

Spectral Reflectance Estimation Using Projector with Unknown Spectral Power Distribution

Hironori Hidaka, Yusuke Monno, Masatoshi Okutomi

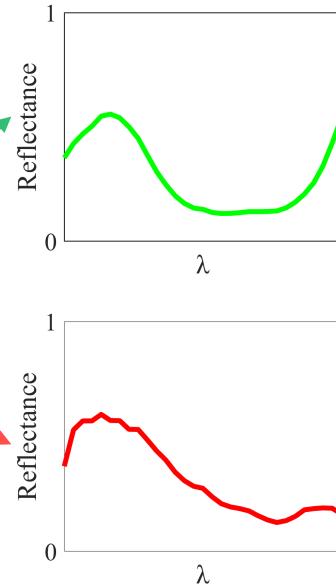
Tokyo Institute of Technology

18 November, 2020

CIC 2020

Introduction

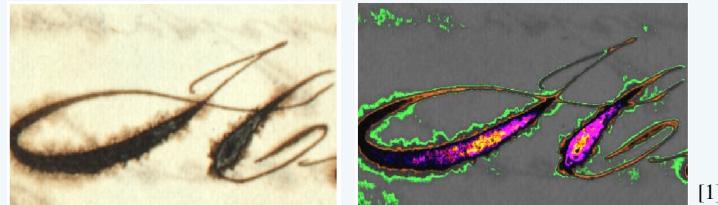
Spectral Reflectance



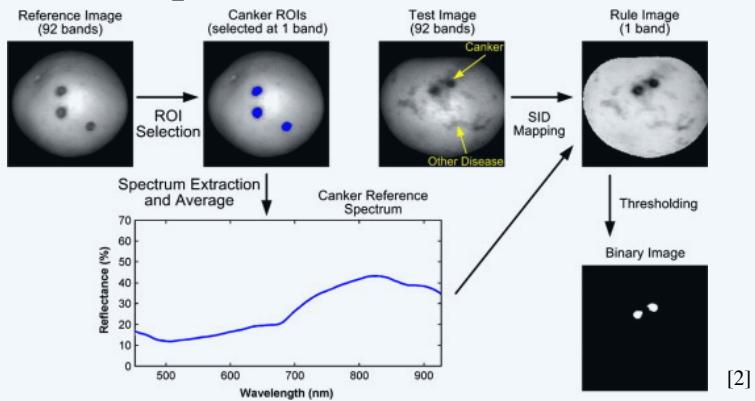
Reflectance in wavelength domain

Application

- Historical works analysis



- Food inspection



[1]. H. Liang, "Advances in multispectral and hyperspectral imaging for archaeology and art conservation," *Applied Physics A*, vol. 106, no. 2, pp. 309–323, 2012.

[2]. J. Qin, K. Chao, M. S. Kim, R. Lu, and T. F. Burks, "Hyperspectral and multispectral imaging for evaluating food safety and quality," *Journal of Food Engineering*, vol. 118, no. 2, pp. 157–171, 2013.

Related Works (Active Lighting Method)

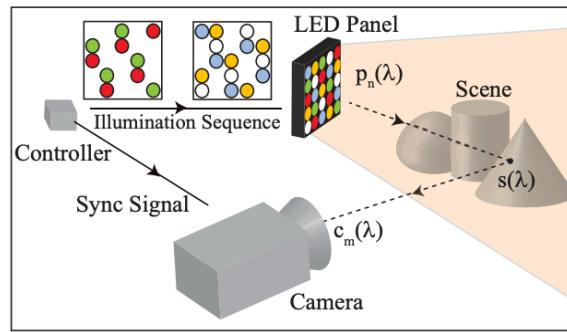
Lighting System

Light source with variable spectrum

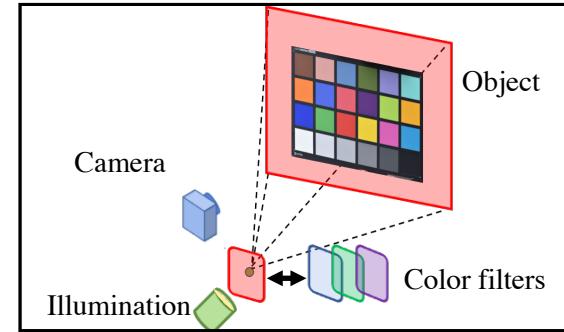
+

Consumer RGB camera

- LED cluster system



- Illumination and color filter



[5]

[6]

[5]. J. Park, M. Lee, M. D. Grossberg, and S. K. Nayar, "Multispectral imaging using multiplexed illumination," Proc. of IEEE Int. Conf. on Computer Vision (ICCV), pp. 1–8, 2007.

[6]. C. Cui, H. Yoo, and M. Ben-Ezra, "Multi-spectral imaging by optimized wide band illumination," Int. Journal of Computer Vision, vol. 86, pp. 140–151, 2010.

Related Works (Active Lighting Method)

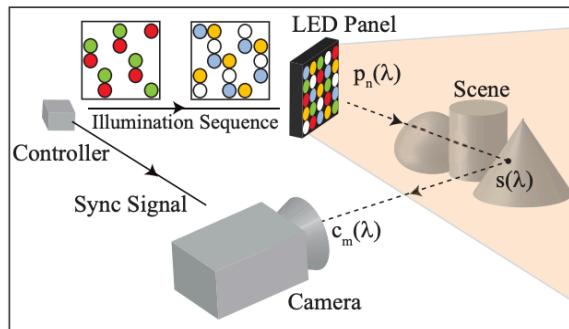
Lighting System

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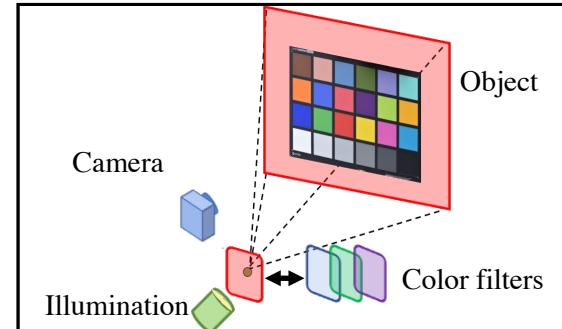


Consumer RGB camera

- LED cluster system

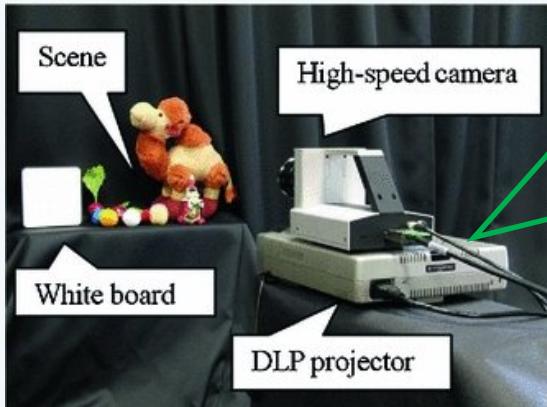


- Illumination and color filter



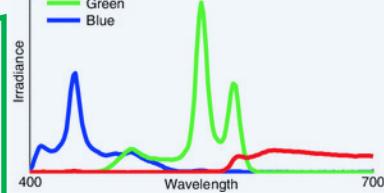
[6]

Projector-Camera System



[7]

Projector SPD



- Projector-Camera setup has better trade-off regarding accuracy and cost
- This setup can be used to acquire the 3D model of an object. [8]
- △ Spectral power distribution(SPD) is assumed to be known.

