Optimal Noise Management Method for a Robust Separation Based Calibration of Color Printing Systems

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Abstract

For many color printing systems, printer calibration is often utilized to return the printer to a known state to ensure consistent color output. In particular, the key visual response of "color balance" is often controlled by the calibration state return. Input color signal noise, generated from the printing system natural variation when printing the calibration target, affects the accuracy and robustness of the calibration outcome. Noise management techniques for managing input color signal noise prior to system calibration are often absent or rely on ad hoc analysis and are usually not based on the return of a well developed printer response that has been extracted from measured signal using advanced noise management methods. This paper describes Part I of an overall method for developing a robust noise management system for printer calibration. In this Part I, the specific development of a high resolution, noise free representation of the printer system state, as defined by quantitative metrics relative to the raw input data is defined and developed.

Introduction

Calibration is a vital step in color workflow and is performed regularly to compensate for device variation in color reproduction [1]. Digital color printing systems are calibrated regularly to return the system to a known state [2]. User calibration for color printing systems normally consists of three steps: 1) print a predetermined calibration target patch set utilizing the target printing system. 2) measure the printed calibration target patches and 3) use the measurement data to generate a tone reproduction curve (TRC) that is applied to the printing system's color workflow to return the system to a known, desireable, and repeatable state. During the printing of the calibration target in the first step, inherent system noise is generated by the printing system and becomes part of the measurement in step 2. The inherent system noise affects the robustness of the calibration by obscuring the real system state with natural variation. The absence of high precision detection of the underlying system state with high confidence often results in inconsistent color output for the same print job even after calibration has been performed.

In this Part I, we propose a method to obtain a high resolution, high confidence, printer system state representing a noise free printer. First we describe the design of the calibration target that minimize spatial and temporal variation. Then we describe the proposed noise management method and the metrics we used to obtain optimal parameters: number of filtering iterations on the measurement data. We demonstrate the results of the proposed iterative noise management method the Results Section.

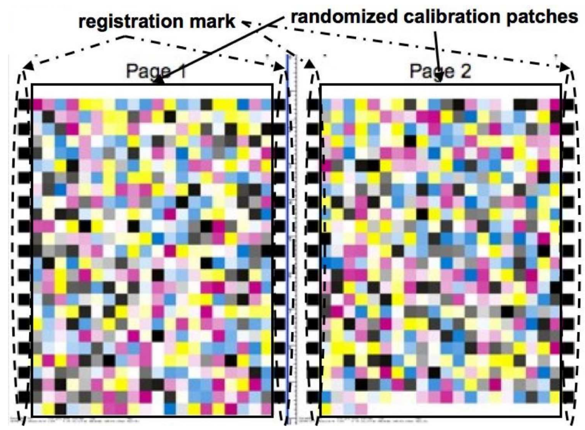

Figure 1. Randomized Calibration Target Containing 256 Values for Each Separation

Separation Based Calibration Target

In order to design customer based data acquisition methods, where a small number of patches are acquired and processed to return the printer to a known state, a method of defining a high resolution printer state, essentially noise free, is needed. In this section, we construct a target, with standard printing 8.5 x 11 paper, that captures all 8 bits (0 to 255) of data from randomly located patches within two pages. A common color printing system has four processing colorants: cyan (C), magenta (M), yellow (Y) and black (K) and each color printed on substrate is a combination of C, M, Y, and K. In this paper we limit the number of process colorants to just the preceding four. Capturing all 8 Bits, randomly in the spatial domain, requires 1024 patches. In color printing workflow, we use $(c\ m\ y\ k)$ to represent any color produced on the printing system using the four process colorant. The range of each channel is from 0 to 255. The bit value of 0 means no colorant is placed on the substrate and 255 means maximum amount of colorant is allowed by the system.

For each patch in a separation based calibration target, only one channel is non-zero and there are 256 patches for each separation. The $(c\ m\ y\ k)$ values for the dth patch in the ith separation can be described as

$$(c\ m\ y\ k) = (d * 1_{(i\,C)}\ \ d * 1_{(i\,M)}\ \ d * 1_{(i\,Y)}\ \ d * 1_{(i\,K)}) \qquad (1)$$

where $1_{(p\,q)} = 1$ when $p = q$ and 0 otherwise, $i \in \{C\ M\ Y\ K\}$ and $0 \leq d \leq 255$.

