An Iterative Cellular YNSN Method for Color Printer Characterization

A. Ufuk Agar and Jan P. Allebach
School of Electrical and Computer Engineering
Purdue University, West Lafayette, IN 47907
{*agar,allebach@ecn.purdue.edu*}

Abstract

We propose an iterative method for color printer characterization. We employ a parametric spectral model for color printers based on cellular YNSN (Yule-Nielsen modified spectral Neugebauer) equations. We find the Yule-Nielsen parameter from least squares regression over a training set of spectral measurements using the Euclidean distance in spectral distributions space as the error criterion. We iteratively divide the cells in the colorant space until the average prediction error ΔE in every cell is less than a given value.

1. Introduction

Modern color management systems require that color printers be characterized in some device independent color space such as CIE (Commission Internationale de L'Éclairage) $L^*a^*b^*$. To characterize a 3 colorant printer in the CIE $L^*a^*b^*$ space, we must evaluate the printer transfer function which maps points in the printer input CMY (cyan, magenta, yellow) colorant space to the points in the printer output CIE $L^*a^*b^*$ space for every point in the CMY space, i.e. every possible colorant combination. The highly complex nonlinear interaction of the colorants with each other and the paper substrate require that a very large number of sample color patches be printed and measured for accurate empirical characterization of a color printer. This characterization should be repeated each time there is a change in the colorants or a change in the paper substrate.

The alternative approach is to model the printer colorimetrically, or spectrally, or to model the printing process physically. Using model based approaches, a color printer can be characterized using a small number of parameters. Therefore, these approaches require considerably fewer measurements than the empirical ones. In this paper, we propose an iterative approach to printer characterization based on cellular YNSN (Yule-Nielsen modified spectral Neugebauer) equations, using a parametric spectral model.

2. Neugebauer Color Mixing Model

One of the very first and the most commonly used spectral model that mathematically describes the color printing process is the Neugebauer color mixing model. Neugebauer [1] noted that there are 8 dominant colors, known as the Neugebauer primaries, namely white(W), cyan(C), magenta(M), yellow(Y), red(R), green(G), blue(B), and black(K) for the case of a 3 colorant CMY color printer. These primaries correspond to one, two, and three color overprints of the colorants C, M, Y or to no colorant on paper (W). Geometrically, Neugebauer primaries can be interpreted as the vertices of a unit cube in the CMY colorant space with the vertices $\{0,0,0\} \equiv W$, $\{1,0,0\} \equiv C$, $\{0,1,0\} \equiv M$, $\{0,0,1\} \equiv Y$, ..., $\{1,1,1\} \equiv K$. An alternative labeling of these primaries is therefore W, C, M, Y, MY, CY, MY, and CMY respectively.

The spectral Neugebauer equations state that

$$R(\lambda) = \sum_{i=1}^{8} w_i R_i(\lambda), \tag{1}$$

where $R(\lambda)$ is the predicted spectral distribution as a function of wavelength λ of a given patch printed using 3 colorants, $R_i(\lambda)$ is the spectral distribution of the patch with only the i-th Neugebauer primary on it, and the weight w_i is the fractional proportion of the i-th Neugebauer primary in the given patch. $R_i(\lambda)$ is defined as

$$R_i(\lambda) = C_i(\lambda)\ S(\lambda), \tag{2}$$

where $C_i(\lambda)$ is the spectral distribution of the colorant combination for i-th Neugebauer primary and $S(\lambda)$ is the spectral distribution of the paper substrate.

Neugebauer employed Demichel's dot overlap model where the dots are assumed to be placed using a random or rotated screen [2],[3]. Furthermore, the colorant layer is assumed to be uniform and the boundaries of the dots are assumed to be well defined. Under these assumptions, the weights w_i are called Demichel coefficients; and they are equal to the probability of occurrence of the respective

Neugebauer primaries on a given patch. They can be interpreted as the expected values of the fractional area coverage of the primaries.