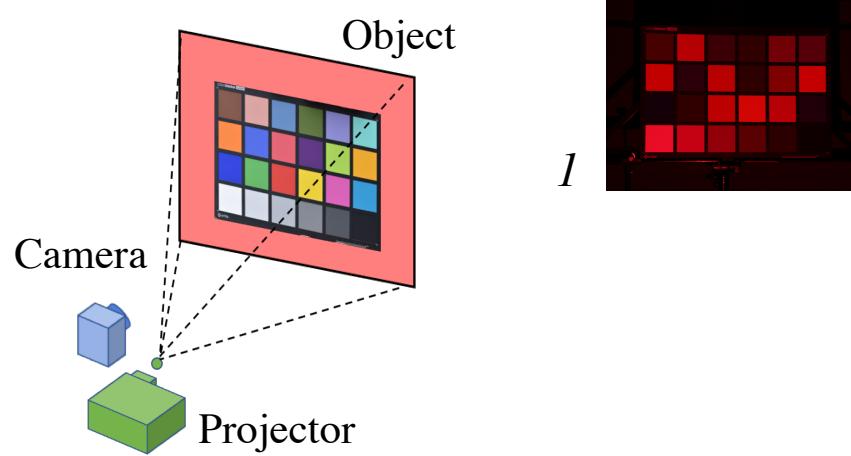
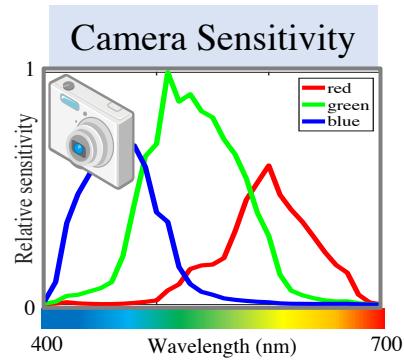
[7]. S. Han, I. Sato, T. Okabe, and Y. Sato, "Fast spectral reflectance recovery using DLP projector," Int. Journal of Computer Vision, vol. 110, no. 2, pp. 172–184, 2014.

[8]. C. Li, Y. Monno, H. Hidaka, and M. Okutomi, "Pro-Cam SSfM: Projector-camera system for structure and spectral reflectance from motion," Proc. of IEEE Int. Conf. on Computer Vision (ICCV)

Our Target

Image Acquisition

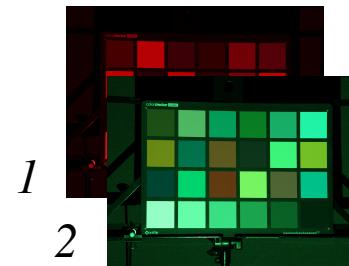
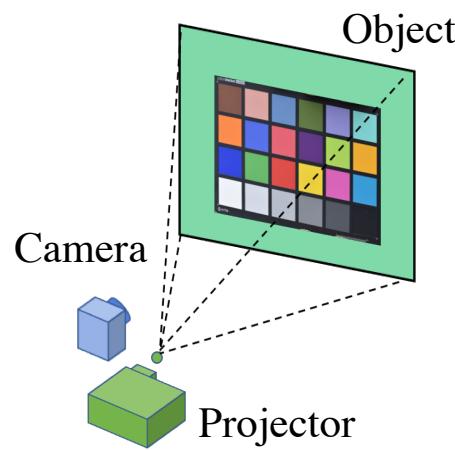
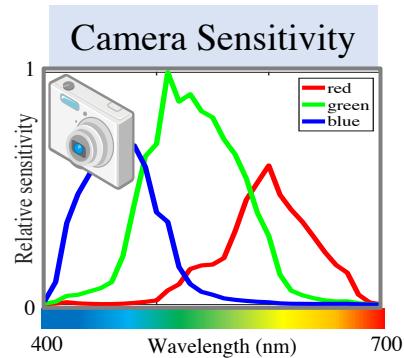
known



Our Target

Image Acquisition

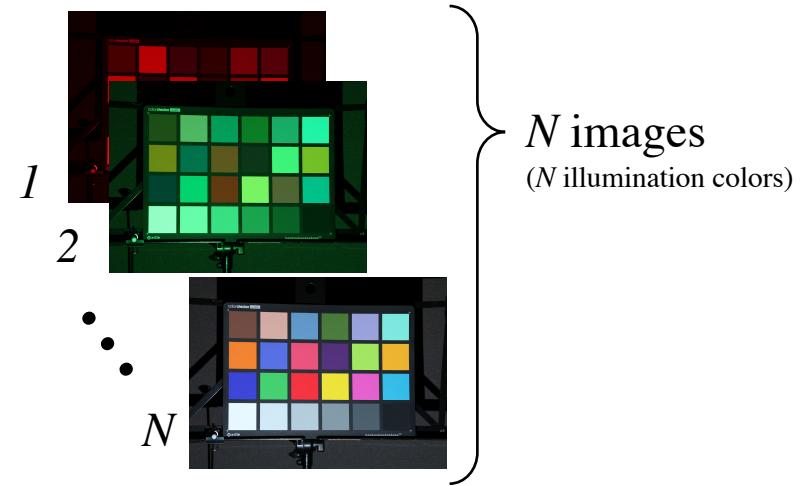
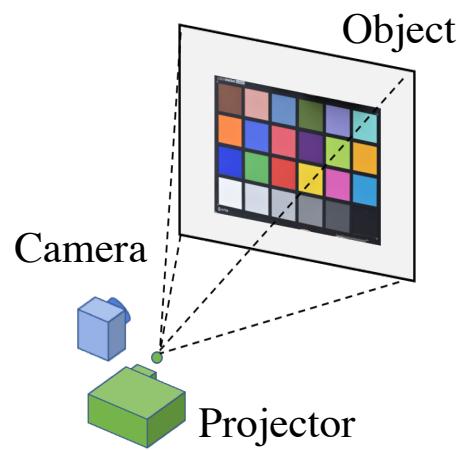
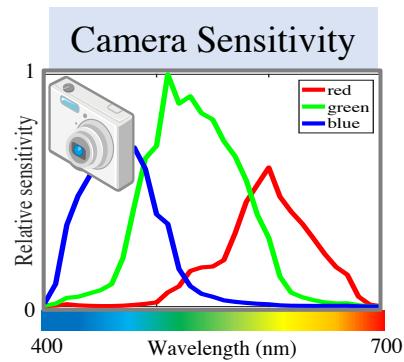
known



Our Target

Image Acquisition

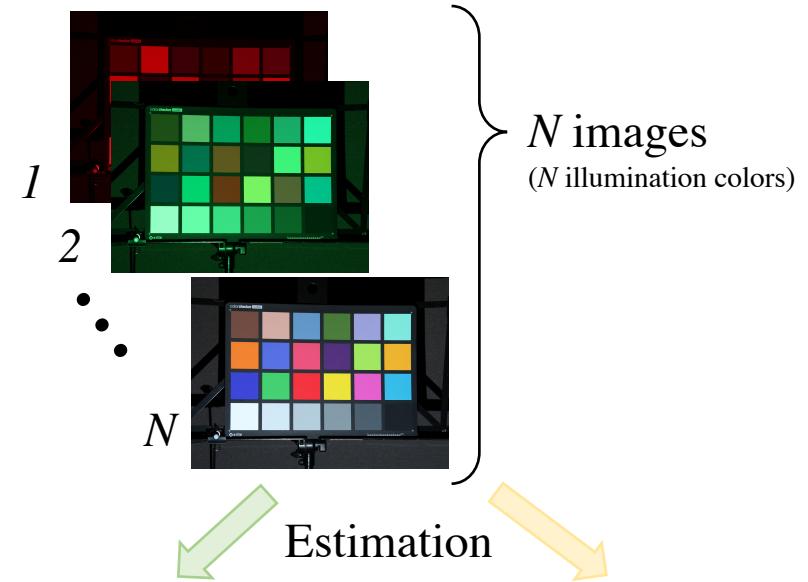
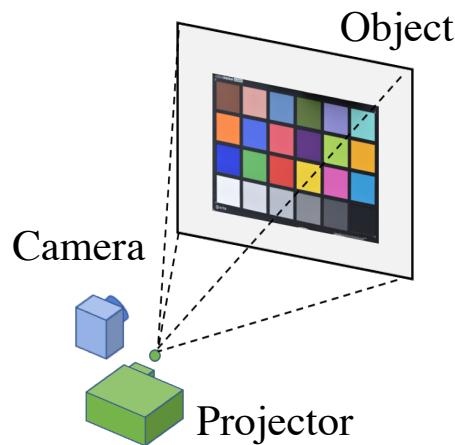
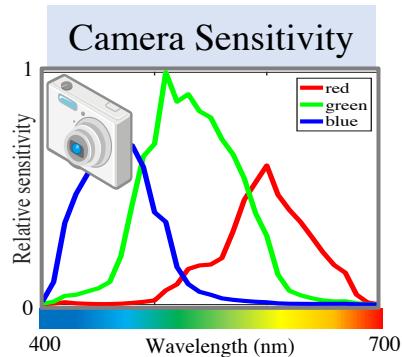
known



Our Target

Image Acquisition

known



Our Work

- Joint estimation of spectral reflectance and spectral power distribution(SPD)
- Make projector illumination basis for SPD estimation.

