

# Compact Single-Shot Hyperspectral Imaging using a Prism

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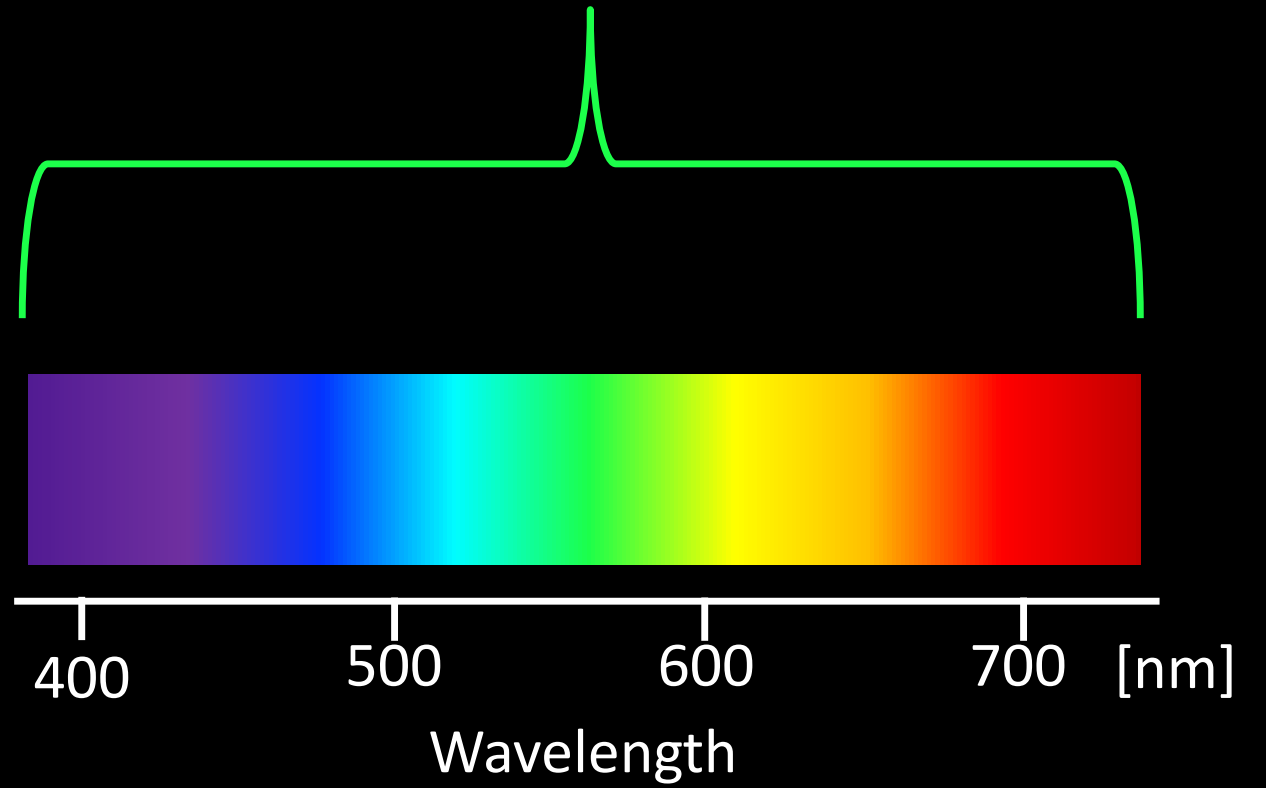
<sup>†</sup> KAIST

\* Universidad de Zaragoza, I3A

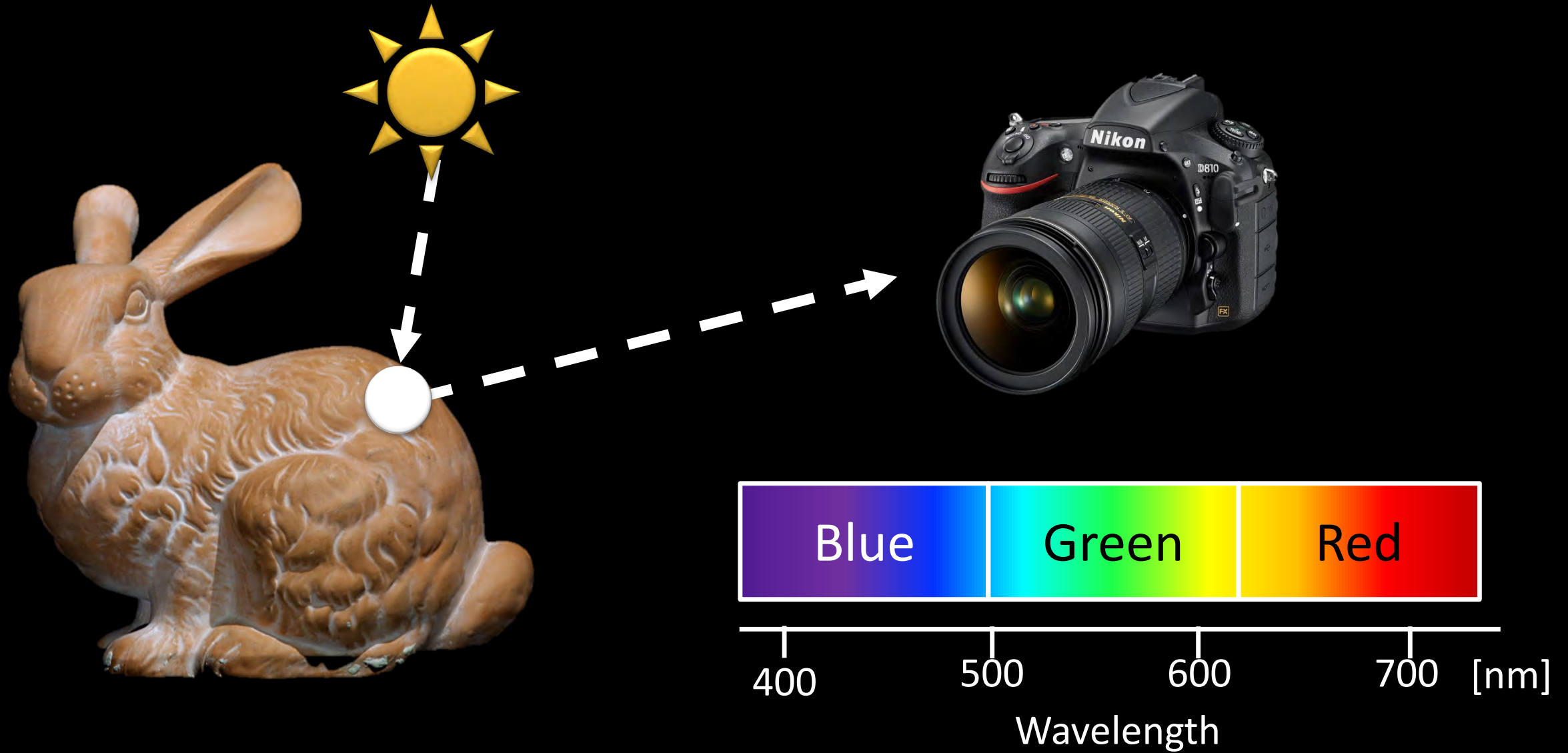
# Spectrum



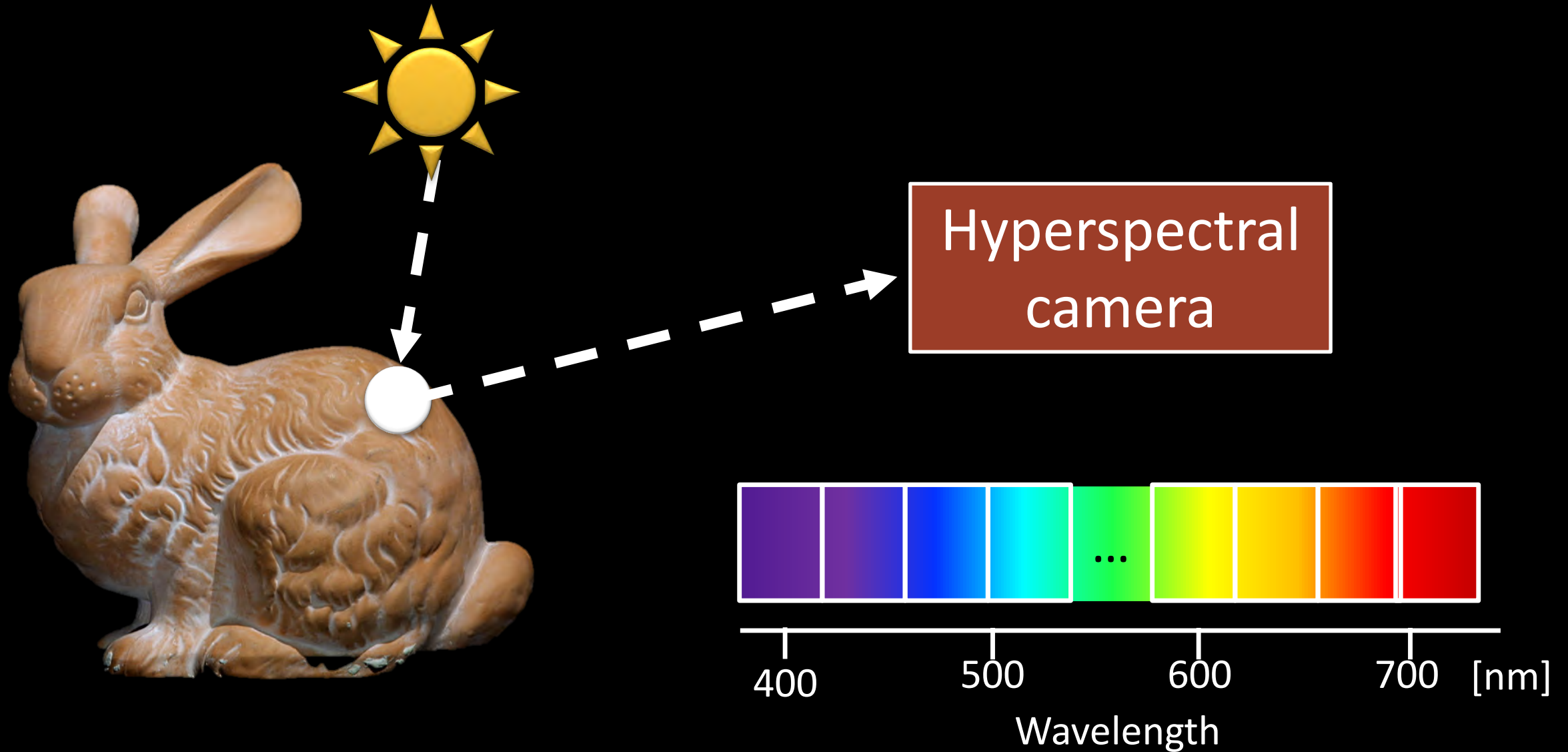
$L(\lambda)$ : Spectrum



# RGB Imaging



# Hyperspectral Imaging



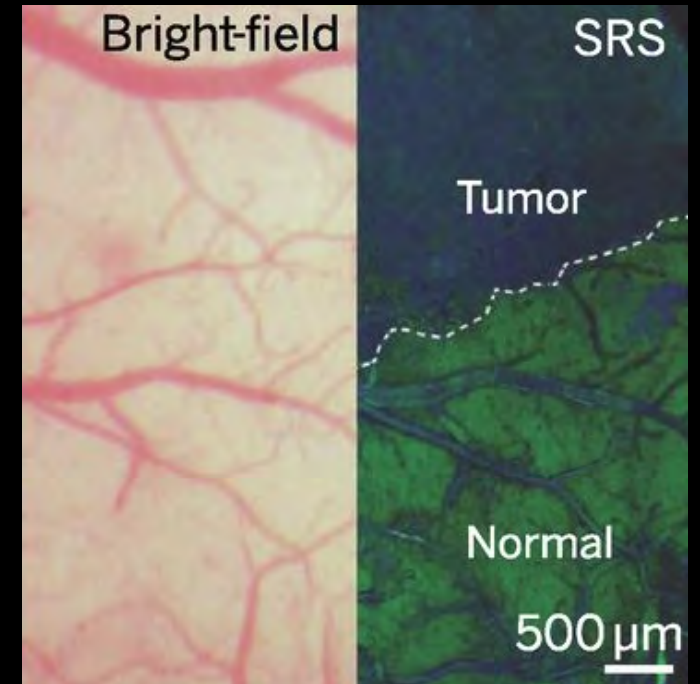
# Hyperspectral Imaging



Geology [1]



Cosmetics [2]



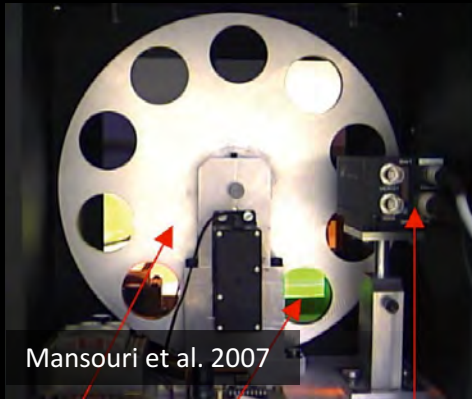
Biology [3]

