

OPTIMIZING OUTPUT DEVICE MODELS IN PRINT PRODUCTION

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ABSTRACT

Process modeling has found application in many industrial processes. In print production, it is a part of device characterization process. Accurate color reproduction is the most important quality factor in print production, and it is achieved through the use of device profiles. Device profiles contain multiple processing elements, and their accuracy depends on the choice of the model, and on the way the model is split through the processing elements. This paper investigates the improvements in quality gained by different arrangements of the model, and the existence of criteria in the data for choosing the optimal solution.

Keywords: ICC profile, device model, print production

1 INTRODUCTION

Process modeling is used in a wide variety of engineering and scientific applications. In print production, it is used to model (characterize) the behavior of input and output devices. The purpose of output device characterization is the prediction of inputs needed to achieve a certain response (output). In the context of color reproduction processes, device modeling a part of color management. When modeling output devices, predicting response to a given input is called forward color management, and predicting the input needed to produce a certain response is called reverse color management. In color managed workflows, the desired response is known. It is the color appearance as similar to the original as possible. Therefore, predicting inputs needed to produce the desired response (reverse color management) is the goal of device modeling in this context.

The need for creating a model arises from the practical inability to measure all of the possible permutations of input variables. Output device inputs are usually RGB or CMYK color values. In the case of 8-bit RGB input values, there are 16 777 216 permutations (with repetition). The model is fitted to a subset of data obtained by measuring the response (in XYZ or Lab color space) for a known limited set of inputs evenly distributed throughout the input space. The model is then used to predict response values for those inputs that were not included in the training set due to the abovementioned practical limitations. As many different models have been developed, each of them has some advantages and disadvantages, and their goodness of fit depends on the data (device characteristics) to be fitted.

2 MODELS

Models are analytical expressions describing the total variation in one quantity, y , by partitioning it into a deterministic component given by a mathematical function of one or more other quantities, x_1, x_2, \dots , and a random component that follows a particular probability distribution. The general form of the model is:

$$y = f(\vec{x}; \vec{\beta}) + \varepsilon \quad (1)$$

In the functional (deterministic) part, \vec{x} denotes the predictor variables, and $\vec{\beta}$ denotes the parameters. The goal of all the modeling processes is finding the parameters β which minimize the error term ε ,

[1]. The parameters are determined using the measured data, usually referred to as training set. Mathematical functions used for this purpose are whole rational functions (polynomials), and the process of finding the optimal parameters β is essentially finding the polynomial coefficients such that the resulting polynomial fits the data as close as possible. This is done by regression. By convention, \mathbf{d} and \mathbf{c} are used to denote the input and output color vectors. \mathbf{d} is a $1 \times m$ vector, where m is the number of color space dimensions, and \mathbf{c} is a $1 \times n$ vector, where n is the number of colorants (primaries). The device characterization function is approximated by the linear relationship $\mathbf{c} = \mathbf{d} \cdot \mathbf{A}$. The samples $\{\mathbf{c}_i\}$ and $\{\mathbf{d}_i\}$ are collected into a $T \times n$ matrix $\mathbf{C} = [\mathbf{c}_1, \dots, \mathbf{c}_T]$, and $T \times m$ matrix $\mathbf{D} = [\mathbf{d}_1, \dots, \mathbf{d}_T]$. The optimal \mathbf{A} , i.e. the least squares fit, is given by $\mathbf{D}^+ \mathbf{C}$, where \mathbf{D}^+ is the generalized inverse, [2]. The transforms are then given by:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \mathbf{A} \begin{bmatrix} R \\ G \\ B \end{bmatrix}; \quad \mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad (2)$$

First-order model is not accurate enough for most devices, and in such cases higher-order polynomial models are used. The transform equation for second-order model becomes:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} & a_{26} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} \end{bmatrix} \begin{bmatrix} R \\ G \\ B \\ R^2 \\ G^2 \\ B^2 \end{bmatrix} \quad (3)$$

The optimal matrix \mathbf{A} is found in the same way as for the first-order model, and the transform equation can be extended to any order polynomial. Nevertheless, it is preferable to use low order polynomials because every extra order adds a bend to the function (local maxima or local minima), and tends to fit noise present in the data, [3].

2.1 Global models

Global models are fitted to the whole range of data. If the device is closely linear, it can be modeled by low order polynomials. However, nonlinear devices require higher order models which always come with risk of over fitting the data. If the polynomial order is too low, the model is not accurate enough, at least in some regions of color space. If it is too high, it can fit noise in the data and again lead to inaccurate predictions. In the extreme case, when the measured values aren't monotonically increasing, the fitted function can predict negative output values for small input values. This case is shown in Figure 1, where four points are fitted with a third order polynomial.