All printing systems have spatial variability within the page and temporal variability from one printed page to the next. To reduce variation of these kinds, patches in the data capture target were randomized spatially and multiple spatially randomized versions were created to capture temporal variability. To randomize the patch location for all four separations, a linear list of numbers from 0-1024 was generated and then randomized using a random number generator so that the calibration patches were placed randomly on the target pages. The correspondence between the linear list and randomized result was stored as the randomization key and is used to re-order the measurement data after printing and measuring.

Xrite Color Port software and an Xrite DTP-70 spectrophotometer were utilized in conjunction with the randomization algorithm to create the calibration targets, with randomly placed digital count values, for each separation. A two page, 8.5x11 inch, DTP-70 target is shown in Figure 2.

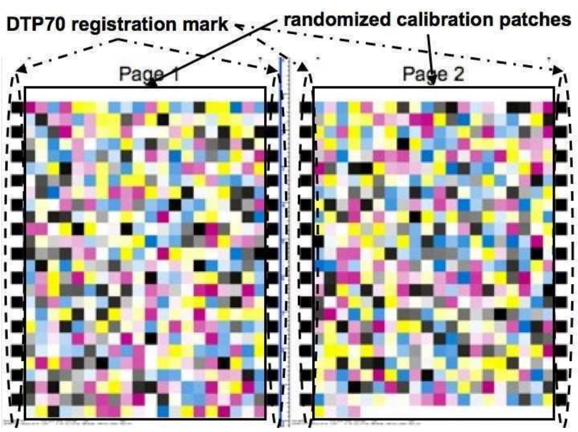

Figure 2. Randomized Calibration Target Containing 256 Values for Each Separation

Optimal Method to Reduce System Noise in Calibration Measurements

Spatial and Temporal Averaging to Reduce Noise

Multiple randomized calibration targets were generated using the method described, and printed using a xerographic color printing system, and then measured by DTP-70. The re-ordered measurements are converted to ΔE_{ab} from paper and shown in Figure 3(a). Large amount of noise is observed in the raw measurement. For any patch, its ΔE_{ab} value is defined as $\Delta E_{ab} = ||m_{paper} - m_{patch}||$, where m_{paper} = CIELAB measurement of the paper white and m_{patch} = CIELAB measurement of the patch of interest. As shown in Figure 3(b), the averaging over multiple calibration targets reduces some system noise, however, the residual noise in the averaged measurement data is still significant. Therefore, random sub-sampling of any of the post-averaged color separations contains significant noise, relative to signal, and calibration results will be affected by that noise. Hence, averaging even as many as five randomized targets is shown to be a limited method of reducing noise, and, from that result, it is clear that a method to remove the remaining noise is needed.

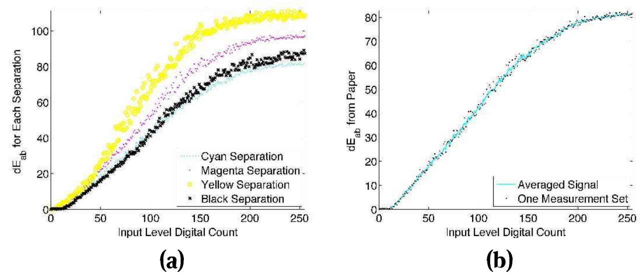

Figure 3. (a) One Measurement Data Set (b) One Measurement Data Set Compared to Average of Five Data Sets for Cyan Separation

Filter Design

Since the printer state separation functions are not known a-priori, and, are not simple polynomials, a function based fit for noise removal was rejected. Methods from time series smoothing, utilized in process control applications [3], were tested and adopted. From standard time series filtering, a very simple low pass filter (2) is proposed for each separation of the averaged measurement.

$$Y[d] = a_1 x[d-1] + a_2 x[d] + a_3 x[d+1] \tag{2}$$

where d is the index of the measurement data for one separation that also corresponds to the digital value of the patch in (1). Since the averaged signal is the only reference available that can be utilized with very high confidence, that signal is treated as the input signal.

The input signal is corrupted with noise from the printing system. Hence, a method and metrics are derived to remove the noise while insuring the maintenance of the underlying printer response. In this endeavor, recognition that the original input data is the reference is of critical importance. Noise reduction methods and metrics derived must make recognition of the raw signal as reference. A version of the above filter is common to streaming time series data. After some testing, and examination of frequency domain response, a moving average filter with coefficients $a_1 = 0\;3$ $a_2 = 0\;4$, and $a_3 = 0\;3$ was selected.

