

Scanner Based Spectrum Estimation of Inkjet Printed Colors

Hadas Kogan, Doron Shaked, Michal Aharon; HP Labs; Haifa, Israel

Abstract

Fast and accurate color measurement devices would have benefited printing in general and specifically commercial and industrial printing presses, however, such devices are expensive and are therefore not always available. On the other hand, a scanner is cheap and available in most print services providers, and is sometimes even integrated in the output paper path of commercial presses, e.g. the HP7500 press. It is commonly agreed that scanners are not color measurement devices - certainly not accurate ones. This paper shows feasibility of providing printer output spectrum estimation using a scanner as the measuring device. Such a method could further be used for colorimetry and color characterization. To do that we need to estimate the color specification of a scanner - or - the mapping function from the spectrum to the scanner measurements, which we will consequently invert. Unlike traditional methods that ignore the printing process, we propose to use the printer color model as a prior knowledge to perform accurate spectrum estimation. The applicability generality and high quality of the proposed method are demonstrated on two different printing processes: a Thermal Inkjet printer and an LEP (HP Indigo) press.

Introduction

Color scanners are widely used and can sometimes be incorporated as an inline measuring device. Therefore, it is desired to use them as color measuring devices for a wide range of applications such as color reproduction, color monitoring, defect detection and printer calibration. In a perfect world, the scanner sensors would be designed to match the color matching functions and thus provide device independent CIELAB measurements. However, due to a variety of physical reasons this is usually not the case and each device has its own coordinates system [3]. The processes of mapping between scanner (R,G,B) response and the actual printed spectrum S or device independent CIELAB values (X,Y,Z) are called scanner *spectral* or *colorimetric* characterization respectively.

One typical approach [1] estimates the spectral reflectance and colorimetric values from a device response using local statistics, by parameterizing the transformation from (R,G,B) values to (X,Y,Z) values in the case of colorimetric characterization, and from spectrum to (R,G,B) values in the case of spectral characterization and learning the transformation from training samples. The accuracy results reported in [1] are an average accuracy $1.7\Delta E$ using a GT-10000 scanner for colorimetric characterization.

In many cases the characterization is for a scanner-printer pair, i.e., the colors scanned are the output of a specific printer. Most methods use this fact by printing and scanning a grid of (C,M,Y) or (C,M,Y,K) patches and constructing Look-Up Tables (LUTs). For instance, the work proposed in [5] composes a 4D LUT to increase accuracy, mapping between (K,R,G,B) to (X,Y,Z) values: for each level of K, patches varying in their

(C,M,Y) values are printed and measured by both the scanner and a spectrophotometer. Then for each fixed level of K, a neural network is used to derive the transformation between (R,G,B) values and CIELAB measurements. They use the digital K value to decide which 3D LUT to use. The authors provide average accuracy results of patches printed by DocuColor 12 printer and scanned by an Epson GT-10000 scanner of around $2 - 3\Delta E$.

Most methods do not use the known physical printing process at all. One exceptional is the work presented in [6], that estimates the spectral reflectance of photographic films using scanner measurements. The proposed method first empirically estimates a 3×3 transformation from (R,G,B) scanner values to (C,M,Y) dye concentrations, then, the dye concentrations are mapped to spectral response using Beer-Bourguier or Kubelka-Munk printing models.

The approach proposed in this work uses the physical printing model as well, where the actual model is chosen to suit the print technology. The proposed method requires to estimate the mapping function from the spectrum to the scanner measurements. Estimating the mapping is important because the scanner response is usually known only to the manufacturer, and even if theoretically known, scanner sensors are not manufactured very accurately. This translates then to the need to find the spectral sensitivities when special devices targeted to estimate the spectral sensitivities are not always available.

The transformation from spectrum to scanner response typically consists two stages: first an inner product of the spectrum with the scanner profiles, then the scanner response is subject to a non linear mapping function that is called OECF (opto-electric conversion function). To measure directly the device OECF most methods use spectrally neutral gray test pattern illuminated by an equal-energy illumination [10]. To measure directly the device profiles the device is illuminated by many narrow band signals and its response is measured [12]. This class of methods requires special devices such as a monochromator and may not be always feasible. Another class of methods consists of indirect methods, where color patches with known spectrum (e.g., measured by a spectrophotometer) are measured by the device and then the device response is calculated. The difficulty with applying indirect methods is that the problem is ill-posed: naturally occurring surfaces have limited variety of spectra, that can be represented by 6–9 basis functions [13]. Therefore, prior assumptions regarding the device response must be applied. Most methods use a subset of the following assumptions: the profiles are positive, smooth, spanned by some basis functions, single modal (i.e., have only one maxima), etc. [14],[11][15].

