# Revisiting Spectral Printing: A Data Driven Approach

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## Abstract

*Spectral printing is a well–established part of imaging that can boast of a rich body of literature. Nonetheless there has been limited commercial uptake of this approach to visual content reproduction, in spite of its clear benefits. The aim of the present paper is therefore to explore what may lie behind this apparent mismatch by looking at how colorimetric (metameric) and spectral reproduction compare on an 11–ink printing system. To aid the above exploration, the paper proposes a new metric for evaluating spectral reproduction in a visually meaningful way and presents an analysis of the spectral properties of colorimetric and spectral reproductions of a variety of original content including spot colors and fine art.*

## Introduction

A key choice when making a print is to decide how it is to relate to original content. This can range from the print becoming the first 'original' (e.g., fine art created digitally, where its viewing on a display is only an intermediate step of the creative process), via its aim being to please (e.g., holiday snaps) to it being as close to a facsimile as possible (e.g., fine art reproduction, proofing). In the last case, the question arises of how broadly the match needs to hold: only under specific viewing conditions or under any (or a broad range of) lighting and viewing. Here the former is a colorimetric (metameric) reproduction while the latter is a spectral one, which has the benefits of mimicking an original more closely so that looking at it gives the same visual experience as looking at the original would, regardless of where they are viewed and who does the viewing. Conversely, the colorimetric case is set up for specific lighting (typically D50 or D65) and with a specific viewer in mind (usually the 2° CIE Standard Observer) and tends to break down under other conditions (hence its 'metameric' label).

As the case looks very strong for spectral reproduction, it is worth putting two caveats on the table: first, how accurately a spectral match can be achieved and second, how much closer it is to an original than the spectral match obtained when colorimetric matching is set up. The two questions are related in that both spectral and colorimetric reproduction have potentially the same spectral variety at their disposal (being a consequence of the inks, substrate and their interactions) where the difference between an explicit spectral match and the spectral fit of the colorimetrically–selected match may be significantly smaller than the mismatch of either of these to the original reflectance spectrum. In other words, a key question is the spectral 'compatibility' of the original content and printing system's potential.

Spectral printing is a topic that can boast of a rich body of literature exploring its various aspects, developing its component building blocks (e.g., spectral capture, printer models (e.g., Taplin 1996), gamut mapping, error metrics for minimization) and applying it in various ways (e.g., fine art reproduction, proofing – including of textiles). Given such a well–established field, it is maybe surprising that it has not found more commercial application and the aim of the present paper is also to look for possible reasons for this fact.

Two test cases will therefore be considered: fine art reproduction and spot color proofing, both of which are, in principle, a very good match to the benefits of spectral reproduction. The spectral properties of originals and the way they relate to the spectral variety accessible using two printing setups will then be evaluated. Finally the closest achievable matches will be quantified using an evolution of existing multi–illuminant $\Delta E$ metrics that aims to be more representative of an original–reproduction pair being viewed under a broad variety of viewing conditions.

Before proceeding with an overview of the state of the art, it may be worth underlining why the above two aspects of spectral characteristics (a physical, 'device dependent' feature) and perceived difference under a variety of conditions (a psychophysical, 'device independent' aspect) are considered side by side. The reason for this is that image reproduction is concerned precisely with the interplay between reproduction capabilities and their effects on a viewer – i.e., the device dependent seen in a device independent way.

## State of the art of spectral match metrics

Before turning to the analysis outlined above, two areas of the literature will be reviewed: dimensionality reduction (allowing for an analysis of spectral 'compatibility') and metrics for evaluating spectral matches.

In terms of dimensionality reduction, the basic idea is that the underlying variance in spectral data is often of lower dimensionality than that of the measured reflectance space (i.e., typically having 31D for a 400–700nm range sampled at 10nm steps) and that it can therefore be expressed as a weighted combination of a smaller number of bases. In other words: $R=\mathbf{B}*w$, where R is a 31x1 reflectance vector, $\mathbf{B}$ is a 31x$n$ matrix containing $n$ bases and w is an $n$x1 set of weights for combining the bases linearly. Then there are numerous choices of how to obtain the bases, how many of them to use and what space to use this representation in.

