Reconstruction of Light Spectra from Multispectral Images

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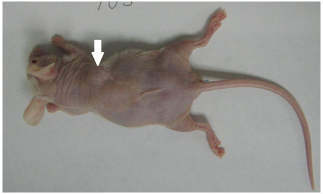
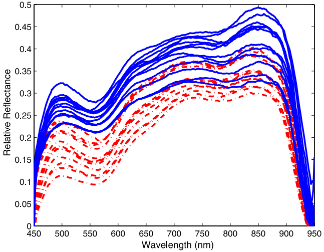
Motivation

Shaw et al. "Hyperspectral imaging and quantitative analysis for prostate cancer detection"





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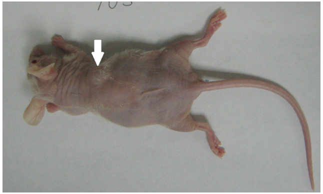
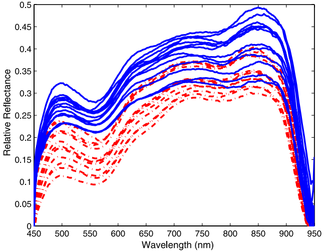
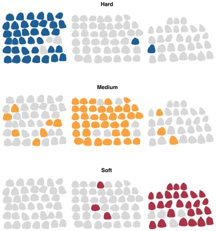
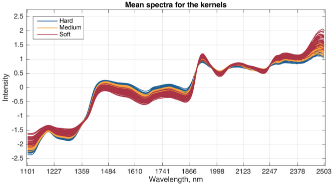
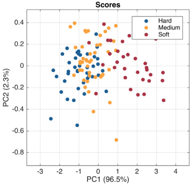








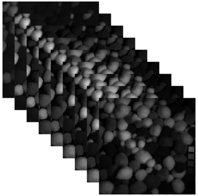


Williams et al. "Classification of maize kernels using NIR hyperspectral imaging"

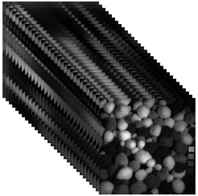
Problem Statement

Imaging

Multispectral images

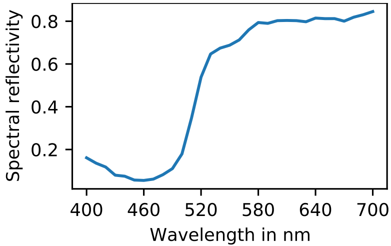


Reconstruction

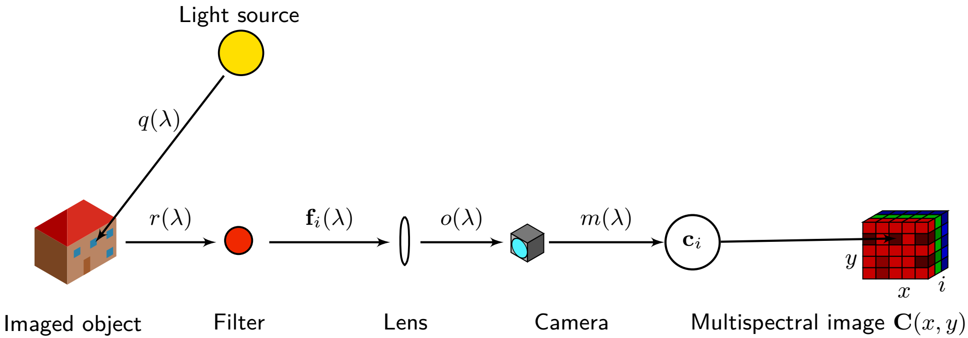


Hyperspectral images

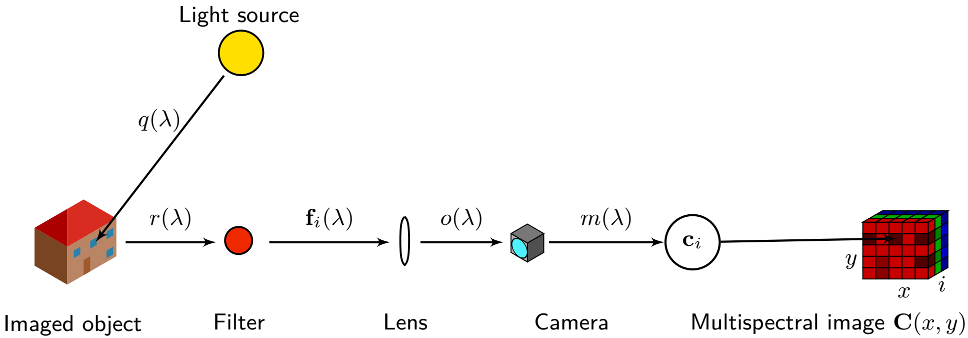
Pixel (250, 325)



