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Color printing on pre–colored textiles

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Abstract

Managing color on a particular imaging system is a well-understood challenge with a wealth of existing models, methods and techniques. In the case of printing systems, these tend to operate in the context of a single substrate, where managing color on every additional substrate is approach as a separate, detached problem. While such a mind-set works reasonably well in general, it breaks down when it comes to printing onto pre-colored textiles, such as pre-dyed fabrics. The present paper therefore introduces a family of approaches that support the use of multiple pre-colored textiles on a given printing system that also allow for a balance between characterization effort and color match accuracy. This, in turn provides solutions that can fit a variety of practical working patterns to maximize overall efficiency and performance.

Introduction

The rise of digital printing in a variety of textile industries is driven by its greater flexibility, both in terms of the content printed and in how precisely run lengths can be tailored to demand. While some applications of printing onto textiles, such as soft signage, can apply solutions developed for the Graphic Arts, others, like sportswear and fashion, face new color challenges.

In the case of dye-sublimation printing, there are two prominent ones: first, the need to determine how to use a printing system's inks to match a given color on a wide variety of pre-colored fabrics and second, the need to deliver color matching on a fabric also in workflows where printing is done onto a transfer paper, from where it is calendered onto the final fabric.

Both challenges turn out to be color characterization and modelling ones. Here, the literature on characterizing the color of print on fabrics presents a variety of approaches, with different levels of color accuracy. Early solutions were attempted via linear models[1,2], followed by a direct application of ICC color management[3] (with 95th percentiles of ΔE2000 errors above 6) and the use of neural networks[4] (yielding prediction errors with a mean of 1.89 ΔE00, 90th percentile of 2.8 ΔE00 and a maximum of 8.5 ΔE00), already well established for recipe formulation when dyeing fabrics[5]. Also, relevant here is the rich and extensive literature on print color prediction on non-textile materials[6,7], where Neugebauer-based approaches[8], the Kubelka–Munk equations[9], the use of polynomials, and that of neural networks are all common, as are combinations of such basic predictive components[10].

However, the above approaches are both less and more constrained than the challenge addressed in this paper. They are less constrained since they apply to cases where the printing substrate is spectrally nearly non-selective, which results in a certain degree of regularity among the colors of the resulting colorant-substrate combinations. It also means that the color of the substrate interacts in a very similar way with all colorant colors, and this, in turn, aids their successful prediction. They are more constrained, since they approach the modeling of a given substrate-colorants system from scratch, while in the case of printing onto colored fabrics, the colorant set is constant, and it is only the fabric substrate color that varies.

A final consideration to introduce, before setting out an approach tailored to making color predictions when printing onto textile substrates of varying color, is the question of what the purpose of such predictions is. The most obvious scenario is the need for a match that complies with color tolerances suitable for a given textile printing application. E.g., in sportswear and fashion this can be in the region of 1.0–1.5 ΔECMC under a variety of light sources, while in soft signage the requirements tend to be around 0.8-1.4 for the 95th percentile of ΔE00s for solid colors and 2.5 for image content. Instead of this being an all or nothing scenario though, where a solution either delivers these tight levels of match or it is not applicable, there is value also in using color modeling as a pre-selection mechanism in a manual-visual process, where model characterization overheads can be balanced against accuracy. For an experienced printer operator, who would spend around one hour per color to match it iteratively by hand from, having a quick, approximate match that would remove some of the early iterations is more useful than a lengthy and resource-intensive process that delivers a match directly. A key factor here is that many print jobs in color textile printing for fashion and sportswear applications involve a relatively small number of individual colors, which then need to be matched on a larger number of pre-colored substrates. A high per-substrate overhead is undesirable here.

To address the specific constraints and opportunities that the prediction of printed color on pre-colored textiles presents, the following sections will present a series of approaches with increasing printing and measurement needs, preceded by a presentation of differences between differently colored substrates, which set the context in which predictions will be made.

Printed color on pre-colored substrates

To explore color modeling on pre-colored substrates, a white and eight strongly colored substrates will be used here. Table 1 shows their colorimetries, Figure 1 the a*b* projections and Figure 2 the color gamuts of the measurements of an 864-patch color chart printed on each of these substrates with the same printing system using CMYK colorants.

