Minimal-Knowledge Assumptions in Digital Still Camera Characterization II: Non-Uniform Distribution

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Abstract

Unlike color scanners, Digital Still Cameras (DSCs) are presented with arbitrary radiance spectra, rather than those possible from combinations of three dyes or four pigments. Accordingly, it is desirable that their colorimetric characterization be as material non-specific as possible. In our earlier paper,[1] we had proposed a generalization to the so-called "Maximum Ignorance With Positivity" assumption of Finlayson and Drew,[2] in which we investigated the effects on accuracy of relaxing the assumption of non-correlated relative radiance spectra. We found that modeling the correlation matrix of the radiance ratio spectrum as a Toeplitz matrix produced a significant improvement in the characterization accuracy. In the current paper, we examine the effects of relaxing the assumption of uniform distribution of the relative radiances.

If the same mean and variance are posited for the relative radiance at every wavelength, we conclude that there is little effect on accuracy. However, if a dependence on wavelength is introduced, a significant improvement in accuracy is demonstrated for several of the camera simulators used in the study. We find that a linear relationship between wavelength and mean relative radiance is sufficient.

The characterization parameters are still compact and material non-specific, and consist of the following:

- Color Matching Functions;
- Camera Sensitivity Spectra;
- Taking and Viewing Illuminants;
- Correlation Width Parameter, α;
- The coefficient of variation, v, of the spectral radiance ratios; and
- The ratio of the mean spectral radiance ratios at 400 and 700nm, q.

We evaluate the accuracy of the new technique relative to older ones likewise based on linear matrixing for several camera sensitivities (one real and two synthetic, including one with 4 channels) and several taking illuminants.

In this paper, we also address a concern which has arisen with the Minimal Knowledge assumptions since the publication of our earlier paper: its ability to contend with spikes in the taking illuminant, particularly with the mercury lines in fluorescent illuminants. We demonstrate that the technique is robust with respect with such features in the taking SPD, provided it is identified.

Introduction

Colorimetric characterization permits conversion of device-dependent coordinates, such as RGB, into device-independent coordinates (e.g., CIELAB), and/or viceversa. It is a central component of color management, and allows color images to be exchanged more easily. Color image digitizing devices have received considerable attention in the literature, though all but the most recent papers have emphasized color scanners rather than Digital Still Cameras (DSCs).

There are many similarities between scanners and DSCs. Both normally employ a solid-state array sensor and Red, Green, and Blue filters. Both normally output RGB coordinates spatially sampled from a rectangular grid. It is tempting to use similar techniques for colorimetric characterization of both.

However, there are fundamental differences between scanners and DSCs. The two which have primary impact on colorimetric characterization are:

With scanners, the taking illuminant is almost always known, because the source is an integral part of the scanner. With DSCs, the source is usually unknown, unless an integral flash is used as the sole light source.

Scanners normally digitize objects having highly constrained spectra arising from three or four dyes or pigments, while DSCs capture original scenes with arbitrary spectra resulting from many dyes, pigments, metallic surfaces, self-luminous objects, etc.

In our earlier paper, we introduced what we referred to as a "Minimal Knowledge" technique for colorimetric characterization of DSCs based on spectral sensitivity information. Unlike the earlier "Maximum Ignorance" assumptions (both with and without the constraint of non-negative radiances) wherein the spectral radiances are assumed to be uncorrelated, Minimal Knowledge permits correlation between radiances at different wavelengths. In the earlier paper, we continued to assume an identical uniform distribution for all spectral radiances. In this paper, we relax this assumption, as well.

