Estimation of Spectral Reflectance From Densitometric Measurements Using Printing Model Prior

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Abstract

Estimating the spectral reflectance of a printed patch is an important task in the printing industry for several purposes such as ICC profiling and maintaining color consistency. However, equipment for accurate spectral reflectance estimation (spectrophotometers) is expensive. In this work we suggest to use known characterization of the printer output in order to achieve accurate estimation of spectral reflectance from only three-channel measurement, such as provided by the standard status T densitometers.

The mean estimation error we achieve on known substrates is $0.13\Delta E$*. Further results indicate an estimation error below* $1\Delta E$ *for a set of unknown substrates.*

Introduction

Measuring color is of prime importance in the printing industry. It is also a very difficult and expensive task. Measuring color requires calibrated sensors, and controlled lighting. Exposure time needs to be long and apertures needs to be wide to reduce noise and possible effects of halftoning. As a result color measurement equipment is expensive and slow, and usually cannot take measurements at the printing speed of a press.

In this paper we propose a new model based approach for inline spectrophotometry. In a nutshell: We do not try to build a general spectrophotometer - this is too expensive. Nevertheless, we propose an accurate reflectance estimator for prints produced by a printer or press using known inks and an approximately known medium. Given a printer or press, its ink and media, we can print only a very limited set of spectra. Actually the variability is roughly approximated by four parameters: The relative amounts of Cyan, Magenta, Yellow, and Black inks used. In this paper, we show that this constraint enables a very accurate spectral estimation.

The mean estimation error we achieve on known substrates is $0.13\Delta E$[1] and the 95% estimation error is $0.34\Delta E$. Further results indicate a mean estimation error below $1\Delta E$ for unknown substrates. To the best of our knowledge this work is novel in the prior it uses and the method it uses to apply them. The level of accuracy we achieve is better by an order of magnitude from the current state-of-the-art.

Prior Art

Maloney and Wandell [2] seem to be the pioneers in the field of spectral reflectance estimation. In their work both the spectral reflectance and the ambient light are modeled as a linear combination of spectral reflectance functions and basis lights respectively. Unfortunately, they only provide a brief verbal description of the procedure, and do not provide any evidence of accuracy. Dupont [3] reports an extensive overview of number of reflectance reconstruction methods. Hawkyard [4] was found to perform the best. Hawkyard assumes that for a given wavelength the reflectance is the weighting sum of the color matching functions weighted by the illuminant spectral power distribution. Wang et al. [5] published an improvement of Hawkyard algorithm, whereby it is converted from being iterative to analytical.

Schettini and Zuffi [6] developed a genetic algorithm-based strategy. They also assume the spectral reflectance is a linear combination of a set of basis function. They tested in their work several such sets of functions, and concluded that the trained basis using the PCA methods outperform all the other sets. Similar ideas are suggested by Connah et al. [7], who discuss a model of reflectance estimation in multispectral imaging system. The estimation error they reports is around 2-4 ΔE for 3 sensors.

Sharma and Wang [8] developed a method of recovering reflectance from colorimetric data under constraints of known reproduction media. They used neural network-based algorithm for transforming between the XYZ values and the spectral reflectance. Their work produced mean ΔE_{94} values of $0.3-0.5$, and 95% $0.7-1.8$ for same media depending on the printing process they trained on. These results are very good, but relate to accurate XYZ measurements that are not usually available.

DiCarlo and Wandell [9] also suggest using knowledge about surface reflectance spectra in order to estimate a measured spectrum. Their method overcomes the limitation of linear estimation methods by extending the estimation function from a hyperplane to a more general surface. Their results show a reduction of 12% in the error, compared to linear estimation.