Here Ramanath *et al.* (2004) present a survey that compares Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Neural Networks (NN) and also covers methods for obtaining sets of all–positive bases (e.g., Non–negative Matrix Factorization) and their results show similar performance for these approaches when using three bases, with PCA performing best for their data. Tzeng (1999) introduces an important consideration to dimensionality reduction – that the choice of space in which bases are computed and where their combinations are made plays an important role. He then goes on to show that the dimensionality reduction of spectra measured from an IT8.7/2 chart (a three–dye photographic print) suggests that six bases are needed, while it is known that there are only three independent components at play. Tzeng shows how a conversion into the Kubelka Munk K/S absorption space before PCA results in the same level of variance >99.9% being spanned by only three bases. Finally, an important question is, how much variance coverage is enough? One approach is to state that 99.9% ought to be plenty and then select the number of bases that give the necessary coverage. Another is to look for meeting a 1 $\Delta E$

threshold under a reference illuminant and choose the number of dimensions to achieve it. Finally, a very well reasoned approach is to use psychophysics to find how many bases it takes to match hyperspectrally–captured scenes. Here Nascimento *et al.* (2005) report that 8 bases were needed for a 55% discrimination threshold (corresponding to a mean ΔE*ab of 0.7–0.8, which corresponds to a ΔE00 of around 0.4 (Sun and Morovič, 2002)) even though 5 bases would have been sufficient to get to the unit ΔE threshold.

Turning to the evaluation of spectral match metrics, Imai *et al.* (2000) and Viggiano (2004) presented two excellent surveys, comparing metrics that range from spectral–only methods like RMS (the root mean square difference between two reflectance spectra) and GFC (Hernández–Andrés *et al.*'s (2001) goodness of fit coefficient), via various weighted version of RMS, e.g., using the diagonal of Fairman's (1987) matrix R derived from tristimulus weights for a given illuminant and observer, to metamerism indices (which report the color difference under a test illuminant – e.g., A – for a match under a reference illuminant – e.g., D65) and even a combined spectral and colorimetric metric: CSCM (López–Álvarez *et al.*, 2005). The conclusions of both these surveys are that none of these metrics can be universally recommended over the others and that their choice is a matter of what application it is being used for. The basic challenge here is that while RMS expresses the physical difference between a pair of spectra, it is not visually meaningful. The fact that the starting point is often a mismatch already under a reference illuminant rather than a strict match is a complication, which means that metamerism indices are often applied not directly to an original–reproduction pair, but to one that has been 'corrected' (e.g., using Fairman's (1997) method) to force a match so that the metameric difference under a test illuminant can be expressed. A different approach is then taken by Alsam and Hardeberg (2004) and Bastani *et al.* (2007) who consider ΔE statistics under multiple illuminants: 6 in the former and 11 in the latter case.

Given the above approaches to dimensionality reduction and spectral match metrics, the following sections will first introduce a new alternative to the reflectance or absorption based PCA approaches, proceed to make a more explicit comparison between original and reproducible spectra, propose a new spectral match metric that extends the multi–illuminant methods mentioned previously and finally apply them to the example original and print conditions.

## Methodology

### *Dimensionality analysis in Yule–Nielsen corrected spectral reflectance*

While Tzeng's K/S based analysis is an important step towards getting at the fundamental sources of variation in surface color, it is an approach that assumes homogeneous mixing of base colorants. This assumption is well suited to the spectral analysis of paintings or analog photographs, but less well to that of halftone prints. Here the basic building blocks are not colorant absorption spectra but Neugebauer primaries upon which optical and physical dot gain act instead. Hence the most appropriate means of analysis is in a Yule-Nielsen corrected (Yule and Nielsen, 1951) spectral reflectance space and what can be expected are bases that relate to Neugebauer primaries, which in turn can either be predicted from colorant K/S spectra. Our method is therefore an extension of Tzeng's approach in that it combines both the subtractive colorant mixing of dot overlaps and the additive optical mixing that follows it. A prerequisite for this approach though is that is assumes that NP relative area coverages can be free varied. While this is not the case in colorant space based approaches to color separation and printer control, the HANS approach (Morovic *et al.*, 2011) directly enables it. Therefore the results of this Yule–Nielsen based analysis apply directly to HANS and present an upper limit that is likely to exceed what can be obtained using colorant space methods. Results for a direct dimensionality-based comparison of the original and reproduction data will be reported in the final paper.