[1] NASA

[3] rshephorse, Flickr

[2] Cheng et al., Vibrational spectroscopic imaging of living systems: An emerging platform for biology and medicine, Science 2015

# Previous Systems



Mansouri et al. 2007

## Spectral scanning

- [Mansouri et al. 2007], [Gat 2000], [Brusco et al., 2006]

- Static scene only
- Low spectral resolution



Habel et al. 2012

## Computed Tomography Imaging Spectroscopy (CTIS)

- [Habel et al. 2012], [Johnson et al. 2007], [Okamoto et al. 1993]]

- Large system
- Low spatial resolution



Kim et al. 2012

## Compressive Coded Aperture Spectral Imaging (CASSI)

- [Kim et al. 2012], [Wagadarikar et al. 2008]], [Gehm et al.,2007]

- Large system
- Low spatial resolution



Cao et al. 2011

## Prism-Mask Multispectral Video Imaging System (PMVIS)

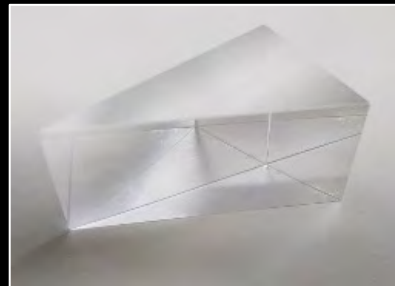
- [Cao et al. 2011]

- Low spatial resolution

# Compact Hyperspectral Camera



- Compact
- Single-shot
- High spatial/spectral resolution



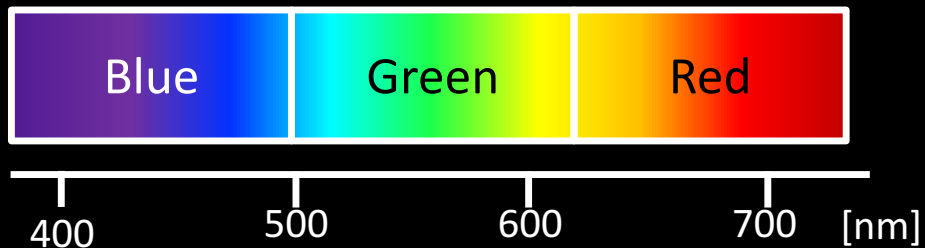
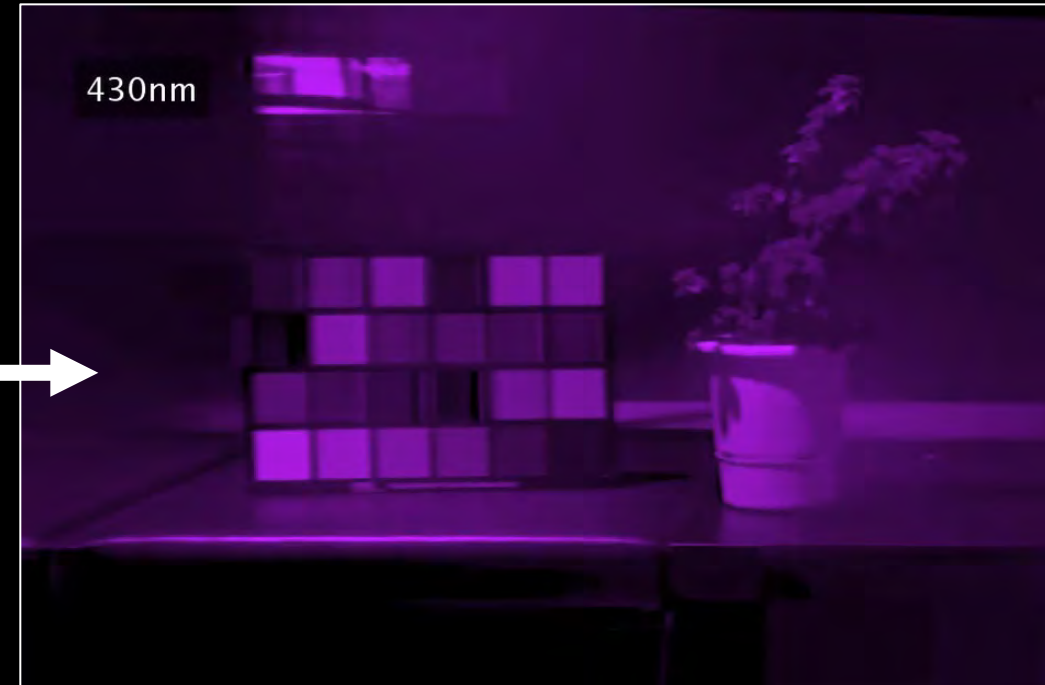
# Input & Output

Input

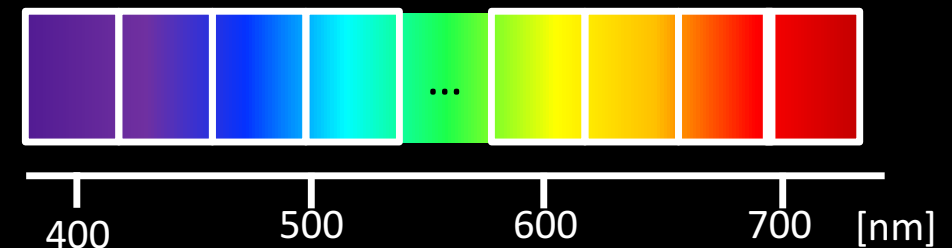


Computational  
method

Output



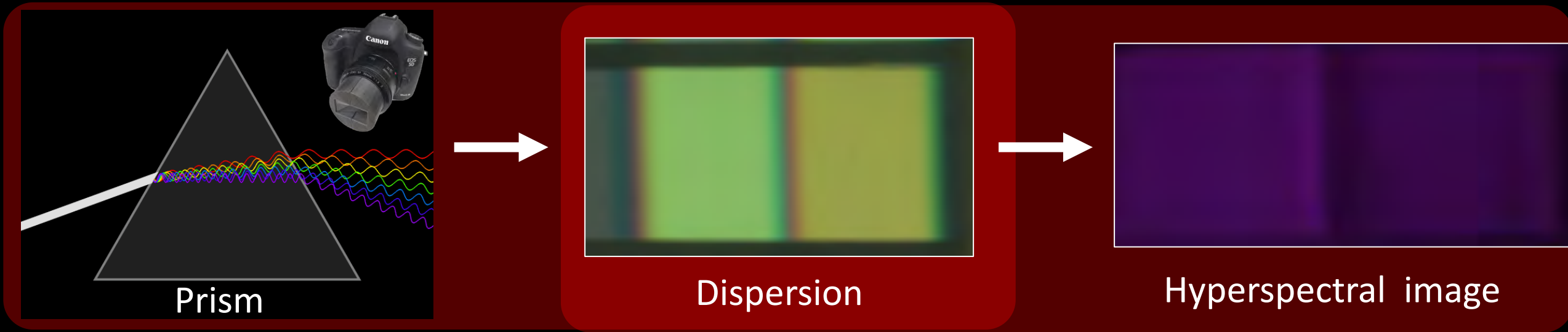
# of channels: 3



# of channels: 23



# Challenges

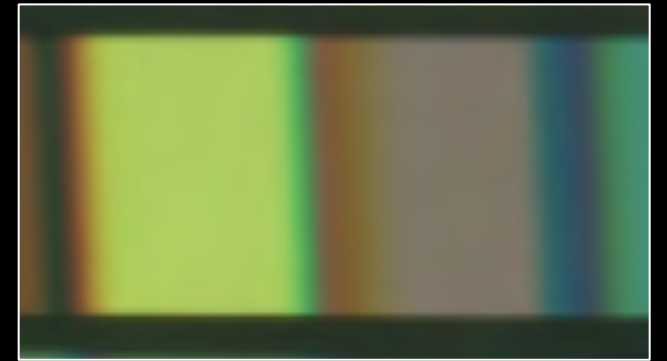
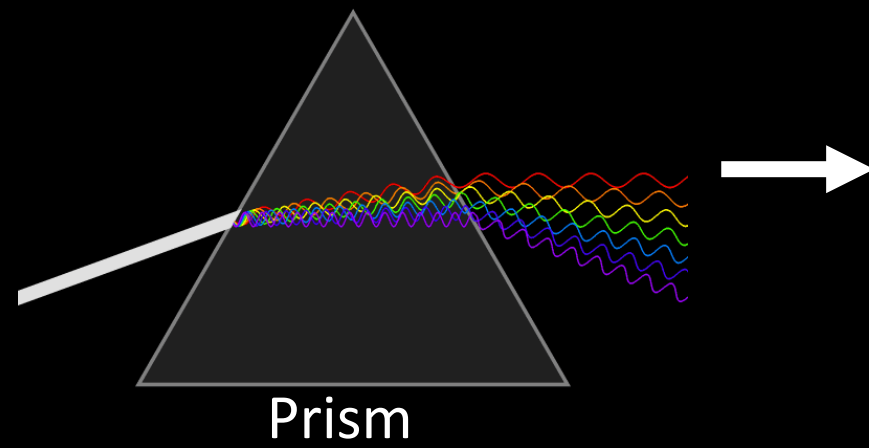


1. How to model the dispersion accurately?

→ Spatially-varying dispersion model

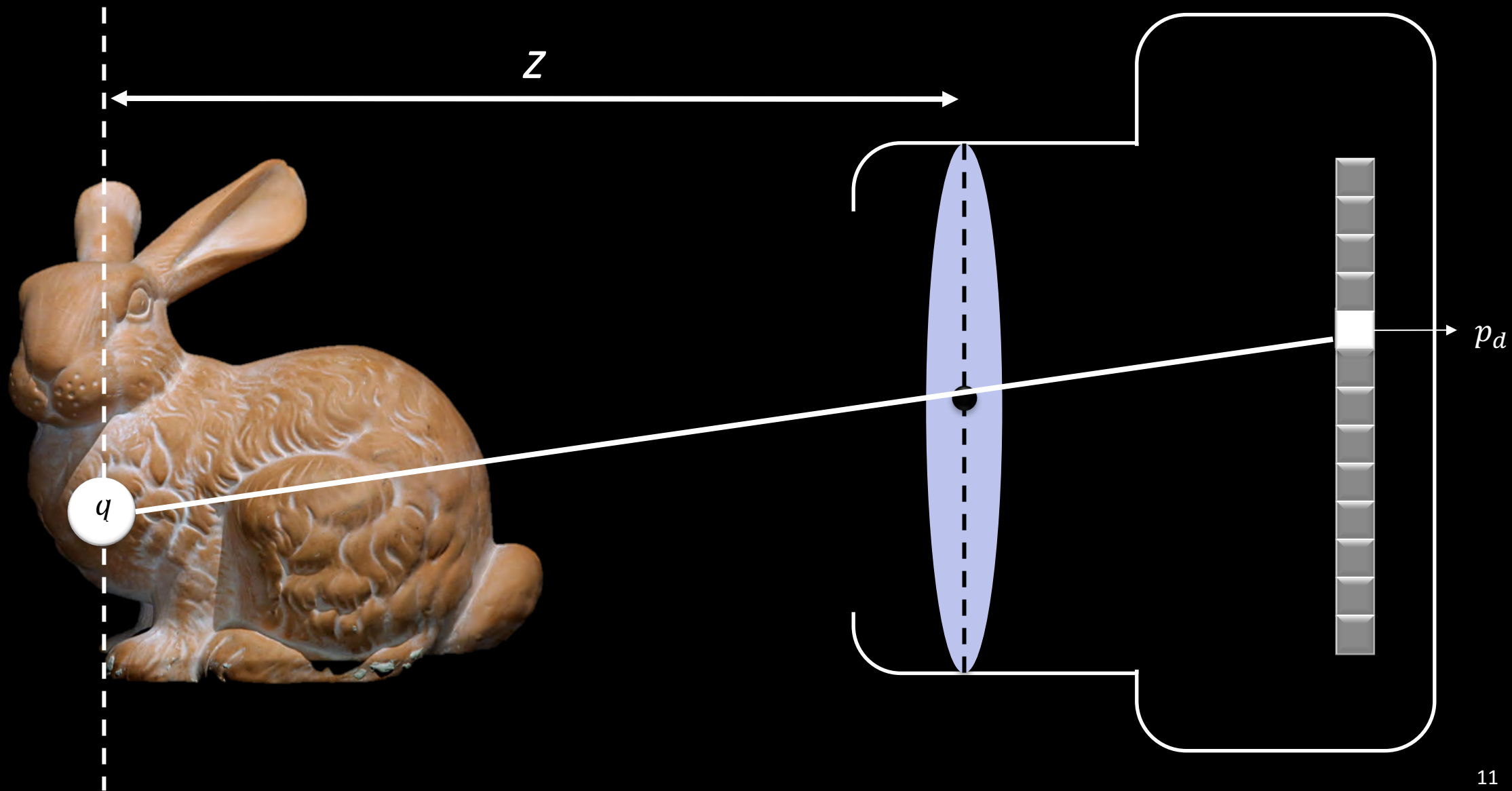
2. How to reconstruct hyperspectral images?