Description

We denote the spectral reflectance of a printed color patch as $\mathbf{s} \in R^l$. Usually $\mathbf{s}$ is a vector representing the average reflectance in 10nm intervals in the visual spectrum range ($380-730$nm), in which case $l = 36$. We are given measurements $m_1, m_2, \ldots, m_n$ of this color patch. The measurements are projections of $\mathbf{s}$ on a set of filters $\mathbf{l}_1, \mathbf{l}_2, \ldots, \mathbf{l}_n$ (sensor sensitivities). For the three channel densitometer $n = 3$. If we arrange the projections as rows in the matrix $\mathbf{L} = [\mathbf{l}_1|\mathbf{l}_2|\ldots|\mathbf{l}_n]^T$, and the measurements as a vector $\mathbf{m} = [m_1, m_2, \ldots, m_n]^T$, we have,

$$\mathbf{L} \cdot \mathbf{s} = \mathbf{m}. \qquad (1)$$

Notice that throughout this work we do not consider the illuminant spectral power distribution. Instead, we assume that the illuminant is a known multiplicative factor in the equation and is

[1] All ΔE values given here refer to ΔE_{2000} [1].

already embedded[2] in the filter profiles matrix $\mathbf{L}$.

When $\mathbf{L}$ is known and $\mathbf{m}$ is measured, we would like to estimate $\mathbf{s}$. For $l \leq n$ this is a simple inverse or a least squares problem. However, in most cases the number of unknowns, l, is much larger than the number of projections, n, which forces us to find a proper prior for a solution. Typical priors used in similar problems are smoothness (minimization of gradients) or minimum energy (which leads to a pseudo-inverse solution). However, the knowledge of the source of the measured patch to be an output of a known press, points to an excellent prior for $\mathbf{s}$ in Equation (1). Although mathematically $\mathbf{s}$ seems to be l-dimensional, it actually depends on a small set of parameters: the coverage of each ink, which implies that for four ink printing the specta span a four-dimensional manifold in R^{36}. Moreover, usually the black ink is spectrally similar to a combination of color inks, and therefore the dimensionality of printed spectra is approximately three.

To describe the connection between the ink coverage values (a_c, a_m, a_y, a_k) and the expected spectrum, we used the Neugebauer Model [11], that describes well the HP-Indigo printing outcome. For other presses that do not conform as well to the Neugebauer model, a better model may have to be used. The Neugebauer model for 4 inks is,

$$N(a_c,a_m,a_y,a_k) = \sum_{d\in D} A_d(a_c,a_m,a_y,a_k)\cdot \mathbf{p}_d, \tag{2}$$

where D is the set of all 16 subsets of $\{c,m,y,k\}$, $\mathbf{p}_d \in R^l$ is the reflectance spectrum when printing full coverage from each ink in the combination $d \in D$ (e.g. $\mathbf{p}_{cyk}$ is the spectrum when printing 100% coverage of cyan, yellow and black), and finally,

$$A_d(a_c,a_m,a_y,a_k) = \prod_{i\in\{c,m,y,k\}} \begin{cases} a_i & i \in d \\ (1-a_i) & i \notin d \end{cases} \tag{3}$$

With the Neugebauer model as our prior, we turn to solve Equation (1). Since the measured print is an output of a press, it is reasonable to believe we know the amounts of inks that were meant to be printed. In this case it is tempting to solve,

$$\min_{\mathbf{s}} \left\|N(a_c,a_m,a_y,a_k) - \mathbf{s}\right\|_2^2 \;\; s.t. \;\; \mathbf{L}\cdot\mathbf{s} = \mathbf{m}. \tag{4}$$

when the coverage values a_c, a_m, a_y, a_k are known, we require the spectral reflectance to match the projections' measurements $\mathbf{m}$, and also to minimize the difference to the expected outcome of the Neugebauer model. Setting this problem would have lead to a direct solution of $\mathbf{s}$. However, considering the fact that the amounts of ink vary due to temporal changes in the press, we decided not to enforce the coverage, and consider the coverage values as unknown. As will be shown later, coverage information can serve to initialize the iterative scheme. Therefore we solve,

$$\min_{\mathbf{s},a_c,a_m,a_y,a_k} \left\|\left(N(a_c,a_m,a_y,a_k) - \mathbf{s}\right)\right\|_2^2 \;\; s.t. \;\; \mathbf{L}\mathbf{s} = \mathbf{m}, \tag{5}$$

or alternatively,

$$\min_{\mathbf{s},a_c,a_m,a_y,a_k} \left\|\left(N(a_c,a_m,a_y,a_k) - \mathbf{s}\right)\right\|_2^2 + \lambda \left\|\mathbf{L}\mathbf{s} - \mathbf{m}\right\|_2^2. \tag{6}$$

[2]In a way, the illuminant may be reflected in the results section of [10], where we tune matrix $\mathbf{L}$ in order to fit the measurements.