Iterative Filtering on Calibration Measurements

While offering reasonable print quality, xerographic methods of placing C, M, Y, and K on a printed page are complex and also incur variation and noise in the resultant ΔE_{ab} measurements. Ink based methods of printing also have natural variation. Removing noise is critical to expose the underlying printer response, but, excessive filtering on the measurement data can destroy the printer response. Hence, three metrics were developed to track both the progress of noise reduction and signal preservation during noise removal from the original raw high resolution measurement data:

1) The cumulative root mean square error of the filtered signal relative to that of the unfiltered signal,

2) a removed noise function defined as the difference between the smoothed patch of a given iteration relative to the unfiltered patch at the same bit count,

3) the second derivative of the cumulative root mean square error.

Based on these metrics a process of filtering the data which removes the noise while minimizing the cumulative error relative to the original data was developed. In practice, the second derivative of the cumulative root mean square error describes that point of departure where cumulative error, between smoothed signal and original data, begins more rapid growth. At this point, the removed noise function is well populated with zero mean. Hence, the inflection point metric, number 2 above, for any input data, defines the number of smoothing iterations chosen to define a noise free signal. For cyan separation, the second derivative of the cumulative noise is shown in Figure 4.

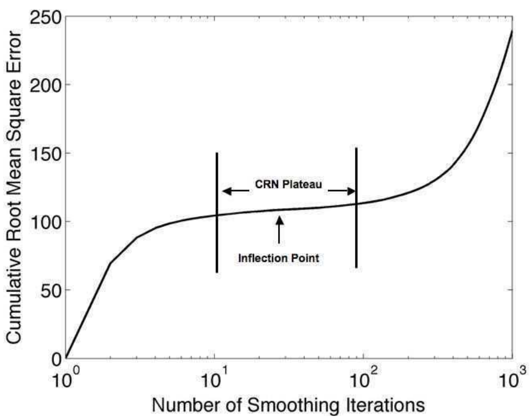

Figure 4. *Second Derivative Cumulative Noise vs Number of Iterations for Cyan Separation*

It is important to note that the removed noise function must maintain a zero mean value. This insures that only random noise has been removed and that offset associated with signal degradation not be present. If signal begins to be removed to the residual noise function, then, that appears as the onset of non-zero mean value. As noted, we find that the inflection point of the cumulative root mean square error reliably represents that location where essentially all random variation has been removed from signal while maintaining the original signal.

For any separation, we define the removed noise for the jth iteration for the dth patch as

$$RN_j[d] = \Delta E_{ab\,j}[d] - \Delta E_{ab\,0}[d] \tag{3}$$

where $j = 1\ 2\ 3 \quad N$, $\Delta E_{ab\,0}$ represents the averaged measurement data without any filtering, and $\Delta E_{ab\,j}[d]$ is obtained by filtering $\Delta E_{ab\,j-1}[d]$ with filter described in (2). Cumulative noise of the jth iteration is:

$$CRN[j] = \sum_d \sqrt{(RN_j[d])^2} \tag{4}$$

Two conditions need to be satisfied when the optimal number of iteration is reached: 1) $E\big[RN_j[d]\big] = 0$ and 2) $CRN''[j] = 0$, where $E[\,\cdot\,]$ is the expected value with respect to d and $CRN''[j]$ is the second derivative of $CRN[j]$ with respect to j. The minimal number of iterations j that satisfies both of the above conditions is the optimal number of iterations that we are searching for.

Results

Five randomized calibration targets were generated and printed using a color xerographic printing system. The printed targets were measured using DTP20 and randomized data were re-ordered to correspond to 0-255 input level. The average was taken using four sets of data and optimal numbers of iterations for each separation were derived from the average using the above proposed method. The optimal numbers of iterations were applied to the fifth data set to reduce the noise in the fifth measurement data set.

Filtering procedure follows the following protocol. First, 1000 iterations of smoothing with the previously noted filter and metrics are performed. For these data and this filter, this always results in exceeding the amount of filtering necessary to move beyond the inflection point of the cumulative root mean square error between smoothed signal and original high resolution data. Following the generation of statistical data on each smoothing iteration, a numerical search locates the point where both conditions $E\big[RN_j[d]\big] = 0$ and $CRN''[j] = 0$ are satisfied.