General Formula for Least-Squares Linear Matrix

We briefly review the least-squares formula for computing a linear matrix for conversion of radiometrically linear camera RGB into tristimulus values. For nc sensor channels (usually 3), ns spectra in the characterization set, and a spectrum sampled at nw wavelengths (31, for a sampling of 400, 410, 420, ..., 700 nm), the formula is:

$$A = (D^t S_t B^t B S_t D)^{-1} D^t S_t B^t B S_v T \quad (1)$$

where:

D is a matrix (n_w x n_c) containing the device sensitivity spectra;

S_t is a diagonal matrix (n_w x n_w, zeros off diagonal) containing the spectral power distribution of the taking illuminant;

B is a matrix (n_s x n_w) containing the radiance ratio spectra of the characterization suite;

S_v is a diagonal matrix (n_w x n_w, zeros off diagonal) containing the spectral power distribution of the viewing illuminant;

T is a matrix (n_w x 3) containing the color matching functions; and

A is the matrix (n_c x 3) which is the best linear fit between radiometrically linear camera responses and the tristimulus values for the spectra in the characterization suite.

For popular illuminants and spectral sampling intervals of 10 or 20nm, the product $S_v T$ may be replaced with tristimulus integration weights tabulated in ASTM E-308.[3]

Inspection of (1) reveals that the results are independent of the scaling of the matrix B. If we multiply B by an arbitrary factor, it may be factored twice from the inverse portion of the formula, and twice from the portion which multiplies the inverse. These will cancel, so the results are independent of the scaling of B. The same applies to the auto-inner-product of B, $B^t B$. We shall use this result later in identifying and eliminating superfluous parameters.

After the matrix A is computed, the tristimulus values may then be predicted for ne objects in an evaluation suite:

$$X_p = C \cdot A \quad (2)$$

where C is a matrix (ne x nc) of radiometrically linear camera responses (usually containing Red in one column, Green in another, and Blue in a third); and X_p is a matrix (ne x 3) of the XYZ tristimulus values predicted for each of the ne objects.

Spikes Caused by Fluorescent Taking Illuminant

A criticism sometimes directed at Minimal Knowledge is that the smooth radiance ratio spectra seem to underemphasize prominent spikes found in some illuminants, particularly those caused by the Mercury lines in scenes captured under fluorescent illumination.[4] We feel this criticism is unjustified if the taking illuminant is correctly identified. (Techniques for identifying taking illuminant are discussed in excellent papers by other authors; a small selection appear in the references.[5-9]) This is because the spectrum to which the smoothness constraint applies has had the taking illuminant divided out; for a uniformly-illuminated scene consisting solely of non-fluorescent diffuse reflectors it would be considered a reflectance spectrum. The joint effect of taking illuminant and such a reflectance spectrum, $b \cdot S_t$, will exhibit the spikes.

Further, Minimal Knowledge does not exclude spikes, discontinuities, cusps, or other types of ill-behavior in the radiance ratio spectra in the characterization suite; it merely considers them less likely (as they are in real life).

Computational Color Constancy

Digital still cameras may be used under different sources, including tungsten, daylight, and fluorescent. Typically, users will view the images on a computer monitor, either as an end unto itself, or before printing, retouching, or incorporating it into a larger document. It is unreasonable to expect users to re-balance their monitor white point to that of the taking illuminant under which each picture was taken! Some form of illuminant compensation is highly desirable.

Note that Equation (1) includes two different illuminants: S_t, the taking illuminant, the spectral power distribution under which an image was captured; and S_v, the viewing illuminant, which is the spectral power distribution under which the colors of the objects in the scene are evaluated. The method (and others based on similar formulae) tacitly incorporates a portion of computational color constancy: provided the taking illuminant is correctly identified, and the viewing illuminant is known, the matrix which is generated is optimized to provide a least-squares match between the radiometrically linear camera RGB of the objects in the characterization suite as captured under the taking illuminant S_t, and the corresponding XYZ tristimulus values as viewed under the viewing illuminant S_v.

Non-Uniform Distribution of Spectral Radiance

Scenes being digitized will possess spectral radiances with lower bounds of zero, but no pat upper bounds.

However, if we assume that the illuminant under which the scene has been captured has been correctly identified, and the correct exposure level has been used by the camera, we may consider ratios of the spectral radiances to those of the illuminant. These are bounded between zero and unity for all diffuse non-fluorescent objects in the scene.