## MIPE – a new spectral match metric

A key requirement for evaluating the degree of spectral match is to quantify how closely an observer thinks a reproduction matches an original under different viewing conditions. Since ΔE metrics best predict perceived differences and have units designed to correspond to just noticeable differences, results in their terms have most direct visual meaning, as opposed to metrics yielding (weighted) reflectance differences. Furthermore, a reproduction is likely not to be strictly metameric – i.e., there will be non–zero differences between an original and a reproduction even under reference conditions (if such are even defined when setting up the spectral match). Hence a viewer may see a difference even when looking at a reproduction under reference conditions. Under other than reference conditions there will be a difference too, which is not only the increment from what a perfect match under reference conditions would deteriorate to (as is the case with metamerism index methods mentioned above). In other words, for a metric to represent the perceived differences between a pair of surfaces, it needs to incorporate the difference present even under reference conditions and express how that difference manifests itself under as great a variety of conditions as possible.

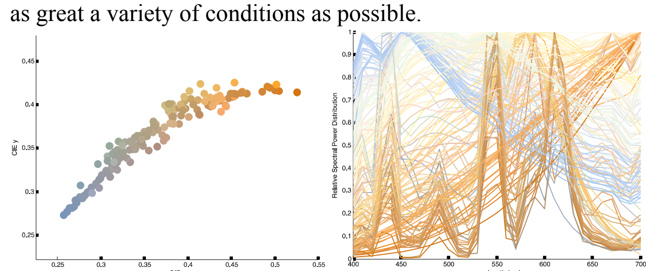

***Figure 1.*** *CIE xy chromaticities of the 173 illuminants (left) and their relative spectral power distributions (right).*

In the method proposed here, we will use the ΔE2000 color difference equations. Since the results of the metric need to express how a reproduction relates to an original under arbitrary, but realistic, viewing conditions, we will use a large database of illuminants and measured light sources. Our choice is Hordley's (2001) set of 173 spectral power distributions (Figure 1), which includes both CIE standard illuminants and a large variety of measured natural and artificial light sources. Finally, instead of reporting only the worst case match (as in the Bastani *et al.* approach) or full per-illuminant statistics, the ΔEs between original and reproduction will be pooled together from across all available illuminants. By reporting the median, $95^{th}$ percentile and maximum for a set of corresponding original–reproduction samples (or even for a single one across all illuminants), the results will indicate how close a match can be expected for an arbitrary, but realistic, light source (median), how much this match varies (median – $95^{th}$ percentile difference) and how far apart the two can get at worst (maximum).

Equation 1 expresses the MIPE metric in mathematical notation, where $MIPE_{MED}$ is the median MIPE for a set of $n$ samples viewed under 173 light sources, $O_{i,s}$ is the $s$-th sample viewed under light source $i$ and $R_{i,s}$ is the corresponding reproduction:

$$MIPE_{MED} = \underset{i=1,s=1}{\overset{i=173,s=n}{median}}(\Delta E2000(O_{i,s}, R_{i,s})) \quad (1)$$

Since this approach starts with a paramer pair (i.e., a pair that even under reference conditions have some different and are therefore not perfect metamers), considers multiple illuminants and reports ΔE predictions, it will be referred to as *Multi–Illuminant Paramer ΔE* – MIPE. Finally, it is also worth noting that MIPE, like all the other metrics discussed in the literature survey, provides color difference predictions for individual color patches (or sets of them) and that it does not address aspects of image appearance.

## Results

### *Test setup*

The dimensionality and spectral match analysis methods described above will be applied to two printing setups (Table 1). Note that the two pigmented, aqueous inks 10–ink sets used in a HP Designjet Z3100 printer differ by one ink only, where the first uses a matte black (k) and the second a glossy one (K). The remaining nine inks are the same in both cases.

