectral Models Applied to Binary Color Printing, Color Research and Application, 25, 1, 2000.

[5] E. J. Stollnitz, V. Ostromoukhov, D. H. Salesin, Reproducing Color Images Using Custom Inks, Proc. of SIGGRAPH’98, in Computer Graphics Proceedings, Annual Conference Series, 267-274, 1998.

[6] K. Iino and R. S. Berns, A Spectral Based Model of Color Printing that Compensates for Optical Interactions of Multiple Inks, AIC Color 97, Proc. 8th Congress International Color Association, 1997.

[7] D. Tzeng, R. S. Berns, Spectral-Based Six-Color Separation Minimizing Metamerism, The Eighth IS&T/SID Color Imaging Conference, Scottsdale, Arizona, USA, November 7-10, 2000.

[8] Z. Silvia, R. Schettini, and G. Mauri. "Spectral-based characterization of inkjet printers by neural and genetic algorithms." IS&TS Conference. Society For Imaging Science & Technology, 2003.

[9] D. Littlewood and G. Subbarayan. Maintaining an accurate printer characterization. Twelfth Color Imaging Conference: Color Science and Engineering Systems, Technologies, and Applications, 12:203–210, 2004.

[10] C. de M. Bezerra, C. J. Hawkyard, H. M. Kulube, S. Reyner, “Color matching for ink-jet prints on paper,” 1997.

[11] McDowell, David Q., Chung, Robert, Kong, Lingjun. Correcting Measured Colorimetric Data for Differences in Backing Material. TAGA Proceedings, pp 302-309, 2005.

[12] P. Green, "A reference printer and color management architecture," Proceedings Volume 6493, Color Imaging XII: Processing, Hardcopy, and Applications; 64930R, 2007.

[13] J. Schanda, ed. Colorimetry: Understanding the CIE system. John Wiley & Sons, p.31, 2007.

[14] P. Green, and Y. Chang. "A method to estimate the UV content of illumination sources." Color Imaging XVI: Displaying, Processing, Hardcopy, and Applications. Vol. 7866. International Society for Optics and Photonics, 2011.

[15] B. Kwame, P. Green, and M. Pointer. "Perceived acceptability of color matching for changing substrate white point." Color Imaging XVIII: Displaying, Processing, Hardcopy, and Applications. Vol. 8652. International Society for Optics and Photonics, 2013.

[16] Jais, I. K. M., Ismail, A. R., & Nisa, S. Q. (2019). Adam optimization algorithm for wide and deep neural network. Knowledge Engineering and Data Science, 2(1), 41-46.

[17] Arcos-García, Á., Alvarez-Garcia, J. A., & Soria-Morillo, L. M. Deep neural network for traffic sign recognition systems: An analysis of spatial transformers and stochastic optimisation methods. Neural Networks, 99, 158-165, 2018.

[18] Haji, S. Hikmat, and A.M. Abdulazeez. "COMPARISON OF OPTIMIZATION TECHNIQUES BASED ON GRADIENT DESCENT ALGORITHM: A REVIEW." PalArch's Journal of Archaeology of Egypt/Egyptology 18, no. 4, 2021.

[19] Géron, Aurélien. Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems. O'Reilly Media, 2019.

Authors Biography

Anastasiia Gudzenchuk received her international master's degree in Color Science in 2017. Since then, she worked as writing system's engineer at the large format printer department of R&D HP inc. and currently works at Color Concepts BV as color scientist. Her work has focused on printer characterization using instruments of machine learning.

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