Both equations try to find the spectral reflectance $\mathbf{s}$ that matches the projections' measurements $\mathbf{m}$, as also minimizes the weighted difference to **one** possible solution of the Neugebauer model.

Problem (6) is equivalent to Problem (5) for a very large λ. Smaller λ values enable some variation from the measurements $\mathbf{m}$. This was proved as most efficient in the presence of measurement noise, and indeed achieved superior results than those of (5).

Numerical Solution

Problem (6) is quadratic in the unkonwn spectrum $\mathbf{s}$. The Neugebauer model is a linear combination of known and fixed spectra. The coefficients of this linear combination are products of the ink coverages values, or their complementaries to one (100% coverage). As a result, Problem (6) is linear in any of the ink coverage values a_c, a_m, a_y, a_k separately. However, it is not linear nor quadratic in all its variables together. We decided to solve Problem (6) iteratively. Each iteration includes the solution to two distinct problems, each updating different variables in order to solve Problem (6). First, we solve for the spectrum $\mathbf{s}$, and then update the ink coverage values a_c, a_m, a_y, a_k.

In order to describe each part in the solution we first rearrange the Neugebauer equation as a linear function of a vector $\mathbf{x}$, whose entries are functions of the ink coverages. Let $\mathbf{x}(a_c,a_m,a_y,a_k)$ be a vector defined as,

$$\begin{aligned}\mathbf{x}(a_c,a_m,a_y,a_k) \;\; = \;\; & [1,\ a_c,\ a_m,\ a_y,\ a_k, \\ & a_ca_m,\ a_ca_y,\ a_ca_k,\ a_ma_y,\ a_ma_k,\ a_ya_k, \\ & a_ca_ma_y,\ a_ca_ya_k,\ a_ca_ma_k,\ a_ma_ya_k, a_ca_ma_ya_k]^T.\end{aligned} \tag{7}$$

Also, let $\mathbf{P}_D$ be a matrix whose columns are the spectra of 100% coverage of all combinations of inks, Finally, let $\mathbf{B} \in R^{16\times16}$ be a matrix with entries in $\{0,1,-1\}$ (as in [10]), so that

$$N(a_c,a_m,a_y,a_k) = \mathbf{P}_D\mathbf{B}\mathbf{x}(a_c,a_m,a_y,a_k). \tag{8}$$

For simplicity, we denote the function minimized in Problem (6) as F

$$\begin{aligned}&F(\mathbf{s},a_c,a_m,a_y,a_k) = \\ &\left\|\left(\mathbf{P}_D\mathbf{B}\mathbf{x}(a_c,a_m,a_y,a_k) - \mathbf{s}\right)\right\|_2^2 + \lambda\left\|\mathbf{L}\mathbf{s} - \mathbf{m}\right\|_2^2.\end{aligned} \tag{9}$$

First, we take the partial derivation of F with respect to $\mathbf{s}$,

$$\frac{\partial F}{\partial \mathbf{s}} = -2\left(\mathbf{P}_D\mathbf{B}\mathbf{x}(a_c,a_m,a_y,a_k) - \mathbf{s}\right) + 2\lambda\mathbf{L}^T\left(\mathbf{L}\mathbf{s} - \mathbf{m}\right). \tag{10}$$

Solving $\frac{\partial F}{\partial \mathbf{s}} = 0$ results,

$$\mathbf{s} = \left(\lambda\mathbf{L}^T\mathbf{L} + \mathbf{I}\right)\left(\mathbf{P}_D\mathbf{B}\mathbf{x}(a_c,a_m,a_y,a_k) + \lambda\mathbf{L}^T\mathbf{m}\right). \tag{11}$$

When considering a fixed spectrum $\mathbf{s}$, and updating the coverage values a_c, a_m, a_y, a_k, it reduces to the inverse Neugebauer problem (since the second term of F does not depend on the ink coverages), and can be solved by any of several methods. We next describe our solution for this problem.

