Spectral based color imaging using RGB digital still cameras: simulated experiments

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1. Introduction

Objective assessment of color is essential in many applications. Traditionally device independent color description is obtained by device colorimetric characterization techniques that relate the imaging device responses, or RGB values, to device-independent CIE tristimulus. These techniques may work well, but they are constrained to a specific illuminant and observer to avoid metamerism. To overcome this problem, multispectral imaging has emerged as a new technology. In the typical multispectral acquisition system, the actual reflectance data are derived from multi-channel images using a characterization method. Estimated reflectances can be used as they are, or combined with given illuminant and observer effects to yield a specific traditional color representation. Despite its advantages, the wide diffusion of multispectral imaging is hampered by several factors; among them the intrinsic cost of the acquisition systems.

The present paper addresses the question of whether spectral-based characterization methods can outperform conventional characterization methods for RGB digital cameras. Furthermore we investigate how low-cost spectral images can be obtained using two acquisitions of the same scene: the former acquired by a traditional RGB imaging device, the latter coupling the same camera with a suitable chosen absorption filter. The combination of the two acquisitions can be considered as acquired by a six band imaging device.

In this paper the performance of 3-channel digital still cameras and of modified (3x2-channel) digital still cameras are evaluated in terms of their capability to estimate spectral reflectance information. The experiments have been carried out using standard color charts and by simulating the behavior of the digital still cameras using the Image Systems Evaluation Toolkit (ISET) that has been developed at Stanford University [1].
2. Apparatus and sample set

All the experiments have been carried out using the Image Systems Evaluation Toolkit (ISET) [1] developed at Stanford University, which makes it possible to simulate the entire image processing pipeline of a digital camera. ISET combines optical modeling and sensor technology simulation, according to the typical digital camera pipeline depicted in Figure 1.

![Figure 1. A typical digital still camera pipeline as it is implemented in the ISET.](image)

The scene is a 2-dimensional map of the spectral irradiance that does not provide information about the distances between objects in the scene and the camera simulator. The imaging optics are modeled using a wave-optics approach which takes into account the finite resolution obtained with finite size optics. The user can vary the size of the aperture of the imaging optics by changing the f/number, which will automatically result in an adjustment of the image irradiance and resolution. Image irradiance is determined using radiometric concepts and includes the effect of the off-axis cos-4\textsuperscript{th} effect, which results in a darkening of the corners with respect to the center of the image when a uniform object is imaged.

Finite resolution is calculated using an optical transfer function (OTF) approach, which is based on the finite aperture as determined by the f/number. To account for wavelength dependent behavior, the OTF is implemented in a spectral manner.

Optical parameters, such as focal length, lens diameter, aperture, optical fall-off, transmittance, and additional simulation of the optics within the sensor pixel itself, based on the number of metal layers, size and position of the photodetector on the substrate, and microlens properties can also be specified.

The image sensor model includes the effects of the spatial sampling of the optical image by the image sensor with finite-size pixels with a given fill-factor. Both pixel size and fill-factor are user-defined parameters. Furthermore, the optical signal collected by each pixel is converted into an electrical signal on a wavelength-basis using a spectral QE. The resulting current is converted into a voltage using a
conversion gain. Both QE and conversion gain are user-defined parameters. To complete the physical signal pipeline, the analog voltage is converted into a digital signal according to the specifications of the user.

It is also possible to model noise, in terms of intrinsic noise, related to the optical signal, (i.e. the photon shot-noise), and noise introduced by the image sensor (read noise and fixed-pattern noise). The latter can be changed by the user depending on pixel properties described in the manufacturer’s specification sheet of the image sensor.

The ISET proceeds with an image-processing pipeline operating on the linear RGB output of the sensor electronics. This pipeline includes various standard algorithms for setting auto-exposure duration, interpolating missing RGB sensor values and transforming RGB values for encoding and display (color-balancing, color-rendering and color-conversion).

In our experiments we are only interested in the RAW RGB device dependent description of the scene. To obtain a device independent description, we apply a matrixing transformation that maps the RAW RGB values into the corresponding sRGB values, based on the values of a known target, the sample set.

Furthermore, we try to reconstruct the spectral reflectances from the RAW RGB device dependent description of the scene, comparing the results in terms of colorimetric $\Delta E_{76}$ error, with those obtained with a traditional RGB imaging method.

The data set used to test our methods is the Macbeth ColorChecker DC (MDC), whose reflectances were measured with a Minolta CM-2002 spectrophotometer.