Pipeline


Light source
$q(\lambda)$
$r(\lambda)$
$\mathbf{f}_i(\lambda)$
$o(\lambda)$
$m(\lambda)$
$\mathbf{c}_i$
y
x
i
Imaged object
Filter
Lens
Camera
Multispectral image $\mathbf{C}(x, y)$

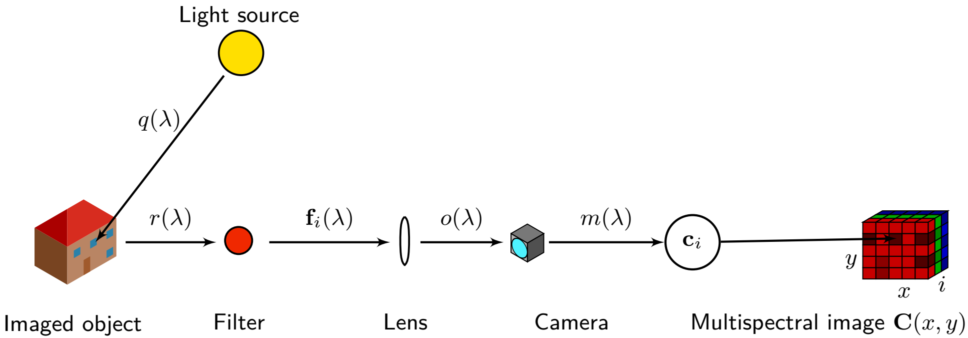
Pipeline



Imaging pipeline

$$\mathbf{c}_i = \int_{\lambda_{\text{min}}}^{\lambda_{\text{max}}} q(\lambda) r(\lambda) \mathbf{f}_i(\lambda) o(\lambda) m(\lambda) \, \mathrm{d}\lambda$$

Pipeline



Imaging pipeline

$$\mathbf{c}_i = \int_{\lambda_{\text{min}}}^{\lambda_{\text{max}}} q(\lambda) r(\lambda) \mathbf{f}_i(\lambda) o(\lambda) m(\lambda) \, \mathrm{d}\lambda$$

- Often light source, **imaged object**, lens, and camera spectral transfer functions not known

Mathematical Formulation

- Reconstructable spectrum: $s(\lambda) = q(\lambda)r\,(\lambda)\,o(\lambda)m(\lambda)$

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- Discretization: $\mathbf{c}_i = \sum_{j=1}^{N} \mathbf{F}_{ij} \mathbf{s}_j$ or $\mathbf{c} = \mathbf{F}\mathbf{s}$
  - $\mathbf{c} \in \mathcal{R}^M$: Multispectral channels for one pixel
  - $\mathbf{F} \in \mathcal{R}^{M \times N}$: Sampled filter as matrix
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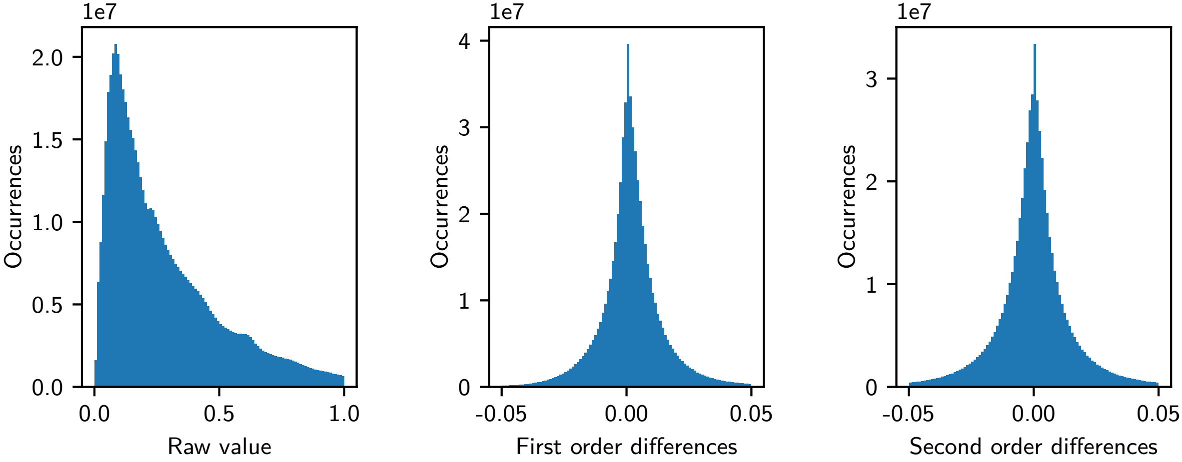
Underdetermined System

