

Optimal LED Selection for Multispectral Lighting Reproduction

Chloe LeGendre* Xueming Yu Paul Debevec
USC Institute for Creative Technologies

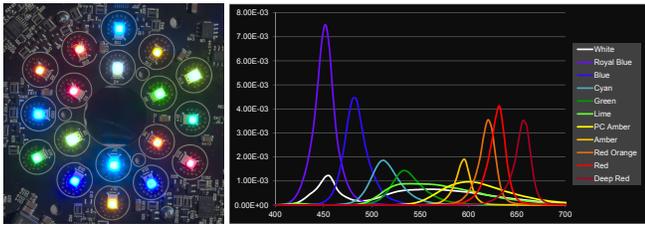


Figure 1: Custom circuit board with 11 different LEDs (some duplicates) and their measured emission spectra.

Abstract

We demonstrate the sufficiency of using as few as five LEDs of distinct spectra for multispectral lighting reproduction and solve for the optimal set of five from 11 such commercially available LEDs. We leverage published spectral reflectance, illuminant, and camera spectral sensitivity datasets to show that two approaches of lighting reproduction, matching illuminant spectra directly and matching material color appearance observed by one or more cameras or a human observer, yield the same LED selections. Our proposed optimal set of five LEDs includes red, green, and blue with narrow emission spectra, along with white and amber with broader spectra.

Keywords: multispectral, relighting, image-based lighting

Concepts: •Computing methodologies → Image manipulation; Computational photography;

1 Introduction

Lighting reproduction [Debevec et al. 2002] surrounds a subject with red, green, and blue (RGB) LEDs, driving them to match the colors and intensities of a real lighting environment. The subject is thus illuminated to appear as they would in the actual scene. However, Wenger et al. [2003] observed poor color rendition using an RGB light source and showed improvement using a 9-channel multispectral light. LeGendre et al. [2016] reproduced omnidirectional lighting in a multispectral light stage with RGB, cyan (C), amber (A), and white (W) LEDs, achieving improved color rendition using RGBW and very close color matches with RGBCAW. Yet, neither [Wenger et al. 2003; LeGendre et al. 2016] discussed a minimal, sufficient set of LEDs for multispectral lighting reproduction.

Wenger et al. [2003] filtered two white LEDs of their 9-channel source to produce dim yellow light, as bright yellow LEDs were not then available. Two new LEDs from Lumileds Lighting, the Luxeon Rebel ES colors Lime and PC Amber, now fill this spectral gap, but they are dimmer than other LEDs and have broader

*e-mail:legendre@ict.usc.edu

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s). © 2016 Copyright held by the owner/author(s). SIGGRAPH '16, July 24-28, 2016, Anaheim, CA,

ISBN: 978-1-4503-4371-8/16/07

DOI: <http://dx.doi.org/10.1145/2945078.2945150>

emission spectra. Both consist of royal blue emitters with emission-broadening phosphors, each with essentially no remaining emitter output. We consider the problem of finding an optimal set of LEDs of distinct spectra to use for multispectral lighting reproduction, choosing among the 11 presently available LEDs with distinct, visible emission spectra. Along with white (W), we consider the 10 Rebel ES colors: Royal Blue (Y), Blue (B), Cyan (C), Green (G), Lime (L), PC Amber (P), Amber (A), Red-Orange (O), Red (R), and Deep Red (D), spectra in Fig. 1. We first determine the number k of LEDs of distinct spectra such that adding an additional LED no longer meaningfully improves lighting reproduction and next determine the optimal subset of k such LEDs to use for reproducing diverse and complex illuminants.

2 Approach

As in Wenger et al. [2003], we consider three metrics for computing the optimal combination of LEDs for multispectral lighting reproduction. Using Spectral Illuminant Matching (SIM), we aim to directly match a target illumination spectrum. Using Metameric Illuminant Matching (MIM), we aim to produce light metameric to a target illuminant, to an observer with known spectral sensitivities. Using Metameric Reflectance Matching (MRM), we aim to produce light that yields color matches for a given observer for certain reflective materials, such as the squares of a color chart. In each case, we solve for relative intensities α_k , which we use to drive our LEDs. We seek to reproduce lighting with only positive spectra, so we constrain α_k to be positive using nonnegative least squares.

