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Data-Driven Light Source Selection for Camera Colorimetric Calibration

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Abstract

The colorimetric calibration of cameras are critical in imaging systems, with the sources used in light booths being widely used in practice. These sources, however, may not good presentations of the sources in real life, which possibly results in poor colors. In this study, we adopted a genetic algorithm and a large dataset of real light sources to identify an optimal set of sources that can better represent the sources in real life. The experiment results suggested that the identified set of sources can result in better color performance. Moreover, the selection of the sources was much less complicated in comparison to manual selections, which can be considered and implemented in practice.

Introduction

The colorimetric calibration is critically important to cameras in a wide range of applications, which helps to ensure that the images can be processed to have faithful colors as perceived by the human visual systems. The selection of the calibration sources is a critical task. On one hand, the sources are expected to produce good performance when using cameras in practice. On the other hand, the number of the calibration sources is expected to be smaller, as it affects the efficiency of the calibration on production line.

Various research work (e.g., [1–4]) and practical applications commonly use several sources (e.g., fluorescent daylight, cool white fluorescent, incandescent ”A” and incandescent ”Horizon”) in standard light booths. These sources, however, were mainly selected for performing visual assessments for applications such as textile, painting, and printing under standard viewing conditions. They were not selected for performing camera calibrations. This motivates us to investigate whether a new set of sources should be used for camera calibration, considering a wide range of sources in real life.

In this work, we proposed a data-driven searching method to address such a problem, and included a large set of spectral power distribuitons (SPDs) of light sources collected in real environment and the spectral sensitivity functions of 28 cameras.

Methodology

Preliminaries

In practical applications, camera colorimetric calibration refers to transform the colors from a camera-specific color spaces (i.e., device-dependent color space) to a device-independent color space (e.g., XYZ, sRGB, P3, or Rec 2020), which is commonly achieved through a linear transformation using a color correction matrix (CCM) $T_{3\times 3}$ (note: the CCM here refers to the transformation without white balancing). Ideally, a unique CCM is needed for each light source for a camera, considering the metamerism between the CIE color matching functions and the camera spectral sensitivity functions [6], but such a method is only used in color reproduction in laboratory. Commonly, CCMs are calibrated under several light sources in laboratory, and interpolations are then performed on these calibrated CCMs based on the white point or CCT estimated by the camera when used in practice.

A simple interpolation method, as recommended by Adobe [14], is based using two CCMs T_{L_1} and T_{L_2} that are calibrated under two light sources L_1 and L_2, with one having a relatively low correlated color temperature (CCT) (e.g., 2700 K) and the other having a relatively high CCT (e.g., 6500 K). For the white point estimated for a certain image L, the CCT_L can be estimated in an interactive way, as explained in Algorithm 1. The estimated CCT CCT_L is then used to interpolate the CCM T_L using $T_L = w_1 T_{L_1} + w_2 T_{L_2}$, where w_1 and w_2 are weightings based on CCT_L, CCT_{L_1}, and CCT_{L_2}, as calculated using Eq 1 and $w_1 + w_2 = 1$. It is worthwhile to mention that the interpolation is performed using the reciprocal of the CCTs, since it is more uniform than the CCTs.

$$w_1 = \frac{\frac{1}{CCT_L} - \frac{1}{CCT_{L_2}}}{\frac{1}{CCT_{L_1}} - \frac{1}{CCT_{L_2}}} \tag{1}$$

Such a method can be improved by considering additional calibration sources. In particular, we can include additional light sources in calibration. Instead of performing the interpolation using two fixed sources, it can performed using two sources L_{near_1} and L_{near_2} that are most similar to the estimated white point in the camera-specific color space. The corresponding matrices can be used for CCT estimation and also the derivation of the CCM. The light sources in the standard light booths are commonly used in such a way for camera calibration.

This method can be expanded to achieve more precise results by incorporating additional calibration light sources. Instead of limiting the process to just two light sources, a broader array of light sources can be utilized to generate a more comprehensive set of CCMs. For any given raw input image, the illumination color is identified using its RGB value in the camera-specific color space. To refine the estimation of the final CCM, the two nearest calibration light sources, L_{near_1} and L_{near_2}, are determined based on their Euclidean distance from the input image's illumination. The CCM interpreted from T_{near_1} and T_{near_2} is expected to yield better results than that interpreted from T_{L_1} and T_{L_2}. In practice, sources in standard light booths are commonly used for camera calibration in this way.