→ Gradient-based reconstruction

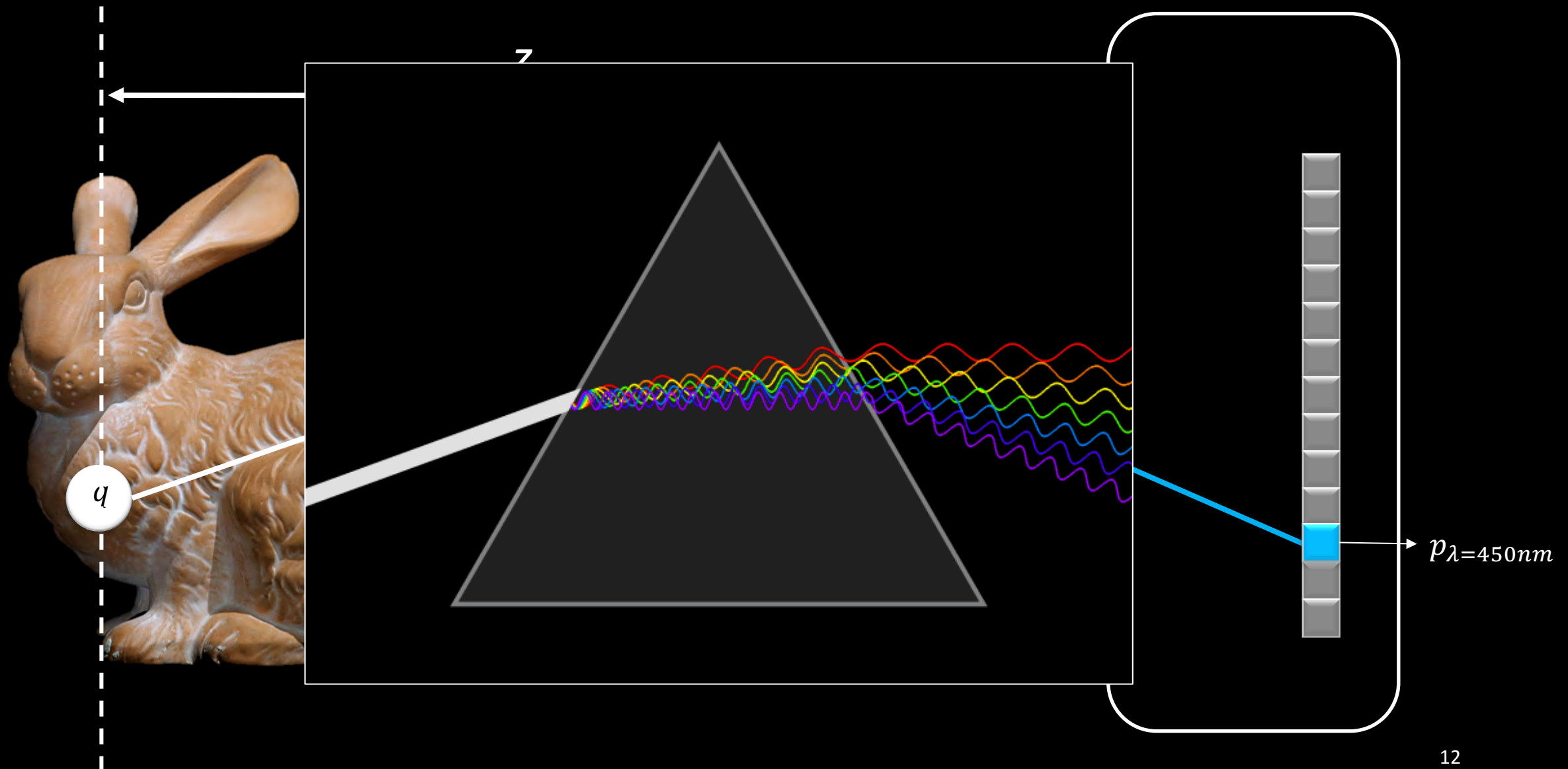


# DISPERSION MODEL

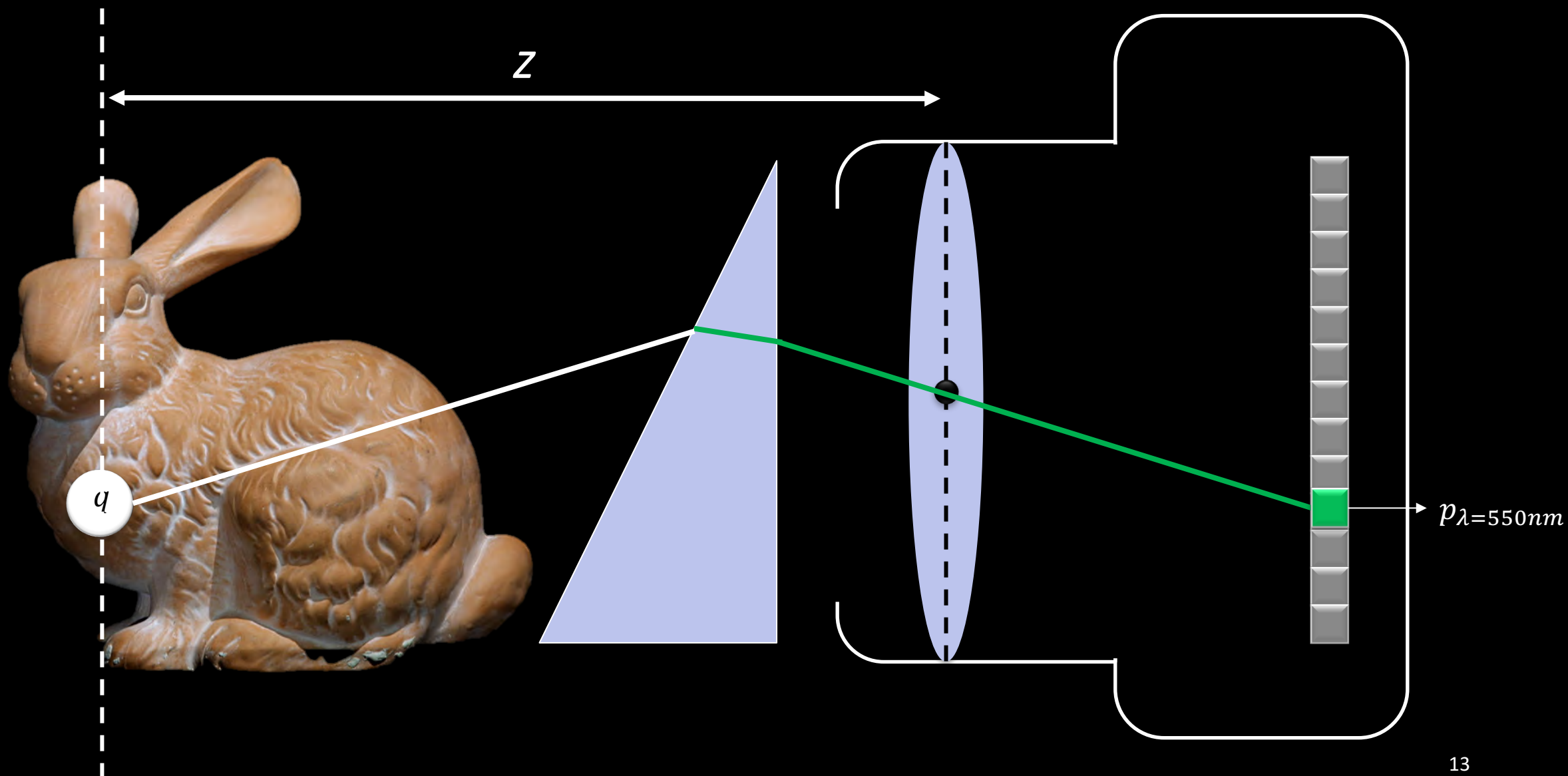
# Without a Prism



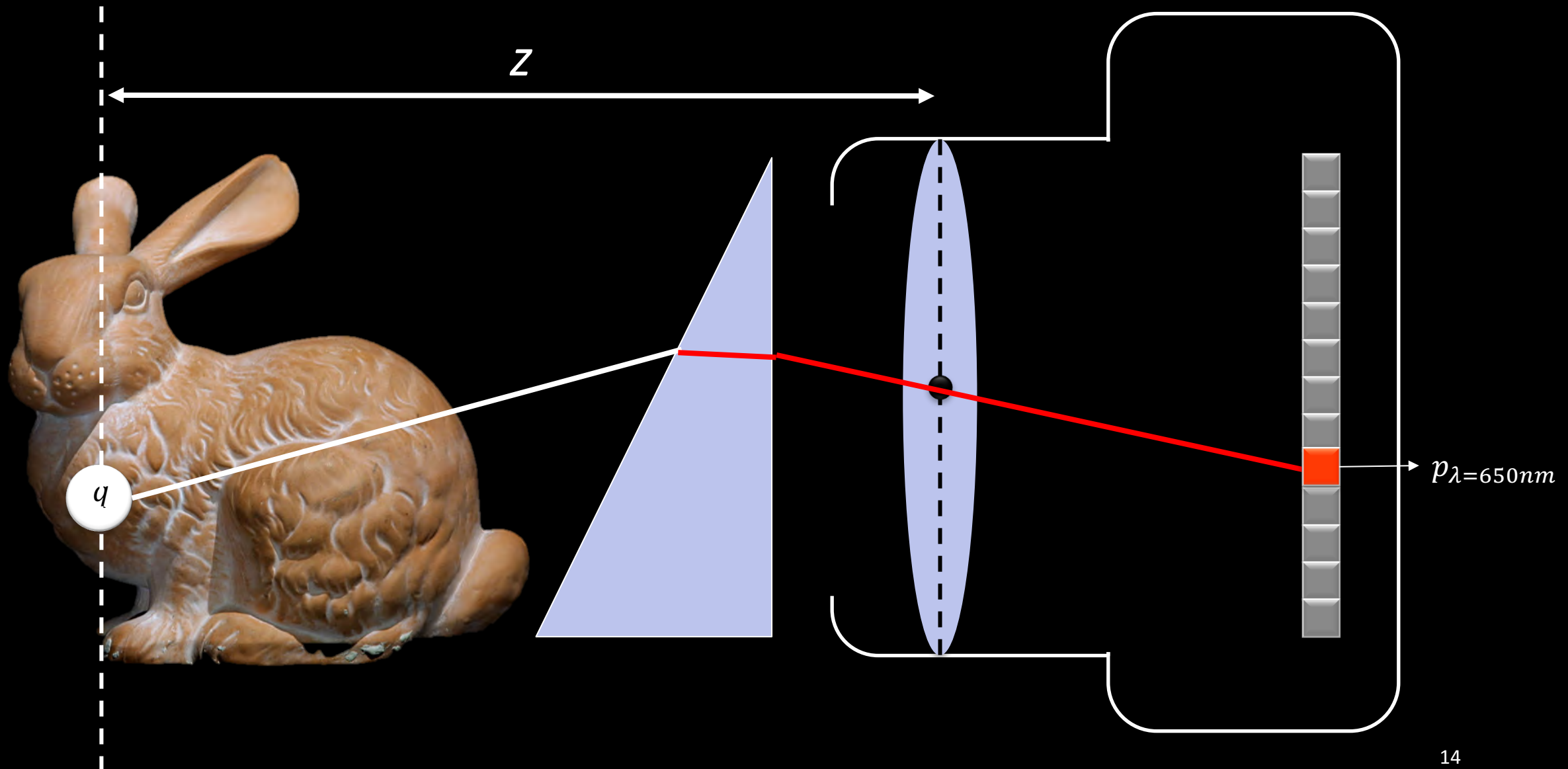
# With a Prism



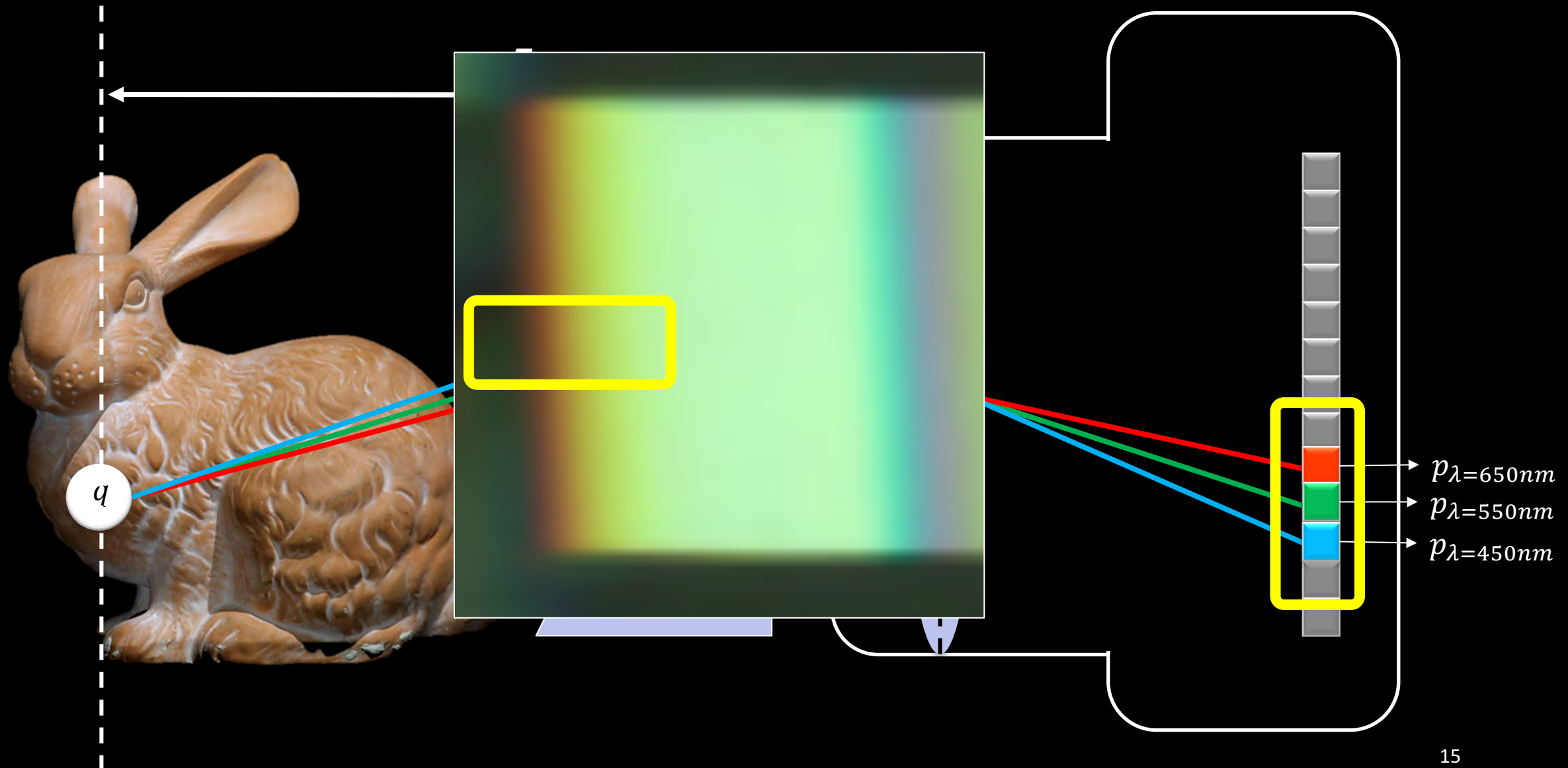
# With a Prism



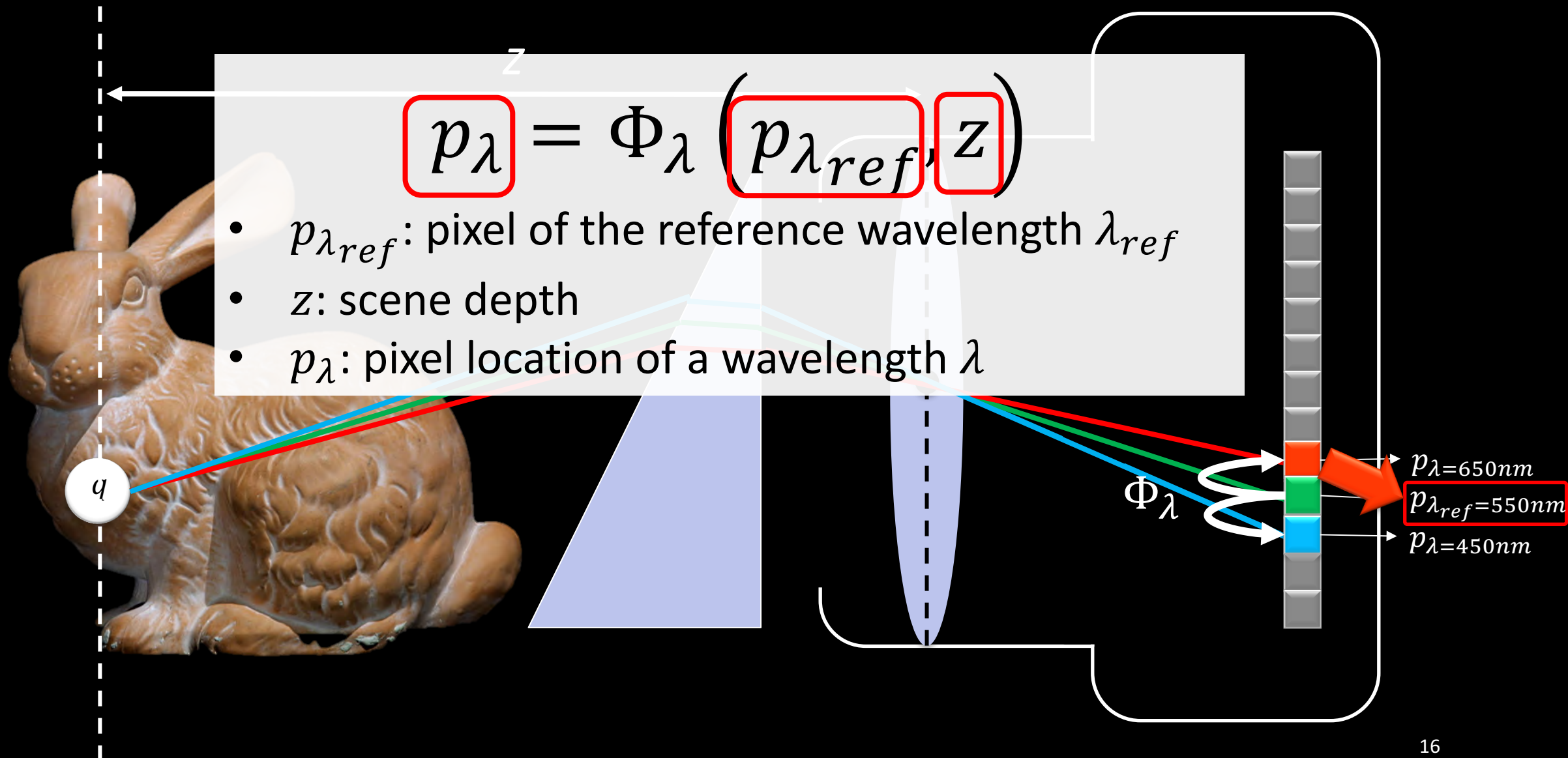
# With a Prism



# With a Prism

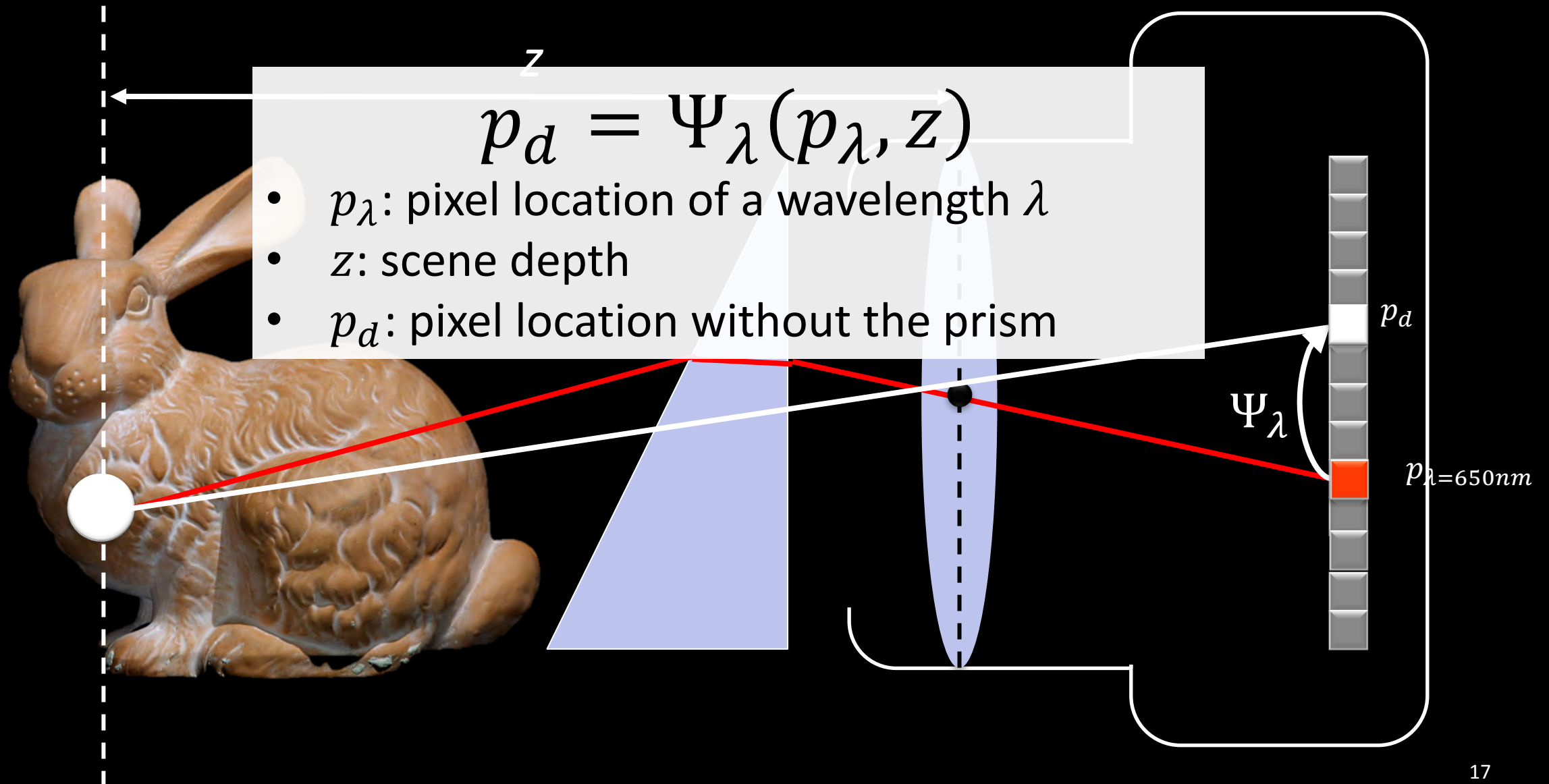


# Dispersion Model





# Refraction Model



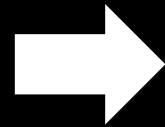
