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Development of a three-dimensional color rendition space for tunable solid-state light sources

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Abstract

The quality of building electric lighting systems can be assessed using color rendition metrics. However, color rendition metrics are limited in quantifying tunable solid-state light sources, since tunable lighting systems can generate a vast number of different white light spectra, providing flexibility in terms of color quality and energy efficiency. Previous research suggests that color rendition is multi-dimensional in nature, and it cannot be simplified to a single number. Color shifts under a test light source in comparison to a reference illuminant, changes in color gamut, and color discrimination are important dimensions of the quality of electric light sources, which are not captured by a single-numbered metric. To address the challenges in color rendition characterization of modern solid-state light sources, the development of a multi-dimensional color rendition space is proposed. The proposed continuous measure can quantify the change in color rendition ability of tunable solid-state light devices with caveats. Future work, discretization of the continuous color rendition space, will be carried out to address the shortcomings of a continuous three-dimensional space.

Motivation

Electric lighting is one of the primary influencers of energy consumption, occupant comfort, and visual task performance. Solid-state lighting (SSL) devices are widely used in buildings thanks to their high efficiency, compact size, robustness, long lifetime, dimmability, and unprecedented control over the spectral power distribution (SPD) [1]. The spectral flexibility of SSL devices offers a wide range of white light spectra that can meet competing goals, such as energy efficiency and color quality of white light sources. White light can be generated by mixing several narrowband LEDs or converting phosphor. Phosphor-coated LEDs (pcLEDs) are typically more compact, provide relatively high luminous flux with lower costs, but they have limited color properties and lower luminous efficacies compared to multi-colored LEDs (mcLEDs) [2]. On the other hand, mcLEDs offer greater spectral output flexibility, but they require feedback mechanisms to maintain color quality [3].

Color rendition is the effect of a light source on the appearance of objects. Color rendition metrics quantify the ability of a light source to render (display) the color of objects – often compared to a reference illuminant, such as daylight or Planckian radiator. Color rendition ability is often used as a proxy of the overall quality of an electric light source, and it is strongly correlated to occupant preference and performance in the built environment, and acceptability of new lighting technologies.

The performance of mcLEDs have been previously investigated for color rendering [4], energy efficiency [5,6], art conservation [7], daylight simulation [8], circadian entrainment [9], and wider gamut in displays [10]. Several researchers investigated the spectral optimization up to eight LEDs by parameterizing energy efficiency and color quality metrics [11]. A study comparing two, three, four, and five-channel white polychromatic light sources showed that an increasing number of channels improve color rendering in exchange for the luminous efficacy of radiation (LER; *K*) [12]. The inverse relationship between color quality and energy efficiency was also reported by several researchers [6,13,14]. In addition, trichromatic LEDs were found to be more sensitive to small variations in color samples, especially for saturated colors, compared to tetrachromatic LEDs [15]. Similarly, other researchers found that tetrachromatic LEDs can outperform trichromatic LEDs in terms of luminous efficacy and color quality when both simulated and real LEDs were considered [9]. Visual experiments investigating the perceived quality of mcLEDs supported observations gained from the computational simulations [16].

Most of the previous optimization studies deployed a single-numbered color rendition metric, such as the color rendering index (CRI) [17]. However, the CRI has several well-documented limitations (only eight desaturated samples, outdated color space and chromatic adaptation transform, penalizing preferable color shifts, discontinuity in reference illuminant, negative values for certain light sources) and it correlates poorly with human visual perception [18,19]. Studies analyzing color rendition metrics' performance indicate that a single metric is not adequate to determine the color quality of electric light sources due to the importance and interplay of parameters, such as fidelity, saturation, naturalness, and discrimination [19]. The shortcomings of CRI expedited a search for new set of metrics to address the multidimensional nature of color rendition. To date, metrics with multi indices have been proposed to quantify different dimensions of color rendition. Among all the new color rendition metrics, the IES TM-30 has been recently adopted by the American National Standards Institute (ANSI) as the recommended practice for quantifying color rendition of electric light sources. ANSI/IES TM-30 provides a method to evaluate the color quality of electric light sources using the fidelity index (R_f), gamut index (R_g), local chroma shift ($R_{cs,hj}$), and color vector graphic (CVG) [20].