The function F is quadratic in respect the the vector $\mathbf{x}$, and the partial derivative w.r.t. $\mathbf{x}$,

$$\frac{\partial F}{\partial \mathbf{x}} = 2\mathbf{B}^T\mathbf{P}_D^T\left(\mathbf{P}_D\mathbf{B}\mathbf{x}(a_c,a_m,a_y,a_k) - \mathbf{s}\right). \tag{12}$$

We suggest to minimize F with respect to a_c, a_m, a_y, a_k in iterations, by minimizing with respect to $\mathbf{x}$, and projecting $\mathbf{x}$ to the proper subspace,

$$\begin{aligned} \mathbf{x}^{[n]} &= \mathbf{x}^{[n-1]} - \varepsilon \cdot \mathbf{B}^T \mathbf{P}_D^T \left(\mathbf{P}_D \mathbf{B} \mathbf{x}^{[n-1]} - \mathbf{s} \right), \\ \mathbf{x}^{[n]} &= \mathbf{x}(\mathbf{x}^{[n]}(2), \mathbf{x}^{[n]}(3), \mathbf{x}^{[n]}(4), \mathbf{x}^{[n]}(5)). \end{aligned} \tag{13}$$

The solution is summarized in Figure 1.

Initialization: set a_c,a_m,a_y,a_k, $k = 1$.
for $k = 1, 2, \ldots, K$

$\mathbf{s} = \left(\lambda \mathbf{L}^T \mathbf{L} + (\mathbf{P})_D \mathbf{B} \mathbf{x}(a_c, a_m, a_y, a_k) + \lambda \mathbf{L}^T \mathbf{m} \right)$.

Solve the inverse Neugebauer problem, assume a fixed $\mathbf{s}$,

- Set: $\mathbf{x}^{[0]} = \mathbf{x}(a_c, a_m, a_y, a_k)$.
- For $j = 1, 2, \ldots, J$
  - $\mathbf{x}^{[j]} = \mathbf{x}^{[j-1]} - \varepsilon \mathbf{B}^T \mathbf{P}_D^T \cdot \left(\mathbf{P}_D \mathbf{B} \mathbf{x}^{[j-1]} - \mathbf{s} \right)$,
  - $\mathbf{x}^{[j]} = \mathbf{x}(\mathbf{x}^{[j]}(2), \mathbf{x}^{[j]}(3), \mathbf{x}^{[j]}(4), \mathbf{x}^{[j]}(5))$.
- Set: $a_c = \mathbf{x}^{[J]}(2)$, $a_m = \mathbf{x}^{[J]}(3)$, $a_y = \mathbf{x}^{[J]}(4)$, $a_k = \mathbf{x}^{[J]}(5)$

Figure 1. *Solution scheme for Problem (6)*

Convergence

The above solution is simple and efficient, yet does not assure a global minimum solution nor convergence. The first stage in each iteration certainly decreases (or does not change) the cost function. This is not guaranteed in the second stage, although can be easily forced (by checking the cost function after each inner iteration). Combining those two facts, the algorithm can be forced to converge. In practice, we found that the algorithm converges without any additional constraints (after approximately 15 iterations).

Results

We tested the above algorithm on spectra measured from prints of HP-Indigo's presses. We considered the 3-channel inline densitometer installed on HP-Indigo's presses, whose density filters are presented in Figure 2. First, we checked the accuracy of spectral estimation within the same media, and then we checked the estimation when considering the full coverage spectra $\mathbf{P}_D$ of one media for the Neugebauer prior, and estimating the spectrum on another media. The density values in those two experiments were computed from spectrophotometric measurements in order to avoid measurement noise.