For MIM, modulation of a target illuminant by the spectral sensitivities of one tristimulus observer yields only three equations, so we can theoretically only solve for optimal weights α_k for 3-channel light sources. However, Wenger et al. [2003] found a minimum norm, positive solution for a 9-channel source. Rather than solve the under-constrained MIM problem, we observe that MIM constraints are enforced in the MRM solve because the flat reflectance spectra of the neutral grayscale squares of the color chart modulate the incident illumination spectrum only by an overall, wavelength-independent scale factor. Similarly, if we sought to include SIM constraints in the MRM solve, we could design a set of theoretical reflectance spectra as pulse functions at increments equivalent to our measurement resolution (10 nm). Minimizing MRM error using a set of such functions is equivalent to minimizing SIM error.

3 Datasets

Towards an observer-agnostic optimal LED selection, we minimize MRM color error using a database of spectral sensitivity functions for 28 cameras [Jiang et al. 2013] and include the CIE 1931 2° standard observer. For test illuminants, we consider CIE illuminant A (tungsten lighting), D65 (average daylight), and F4 (fluorescent, used for calibrating the CIE color rendering index, with CRI = 51). Since light sources of a light stage frequently reproduce indirect illumination, we also consider D65 modulated by measured reflectance spectra of grass and sand from the USGS Digital Spectral Library (SPLIB06a). We also consider diffuse skylight, which we measured at midday using a Photo Research PR-650 spectroradiometer. We use the 24 reflectance spectra of the X-Rite ColorCheckerTM chart for MRM. As the spectral resolu-

tion and sampling extent vary across datasets, we resample each spectrum with trapezoidal binning between 400 and 700 nm to the coarsest resolution, 10 nm. As camera spectral sensitivity functions are typically broad, re-sampling error should be small. We affix each LED onto a custom circuit board and measure the emission spectra (Fig. 1) using the PR-650 spectroradiometer.

4 Results

Fig. 2 shows the SIM sum of squared errors (SSE) (400-700 nm) for the normalized test illuminants, for several LED combinations. Optimal weights α_k are determined for each LED combination for each illuminant. We report the theoretical error using all 11 LEDs, the minimal error combinations of 6 and 5 LEDs, RGBW, and RGB. As there are 462 combinations of 6 LEDs to construct from 11 LEDs, we always include RGBW in our sets of 5 or 6 LEDs, as these are useful for other light stage applications. We therefore evaluate 21 combinations, varying two LEDs of a 6-channel source.

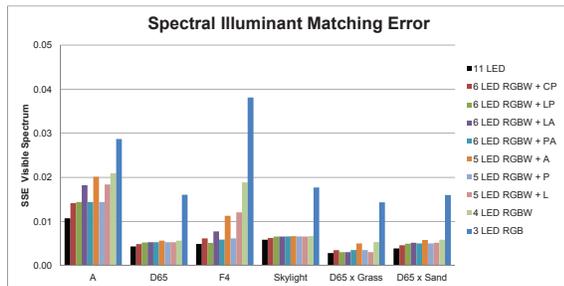


Figure 2: Spectral SSE, 400-700 nm, using SIM for six different illuminants, for various combinations of LEDs.

The black bars of Fig. 2 represent the theoretically minimal SSE when using 11 LEDs of distinct spectra. D65, Skylight, and the D65 modulated spectra are reproduced comparably with 4 LEDs as with 11 LEDs. The 5-channel RGBWP solve reproduces illuminants A and F4 comparably to the 11-channel solve.

Fig. 3 shows the theoretical MRM average error for computed tristimulus values, relative to the color chart white square values. For each LED combination, we solve for optimal weights α_k for each observer separately and report the average color error across the 24 color squares and the 29 observers (28 cameras and human observer). Therefore, we constrain that the LEDs used must be consistent across observers, but the LED intensities α_k may vary.