We choose to estimate the scanner profiles and OECF using an indirect method, as it does not require special devices and may be used anywhere. Our method estimates simultaneously the scanner profiles and OECF.

We will first present our scanner characteristics estimation

technique, then we will show how to estimate the printed spectrum from the scanner measurements. The applicability of our approach is demonstrated on two different printing processes, a Thermal Inkjet printer and an LEP (HP Indigo) press.

Estimating the measurement device's characteristics

First, we present the proposed scanner response estimation method. Using vector notation, and sampling the visible spectrum in K equally sampled wavelengths (K is typically 36), a scanner response $(R, G, B) = (m_{1j}, m_{2j}, m_{3j})$ to a given spectrum S_j is modelled as: $m_{ij} = \mathcal{F}_i(P_i S_j + n), i \in \{1, 2, 3\}$. Where \mathcal{F}_i is a non linear optoelectric conversion function (OECF), P_i is a $1 \times K$ vector of the device profile, S_j is a $K \times 1$ vector of the reflectance spectrum and n is a Gaussian noise ([4] and references therein). We estimate simultaneously the scanner profiles and OECF as an inverse problem. Unlike direct methods which require special equipment such as monochromator and spectrally neutral test pattern, an indirect method requires only a spectrophotometer and is easy to implement. The proposed scanner response estimation method follows arguments close to those used in [4], but our optimization approach is slightly different.

For each of the three scanner sensors, we find \mathcal{F}_i, P_i for $i \in \{1, 2, 3\}$ by solving the following optimization problem:

$$\min_{\mathcal{F}_i, P_i} \|P_i S - \mathcal{F}_i^{-1}(m_i)\|_2^2 \quad s.t. \quad A1, A2, A3, A4 \quad (1)$$

S is a matrix whose columns are the spectra of different color patches and $(m_1, m_2, m_3) = (R, G, B)$ are raw vectors of scanner responses. The proposed scanner response estimation method assumes that: (A1) P is smooth; (A2) $0 \leq P \leq 1$, for measurements that are normalized to 1. Further, the proposed method transforms the non-linear problem to a linear one by assuming that (A3) $\mathcal{F}_i^{-1} = \sum_{j=0}^k c_{ij} m_{ij}^j$ is a polynomial of some degree k (a predefined parameter whose value is determined empirically) and (A4) $\mathcal{F}_i^{-1}(0) = 0$ and $\mathcal{F}_i^{-1}(1) = 1$ (it usually holds because we assume that the OECF doesn't change the dynamic range. This assumption can be relaxed as well).

From (A3) it holds that,

$$\begin{aligned} \mathcal{F}_i^{-1}(m_{ij}^j) &= c_{i0} + c_{i1} m_{ij} + c_{i2} (m_{ij})^2 + \dots + c_{ik} (m_{ij})^k \\ &= c_i M_{ij} \end{aligned}$$

where $c_i = [c_{i1}, c_{i2}, \dots, c_{ik}]$ and

$$M_{ij} = [m_{ij}, (m_{ij})^2, \dots, (m_{ij})^k]^T \quad (2)$$

Where $c_{i0} = 0$ and $W c_i = 1, W = \mathbf{1}^K$ from A3.

Instead of minimizing the function in Equation 1, we minimize an equivalent function, where the minimization is under assumptions A1 – 3,

$$(c_i, P_i) = \underset{W c_i = 1, 0 \leq P_i \leq 1}{\operatorname{argmin}} \{ \|P_i S - c_i M_i\|_2 + \lambda D P_i \}, s.t.$$

Where M_i is a matrix of size $k \times N$ which columns are given by 2, and D is given by:

$$D = \begin{pmatrix} -1 & 1 & 0 & \dots & 0 \\ 0 & -1 & 1 & \dots & 0 \\ & & \dots & & \\ 0 & 0 & \dots & -1 & 1 \end{pmatrix} \quad (3)$$

$D P_i$ is small for smooth P_i 's and λ is a parameter that controls the weight that is given to the smoothness assumption.

Solving the optimization problem simultaneously for c_i and P_i is hard, therefore we solve in two stages: first, we assume c_i and solve for P_i , then we use P_i to estimate c_i . We repeat these two stages until convergence is reached. A summary of the algorithm appears in Fig. 1. The algorithm is applied for $i = 1, 2, 3$ to estimate the three sensors, R, G, B , and the estimation results of the scanner profiles and OECF for an Epson GT-10000 appear in Fig. (a-b).

