Spectral tuning of luminance cameras: A theoretical model and validation measurements

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Presently, luminance distribution measurement devices, using High Dynamic Range technology, are increasingly used as they provide a lot of relevant data related to the lit environment at once. However, the accuracy of these devices can be a concern. It is expected that the accuracy would be improved by incorporating the effect of the camera spectral responsivity and the spectral power distribution of the illuminant under which the measurements are conducted. This study introduces two optimization criteria incorporating these aspects to improve the spectral match and the performance of luminance distribution measurement devices. Both criteria are tested in a theoretical model and in practical measurements using two cameras and three illuminants: LED, halogen and fluorescent. Both methodologies support the hypothesis that the conventional method to determine the luminance introduces spectral mismatches that can be limited by optimizing relative to the spectral responsivity of the camera. Additionally, substantial evidence was found, by both the theoretical model and the validation measurements, that the spectral power distribution of the illuminant also has an effect on the performance.

1. Introduction

In the past, general lighting was typically measured using illuminance-based devices because it is easy to measure. However, with technological advances, luminance-based measurement devices are gaining more popularity, as luminance is closely related to the human visual perception of brightness.\textsuperscript{1} In addition, the luminance distribution contains information on multiple lighting quality aspects such as the distribution, directionality, dynamics of light and glare.\textsuperscript{2} Furthermore, daylight simulations can benefit from the implementation of actual measured sky luminance distributions\textsuperscript{3} instead of generic sky models.\textsuperscript{4} Moreover, an increasing number of automated daylight systems are implemented in the built environment. These kind of systems can benefit from the actual and real luminance distributions, capturing the environment and the fast variations of daylight, to optimize user comfort and energy performance in a closed loop control system.\textsuperscript{5,6}

It has been shown that the luminance distribution can be measured with camera...
systems,6–10 using the floating point Red Green Blue (RGB) values of High Dynamic Range (HDR) images.11 The HDR technology is essential as it is able, in contrast to standard 8-bit images, to capture high luminance ranges. To calculate the luminance, the RGB colour space is generally converted to the XYZ colour space because the CIE XYZ colour space has been developed such that the colour matching function \( f(\lambda) \) is analogous to the luminous sensitivity curve of the human eye for photopic vision \( V(\lambda) \).12 The transformation of RGB to XYZ is done using conversion matrices either proposed by Pascale13 or developed according to the methodology described by Wyszecki and Stiles.14 These matrices show a dependency on the colour primaries of the selected colour space and the white point applied by the camera.6 Subsequently, the luminance, represented by the Y channel, is computed based on a linear combination of the RGB values, with the r, g and b weighting factors extracted from the conversion matrix.15 To extract validated data, a photometric calibration is required for each individual measurement.7,16

Generally, the standard Red Green Blue (sRGB) colour space is assumed because this colour space is used in most applications such as internet and printing applications.11 This assumption means that this colour space is expected to provide a reasonable approximation of the camera sensor’s spectral responsivity;7,15 however, Ramanath et al.17 states that ‘the data captured by the sensor is in the colour space of the camera and has little to do with colorimetric (human) values’. Moreover, Wu et al.18 indicate that the spectral responsivity of the camera can have a severe disparity with the RGB colour space as manufacturers aim to achieve compelling colours. The sRGB colour space is a rendered or output-referred colour space designed for an output medium,11,17 while HDR images are scene-referred images because the pixels are directly related to the radiance of the captured scene.11 An HDR image cannot be displayed without tone-mapping, which can be considered the transformation of a scene referred to an output-referred image.19

HDR images are generally formed by merging multiple output-referred images. The commonly used HDR builder requires JPEG or Tagged Image File Format (TIFF) files with an 8-bit depth per channel.20 During the imaging pipeline for output-referred images, multiple corrections and transformations are applied to achieve a visually appealing image17 while losing valuable information. To account for this information loss, radiometric calibration is required which directly relates the HDR pixel values to the scene irradiance,21 while also accounting for proprietary corrections in the image pipeline. Moreover, Lenseigne et al.22 showed that the spectral responsivity of the HDR has large similarities, including the effect of white balancing, to the raw spectral responsivity, indicating that the colour space of the HDR image is camera dependent and not necessarily similar to the spectral sRGB responsivity.

Additionally, the sRGB colour space can theoretically lead to negative RGB values, as it assumes negative sensitivities for certain wavelengths in the visible spectrum to prevent information losses, while this is physically not feasible for a three-channelled camera. Summarized, the assumption of the sRGB colour space seems not fitting. As a result, it is hypothesized that the r, g and b weighting factors based on the sRGB colour space transformation, hereafter referred to as the conventional method, will result in significant spectral mismatches.

Second, the conventional method is dependent on the spectral power distribution (SPD); the white point, one of the conversion matrix’ parameters, is reliant on a standard illuminant, for sRGB this is standard illuminant D65. The white point is the chromaticity that corresponds to the image area that is perceived as white for a specific illuminant.23
Kruisselbrink et al.\textsuperscript{6} showed that this white point is reliant on the correlated colour temperature (CCT), and hence SPD dependent, potentially causing significant deviations in luminance values further from the CCT of the standard illuminant.

Moreover, the CIE\textsuperscript{24} states that using a photometer with a spectral responsivity that differs from the spectral luminous efficiency function for photopic vision ($V(\lambda)$) gathers incorrect measurements. Nevertheless, the measurements can be corrected with a spectral mismatch correction factor when the relative SPD of the light source and relative spectral responsivity of the photometer are available. It is indicated that this is very important for narrow band illuminants such as LEDs, implying that the SPD can influence the spectral performance of a sensor. Furthermore, Cai\textsuperscript{25} performed identical HDR luminance measurements under different types of illuminants and found significant differences in accuracy as was earlier hypothesized by Cai and Chung.\textsuperscript{26} Therefore, the second hypothesis is that the optimal r, g and b weighting factors depend on the relative SPD of the illuminant.