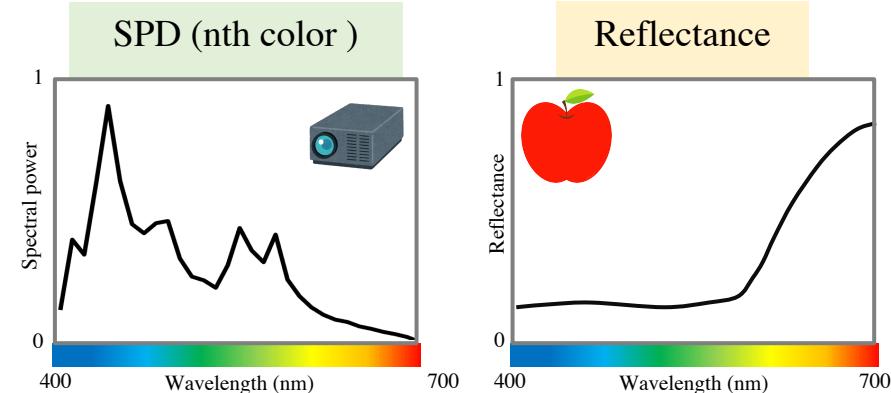
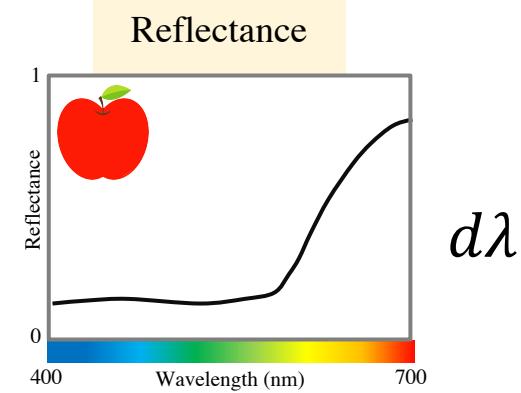
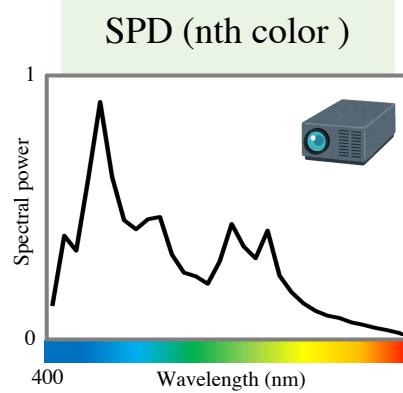
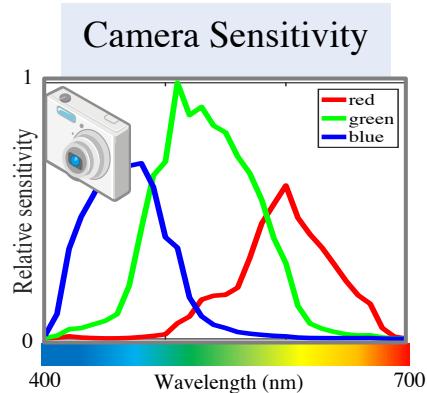


Image Formulation Model

Imaging Model

$$I_n = \int_{\Omega} c(\lambda) s_n(\lambda) r(\lambda) d\lambda \quad (\Omega = [400\text{nm}, 700\text{nm}])$$

$$\text{Image} = \int (I_n^r, I_n^g, I_n^b)$$



$c(\lambda)$

$s_n(\lambda)$

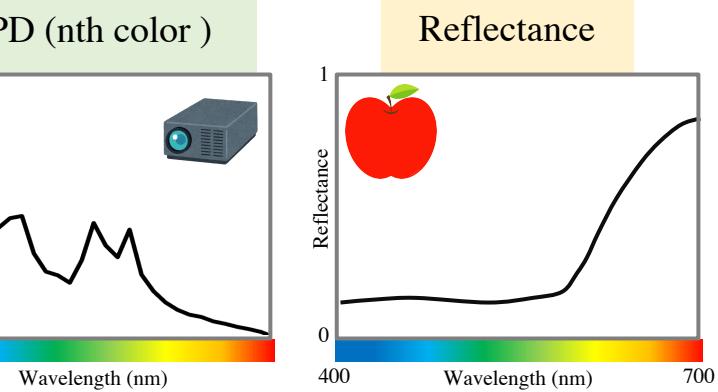
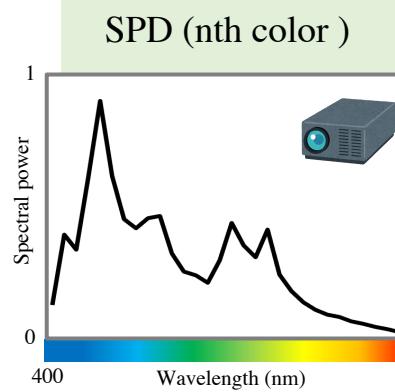
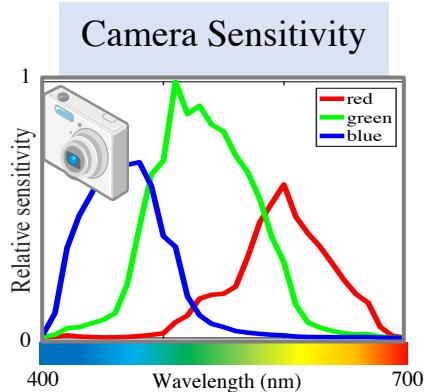
$r(\lambda)$

Image Formulation Model

Imaging Model

$$I_n = \mathbf{c}^T \text{diag}(\mathbf{s}_n) \mathbf{r} \quad ([400\text{nm}, 700\text{nm}] \text{ in } 10\text{nm})$$

$$\begin{matrix} \text{Image} \\ \boxed{\text{apple}} \end{matrix} = \sum \lambda \begin{pmatrix} I_n^r, I_n^g, I_n^b \end{pmatrix}$$



\mathbf{c}

\mathbf{s}_n

\mathbf{r}

Spectral Reflectance Model

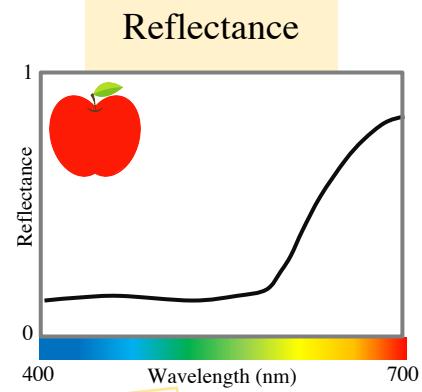
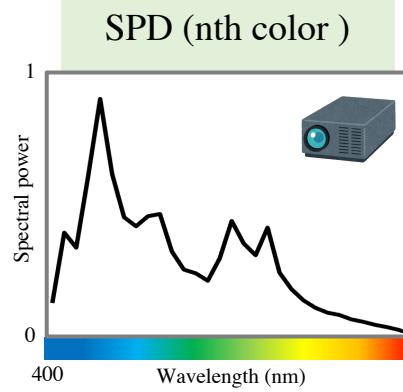
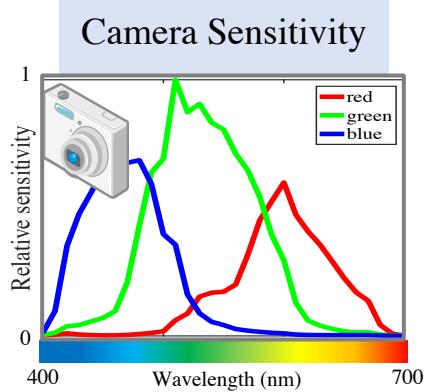
Imaging Model

$$I_n = \mathbf{c}^T \text{ diag}(\mathbf{s}_n) \mathbf{r} \quad ([400\text{nm}, 700\text{nm}] \text{ in } 10\text{nm})$$