Using Yule-Nielsen model for spectrum estimation of color patches printed by a thermal inkjet

Now we will describe the second part of the proposed scheme: estimating the spectrum of a printed patch given the (R, G, B) measurements, using the estimated scanner profiles and OECF. Unlike previous methods, we choose to use the knowledge of the specific printing technology as a prior knowledge to increase the estimation accuracy. Different printing technologies have different models linking between the ink coverages on some substrate and the reflected spectrum. By using the appropriate printing model as a prior knowledge we can reach highly accurate spectrum estimation. This approach was previously used for spectral reflectance estimation of patches printed by an Indigo press from inline densitometer measurements [7] and provided excellent results. We demonstrate that it is possible to use the same principle to estimate the spectrum response also from scanner measurements, and for at least two different printing technologies: LEP and thermal Inkjet.

In general, let us assume that x is a vector of ink coverages, e.g. if the printer uses 4 inks x is a 1×4 vector. Assume that \mathcal{M} is the printing model function that maps between x and the spectral response of the printed patch. By solving the following general optimization problem we will find a spectrum that is both a possible output of the printing process, and its projections on the scanner profiles are close to the linearized scanner measurements:

$$(x, s) = \underset{s}{\operatorname{argmin}} \{ \| \mathcal{M}(x) - s \|_2^2 + \lambda \| P s - m \|_2^2 \} \quad (6)$$

where s is the unknown $K \times 1$ spectrum, P is a $3 \times K$ matrix containing the three scanner profiles and m is the linearized (R, G, B) measurements (i.e., after applying \mathcal{F}^{-1}). Even if the digital coverage is known, the actual coverage is unknown unless the printer is perfectly calibrated, so we choose to assume that the coverage x is unknown and is an output of the optimization process.

A critical step to ensure the results accuracy is to use an appropriate model for each printing technology. For Indigo press, we use the cellular Neugebauer model [8], that requires measuring the reflectance of 81 patches of all the (C, M, Y, K) combinations of $[0, 0.5, 1]$ (we will denote the reflectance measurements of those patches by the term *Neugebauer parameters*), then a general spectrum S can be represented by a linear combination of the 16 closest Neugebauer parameters. Neugebauer model employs Demichel's dot overlap model for the surface coverage of each primary. The algorithm proposed in [7] is applied to solve (6).

The cellular Neugebauer model applied in [7] for Indigo presses does not suit well the inkjet printing process, and we used the empirically accurate cellular Yule-Nielsen model [8]. Yule-Nielsen introduced an exponent n , determined empirically, into

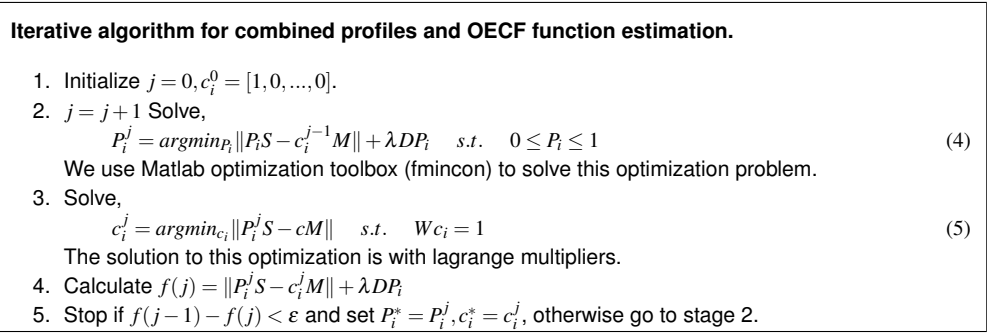


Figure 1. A summary of our profiles and OECF estimation algorithm.

Neugebauer equation. According to the Yule-Nielsen model, a general spectrum S can be described as:

$$S = \left(\sum_i a_i R_i^{\frac{1}{n}} \right)^n \quad \text{s.t.} \quad \sum_i a_i = 1, a_i > 0 \quad (7)$$

Where $R_i, 1 < i < 27$ are the spectral reflectance of Neugebauer parameters: all the (C, M, Y) combinations of $[0, 0.5, 1]$. Usually we consider only the parameters that are closest to the CMY coverage of S : the relevant cube corners [8],[7], so actually each spectrum is a linear combination of only 8 spectra. With inkjet prints, the simple Demichel model does not describe well the surface coverage of each primary [9]. To avoid a more complicated model that accounts for ink spreading and other physical phenomena, we just assume that surface coverages are positive and that their sum is 1, and we solve the following optimization problem:

$$(a, s) = \operatorname{argmin} \{ \| (R^{1/n} a)^n - s \|^2 + \lambda \| P s - m \|^2 \}, \text{s.t.} \\ 0 < a, \sum_i a_i = 1$$

The solution is by iteratively assuming a and solving for s , then using s to solve for a . The algorithm details are presented in Fig. 2.