In our test we printed a full grid of $5^4 = 625$ patches (grid of 25% in the coverage of each separation) on three different types of papers. We used different types of papers for two main reasons. First, in order to test the behaviour on different media, and second, in order to estimate generalization capabilities from one media to another.

All patches were numerically projected on the three density filters Figure 2. The spectrum estimation was done using these three projections, following the numerical scheme of Figure 1.

In the test we considered three sets of spectra for the Neugebauer parameters $\mathbf{P}_D$. The three sets where measured from corresponding patches of the three printed papers. We tested all patches assuming each of the three sets of spectra (three types of papers, each examined with three types of parameter sets, results in nine sets of results).

The mean ΔE values and 95% errors are reported in Table 1. As expected, the results on the diagonal (spectrum estimation where the model is taken from the same type of paper) are substantially better than the off-diagonal results. Also, we can see a better match between the Coated and Un-Coated white papers compared to the match with the yellowish paper. Moreover, notice that assuming a white paper parameter set, in estimation of a colored medium produces much better results than assuming a color paper parameter set and estimating spectrum on a white paper. This is understandable, as the color pigments in the colored papers can be considered more ink, while the counter case of less ink is impossible.

ΔE_{2000} / 95% result	paper model (A)	paper model (B)	paper model (C)
(A)	0.36 / 0.59	0.41 / 0.93	1.59 / 3.89
(B)	0.56 / 0.98	0.34 / 0.66	1.25 / 2.83
(C)	0.98 / 1.75	1.02 / 1.84	0.29 / 0.59

Test 1 results: the mean error and 95% error in estimating the spectra of 625 patches on three different types of paper - White coated (A), White uncoated (B), Yellowish(C) - assuming three different sets of spectra for the Neugebauer model.

Two examples are presented in Figure 3. The left figure presents an estimation of the spectral reflectance of a coated paper with model parameters taken from the coated paper while the right figure presents an estimation of the spectral reflectance of an uncoated paper with the coated paper model parameters.

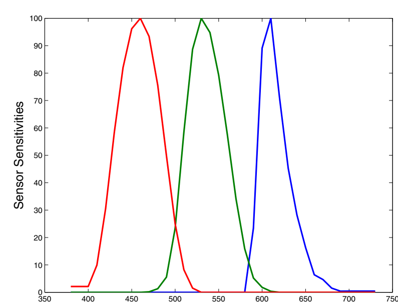

Figure 2. *The three densitometer sensitivity functions available in HP-Indigo's presses.*

Modifications

The solution described above suffers from two major problems,

- The Neugebauer Model is not accurate enough in representing the expected spectrum.
- Assuming the spectrum of black ink is similar to the spectrum of a certain combination of cyan magenta and yellow

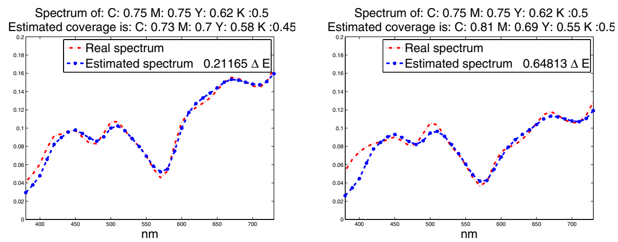

Figure 3. *Results of the spectrum estimation algorithm described in Figure 1. The left figure presents one result printed on coated paper, and examined assuming the spectra $\mathbf{P}_D$ of the coated paper, and on the right the patch was printed on a coated paper, but the parameter set of the uncoated paper was assumed.*

inks, there are many good candidates for local minima for F, corresponding to different {C,M,Y,K} coverages that yield the similar spectrum. We would not want the algorithm to choose a random coverage solution.

We address these two issues by modifying the problem (Equation 6) and its solution scheme.