**Table 1: Printing systems evaluated.**

| Label | Characteristics |
|---|---|
| Matte | Inks: cMmYnNkRGB<br>Substrate: Hahnemühle Smooth Fine Art |
| Glossy | Inks: cMmYnNKRGB<br>Substrate: HP Premium Instant–dry Gloss Photo |

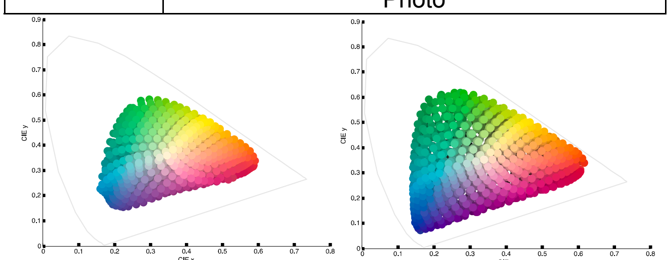

***Figure 2.** Regular samples of printer gamuts printed and measured on HP Z3100 using matte (left) and glossy (right) substrates, spanning the gamut of all possible 10-ink combinations.*

Measurements of the printer's output were made using an XRite i1 spectrophotometer, taking 31 measurements from 400 nm to 700 nm at 10 nm intervals using a 45°/0° geometry.

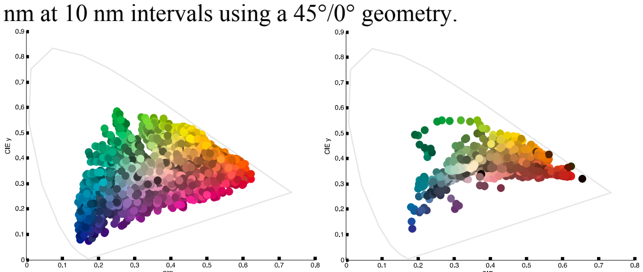

***Figure 3.** CIE xy chromaticity diagrams of the spot color (left) and fine-art (right) data sets.*

The following two sets of source spectra (Table 2) were then compared with the above printing systems. For illustrative purposes they are plotted in terms of their CIE xy chromaticities under CIE D50 (Figure 3).

**Table 2: Original data sets.**

| Label | Characteristics |
|---|---|
| Spot color | PANTONE patches on three substrates: uncoated, matte and coated with 1224 patches per substrate (3672 samples in total, resulting from mixing the Pantone system's 15 base inks) |
| Fine art | Measurements taken from fine art originals (1168 samples) |

### *Dimensionality Reduction*

Given a set of reflectances, the proportion of the first N singular values of its covariance matrix determines the % spectral variance represented by an N-dimensional basis. However, this doesn't intuitively convey the degree to which a reflectance will match or mismatch an original reference under a variety of viewing conditions. For example, a basis of three dimensions can represent >99.8% variance of a data set (see Table 3 below), yet this corresponds to a 95$^{th}$ %tile MIPE of 5 ΔE00 and a maximum of over 24 ΔE00. The following two tables show the relationship of this strict way of looking at dimensionality (shown in the second column), compared to the MIPE metric statistics (shown in the 3$^{rd}$ to 5$^{th}$ column) proposed here for the glossy data set (Table 3) and the matte data set (Table 4). Comparisons are performed in a Yule-Nielsen corrected reflectances space with an empirically determined wavelength independent factor of 4.

**Table 3: Dimensionality analysis of glossy data set, comparing % variance coverage and the MIPE metric for N=1 to 10 for the glossy data sets.**

| dim | % var. | MIPE | | |
|---|---|---|---|---|
| | | med. | 95$^{th}$ %$^{tile}$ | max |
| 1 | 96.60 | 14.3 | 40.7 | 53.7 |
| 2 | 98.69 | 6.4 | 33.5 | 51.6 |
| 3 | 99.83 | 2.0 | 4.9 | 24.4 |
| 4 | 99.92 | 1.3 | 3.2 | 17.6 |
| 5 | 99.95 | 1.0 | 2.4 | 11.3 |
| 6 | 99.97 | 0.5 | 1.3 | 5.9 |
| 7 | 99.99 | 0.1 | 0.4 | 3.1 |
| 8 | 100.0 | 0.1 | 0.3 | 2.4 |
| 9 | 100.0 | 0.1 | 0.2 | 1.4 |
| 10 | 100.0 | 0.0 | 0.1 | 1.4 |

The comparison above shows that considering strictly numerical metrics, such as the % variance coverage is limited in the context of determining the dimensionality of a data set with a view towards spectral reproduction. The MIPE metric instead is expressed in a domain that can be easily interpreted since it represents ΔE00 statistics across a large variety of illuminants, and moreover relates directly to the space of target conditions for a spectral match, namely a variety of illuminants under which a reproduction might be viewed.