Research investigating the variability in the color rendition metrics indicate that even a two-dimensional metric might not be enough to describe color rendition quality of light sources [21]. For example, two light sources with the same R_f and R_g values can render object colors vastly different. The difference can be captured by CVG, which is a graphical representation of color gamut. Fortunately, it is possible to quantify the change in the gamut shape using mathematical methods, such as ellipse fitting [21,22], or singular value decomposition. The deficit in characterizing the color rendition for light sources signals the need for a multi-dimensional approach to the color rendition that goes beyond fidelity and gamut metrics, especially for tunable lighting systems. While the colorimetric specification of fixed-state lighting products (single spectrum) is straightforward, there is no established method or guideline to communicate the color rendition variation in a given tunable lighting system. Therefore, a multi-dimensional color rendition model is needed to capture the full potential of mcLEDs.

Methods

Here, a continuous color rendition space is conceptualized and tested to characterize and compare the color quality of tunable lighting systems based on the ANSI/IES TM-30-18 R_f, R_g, and $R_{cs,hj}$ values [20]. The tested color rendition space (CRS) is a three-dimensional graphical tool demonstrating the variability in the color rendition of tunable lighting systems. The three dimensions of the CRS were chosen from the ANSI/IES TM-30: fidelity index R_f, gamut index R_g and hue bin (j_{max}) with the maximum chroma shift ($R_{cs,hj}$), as shown in Fig. 1 and 2. The x and y axes demonstrate the range of R_f and R_g values, and the third dimension is the hue bin j that has the maximum $R_{cs,hj}$ value. In the CRS, each data point is a unique SPD, and the volume of the CRS represents the range of SPDs available under the multi-colored lighting system. The volume of the CRS (V_{CSR}) can be calculated using a convex hull algorithm [23], such as MATLAB®'s built-in *convhull* function.

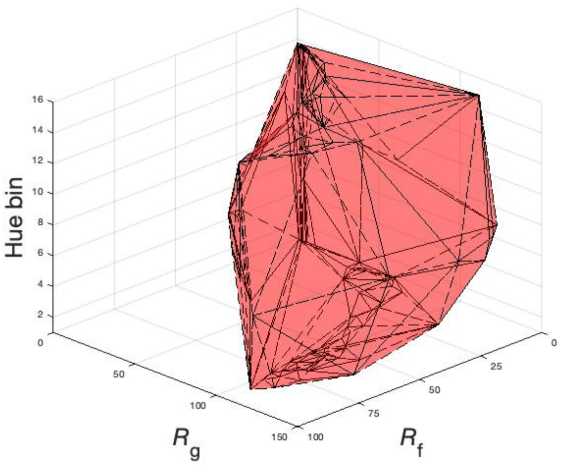

Figure 1. The color rendition space (CRS) of a three-channel LED system with axes representing ANSI/IES TM-30 based indices; fidelity index R_f, gamut index R_g, and hue angle bin j_{max}. The volume of the CRS (V_{CRS} = 97,161) is calculated using a convex hull algorithm.

A dataset previously used for spectral optimization [6] was deployed to analyze the color rendition variability under multi-color LED systems. The dataset consisted of 164,582 theoretical LED spectra with peak wavelengths ranging between 395 nm and 705 nm and full width at half maximum (FWHM) ranging between 5 nm and 150 nm. LED combinations were a mixture of three, four, five, six, and seven LED channels with different peak wavelengths and FWHMs. There were 20,000 three-channel, six-channel, and seven-channel LED combinations, 30,000 five-channel LED combinations, and 74,582 four-channel LED combinations. The dataset was filtered to limit LED combinations to 3500 K ±50 K and Duv between -0.018 and 0.016. Studies on color rendition show that 3500 K is a neutral correlated color temperature (CCT) that enables a broad variety of gamut shapes [24]. The wide variety of gamut shapes also enable a better analysis of R_f and R_g for the proposed 3D color rendering volume.