Results and conclusion

We tested the proposed method on an Epson GT-10000 scanner, printing and scanning 1000 patches whose coverages are randomly selected with an Indigo press on glossy paper, and 1000 random patches with an HP photosmart 8700 printer on HP premium photopaper. We measured the spectra of the patches with a Gretag spectrophotometer and scanned each page ten times, each time placed on a slightly different location on the scanner. We sampled each scan and averaged the values of each patch to eliminate measurement and spatial noise. We estimated the scanner response using 1000 patches (500 printed by Indigo and 500 printed by the Inkjet), see Fig. 3. We tested the spectrum accuracy of the spectrum estimation algorithm on the rest, by calculating the ΔE_{00} under different illuminations, see Fig. 4.

The good accuracy in terms of low ΔE we got, both on patches printed with LEP printing technology and thermal inkjet, indicates the high quality and generality of the proposed estimation process.

References

[1] H.L. Shen and J.H. Xin, Colorimetric and Spectral Characterization of a Color Scanner Using Local Statistics, journal of imaging science and technology, August, 2004.

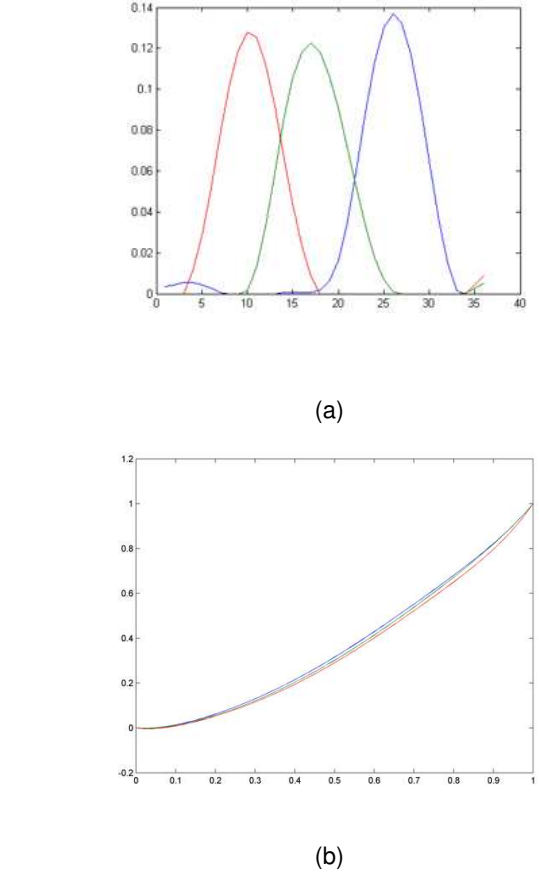


Figure 3. (a) presents the estimated scanner profiles and (b) presents the estimated OECF.

	D(50)	D(65)	C
Indigo	1.079/2.337	0.876/2.117	1.027/2.3
Inkjet	1.07/2.24	0.89/2.25	1.03/2.23

Figure 4. The results shown in this table present the spectrum estimation accuracy in terms of $(\Delta E_{mean} / \Delta E_{95\%})$ under different illuminations. The results were obtained on 500 random patches printed on Indigo press and 500 random patches printed on a thermal Inkjet.

[2] S. Bianco, F. Gasparini, R. Schettini and L. Vanneschi, Polynomial modeling and optimization for colorimetric characterization of scan-

Iterative algorithm for spectrum estimation of color patches printed with an inkjet printer.

Initialize \mathbf{a}^0 , $j=1$, $\varepsilon^0 = 1000$. Repeat iteratively:

- calculate $N_{est}^j = (R^{1/n} \mathbf{a}^{j-1})^n$
- Solve: $s_{est}^j = \operatorname{argmin}_s \{ \|N_{est}^j - s\|_2^2 + \lambda \|Ps - m\|_2^2 \}$ (a direct solution).
- Solve: $\mathbf{a}_{est}^j = \operatorname{argmin}_a \{ \|R^{1/n} \mathbf{a} - (s_{est}^j)^{1/n}\|_2^2 \}$ s.t. $0 < \mathbf{a}$, $\sum_i a_i = 1$ (a quadratic optimization with constraints).
- Calculate: $\varepsilon^j = \| (R^{1/n} \mathbf{a})^n - s_{est}^j \|_2^2 + \lambda \|Ps_{est}^j - m\|_2^2$
- Stop if $abs(\varepsilon^j - \varepsilon^{j-1}) < T$, with T a predefined threshold.