3. Imaging methods

3.1. RGB imaging

The virtual camera simulator (ISET) is used to simulate a typical RGB digital still camera. The RAW digital data $D_i = \{D_i\}$, $i = 1,2,3$ (corresponding to the RGB device dependent values) of a typical digital still camera can be mathematically modeled for each pixel as follows:

$$D_i = n_i + t \sum_{\lambda=400}^{700} R_\lambda I_\lambda S_\lambda, i,$$  \hspace{1cm} (1)

where $R = \{R_\lambda\}$ is the scene reflectance at the given pixel position, $I = \{I_\lambda\}$ is the spectral power distribution of the incident light, supposedly spatially uniform, $S_\lambda = \{S_\lambda\}$.
\( i=1,2,3 \) are the spectral sensitivities of the camera filters, \( t \) is the exposure time and \( n \) is an additive noise term.

Equation (1) computes the device dependent RGB values for a given pixel; to obtain a device independent representation of it, we have to build the best 3-by-3 matrix transformation \( M \) (called matrixing) that transforms the RAW RGB values (\( D \)) into the corresponding sRGB device independent values (\( sD=\{sD_i\} i=1, 2, 3 \)):

\[
sD = DM
\]

There are several methods in literature to compute such a matrix \( M \) (Least Squares, White Point Preserving Least Squares, Polynomial Regression, Non Maximum Ignorance [3,4,5]). The simplest, here adopted, is to compute the best least squares 3-by-3 matrix for a given data set of known colors. The chosen sample set is the MDC under the CIE D65 standard illuminant [6]: half of the MDC samples, randomly chosen, was used as the training set to build the matrixing transformation \( M \), the remainder was used as the test set.

3.2. Spectral imaging using a singular RGB camera acquisition

In the second experiment, the RAW values coming from the ISET are used to estimate the generalized pseudo inverse matrix \( M_R \), incorporating singular value decomposition, to reconstruct the spectra of the colors of the training set, \( R=\{R_\lambda\} \), where \( \lambda \) ranges between 400 and 700 nm and is sampled with a step of 10 nm:

\[
R = DM_R
\]

The matrix \( M_R \) is no more a 3-by-3, but a 3-by-31. As for the previous imaging method, there are several ways to calculate the matrix \( M_R \), such as Least Squares with Toeplitz matrix, Smoothing Inverse and Linear Models [7,8]. The Generalized Pseudo Inverse is adopted here to estimate \( M_R \):

\[
D^T R = D^T DM_R, \quad (D^T D)^{-1} R = M_R.
\]

The matrix \( M_R \) so obtained was applied to reconstruct the spectra of the test set, and the results were evaluated both in terms of colorimetric \( \Delta E_{76} \) error and spectral RMSE error.
3.3. Spectral imaging using two RGB camera acquisitions
According to this approach, in the third experiment, two acquisitions of the same scene are taken: the former is acquired by a traditional RGB camera, the latter coupling the same camera with a suitable chosen absorption filter (Figure 2). Using the ISET this simply corresponds in placing the absorption filter in front of the Color Filter Array (CFA). The combination of the two acquisitions can be considered as the acquisition of a six band imaging device [9,10].

Figure 2. Flowchart of the analysis of the imaging approach: the two acquisitions give six color values \((R, G, B, R', G', B')\) that are used to reconstruct the reflectance spectra.

The absorption filter was chosen among those filters available in the Schott filter glass catalogue [2] as the one that gives the best color accuracy for both \(\Delta E_{76}\) and RMSE color errors on the training set (Figure 3).
Figure 3. Mean colour errors ($\Delta E_{76}$ under D65) versus the mean spectral error (RMSE) using seven different absorption filters.

The RAW R’G’B’ digital output, $D_{AF} = \{ D_{AF,i} \}$, $i=1, 2, 3$, can be mathematically modeled as follows:

$$D_{AF,i} = n_i + t_{AF} \sum_{\lambda=400}^{700} F_{\lambda} R_{\lambda} I_{\lambda} S_{\lambda,i}$$  \hspace{1cm} (6)

where $F = \{ F_\lambda \}$ is the spectral transmittance of the absorption filter selected, and the other quantities are the same as equation (1). This time we have three more information to reconstruct the spectra $S$ of the MDC, and equation (3) becomes:

$$S = [DD_{AF}]M'_R$$  \hspace{1cm} (7)

where now $M$ is a 6-by-31 matrix.

4. Results

The spectral sensitivities of the ISET are plotted in Figure 4, while the spectral transmittance of the selected absorption filter (‘vg9’) and the three modified spectral
sensitivities obtained by coupling the original filters with the selected one are reported respectively in Figures 5 and 6.