We continue, as before, to populate the matrix B^tB in Equation (1) using the means and standard deviations of, and correlations between, the radiance ratio spectra in an infinitely large characterization set (indeed, the most practical way in which to handle an infinite characterization suite is statistically); however, we no longer necessarily assume identical uniform distributions.
Although not sufficient for higher-order polynomial models (see, for example, Ref. [10]), these statistics are sufficient for the first-order model implied in Equation (2) above.

Population of B^tB Matrix

The auto inner product matrix B^tB is determined by the statistics of the spectral radiance ratios. Specifically, the general element of B^tB will be:

$$b_{ij} = \mu_i \cdot \mu_j + \rho_{ij} \cdot \sigma_i \cdot \sigma_j = \mu_i \cdot \mu_j \cdot (1 + \rho_{ij} \cdot v_i \cdot v_j) \quad (3)$$

where:
μ_i is the mean radiance ratio at wavelength i;
σ_i is the standard deviation of the radiance ratio at wavelength i;
ρ_{ij} is the correlation between the spectral radiance ratios at wavelengths i and j; and
v_i is the coefficient of variation (standard deviation divided by mean) at wavelength i.

(Variables with a single subscript j have analogous meanings to their counterparts with a single subscript i.)

As in our original formulation of Minimal Knowledge, we model the correlation as a function of separation in wavelength:

$$\rho_{ij} = \alpha^2/[\alpha^2 + (\lambda_i - \lambda_j)^2] \quad (4)$$

where α is the separation in wavelength at which the correlation drops to one-half. As α approaches zero, Minimal Knowledge approaches Maximum Ignorance With Positivity, which may be considered a special case of Minimal Knowledge.
If we assume mean and variance are independent of wavelength (as we do in our first computational experiment), Equation (3) reduces to:

$$b_{ij}(\text{exp } 1) = \mu^2 \cdot (1 + \rho_{ij} \cdot v^2) \quad (3a)$$

If the radiance ratios are identically distributed, the squared mean will cancel when Equation (1) is applied, so any non-zero value will produce identical results. In such cases, there will be two parameters: v, the coefficient of variation, and α, the half width at half-height of the correlation. In Experiment 1, we investigate the effects of varying both parameters simultaneously.

We also wish to consider the case where the mean is allowed to vary as a function of wavelength. While there are an infinity of ways in which this may be accomplished, we restrict ourselves here to a simple linear relationship between mean radiance ratio and wavelength. We further limit the scope here by assuming the coefficient of variation is independent of wavelength. While we realize this is an arbitrary constraint, we feel compelled to do so in the interest of keeping the possibilities manageable.

We define the quotient of the mean spectral radiance ratios at 400 and 700nm as q:

$$q = \mu_{400} / \mu_{700} \quad (5)$$

Using the point-slope form of a line, and performing some algebraic distribution, the mean spectral radiance ratio at any wavelength is modeled as:

$$\mu_i (\text{exp } 2) = \mu_{550} [1 + h \cdot (\lambda_i - 550\text{nm})] \quad (6)$$

where:

$$h = (1 - q) / (1 + q) / 150\text{nm} \quad (7)$$

The mean spectral radiance ratio at 550nm, μ_{550}, is a multiplicative constant in the matrix B, and, as was pointed out before, its value is arbitrary. We elect to make this 1/2, without loss of generality. Note that a q of unity returns us to the assumption of uniformly distributed spectral radiance ratios.

The free parameters under this set of assumptions, then, are:
α, the correlation half-width at half-height;
v, the coefficient of variation; and
q, the ratio of mean spectral radiance ratios at 400nm and 700nm, respectively.

In Experiment 2, we vary the parameters α and q simultaneously. For reasons discussed below, we keep the coefficient of variation constant.

Experimental Conditions — Experiments 1 &2

Digital Camera Simulators

We simulate a digital still camera by multiplying a taking illuminant by the known camera sensitivities (which may, in practice, be determined by Method A in ISO 17321). Radiometrically linear RGB are used; if a camera applies an opto-electric transfer function, its inverse would be applied to the data under consideration. For testing accuracy we use the reflectance spectra of 170 objects collected by Vrhel.

