Quality Assessment of Spectral Reproductions: the Camera's Perspective

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Abstract. This study introduces a computationally efficient framework to measure the difference between two reflectance spectra in terms of how an arbitrary RGB camera can distinguish between them under an arbitrary light source. Given one set of selected illuminants and one of selected camera models (red, green and blue sensors' spectral responses), results indicate that both sets can be reduced in order to alleviate the computational load of the task while losing little accuracy in measurements.

Keywords: spectral reproduction, spectral printing, illuminant, camera model.

1 Introduction

Imagine looking at two paintings, seemingly identical under the light of day. One is an original, the other is a printed reproduction. Chances are, although they produce the same color sensation under that particular light, there exist other illuminants under which they appear different to the human eye. This is due to the fact that the reflectances of the original painting's pigments are almost impossible to reproduce exactly with common printing technologies and only an approximation can be obtained. As long as it allows for a good match under a standard illuminant such as CIED50 (daylight), this approximation is usually considered as acceptable [14]. Nevertheless, a variety of applications require that the reproduction matches the original under more than just one illuminant (replication of artwork, security printing, catalogues, camera calibration,...). For *spectral* reproduction (as opposed to *colorimetric*), the match between two reflectances is usually computed by means of a purely computational measure such as the Mean Square Error (MSE) [3]. Incidentally, the quality of a reproduction can only be assessed with respect to the application in which it will be used. For instance if the reproduced painting needs only to *look* like the original, the aim is then to mimic human perception. In that case, the MSE conveys very little meaning and a more perceptually-driven approach is needed [10]. If the goal is instead that both paintings should produce the same signal when captured by an RGB camera, quality needs to be measured in different terms. One approach

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is to check whether an arbitrary camera can distinguish between them under an arbitrary light source. If it cannot, then the reproduced painting is perfectly identical to the original as far as the camera is concerned. Similarly, applications pertaining to the calibration of RGB cameras with a printed color target (e.g. for jaundice detection in newborns [5]) also need to rely on such measure of *spectral fidelity* for reliability. There are however two main challenges underlying this approach: defining an "arbitrary light source" and an "arbitrary camera".

To overcome the first challenge, a method was recently introduced [10] to measure the perceived quality of a spectral reproduction in terms of perception and for a given set of more than 70 light sources of various kinds, in a manner that does not require to estimate and compare the color sensations produced under each of these sources. It was showed indeed that it is sufficient to compute the color sensation under one or two representative light source(s) to accurately measure the perceived difference between original and reproduction under any light from the set. As for the second challenge, Jiang *et al.* showed [7] that the spectral sensitivities of a group of 28 cameras can be well represented with only two sets of responses. Here I combine both methods to reduce the computational load of spectral fidelity assessment.

In the remainder of this paper, I first define a measure of spectral fidelity for a single-illuminant and single-camera configuration. I then tackle the problem of considering multiple illuminants and multiple cameras and demonstrate in particular that the results of the measure obtained from a set of 40 illuminants and 28 cameras can be well approximated by using only one representative illuminant and one representative camera.

2 A measure of spectral image quality for RGB cameras

2.1 One illuminant, one camera

A spectral reproduction has perfect quality with respect to human perception if it is indistinguishable from the original under an arbitrary light source [10]. I propose to use the same definition for camera acquisition. Whereas human perception of color difference can be modeled by means of device-independent representations such as CIELAB or the more recent LAB2000HL [11], a camera needs only two stimuli to produce a different signal to distinguish between them. Whether two different radiances $\gamma_\mathbf{1}$ and $\gamma_\mathbf{2}$ will produce the same values in the camera's RGB space depend mostly on the spectral sensitivity of the camera's sensors, noted $\mathbf{S} = [\mathbf{r}, \mathbf{g}, \mathbf{b}]$ (where $\mathbf{r}$, $\mathbf{g}$ and $\mathbf{b}$ are column vectors of size N, representing respectively the sensor responses for its red, green and blue channels). The bit depth (precision) with which the stimulus is encoded, also plays an important role, however no significant difference was found between depths of 16 and 8 bits in these experiments. Most cameras working in this range, bit depth seems to not be an influential parameter here. If two input stimuli give the same RGB triplet, no matter how the RAW image (i.e. the direct response of the camera to the scene's radiance) is normalized to the final (typically sRGB) image, the discriminative information is lost during the acquisition process. On the other hand, when the produced signal are different, there is a way to distinguish between the two radiances with the camera. This is an all-or-nothing situation: either the camera can capture the discriminative information or not. Note that using some kind of distance measure (e.g. Euclidean) between RGB triplets in the camera's space could potentially give further indications as to the difference between them. However it would be difficult to assess the significance of such color differences without further information about how the RAW image would be further processed.