Image

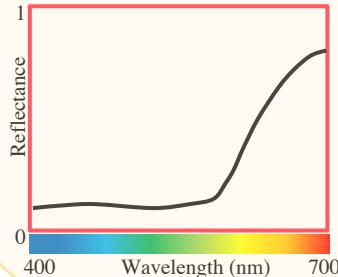


$$(I_n^r, I_n^g, I_n^b) = \sum_{\lambda}$$



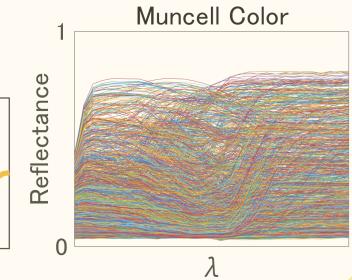
Spectral reflectance $r(\lambda)$

$$r(\lambda) = \sum_k^{N_r(=6)} \alpha_i b_i^{\text{ref}}(\lambda) = \mathbf{B}^{\text{ref}} \boxed{\boldsymbol{\alpha}}$$



$$= \alpha_1 b_1^{\text{ref}}(\lambda) + \alpha_2 b_2^{\text{ref}}(\lambda) + \dots + \alpha_{N^r} b_{N^r}^{\text{ref}}(\lambda)$$

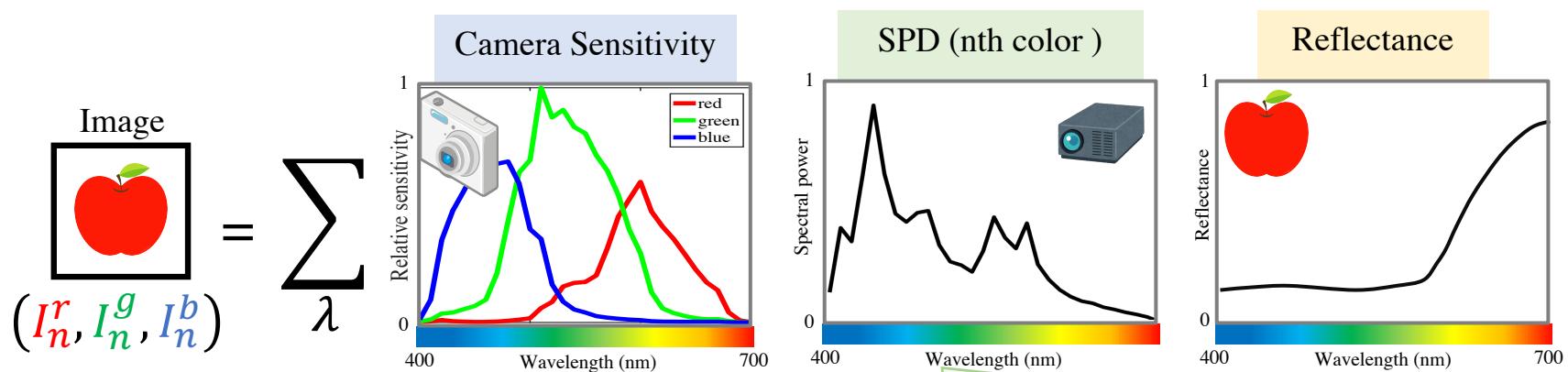
\mathbf{B}^{ref} : Ref Basis Matrix
($N_{\lambda} \times N_r$)



Projector SPD Model

Imaging Model

$$I_n = \mathbf{c}^T \text{ diag}(\mathbf{s}_n) \mathbf{r} \quad ([400\text{nm}, 700\text{nm}] \text{ in } 10\text{nm})$$



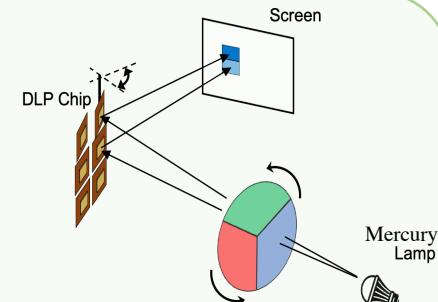
Spectral power distribution(SPD) $s_n(\lambda)$

$$s_n(\lambda) = \gamma_{r,n}s_r(\lambda) + \gamma_{g,n}s_g(\lambda) + \gamma_{b,n}s_b(\lambda)$$

Primary RGB color is described in low dimensional model

$$\mathbf{s}_r = \mathbf{B}_r^{ill} \beta_r, \quad \mathbf{s}_g = \mathbf{B}_g^{ill} \beta_g, \quad \mathbf{s}_b = \mathbf{B}_b^{ill} \beta_b$$

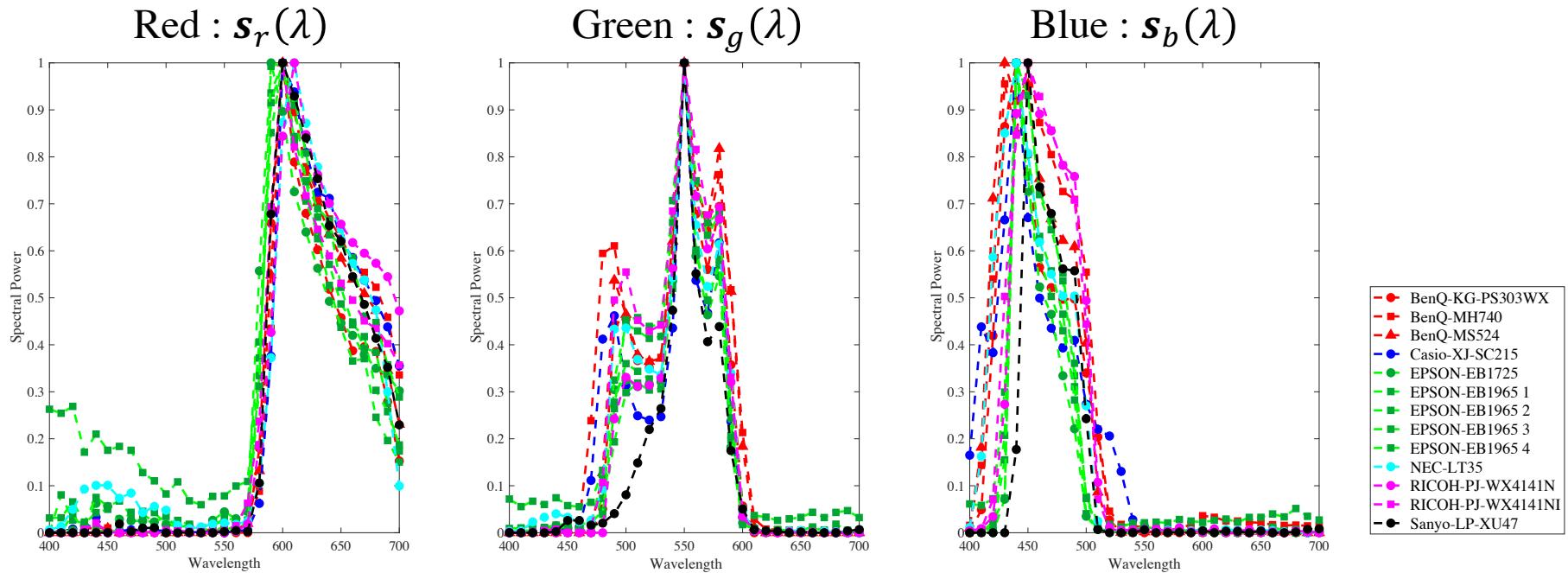
$\mathbf{B}_r^{ill}, \mathbf{B}_g^{ill}, \mathbf{B}_b^{ill}$: Ill Basis Matrix
 $(N_\lambda \times N_s)$



Projector SPD Dataset

Collect RGB projector spectral dataset for RGB primary basis function.