In the literature, a number of studies\textsuperscript{18,27–32} have been found that optimized a camera system to capture spectral efficiencies as accurately as possible. Borisuit et al.\textsuperscript{27,28} suggested applying an optical filter to the sensor to match the $V(\lambda)$\textsuperscript{27} and the circadian sensitivity function $C(\lambda)$,\textsuperscript{28} resulting in spectral mismatch errors of 8.3% and 10.4%, respectively. Similarly, Wu et al.\textsuperscript{18} developed an optical filter to match $V(\lambda)$ by minimizing the least error in the $l^2$ norm space using a pool of 256 bandpass filters. Additionally, to further optimize the spectral match, the r, g and b weighting factors were also determined using the least error in the $l^2$ norm space, leading to a limited spectral mismatch of only 8.9% instead of the original 52.9%. Alternatively, Geisler-Moroder and Dür\textsuperscript{29} optimized the r, g and b weighting factors by solving a Gramian matrix to approximate the $C(\lambda)$ based on rendered HDR images. Nevertheless, the relative errors were all greater than 5%. Similarly, Cauwerts et al.\textsuperscript{31} optimized the colour transform matrix, for photometric measurements, by minimizing the least square error in the XYZ colour space using 18 colour samples lit by an incandescent light source, resulting in a mean absolute percentage error of 3.4% instead of 4.4%. Also Fliegel and Havlin\textsuperscript{30} optimized the $V(\lambda)$ match by minimizing the mean squared error of a single exposure resulting in a 10% deviation in luminance for standard illuminant A.

To assess the hypotheses, the weighting coefficients are optimized according to a theoretical model introducing the spectral responsivity of two cameras and the SPDs of three illuminants: LED, halogen and fluorescent. Moreover, the theoretical model is validated with practical measurements. Based on the measurement accuracy of the theoretical model and the practical measurements, the hypotheses are assessed.

2. Theoretical model

In this section, two optimization criteria are developed for an image-based system, in addition to the conventional method, with the objective to improve the accuracy of the luminance distribution measurement. This is achieved by improving the spectral match of the cameras relative spectral responsivity by tuning the r, g and b weighting factors. Additionally, one performance indicator is proposed which helps to assess both optimization criteria and the conventional method, similarly and independently.

2.1 Conventional method

For the conventional method, the luminance ($L_{\text{conv}}$) is calculated based on a linear combination of the RGB coefficients using
fixed r, g and b weighting factors according to equation (1) that resemble the luminous efficiency curve $V(\lambda)$.

These coefficients are originating from the transformation of the sRGB to XYZ colour space based on the reference primaries, CIE standard illuminant D65, and standard CIE Colorimetric Observer with 2° field of view.

$k_v$ is a photometric calibration factor, required for valid results

$$L_{corr} = k_v \cdot (0.2125 \cdot R + 0.7154 \cdot G + 0.0721 \cdot B)$$ (1)

### 2.2 Optimizations

Two different optimization criteria are developed to optimize the spectral match between the relative spectral responsivity $s_{rel}(\lambda)$ of the camera and the 10 degree $V(\lambda)$ curve, as recommended by CIE committee W-1.3.1, because it is more representative for the human eye compared to the 2 degree $V(\lambda)$ function. Both criteria aim to find the optimal r, g and b weighting factors.

#### 2.2.1 Criterion 1

The first optimization criterion is based on the General $V(\lambda)$ Mismatch Index $f'_1$, which is an indicator used to specify the spectral properties of photometers for general measurements. The $f'_1$ index is suitable for a general description of the photometer’s performance describing the relation between the $V(\lambda)$ and the approximated $V(\lambda)$ of the photometer. However, this index, in the current use, is only appropriate for SPDs similar to standard illuminant A. In this study, the $f'_1$ index is applied to luminance cameras, since one image pixel originating from the luminance distribution can be considered as a single reading from a spot luminance meter. Equations (2) and (3) describe the $f'_1$ index for the nth relative SPD $\Phi_n(\lambda)$ and relative spectral responsivity $s_{rel}(\lambda)$ of the camera based on the normalized spectral responsivity function $s^*_rel$. The $f'_1$ index is determined for the visible spectrum ranging from the 380 nm to 780 nm

$$s^*_rel(\lambda) = s_{rel}(\lambda) \cdot \frac{\int_{380 \text{ nm}}^{780 \text{ nm}} \Phi_n(\lambda) \cdot V(\lambda) \, d\lambda}{\int_{380 \text{ nm}}^{780 \text{ nm}} \Phi_n(\lambda) \cdot s_{rel}(\lambda) \, d\lambda}$$ (2)

$$f'_1 = \frac{\int_{380 \text{ nm}}^{780 \text{ nm}} |s^*_rel(\lambda) - V(\lambda)| \, d\lambda}{\int_{380 \text{ nm}}^{780 \text{ nm}} V(\lambda) \, d\lambda}$$ (3)

