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Predicting Camera Color Quality

Roy S. Berns, Gray Sky Imaging, Rochester, NY, USA

Abstract

Color quality can be measured two ways. The first is target based where color-difference statistics are reported comparing image data with measurement-based colorimetric data. The second is based on measuring the camera sensor's spectral sensitivities and calculating their similarity to a standard observer, for example, μ-factor. A computational experiment was performed where synthetic images of a variety of targets were rendered for four camera systems having μ-factors of 0.79, 0.88, 0.94, and 0.99. Each camera was profiled using the same target. Although profile color accuracy was acceptable for all the cameras, this did not predict the color accuracy for independent targets. μ-factor was a better predictor of color quality and its use is recommended when evaluating cameras for cultural heritage applications.

Introduction

Historically, building camera profiles was similar to creating display profiles where there was a linear component (e.g., RGB to XYZ using a matrix transformation) and three gamma curves. This was concatenated with an encoding space such as sRGB. For most cameras, the color quality was barely acceptable and as a consequence, visual editing was required. A recent development is the use of a multi-dimensional look-up table (MLUT) and interpolation for camera profiling. This has long been used when profiling printers because of the complexity of modeling the optical behavior of ink on paper and the need to transform three dimensions into four or more dimensions, e.g., RGB to CMYK or CMYKRGB. There is a unique MLUT for each ink and substrate, based on printing and measuring over 1,500 color patches. When applying this approach to camera profiling, there is usually a single MLUT, based on imaging a color target. Ideally, the target should have a large number of colors uniformly distributed in CIELAB, a large color gamut, and use colorants similar to those of the materials to be imaged. The most common target used to profile cameras is the X-rite ColorChecker Digital SG, having 140 patches that are poorly distributed in CIELAB and made using colorants that often do not represent the materials. Depending on the camera and materials, the MLUT may or may not produce high color-quality images.

A property of cameras often overlooked by photographers is the spectral sensitivities of the camera sensor. These sensitivities determine whether the camera records color similar to a color-normal standard observer. The reason for being overlooked is that manufacturers do not provide spectral sensitivity data or a metric that quantifies similarity to a standard observer. A commonly-used metric was derived by Vora and Trussel [1], known as μ-factor ("mu factor"). This metric is based on seminal research by Neugebauer [2] and is similar to a correlation coefficient. A μ-factor of unity means the camera records color identically to a standard observer. μ-factor has the advantage of not requiring a target and profile.

The purpose of this paper is to demonstrate the usefulness of μ-factor in predicting color quality and the uselessness of reporting the CIEDE2000 statistics of the profiling target for the same task.

Experimental

Calculating μ-factor requires the measurement of a camera sensor's spectral sensitivity. Image Engineering has a database of many cameras [3]. μ-factor was calculated for each camera using the spectral radiance of strobe lighting with a correlated color temperature of 5659K [4] as the studio lighting and D50 as the standard illuminant. A RGB trilinear-array scan back was added to the database. Values ranged between 0.94 and 0.79. Three cameras were selected: the highest μ-factor of 0.94, an intermediate μ-factor of 0.88, and the lowest μ-factor of 0.79, labelled as Camera H, M, and L, respectively ("high," "medium," and "low"). The spectral sensitivities are plotted in Figure 1. Camera L was the scan back.

