Supplementary Document: Recovering Spectral Reflectance under Commonly Available Lighting Conditions

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1. Color Difference Equation

A general form of the color difference equation can be expressed as

$$\Delta E = \sqrt{\left(\frac{\Delta L}{S_L}\right)^2 + \left(\frac{\Delta C}{S_C}\right)^2 + \left(\frac{\Delta H}{S_H}\right)^2} \quad (1)$$

where ΔL, ΔC, and ΔH are the difference in lightness, chroma and hue respectively. S_L, S_C, and S_H are the weighting functions mainly used to improve the perceptual uniformity of the CIELAB color space.

Based on Eq. 1, CIEDE2000 is able to correlate even better with the perceptual color difference by including an interactive term to improve the performance for blue colors, and a scaling factor for CIELAB a* scale for improving the performance for gray colors [1]. More details of CIEDE2000 can be found here [1], and the code is published on the website.

2. Noise Analysis

Additive Gaussian Noise Assuming that the noise in all three channels are independent Gaussian noise with variance of τ^2, the variance in the recovered spectral reflectance due to the noise is:

$$\mathbf{v} = \tau^2 \text{diag}(\mathbf{W}\mathbf{W}^T). \quad (2)$$

As shown, the variance of the estimated spectral reflectance depends only on the matrix $\mathbf{W}$ (for a given noise level). Thus, we can use the following equation as the predictor for the overall performance for two given lighting conditions,

$$Z = \text{Trace}(\mathbf{W}\mathbf{W}^T). \quad (3)$$

Smaller Z means more accurate spectral recovery.

When gaussian additive noise is considered only, $\Delta\mathbf{R}$ by Eq. 7 in the paper is not related to reflectance of the samples. Therefore, the second predictor does not exist in this case.

Photon Noise The RMS of the estimated reflectance with the original spectral reflectance is:

$$||\Delta\mathbf{R}||^2 = \mathbf{1}^T \cdot \mathbf{W}^2 \cdot \text{Var}(\mathbf{n}), \quad (4)$$

where $\mathbf{W}^2$ means element-wise square. Combining Eq. 8 in the pape and Eq. 4, we have

$$||\Delta\mathbf{R}||^2 = k\mathbf{1}^T \cdot \mathbf{W}^2 \cdot \mathbf{TC} \cdot \mathbf{R}. \quad (5)$$

For the first predictor, we want to know for all spectral reflectance, what are the optimal illumination conditions to estimate with the proposed method. That means we need to optimize for $\mathbf{E}(||\Delta\mathbf{R}||^2)$ for all possible $\mathbf{R}$. Thus, Eq. 9 in the paper becomes a good predictor.

3. More Applications

3.1. Spectral Imaging of Fine Arts by Fluorescent/ Tungsten Light

Firelight was imaged under the fluorescent light and tungsten light in Fig. 1 (a) and (b). The measured and estimated reflectance at selected areas on the painting were compared in Fig. 1 (e). The rendering of the painting was made under CIE D65 and IllA in Fig. 1 (c) and (d).

3.2. Spectral Imaging of Fine Arts by Camera Flash

While the spectral reflectance of the paintings can be well recovered using the fluorescent and tungsten lighting combinations, it is less likely to carry a fluorescent light source around. Instead, camera flash is often used as a second light source for photography. It is of interest then to learn the spectral recovery under the museum lighting (tungsten light) and the camera flash.

Orchid was imaged under the tungsten light w/ and w/o the camera flash (Canon SpeedLite®) in Fig. 2 (a) and (b). The measured and estimated reflectance at selected areas (P1-P4) on the painting were compared in Fig. 2 (c). The spectral recovery performance using the camera flash was evaluated, overall our results matched with the ground truth.