For cameras the relative spectral responsivity $s_{rel}(\lambda)$ is a summation of the relative spectral responsivity for $R(\lambda)$, $G(\lambda)$ and $B(\lambda)$ tristimuli, respectively, with weighting factors r, g and b (equation (4)), analogous to the conventional method. A normalization factor $N_{r,g,b}$ is applied such that the area of $s_{rel}(\lambda)$ is equal to the area of $V(\lambda)$ (equation (5)). This factor does not have any physical meaning but is applied to make $s_{rel}(\lambda)$ independent to energy/area differences between different combinations of $R(\lambda)$, $G(\lambda)$ and $B(\lambda)$ such that only the effect of the improved spectral match is shown

$$s_{rel}(\lambda) = (r \cdot R(\lambda) + g \cdot G(\lambda) + b \cdot B(\lambda)) \cdot N_{r,g,b}$$ (4)

$$1 = \frac{\int_{380 \text{ nm}}^{780 \text{ nm}} V(\lambda) \, d\lambda}{\int_{380 \text{ nm}}^{780 \text{ nm}} s_{rel}(\lambda) \, d\lambda}$$ (5)

To limit the spectral mismatch of $s_{rel}(\lambda)$ relative to the $V(\lambda)$, the $f'_1$ index is optimized according to equation (6). It was chosen to limit the weighting factors to a range of zero to one with increments of 0.01 under the constraint that $r + g + b = 1$. The extension of the range i.e. $r + g + b > 1$ has no effect.
since it results in similar optimizations with different normalization factors \((N_{r,g,b})\).

\[
\arg \min f_1, \text{ subject to : }
\begin{cases}
  r \in (0, 1) \\
  g \in (0, 1) \\
  b \in (0, 1) \\
  r + g + b = 1
\end{cases}
\tag{6}
\]

2.2.2 Criterion 2

Criterion 2 aims to match the \(V(\lambda)\) weighted SPD with the \(s_{rel}(\lambda)\) weighted SPD, whereas criterion 1 merely aims to optimize the \(V(\lambda)\) match. Therefore, the root mean square of the absolute difference between the \(V(\lambda)\) weighted SPD and the \(s_{rel}(\lambda)\) weighted SPD is calculated for each 1 nm increment according to equation (7). The \(r\), \(g\) and \(b\) weighting factors are optimized such that the root mean square of this difference is minimized according to equation (8). This optimization criterion can only be used relatively.

\[
\Delta \Phi_{\text{RMS}} = \sqrt{\frac{1}{780 - 380} \int_{380}^{780} \left| \Phi_n(\lambda) \cdot V(\lambda) - \Phi_n(\lambda) \cdot s_{rel}(\lambda) \cdot N_{r,g,b} \right|^2 d\lambda} \tag{7}
\]

\[
\arg \min \Delta \Phi_{\text{RMS}}, \text{ subject to : }
\begin{cases}
  r \in (0, 1) \\
  g \in (0, 1) \\
  b \in (0, 1) \\
  r + g + b = 1
\end{cases}
\tag{8}
\]

2.3 Performance indicator

To assess criteria 1 and 2, independently, a performance indicator is introduced that defines the relative difference to the physical luminance. The relative difference in luminance \(\delta_{L,n}\) is calculated based on the difference between the \(V(\lambda)\) weighted SPD (equation (9)) and the \(s_{rel}(\lambda)\) weighted SPD (equation (10), including the photometric calibration factor \((k_r)\) according to equation (11).

\[
L_{V,n} = \int_{380}^{780} \Phi_n(\lambda) \cdot V(\lambda) \, d\lambda \tag{9}
\]

\[
L_{s_{rel},n} = k_r \cdot \int_{380}^{780} \Phi_n(\lambda) \cdot s_{rel}(\lambda) \, d\lambda \tag{10}
\]

\[
\delta_{L,n} = \frac{L_{s_{rel},n} - L_{V,n}}{L_{s_{rel},n}} \tag{11}
\]

2.4. Input characteristics

The inputs required for the optimizations are the spectral responsivity of a camera for the R, G and B channels and the SPD of the respective illuminant. In this research, optimizations were performed for two different cameras, the Sony IMX219 (Cam 1) and the OmniVision OV5647 (Cam 2), respectively, with known spectral responsivities in the range of 400 nm to 700 nm with 1 nm increments originating from Koen Hufkens\textsuperscript{34} as shown in Figure 1. Additionally, three different illuminants; LED (\(\Phi_1\)), halogen (\(\Phi_2\)) and fluorescent (\(\Phi_3\)) were used, which are also shown in Figure 1. The SPDs of the illuminants were measured with a Konica Minolta CL500a as explained in Section 3.1.

3. Method

To validate the previously described model, measurements were conducted with Cam 1 and Cam 2 under the exact same SPDs. Therefore, luminance distribution measurements were conducted with Cam 1 and Cam 2, while simultaneously point luminance
measurements were conducted as a reference. The luminance, using the cameras, was calculated according to the conventional method, theoretical optimization of criterion 1 and theoretical optimization of criterion 2. Eventually, the performance of the methodologies was compared with the point luminance measurements according to equation (11).

3.1 Measurement setup

The measurements were conducted in a dark windowless room (4.4 m × 3.6 m × 2.7 m) in which a lightbox was placed. The lightbox, measuring 1.2 m wide, 0.8 m deep and 0.8 m high, with a white painted interior (ρ₁ = 0.85) was placed on a table in the middle of the room. The lightbox was consecutively fitted with three illuminants, a LED (Philips SmartBalance tunable white RC484B) at 4400 K, a halogen (Philips IR 250CH 250W) and a fluorescent illuminant (Freshlight Pure light 32W), respectively, with properties according to Figure 1 and with luminance ratios within the entire scene of approximately 1:2250, 1:1400 and 1:1000, respectively. Baffles were applied for the halogen and fluorescent illuminants to prevent direct light on the camera sensor that might cause overflow.

To indicate the effect of the illuminant’s SPD, the luminance should be measured with a minimum of spectral disruptions to preserve the original SPD. Therefore, 10 grey samples were applied because it is not possible to measure the luminance of the illuminant directly. The targets were successively placed at the back wall in the middle of the lightbox. Grey targets have a relative uniform spectral reflectance; by applying 10 different samples, we intended to limit the effect of the imperfect uniform reflectances. The reflectances of these samples were 0.12, 0.18, 0.26, 0.28, 0.38, 0.41, 0.43, 0.74, 0.90 and 0.93, respectively.