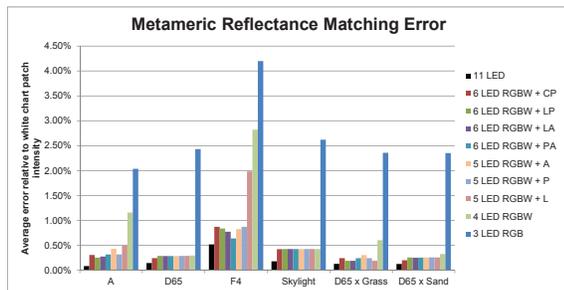


Figure 3: Average squared error of tristimulus values from all 24 color chart squares for six different illuminants, using MRM. Each bar represents the average error across 29 observers.

5-channel RGBWA and RGBWP solves again have similar error to the full 11-channel solve for MRM, with average error under 0.5% for illuminants A, D65, Skylight, and the D65 modulated spectra, and under 1% for illuminant F4. For a given LED arrangement and illuminant, average errors for various observers are similar.

While for Fig. 3 we tailor the light intensities α_k to each observer, we also solve for one optimal set of intensities α_k for each illuminant for all observers and again report the average error across all chart squares and observers. Fig. 4 shows the theoretical difference in the MRM color error as a function of the solving method (SIM, all-observers MRM, single-observer MRM). The single-observer MRM solves yield lower color error than the all-observer MRM solves, but the all-observer MRM error is still low, owing to the general similarity of camera spectral sensitivity functions.

For all illuminants and LED configurations, SIM yields more color error than even the all-observer MRM, indicating that lighting reproduction may benefit from a generic assumption about spectral sensitivity functions in the absence of measured observer response.

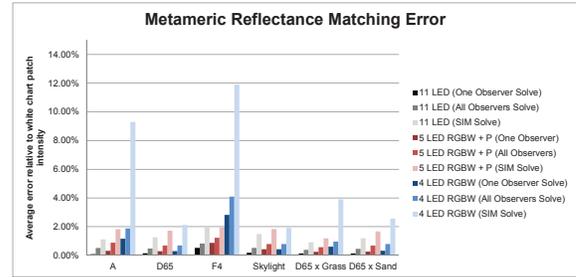


Figure 4: Average squared error of tristimulus values from all 24 color chart squares for six different illuminants, using SIM, MRM (single-observer), and MRM (all-observers). Each bar represents the average error across 29 observers.

5 Conclusion

We have demonstrated that material color appearance under various direct and indirect illuminants may be accurately matched using as few as five LEDs of distinct spectra for multispectral lighting reproduction: red, green, blue, white, and broad-spectrum PC Amber. Using more than these five LEDs of distinct spectra yields diminishing returns. Spectral illuminant matching and color appearance matching via metameric reflectance yield the same optimal set of five LEDs for the illuminants and observers considered.

References

- DEBEVEC, P., WENGER, A., TCHOU, C., GARDNER, A., WAESE, J., AND HAWKINS, T. 2002. A lighting reproduction approach to live-action compositing. In *Proc. 29th Annual Conference on Computer Graphics and Interactive Techniques*, ACM, New York, NY, USA, SIGGRAPH '02, 547–556.
- JIANG, J., LIU, D., GU, J., AND SUSSTRUNK, S. 2013. What is the space of spectral sensitivity functions for digital color cameras. In *Applications of Computer Vision WACV, 2013 IEEE Workshop on*, 168–179.
- LEGENDRE, C., YU, X., LIU, D., BUSCH, J., JONES, A., PATANAIK, S., AND DEBEVEC, P. 2016. Practical multispectral lighting reproduction. *ACM Trans. Graph.* 35, 4 (July).
- WENGER, A., HAWKINS, T., AND DEBEVEC, P. 2003. Optimizing color matching in a lighting reproduction system for complex subject and illuminant spectra. In *Proceedings of the 14th Eurographics Workshop on Rendering*, Eurographics Association, Aire-la-Ville, Switzerland, EGRW '03, 249–259.