We used three camera sensitivities. One was based on a monochrome camera with a filter wheel operated in the 3- shot mode; the sensitivity spectrum of the monochrome camera was kindly provided by Dr. Francisco Imai of the Munsell Color Science Laboratory at RIT and the Wratten filter transmittance spectra were obtained from the literature.[11]

Our other two sensitivities were synthetic and had Gaussian bandpass functions. The first of these had peak sensitivity wavelengths based on the Prime wavelengths which are reported to be nearly optimal for a three-sensor system.[12] The other used four sensitivities to illustrate the applicability of this technique (and the potential applicability of similar methods) to cameras with more than 4 channels. We summarize these in Table 1.

Table 1. Cameras used in Experiments 1 & 2

3-Shot: A digital monochrome camera with sequential exposure through 3 Wratten filters: 23A (Orange/Red), 58 (Green), and 47 (Blue).
Prime: A synthetic camera with Gaussian bandpass functions; peak sensitivity wavelengths of 605nm (Red), 540nm (Green), and 450nm (Blue), and fullwidth at half-height bandwidths of 60nm, 60nm, and 45nm, respectively.
4-Channel: A synthetic camera with Gaussian bandpass functions; peak sensitivity wavelengths of 625nm (Red), 570nm (Yellow/Green), 520nm (Green/Cyan), and 425nm (Blue), and full-width at half-height bandwidths of 60nm, 60nm, 60nm, and 45nm, respectively.

Taking and Viewing Illuminants

We have exercised the technique under five taking illuminants: A, D50, D65, D75, and F2. Because users typically view captured images on a computer monitor, we used a single viewing illuminant, D65, which is the white point of the sRGB monitor.[13]

Evaluation Criteria

In order to evaluate the accuracy of a characterization, we compare colors predicted by the model given in Equation (2) to actual tristimulus values for the 170 object spectra of Vrhel and Trussel.[14] The latter has become a *de facto* standard evaluation suite. The predicted tristimulus values are compared to the correct ones using ΔE^*_{ab}. Selected statistics of the resulting ΔE^*_{ab} distribution are computed.

Without question is it good to have a small average ΔE^*. The average is an indication of how large the color error will be for a typical input combination. However, a very large error, even if it occurs infrequently, may negate even a small mean. Accordingly, we consider also the 90^{th} percentile in the distribution of ΔE^*_{ab} to provide an indication of how large are the largest of the errors.

These two criteria will be used regardless of whether the taking and viewing illuminants are the same or different. Although larger average and 90th percentile ΔE^*s would be expected when the two illuminants are quite different (such as an S_t of Illuminant A and an S_v of D65), different methods of computing the transformation matrix for the same pair of illuminants may be directly compared.

Experimental Conditions — Experiment 1

In Experiment 1, we continue to assume a Toeplitz correlation matrix, and identical distribution of the radiance ratio spectra, but not necessarily a uniform distribution as had been assumed in our previous paper. As was pointed out earlier, this introduces one additional free parameter, the coefficient of variation, v, over and above the existing parameter α (the half-width at half-height of the correlations). The coefficient of variation of a uniform distribution with a lower bound of zero is $\sqrt{3} / 3$. We wish to include this value, as well as larger and smaller values. Accordingly, we will consider coefficients of variation of $\sqrt{1/3}$, $\sqrt{2/3}$, $\sqrt{3/3}$, $\sqrt{4/3}$, $\sqrt{5/3}$, $\sqrt{6/3}$, $\sqrt{7/3}$, and $\sqrt{8/3}$, admitting skewed positive and skewed negative distributions (in addition to the unskewed uniform).

We considered α values ranging from 0nm (Maximum Ignorance With Positivity, or MIWP) to 200nm, in 25nm increments. Although it does not correspond to an actual level of α, we also include Maximum Ignorance without Positivity (MI).

Results and Discussion — Experiment 1

In all cases, the coefficient of variation v had no significant effect. Plots of both average and 90th percentile of ΔE^*_{ab} as functions of v were essentially flat. The parameter α, however, exhibited a significant effect. For the 3-shot camera, troughs were exhibited in the general vicinity of 100nm, indicating an optimum near there. For the synthetic cameras, which had generally narrower bandwidths, the optimal value of α was smaller, usually 50 - 75 nm. In all cases, the α = 75nm solution was better than either the MI or MIWP solutions.