An important optical phenomenon that the Demichel dot overlap model fails to account for is optical dot gain. Optical dot gain is defined as the change in measured reflectance due to interactions between the colorants and the paper substrate, mainly due to lateral scattering of light in the substrate. Yule and Nielsen [4] modified the Neugebauer equation to take into account optical dot gain for a monochrome printer and empirically found the following power law expression

$$R(\lambda)^{\frac{1}{n}} = w_B R_B(\lambda)^{\frac{1}{n}} + w_W R_W(\lambda)^{\frac{1}{n}}, \qquad (3)$$

where $R_B(\lambda)$ and $R_W(\lambda)$ are the spectral distributions of the black ink and white paper respectively. The factor n is called the Yule-Nielsen factor. It is empirically derived from the best fit of the model to the training data set.

Viggiano [5] extended the Yule-Nielsen equation (3) to the case of color halftones and obtained the following Yule-Nielsen modified spectral Neugebauer equation.

$$R(\lambda)^{\frac{1}{n}} = \sum_{i=1}^{8} w_i R_i(\lambda)^{\frac{1}{n}}. \qquad (4)$$

It has been shown that inclusion of the Yule-Nielsen factor significantly improves the fit of the model to the training data set [2], [3].

Like the Yule-Nielsen factor, the cellular framework introduced by Heuberger *et al* also increased the accuracy of Neugebauer color mixing models considerably [6], [7]. This framework is the geometric extension of the unit cube in CMY to a uniformly sampled lattice structure in CMY. The unit cube in CMY is subdivided into smaller subcells with vertices at uniformly sampled grid points in the CMY domain. In addition to the spectral distributions of the 8 Neugebauer primaries, the spectral distributions of the vertices of the subcells are also measured. This finer structure provides a higher level of accuracy at the cost of more spectral measurements [7], [3].

3. Model Based Color Printer Characterization

Many researchers have studied the application of the color mixing models described above and other color mixing models to the problem of color printer characterization. Rolleston and Balasubramanian [7] compared the performances of colorimetric and spectral, Yule-Nielsen modified and simple, non-cellular and cellular Neugebauer equations. Kang [8] also compared the accuracy of spectral Neugebauer and Yule-Nielsen modified spectral Neugebauer equations along with three other color mixing models: Clapper-Yule multiple internal reflections model, Beer-Bouger law, and Kubelka-Munk theory. Balasubramanian [3] studied the effects of using the cellular framework and incorporating the Yule-Nielsen factor in the spectral Neugebauer equations.

Emmel *et al* [9] used a grid-based method to colorimetrically predict the behavior of color printers which accounts for the varying density of the colorants on the dots and the light diffusion in the underlying paper substrate. Chang *et al* [10] proposed a method based on Newton's minimization technique to estimate the fractional proportions of the Neugebauer primaries more accurately using additional non-primary Neugebauer colors. Lee [11] applied an optimization technique called sequential quadratic programming to estimate the Yule-Nielsen modified spectral Neugebauer model parameters for a color halftone printer. Balasubramanian [12] carried out a weighted least squares regression over the training set of spectral distribution measurements to create a Yule-Nielsen modified spectral Neugebauer model.

Hua and Huang [13] employed a model which they called the advanced cellular YNSN (Yule-Nielsen modified spectral Neugebauer) model where the weighting coefficients w_i in (4) showing the fractional proportions of the Neugebauer primaries are functions of wavelength λ instead of constants. Meireson and Van De Capelle [14] proposed a new mathematical expression for the color mixing in HIFI color printers (color printers with more than 4 colorants) that is motivated by the Yule-Nielsen modified spectral Neugebauer model and the Kubelka-Munk theory.

4. Our Method

For a 3 colorant CMY color printer, we start by measuring the spectral distributions and calculating the CIE $L^*a^*b^*$ values of the $27(3 \times 3 \times 3)$ samples corresponding to the various combinations of 0%, 50% and 100% C, M, and Y colorants. These samples can be interpreted as the points of the grid formed by dividing the unit cube in the CMY colorant space, at the planes $C = \frac{1}{2}$, $M = \frac{1}{2}$, $Y = \frac{1}{2}$. The 8 vertices of this subdivided unit cube correspond to the 8 Neugebauer primaries.