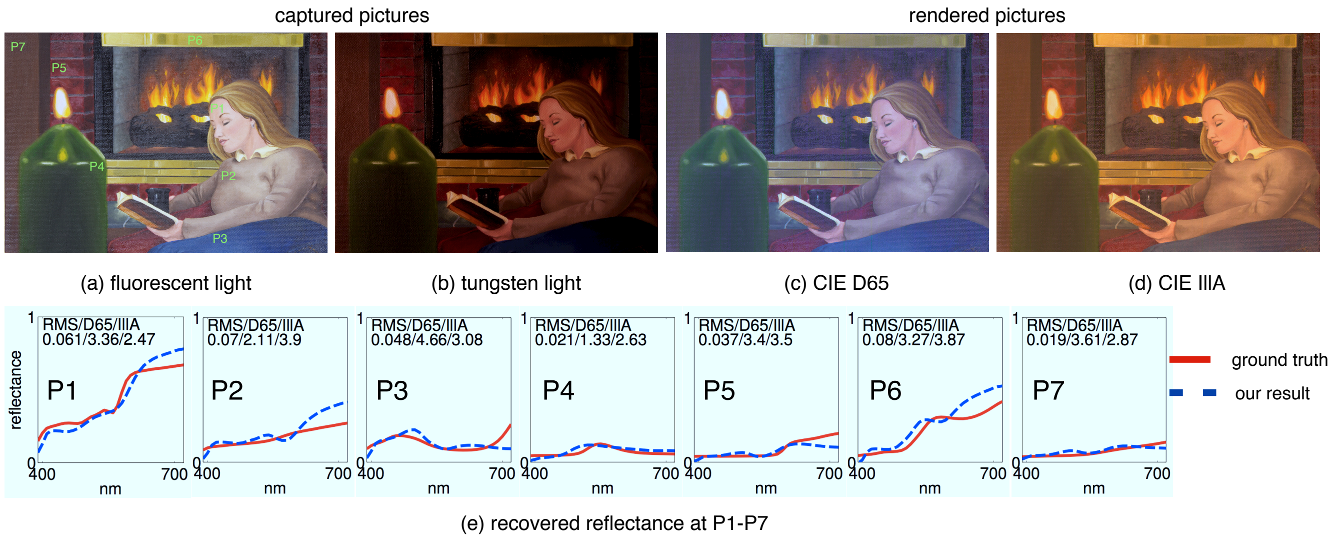

Figure 1. The spectral recovery and rendering of Firelight. (a) and (b) The captured pictures under the fluorescent light and tungsten light. (c) and (d) The rendering of the painting under CIE D65 and IllA. (e) The recovered reflectance at selected areas on the painting.

However, the results were not as good as those using other light sources, fluorescent/ tungsten light, *e.g.*, mainly because the portable camera flash was not a stable light source.

3.3. Spectral Recovery of Beef

The inspection and grading of meat and poultry are of great importance to minimize microbiological contamination of meat, and to ensure the food quality. The reflectance of the beef can be used as a quality control measure to help grade the beef by distinguishing the amount of marbling. An experiment was designed to recover the spectral reflectance of the beef bought in the supermarket under the tungsten light and the studio flash light as shown in Fig. 3 (a) and (b). The recovered reflectance and the rendering of the beef are shown in Fig. 3 (c) and (d).

3.4. Smartphone Nokia N900®

Smartphones and other mobile platforms are gradually changing how we operate our daily life by integrating both the eyes (the camera) and brain (the computing unit) on a cell phone. The wide availability and ease of use of smartphones has also made it easier than ever before to access information in a real-time and more portable way.

While a handheld spectrophotometer can be used to measure the spectral reflectance of materials, the use of cell phone cameras has the benefit of lower cost and acquisition of the scene reflectance rather than of a small uniform area on a surface.

An experiment was designed to evaluate the spectral recovery performance of smartphones by validating CCDC®. Nokia N900® was used because the operating system of the model was open-sourced. Moreover, the picture under one (rather than two) lighting condition was used to recover the scene reflectance.

In Fig. 4, the spectral recovery of CCDC® was made under the tungsten light by Nokia N900®. The estimated and measured reflectances matched well in general except for patches of reddish color. The mean spectral RMS was 0.047, and the color difference under CIE D65 and CIE IllA were 3.9 and 3.2.

Overall the recovered spectral reflectance was more accurate using pictures taken under two rather than one lighting condition (Table. 3 in the paper). Accuracy might be improved by taking another picture using the phone flash as a secondary lighting. However, it was limited by the stability of the flash intensity and how well images were registered, as tripod was usually not used with smartphones.

We calculated ρ on the experimental data to tell which reflectance is likely to be estimated well under the tungsten light. In Fig. 4 (b), two patches of small and large value of ρ were selected, and their estimated and measured reflectance (after normalization) compared. The greater the ρ, the worse the spectral recovery performance.

References

[1] M. R. Luo, G. Cui, and B. Rigg. The development of the cie 2000 colour-difference formula:ciede2000. *Color Research and Application*, 26:341–450, 2000. 1

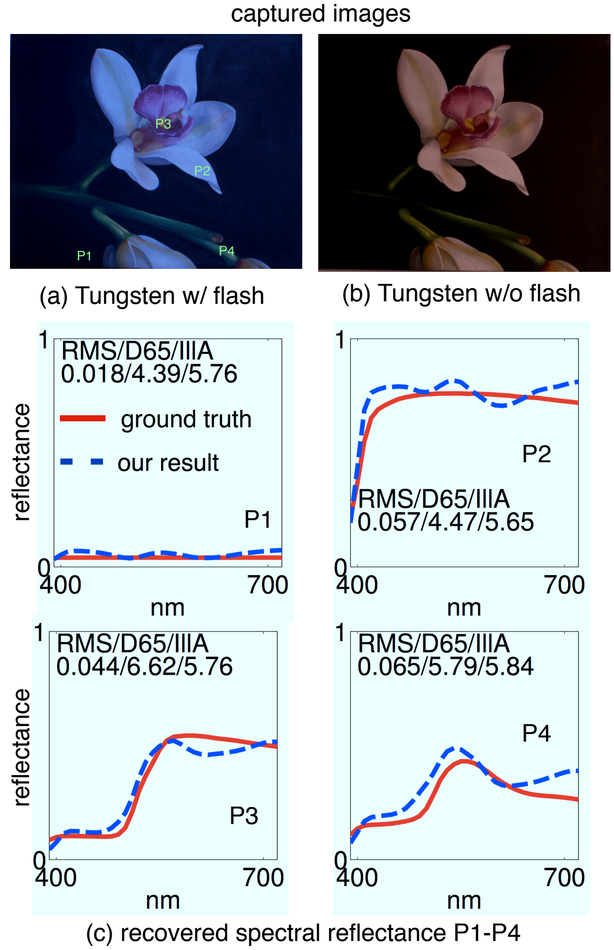

Figure 2. The spectral recovery of Orchid. (a) and (b) The captured pictures under the tungsten light w/ and w/o the camera flash (c) The recovered reflectance at selected areas on the painting.