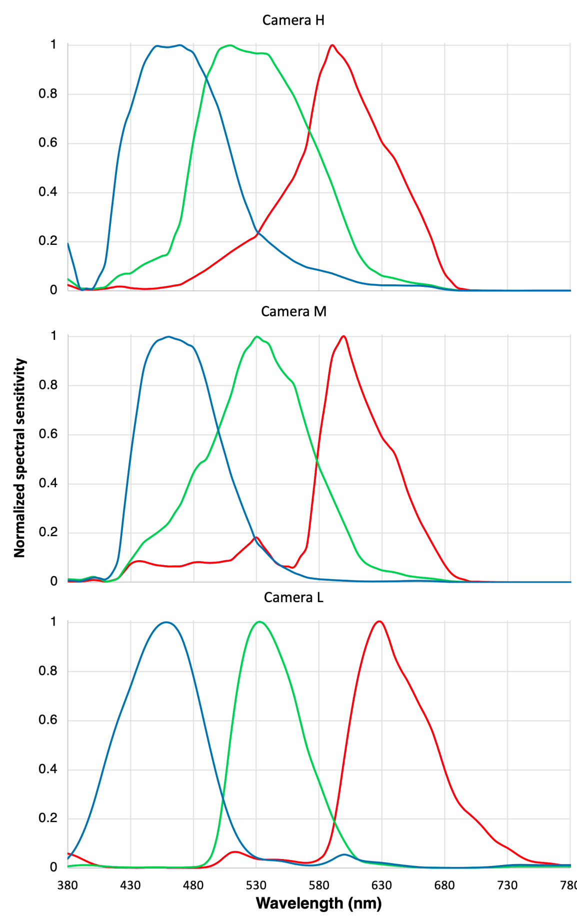

***Figure 1**. I Normalized spectral sensitivities of Cameras H, M, and L.*

Sixteen-bit spectral images were synthesized for four targets using their spectral reflectances: The X-rite ColorChecker Digital SG, the Avian Rochester DT Next Generation Target V2 [5], the Artist Paint Target [6], and the spectral database developed by the Illuminating Engineering Society for evaluating the color rendering of light sources [7]. (A neutral was added so there were 100 patches.) Eighty-one images for each target were rendered, corresponding to 380 – 780 nm in 5 nm increment.

Gamma-(1/2.4)-encoded images were synthesized from the spectral images, the camera spectral sensitivities, and the strobe spectral radiance. The 16-bit images were flat-fielded so that the perfect reflecting diffuser had a maximum signal of unity. One-over-gamma encoding is common with large format cameras used in cultural heritage imaging. It is also good practice when building MLUT profiles because the camera signals and CIELAB have similar linearity. The synthetic image for Camera H is shown in Figure 2. The images for Cameras I and L appeared similar.