Point luminance measurements were conducted with a Konica Minolta LS-100 luminance meter with an accuracy of ±2% and a general V(λ) mismatch of 8%. Moreover, luminance distribution measurements were performed with two camera sensors, Sony IMX219 (Cam 1) and OmniVision OV5647 (Cam 2), combined with a fisheye lens (FOV 187°) and single-board computer controlled over SSH with an average accuracy ranging from ±5% to ±20%. Both devices were calibrated in advance. The camera settings were fixed and identical for both cameras as far as possible (Table 1). HDRgen²⁰ was used to merge seven exposures into a single HDR

![Figure 1 Spectral responsivities of the R (solid), G (dashed) and B (dotted) channel for Cam 1 and Cam 2 including the white balancing. Moreover, it indicates the spectral content of the illuminants used, the LED (solid), halogen (dashed) and fluorescent (dotted) SPDs, respectively.](image-url)
image locally on the single-board computer. Additionally, unique vignetting filters, based on measurements in an integrating sphere, using a second degree exponential were applied for each camera sensor. Overflow was automatically detected, although it did not occur due to the baffles. Post-processing was done using MATLAB r2017a and consisted of luminance calculation and calibration. The LS-100 and the luminance cameras were placed, side by side, at 1.5 m from the respective grey sample while being focused at the centre of the grey sample. The measurement setup is further elaborated in Figures 2 and 3. The SPDs of the illuminants, shown in Figures 1 and 4, were measured in advance of each individual measurement in the middle of the lightbox using a Konica Minolta CL500A illuminance spectrophotometer with an accuracy of ±2% and a general \( V(\lambda) \) mismatch of 1.5%. These SPD measurements also functioned as input for the theoretical model.

### 3.2 Protocol

In total, 90 measurements were simultaneously conducted for all three devices. The measurements were conducted simultaneously because some minor variations were exhibited during the measurements with the illuminance spectrophotometer for the halogen illuminant mainly. Three positions (P1–P3) were distinguished at 1.5 m from the sample as shown in Figures 2 and 3. To account for the potential differences between measurement positions, the equipment was rotated such that each device conducted a luminance measurement for each condition (10 samples and 3 illuminants) at all three positions. Hence, each condition was measured thrice, resulting in a total of 90 measurements.

#### Table 1: Fixed camera settings for Cam 1 and Cam 2

| Model            | Aperture | Resolution | ISO | White Balance | \( EV_{\text{min}} \) | \( EV_{\text{max}} \) |
|------------------|----------|------------|-----|---------------|-----------------------|-----------------------|
| Cam 1 Sony IMX219| f/2      | 901 × 676  | 100 | 1.3, 1, 1.3   | 4,3                   | 18,8                  |
| Cam 2 OmniVision OV5647| f/2.9   | 901 × 676  | 100 | 1.3, 1, 1.3   | 5,1                   | 19,4                  |

\( EV_{\text{min}} \) represents the longest exposure value, while \( EV_{\text{max}} \) represents the shortest exposure value.
3.3 Analysis methods

Each luminance distribution measurement provided one single HDR image applied with a luminance mask identical to the opening angle of LS-100 luminance meter (Figure 3). Based on the HDR image, the luminance was calculated for each illuminant by the conventional method and both optimizations, by applying the respective r, g and b weighting factors originating from the theoretical optimization found in Table 3. An individual photometric calibration (Section 2.3, $k_r$) was applied for each camera and method (conventional, criterion 1 and criterion 2). This calibration factor was developed such that average measured results are equal to the average expected results for the conventional method, criterion 1 and criterion 2, respectively. Subsequently, inferential statistical methods, such as one-sided and two-sided unpaired t-tests, with a confidence interval of 95% were applied. Moreover, Lin’s Concordance Correlation Coefficient ($\rho_c$) was used to indicate the accuracy and precision relative to the reference measurement. In contrast to Pearson’s correlation coefficient, $\rho_c$ is able to assess both the precision and accuracy.

4. Results

In this section, the results of the theoretical model, or the expected results, and the measurement results both generally indicated by the performance indicator representing the relative difference in luminance (equation (11)) are shown. Additionally, a comparison between the results, using inferential statistics, is presented.

4.1 Theoretical model

Table 2 displays the average results of the optimizations according to the theoretical model calculated using MATLAB r2017a, with the average optimized r, g and b weighting factors, the General $V(\lambda)$ Mismatch Index $f'_1$ (equation (3)), the root mean square of the difference between $V(\lambda)$ and $s_{rel}(\lambda)$ weighted SPDs ($\Delta \Phi_{RMS}$, equation (7)) and the relative difference in luminance ($\delta_L$, equation (11)). The table indicates that both the $f'_1$ and $\Phi_{RMS}$ were improved for both optimizations. However, on average, the $\delta_L$ generally did not improve, while the average standard deviation was reduced, indicating an improved precision.

The theoretical optimization results are illustrated per wavelength in Figure 4. The dashed black line highlights the weighted SPD with a perfect $V(\lambda)$ match. As clearly seen, the conventional method, but also the optimizations, differ notably from this perfect $V(\lambda)$ match, as already indicated by the $f'_1$ values in Table 2. Moreover, the results of the optimizations for the LED and halogen using criteria 1 and 2 were rather similar; however, for the fluorescent illuminant, the differences were more distinct. In most cases, the
Figure 4  The relative spectral sensitivity of camera 1 and 2 weighted by the SPD (dotted) of the LED, halogen and fluorescent illuminants for the theoretical conventional method (black), criterion 1 (grey), criterion 2 (light grey) and perfect \( V(\lambda) \) match (dashed).