Table 1: Substrate names and colorimetries

Name	*CIELAB*
White	93.42, 2.32, -8.90
Cyan	67.59, -23.13, -25.78
Magenta	52.22, 54.62, -10.94
Yellow	84.59, 6.80, 79.73
Brown	39.19, 16.56, 15.51
Orange	76.37, 27.96, 71.96
Red	46.09, 58.03, 32.49
Green	70.85, -35.32, 39.49
Blue	35.24, 1.72, -30.15

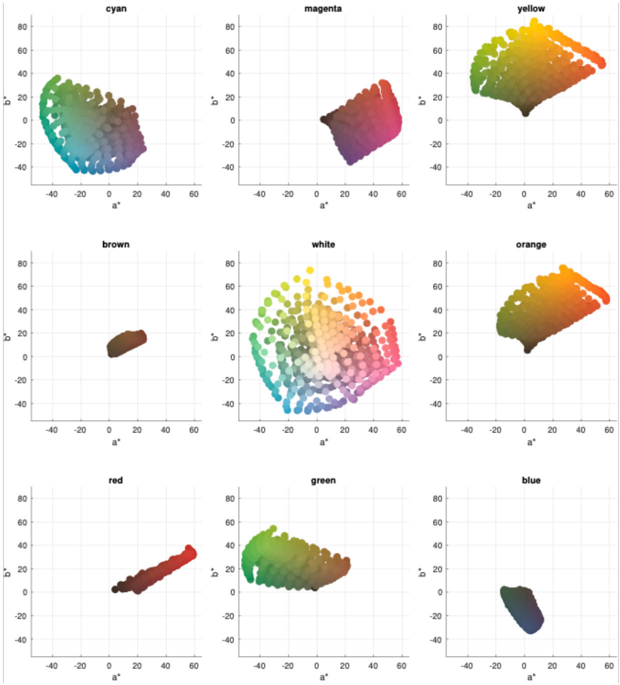

***Figure 1.** a*b* projections of 864 color patches printed on nine substrates.*

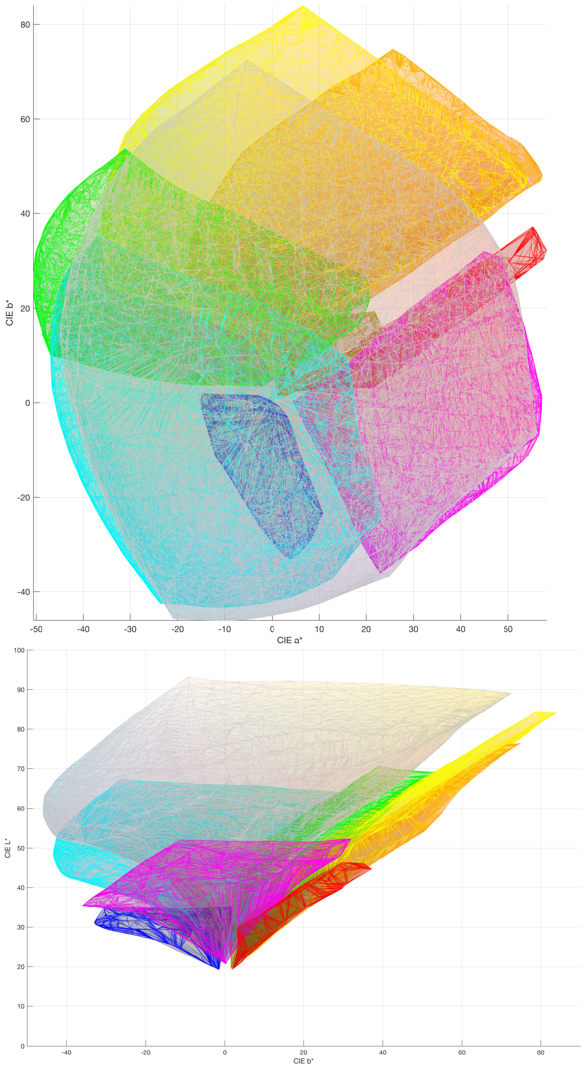

***Figure 2.** Color gamuts of 864 color patches printed on nine substrates.*

As can be seen, the consequences of printing the same content onto these nine substrates are dramatic, with gamut volumes ranging from as little as 698 cubic CIELAB units on brown to 193K on white.