There was, as expected, less accuracy in general as the taking illuminant differed increasingly from the viewing illuminant. The least accuracy was obtained for a taking illuminant St of Illuminant A.

In addition, with other factors constant, the best results were obtained, not surprisingly, with the 4 channel camera. The Prime wavelength camera was second best, and the 3-shot camera was third.

Experimental Conditions — Experiment 2

In Experiment 2, we varied both the parameter α and the ratio of mean spectral radiance ratio at 400 and 700 nm. Because the coefficient of variation, v, had so insignificant an effect in Experiment 1, it was kept at its original value of $\sqrt{3}/3$, as it had been before. (As expected, when we later substituted different values of v in these calculations, the results were essentially unchanged.)

Again, the parameter á varied in 25 nm increments from 0 to 200nm, with the additional condition of MI added. Logarithmically uniformly spaced q values of 1/4, √2/4, 1/2, √2/2, 1 (which corresponds to identically distributed radiance ratios), √2, 2, √8 and 4 were used.

Table 2. Results from Experiment 2.

Results for 3-Shot Camera

Taking Illum		MI	MIWP	MK (old)	MK (new)
A	avg:	5.72	6.82	4.72	3.53
	90%	8.50	11.37	8.26	5.55
D50	avg:	5.85	5.42	4.03	3.05
	90%	9.15	9.14	7.12	4.98
D65	avg:	6.29	4.85	3.83	2.89
	90%	9.63	8.04	6.63	4.61
D75	avg:	6.46	4.66	3.76	2.83
	90%	9.69	7.62	6.53	4.60
F2	avg:	6.59	3.26	2.34	1.94
	90%	10.50	7.51	4.45	3.73

Results for Prime Wavelength Camera:

Taking Illum		MI	MIWP	MK (old)	MK (new)
A	avg:	5.26	3.54	1.81	1.66
	90%	8.95	7.61	4.16	3.53
D50	avg:	4.91	3.98	1.64	1.56
	90%	7.49	8.68	3.71	3.87
D65	avg:	4.84	3.99	1.77	1.62
	90%	6.96	8.62	3.98	3.79
D75	avg:	4.84	4.01	1.86	1.67
	90%	7.07	8.60	4.30	3.78
F2	avg:	7.95	7.47	2.47	2.15
	90%	11.92	16.41	5.30	5.10

Results for 4-Channel Camera:

Taking Illum		MI	MIWP	MK (old)	MK (new)
A	avg:	4.37	5.06	1.93	1.29
	90%	6.97	8.78	3.14	2.21
D50	avg:	4.47	5.02	1.89	1.30
	90%	7.01	8.75	2.98	2.31
D65	avg:	4.10	4.63	1.77	1.24
	90%	6.25	8.19	2.89	2.40
D75	avg:	3.95	4.48	1.73	1.21
	90%	6.21	7.97	2.86	2.52
F2	avg:	4.53	4.09	0.98	0.72
	90%	6.81	8.86	2.08	1.69

Averages and 90th percentiles of the ΔE^*_{ab} distributions generated by the Maximum Ignorance (MI), Maximum Ignorance With Positivity (MIWP), Minimal Knowledge with uniform distribution (MK old), and Minimal Knowledge with q ratio = 1/2 (MK new). Correlation Width parameter α = 50nm for both MK conditions.

Results and Discussion — Experiment 2

In many cases, accuracy was improved for the q values less than unity, while accuracy always suffered when q > 1 was tested. This is not surprising, as an examination of the evaluation data suite shows a strong contingency of mean radiance ratio on wavelength with a q of about 1/4.

The optimal value of α was usually between 50 and 100nm, with the 50nm results at or close to optimum. Accordingly, we report the results, in Table 2, for α = 50nm. As in Experiment 1, the most accurate results for a given taking illuminant and parameter set were with the 4-channel camera, with the Prime wavelength camera in second. Also, as before, the most accurate predictions tended to come when the taking and viewing illuminants matched.