Cellular Neugebauer Model

The cellular model increases the accuracy of the spectral reflectance evaluation by taking into account measured spectra of partial ink coverage [12].

The cellular model applies the regular Neugebauer model on smaller coverage ranges. Imagine a four-dimensional cube, divided into n parts in each separation, in which the spectral reflectance of all $(n+1)^4$ nodes are known. The estimation of a value inside a cell is done by applying the regular model with the 16 nodes that bound this cell per-se whose spectrum will now comprise the $\mathbf{P}_D$ matrix. To better clarify this explanation we give an example. Lets consider we know all spectra of ink coverage 0, 0.5 and 1 of all combinations of C,M,Y,and K ($n = 2$, total of $3^4 = 81$ spectra), and we define P_{c_x,m_x,y_x,k_x}, where $x \in \{0, 0.5, 1\}$ as the corresponding spectra. For estimating the spectrum of $c = 0.2, m = 0.6, y = 0.3, k = 0.8$ we apply the regular Neugebauer model on the cell $I = (1,2,1,2)$ (lower ranges in cyan and yellow, upper ranges in magenta and black), with variables of $c = 0.4$, $m = 0.2$, $y = 0.6$, $k = 0.6$, and the spectra that are considered for this cell's model parameters, $\mathbf{P}_D^I$, are all $P_{c_{x_1},m_{x_2},y_{x_3},k_{x_4}}$ combination for $x_1 \in \{0, 0.5\}$, $x_2 \in \{0.5, 1\}$, $x_3 \in \{0, 0.5\}$, $x_4 \in \{0.5, 1\}$.

We use the more accurate cellular Neugebauer model as our prior. In the first part of each iteration in Figure 1 (updating the spectrum), only the estimation part modifies in order to fit the cellular model (the Neugebauer coefficients are changed, and $\mathbf{P}_D$ turns to $\mathbf{P}_D^I$ and includes the vertices of the cell). In the second part, we iterate as before for finding better coverage values in the same way, only considering the current cell. After each iteration the new coverage values are examined, and in the case one of the values increases to 100% or decreases to 0% the index of the cell is changed accordingly (as do also the relevant coverage value and model parameters, $\mathbf{P}_D^I$).

Results improvement by using the cellular model

We conducted two similar tests to the ones described in the result section and recalculate with the cellular model. A figure similar to Figure 3 is presented in Figure 4. In addition results

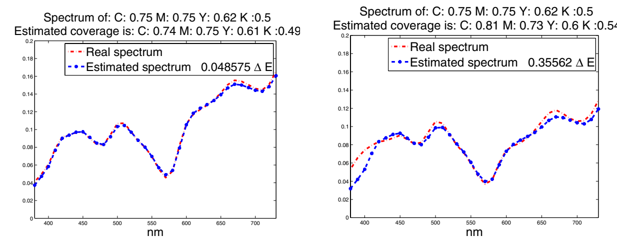

Figure 4. *Results of the spectrum estimation algorithm. The left figure presents one result printed on coated paper, and examined assuming the spectra $\mathbf{P}_D$ of the coated paper, and on the right the patch was printed on a coated paper, but the parameter set of the uncoated paper was assumed.*

similar to Table 1 are presented in Table 2. Notice the vast improvement in all results compared to Table 1. This improvement is due to the improved accuracy provided by the cellular Neugebauer model.

ΔE_{2000} / 95% result	paper model (A)	paper model (B)	paper model (C)
(A)	0.13 / 0.33	0.29 / 0.75	1.59 / 3.93
(B)	0.33 / 0.67	0.14 / 0.36	1.06 / 2.55
(C)	0.81 / 1.60	0.63 / 1.34	0.12 / 0.32

Test 2 results: the mean error and 95% error in estimating the spectra of 625 patches on 3 different types of paper - White coated (A), White uncoated (B), Yellowish(C) - assuming 3 different types of models for the cellular Neugebauer model.