Table 2  Average theoretical optimization results of the \( r \), \( g \) and \( b \) weighting factors using LED, halogen and fluorescent illuminants

|        | \( r \)    | \( g \)   | \( b \)   | \( f'_1 \)    | \( \Delta_{RMS} \) | \( \delta_L \) |
|--------|------------|-----------|-----------|---------------|-------------------|--------------|
| Cam 1  |            |           |           |               |                   |              |
| Conventional     | 0.2125     | 0.7154    | 0.0721    | 42.9% (0.2%)  | 9.8% (2.3%)       | -7.3% (9.8%) |
| Criteria 1        | 0.10 (0.02)| 0.90 (0.02)| 0.00 (0.00)| 37.3% (0.2%)  | 8.1% (1.9%)       | -7.7% (5.3%) |
| Criteria 2        | 0.07 (0.05)| 0.93 (0.05)| 0.00 (0.00)| 37.7% (0.6%)  | 8.0% (1.9%)       | -9.3% (3.0%) |
| Cam 2  |            |           |           |               |                   |              |
| Conventional     | 0.2125     | 0.7154    | 0.0721    | 36.6% (3.2%)  | 9.1% (3.2%)       | -4.6% (10.5%)|
| Criteria 1        | 0.08 (0.02)| 0.92 (0.02)| 0.00 (0.00)| 25.9% (0.1%)  | 6.1% (2.0%)       | -3.5% (5.3%) |
| Criteria 2        | 0.10 (0.07)| 0.90 (0.07)| 0.00 (0.00)| 26.6% (0.6%)  | 5.6% (2.5%)       | -5.5% (4.6%) |

The average performance is indicated by the \( f'_1 \), \( \Delta_{RMS} \) and \( \delta_L \) with standard deviations in parentheses.

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optimizations achieved a better spectral match than the conventional method. Cam 2 achieved a better fit, mainly around 525 nm, because the spectral responsivity of Cam 2 for the green channel was more compact as illustrated in Figure 1.

The optimization results for the individual illuminants, cameras and methods are presented in Table 3 and Figure 4. The relative spectral sensitivities of Figure 4 were achieved using the r, g and b weighting factors displayed in Table 3. The weighting factors differ significantly compared to the weighting factors of the conventional method. The main difference related to the conventional method is in the weighting factor of the blue sensitivity, which was zero for both optimizations and 0.0721 for the conventional method. Additionally, the weighting factors for the halogen illuminant are very different compared to the LED and fluorescent illuminant. In contrast to Table 2, the performance of the optimized weighting factors provided a higher accuracy indicated by a lower $\delta_L$ because the results are absolute and separated per illuminant. The expected improvements were the highest for the halogen illuminant; moreover, Cam 2 showed larger improvements than Cam 1.

### Table 3

|       | $\delta_{L,conv}$ | $r_0$ | $g_0$ | $b_0$ | $\delta_{L,f}$ | $r_{RMS}$ | $g_{RMS}$ | $b_{RMS}$ | $\delta_{L,RMS}$ |
|-------|------------------|-------|-------|-------|----------------|-----------|-----------|-----------|-----------------|
| **Cam 1** |                  |       |       |       |                |           |           |           |                 |
| LED   | 14.0%            | 0.12  | 0.88  | 0.00  | 12.2%          | 0.11      | 0.89      | 0.00      | 12.1%          |
| Halogen | 7.2%            | 0.07  | 0.93  | 0.00  | 0.0%           | 0.00      | 1.00      | 0.00      | 5.0%           |
| Fluorescent | 14.0%     | 0.11  | 0.89  | 0.00  | 10.7%          | 0.10      | 0.90      | 0.00      | 10.5%          |
| Average | 11.6%          | 0.10  | 0.90  | 0.00  | 7.6%           | 0.07      | 0.93      | 0.00      | 9.2%           |
| **Cam 2** |                  |       |       |       |                |           |           |           |                 |
| LED   | 12.1%            | 0.09  | 0.91  | 0.00  | 7.8%           | 0.12      | 0.88      | 0.00      | 8.3%           |
| Halogen | 10.3%           | 0.05  | 0.95  | 0.00  | 4.0%           | 0.01      | 0.99      | 0.00      | 1.0%           |
| Fluorescent | 11.9%      | 0.09  | 0.91  | 0.00  | 6.6%           | 0.18      | 0.82      | 0.00      | 9.3%           |
| Average | 11.3%           | 0.08  | 0.92  | 0.00  | 6.1%           | 0.10      | 0.90      | 0.00      | 6.2%           |

### 4.2 Measured results

Based on the HDR images captured during the measurements, the luminance was determined for the conventional method and the optimizations. For the optimizations, the r, g and b weighting factors were originating from the theoretical optimization presented in Table 3.

Figure 5 illustrates the relative difference in luminance for the two cameras compared to the point luminance measurements conducted with the Konica Minolta LS-100. Additionally, the absolute luminances measured with the Konica Minolta LS-100 are displayed. Figure 5 shows that the relative difference in performance between the three different methods was relatively constant for the 10 samples. Only Cam 2 exhibited substantial differences in performance between samples under the fluorescent illuminant. Moreover, the relative differences found between illuminants and cameras were substantially different. Both luminance cameras exhibited the lowest performance for the halogen illuminant; furthermore, the optimizations even had a negative effect on the relative difference in luminance for the halogen illuminant compared to the conventional method. The other illuminants, except the
The average performance of the optimizations for the illuminants and cameras, including error bars representing the standard deviation, are shown in Figure 6. It shows that the results for the LED and fluorescent illuminants, for both cameras, were rather similar. A small improvement of $\delta_L$ was achieved for both optimizations relative to the conventional method. However, for the halogen illuminant, the difference was higher and in the opposite direction. As a result, the average results for cameras 1 and 2 did not show an improvement because the improvement for the LED and fluorescent illuminants was compensated by the deterioration under the halogen illuminant. The results between Cam 1 and Cam 2 were relatively analogous with the exception that for Cam 1, the optimization according to criterion 1 was generally having a more pronounced effect, whereas for Cam 2, the optimization according to criterion 2 was more pronounced.