**Figure 4.** Spectral sensitivities of the ISET color filter array sensors.

**Figure 5.** Spectral transmittance of the selected 'vg9' absorption filter.
The three transformation matrices, obtained respectively by the three experimental settings explained in Section 2 were compared with respect to both the training and the test sets. The acquisitions were made under the CIE D65 standard illuminant and the errors were evaluated under the same illuminant.

In Table 1 the results obtained on the training set are reported in terms of $\Delta E_{76}$ (for all the experiments) and RMSE (only for the second and the third).

<table>
<thead>
<tr>
<th>Exp #</th>
<th>exposure time (ms)</th>
<th>$\Delta E$ min</th>
<th>$\Delta E$ max</th>
<th>$\Delta E$ mean</th>
<th>$\Delta E$ std</th>
<th>RMSE min</th>
<th>RMSE max</th>
<th>RMSE mean</th>
<th>RMSE std</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (M)</td>
<td>24.7</td>
<td>1.15</td>
<td>46.73</td>
<td>10.86</td>
<td>6.94</td>
<td>n.a.</td>
<td>n.a.</td>
<td>n.a.</td>
<td>n.a.</td>
</tr>
<tr>
<td>2 (M_0)</td>
<td>24.7</td>
<td>0.14</td>
<td>42.30</td>
<td>5.49</td>
<td>6.10</td>
<td>0.00800</td>
<td>0.15064</td>
<td>0.03541</td>
<td>0.02573</td>
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<tr>
<td>3 (M'_0)</td>
<td>44.0</td>
<td>0.027</td>
<td>4.18</td>
<td>0.57</td>
<td>0.55</td>
<td>0.00532</td>
<td>0.11225</td>
<td>0.01725</td>
<td>0.01289</td>
</tr>
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</table>

Table 1. Results obtained in the 3 different experiments in terms of $\Delta E_{76}$ colour differences and RMSE spectral error in the reconstruction of the MDC training set.

In Table 2 the results obtained on the test set are reported with respect to the same error metrics.
<table>
<thead>
<tr>
<th>Exp #</th>
<th>exposure time (ms)</th>
<th>ΔE min</th>
<th>ΔE max</th>
<th>ΔE mean</th>
<th>ΔE std</th>
<th>RMSE min</th>
<th>RMSE max</th>
<th>RMSE mean</th>
<th>RMSE std</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (M)</td>
<td>24.7</td>
<td>1.61</td>
<td>38.73</td>
<td>11.30</td>
<td>5.85</td>
<td>n.a.</td>
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<td>n.a.</td>
<td>n.a.</td>
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<tr>
<td>2 (M₂)</td>
<td>24.7</td>
<td>0.43</td>
<td>32.65</td>
<td>6.04</td>
<td>5.66</td>
<td>0.00066</td>
<td>0.15249</td>
<td>0.03695</td>
<td>0.02551</td>
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<tr>
<td>3 (M₃)</td>
<td>I: 24.7 II: 44.0</td>
<td>0.056</td>
<td>3.56</td>
<td>0.64</td>
<td>0.49</td>
<td>0.00201</td>
<td>0.08316</td>
<td>0.01826</td>
<td>0.01275</td>
</tr>
</tbody>
</table>

**Table 2.** Results obtained in the 3 different experiments in terms of ΔE₇₆ colour differences and RMSE spectral error in the reconstruction of the MDC test set.

As can be seen from Table 1 and 2, the equipment simulated in the third experiment was able to achieve very good results. Although these came from a simulated digital camera and not from a real one, they are very close to the ones obtained on real experiments with other considerably more complex and expensive technologies [11].

As a final analysis, the transformation vectors from camera RAW values to spectral reflectances, i.e. the rows of the matrices of the second and the third experiments, are reported respectively in Figure 7 and 8.

![Figure 7](image-url)

**Figure 7.** Transform vectors from camera RAW values to spectral reflectances for the second experiment, where $M_R$ is a 3-by-31 matrix.
Figure 8. Transform vectors from camera RAW values to spectral reflectances for the third experiment, where $M_R$ is a 6-by-31 matrix.

Conclusions

The experiments showed that very good results can be achieved by simply using the RGB camera as a spectral based imaging device. These results can be further improved combining two different shots of the same scene acquired using the RGB camera with and without a properly chosen absorption filter. On the basis of these results we believe that the development of low-cost spectral based imaging devices having performance very close to more expensive and complex multispectral devices will be possible in the future.

Bibliography