**Table 4: Dimensionality analysis of glossy data set, comparing % variance coverage and the MIPE metric for N=1 to 10 for the matte data sets.**

| dim | % var. | MIPE | | |
|---|---|---|---|---|
| | | med. | $95^{th}$ $\%^{tile}$ | max |
| 1 | 98.3 | 9.6 | 32.2 | 47.5 |
| 2 | 99.4 | 5.1 | 29.8 | 45.5 |
| 3 | 99.9 | 1.2 | 3.7 | 14.3 |
| 4 | 100.0 | 0.7 | 2.3 | 12.0 |
| 5 | 100.0 | 0.6 | 2.2 | 12.0 |
| 6 | 100.0 | 0.3 | 0.8 | 3.5 |
| 7 | 100.0 | 0.2 | 0.5 | 2.3 |
| 8 | 100.0 | 0.1 | 0.3 | 2.0 |
| 9 | 100.0 | 0.0 | 0.1 | 1.5 |
| 10 | 100.0 | 0.0 | 0.1 | 0.7 |

### *Metameric vs Spectral Reproduction Accuracy*

Since any reproduction can be evaluated both in spectral and colorimetric terms and the choice of approach essentially translates to different ways of selecting from among the possible outputs of a printing system, the spectral match of a conventional color reproduction will be looked at first, before proceeding to evaluating spectrally determined reproductions.

The spectral match between originals and their colorimetric (metameric) reproductions, as obtained using the color reproduction mechanisms of ICC profiles is shown in Table 5. Note that a color separation based on Morovic's (2007) maximum gamut approach and an ICC profile computed for the printer's device RGB interface built on top of the above separation were used for the colorimetric reproduction.

**Table 5: MIPE spectral accuracy of colorimetric reproductions.**

| MIPE | Median | $95^{th}$ | Maximum |
|---|---|---|---|
| Spot color – matte | 1.6 | 5.7 | 15.4 |
| Spot color – glossy | 1.7 | 3.6 | 13.6 |
| Fine art – matte | 4.6 | 7.5 | 13.4 |
| Fine art – glossy | 2.0 | 4.6 | 12.7 |

The median MIPE metric for this data is always below 5 ΔE and often below 2.5 ΔE. We shall consider these two values as a rough rule-of-thumb threshold for a mismatch being respectively objectionable and just noticeable for complex imagery. From the results in Table 5 we cannot say that differences would not be seen, but that across all possible illuminants considered in this metric there will only be *few* under which *few* of the surfaces – typically a combined < 5% of the cases, with the exception of fine art reproductions on matte media – will differ sufficiently for it to be objectionable. Still, if those surfaces are large uniform areas and the illuminants ones under which reproductions are viewed, this is non–negligible and it is worth exploring whether a better match could be had. Finally, it is also worth bearing in mind that the printer used here had a level of print–to–print consistency, with a median of 0.5 ΔE00 and a maximum of 1.2 ΔE00. Consequently any MIPE differences below these levels should not be considered significant.

In summary, the above results represent the spectral reproduction accuracy of a system tuned to result in a metameric match under CIE D50. For comparison, the colorimetric reproduction accuracy under these canonical conditions is shown in Table 6.

**Table 6: Color accuracy of colorimetric reproduction.**

| ΔE00 under D50 | Median | $95^{th}$ | Maximum |
|---|---|---|---|
| Spot color – matte | 1.5 | 5.6 | 14.1 |
| Spot color – glossy | 1.5 | 3.1 | 10.0 |
| Fine art – matte | 4.5 | 7.3 | 13.1 |
| Fine art – glossy | 1.8 | 4.1 | 7.5 |

What we observe is that the ΔE00 statistics for the canonical conditions (CIE D50) are of the same order of magnitude as those taken across the full set of illuminants used in the MIPE metric in Table 5 earlier. According to this result, the match of original vs. reproduction under any illuminant will be approximately as good as under D50.

Thus far we have simply examined current colorimetric (metameric) reproduction accuracy from a spectral point of view. Next, we characterize the spectral domains of the printer-media combinations to explore the potential benefit of controlling print spectrally. Here we take advantage of the flexibility of a HANS pipeline that enables print control via convex combinations of a system's Neugebauer Primaries which in turn allows the application of PCA in a suitably Yule-Nielsen corrected spectral reflectance space.