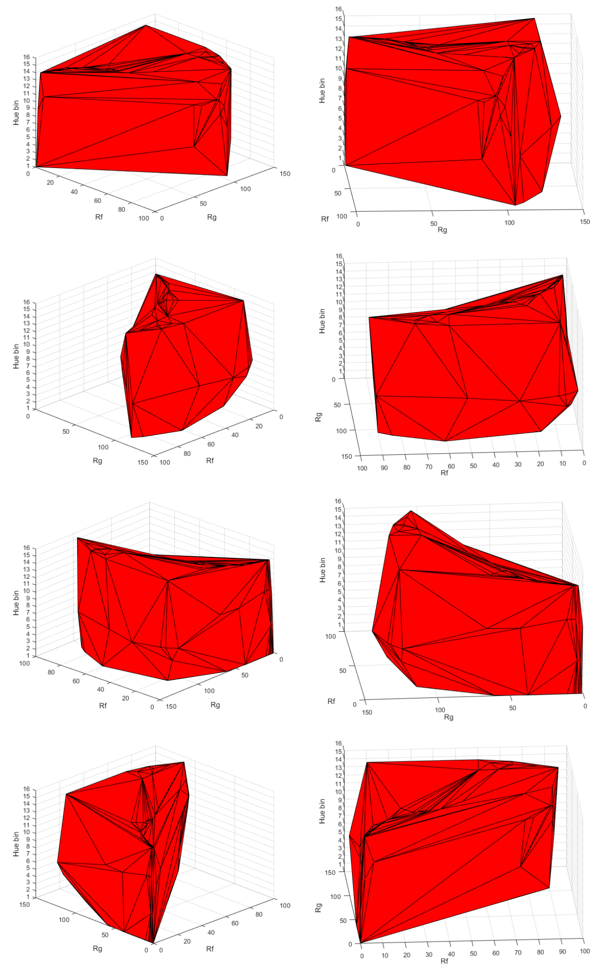

Figure 2. The color rendition space (CRS) of multi-primary LED systems can be presented using different viewing angles and surface transparencies to emphasize the three-dimentional nature of the CRS volume.

Results

Out of 164,582 theoretical LED spectra, only 5,773 SPDs were within 3500 K ±50 K range. Filtered four-channel combinations (2,687 SPDs) contributed more compared to other filtered channels (> 1034 SPDs). The increased contribution of four-channel combinations was normal since unfiltered four-channel LED combinations (74,582 SPDs) were more than twice the other unfiltered combinations (20,000 and 30,000 SPDs).

The variation in the color quality of three, four, five, six, and seven-channel LEDs was compared using the fidelity index R_f, gamut index R_g, the volume of the CRS (V_{CSR}), and luminous efficacy of radiation (LER), as shown in Table 1. The LER range reached a plateau (i.e., change in the decimal point) when four channels were combined, while R_f and R_g did not reach a plateau until up to seven and six-channels were combined, respectively. For all combinations, local chroma shift $R_{cs,hj}$ maximized at 15 out of 16 hue bins, creating a wide range of gamut shapes. The only exception was the hue bin j_3 (orange).

Table 1. The comparison of the color quality and luminous efficacy of radiation (*K*) characteristics of tunable lighting systems between three and seven channels.

Number of channels	*3*	*4*	*5*	*6*	*7*
i	*684*	*3,371*	*4,404*	*5,097*	*5,773*
V_{CRS}	*97k*	*112k*	*113k*	*114k*	*112k*
$R_{f,min}$	*0.1*	*0.1*	*0.1*	*0.1*	*0.1*
$R_{f,max}$	*94.4*	*95.7*	*95.7*	*95.8*	*98.4*
$R_{f,avg}$	*47.6*	*60.7*	*60.8*	*61.3*	*62.0*
ΔR_f	*94.4*	*95.6*	*95.6*	*95.8*	*98.4*
$R_{f,min}$	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*
$R_{f,max}$	*141.1*	*143.3*	*145.2*	*147.9*	*147.9*
$R_{f,avg}$	*72.2*	*85.3*	*85.6*	*86.0*	*86.5*
ΔR_f	*140.6*	*142.9*	*144.7*	*147.4*	*147.4*
K_{min} (lm/W)	*32.8*	*32.8*	*32.8*	*32.8*	*32.8*
K_{max} (lm/W)	490.2	490.8	490.8	490.8	490.8
K_{avg} (lm/W)	*292.3*	*285.5*	*283.8*	*282.9*	*281.5*
ΔK (lm/W)	*457.4*	*457.9*	*457.9*	*457.9*	*457.9*

The tradeoff between the luminous efficacy of radiation and light quality was noted in the average values of LER and color rendition indices R_f and R_g. While color rendition indices increased on average, the average LER reduced. This supports the previously established inverse relationship between color quality and energy efficiency for electric light sources [6,13,14].