Assuming that $\gamma_\mathbf{1}$ and $\gamma_\mathbf{2}$ are combinations of a single light source $\mathbf{i}$ with two different reflectances $\mathbf{r_1}$ and $\mathbf{r_2}$ ($\gamma_\mathbf{1} = \mathbf{r_1} \odot \mathbf{i}$ and $\gamma_\mathbf{2} = \mathbf{r_2} \odot \mathbf{i}$, where $\odot$ denotes the entrywise product, also known as Hadamard product), and that $\mathbf{r_2}$ is a reproduction of $\mathbf{r_1}$, the colorimetric fidelity of the former with respect to the latter with respect to $\mathbf{i}$ is then either null or perfect (0 or 1). Note that this fidelity can alternatively be referred to as the *difference* between the two spectra. I define the *single Camera-measured Color Difference* (sCCD) between $\mathbf{r_1}$ and $\mathbf{r_2}$, under illuminant $\mathbf{i}$ and for camera σ as follows:

$$\mathrm{sCCD}_{\mathbf{i},\sigma}(\mathbf{r_1};\mathbf{r_2}) = f\left((\mathbf{r_1} \odot \mathbf{i})\,\mathbf{S}_\sigma; (\mathbf{r_2} \odot \mathbf{i})\,\mathbf{S}_\sigma\right) \tag{1}$$

where

$$f(x;y) = \begin{cases} 0, & \text{if } x = y. \\ 1, & \text{otherwise.} \end{cases} \tag{2}$$

and $\mathbf{r_1}$, $\mathbf{r_2}$ and $\mathbf{i}$ are row vectors of size N and $\mathbf{S}_\sigma$ is the set of spectral responses of camera σ.

2.2 Several illuminants, several cameras

Given a set $\mathbf{\Theta}$ of spectral power distributions of important light sources, and given a set $\mathbf{\Upsilon}$ of spectral responses of different RGB cameras[1], I define the *multiple Camera-measured Spectral Difference* (mCSD) between $\mathbf{r_1}$ and $\mathbf{r_2}$ as the proportion of combinations illuminants/camera for which the reflectances are distinguishable:

$$\mathrm{mCSD}_{\mathbf{\Theta},\mathbf{\Upsilon}}(\mathbf{r_1};\mathbf{r_2}) = \frac{1}{|\mathbf{\Upsilon}|}\sum_{\sigma\in\mathbf{\Upsilon}}\left[\frac{1}{|\mathbf{\Theta}|}\sum_{\mathbf{i}\in\mathbf{\Theta}}\mathrm{sCCD}_{\mathbf{i},\sigma}(\mathbf{r_1};\mathbf{r_2})\right] \tag{3}$$

However, computing every single $\mathrm{sCCD}_{\mathbf{i},\sigma}(\mathbf{r_1};\mathbf{r_2})$ can represent a significant computational burden if many reflectances are to be compared, for instance when performing (or optimizing [12]) spectral gamut mapping for a whole multispectral image. In a previous work [10], it was demonstrated that $\mathbf{\Theta}$ can be well represented by means of one or two representative illuminants when measuring spectral fidelity in terms of perception. Here, I propose a similar approach to