- Typically: $M << N$ $\rightarrow$ Underdetermined linear system of equations
- Prior knowledge must be embedded

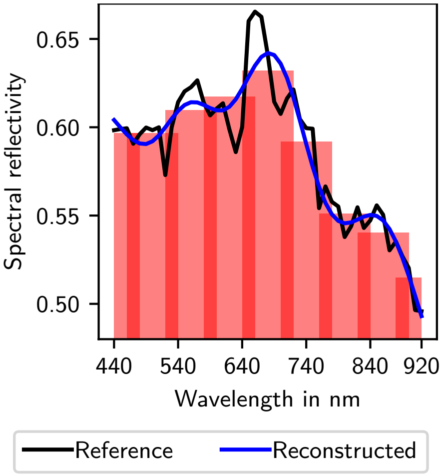
Spectra Statistics



Smoothed Pseudoinverse

- Optimization problem:

$$\hat{\mathbf{s}}^{\mathsf{SP}} = \underset{\mathbf{s}}{\operatorname{argmin}} \quad ||\mathbf{D}\mathbf{s}||_2^2$$
$$\text{s.t.} \qquad \mathbf{c} = \mathbf{F}\mathbf{s}$$



Pratt et al. "Spectral estimation techniques for the spectral calibration of a color image scanner"

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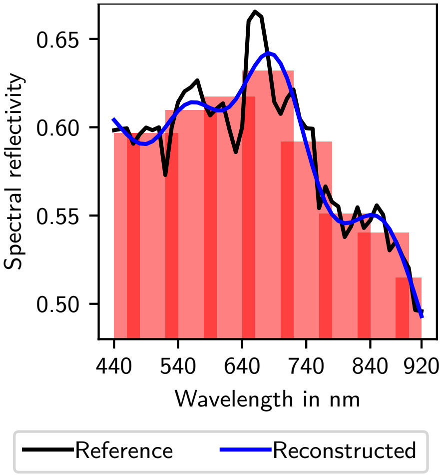
- First-order difference matrix:

$$\mathbf{D}_1 = \begin{pmatrix} 1 & -1 & 0 & \cdots & 0 \\ 0 & 1 & -1 & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & 1 & -1 \end{pmatrix}$$



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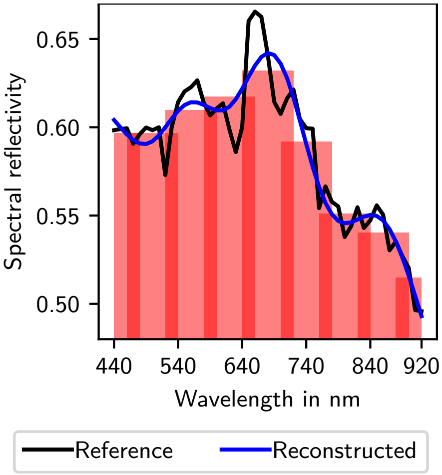
- Closed-form solution with $\mathbf{M} = \mathbf{D}^{\mathsf{T}}\mathbf{D} + \alpha\mathbf{I}$:

$$\hat{\mathbf{s}}^{\mathsf{SP}} = \mathbf{M}^{-1}\mathbf{F}^{\mathsf{T}}(\mathbf{F}\mathbf{M}^{-1}\mathbf{F}^{\mathsf{T}})^{-1}\mathbf{c}$$