It is also possible to visualize the color rendition variability using arbitrary volume calculations (as shown in Fig. 3) as an alternative to V_{CSR}. The alternative volumes are easier to calculate compared to V_{CSR} since they are simple multiplications. However, these methods do not allow a three-dimensional graphical representation of the data due to the interdependence of the number of SPDs (i) and color rendition indices (i.e., the total number of SPDs cannot be the third dimension in the CRS since it is the sum of data points).

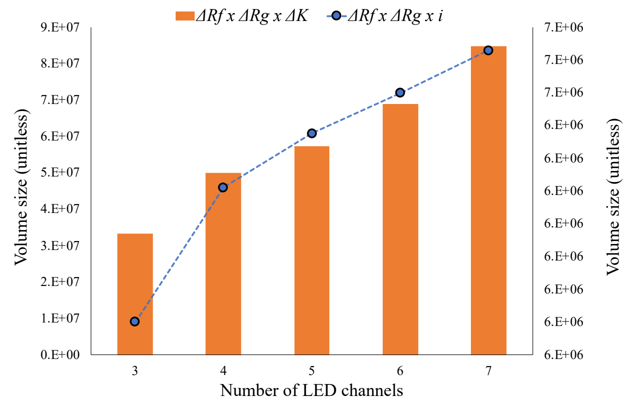

Figure 3. Two alternative volume calculations to quantify the variability in the color rendition of tunable light sources: $V_{alt1} = \Delta R_f \times \Delta R_g \times i$ (blue dots) and $V_{alt2} = \Delta R_f \times \Delta R_g \times \Delta K$ (orange columns) as a function of the number of LED channels.

The differences between the color rendition ability of lighting systems with different number of LED channels can be visually represented using CRS, as shown in Fig. 4. The *x* and *y* axes show the range of the fidelity R_f and gamut R_g indices for each combination, and the *z*-axis is the hue bin with the largest local chroma shift $R_{cs,hj}$. The most notable shift in the CRS shape was the increased range of R_g gamut values, especially for hue bins 1, 2, and 16 (red and purple). Although the total volume of the CRS did not vary greatly after four (or more) LED channels were mixed, the increased number of SPDs in the red region was a notable difference. The increased number of SPD combinations in a given lighting system can be beneficial for users due to the psychological and physiological prominence of red for humans [25]. Studies indicate that humans pay particular attention to red colored objects when making subjective evaluations of the visual environment [25,26]. This effect is likely connected to the evolutionary importance of detecting shifts in the color of human complexion (e.g., being able to detect illness by assessing skin color) and separating rotten fruits from good ones in foliage, which can increase the likelihood of human species' survival.

It should be noted that the analysis presented here do not apply to an individual lighting system with predefined characteristics. In each group, there were LED combinations that varied in terms of peak wavelengths and FWHM. This means that this study compares the color rendition ability of tunable lighting systems independent of the colorimetric properties of LEDs.

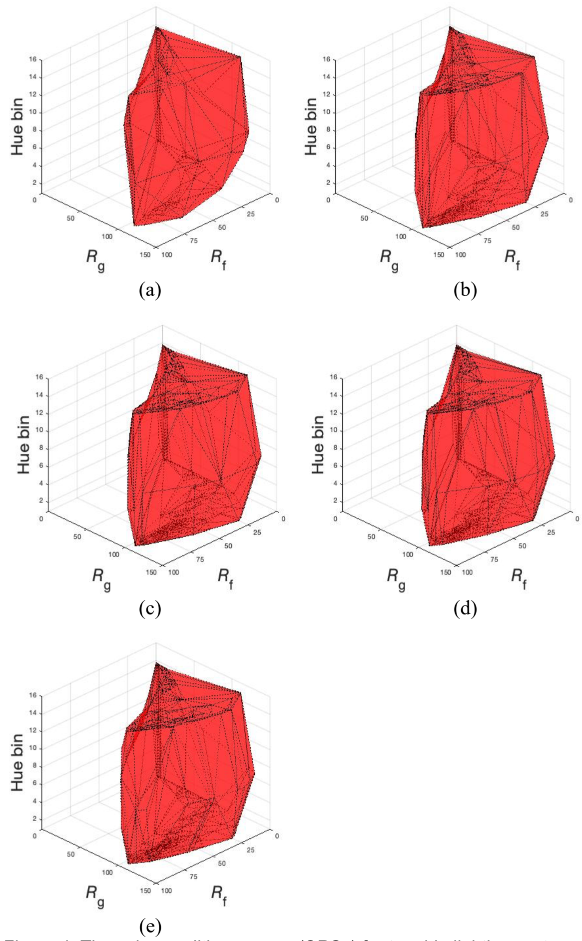

Figure 4. The color rendition spaces (CRSs) for tunable lighting systems with three (a), four (b), five (c), six (d), and seven (d) narrowband LED channels.