Using the Yule-Nielsen modified spectral Neugebauer equation (4) and the spectral distributions of the 8 Neugebauer primaries, $R_i(\lambda), i = 1, 2, \ldots, 8$, we carry out a least squares regression over the spectral distributions of the remaining 21 samples. We assume that w_i is the fractional proportion of the i-th Neugebauer primary in the given sample. We find the Yule-Nielsen factor n that minimizes RMS (root-mean-squared) Euclidean distance between the predicted and measured spectra in the 36 dimensional spectral distributions space ($R(\lambda)$, sampled at $\lambda = 380, \ldots, 730$ nm) , for the 21 training non-primary

color samples.

Once the Yule-Nielsen factor and hence the spectral model for the printer are determined, we measure the accuracy of the model. We calculate the ΔE prediction errors for the 21 training samples and find the RMS ΔE prediction error at the vertices of each of the 8 subcells in the unit cube formed by dividing it at the planes $C = \frac{1}{2}$, $M = \frac{1}{2}$, $Y = \frac{1}{2}$. We further divide the subcells with RMS ΔE prediction error above a given threshold into 8 subcells.

After each subdivision, we measure the accuracy of the model in terms of RMS ΔE, at the vertices of the newly created 8 subcells by going back to the grid structure right before the subdivision and predicting the reflectance spectra of the grid points that we will be adding to the grid structure with the given subdivision.

We continue dividing the subcells into 8 until the RMS ΔE prediction error in every subcell is below a given threshold value or until we reach the resolution of the finest grid in the CMY colorant space. This method of *"looking back"* into the previous grid structure to make decisions to go finer in the grid structure allows us to efficiently create grid structures without the cost of additional testing spectral measurements. Our iterative subdivision technique results in a probably unbalanced, oct-tree structured grid.

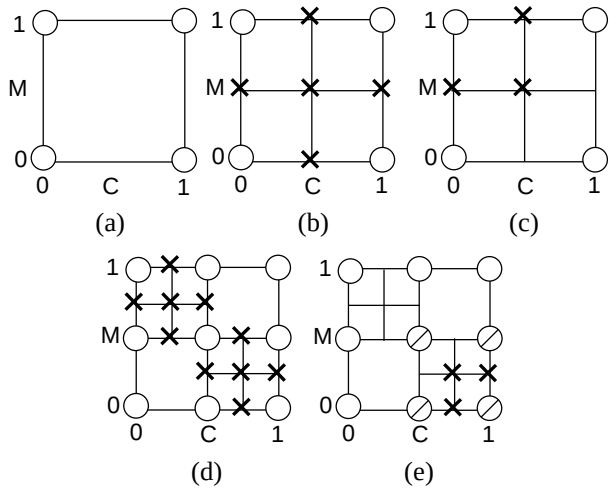

Figure 1: *The iterative division technique for a 2-D grid structure.*

In Fig. 1, we show in 2-D for ease of presentation the iterative subdivision technique explained above on the $Y = 0$ plane of the CMY unit cube. We start with a unit square grid structure with 4 grid points as shown in Fig. 1a. We divide the unit square into 4 subcells at the lines $C = \frac{1}{2}$ and $M = \frac{1}{2}$. We now have a grid structure with 9 grid points , 5 of which are newly added to the grid structure and are shown with $\times$ in Fig. 1b. We predict the spectral distributions of these 5 points using the original 4 grid points, shown with $\bigcirc$ in Fig. 1b. For each of the newly formed subcells, we find an RMS ΔE prediction error using the 3 newly added grid points per subcell, *e.g.* Fig. 1c shows the 3 grid points (shown with $\times$) used in calculating the RMS ΔE prediction error for the upper left subcell. We further divide the subcells with RMS ΔE prediction error greater than a threshold. Let us assume that only the prediction errors in the upper left and the lower right subcells exceed the given threshold value. We divide both of these subcells into 4 subcells and obtain the grid structure shown in Fig. 1d, where again the previously existing grid points are shown with $\bigcirc$ and the newly added ones are shown with $\times$. Now, for each of these recently created 8 subcells, we need to *"look back"* to the previous grid structure and compute the accuracy of the model by interpolating the spectral distributions of the 3 vertices of each subcell which are recent additions to the grid structure. For example, to find the RMS ΔE prediction error for the lower right subcell of the lower right subcell, we predict the spectral distributions of the 3 grid points shown with $\times$ in Fig. 1e using the 4 closest grid points shown with $\oslash$. We terminate dividing the subcells when the RMS ΔE prediction error is below a given threshold value or when we reach the resolution of the finest grid in the $Y = 0$ CM colorant plane, in every subcell.