Algorithm 1: CCT estimation algorithm

Input: RGB_L: the RGB value of the estimated white point in the camera-specific color space
CCT_{L_1} and CCT_{L_2}: the CCT of L_1 and L_2
T_{L_1} and T_{L_2}: the CCM of L_1 and L_2
δ: an error item to stop the iteration (e.g., can be set to 10)

Output: CCT_L: the CCT of L

$CCT_{last} \leftarrow CCT_{L_1}$;
$CCT_L \leftarrow CCT_{L2}$;
while $|CCT_{last} - CCT_L| > \delta$ **do**
  $CCT_{last} \leftarrow CCT_L$;
  if $CCT_L < CCT_{L_1}$ **then**
    $T \leftarrow T_{L_1}$
  end
  else if $CCT_L < CCT_{L_2}$ **then**
    $w_1 \leftarrow \frac{\frac{1}{CCT_L} - \frac{1}{CCT_{L_2}}}{\frac{1}{CCT_{L_1}} - \frac{1}{CCT_{L_2}}}$;
    $w_2 \leftarrow 1 - w_1$;
    $T \leftarrow w_1 T_{L_1} + w_2 T_{L_2}$
  end
  else
    $T \leftarrow T_{L_2}$
  end
  $XYZ_L \leftarrow T \times RGB_L$;
  $CCT_L \leftarrow XYZtoCCT(XYZ_L)$;
end

Problem formulation

With the above in mind, we aim to select a set of light sources ϕ_{opt} that can be considered as good representations of the sources in real life and result in more accurate estimation of CCT, and also try to limit the number of the sources in the set.

In other words, given a RAW image captured by a camera u under a light source i, with the white point of $RGB_{u,i}$ and a set of calibration light source ϕ_{opt}, the objective function can be defined as the difference of the reciprocal of the CCT values between the ground-truth and the estimation. Moreover, the selection of the calibration sources should consider different cameras, so that such a set can be used for different cameras.

$$\ell_{CCT} = \frac{1}{|\psi_{cam}|} \sum_{u \in \psi_{cam}} \frac{\sum_{i=1}^{m} \left| \frac{1}{CCT_i} - \frac{1}{CCT^*_{u,i}} \right|}{m} \tag{2}$$

where ψ_{cam} represents a set of cameras that are considered, m is the total number of light sources, CCT_i is ground-truth CCT value of a light source i derived from the source's spectrum, and $CCT^*_{u,i}$ is the estimated CCT of the light source i that is derived using Algorithm 1 using the two calibration sources in ϕ_{opt} that have the most similar white point to the light source i in a camera-specific color space.

Search algorithm

The search for the optimal set of light sources ϕ_{opt} can be formulated as a subset selection problem, where the goal is to find the best set of light sources among all possible combinations. The number of combinations to consider can be quite large, given by C^n_m, where m is the total number of light sources to be considered and n is the number of calibration light sources selected.

Instead of exhaustively evaluating all possible combinations, a genetic algorithm can be an alternative with a higher efficiency. It iteratively refines the selections to converge towards an optimal set [8].

To perform the search, the algorithm encodes each possible solution s_i as a binary vector of size m, where only n elements of this vector are assigned a value of 1, indicating that the corresponding source is selected as the calibration source. For example, the solution of $[1,1,0]$ represents a case where there are three light sources and the first and second are selected. The pseudo-code, as written in Algorithm 2, outlines the algorithm. It is important to note that the crossover and mutation operations can be defined arbitrarily, as long as the subset constraint is satisfied.

In this particular implementation, the crossover operation selects values randomly from both parents. It alternates between choosing a value from the first or second parent until enough numbers are selected to form a valid solution. The mutation operation randomly replaces a selected light source with another one that has not been selected yet. The algorithm employs tournament selection [9] as the strategy for selecting parents for the next generation.

The complexity of this algorithm is linearly correlated to the product of the population size and the number of search iterations, which is significantly smaller than the number of all possible combinations of light sources C^n_m. Thus, it allows a balance between computational efficiency and the performance, which enables to derive a good set of light sources.

Experiment and results

The experiment was performed using a total of 415 light sources, which cover a wide range of sources with the spectra collected in our previous study [10]. Figure 1 shows the chromaticities of these light sources in the CIE 1931 chromaticity diagram. On the other hand, the experiment was carried out to consider 28 cameras, whose spectral sensitivity functions were measured in [11], with 20 of the cameras randomly selected as the training set and the other eight cameras, including Canon 1D MarkIII (MarkIII), Canon 20D (20D), Canon 500D (500D), Nikon D300s (D300s), Nikon D700 (D700), Olympus E-PL2 (E-PL2), Phase One (One), and Point Grey Grasshopper 50S5C (50S5C), selected as the testing set. For comparison, six light sources that are commonly used in light booths were used as a baseline condition, including Horizon (HZ), Incandescent light (A), Cool White Fluorescent (CWF), Triphosphor Lamp (TL84), Ultralume 3000 (U30), and Daylight 6500 K (D65). The Xrite ColorChecker was used to derive the CCMs, and the CCT was calculated using [13] was followed for computing the CCT.