Discussion

The proposed three-dimensional CRS is a conceptually useful tool to compare the ability of tunable lighting systems with caveats. The limitations of the proposed data treatment (convex hull approach) are the continuous nature of the data and the lack of recognition for non-existing SPDs in the volume. For example, the resulting CRSs in Fig. 4. appear to be continuous volumes, which might mislead users to think that an mcLED can generate every SPD in that volume. However, depending on the closing envelop of the convex hulls which connects individual dots to create a volume, the mcLED might not be able to generate every SPD in that convex hull space. While this limits the performance of the discussed CRS model, an assumption can be made about linearity of the in-between inflated data (i.e., the empty space between data points could be assumed similar in magnitude across the number of LED channels). However, the linearity asumption should be tested by using a discrete scale or volume.

Continuous scales of the CRS can be converted to discrete data by identifying unit sizes. Discretizing continuous data would result in unit cubes (*voxels*) that can allow quantifying the number of “unique” SPDs within a mcLED. This discritization concept has been previously applied to quantifying circadian metric variability [27] and damage to artwork [28] for tunable LED light sources. For color rendition, the accuracy of the discretized CRS would largely depend on choosing appropriate thresholds for the voxels. The threshold can be the smallest detectable difference, similar to *just-noticeable difference* (JND) concept in psychophysics, or *significant figures* concept that is widely used in mathematics and engineering. For example, if fidelity index $R_f = 1$ is defined as a threshold, $R_f = 83.2$ and $R_f = 82.8$ would be in the same unique voxel, while $R_f = 83.8$ and $R_f = 84.1$ would belong to another unique voxel.

It should be noted that there are no JNDs for color rendition metrics since color rendition metrics often average individual color differences. In TM-30 fidelity and gamut indices are calculated based on differences of 99 color samples representative of architectural surfaces. In practice, lighting professionals require a reasonable measure of color quality for electric light sources using a one-dimensional metric (e.g., 0 = worst, 100 = best). The continuous range in often categorized for practical reasons, such as 60 poor, 70 acceptable, 80 very good, 90 and above excellent. This was the case with CRI for a long time.

Another consideration for the threshold characterization is the inherent variation between observers, potentially due to cone cell responses and aging of the eye [29]. Differences were found in color matching experiments between observers with non-deficient color vision, and the Commission Internationale de l’Éclairage (CIE) published “physiologically relevant” cone fundamentals to account for the inter-observer variations. A recent study indicates that TM-30 fidelity and gamut indices can vary up to 5-10 units due to the inter-observer differences [30]. Therefore, the optimal unit size for fidelity and gamut indices might be larger than 1 since the inter-observer variations might be large, if not challenging to quantify.

While the CRS example is explained using ANSI/IES TM-30 color rendition indices, it is possible to use other color quality metrics to represent multi-dimensional nature of color perception of objects. Several color rendition metrics already exist to quantify different dimensions, such as color fidelity, gamut area, discrimination, color memory, and preference of objects under electric light sources [19,31].

Conclusions

Tunable lighting systems have the potential to address building occupants’ varying needs. While the color quality of traditional light sources with fixed spectra can be analyzed using color rendition metrics, they are not adequate for tunable lighting systems. The proposed color rendition space can be used to quantify the variability in color rendition of tunable lighting systems. The color rendition space can be adopted for any number of multi-colored LED systems.

In the analyzed dataset of three to seven multi-color LEDs, color rendition and luminous efficiency reached an early plateau. Fidelity and gamut indices did not vary greatly when four or more LED channels were mixed, but there was a larger variety of spectra that enhanced the saturation of red objects, which is a predictor of observer visual preference. A larger dataset is needed for a broader analysis of the effect of additional channels (more than seven) on color rendition and luminous efficacy. Regardless of the size of the data (number of LED channels in a lighting system), a color rendition space can be deployed to compare the color rendition ability of multi-channel lighting systems.

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