# Dispersion Model from Refraction Models

$$\begin{array}{ccc} \text{Refraction model} & & \text{Dispersion model} \\ p_d = \Psi_\lambda(p_\lambda, z) & \longrightarrow & p_\lambda = \Phi_\lambda(p_{\lambda_{ref}}, z) \end{array}$$

# Dispersion Model from Refraction Models

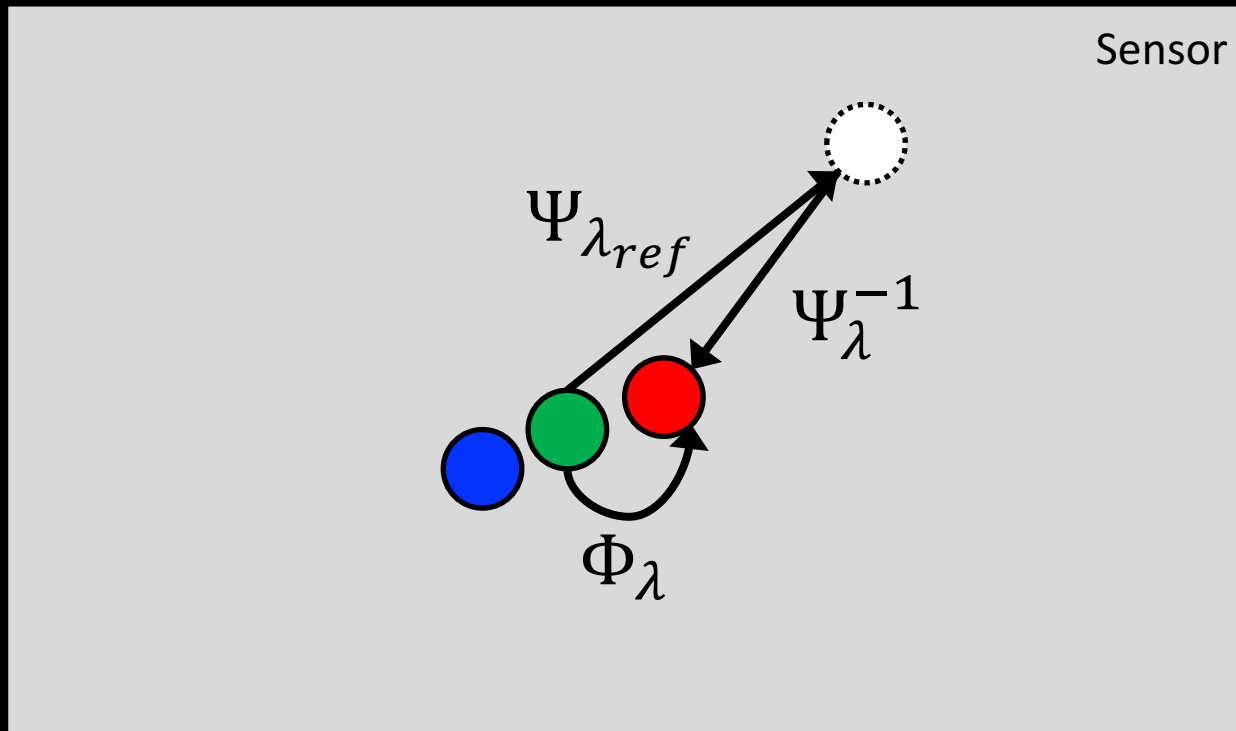
Refraction model





$$p_d = \Psi_\lambda(p_\lambda, z)$$



Dispersion model

$$p_\lambda = \Phi_\lambda(p_{\lambda_{ref}}, z)$$

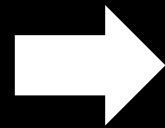


-  :  $p_d$
-  :  $p_{\lambda=650nm}$
-  :  $p_{\lambda_{ref}=550nm}$
-  :  $p_{\lambda=450nm}$