Constraints on the solutions for the coverage

Assuming the spectrum of black ink is similar to the spectrum of a certain combination of cyan magenta and yellow inks, there are infinitely many coverages {C,M,Y,K} that yield the same spectrum.

In the scheme in Figure 1, the ink coverage combination strongly depends on the initial solution we provide. In order to illustrate this phenomena we projected one specific spectrum (estimated by the cellular model, with coverage values of $c = 0.3, m = 0.5, y = 0.2, k = 0.3$) on the 3-channels densitometer presented in Figure 2. We then estimated the initial spectrum and coverage values using these projections with variable initial solutions for the coverage. We received a wide range of coverage solutions presented on the left side of Figure 5 (sorted by the amount of estimated black). It can be seen that when the estimated amount of black increases, the estimated amounts of the other inks decrease. The blue line in that Figure represents the error (in ΔE) between the initial spectrum and the estimated one.

As can be seen by the estimation error graph, this dependency on the initial solution for the coverage is relevant mainly to the coverage solution values. The resulted spectra are less varying, as can also be seen in the right side of Figure 5 . There, all resulted spectra are more or less the same, in particular, around the

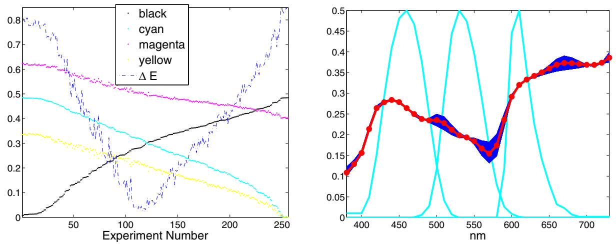

Figure 5. LEFT: The solution space for the coverage. The dots represent the coverage ratios of each ink (sorted by the coverage of the black) when starting with different initial conditions. The blue line represents the error in ΔE. RIGHT: Variety of solutions for the spectrum when the initial solution for the coverage varies. In red is the original spectrum, in blue are all estimated spectra. In cyan are the profiles of the used densitometers. It can be seen that the estimated spectra match the original one, in particular, around the densitometers' modes.

modes of the densitometers (diversity from the original spectrum was between $0\Delta E$ and $0.8504\Delta E$, with mean value of $0.1714\Delta E$ and standard deviation $0.2591\Delta E$).

We prefer to receive the coverage combination which most resembles the input combination to the press, under the assumption that the deviation of the press was minimal. For that purpose, we updated Equation 9

$$F(\mathbf{s}, a_c, a_m, a_y, a_k) = \left\| \left(\mathbf{P}_D \mathbf{B} \mathbf{x}(a_c, a_m, a_y, a_k) - \mathbf{s} \right) \right\|_2^2 + \quad (14)$$
$$\mu \left\| \mathbf{W} \left(\begin{bmatrix} a_c \\ a_m \\ a_y \\ a_k \end{bmatrix} - \begin{bmatrix} a_c^0 \\ a_m^0 \\ a_y^0 \\ a_k^0 \end{bmatrix} \right) \right\|_2^2 + \lambda \left\| \mathbf{L}\mathbf{s} - \mathbf{m} \right\|_2^2 .$$

where $a_c^0, a_m^0, a_y^0, a_k^0$ are the input coverage values to the press, and $\mathbf{W}$ is a diagonal weight matrix that weights the possibility of deviation in each separation. The weight μ for the additional term should be very small as we would not want it to affect the minimization of the other two terms.

Combining this in our numerical scheme, together with assuming the cellular Neugebauer model, results the solution described in details in [10].

In addition, when one of the inks was not used at all (knowing the combination of colors the press used) we incorporate this knowledge in our solution, and refer to a restricted Neugebauer model with lower dimension. In these cases we may expect a much more accurate coverage estimation. Limiting the dimension of the model and solving the restricted version is a relatively simple generalization.

Summary

We have described a novel algorithm for spectral reflectance estimation from simple measurements using color model as prior. The algorithm also provides estimation of the amounts of ink that were laid on the paper. Further results indicate stability to uncertainty in measurement device and to measurement noise.

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