To get a sense of the challenge of dealing with color when printing on such distinctly colored substrates, the accuracy of ICC output profiles built on the basis of these 864 measurements is also telling. For the white substrate the profile's median error is 1.1 ΔE00, the 95^{th} percentile is 1.7 ΔE00 and the maximum is at 2.8 ΔE00. Instead, the worst case in the set is for the yellow, orange and red substrate, where the profiles for yellow has a median error of 5.5 ΔE00, a 95^{th} percentile of 15.4 ΔE00 and a maximum of 20.6 ΔE00. In other words, the profile would give excellent results for a soft signage application on the white substrate, but would be totally unacceptable on a yellow one and in both cases it would take a significant amount of time to print, calender and measure the color charts needed for building them.

Level 0: substrate only

The most basic attempt that could be made to predict the colors printed on a pre-colored substrate would be to attempt to do so based solely on a full set of measurement from a canonical substrate (e.g., the white one) and a single measurement of the blank substrate on which predictions of printed color need to be made.

Let us take the blue substrate as an example, where building an ICC profile directly have average results (median: 3.3 ΔE00, 95^{th} percentile: 9.3 ΔE00, maximum 10.4 ΔE00) and which has a gamut volume of 2247 cubic CIELAB units. The color differences between corresponding color patches printed on white versus blue substrates (i.e, having the same per-ink quantities and printed patterns) have a median of 34.5 ΔE00, a 95^{th} percentile of 51.9 ΔE00 and a maximum of 57.5 ΔE00 (Figure 3). In other words, the color on a white substrate gives little indication of what the same content printed on the blue substrate will look like and a printer operator's attempt at matching some color in the gamut available on the blue substrate effectively starts from scratch.

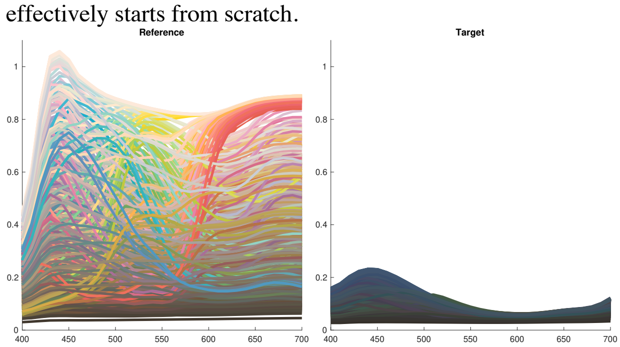

***Figure 3.** Reflectances of 864 printed patches on canonical, white substrate (left) and on pre-colored, blue substrate (right).*

A simple approach here consists of taking the measurements of the color patches on the white substrate and making a prediction of what their colors would be on the blue substrate using the Kubelka–Munk equations. More specifically, the Kubelka–Munk model is only needed for separating the ink layer as a whole (without having to care about its components) and the substrate. Treating the ink layer as one and assuming that it is perfectly transparent means that it is not necessary to deal with the per-ink or combined degrees of opacity, which simplifies the general Kubelka–Munk model from:

$$X=R+(ST^2)/(1-SR) \quad (1)$$

(where X is total reflectance, S is substrate reflectance, T is ink layer transmissivity and R ink layer reflectivity) to

$$X=ST^2 \quad (2)$$

making the prediction of what a transparent ink layer on one substrate would be like when applied to another a simple division by the known substrate and multiplication by an unknown one:

$$X_N = (S_C T_C^2/S_C)*S_N \quad (3)$$

(where N denotes the new substrate and C the canonical one), which is the same as

$$X_N = (X_C/S_C)*S_N \quad (4)$$

This highly-simplified model assumes that ink-substrate interactions are the same on the new and the canonical substrate, which is rarely the case. Nonetheless, the improvement versus the direct difference between the two substrates very large, with the simple single-measurement Kubelka-Munk approach having median: 9.9 ΔE00, 95th percentile: 13.6 ΔE00, maximum 20.1 ΔE00 prediction errors on the blue substrate.

While the above results still show high errors, the median has been reduced from 34 to 10 and the 95th percentile from 50 to 13. This means that a neighborhood can be predicted that is sufficient to generate a number of alternatives from which a printer operator can make choices. This in turn can reduce the number of iterations needed in the absence of a model.

Level 1: substrate only + priors

Without going beyond the need to measure the pre-colored substrate on which color prediction is to be done, it is possible to improve prediction performance if more data about pre-colored substrates is available *a priori*. Printing and measuring a set of pre-colored substrates beforehand allows to build a prediction that is not tied to any one of them but uses the data available from all of them.