4.3 Comparison

Based on the theoretical method introduced in Section 2, we were able to form expectations of our measurement results. However, the expected results, as indicated in Figure 6 (grey), did not exactly match the measured results. Based on a t-test, it was also found that the measured $\delta_L$ for all samples (illuminants, cameras and methods) were
significantly different \((p < 0.001)\) compared to the expectations. Nevertheless, the trend between the measured and the expected values were very much alike, almost as if a shift in relative differences was enforced. To elaborate on these trends, the relative differences between the conventional method and the two optimization criteria were further illustrated in Figure 7. Figure 7 supports the hypothesis that the trend between the expected and measured performance was much alike. However, for Cam 2, some larger differences were found for the halogen and fluorescent illuminants. The majority of the measured relative differences were visually similar to the expected relative differences (Figure 7). However, a t-test showed that all measured differences were significantly different \((p < 0.001)\) from the expectations.

Additionally, Table 3 shows that the optimizations according to criterion 1 and criterion 2 were expected to have an improved performance compared to the conventional method, as indicated by a lower \(\delta_L\). Therefore, a t-test was applied to evaluate whether criterion 1 and 2 had a significant lower
measured $\delta_L$ for the three illuminants and two cameras compared to the conventional method. The $p$-values in Table 4 show that both optimizations for the LED illuminant performed significantly better than the conventional method. Similarly, the improvements due to the optimizations for the fluorescent illuminant were significant for Cam 1.

Using an alternative approach, the difference between optimization methods and the conventional method were analysed using Lin’s Concordance Correlation Coefficient, and the result is presented in Figure 8. Nearly all combinations had an almost perfect (<0.99) agreement with the reference measurement. However, only a substantial (<0.95–0.99) agreement was achieved for all conventional methods for Cam 1 and all measurements with the halogen illuminant. A t-test was implemented to test whether the correlation ($\rho_c$) was significantly higher for the optimizations according to criterion 1 and 2 than for the conventional method.

**Table 4** $p$-Values of a one-sided t-test (X–Y<0) with X as the conventional method and Y as criteria n as measured in the lightbox with a confidence interval of 95%

|          | LED | Halogen | Fluorescent |
|----------|-----|---------|-------------|
| Cam 1    |     |         |             |
| Criteria 1| <0.001| 1.00   | <0.001      |
| Criteria 2| <0.001| 1.00   | <0.001      |
| Cam 2    |     |         |             |
| Criteria 1| <0.001| 1.00   | 0.49        |
| Criteria 2| <0.001| 1.00   | 1.00        |

*Figure 7* The relative difference in luminance between the conventional method and optimizations according to the theoretical model and measurements. The dark grey bars represent optimization criteria 1, whereas the light grey bars represent optimization criteria 2. Error bars describing the standard deviation are added to elaborate on the spread.
To conduct this test, normally distributed data (truncated to 0–1) was generated with $\rho_c$ as mean and the standard deviation based on the confidence interval. Based on the $p$-values in Table 5, it can be concluded, for Cam 1, that both criteria 1 and 2 for the LED and fluorescent illuminants performed better than the conventional method, similar as found in Table 4. Again, this was not the case for the halogen illuminant. Contrary to Cam 1, the results in Table 5 for Cam 2 were not identical to the results found in Table 4. The correlation of criterion 1 under the fluorescent illuminant and of criterion 2 under the halogen illuminant were significantly better than the conventional method, whilst Table 4 did not find a significant difference.

For a majority of cases, the two optimization criteria provided similar results indicating that one of the two might be redundant. However, a t-test (Table 6) showed that $\delta_L$ of criterion 1 and criterion 2 were significantly

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**Figure 8** Lin’s concordance correlation coefficient of cameras 1 and 2 relative to the three illuminants and the conventional method, criterion 1 and criterion 2

**Table 5** $p$-Values of a one-sided t-test ($X-Y>0$) with $X$ as $\rho_c$ originating from the conventional method and $Y$ as $\rho_c$ originating from criteria $n$ with a confidence interval of 95%

|        | LED       | Halogen   | Fluorescent |
|--------|-----------|-----------|-------------|
| Cam 1  |           |           |             |
| Criteria 1 | $<0.001$  | 1         | $<0.001$    |
| Criteria 2 | $<0.001$  | 1         | $<0.001$    |
| Cam 2  |           |           |             |
| Criteria 1 | $<0.001$  | 0.999     | $<0.001$    |
| Criteria 2 | $<0.001$  | 0.035     | 1           |

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different except for the samples measured under the LED illuminant.

Similar differences were found for the concordance correlation coefficients between criteria 1 and 2 using a t-test as shown in Table 7. However, in contrast to Table 6, the difference for Cam 2 under the LED illuminant was also significant.

### 5. Discussion

The study showed that image-based luminance distribution measurements can be improved by optimizing the r, g, and b weighting coefficients based on the camera’s spectral responsivity and the SPD of the respective illuminant. It was hypothesized that both these aspects could improve the accuracy of the luminance distribution relative to the conventional method. This was tested using a theoretical model and validated with measurements.