# Dispersion Model from Refraction Models

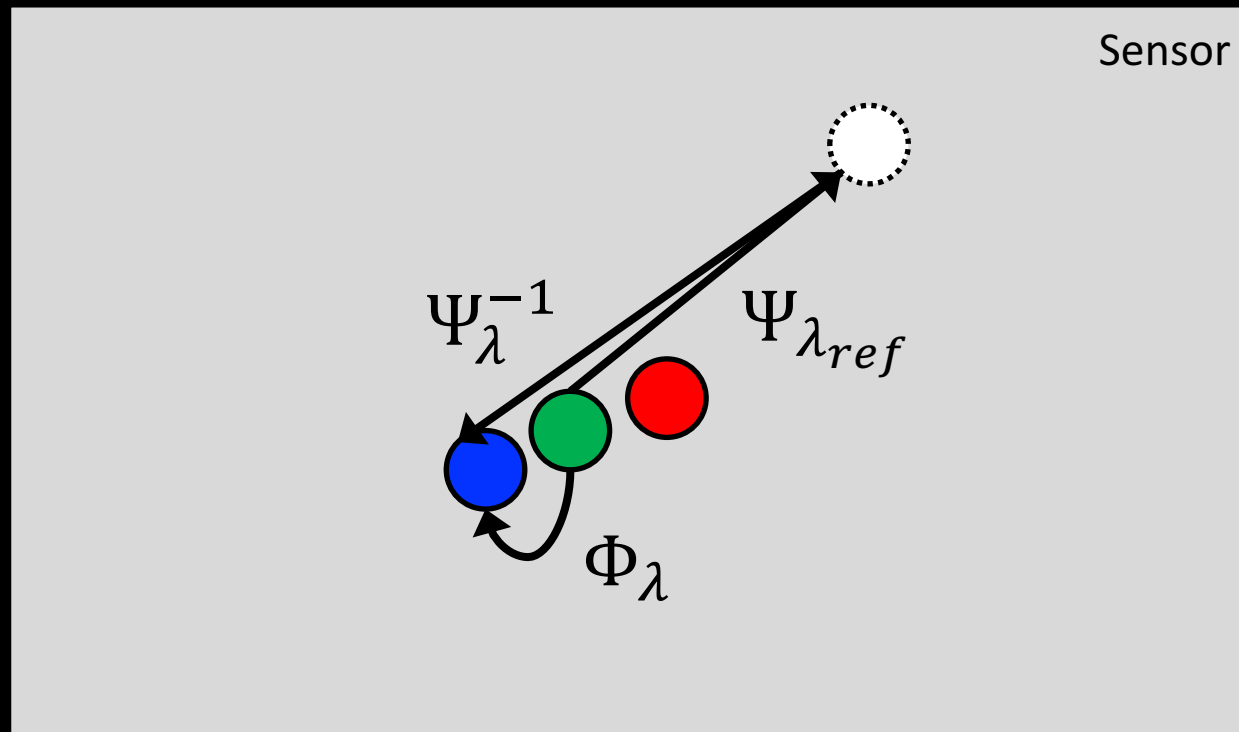
Refraction model





$$p_d = \Psi_\lambda(p_\lambda, z)$$



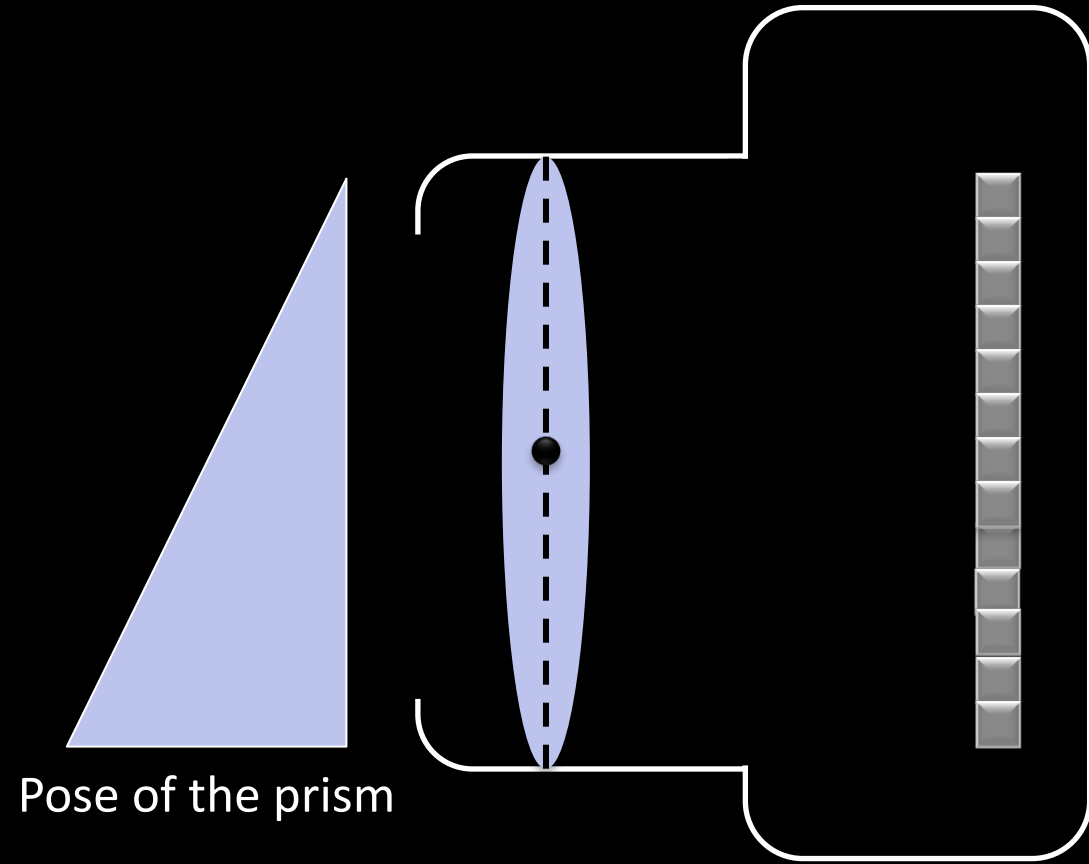
Dispersion model

$$p_\lambda = \Phi_\lambda(p_{\lambda_{ref}}, z)$$



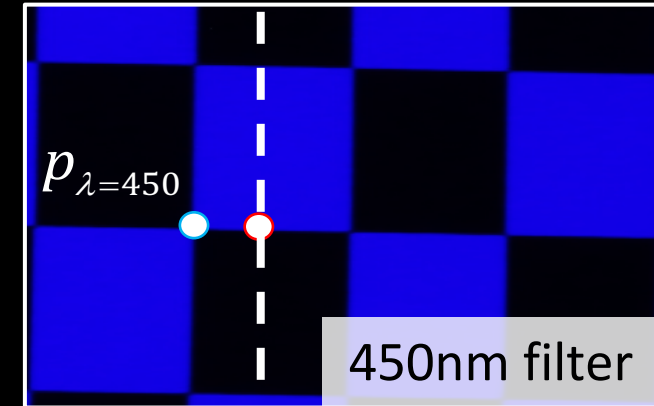
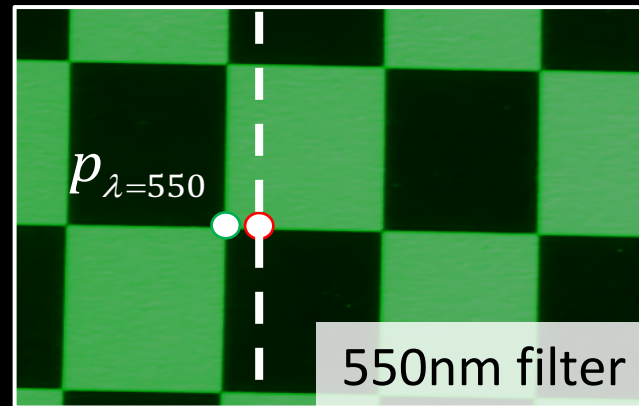
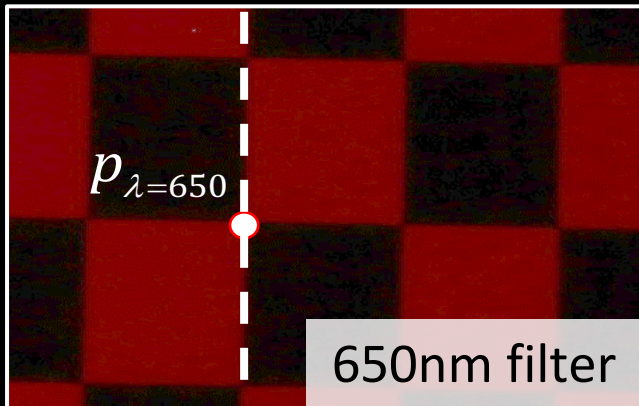
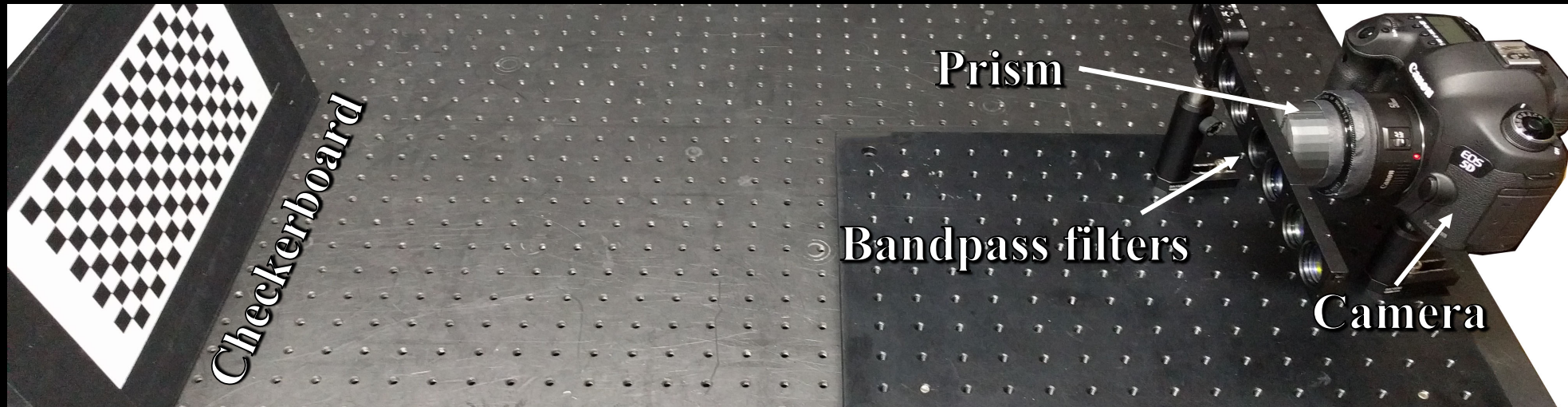
-  :  $p_d$
-  :  $p_{\lambda=650nm}$
-  :  $p_{\lambda_{ref}=550nm}$
-  :  $p_{\lambda=450nm}$