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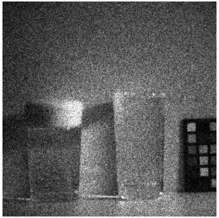
Noise

- Image noise often generated by low exposure time, e.g., video



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- Image noise often generated by low exposure time, e.g., video
- Most important noise sources:
  - Content-dependent shot noise (Poisson)
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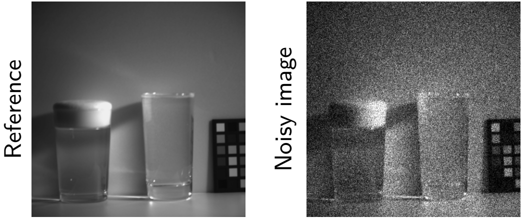

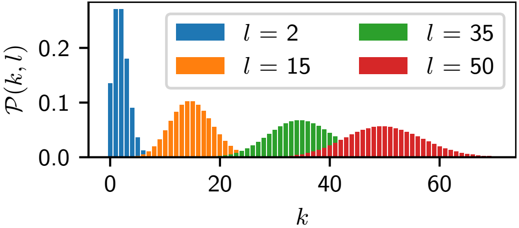

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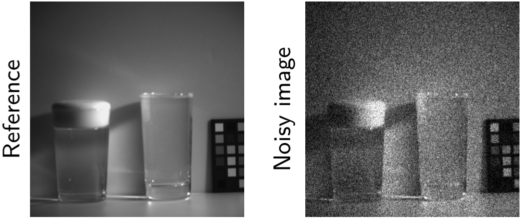

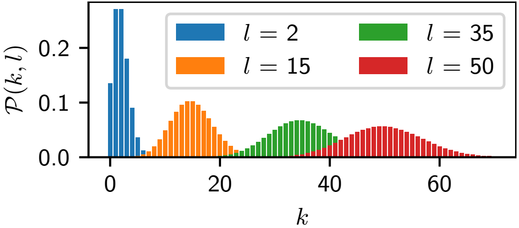

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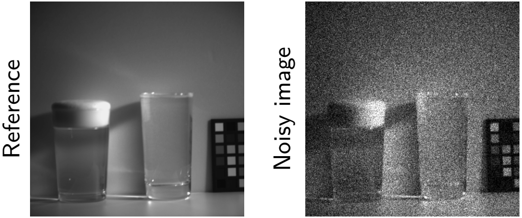

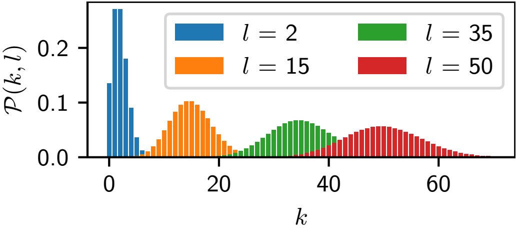

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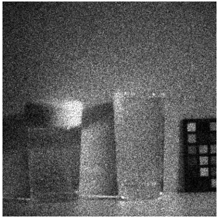
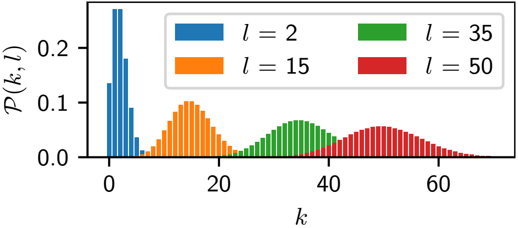
- Poisson distribution can be approximated by a Gaussian for higher means
- Model: Additive white Gaussian noise ($\mathbf{n}$):

$$\mathbf{c} = \mathbf{F}\mathbf{s} + \mathbf{n}$$

Reference

Noisy image





Wiener Filter

- Reminder: $\mathbf{c} = \mathbf{F}\mathbf{s} + \mathbf{n}$

Pratt et al. "Spectral estimation techniques for the spectral calibration of a color image scanner"