Figure 2. A summary of the proposed spectrum estimation algorithm of color patches printed with an inkjet printer.

ners, Journal of Electronic Imaging, OctDec 2008.

- [3] B. A. Wandell and J. E. Farrell, Water into Wine: Converting Scanner RGB to Tristimulus XYZ, Proc. SPIE Vol. 1909, p. 92-101.
- [4] H.L. Shen, J.H. Xin, D.X. Yang, D.W. Lou, Estimation of Optoelectronic Conversion Functions of Imaging Devices Without Using Gray Samples, Color Research and Application, Feb 2008.
- [5] B.S. Lee, R. Balab, G. Sharmac, Novel scanner characterization method for color measurement and diagnostics applications, Proc. of SPIE-IST Electronic Imaging, SPIE, 2006.
- [6] R.S. Berns, M.J. Shyu, Colorimetric characterization of a desktop drum scanner using a spectral model, journal of electronic imaging, October 1995.
- [7] M. Aharon, D. Shaked, B. Oicherman, R. Keshet, A. Pnueli, and H. Nachlieli, HP labs Israel, Estimation of Spectral Reflectance from Densitometric Measurements Using Printing Model Prior, CIC, November 2009, Vol. 17 pages 301-305.
- [8] H.R. Kang, Color Technology for Electronic Imaging Devices. published by SPIE.
- [9] N. P. Garg, A. K. Singla and R. D. Hersch, Calibrating the Yule-Nielsen Modified Spectral Neugebauer Model with Ink Spreading Curves Derived from Digitized RGB Calibration Patch Images, Journal of Imaging Science and Technology 2008.
- [10] Martinez-Verdu F, Pujol J, Capilla P. Characterization of a digital camera as an absolute tristimulus colorimeter. J Imaging Sci Technol 2003;47:279295.
- [11] R. S. L. V. S. Bianco, F. Gasparini, Polynomial modeling and optimization for colorimetric characterization of scanners, *Journal of Electronic Imaging*, vol. 17, 2008.
- [12] J. T. P. Vora, J. Farrell and D. Brainard, Digital color cameras - 2 - spectral response, tech. rep. hpl-97-53, HP Labs, 1997.
- [13] L. T. Maloney, Evaluation of linear models of surface spectral reflectance with small numbers of parameters, *Journal of the Optical Society of America*, pp. 1673–1683, 1986.
- [14] P. M. H. G. D. Finlayson, S. Hordley, Recovering Device Sensitivities with Quadratic Programming, *The Sixth Color Imaging Conference: Color Science, Systems, and Applications*, 1999.
- [15] P. Carvalho, A. Santos, and P. Martins, "Recovering imaging device sensitivities: a data-driven approach," in *Image Processing, 2004. ICIP'04. 2004 International Conference on*, vol. 4, 2004.
- [16] V. Cheung, S. Westland, and M. Thomson, Accurate estimation of the nonlinearity of input/output response for color cameras, *Color Research & Application*, vol. 29, no. 6, pp. 406–412, 2004.

Author Biography

Hadas Kogan received her Bsc. (summa cum laude) and Msc. (cum laude) in Electrical Engineering from the Technion, the Israeli institution of technology, in 2001 and 2007 respectively. She then worked for three years in Rafael Ltd. in the area of data integration. Since then she has

worked in HP labs israel. Her work in HP has focused on print and color quality assurance.

Doron Shaked received his DSc. from the Technion, Israel Institute of Technology in 1995. Since then he has been with Hewlett Packard Laboratories Israel in Haifa, where as a principal researcher he led a multi talented research team focused on automating printing technologies and image enhancement. Since 2009 Doron is Director of HP Labs Israel, an excellence center in imaging, data mining, and analytics.

Michal Aharon received her Bsc. (summa cum laude), Msc. (cum laude), and PhD degrees in Computer Science from the Technion, the Israeli institution of technology, Haifa in 2001, 2004 and 2007 respectively. Both the Msc. and PhD. dissertations are in the field of image and signal processing, concentrating on dimensionality reduction and sparse representation of signals. Michal has been working at HP laboratories in Israel since November 2006. She concentrates both on color science and on data analysis applications.