# PRISM CALIBRATION



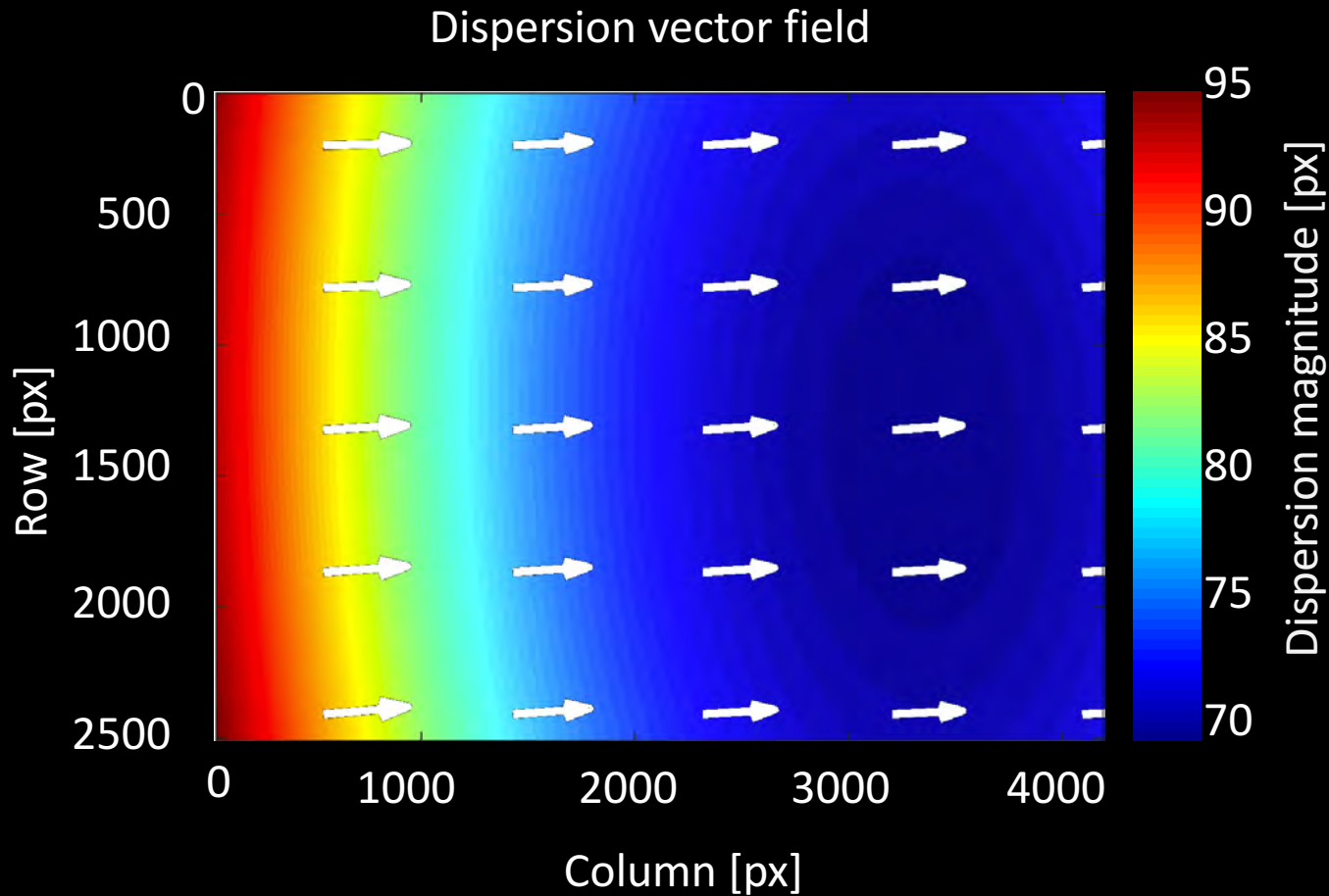
\* Camera geometric and radiometric calibrations are performed first without the prism

# Prism Pose Calibration



- Find the pose of the prism which explains the observed dispersion best
- Estimated pose of the prism  $\rightarrow$  refraction model  $\Psi \rightarrow$  dispersion model  $\Phi$

# Spatial Dependency

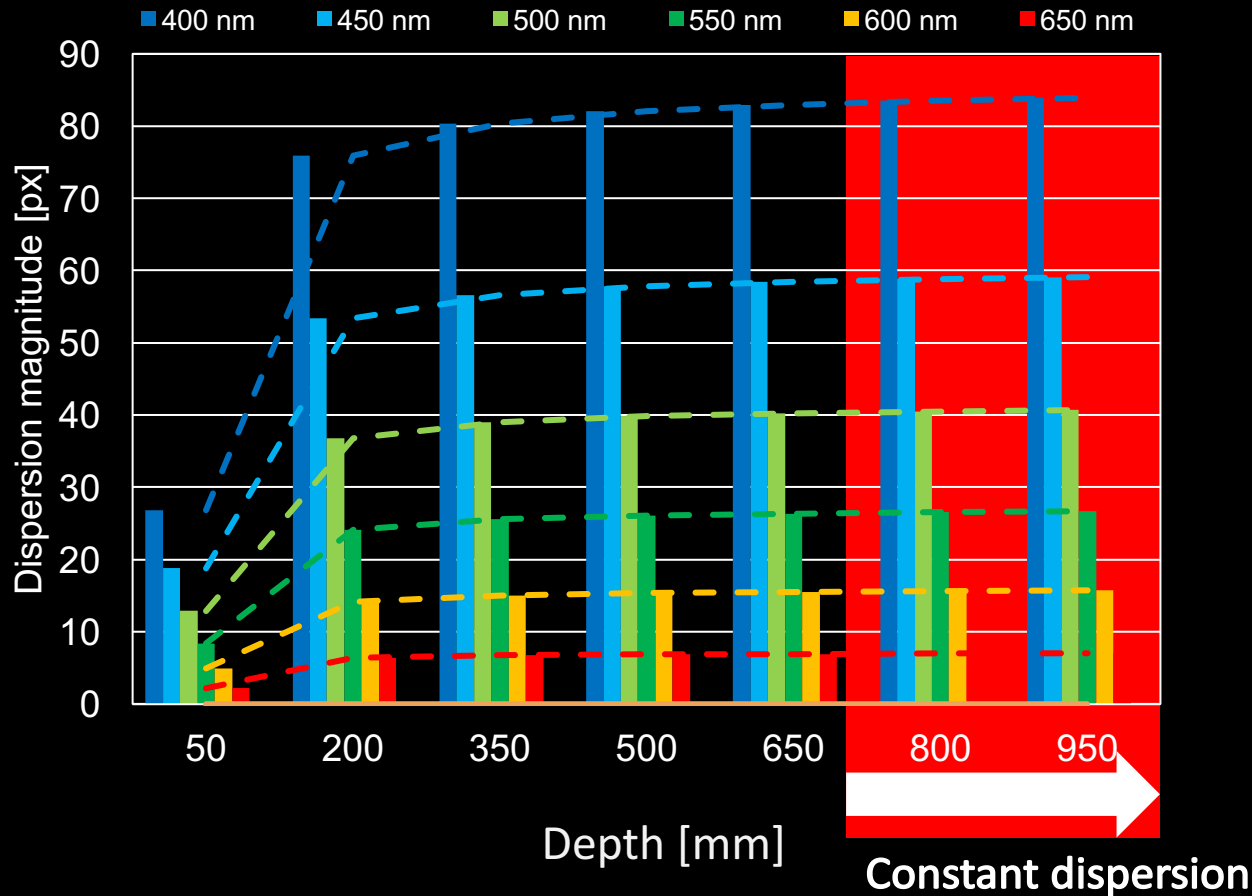


- Dispersion direction is nearly invariant to the spatial position
- Dispersion magnitude has large dependency on the spatial position

➔ Spatially-varying dispersion

$$p_{\lambda} = \Phi_{\lambda} \left( p_{\lambda_{ref}}, z \right)$$

# Depth Dependency



- For depth over  $\sim 700\text{mm}$ , dispersion profile becomes nearly constant.

➔ Depth-invariant dispersion

$$p_{\lambda} = \Phi_{\lambda} \left( p_{\lambda_{ref}} \right), \text{ for } z > 700\text{mm}$$





Dispersion



Hyperspectral image

# HYPERSENSPECTRAL IMAGE RECONSTRUCTION

# Image Formation

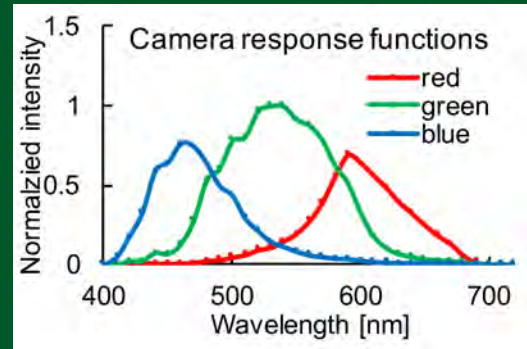
$$\mathbf{j} = \mathbf{\Omega} \mathbf{\Phi} \mathbf{i}$$