The intuition here is that while the substrate subtraction/addition (division/multiplication) in the Level 0 example follows first principles, it assumes simplistic or constant colorant-substrate interactions, which can be improved by a generic mapping. Spectral regression can be derived from a number of corresponding sets of measurements between canonical and pre–colored substrates to build a substrate-independent mapping, i.e., a single mapping, independent of substrate color.

Let M_i be a set of reflectance measurements of the same content (e.g., the 864-patch chart used here) on a variety of substrates, where X_C corresponds to the canonical substrate and X_i to coloured substrates, with the substrate itself having been divided out as in Level 0. A mapping T is then solved for such that it minimizes

$$||f([X_1, X_2, \ldots X_n])*T - [X_C, X_C, \ldots, X_C]\,|| \quad (5)$$

where f is some transformation of the reflectance data in X_i (e.g., a polynomial expansion). T then is common to all colored substrates and can be applied to improve on the Level 0 approach as follows. First, the substrate is removed from the canonical substrate reflectances X_C:

$$X'_C = X_C/S_C \quad (6)$$

Second, media-common mapping T is applied to get substrate-independent X''_C:

$$X''_C = X'_C*T \quad (7)$$

Third, the new substrate is added back to get predicted reflectances X_i:

$$X_i = X''_C*S_i \quad (8)$$

The T correction obtained from pre-colored substrate priors results in prediction errors with median: 6.5 ΔE00, 95th percentile: 13.4 ΔE00, maximum 17.0 ΔE00 on the blue substrate, which translates into identifying a tighter neighborhood from which manual iteration can start.

Level 2: printed primaries

The next level of complexity that can be introduced is to require some minimal printing on the pre-colored substrate on which color predictions need to be made. The least amount of printing that can be used is of only the printing primaries themselves. E.g., in our case of a set of CMYK inks. Based on the four spectral reflectance measurements of the inks, plus the spectral reflectance of the blank substrate (which can quickly be measured by hand), coupled with the corresponding five reflectances from the canonical setup, a per-wavelength reflectance-to-reflectance mapping can be computed using least squares minimization. Even such minimal printed and measured data from a pre-colored substrate results in significant improvements, leading to prediction errors of median: 3.4 ΔE00, 95th percentile: 6.4 ΔE00, maximum 13.0 ΔE00 on the blue substrate, effectively halving most error statistics from the Level 1 approach. This means that for many colors a printer operator may only need a single, or two iterations before identifying a match.

Level 3: printed primaries + secondaries

Supplementing the Level 2 data with measurements of the CMY primaries – i.e., RGB – and therefore using 8 instead of 5 measurements leads to prediction errors of median: 1.5 ΔE00, 95th percentile: 3.9 ΔE00, maximum 7.6 ΔE00 on the blue substrate. This is a good balance between printing and measurement effort and iterations needed and provides a practical solution for an experienced printer operator.

Level 4: full characterization

Finally, a prediction of color on the pre-colored textile can also be made on the basis of a full set of measurements. A mapping, F can be computed here by minimizing the following L2 norm:

$$||X_P*F - C_P|| \quad (9)$$

where X_P and C_P are polynomial expansions of reflectances from the pre-colored and canonical substrates respectively such that w is a single row of X_P or C_P for an n-wavelength case (e.g., 400-700 nm at 10 nm intervals would give an n of 31):

$$[s\ \ w(1),\ \ w(2),\ \ \ldots,\ \ w(n),\ \ w(1)*w(2),\ \ w(1)*w(3),\ \ \ldots\ ,\ \ w(n\text{-}1)*w(n),\ \ w(1)^2, w(2)^2, \ldots, w(n)^2] \tag{10}$$

where s is a scalar/offset term (e.g., with a value of 1) w_i*w_j are the cross-terms and w_i^2 the second order terms. A trivial solution to such minimization is:

$$F = (X_P{}^T*X_P)^{-1}*X_P{}^T*C_P \tag{11}$$

(where $(A^T*A)^{-1}$ is the Moore-Penrose inverse or pseudo-inverse), but more robust solutions are available, e.g., in MATLAB or numpy that use different approaches via matrix decompositions such as SVD.

Applying this model to the data from the canonical, white substrate and the blue substrate results in prediction errors of median: 0.3 ΔE00, 95th percentile: 0.7 ΔE00, maximum 1.9 ΔE00, which substantially outperform a direct use of ICC profiles and deliver prediction accuracy that meets the most demanding use cases. This is particularly relevant when larger numbers of colors need to be matched or when matching needs to be done by printer operators not experienced in establishing color matches iteratively.