Wiener Filter

- Reminder: $\mathbf{c} = \mathbf{F}\mathbf{s} + \mathbf{n}$
- Covariances (independence between noise and spectrum, zero mean):
  - Hyperspectral covariance: $\mathbf{K}_\mathsf{r} = \mathcal{E}\{\mathbf{s}\mathbf{s}^\mathsf{T}\}$
  - Multispectral covariance: $\mathbf{K}_\mathsf{c} = \mathcal{E}\{\mathbf{F}\mathbf{s}\mathbf{s}^\mathsf{T}\mathbf{F}^\mathsf{T}\} + \mathcal{E}\{\mathbf{n}\mathbf{n}^\mathsf{T}\} = \mathbf{F}\mathbf{K}_\mathsf{r}\mathbf{F}^\mathsf{T} + \mathbf{N}$
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$$\hat{\mathbf{s}}^{\mathsf{WF}} = \mathbf{K}_\mathsf{rc}\mathbf{K}_\mathsf{c}^{-1}\mathbf{c} = \mathbf{K}_\mathsf{r}\mathbf{F}^\mathsf{T}(\mathbf{F}\mathbf{K}_\mathsf{r}\mathbf{F}^\mathsf{T} + \mathbf{N})^{-1}\mathbf{c}.$$

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- Smoothed pseudoinverse:

$$\hat{\mathbf{s}}^{\mathsf{SP}} = \mathbf{M}^{-1}\mathbf{F}^\mathsf{T}(\mathbf{F}\mathbf{M}^{-1}\mathbf{F}^\mathsf{T})^{-1}\mathbf{c}$$

Pratt et al. "Spectral estimation techniques for the spectral calibration of a color image scanner"

Spatio-spectral Wiener Filter

- Idea: Exploit spatial correlation to encounter noise

Murakami et al. "Color reproduction from low-SNR multispectral images using spatio-spectral Wiener estimation"

Spatio-spectral Wiener Filter

- Idea: Exploit spatial correlation to encounter noise
- Adjust correlation matrix:

$$\hat{\mathbf{S}}^{\mathsf{SSW}}(x,y) = \mathbf{P}\mathbf{K}\hat{\mathbf{F}}^{\mathsf{T}}(\hat{\mathbf{F}}\mathbf{K}\hat{\mathbf{F}}^{\mathsf{T}} + \hat{\mathbf{N}})^{-1}\mathbf{C}_{\mathsf{b}}^{x,y}$$

- $\hat{\mathbf{F}}$ and $\hat{\mathbf{N}}$ extended (block-)diagonal matrices
- $\mathbf{C}_{\mathsf{b}}^{x,y}$: Vectorized image block
- $\mathbf{P}$: Picks out spectrum of pixel in the center

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- $\hat{\mathbf{F}}$ and $\hat{\mathbf{N}}$ extended (block-)diagonal matrices
- $\mathbf{C}_{\mathsf{b}}^{x,y}$: Vectorized image block
- $\mathbf{P}$: Picks out spectrum of pixel in the center
- Combine spatial and spectral covariance:

$$\mathbf{K} = \mathbf{K}_{\mathsf{s}} \otimes \mathbf{K}_{\mathsf{r}}.$$

- $\otimes$: Kronecker product

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Spatio-spectral Wiener Filter

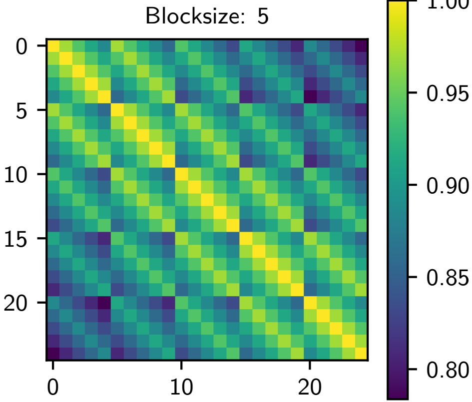
- Spatial correlation modeled by first order Markov process:

$$\mathbf{K}_{\mathsf{s}} = \mathbf{R}(p) \otimes \mathbf{R}(p)$$

- with (blocksize B_{r}, decay p):

$$\mathbf{R}(p) = \begin{pmatrix} p^0 & p^1 & \cdots & p^{B_{\mathsf{r}}-1} \\ p^1 & p^0 & \cdots & p^{B_{\mathsf{r}}-2} \\ \vdots & \vdots & \ddots & \vdots \\ p^{B_{\mathsf{r}}-1} & p^{B_{\mathsf{r}}-2} & \cdots & p^0 \end{pmatrix}$$