To characterize the spectral domain of a printing system, two data sets have been printed and measured in each case. The first is a common profiling target that samples the device's RGB interface regularly (utilizing the color separation that the printer or RIP uses), while the second is a chart comprising the set of Neugebauer Primaries of the printer (independent of color separation) at the maximum area coverage permitted by the substrate's ink-limit. Figure 4 shows the CIE xy chromaticities of this Neugebauer chart.

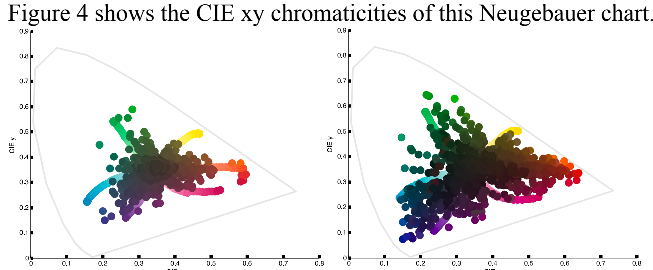

*Figure 4. Neugebauer Primary printer characterization charts on matte (left), and glossy (right) substrates.*

To derive a PCA basis for both systems, we use both the RGB sampling data as well as the NP charts. The former consists of uniform samples, albeit not utilizing the full spectral variation the printer is capable of, which in turn is expressed in the latter made up of the Neugebauer Primaries, albeit highly non-uniform in color space. Figure 5 shows the first 6 PCA bases for both substrates.

These bases describe the respective domains of reproducible reflectances on each of the systems. Assuming the ability to control the printing system in the spectral domain (directly enabled by HANS, but also possible to some extent using other methods) we next look at the best–case spectral matches.

For a given, arbitrary reference reflectance (the original to be reproduced), we solve for the closest reflectance within the domain of an ND PCA basis of a printing system and then check if it is inside the convex hull of the printing system. If it is outside the convex hull we map it to the closest point on the ND hull, which gives the closest printable reflectance within the basis. Note that such gamut mapping does not minimize the MIPE metric but Euclidean distance in the PCA basis, hence there may be other reflectances within the basis that reduce MIPE error further still. Figure 6 illustrates the spectral gamut and the data that is being reproduced (also projected to the same basis) for the case of a 3D PCA domain for each of the three substrates. Performing this form of gamut mapping guarantees that we only consider reflectances that, under ideal conditions, can be printed.

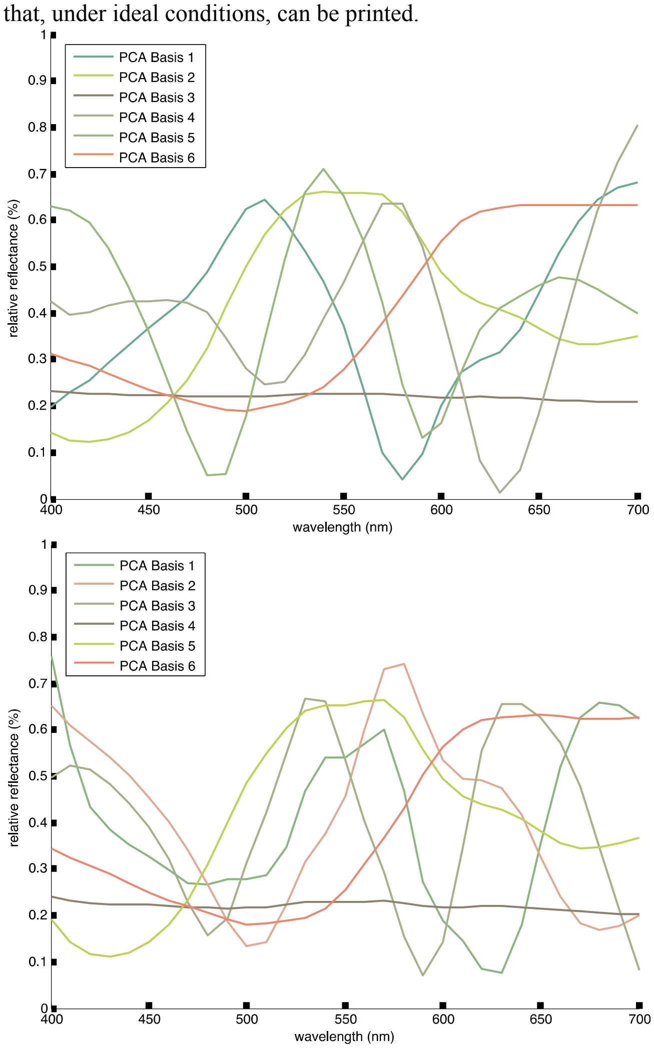


***Figure 5.*** *First six Principal Components of printed and measured data sets in Yule-Nielsen corrected reflectance space on matte (top) and glossy (bottom) substrates. (Note: the PCAs have been shifted by 0.4 in order to attribute pseudo-color to reflectances that otherwise would have negative values).*