Table 2: ΔE00 color differences between prints on white and blue substrates (P – printing required on blue substrate, M – number of measurements on pre-colored textile needed for prediction).

Scenario	*P*	*M*	*Med.*	*95th p.*	*Max.*
Direct	No	0	34.5	51.9	57.5
ICC profile	Yes	864	3.3	9.3	10.4
L0: substrate	No	1	9.9	13.6	20.1
L1: sub + prior	No	1	6.5	13.4	17.0
L2: primaries	Yes	5	3.4	6.4	13.0
L3: L2 + sec.	Yes	8	1.5	3.9	7.6
L4: full char.	Yes	864	0.3	0.7	1.9

Table 2 summarizes the various levels of color prediction performance, from where it can be seen that a variety of levels of performance and needs for measurement and printing are available so that solutions can be tuned to specific workflows and applications.

Calendering

An additional element involved in predicting color printed on textiles applies when the process involves two stages, as in dye-sublimation printing. There a print is made onto a transfer paper, which is then placed in contact with the textile and passed through a calendering machine where, under pressure and heat, the ink is sublimated from the transfer paper and onto the textile. In this case, color measurements can be made of the print on paper and of the final print on the textile and it is beneficial to be able to predict the final color on a textile from the intermediate color on the transfer paper.

Here Figure 4 shows reflectances on Coldenhove HS 95 gsm paper and then after calendering on an Argentona Anibal polyester blend fabric, printed with a HP Stitch S300 printer that uses CMYK dye-sublimation inks. The color differences between corresponding color patches were median: 18.2 ΔE00, 95th percentile: 26.0 ΔE00, maximum 30.4 ΔE00.

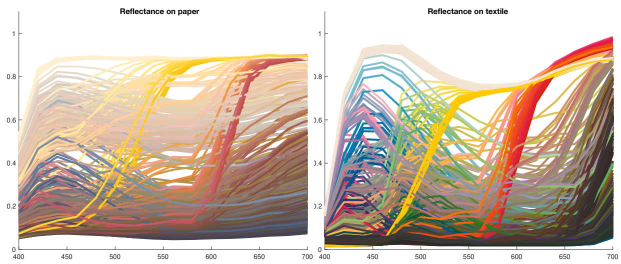

Figure 4. *Reflectances on transfer paper(left) and fabric (right).*

Applying the same full characterization approach as used on the pre-colored substrate case resulted in prediction errors with median: 1.5 ΔE00, 95th percentile: 4.5 ΔE00, maximum 7.7 ΔE00. This is a significant improvement as compared with the direct differences but is not at a level required by most applications.

To improve prediction accuracy, the initial model was extended by taking its predictions as the input to a second minimization using the same polynomial expansion. I.e., first minimizing a mapping between reflectances on paper and on textile, followed by minimizing another mapping between the first mapping's predictions and the textile reflectances. The result is a progressive model that resembles the layers of a neural network, although its parameters are computed in a sequential, forward manner. Applying such a progressive approach resulted in prediction errors with median: 0.6 ΔE00, 95th percentile: 1.8 ΔE00, maximum 3.4 ΔE00.

Conclusions

Predicting the color of printing on textile materials introduces new challenges due to the use of pre-colored substrates and the use of intermediate stages. Approaching the need for color control here benefits from taking into account both what varies and what remains the same between different use cases and the needs and constraints of those who are tasked with achieving color matches.

A sequence of increasingly more resource-intensive ways of predicting printed color on pre-colored substrates was presented, which offers a continuum of performance versus effort combinations that range from requiring no printing, via the use of very low numbers of printed and measured color patches to the use of full characterization charts. They then deliver solutions that range from accelerating a manual matching process to directly providing a match.

Underpinning these approaches are the use of both analytical models (Kubelka-Munk) and general-purpose computational methods (regression) as well as their combinations.

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Peter Morovič received his Ph.D. in computer science from the University of East Anglia (UK) in 2002 and holds a B.Sc. in theoretical computer science from Comenius University (Slovakia). He has been a senior color and imaging scientist at HP Inc. since 2007, has published 50+ scientific articles and has 150+ US patents filed (116 granted) to date. His interests include 2D/3D image processing, color vision, computational photography, computational geometry. His Erdős number is 4.

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