Dispersed RGB image



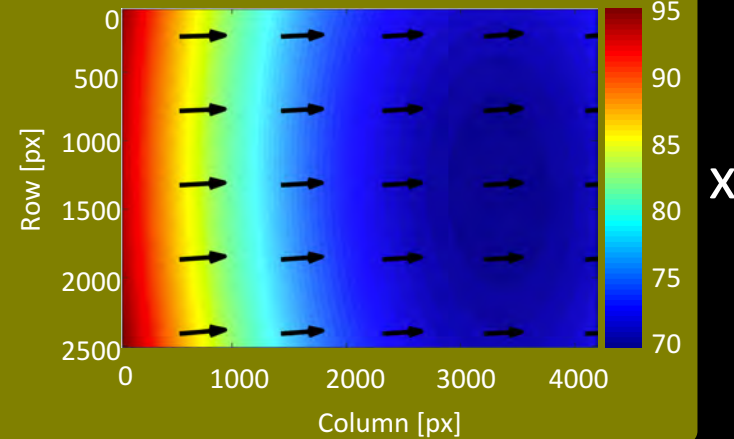
=

Camera response function



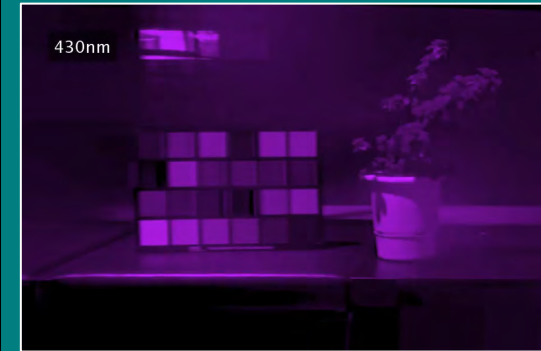
x

Dispersion matrix



x

Hyperspectral image



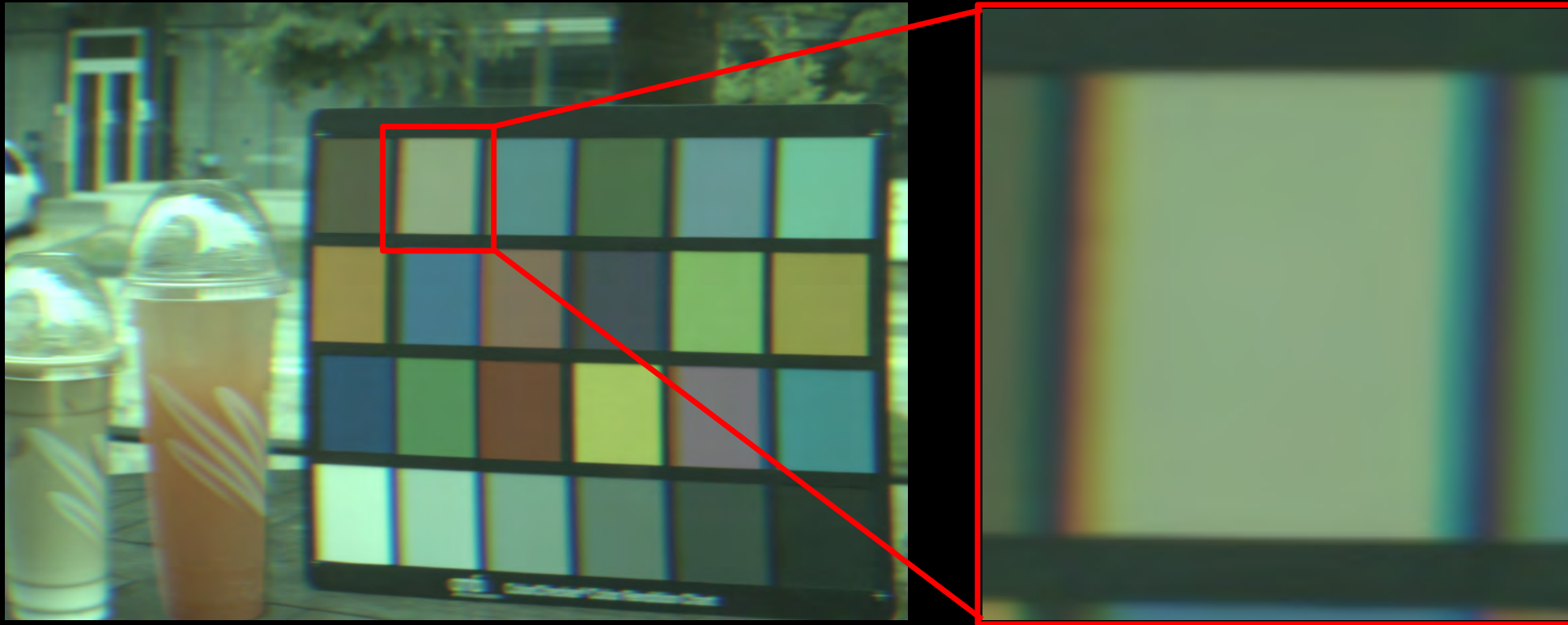
Known

Known

Known

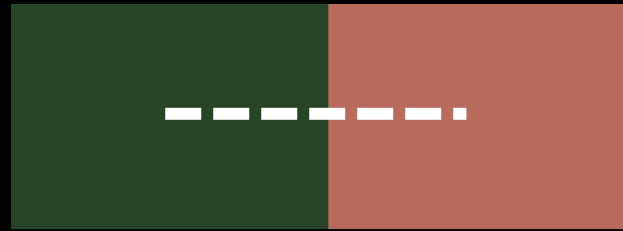
Unknown

# Sparse Spectral Cues

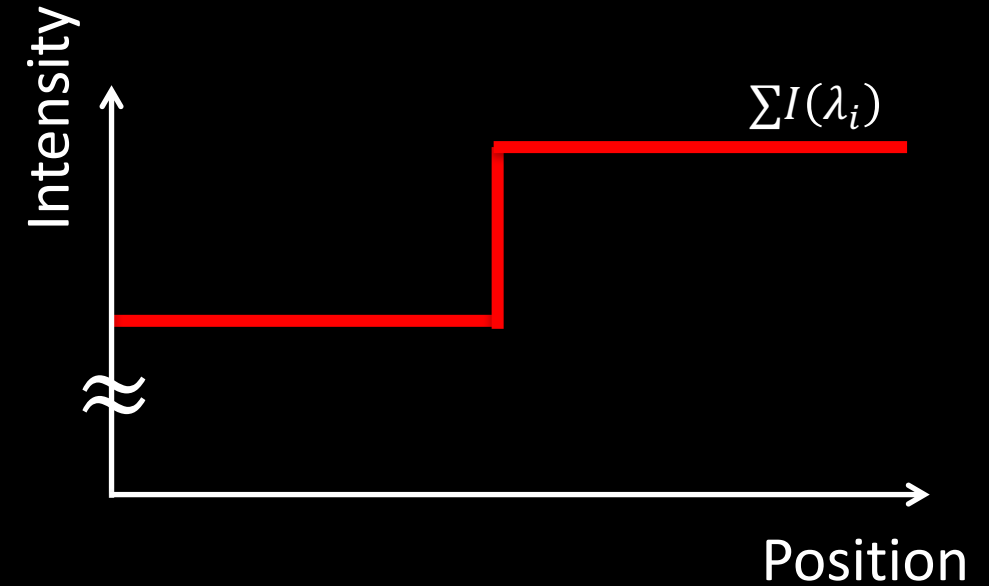
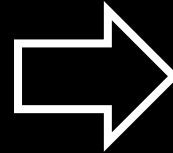
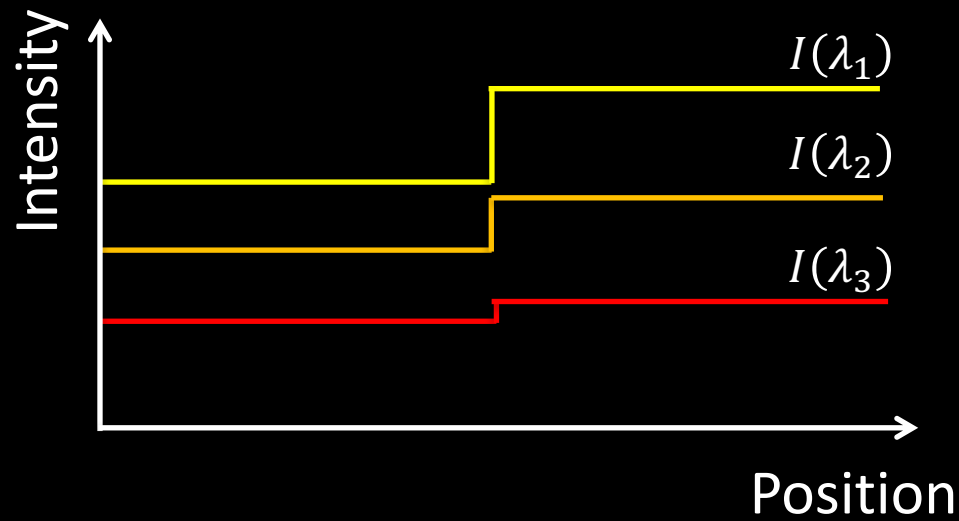
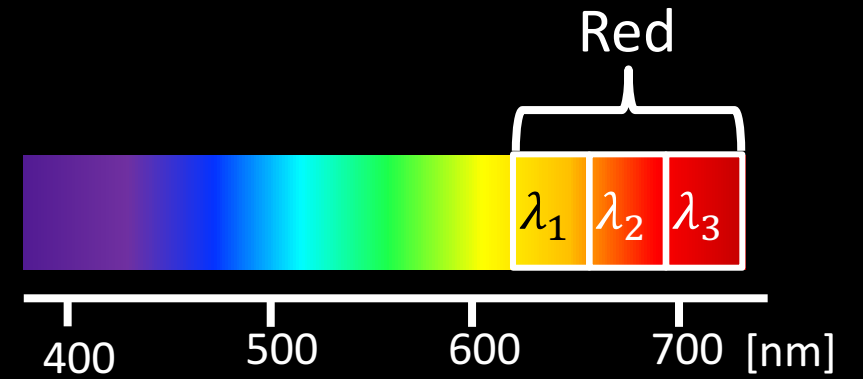


- Spectral cues only exist around edges
- Direct reconstruction is severely ill-posed

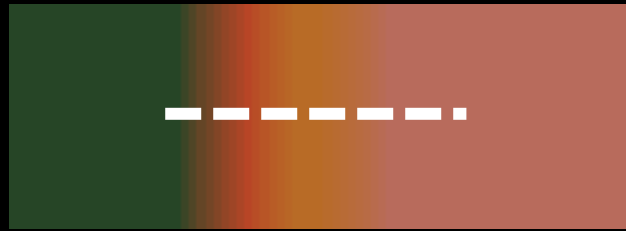
# Spectral Cues around the Edge Region



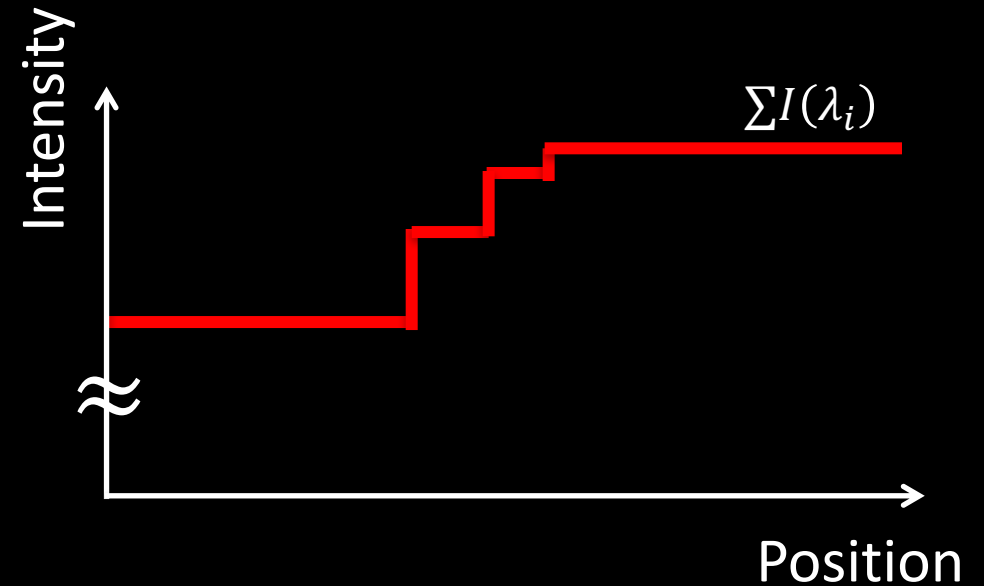
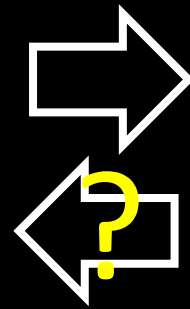
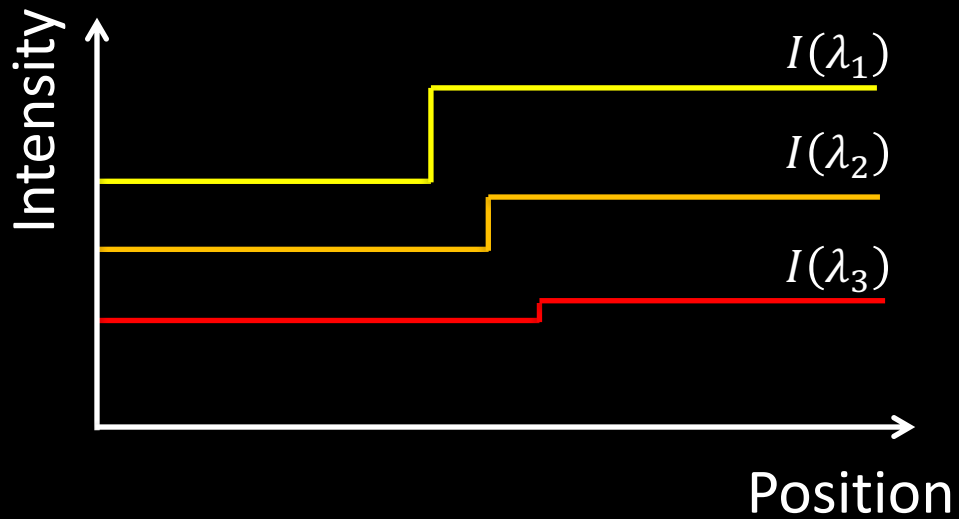
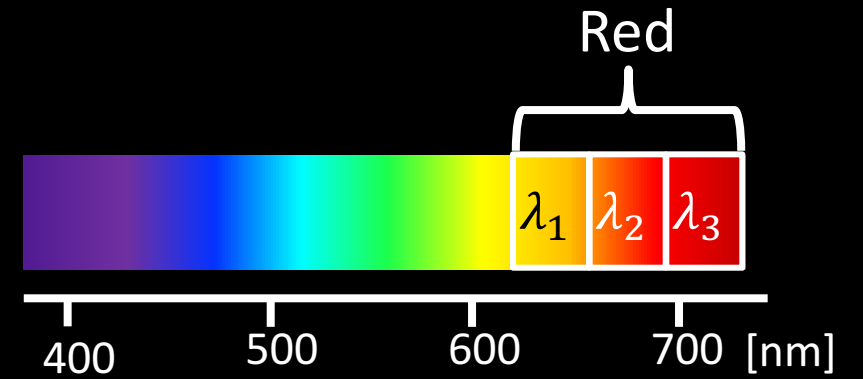
Without dispersion



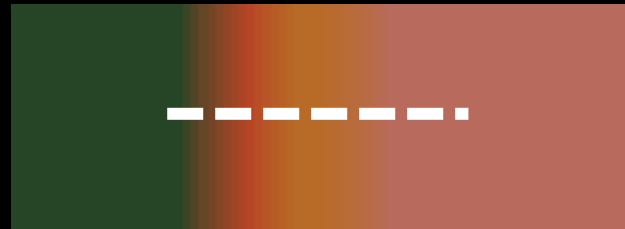
# Spectral Cues on the Edge Region



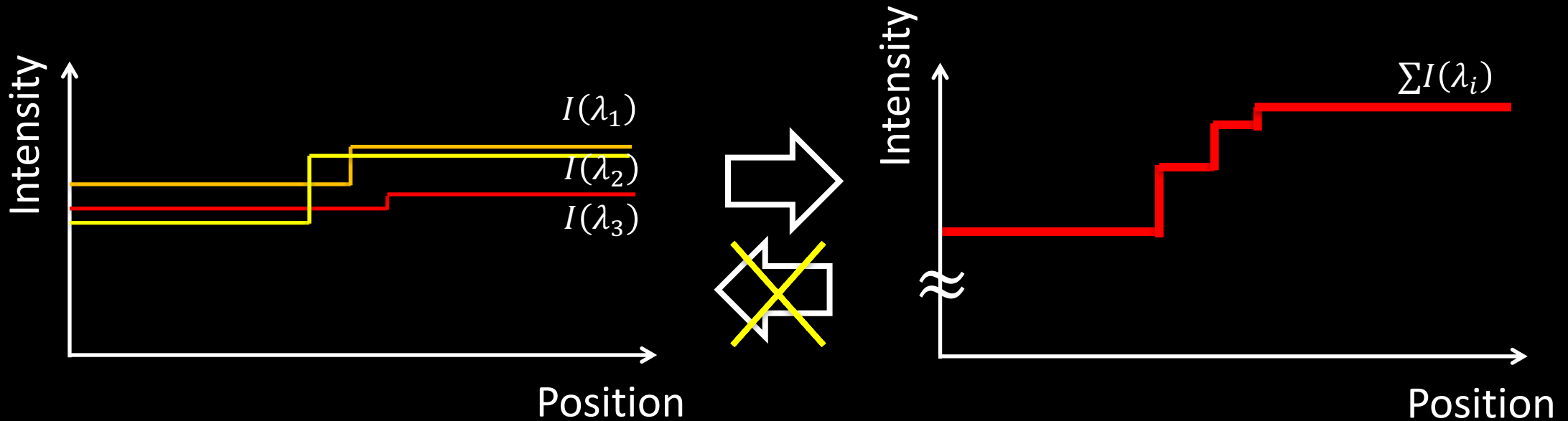
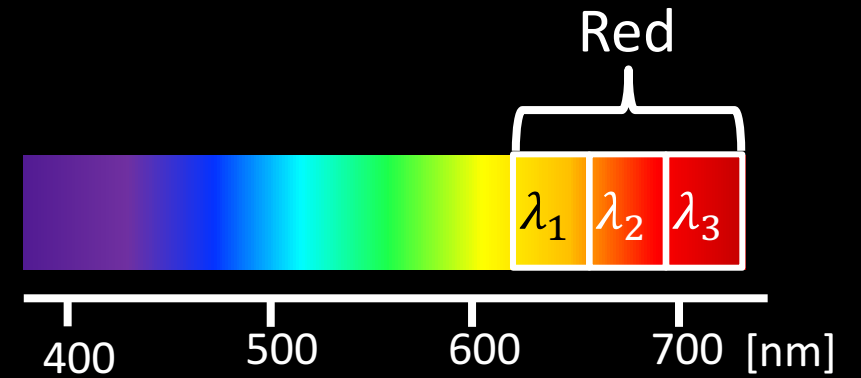
With dispersion