- $\mathbf{R}(p) \otimes \mathbf{R}(p)$ for vertical and horizontal direction



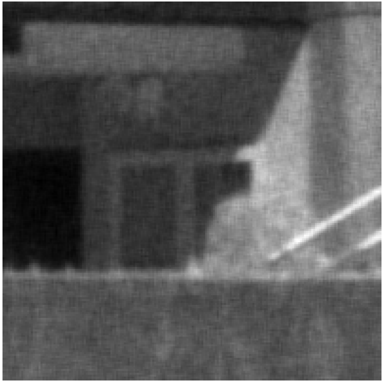
Murakami et al. "Color reproduction from low-SNR multispectral images using spatio-spectral Wiener estimation"

Novel Reconstruction Method

- Idea: Generate guide image from multispectral images
- Independence of noise leads to much less noise in guide image

Guide image

Noisy image

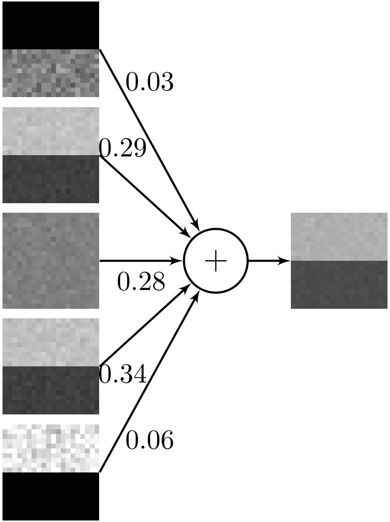


Filtering result

Structure-preserving Reflectance Estimation

- Guide is weighted average of multispectral images:

$$\mathbf{G}(x,y) = \sum_{i=1}^{M} \mathbf{w}_i \check{\mathbf{C}}_i(x,y) + \sum_{i=1}^{M} \mathbf{w}_i \mathbf{n}_i = \\ = \mathbf{w}^\mathsf{T} \check{\mathbf{C}}(x,y) + \mathbf{w}^\mathsf{T} \mathbf{n}$$



Sippel et al. "Structure-preserving spectral reflectance estimation using guided filtering "

Structure-preserving Reflectance Estimation

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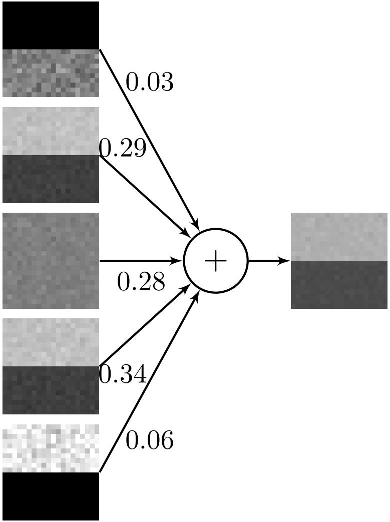
$$= \mathbf{w}^\mathsf{T} \check{\mathbf{C}}(x,y) + \mathbf{w}^\mathsf{T}\mathbf{n}$$

- Optimize SNR:

$$\underset{\mathbf{w}}{\operatorname{argmax}} \frac{\mathcal{E}\left[\mathbf{w}^\mathsf{T} \check{\mathbf{C}}(x,y) \check{\mathbf{C}}(x,y)^\mathsf{T} \mathbf{w}\right]}{\mathcal{E}\left[\mathbf{w}^\mathsf{T} \mathbf{n}\mathbf{n}^\mathsf{T} \mathbf{w}\right]}$$



Sippel et al. "Structure-preserving spectral reflectance estimation using guided filtering "

Structure-preserving Reflectance Estimation

- Guided filtering idea: Guide indicates regions with edges and smooth regions

He et al. "Guided Image Filtering"

Structure-preserving Reflectance Estimation

- Guided filtering idea: Guide indicates regions with edges and smooth regions
- Assumption: Noiseless image $\check{\mathbf{S}}_i(u,v)$ is linear combination of $\mathbf{G}$:

$$\check{\mathbf{S}}_i(u,v) = a_{x,y}\mathbf{G}(u,v) + b_{x,y} \quad \forall (u,v) \in w_{x,y}$$