When performing the search algorithm, the population size was set to 500, and the number of search iterations was

Algorithm 2: Optimal light sources search algorithm

Input: ϕ_{ill}: a set of all possible light sources
ψ_{cam}: a set of cameras
N: number of selected calibration sources
P: population size for the search
E: number of search iterations

Output: ϕ_{opt}: a set of light sources selected

for $i \leftarrow 1$ *to* P **do**
  $s_i \leftarrow random\_encoding(N, |\phi_{ill}|)$;
end
$S_{par} \leftarrow \{s_1, s_2, ..., s_P\}$, $o_{best} \leftarrow \infty$, $s_{best} \leftarrow \vec{0}$;
for $e \leftarrow 1$ *to* E **do**
  for $i \leftarrow 1$ *to* P **do**
    $o_i \leftarrow \ell_{fit}(s_i, \phi_{ill}, \psi_{cam})$;
    if $o_i < o_{best}$ **then**
      $o_{best} \leftarrow o_i$, $s_{best} \leftarrow s_i$;
    end
  end
  $S_{chi} \leftarrow selection(S_{par}, O_{par})$;
  while $|S_{chi}| \neq |S_{par}|$ **do**
    $\{s_a, s_b\} \leftarrow random\_pick(S_{par})$;
    $S_{chi} \leftarrow (S_{chi} \cup crossover(s_a, s_b))$;
  end
  $S_{par} \leftarrow mutation(S_{chi})$;
end
$\phi_{opt} \leftarrow decode(s_{best})$;

set to 300. The implementation of the algorithm was carried out using the pymoo library [12].

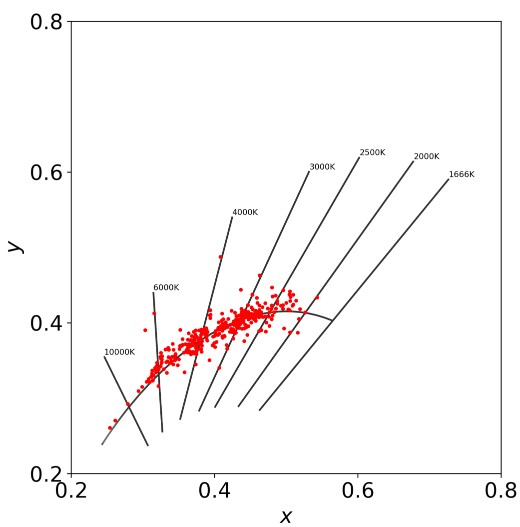

Figure 1. Chromaticities of the 415 light sources in the CIE 1931 chromaticity diagram

Result

The first experiment was carried out following Adobe's recommendation, with only two sources selected for calibration. In particular, Illuminant A and D65 were selected as the baseline for comparison. The spectra of the two selected sources are shown in Figure 2. Table 1 summarizes the results, in terms of the average error of the reciprocal of CCT. The sources that were selected as the calibration sources were excluded when evaluating the performance. It is obvious that the selected sources were able to reduce the error by 11.97% on average, though the performance varied with cameras due to the different spectral sensitivity functions. The most significant reduction was around 30%. Moreover, the CCT values of the two selected sources are $3416K$ and $4356K$, whose difference is much smaller than that between Illuminant A and D65, whcih could be due to the distribution of the 415 sources.

Table 1: Comparison of the performance using Illuminant A and D65 versus two selected sources, in terms of the average error of the reciprocal of CCT.

Camera	A and D65 ($\times 10^{-5}$)	Two selected sources ($\times 10^{-5}$)	Error↓
50S5C	4.27	3.91	8.43%
One	3.80	3.41	10.33%
D700	0.83	0.75	9.74%
MarkIII	1.11	1.00	9.79%
D300s	1.23	0.86	29.83%
E-PL2	1.45	1.16	20.15%
500D	1.30	1.27	2.90%
20D	0.86	0.82	4.57%
Average	1.86	1.65	11.97%

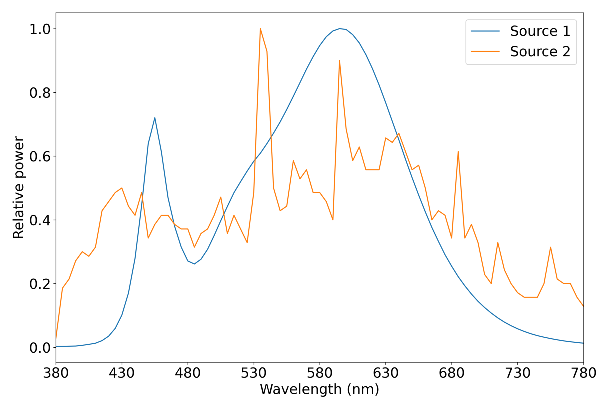

Figure 2. Spectra of the two selected sources, with CCTs of 3416K and 4353K

In the second experiment, we considered to select six sources, and the six sources used in the viewing booths used as the baseline, with the results summarized in Table 2 and the spectra shown in Figure 2. It can be observed that using six sources can generally result in smaller errors, in comparison to using two sources. Also, the selected sources can generally reduce the errors by 10% on average, though the performance still varied with cameras.