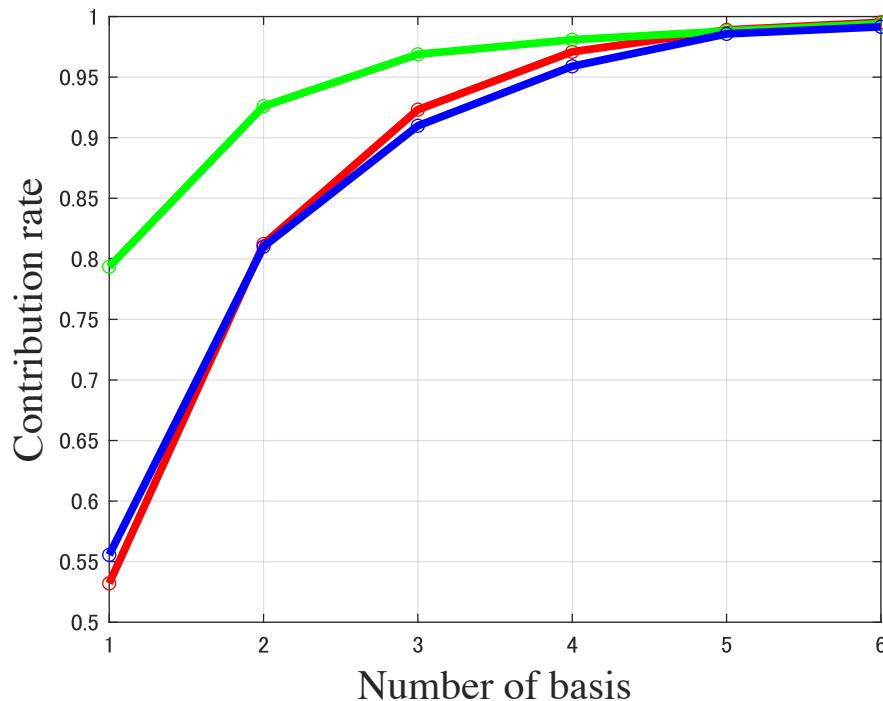
- This dataset is made from only mercury lamp projector



Projector SPD Basis

RGB spectra basis are made from projector spectral dataset

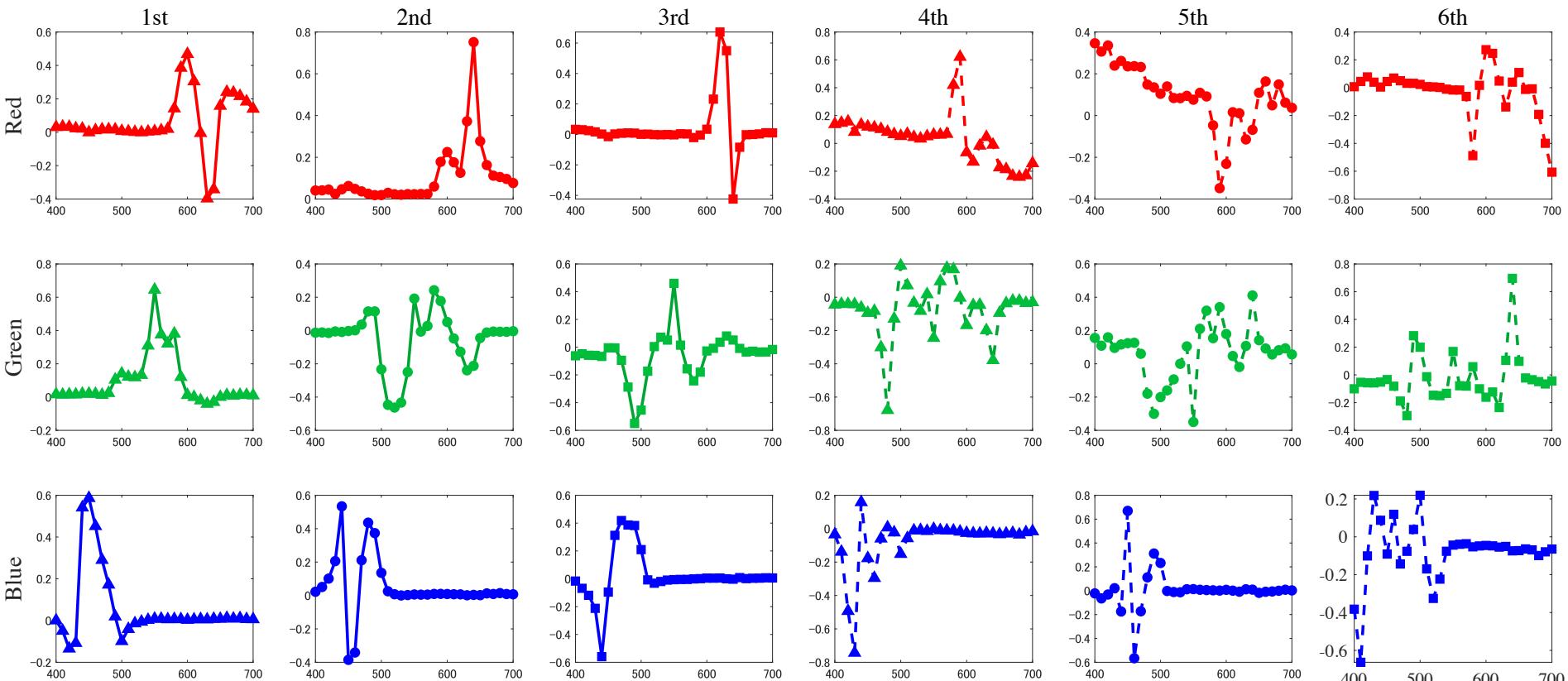
- From contribution rate, we choose the number of basis of each primary color is 6



Projector SPD Basis

RGB spectra basis are made from projector spectral dataset

- From contribution rate, we choose the number of basis of each primary color is 6



Spectral Reconstruction

Cost Function

$$E(\alpha, \beta) = \frac{1}{NP} \sum_m \sum_n \sum_p (I_{m,n,p} - \frac{\mathbf{c}_m^T \text{diag}(\mathbf{s}_n) \mathbf{r}_p}{\hat{I}_{m,n,p}})^2$$

Channel

Illumination

Pixel

Color rendering term

$$+ \frac{\sigma_1}{N} \sum_n \left\| \frac{\delta^2 \mathbf{s}_n}{\delta^2 \lambda} \right\|_2^2 + \frac{\sigma_2}{P} \sum_p \left\| \frac{\delta^2 \mathbf{r}_n}{\delta^2 \lambda} \right\|_2^2$$

Spectral smoothness term

\mathbf{s}_n : SPD of n-th illumination color

\mathbf{r}_p : Spectral reflectance of p-th pixel

\mathbf{c}_m : Camera sensitivity of m-th channel

N : The number of illumination colors

P : The number of pixels

Spectral Reconstruction

Cost Function

$$E(\alpha, \beta) = \frac{1}{NP} \sum_m \sum_n \sum_p (I_{m,n,p} - \alpha_p^T \mathbf{B}^{ref T} \text{diag}(\mathbf{c}_m^T) \mathbf{B}^{ill} \Gamma(\gamma_n) \beta)^2$$

$\mathbf{W}_{m,n}$

Channel m
Illumination n
Pixel p

$$+ \frac{\sigma_1}{N} \sum_n \left\| \frac{\delta^2 \mathbf{B}^{ill}}{\delta^2 \lambda} \Gamma(\gamma_n) \beta \right\|_2^2 + \frac{\sigma_2}{P} \sum_p \left\| \frac{\delta^2 \mathbf{B}^{ref}}{\delta^2 \lambda} \alpha_p \right\|_2^2$$

Color rendering term

Spectral smoothness term

- | | |
|--|--|
| $\mathbf{B}^{ill} \Gamma(\gamma_n) \beta$ | s_n : SPD of n-th illumination color |
| $\mathbf{B}^{ref} \alpha_p$ | r_p : Spectral reflectance of p-th pixel |
| \mathbf{c}_m : Camera sensitivity of m-th channel | |
| N : The number of illumination colors | |
| P : The number of pixels | |
| $\Gamma(\gamma_n)$: Matrix encoding the gains for primary of n-th color | |

Spectral Reconstruction

Cost Function

$$E(\alpha, \beta) = \frac{1}{NP} \sum_m \sum_n \sum_p (I_{m,n,p} - \alpha_p^T \mathbf{W}_{m,n} \beta)^2 \quad \text{color rendering term}$$

Channel m
Illumination n
Pixel p

$$+ \frac{\sigma_1}{N} \sum_n \left\| \frac{\delta^2 \mathbf{B}^{ill}}{\delta^2 \lambda} \Gamma(\gamma_n) \beta \right\|_2^2 + \frac{\sigma_2}{P} \sum_p \left\| \frac{\delta^2 \mathbf{B}^{ref}}{\delta^2 \lambda} \alpha_p \right\|_2^2 \quad \text{Spectral smoothness term}$$