- Usually true in small window $w_{x,y}$

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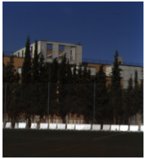
- Average in smooth regions via $b_{x,y}$
- Use linear regression in regions with edges via $a_{x,y}$

He et al. "Guided Image Filtering"

Evaluation

- Images from natural scenes
- Wavelengths: 440nm to 920nm
- 10nm steps $\rightarrow$ 49 hyperspectral channels



Eckhard et al. "Outdoor scene reflectance measurements using a Bragg-grating-based hyperspectral imager"

Evaluation

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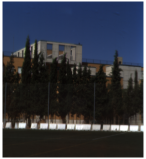
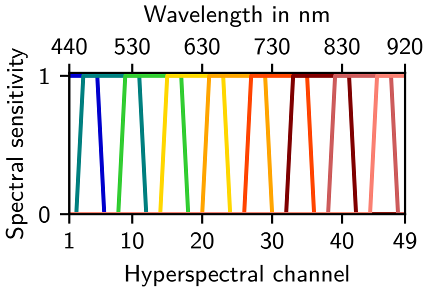
- Wavelengths: 440nm to 920nm
- 10nm steps $\rightarrow$ 49 hyperspectral channels
- Filters: Different colors indicate different filters





Eckhard et al. "Outdoor scene reflectance measurements using a Bragg-grating-based hyperspectral imager"

Evaluation

- Metric spectral angle:

$$\mathsf{SA}(\mathbf{s}, \hat{\mathbf{s}}) = \arccos\left(\frac{\mathbf{s}^{\mathsf{T}}}{||\mathbf{s}||_2} \frac{\hat{\mathbf{s}}}{||\hat{\mathbf{s}}||_2}\right)$$

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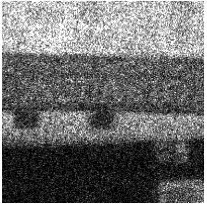
Reference

Intensity level 10



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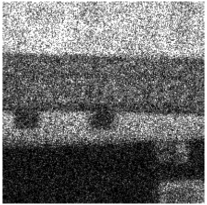
Intensity level 10



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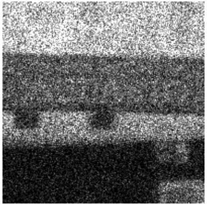
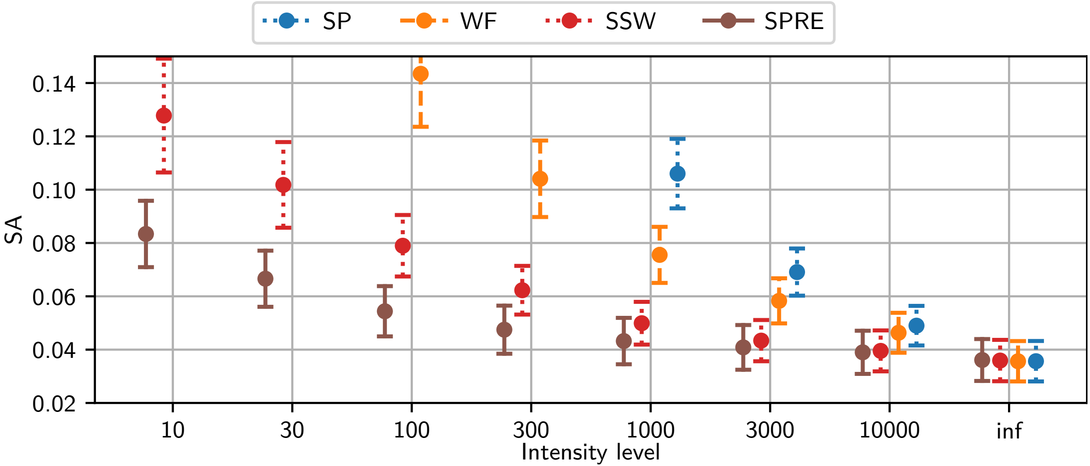
  - Intensity level l indicates lighting conditions
  - Low intensity level corresponds to high noise influence

Reference

Intensity level 10



Evaluation


SP
WF
SSW
SPRE
SA
0.14
0.12
0.10
0.08
0.06
0.04
0.02
10
30
100
300
1000
3000
10000
inf
Intensity level

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- Novel reconstruction method for noisy scenarios based on guided filtering