Table 2: Comparison of the performance using six sources in the viewing booths versus six selected sources, in terms of the average error of the reciprocal of CCT.

Camera	Sources in booths ($\times 10^{-5}$)	Six selected sources ($\times 10^{-5}$)	Error↓
50S5C	3.06	3.01	1.60%
One	3.64	3.72	-2.24%
D700	0.81	0.73	10.92%
MarkIII	0.97	0.92	5.15%
D300s	1.03	0.87	15.56%
E-PL2	1.32	1.16	12.59%
500D	1.37	1.19	12.95%
20D	0.89	0.73	18.06%
Average	1.64	1.54	9.32%

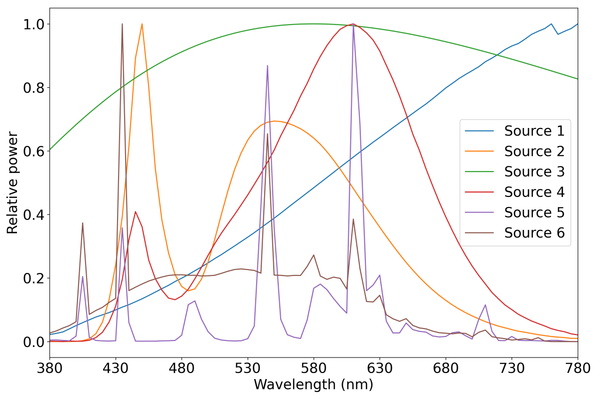

Figure 3. Spectra of the six selected sources, with CCTs of 2741K, 5346K, 5099K, 2660K, 2709K, and 6770K

Optimal number of calibration sources

It is logic to hypothesize that greater number of calibration sources can generally improve the accuracy, which is also suggested in Tables 1 and 2. Thus, we aimed to test such a hypothesis by setting different numbers of calibration sources, from 2 to 20. Figures 4 shows the results, in terms of the error of reciprocal of CCT.

The results clearly supported our hypothesis, and the performance would no longer improve when the number of the sources reached 14.

Discussion

The results presented above provide a good perspective to consider how to perform camera color calibration nowadays. With the wider range of light sources and easier method to produce different sources in laboratory, it merits further investigations on the light source selections. Also, the investigations here only focus on the estimation of CCT, and further investigations on color accracy is needed.

On the other hand, further validations are needed if additional cameras are included, since the spectral sensitivity functions significantly affect the color accuracy of cameras.

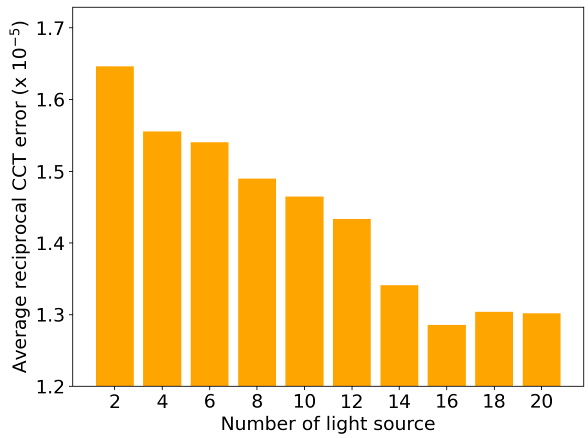

Figure 4. Change of performance, in terms of the average error of reciprocal of CCT, with the number of selected sources for calibration.

Conclusion

This study was designed to investigate whether camera colorimetric calibration should be performed using a better set of calibration sources, instead of the sources commonly used in standard viewing booths. We used a generic algorithm to derive an optimal set of calibration sources that can improve the accuracy of the CCT estimation. In total, 415 sources whose spectra were collected in real life and 28 cameras were considered. The results clearly suggest that a set of calibration sources that are carefully selected can increase the accuracy of CCT estimation, with an average increase of 10%. Also, the greater the number of the calibration sources can effectively improve the accuracy, but such an improvment stops around 15 sources. Further investigations are needed to consider different cameras and also color reproduction accuracy, all of which can bring direct benefits to the industry.

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