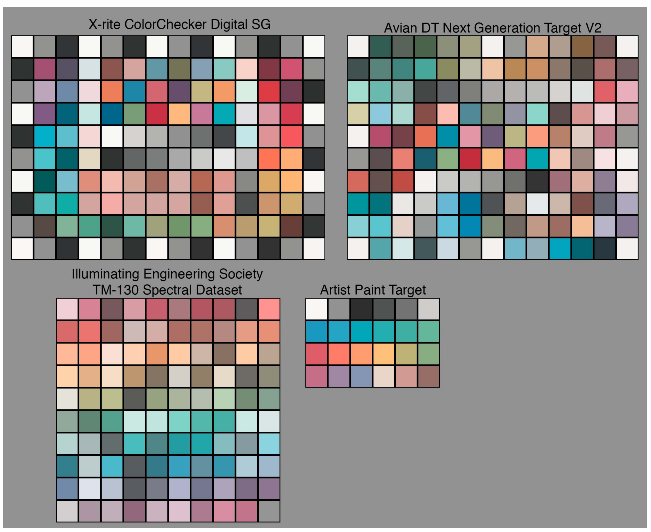

Figure 2. *Camera H camera-raw image. (Image converted to sRGB.)*

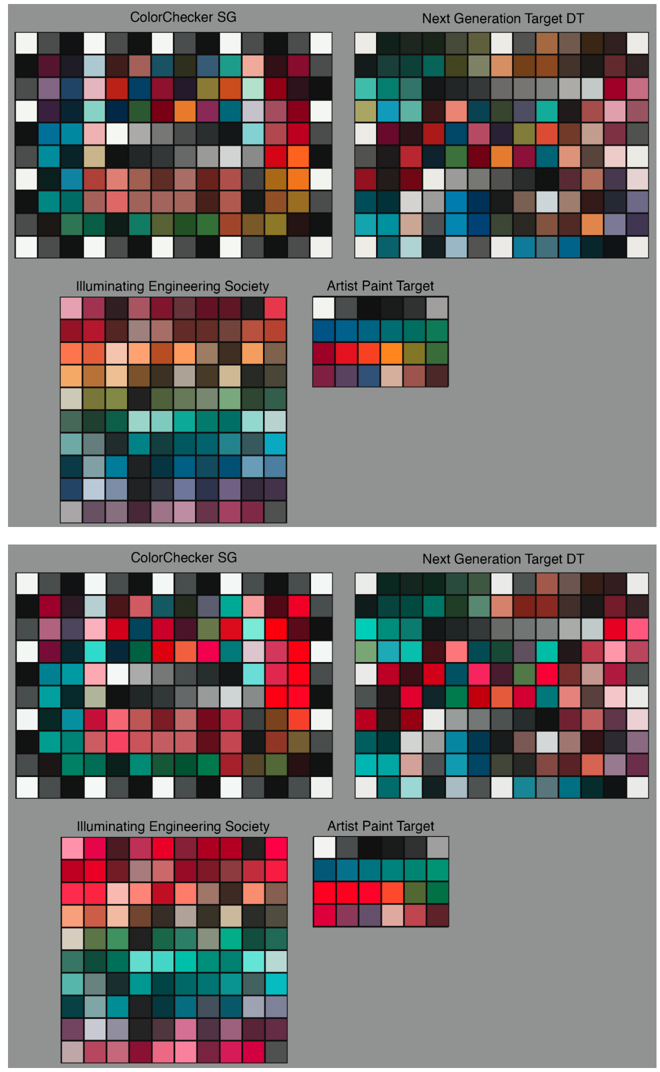

Figure 3. *Camera D camera-raw images. (Image converted to sRGB.)*

ColorBurst SpectraCore Camera Profile software was used to produce MLUT profiles for Cameras H, M, and L using the image and CIELAB data for D50 and the 1931 standard observer of the ColorChecker Digital SG. Each profile was assigned to each corresponding image in Photoshop. The images were converted to 16-bit ProphotoRGB, also using Photoshop.

A Bi-Color LED system is under development at Gray Sky Imaging where two images are captured, one for each LED. This approach has been named Dual-RGB by Berns and described in Reference 8. Camera H and the two LEDs were used to calculate two images, labelled as Camera D ("Dual-RGB"), shown in Figure 3. This system resulted in a μ-factor of 0.99. Linear regression (pseudoinverse) was used to estimate a transformation matrix from $(RGB)_1$ and $(RGB)_2$ to XYZ using the ColorChecker Digital SG image and XYZ data. A single matrix was calculated by the concatenation of the XYZ matrix and the ProPhotoRGB XYZ to linear-RGB matrix. The concatenated matrix followed by gamma-(1/1.8)-encoding resulted in a single ProPhotoRGB image, shown in Figure 4.

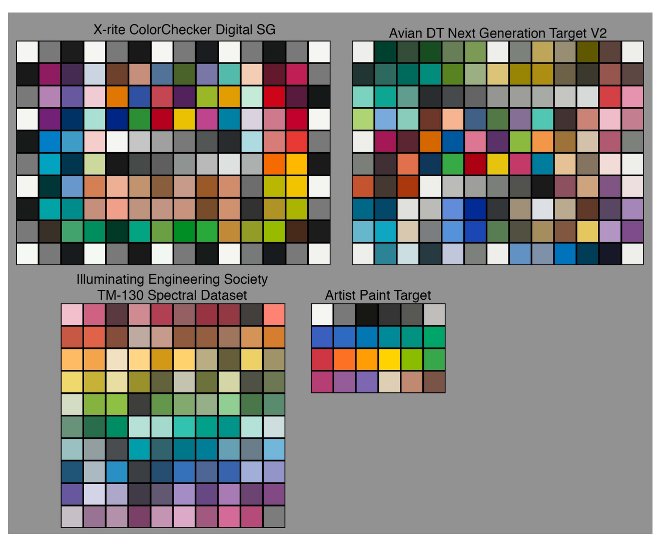

Figure 4. *Camera D color-managed image. (Image converted to sRGB.)*

The average RGB was recorded of the central 40% of each color patch for each camera and converted to CIELAB (D50, 1931 standard observer). CIEDE2000 total color differences were calculated between reference and image data.