Constraints

- non-zero constrain of illumination

$$\mathbf{B}_r^{ill} \beta_r \geq \mathbf{0}, \mathbf{B}_g^{ill} \beta_g \geq \mathbf{0}, \mathbf{B}_b^{ill} \beta_b \geq \mathbf{0}$$

- non-zero constrain of reflectance

$$\mathbf{B}^{ref} \alpha_k \geq \mathbf{0}$$

- Remove the ambiguity of reflectance and illumination

$$\mathbf{B}^{ill} \Gamma(\gamma_n) \beta(\lambda_f) = 1$$

Alternate Spectral Estimation

Cost Function

$$E(\alpha, \beta) = \frac{1}{NP} \sum_m \sum_n \sum_p (I_{m,n,p} - \alpha_p^T \mathbf{W}_{m,n} \beta)^2$$

color rendering term

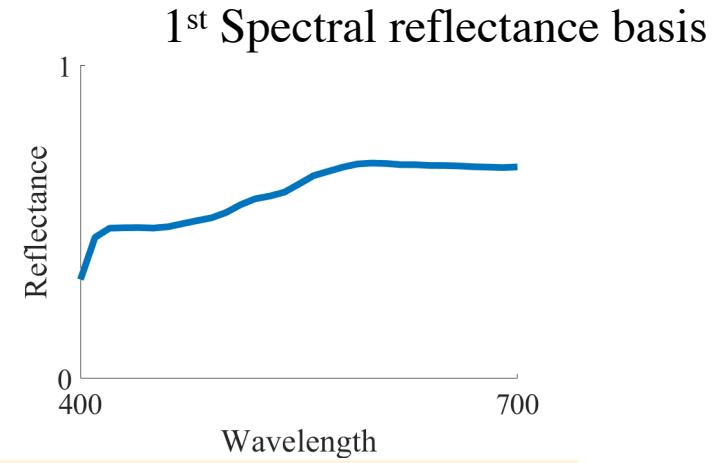
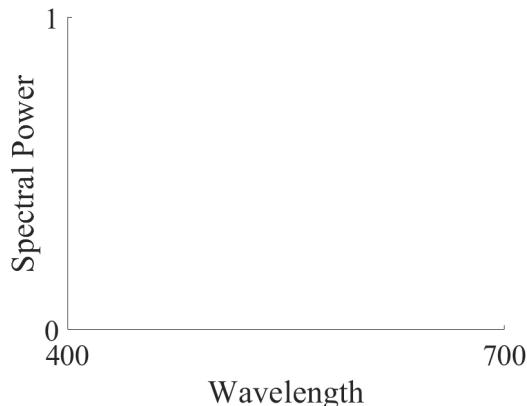
Spectral smoothness term

Channel
Illumination
Pixel

$$+ \frac{\sigma_1}{N} \sum_n \left\| \frac{\delta^2 \mathbf{B}^{ill}}{\delta^2 \lambda} \Gamma(\gamma_n) \beta \right\|_2^2 + \frac{\sigma_2}{P} \sum_p \left\| \frac{\delta^2 \mathbf{B}^{ref}}{\delta^2 \lambda} \alpha_p \right\|_2^2$$

Solution

α_p (Reflectance) and β (illumination SPDs) are alternately derived



Alternate Spectral Estimation

Cost Function

$$E(\alpha, \beta) = \frac{1}{NP} \sum_m \sum_n \sum_p (I_{m,n,p} - \alpha_p^T \mathbf{W}_{m,n} \beta)^2$$

color rendering term

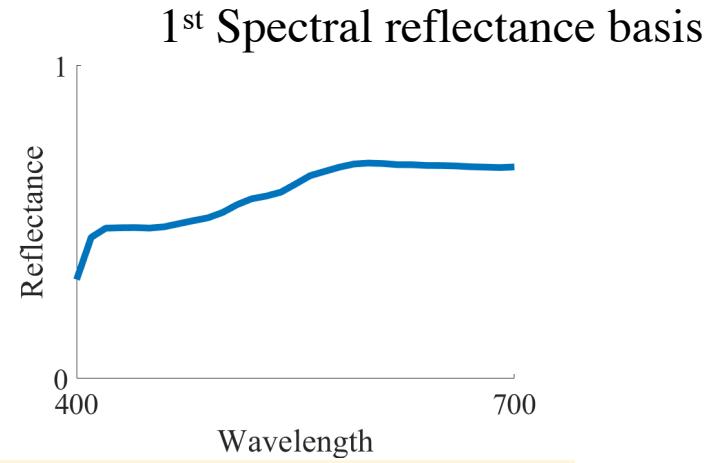
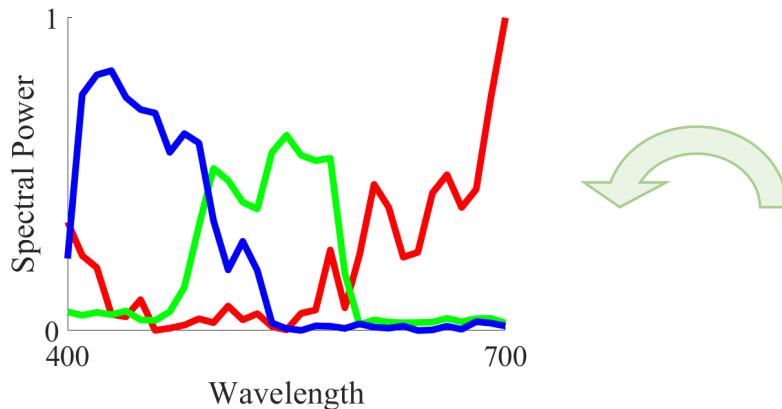
Spectral smoothness term

Channel
Illumination
Pixel

$$+ \frac{\sigma_1}{N} \sum_n \left\| \frac{\delta^2 \mathbf{B}^{ill}}{\delta^2 \lambda} \Gamma(\gamma_n) \beta \right\|_2^2 + \frac{\sigma_2}{P} \sum_p \left\| \frac{\delta^2 \mathbf{B}^{ref}}{\delta^2 \lambda} \alpha_p \right\|_2^2$$

Solution

α_p (Reflectance) and β (illumination SPDs) are alternately derived



Alternate Spectral Estimation

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$$E(\alpha, \beta) = \frac{1}{NP} \sum_m \sum_n \sum_p (I_{m,n,p} - \alpha_p^T \mathbf{w}_{m,n} \beta)^2$$

color rendering term

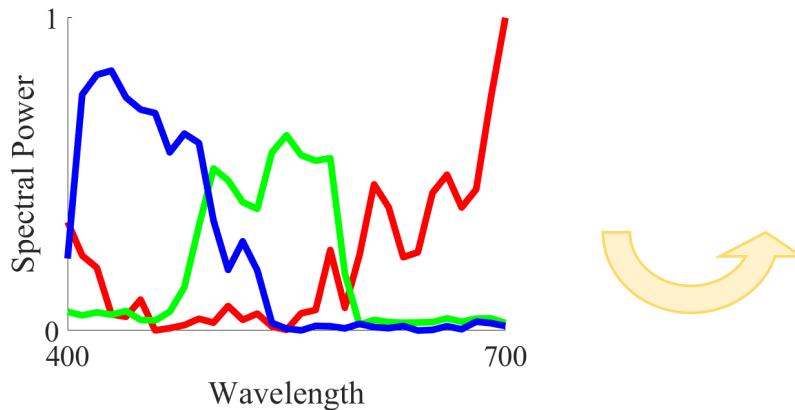
Spectral smoothness term

Channel
Illumination
Pixel

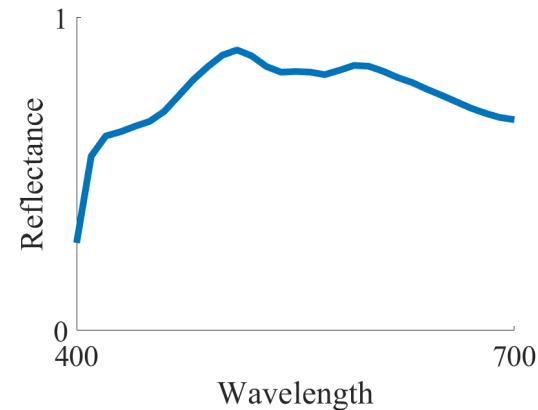
$$+ \frac{\sigma_1}{N} \sum_n \left\| \frac{\delta^2 \mathbf{B}^{ill}}{\delta^2 \lambda} \Gamma(\gamma_n) \beta \right\|_2^2 + \frac{\sigma_2}{P} \sum_p \left\| \frac{\delta^2 \mathbf{B}^{ref}}{\delta^2 \lambda} \alpha_p \right\|_2^2$$