The results of the theoretical model showed that the conventional method introduces significant spectral mismatches up to approximately 40% (Table 2), as was also indicated by Wu et al. The DIN 5032 Part 7 distinguishes four performance categories, classes L, A, B and C, for the general spectral $V(\lambda)$ mismatch. The maximum $\delta_f$ index for each class is 1.0%, 1.5%, 3.0% and 5.0%, respectively, emphasizing the significance of a mismatch of 40%. As a result, the relative difference in luminance, found for the conventional method, can also be considered significant. However, on average, the optimizations did not always improve the relative difference in luminance, as indicated in Table 2, but a small increase in the spectral match was achieved. This is because these optimizations were bound to the fixed spectral responsivities $R(\lambda)$, $G(\lambda)$ and $B(\lambda)$, which sets limitations to the optimizations.

However, the results, per illuminant, shown in Table 3, showed that the optimized r, g, and b weighting factors based on the SPD improved the accuracy as was hypothesized. In correspondence to Geisler-Moroder and Dürr, the relative error, for the theoretical model, was generally higher than 5%. Table 3 also shows that for these specific cameras, the B channel is not required because especially the G channels show large similarities to the $V(\lambda)$. Nevertheless, this match is far from perfect, therefore, it is corrected by the R channel as the peak of the G channels are below 555 nm. Additionally, energy in the blue area, which has relatively little relevance for $V(\lambda)$, is still captured due to the large overlaps between the spectral responsivities of the G and B channels, thus, making the correction even suitable for a high blue content illuminants such as daylight. Moreover, substantial differences were found between the different optimization criteria, depending on the camera and illuminant. Nevertheless, both criteria perform better than the conventional method. It was found that criterion 1 is a robust optimization as indicated by less variation in r, g and b weighting factors, while criterion 2 generated less spread in the relative difference in luminance.

The measurement results also showed differences between the two cameras.

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**Table 6** $p$-Values of a two-sided t-test ($X - Y \neq 0$) with $X$ as $\delta_L$ for criteria 1 and $Y$ as $\delta_L$ for criteria 2 with a confidence interval of 95%

|          | LED       | Halogen   | Fluorescent |
|----------|-----------|-----------|-------------|
| Cam 1    | 0.104     | <0.001    | -0.001      |
| Cam 2    | 0.0733    | <0.001    | 0.005       |

**Table 7** $p$-Values of a two-sided t-test ($X - Y \neq 0$) with $X$ as $\rho_c$ originating from criteria 1 and $Y$ as $\rho_c$ originating from criteria 2 with a confidence interval of 95%

|          | LED       | Halogen   | Fluorescent |
|----------|-----------|-----------|-------------|
| Cam 1    | 0.391     | <0.001    | 0.033       |
| Cam 2    | <0.001    | <0.001    | -0.001      |
For instance, Cam 2 had lower relative differences in luminance compared to Cam 1, for the conventional method. This indicated that the spectral mismatch of Cam 2 was lower than Cam 1, as shown by the results of the theoretical model (37%–43%, Table 2). Apparently, the spectral responsivity of Cam 2 was more similar to sRGB responsivity than Cam 1; nevertheless, the errors that were introduced are still substantial. During the optimizations, by incorporating the spectral responsivity of the camera, lower spectral mismatches were achieved, always resulting in improved accuracies. The lowest spectral mismatch corresponds to the highest performance (Table 2). Hence, there is strong evidence that the conventional method introduces spectral mismatches at the expense of the measurement accuracy.

The measurement results showed that the performance of Cam 1 and Cam 2 under the LED and fluorescent illuminants were significantly improved for both illuminants (Table 4), except for Cam 2 under the fluorescent illuminant using optimization criterion 2. However, this table also indicates that the optimizations could not improve the performance of both cameras under the halogen illuminant, it even resulted in a decreased performance. However, this can be explained by methodological issues, described later in this section. In contrast to the theoretical model, there is only limited evidence to acknowledge that the SPD has an effect on the optimal r, g and b weighting factors.

Also, the measurement results, shown in Figure 5, showed some differences between criteria 1 and 2, albeit smaller than in the theoretical model. Nevertheless, the differences were generally significant (Table 6). These relative differences are in correspondence to Fliegel and Havlin30 (10%), but significantly higher than found by Cauwerts et al.31 who used DSLRs and an extensive calibration process. For Cam 1, criterion 1 seems to perform slightly better, aside from the halogen illuminant, while for Cam 2, criterion 2 seems to perform better.

Both the theoretical model and the practical measurements provided some evidence that both hypotheses can be accepted. However, the relative differences in luminance for these two approaches differed significantly (Table 4) against expectation. Visually (Figure 6), the trends of improvement look rather similar for the theoretical and practical method, indicating that the relative difference in luminance was shifted, for instance, due to the calibration factors applied to the practical measurements. However, inferential statistics showed that also the trend was significantly different (Figure 7). There are a number of potential explanations for the differences between the two methodologies, both at the theoretical side as well as at the practical side.