Results and Discussion

Color-difference statistics and μ-factors are listed in Table I. Comparing the μ-factors and normalized spectral sensitivities shown in Figure 1, the spectral sensitivity widths decreased as μ-factor reduced. In addition, Camera L has its red channel's peak wavelength shifted to longer wavelengths. Camera L is the scan back that uses a trilinear array. These types of sensors were not designed for scene-referred imaging. Rather, they were designed to measure color film density, resulting in narrow spectral sensitivities centered near the peak spectral densities of cyan, magenta, and yellow photographic dyes. Based on μ-factor alone, Camera D should have the best color quality and Camera L should have the worst.

Table I. μ-factor and CIEDE2000 total color difference statistics (average, 90th percentile, maximum) for each listed camera and target (CCSG = ColorChecker Digital SG, APT = Artist Paint Target, NGT = DT Next Generation Target V2, IES = Illuminating Engineering Society TM 130 Spectral Dataset). (The profiling target, CCSG, is shown in italics.)

Camera	μ	Target	CIEDE2000		
			Ave	90th P	Max
D	0.99	*CCSG*	*0.1*	*0.2*	*0.4*
		APT	0.2	0.3	0.5
		NGT	0.1	0.3	0.5
		IES	0.1	0.2	0.6
		Average	**0.1**	**0.3**	**0.5**
H	0.94	*CCSG*	*0.2*	*0.3*	*1.2*
		APT	0.6	1.2	1.5
		NGT	0.6	1.2	2.5
		IES	0.9	1.7	3.0
		Average	**0.6**	**1.1**	**2.1**
M	0.88	*CCSG*	*0.2*	*0.4*	*1.6*
		APT	0.6	1.4	1.7
		NGT	0.7	1.5	4.4
		IES	1.2	2.6	4.7
		Average	**0.7**	**1.5**	**3.1**
L	0.79	*CCSG*	*0.3*	*0.7*	*2.4*
		APT	1.7	3.7	8.4
		NGT	1.6	3.7	7.3
		IES	3.2	7.6	12.9
		Average	**1.7**	**3.9**	**7.8**

The profiling software produced excellent results for Cameras H, M, and L where the ColorChecker Digital SG calibration target had average color accuracy of 0.2 – 0.3 CIEDE2000 (gray-shaded cells of Table I). The Bi-Color LED system, Camera D, had the smallest average at 0.1. All four cameras well exceed FADGI 4 Star color-accuracy requirements for paintings and other two-dimensional art where the average CIEDE2000 must be less than 2 [9]. The four images looked nearly identical when viewed on a color managed display.

The color-difference statistics for the average of the three independent targets (APT, NGT, and IES) for each camera system as a function of μ-factor are plotted in Figure 5. Color-quality differences between cameras become apparent when independent data are evaluated. Performance was correlated with μ-factor. The mean, 90th percentile, and maximum color differences increased as μ-factor decreased. Also, the range of values increased appreciably as μ-factor decreased. Camera D ranged from 0.1 – 0.5 CIEDE2000; camera L ranged from 1.7 – 7.8 CIEDE2000.

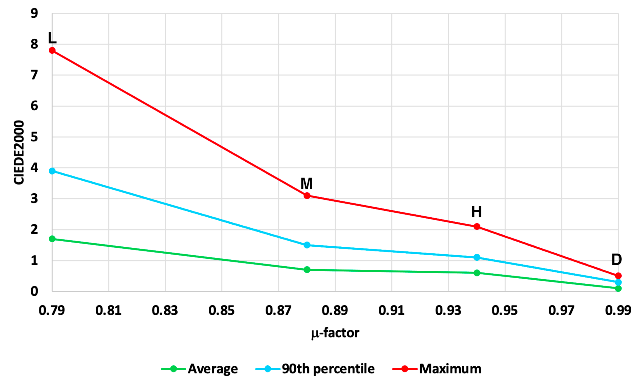

Figure 5. Statistic averages for the independent targets as a function of μ-factor for each listed camera system.