Solution

α_p (Reflectance) and β (illumination SPDs) are alternately derived



SPD (projector primary RGB)



Spectral reflectance (point p)

Alternate Spectral Estimation

Cost Function

$$E(\alpha, \beta) = \frac{1}{NP} \sum_m \sum_n \sum_p (I_{m,n,p} - \alpha_p^T \mathbf{w}_{m,n} \beta)^2$$

color rendering term

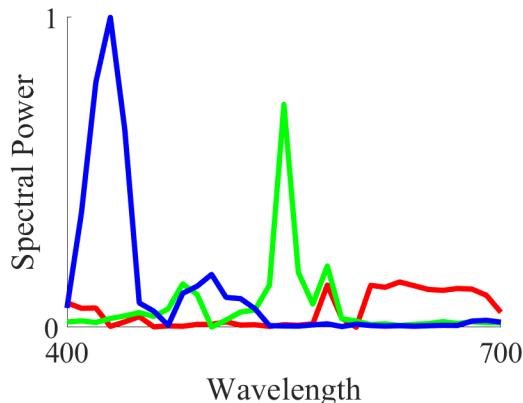
Spectral smoothness term

Channel
Illumination
Pixel

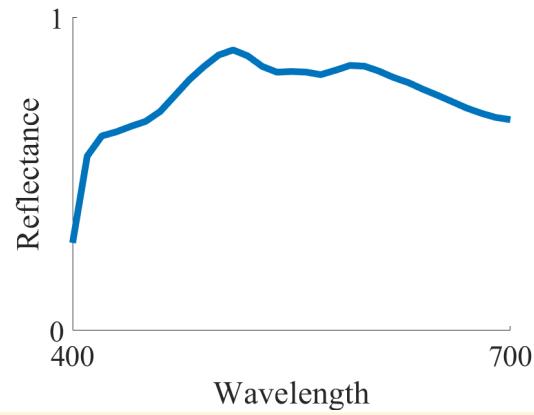
$$+ \frac{\sigma_1}{N} \sum_n \left\| \frac{\delta^2 \mathbf{B}^{ill}}{\delta^2 \lambda} \Gamma(\gamma_n) \beta \right\|_2^2 + \frac{\sigma_2}{P} \sum_p \left\| \frac{\delta^2 \mathbf{B}^{ref}}{\delta^2 \lambda} \alpha_p \right\|_2^2$$

Solution

α_p (Reflectance) and β (illumination SPDs) are alternately derived



SPD (projector primary RGB)



Spectral reflectance (point p)

Alternate Spectral Estimation

Cost Function

$$E(\alpha, \beta) = \frac{1}{NP} \sum_m \sum_n \sum_p (I_{m,n,p} - \alpha_p^T \mathbf{W}_{m,n} \beta)^2$$

color rendering term

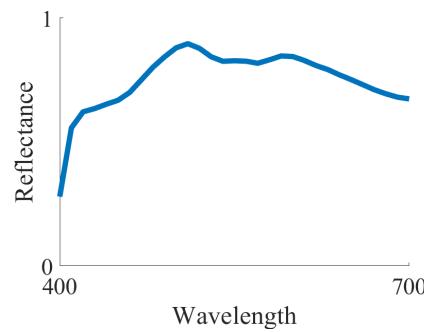
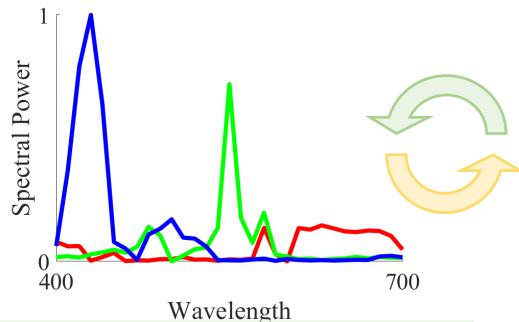
Spectral smoothness term

Channel
Illumination
Pixel

$$+ \frac{\sigma_1}{N} \sum_n \left\| \frac{\delta^2 \mathbf{B}^{ill}}{\delta^2 \lambda} \Gamma(\gamma_n) \beta \right\|_2^2 + \frac{\sigma_2}{P} \sum_p \left\| \frac{\delta^2 \mathbf{B}^{ref}}{\delta^2 \lambda} \alpha_p \right\|_2^2$$

Solution

Repeat alternate estimation until the cost converges.



Convergence Judgement

$$E(\alpha^{k+1}, \beta^{k+1}) - E(\alpha^k, \beta^k) < \sigma$$

k : iteration time
 σ : threshold

Experiments

Setup

- **Camera**

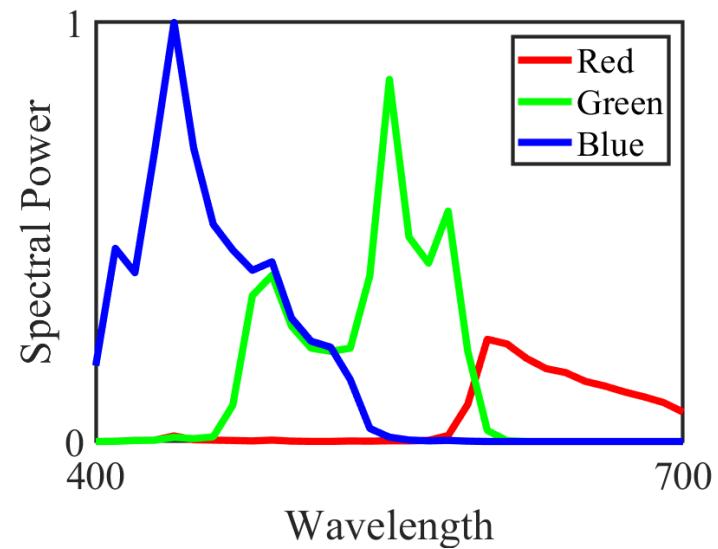
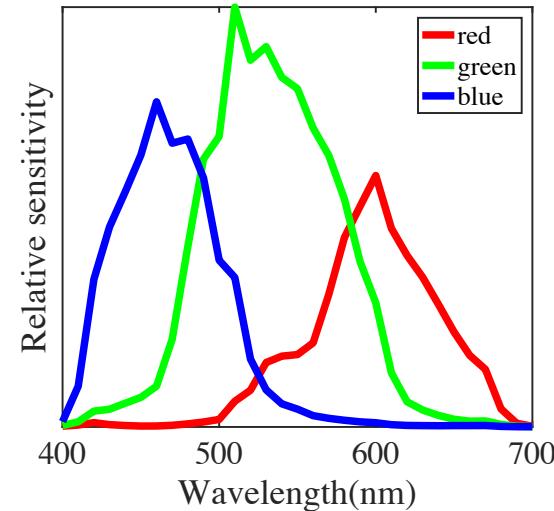
Canon 5D Mark II

(camera sensitivity is already
known from other paper)

- **Projector**

Casio XJ-SC21

Mercury lamp DLP projector



Experiments

Target Object

- Macbeth Color Chart 18 chromatic patches (Real Image)
- Capture 7 images under Red, Green, Blue, Cyan, Magenta, Yellow, and White light