In the above plots there are 337 and 483 out of 3372 spot color reflectances out-of-spectral-gamut for the matte and glossy substrates respectively. Note that while the matte substrate results in the smaller gamut and the glossy in the larger, a 3D PCA describes the system better in the matte case. Hence for a low dimensional basis, the higher dimensional the system, the more samples are out of gamut.

Looking at spectral accuracy using MIPE results in the values shown in Tables 7 and 8 where both overall statistics and those of reflectances strictly inside the gamut are reported. The latter results are independent of gamut mapping and only rely on the ability of a printing system to represent the same spectral variety as that of the original source data while the former relate better to the degree of visual agreement that can be expected across the various original-reproduction combination.

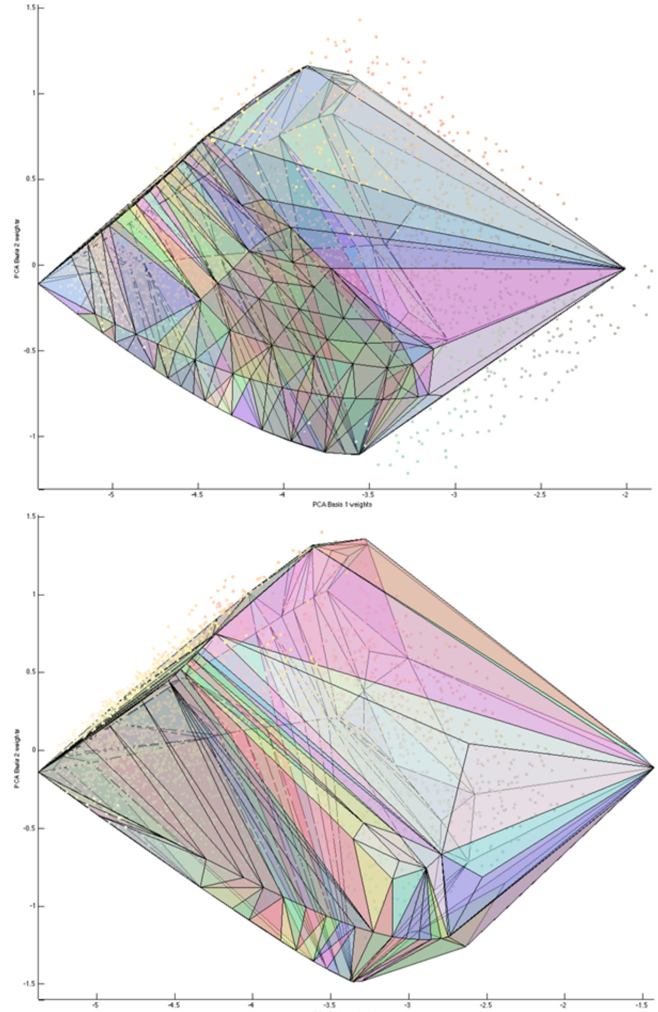

***Figure 6.*** *Spectral gamuts (in a 3D PCA basis with 2D projections shown) for matte (top) and glossy (bottom) substrates shown as tessellated convex hulls and the full set of spot colors (points) mapped to the respective 3D Yule-Nielsen Reflectance PCA domains. Colors represent colorimetry of the original reflectances (under D50 for sRGB visualization).*