The inflection point is defined as the location where the second derivative of the signal change signs. For cyan separation, the inflection point in Figure 4 is 12 and $E\big[RN_{j=31}[d]\big]$ of condition 1 is 0.0061, a very small value that can be treated as zero. Utilizing the inflection point as the location of optimal smoothing the averaged data set that represents the average of 4 measurements and the optimally smoothed ΔE_{ab} curves can now be constructed and compared. The optimally filtered ΔE_{ab} curve for cyan is shown below in Figure 5 with the averaged data from the 4 input targets. The same search can be applied to other separations to obtain the optimal number of iterations for each separation. The resultant optimal iterations for each separation is listed in Table 1.

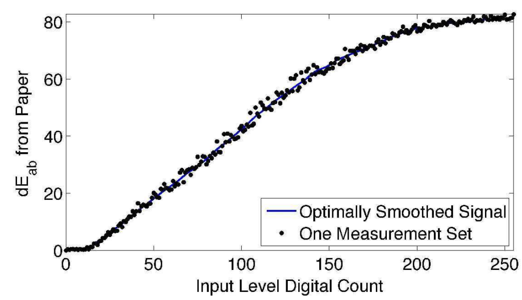

Figure 5. *Optimally Smoothed Printer Response v.s. Averaged Measurement for Cyan Separation*

Optimal Number of Iterations for Each Separation

Separation	Number of Iterations
Cyan	12
Magenta	16
Yellow	16
Black	13

Then the optimal number of iterations for each separation could be directly used for noise removal on the fifth data set. The printer response verses the measurement data for cyan separation is shown in Figure 6 and the expected value of the noise is -0.0099. The noise signal removed by the optimal number of iterative filtering is shown in Figure 7.

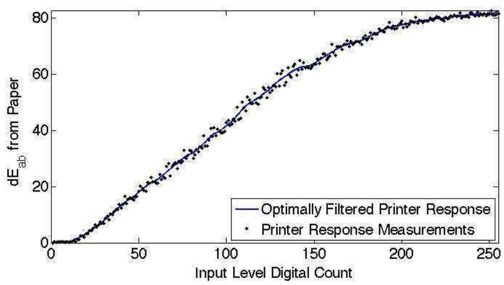

Figure 6. Printer Response Based on Optimal Filtering v.s. One Set of Measurement for Cyan Separation

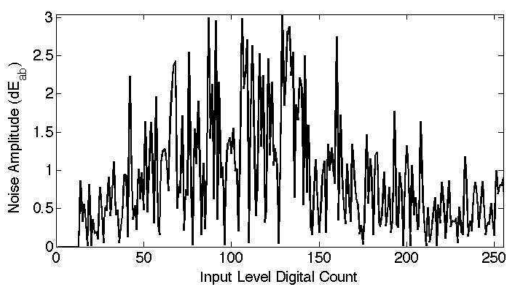

Figure 7. Noise Removed from Measurement Data for Cyan Separation

However, at customer sites, using all 8 bits of data for each separation is a prohibitively large number of patches for customers to scan. Hence, in Part II of this paper we develop methods of optimal filtering on subsampled color data that utilize the noise free reference curve developed here. In Part II, we describe methods of obtaining a close approach to the noise free, high resolution color target data, with 1/4 rate subsampling.

Conclusion

Calibration is a vital step in color workflow and is performed regularly to compensate for device variation in color reproduction. Input color signal noise, generated from the printing system natural variation when printing the calibration target, affects the accuracy and robustness of the calibration outcome. In this paper, an optimal noise management method to reduce system noise in the calibration target measurement is developed and the first part of that, definition of a noise free, high resolution, reference is derived. The result is a high reliabie, noise free, dEab target for each separation. This noise free target will be shown, in Part II of this paper, to be the key to develop a capable sub-sample method for calibration patch design. The proposed method has utilized methods from time series filter development to develop a filter and obtain the optimal number of filtering iterations for each separation during calibration that can reliably remove noise and preserve the signal. The obtained filter coefficients and optimal number of iterations can then be applied to all the calibration measurements without running the numerical search in the field or printing multiple number of calibration targets.

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Author Biography

Mu Qiao received his Bachelor, Master and Ph.D. degree from Electrical and Computer Engineering of Purdue University in 2002, 2004 and 2008 respectively. He currently works in Shutterfly as an imaging science engineer. Before joining Shutterfly, he worked at Xerox Corp. in 2007 as a summer research intern in Xerox Innovation Group and returned to Xerox in 2008 as full time employee in Global Production Delivery Group. His research interests are image processing and analysis, color management, variable data printing, and document management.