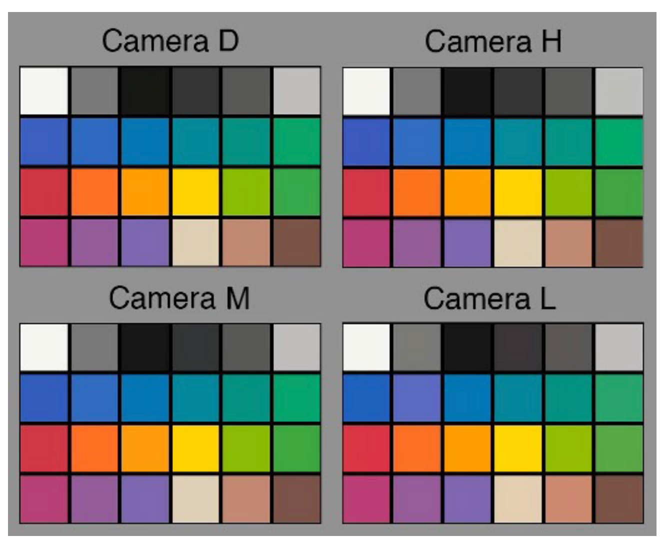

Figure 6. Color-managed Artist Paint Target images for each listed camera. (Image converted to sRGB.)

Images of the Artist Paint Target are shown in Figure 6. This target is difficult to image accurately because it contains ultramarine (row 2, column 1) and cobalt blue (row 2, column 2). Using Camera

D as the reference camera, having 0.2 and 0.3 CIEDE2000 for ultramarine and cobalt, there are clear visual differences. The scan back's shifted red spectral sensitivity resulted is large errors of 3.7 and 8.4 CIEDE2000 for these blue colorants.

Conclusions

A camera's color quality cannot be predicted from the color accuracy of the profiling target. All four cameras had excellent color-difference statistics for the profiling target, far exceeding FADGI 4 Star. Based on this metric, all the cameras should have outstanding performance in practice, represented by the validation targets. They do not. Only Camera D would not require visual editing, having a maximum color error of 0.6 CIEDE2000 for all the target samples. Camera L would require extensive visual editing. This result calls into question the FADGI Star rating for quantifying color accuracy.

A camera's color quality can be predicted from its similarity to color matching functions, quantified by μ-factor. The color accuracy of all the targets improved with an increase in μ-factor. Furthermore, the range of color differences reduced as μ-factor approached unity. Having a camera with a high μ-factor means that the camera will have excellent color quality, irrespective of the profiling target and type of profile. It is unfortunate that camera manufacturers do not report a metric that measures similarity to color matching functions. We are left with measuring spectral sensitivity ourselves or finding a colleague or company willing to do so. Perhaps in the future, a metric such as μ-factor can be added to objective measures of defining color quality.

A reasonable question is why don't cameras have μ-factors of unity? Briefly, there is a tradeoff between color and spatial image quality [10]. For most applications, high spatial quality is more desirable than high color quality. Secondly, cameras are designed to produce beautiful images, not color-accurate images. For cultural-heritage imaging, we are using cameras not designed for this purpose. The only way to improve color accuracy that is target independent is the use of multi-spectral or hyperspectral camera systems. Camera H was used as a multi-spectral camera (Camera D) by using a bi-color source optimized for high color accuracy.

Acknowledgments

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Author Biography

Roy S. Berns is the Chief Technical Officer at Gray Sky Imaging in Rochester, NY. Previously, he was the Richard S. Hunter Professor at Rochester Institute of Technology, USA where he developed both M.S. and Ph.D. degree programs in Color Science. He received B.S. and M.S. degrees in Textiles from the University of California at Davis and a Ph.D. degree in Chemistry from Rensselaer Polytechnic Institute. Berns has received scientific achievement awards from the Inter-Society Color Council, the Society of Imaging Science and Technology, the Colour Group of Great Britain, and the International Association of Colour.