Input Images

Red



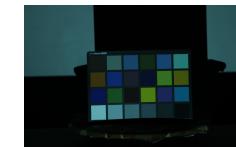
Green



Blue



Cyan



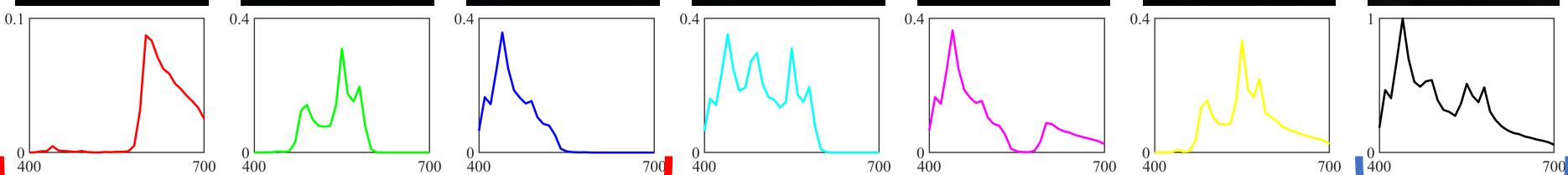
Magenta



Yellow



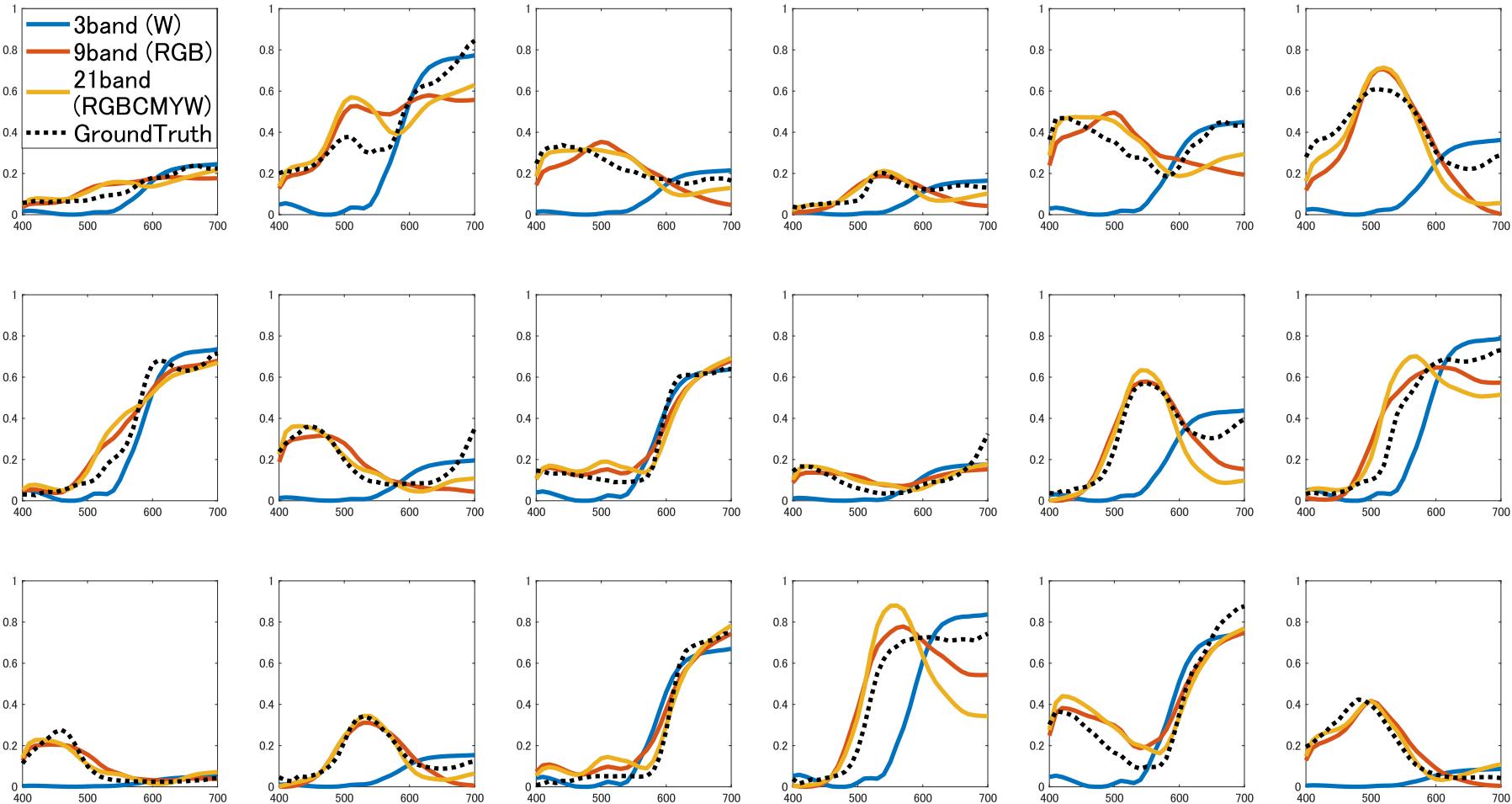
White



21band

Spectral Reflectance Result

Spectral Reflectance



Spectral Reflectance Result

Spectral Reflectance RMSE Table

Table 1: RMSE result for each patch of the colorchart

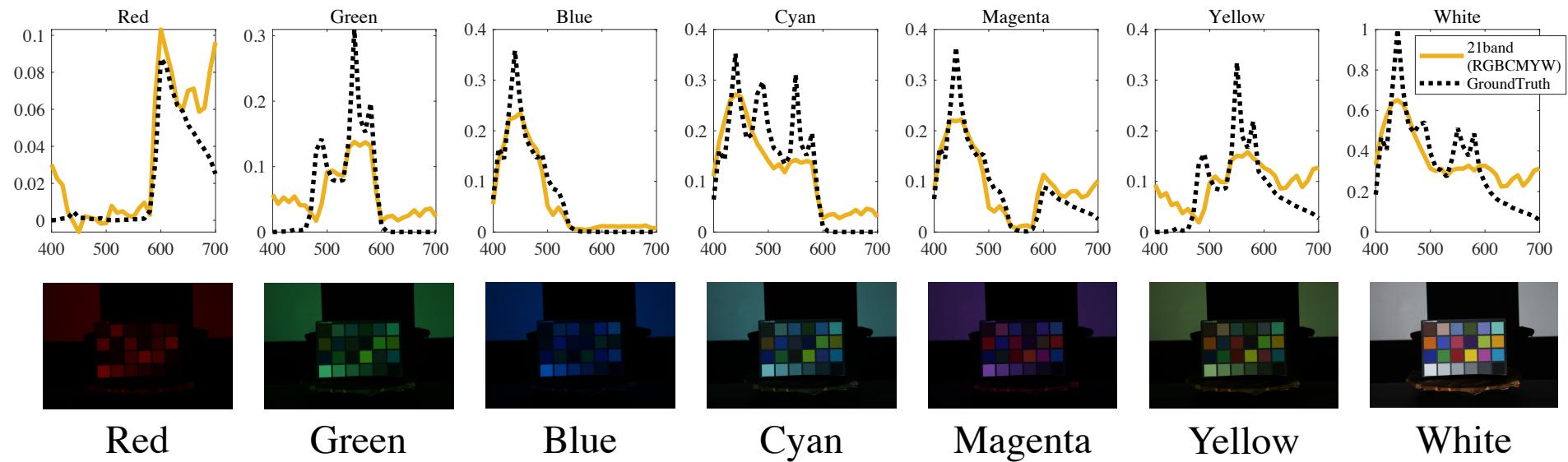
Patch	1	2	3	4	5	6	7	8	9	10
3band	0.046	0.074	0.122	0.185	0.186	0.149	0.203	0.076	0.087	0.077
9band	0.036	0.064	0.033	0.133	0.089	0.046	0.081	0.051	0.069	0.047
21band	0.035	0.083	0.031	0.131	0.066	0.036	0.045	0.063	0.058	0.037

Patch	11	12	13	14	15	16	17	18	Average
3band	0.083	0.225	0.261	0.232	0.181	0.366	0.142	0.227	0.1620
9band	0.050	0.115	0.135	0.089	0.091	0.131	0.105	0.052	0.0787
21band	0.041	0.210	0.102	0.132	0.086	0.116	0.143	0.036	0.0785

- RMSE for each patch is almost the same whether you use 3 or 7 images.
We think it is because each case projected the linear combination of primary colors and the amount of input information is not changed.

SPD Result

Spectral power distribution (SPD)



Conclusion

- We create a dataset of the spectral power distribution (SPD) of the projector and make a model for projector SPDs by basis functions
- It was shown that even if the spectral power distribution (SPD) of the projector is unknown, it is possible to estimate the spectral reflectance and SPD at the same time to some extent.