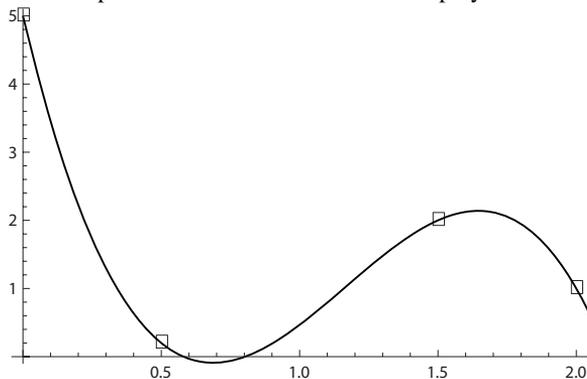


Figure 1. Polynomial fitting with negative values

2.2 Local models

Local models use low degree polynomials on subsets of data. The obvious benefit of this approach is that nonlinear devices can be modeled more accurately using simpler models which don't tend to fit

noise. However, this results in a large number of models and, except in the case of splines, rough edges between models.

2.3 Local model selection proposal

The current most common approach to device modeling is the use of local models. Usually a first order or a second order model is applied to equal ranges of input/output values. This results in a large number of models.

The authors of this paper suggest the modeling method that first analyzes the data, and then selects a smaller number of local models based on the data distribution. The main criteria for polynomial order selection is the data curvature in different ranges of the data. The curvature can be examined by calculating gradients between pairs of points and examining their constancy. Example of a subset of data for the analysis is shown in Table 1. Normally, a whole range of inputs [0, 255] would be needed. If the gradients do not change significantly on a given interval, a simple first order model will suffice. However, if the gradients change significantly on a relatively small interval, a second order, or even third order polynomial would be needed to fit that data.

Table 1. Example of data subset for analysis

RGB	X		Δ RGB	Δ X	Δ X/ Δ RGB
12	3,321191		13	0,532887	0,040991
25	3,854078		13	1,597002	0,122846
38	5,45108		13	1,030235	0,079249
51	6,481315		17	2,359482	0,138793
68	8,840797		8	0,959208	0,119901

3. EXPERIMENTAL

For the purpose of this study, data was collected from a desktop ink-jet printer. The characterization data was obtained using commercial software. The data was obtained by printing a chart of 288 color patches and measuring them by a spectrophotometer. The software created a text file containing the input *RGB* values and their corresponding spectral values for each patch. Special software was written for the purpose of data analysis. That software was used to convert the spectral data into *XYZ* tristimulus values, and extract *XYZ* responses for inputs where $R=G=B$. Theoretically, if the device is calibrated, equal *RGB* input values should produce neutral gray color patches. Unfortunately, neutral grays are obtained with unequal *XYZ* values.

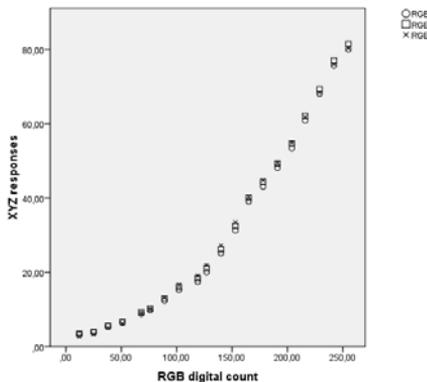


Figure 2. *XYZ* responses of the observed printer

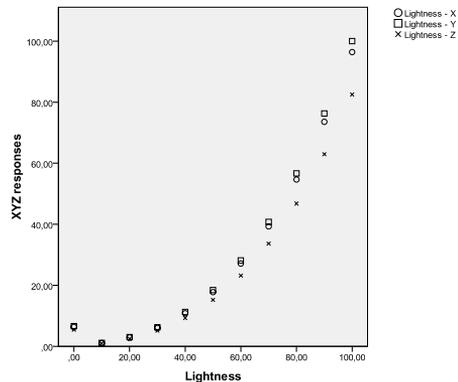


Figure 3. Theoretical *XYZ* values

The scatter plot shown in Figure 2 reveals that in the case of the observed printer, the measured *XYZ* responses have more similar values in darker regions of the color space, and their difference increases toward the lighter regions, but then starts to decrease again. If the responses were neutral gray, the

difference between responses would continue to increase (X values would be greater than Z , and Y would be greater than X). This is clearly displayed in Figure 3.

4. DISCUSSION

Since the results presented in previous section suggest that in some cases XYZ values can differ significantly, the question is whether one of them, for example X as shown in Table 1 can be representative of the other two for local models selection. In any case, these differences could be corrected by the use of a one dimensional lookup table. The standard ICC profile tag consists of a one dimensional lookup table on the entrance, a three dimensional lookup table in the middle, and another one dimensional lookup table on the exit. A three dimensional lookup table is the main element where for a set of inputs, output values are stored. One dimensional tables are optional and serve for storing functions which map input values, for example RGB , into a new set of values $R'G'B'$ in order to improve model performance. They are most commonly used to describe reproduction curves of each colorant, or to grey balance the device. The authors of this paper propose their use for mapping RGB inputs where $R=G=B$ to a new set of values $R'G'B'$ which result in $X=Y=Z$ response. It is obvious that the smallest of the tristimulus values should be used as a reference because it is impossible to extrapolate above the maximum digital count of 255.

5. CONCLUSION

This study suggests that model performances could be improved in the way described in previous sections. However, to confirm this, a more comprehensive study should be carried out. This will be the topic of further research which will require a software implementation to be developed and tested. Further research should also answer whether the adjustment of the tristimulus values results in any improvement, or any of them can be used for model selection.

6. REFERENCES

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