The model on which the expected results were based is a simplified model that does not account for the image pipeline. During this image pipeline, multiple corrections are introduced such as demosaicing, gamma correction and colour transformation to achieve a visually pleasing image. During the HDR building process, these corrections are partly corrected by the camera response curve. However, the camera response curve was in this case, and also typically, approximated using the algorithm by Mitsunaga and Nayar21 using HDRgen. Approximation errors in this function can lead to both a decrease or increase relative to the expected results. Moreover, the cameras exhibited noise that might have compromised the accuracy which was not accounted for in the theoretical model. For the theoretical model, the spectral responsivities of Cam 1 and Cam 2 (Figure 1) were taken from the specification sheets.34 The spectral responsivities of Cam 137 and Cam 210 were also measured, by third parties, using monochromators. Some differences can be found, mainly around 700 nm, the responsivities from the specification sheets are much
higher. This might be caused by inconsistencies between cameras of the same make and model. For this exact reason, in best practice, the camera response curve is determined for each individual sensor. However, this might also be caused due to a potentially applied infrared filter, which seems not present in the specification sheets. This can explain why large differences were found between the theoretical model and practical measurements, especially for the halogen illuminant that had a lot of energy in this area. Due to the assumed high spectral responsivity in the red area, low weighting factors were applied for the R channel. In the case of an infrared filter, this leads to an underestimation of the red light, which is exactly exhibited for the underestimated halogen in Figure 6. Therefore, we can conclude that the contradictory results for the halogen illuminant are caused by the inconsistent input instead of an inadequate optimization algorithm. After all, the theoretical model (Table 3) showed improvements for all illuminants. Consequently, when possible, it is advised to measure the spectral responsivity of the camera instead of using the specification sheets.

Moreover, for practical reasons, the measurements could not exactly replicate the theoretical model. Instead of direct measurements of the illuminant, indirect measurements, using ten different grey samples, were applied introducing a spectral responsivity that was not always perfectly uniform. These indirect measurements were chosen because direct measurements of the illuminant led to luminance values that were too high to capture using luminance cameras. Additionally, light sources are not completely uniform. As a result, it was not possible to compare the absolute luminance values of the theoretical model with the measured luminance; nevertheless, the relative difference in luminance could be compared. Grey targets were used to disrupt the SPD of the illuminant as little as possible. For instance, using coloured targets would add an additional level of complexity, as this would also introduce the spectral reflectance, which is also variable over the space, next to the spectral responsivity and the SPD of the illuminant. Moreover, the reference luminance measurements using the Konica Minolta LS-100 had an uncertainty of ±2%, according to the specifications, which might have caused these differences.

Additionally, a photometric calibration factor was applied to the practical measurements to limit the inaccuracies introduced by the hardware. It was found that the calibration factor, besides the average luminance, also influenced the standard deviation of the relative luminance. Therefore, it can be concluded that this calibration factor had a large effect on the measurement results. The calibration factor can be determined in multiple ways; in this research, it was chosen to calibrate the luminance cameras, for all methods, such that the average relative difference in luminance was similar to the expected relative difference in luminance. This allowed us to examine the relative differences in luminance and its trends for each individual illuminant.

Even though this study aimed to answer the fundamental questions whether the spectral responsivity and the SPD of the illuminant should be integrated in the luminance distribution measurement, the practical aspects should not be neglected. It can be argued that instead of optimizing the r, g and b weighting factors, the easy solution would be to apply a calibration factor to each individual camera, similar to the work performed by Jung and Inanici, and/or the illuminant, especially for ad-hoc measurements. However, this requires an additional measurement device to take the calibration measurements when the conditions change. This is a consideration for the end user, related to the desired accuracy. The optimizations stated in this research could be
implemented and automated on the luminance camera, the only requirement is that the spectral responsivity of the camera is measured once, or extracted from databases, and that information is acquired about the SPD. The authors envision that such a system can be used during long-term measurements and/or in lighting control systems. This means that the luminance camera has a fixed position, which would generally mean that there is one fixed SPD, the luminaires, with the addition of a variable daylight SPD. To account for these SPDs, some measurements are required, but these are not more extensive than general commissioning. Also, a number of studies have already proven that it is possible to estimate the illuminant based on camera readings. Alternatively, one could choose to only implement the spectral responsivity of the camera, which is proven to improve the accuracy (Section 4.3). Moreover, these optimizations have a physical basis where a photometric calibration only corrects faulty measurements. Ultimately, a combination of both would achieve the highest accuracy because the optimizations also do not have a perfect spectral match. Another possibility is to improve the spectral match by applying an optical filter, which has shown that low spectral mismatches can be achieved, something that is not feasible with digital corrections as presented in this study.

6. Conclusion

The theoretical model and practical measurements showed that the spectral responsivity of the camera had an effect on the accuracy of the luminance measurement. Therefore, it can be concluded that the r, g and b weighting factors originating from the sRGB colour space can lead to significant mismatches; however, these mismatches can be of different scale depending on the camera and its spectral responsivity.

Moreover, we found substantial evidence that the SPD had an influence on the accuracy of the luminance distribution. Generally, the r, g and b weighting factors originating from an optimization including the SPD led to improved performance. Only the practical measurements under the halogen illuminant resulted in a decreased performance; however, this was caused by inaccuracies in the applied spectral responsivities of the camera close to 700 nm which did not contain an infrared filter. Nevertheless, the optimization algorithms in this study seem to work. After all, the theoretical model showed improvements for all illuminants.

Two optimization criteria were developed that performed significantly differently, incorporating the spectral responsivity and the SPD; however, criterion 1 performed better on average. Nevertheless, it could not be concluded which criterion was most suitable for what situation.

For further assessment, it is recommended to generalize these conclusions by performing similar measurements with and without daylight (high blue content) using different cameras that have a significantly different spectral responsivity, allowing different scales of potential improvement. Also, a different approach should be developed to improve the theoretical model such that cameras can be analysed quickly and on a large scale.

Implementation of these control algorithms can be complex, especially implementing the effect of the illuminant can be complicated. For long-term measurements, it is relevant to implement the spectral responsivity of the camera and/or the SPD of the illuminant because this does not make it necessary to perform a photometric calibration for each measurement. Ultimately, the end user should make the choice about what method to use. However, for ad-hoc measurements, it is more practical to use the conventional method with an additional photometric calibration.
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