Experimental Conditions — Experiment 3

A third experiment was conducted, using 1728 different synthetic camera sensitivity sets. The Red sensitivities had peaks at 600, 605, 610, and 615nm and full-width at halfheight bandwidths of 55, 60, and 65nm; the Green had peaks of 530, 535, 540, and 545nm and bandwidths of 50, 55, and 60nm; and the Blue had peaks at 440, 445, 450, and 455nm with bandwidths of 40, 45, and 50nm. Thus, 12 different Red sensitivities, 12 Green sensitivities, and 12 Blue sensitivities were all exercised in a 12^3 factorial plan.

Solutions using Maximum Ignorance, Maximum Ignorance with Positivity, Minimal Knowledge (v = √3/3, q = 0; the original MK), and Minimal Knowledge (v = √3/3, q = 1/2) were computed for each of the five illuminants and each of the 1728 camera sensitivities for a total of 8640 combinations. (An α of 50nm was used for both the original and the new MK solutions.)

Results — Experiment 3

Of the 8640 combinations, the average ΔE* was lower for the new technique than for the better of MI or MIWP in all but 3 cases (99.96% of the time). The ΔE*s averaged 44% lower for the new method. Further, the 90th percentile ΔE* was lower for the new method all but 38 times (99.6% of the cases), and the 90 percentiles, on average, were 43% lower for the new method.

The new method also demonstrated improvement over the original Minimal Knowledge assumptions. The average ΔE* was lower for the new technique for all 8640 combinations, and the average was 16% lower. The 90th percentile was lower for the new MK all but 113 times (98.6% of the cases), and averaged 14% lower.

Conclusions

The Minimal Knowledge assumptions for DSC characterization have been extended by relaxing the assumption of uniformly and identically distributed spectral radiance ratios. The assumption of uniformity was found to have virtually no effect on the accuracy of the characterization when only it was relaxed. However, when the assumption of identically distributed spectral radiance ratios was also relaxed, a significant increase in characterization accuracy was observed.

The minimal knowledge assumptions as developed in this paper involve the following parameters:

- the correlation width parameter, α;
- the coefficient of variation, v; and
- the ratio of mean spectral radiance ratio at 400 and 700 nm, q.

Of these three parameters, all of which are material independent, the first had been included in the original formulation of Minimal Knowledge, and the second was found to have no significant effect. The third, however, permitted an increase of approximately 15 percent over the results obtained by the original formulation of Minimal Knowledge, and over 40% better than those obtained by either set of Maximum Ignorance assumptions.

In order to characterize a DSC, one also needs, in addition to these three parameters, the sensitivity spectra of the device and the spectral power distributions of the taking and viewing illuminants. Separate characterizations would be performed for each combination of taking and viewing illuminants.

We have found that an α of 50nm and a q ratio of ½ provide excellent results. While it was found that the parameter v had no significant effect, we have used a value of $\sqrt{3}/3$ to obtain the improved results cited.

Briefly investigated was the ability of the Least Squares formula to address cameras with four channels. Minimal Knowledge, particularly in its new incarnation, was able to provide significant increase in accuracy with the addition of a fourth channel, while the Maximum Ignorance techniques were not.

Also demonstrated was the ability of Minimal Knowledge (and the potential ability of similar techniques based on the least squares formula given in Equation [1]) to accurately compensate for differences between taking and viewing illuminants, provided both are known.

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Biography

J A Stephen Viggiano is Principal and Founder of Acolyte Color Research, for which he provides consulting services, algorithm design, and color- and image quality evaluation services. Prior to closing its image science division, RIT Research Corporation had employed Steve for over 14 years, where he had risen to the rank of Principal Scientist. Steve has taught graduate and undergraduate courses in image reproduction theory, printing inks, paper, color, and research methods at RIT.

Steve holds an AB degree in Mathematics from Thomas Edison College, and Master's Degrees from RIT in Printing Technology and Mathematical Statistics. He is a member of CIE TC8-02 (Color Differences in Images, for which he authored the section on statistics) and TC8-03 (Gamut Mapping).