[1] Note that this framework stands for cameras with any number of channels.

approximate $\text{mCSD}_{\mathbf{\Theta},\mathbf{\Upsilon}}(\mathbf{r_1};\mathbf{r_2})$ and suggest that both the illuminants and cameras sets can be reduced to improve the computational efficiency of the metric, such that:

$$\text{mCSD}_{\mathbf{\Theta},\mathbf{\Upsilon}}(\mathbf{r_1};\mathbf{r_2}) \approx \text{mCSD}_{\mathbf{\Theta}',\mathbf{\Upsilon}'}(\mathbf{r_1};\mathbf{r_2}) = \frac{1}{|\mathbf{\Upsilon}'|}\sum_{\sigma\in\mathbf{\Upsilon}'}\left[\frac{1}{|\mathbf{\Theta}'|}\sum_{\mathbf{i}\in\mathbf{\Theta}'}\text{sCCD}_{\mathbf{i},\sigma}(\mathbf{r_1};\mathbf{r_2})\right] \tag{4}$$

where $\mathbf{\Upsilon}'$ and $\mathbf{\Theta}'$ are respectively the reduced (and representative) sets of cameras and illuminants, with $|\mathbf{\Upsilon}'| << |\mathbf{\Upsilon}|$ and/or $|\mathbf{\Theta}'| << |\mathbf{\Theta}|$.

In order to compute the reduced sets, two approaches were considered: Principal Component Analysis (selection of the K components with highest eigenvalues) as well as the average of the set, as suggested recently in [8]. Note that in the case of $\mathbf{\Upsilon}'$, these reduction methods are performed on the red, green and blue sets of sensitivity functions separately (i.e. the average of $\mathbf{\Upsilon}$ would consist of three average functions). In the next section, $\text{mCSD}_{\mathbf{\Theta},\mathbf{\Upsilon}}(\mathbf{r_1};\mathbf{r_2})$ and $\text{mCSD}_{\mathbf{\Theta}',\mathbf{\Upsilon}'}$ are compared in different configurations.

3 Experimental results

3.1 Data

These experiments were performed using the representative Standard Object Colour Spectra (SOCS) database [13] as testing data. For each reflectance in that database, two spectral reproductions were created [9]:

- The pseudo-inverse 31-channels reconstruction from a simulated 6-channel filter wheel camera.
- The reconstruction from the LabPQR interim connection space [4].

In both cases, training (respectively of the pseudo-inverse tranform and PQR basis), was performed using spectral measurements of the 1269 Munsell matte colour chips from the University of Joensuu's spectral database [6]

Additionally, I used a collection of 40 illuminants' spectral power distributions noted $\mathbf{\Theta}_{\text{All}}$, made of four equally-sized subgroups: 10 daylights ($\mathbf{\Theta}_{\text{Day}}$), 10 tungsten lights ($\mathbf{\Theta}_{\text{Tun}}$), 10 fluorescent lights ($\mathbf{\Theta}_{\text{Fluo}}$) and 10 LED lights ($\mathbf{\Theta}_{\text{LED}}$). These illuminants were selected randomly from the National Gallery's set [2] as well as from the University of Eastern Finland's daylights set [1] and the CIE standard illuminants. They were all normalized to have a maximal value of 1.

For modeling RGB cameras, I used the database of spectral sensitivities made available by Jiang *et al.* [7]. It consists of 28 cameras: 9 Canon, 10 Nikon and 9 of other brands. Two different bit depths were simulated (8 and 16 bits) by reducing the precision of the result of the application of these sensitivities to the radiances obtained from the aforementioned sets of reflectances and illuminants. Note that all computations were made in double precision. However, no significant changes were observed between results at these two depths.