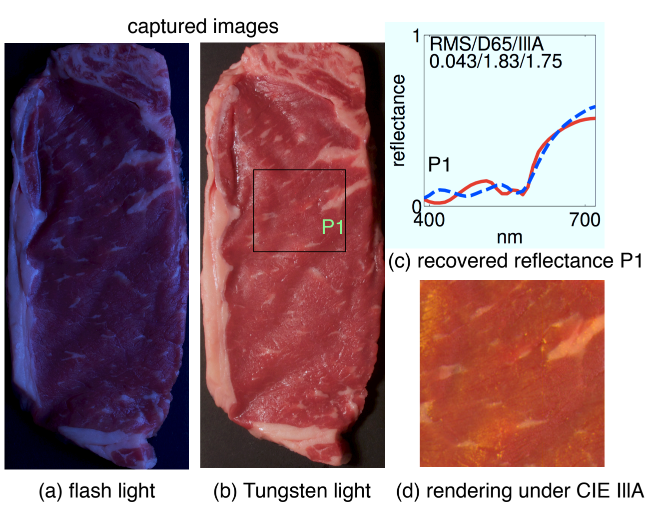

Figure 3. The spectral recovery of beef. (a) and (b) The captured pictures under the studio flash light and the tungsten light (c) The recovered reflectance at selected area (P1) on the beef. (d) The rendering of a portion of the beef (within the black rectangle) under CIE IllA

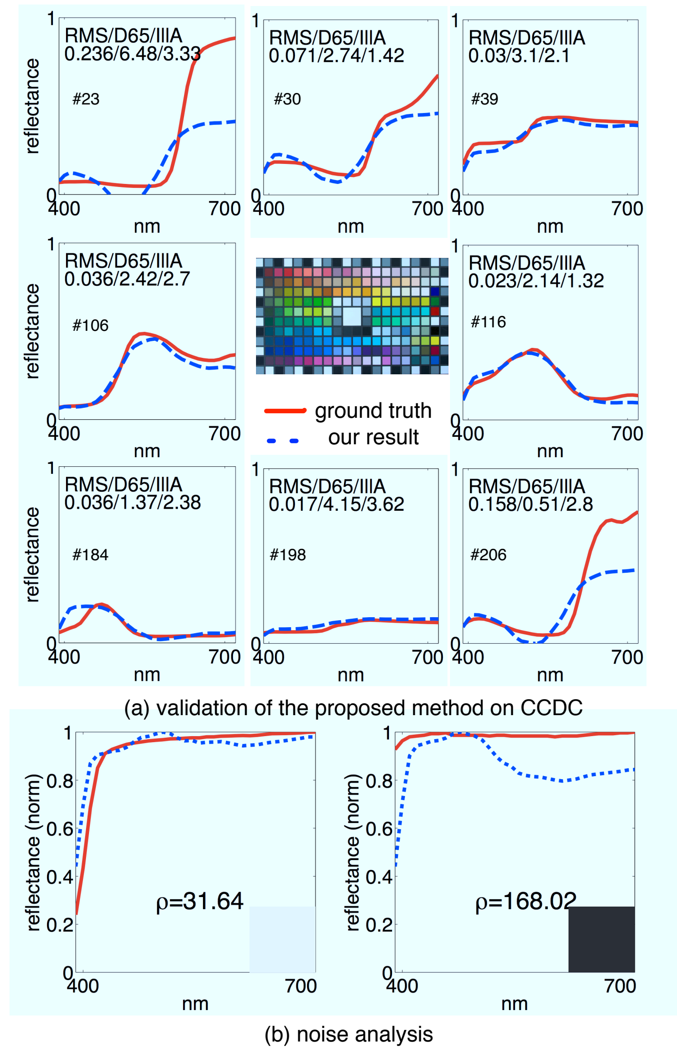

Figure 4. The validation of CCDC®using the camera phone, Nokia N900®, under the tungsten light only. (a) The estimated and measured reflectance of certain patches in CCDC®. The numbers on the top of each plot are the spectral RMS error, and color difference under CIE D65 and IllA. The patch index (#) is shown as well. A close spectral and colorimetric match could be achieved generally between the ground truth and our results except for patches of reddish colors. (b) Noise analysis was performed by calculating ρ to tell which reflectance is likely to be predicted better under the tungsten light. Two patches were selected with small and large ρ. A smaller ρ means a better spectral match.