Optimizing a Three-Channel Sensor Spectral Sensitivity Using A Genetic Algorithm

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Abstract: Previous spectral error estimation studies are focused only on daylight. Spectral sensitivity of three sensors are optimized for electric light sources using genetic algorithm, which resulted in reduced errors between actual and estimated spectra.

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1. Introduction

A multi-channel spectrum imaging system enables accurate spectral measurement across changes in illumination and ensures color matches for all observer types [1]. Multi-channel imaging is important for areas that require high-end color reproduction and spectral data collection, such as artwork reproduction and conservation [2], archeology [3], telemedicine [4], agriculture [5], study of minerals and gems [6], and integrative lighting systems [7]. Research on multi-channel imaging systems also impacts filter design [8] and target analysis [9], where spectral mismatches are considered detrimental for the optical systems. However, previous studies comparing and evaluating the mismatches in spectral power distributions (SPDs) are daylight oriented [10–13]. Optical imaging systems that are aimed to detect spectra during night time (i.e., sky glow, ecological impacts of lighting) require spectral analysis of electric light sources [14]. Here, the optimal spectral sensitivity of a three-channel sensing system is described using electric and natural light sources (i.e., one standard illuminant and ten commercially available electric light sources).

2. Methods

The spectral properties of three theoretical sensors were optimized using a genetic algorithm (GA) to minimize the error between reconstructed (estimated) and actual light source spectra. A GA is a computational tool inspired by the natural selection [15], and it is widely used in engineering and lighting research to find optimal solutions for a given problem [16,17]. The spectral sensitivity of each sensor was generated using a Gaussian distribution and characterized by their peak wavelengths and bandwidths (i.e., the full width at half maximum (FWHM)).

The differences between reconstructed (estimated) and measured spectrum were analyzed using spectral curve difference metrics. Root mean square error (RMSE) is a simple, but widely used, metric for spectral estimation evaluation [18,19]. In addition to RMSE, two other metrics (integrated irradiance error (IIE) [10] and goodness-of-fit (GFC) coefficient [11]) were also considered for spectral analysis. While RMSE and IIE range between 0 and 1 (a smaller value denotes smaller error), a spectrally accurate estimation requires a

GFC > 0.995 ("acceptable" fit), a "good" spectral fit requires a GFC > 0.999, and GFC > 0.9999 is needed for an "excellent" fit [11, 12]. Instead of a mean absolute average, the root-mean-square of three metrics was used, which is found to be more sensitive to distance differences and more appropriate when the error distribution is expected to be Gaussian [20].

3. Results and discussion

The optimal peak wavelength and bandwidth of the three sensors are λ_{sens1} = 380 nm, $FWHM_{sens1}$ = 160 nm, λ_{sens2} = 563 nm, $FWHM_{sens2}$ = 194 nm, λ_{sens3} = 750 nm, $FWHM_{sens3}$ = 166 nm. The resulting error for each light source and error measures are summarized in Table 1. The highest RMSE was found for daylight illuminant and the smallest error was recorded for low-pressure sodium. There was one "excellent" fit for GFC (LPS), eight "good" fits, and two "acceptable" fits. None of the light sources were below the "acceptable" level for GFC. The reconstructed spectra for tri-phosphor fluorescent and phosphor-coated LED with additional red peak performed the best according to IIE.

The results obtained here are comparable to other spectral mismatch studies, where values for daylight ranged between IIE = 0.032 [10], GFC = 0.9900 [11], RMSE = 0.3715, GFC = 0.9997, IIE = 0.0133 [14], and GFC = 0.9985, IIE = 0.70 [13]. Although some of the GFC values in these previous studies are marginally better than results presented here, the RMSE and IIE scores found in previous studies are lower compared to data gained through GA.

Table 1. Spectral properties of the reference light sources and the error between the estimated and measured spectra according to three spectral mismatch metrics.

Light source	**RMSE**	**GFC**	**IIE**
Incandescent	0.0327	0.9988	0.0451
Daylight D65	0.0373	0.9989	0.0439
Phosphor-coated LED	0.0208	0.9993	0.0348
Phosphor-coated LED + red peak	0.0090	0.9994	0.0327
Cool white fluorescent	0.0125	0.9995	0.0390
Daylight fluorescent	0.0108	0.9993	0.0394
Tri-phosphor fluorescent	0.0068	0.9996	0.0345
Metal Halide	0.0090	0.9993	0.0462
Mercury	0.0072	0.9997	0.0432
High-pressure sodium	0.0093	0.9997	0.0369
Low-pressure sodium	0.0037	1.000	0.0353

Accurate and inexpensive spectral estimation can enable more diverse applications of multispectral sensing where the light source spectrum plays a vital role. Optimizing the sensor sensitivities for the commercially available electric light source can allow manufacturers to improve the accuracy of sensing systems. Although the spectral optimization of three sensors resulted in small spectral matching errors, it is possible to increase the accuracy even further by using more sensors or changing optimization parameters.

4. References

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