3.2 Methodology

In order to evaluate how $\text{mCSD}_{\boldsymbol{\Theta}',\boldsymbol{\Upsilon}'}$ can approximate $\text{mCSD}_{\boldsymbol{\Theta},\boldsymbol{\Upsilon}}(\mathbf{r_1};\mathbf{r_2})$, I computed the score given by each of them on every pair original/reproduction (original $\mathbf{r_1}$ from SOCS and reproductions $\mathbf{r_2}$ as described above) and measured the Pearson correlation coefficient ρ between the two sets of results. A high correlation means that the reduced set approximates well the full set for the application under consideration.

3.3 Results

Table 1 give the results obtained. I note K_σ and K_i the number of principal components extracted to represent $\boldsymbol{\Upsilon}$ and $\boldsymbol{\Theta}$, respectively.

Table 1. Pearson's correlation coefficients ρ between $\text{mCSD}_{\boldsymbol{\Theta},\boldsymbol{\Upsilon}}$ and $\text{mCSD}_{\boldsymbol{\Theta}',\boldsymbol{\Upsilon}'}$.

$\boldsymbol{\Upsilon}'$ (V) $\boldsymbol{\Theta}'$ (>)	PCA $K_i = 1$	PCA $K_i = 2$	PCA $K_i = 3$	average $\mathbf{i}$	all illuminants
PCA $K_\sigma = 1$	0.90	0.98	0.98	0.84	0.97
PCA $K_\sigma = 2$	0.97	0.99	0.98	0.95	0.98
PCA $K_\sigma = 3$	0.96	0.98	0.98	0.92	0.96
average σ	0.90	0.98	0.98	0.95	0.95
all cameras	0.88	0.96	0.99	0.95	**1**

These results suggest that it is indeed possible to alleviate the tedious computation of $\text{mCSD}_{\boldsymbol{\Theta},\boldsymbol{\Upsilon}}$ by drastically reducing the size of the sets of illuminants and camera sensitivities. Even reducing the size of both sets to one (i.e. one representative illuminant and one representative set of RGB spectral sensitivities) yields scores which are highly correlated ($\rho = 0.90$) to those of $\text{mCSD}_{\boldsymbol{\Theta},\boldsymbol{\Upsilon}}$. Note, however, that the number of selected Principal Components influences the number of $\text{sCCD}_{\mathbf{i},\sigma}(\mathbf{r_1};\mathbf{r_2})$ values to compute an average of, with Equation (4). If only one component is extracted from both sets for instance, the resulting score corresponds to a difference based on *one* representative camera and under *one* representative illuminant which, as described before, can either be 0 (the reflectances are distinguishable) or 1 (the reflectances are not distinguishable). This implies that the smaller the size of $\boldsymbol{\Theta}'$ and $\boldsymbol{\Upsilon}'$, the coarser the scale of possible spectral fidelity scores.

Interestingly, it seems easier to represent $\boldsymbol{\Upsilon}$ than $\boldsymbol{\Theta}$ as using the first PC of $\boldsymbol{\Upsilon}$ and all of $\boldsymbol{\Theta}$ yields a correlation of 0.97 versus 0.88 in the dual case (first PC of $\boldsymbol{\Theta}$ and all of $\boldsymbol{\Upsilon}$). Also, note that increasing K_σ does not necessarily increase ρ as the values for $K_\sigma = 3$ are systematically smaller than those for $K_\sigma = 2$. This suggests that, despite the fact that PCA permits to obtain results that correlate to a very large extent to those of $\text{mCSD}_{\boldsymbol{\Theta},\boldsymbol{\Upsilon}}$, other dimensionality reduction approaches may be more appropriate to reduce the size of $\boldsymbol{\Upsilon}$ in this context.

4 Conclusion and future work

I presented a computationally efficient framework to measure the difference between two reflectance spectra in terms of how an arbitrary RGB camera can distinguish between them under an arbitrary illuminant. Results indicate that it is not necessary to compute the signals produced by the reflectances in all the cameras RGB spaces and under all illuminants considered. Future work on this topic will include the investigation of other means to measure a camera's sensitivity to a difference between two radiances, particularly in the presence of noise. Other methods to reduce the dimensionality of the sets of cameras and illuminants should also be considered.

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