**Table 7: Spectral accuracy of best spectral match to spot color originals within ND PCA basis of printer's domain (brackets show % of within-gamut samples) using MIPE (brackets show metric for within-gamut samples only).**

| | PCA | MIPE (in-gamut) | | |
|---|---|---|---|---|
| | (in-gamut %) | Median | $95^{th}$ | Maximum |
| matte | 3D (87%) | 2.6 (2.4) | 6.8 (6.3) | 20.0 (20.0) |
| | 4D (68%) | 2.2 (1.8) | 6.1 (4.8) | 14.8 (12.2) |
| | 5D (54%) | 2.1 (1.6) | 6.0 (4.6) | 14.4 (12.2) |
| | 6D (39%) | 1.4 (0.7) | 5.7 (2.9) | 14.4 (6.7) |
| glossy | 3D (89%) | 2.3 (2.2) | 5.9 (5.8) | 21.7 (21.7) |
| | 4D (74%) | 1.9 (1.8) | 4.7 (4.5) | 16.9 (9.7) |
| | 5D (62%) | 1.6 (1.3) | 4.3 (3.4) | 16.7 (9.4) |
| | 6D (49%) | 1.0 (0.5) | 3.2 (2.2) | 14.4 (8.6) |

**Table 8: Spectral accuracy of best spectral match to fine art originals within ND PCA basis of printer's domain (brackets show % of within-gamut samples) using MIPE (brackets show metric for within-gamut samples only).**

| | PCA (in-gamut %) | MIPE (in-gamut) | | |
|---|---|---|---|---|
| | | Median | 95$^{th}$ | Maximum |
| matte | 3D (90%) | 2.1 (1.9) | 5.6 (5.2) | 19.4 (11.6) |
| | 4D (86%) | 1.5 (1.3) | 4.7 (4.0) | 18.1 (11.0) |
| | 5D (62%) | 1.3 (1.0) | 4.5 (3.9) | 18.0 (11.1) |
| | 6D (48%) | 0.7 (0.5) | 3.9 (1.9) | 18.6 (9.0) |
| glossy | 3D (99%) | 2.3 (2.3) | 5.8 (5.7) | 11.9 (11.9) |
| | 4D (94%) | 1.5 (1.4) | 4.8 (4.4) | 12.5 (10.5) |
| | 5D (80%) | 1.1 (1.0) | 3.8 (3.2) | 12.1 (10.4) |
| | 6D (62%) | 0.6 (0.5) | 2.3 (1.3) | 10.7 (5.0) |

Note that spectral gamut coverage for the above data sets decreases with an increasing dimension of the printer-system basis. This is contrast with the PCA analysis of a single data set where the more basis functions are used, the better they characterize the data set. While more spectral variation can be represented with an increasing number of bases, the fact that the reference reflectance data differs in the space it occupies becomes more apparent as the higher order PCA bases differ more between the printing system and the data to be represented. Conceptually this is also analogous to the difference between a chromaticity diagram and a full 3D color space – while many colors may be within a chromaticity gamut boundary, when luminance is taken into account, not all of them turn out to be actually in gamut. Also note that there may be cases where an increased N also increases the maximum MIPE error, which again may seem counter intuitive, but is due to the fact that the analysis is performed in a Yule-Nielsen corrected reflectance space (as described earlier), while the MIPE metric is evaluated on reflectances.

## Conclusions

Spectral printing is an exciting alternative to colorimetric (metameric) reproduction, but an analysis of typical spectral content shows a mixed bag of spectral versus colorimetric selection performance gains. While in some cases (e.g., fine art reproduction on glossy substrate) the benefits of determining reproduction properties spectrally brings a 2x improvement (of 2.3 versus 4.6 $\Delta E$ in the spectral versus colorimetric cases, comparing the 95$^{th}$ percentiles from Tables 5 and 8), in other cases (e.g., spot colors on matte substrate) the results are essentially the same and going to the trouble of driving a printer spectrally would be unnecessary.

A likely reason for the good spectral performance of colorimetric reproductions in some cases is the fact that printers, inks and substrates are designed to ensure that prints are color constant and have low metamerism versus relevant references. This, coupled with the relative smoothness and color constancy of 'natural' reflectances, means that colorimetric reproduction already tends to spectra that are not far off actual original ones and in the cases where it ends up being a weak match it is often because of spectral gamut limitations that also constrain spectrally-determined reproduction.

Current systems are therefore well tuned for metameric reproduction and do a good job even in terms of the spectral domain. Systems designed specifically for spectral reproduction may be able to improve accuracy, facilitate the coveted ability to print exact metamers that match under one light perfectly and mismatch with a large error under other illuminants and perform even better for security applications like those presented by Hersch (2011). Overall it looks like the future of spectral printing lies in application to specific, niche cases and not in a full, spectral workflow succeeding the current colorimetric one.

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