5. Experimental Results

We have tested our iterative color printer characterization method on a HP 692C 300dpi color inkjet printer with 3 colorants (CMY). Our test data consisted of the spectral distributions of 4913 print samples uniformly located in the CMY space (the points in a uniform grid of size $17 \times 17 \times 17$) measured with a Gretag SPM50 spectrophotometer and their calculated CIE $L^*a^*b^*$ values under $D50$ illumination. The 27 samples (8 primary and 21 non-primary colors) in the grid one level finer than the unit cube (unit cube divided into 8 subcells) were used to calculate the Yule-Nielsen factor n. Through a least squares regression in $R(\lambda)$, the optimal value for n was found to be 1.6. Then, the iterative subdivision of the subcells was carried out using different thresholds for each level of the grid.

After the algorithm terminated, the selected grid points were used to interpolate the spectral distributions of 4913 test samples using the cellular Yule-Nielsen modified spectral Neugebauer model (4) with a Yule-Nielsen factor n of 1.6. We then computed RMS ΔE prediction error between the 4913 samples and their interpolated values. For comparison, we have also computed RMS ΔE prediction errors for uniform grids of size $27(3\times3\times3)$, $125(5\times5\times5)$, $729(9 \times 9 \times 9)$, and $4913(17 \times 17 \times 17)$, with and without using a Yule-Nielsen factor n of 1.6. Fig. 2 displays the variation of RMS ΔE between the predicted and measured spectra of the test samples, as a function of the number of

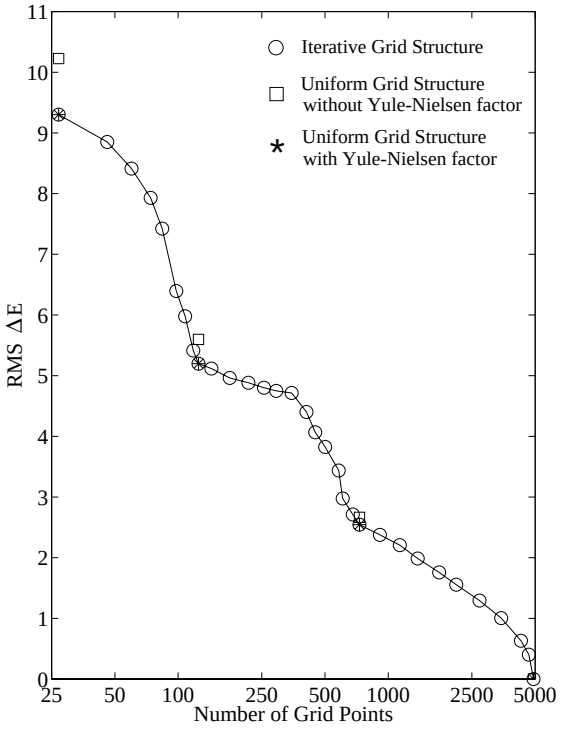

Figure 2: *RMS ΔE error performance.*

grid points selected by the iterative algorithm; and compares its performance to uniform grids. The error performance of our algorithm equals that of uniform grids using a Yule-Nielsen factor and performs better than linear prediction using uniform grids without a Yule-Nielsen factor. With our method, we can create a grid of size that does not correspond to a uniform grid structure to achieve a given target RMS ΔE prediction error. For example, to achieve an RMS ΔE performance better than or equal to 3 units, a uniform grid structure requires that we use the $9 \times 9 \times 9$ grid structure with 729 grid points. With our approach, we can achieve this level of performance with about 607 grid points. Similarly, to achieve an RMS ΔE performance better than or equal to 1 unit, a uniform grid structure requires the full 4913 point data set as grid points, whereas our method can achieve this level of prediction accuracy with about 3448 grid points.

6. Conclusion

In this paper, we developed an iterative method to characterize color printers employing a parametric cellular YNSN (Yule-Nielsen modified spectral Neugebauer) model. Our results indicated that our method offers a means for choosing lookup table sizes that do not correspond to a uniform grid structure and creating a grid structure that will achieve a given target RMS ΔE prediction performance.

7. References

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