# Spectral Cues on the Edge Region

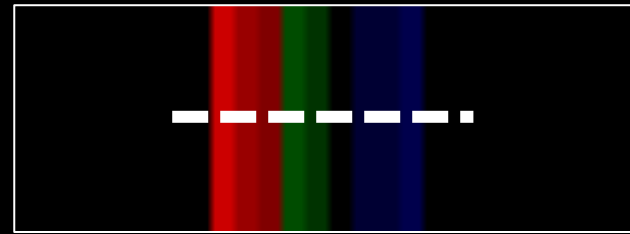


With dispersion

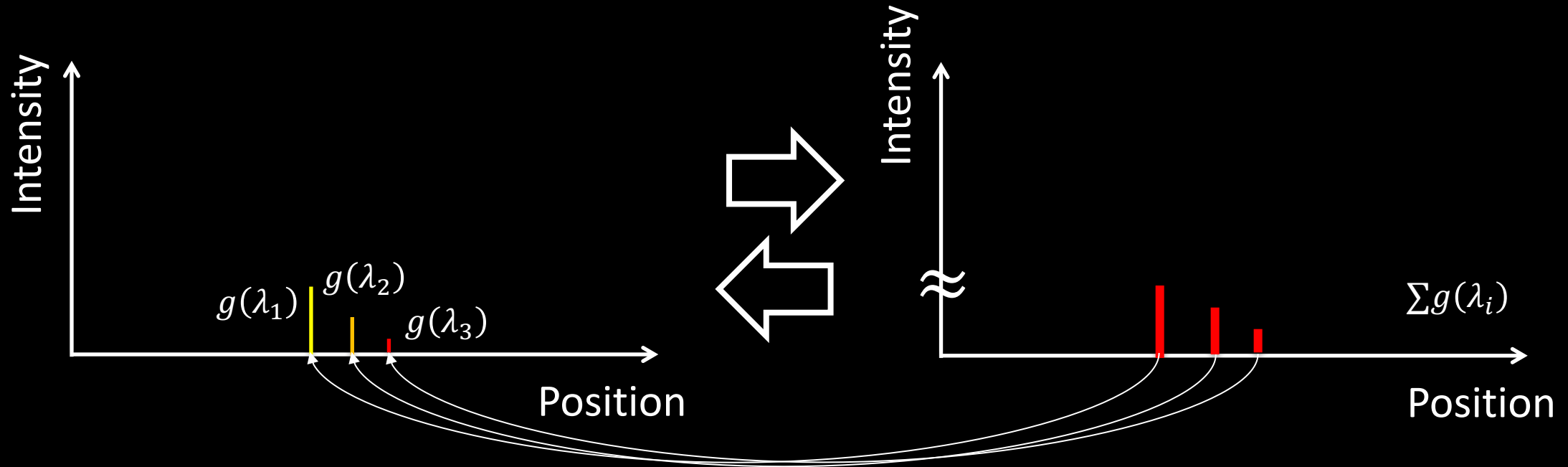
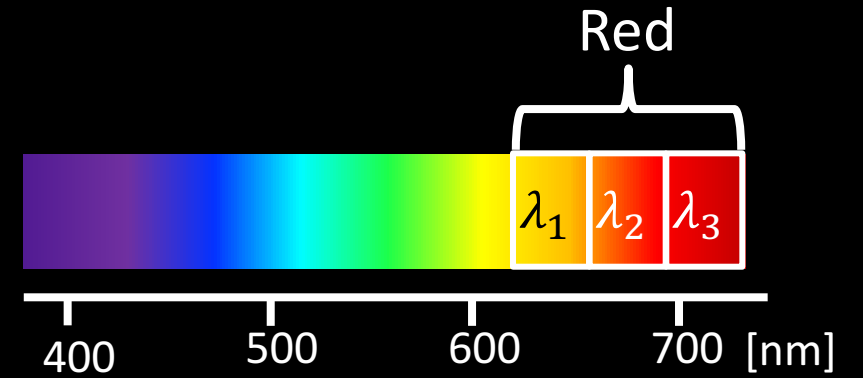


- For edge regions, there could be many solutions which give the same observation

# Gradient Domain

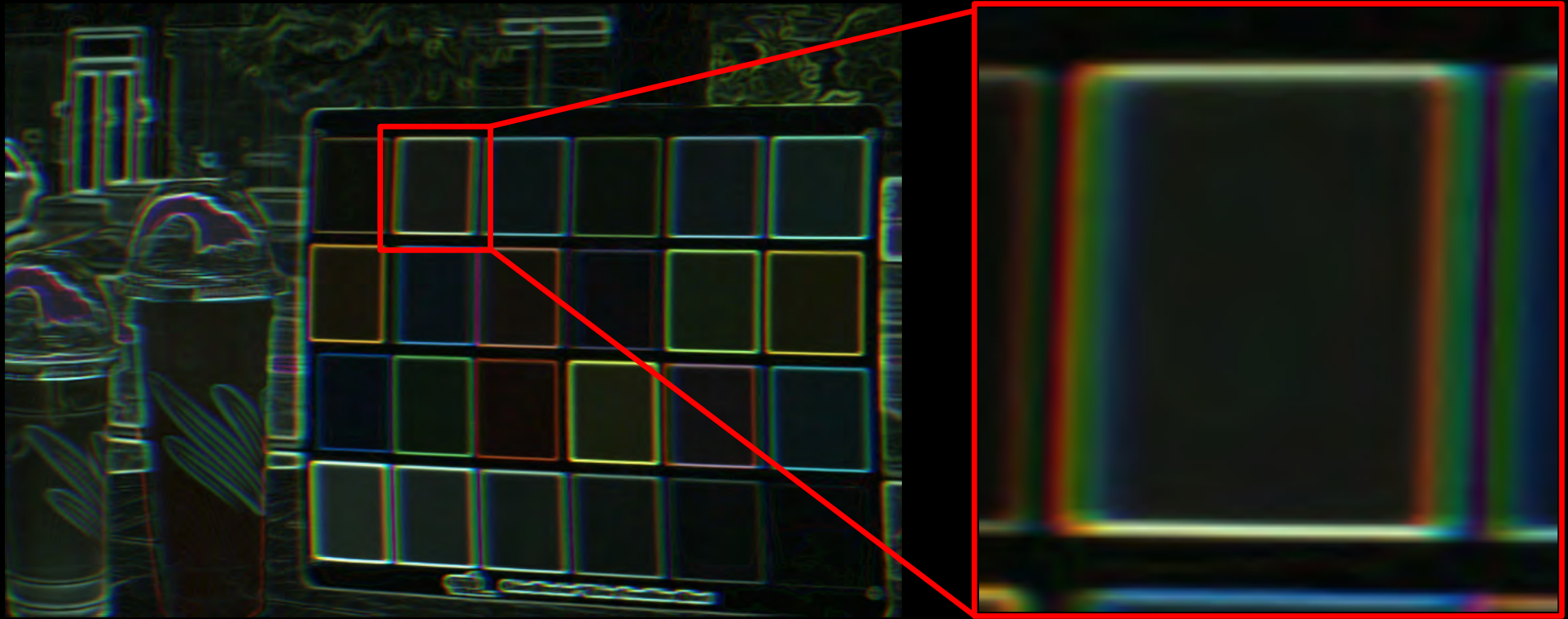


With dispersion



- For edge regions, we can mitigate ill-posedness in the gradient domain

# Edges and Gradient Domain



1. Reduce the region of interests on the pixels around edges
2. Solve the problem in the gradient domain



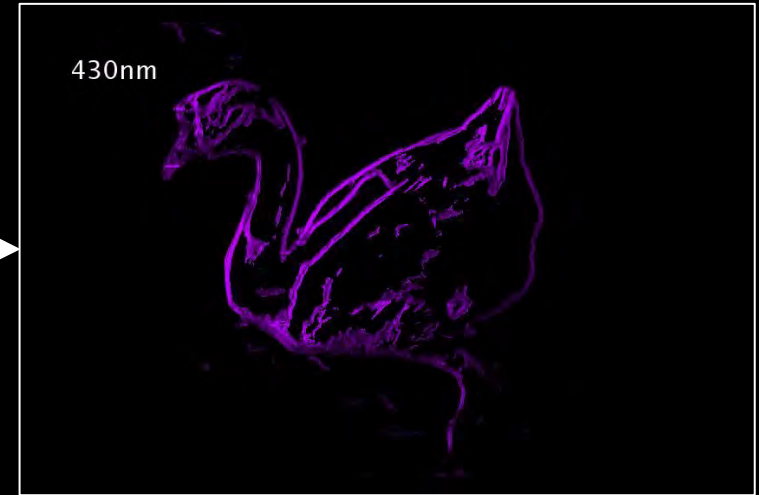
# Workflow



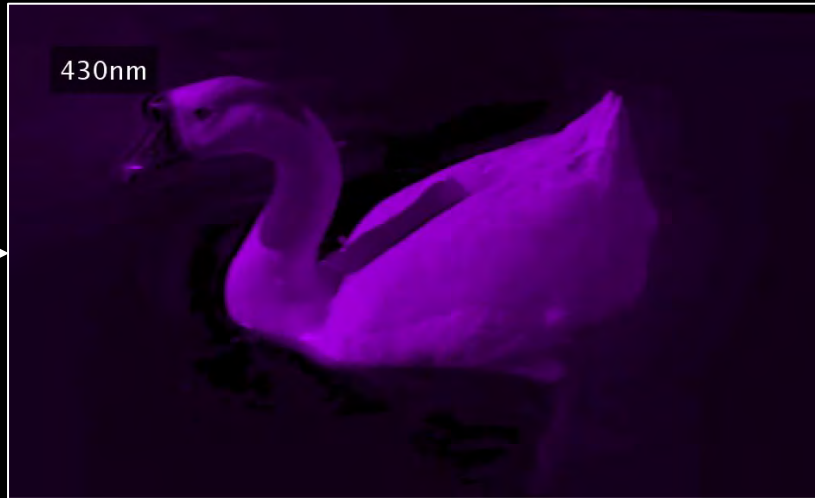
Input



Edge restoration



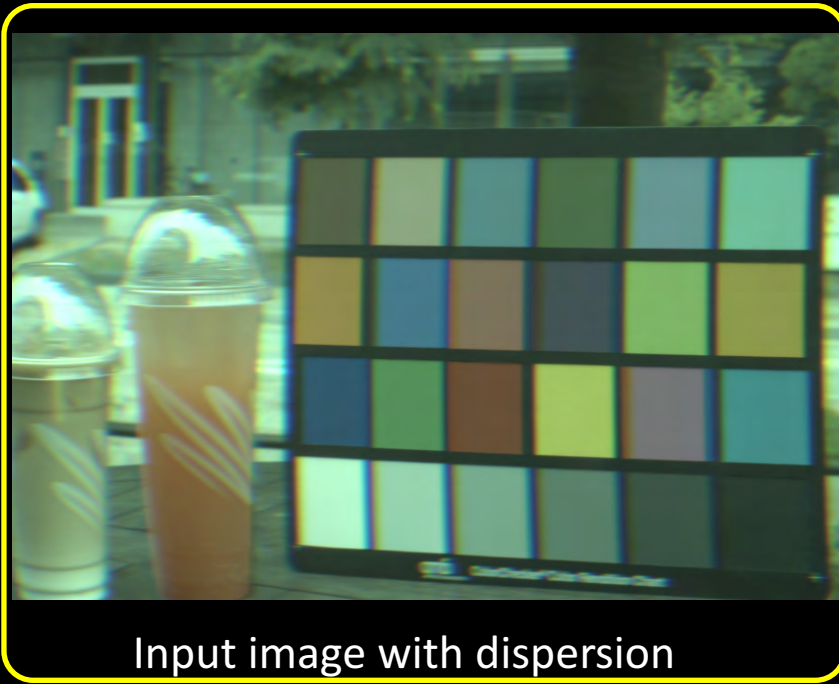
Spectrum in the gradient domain



Spectrum estimation in the intensity domain

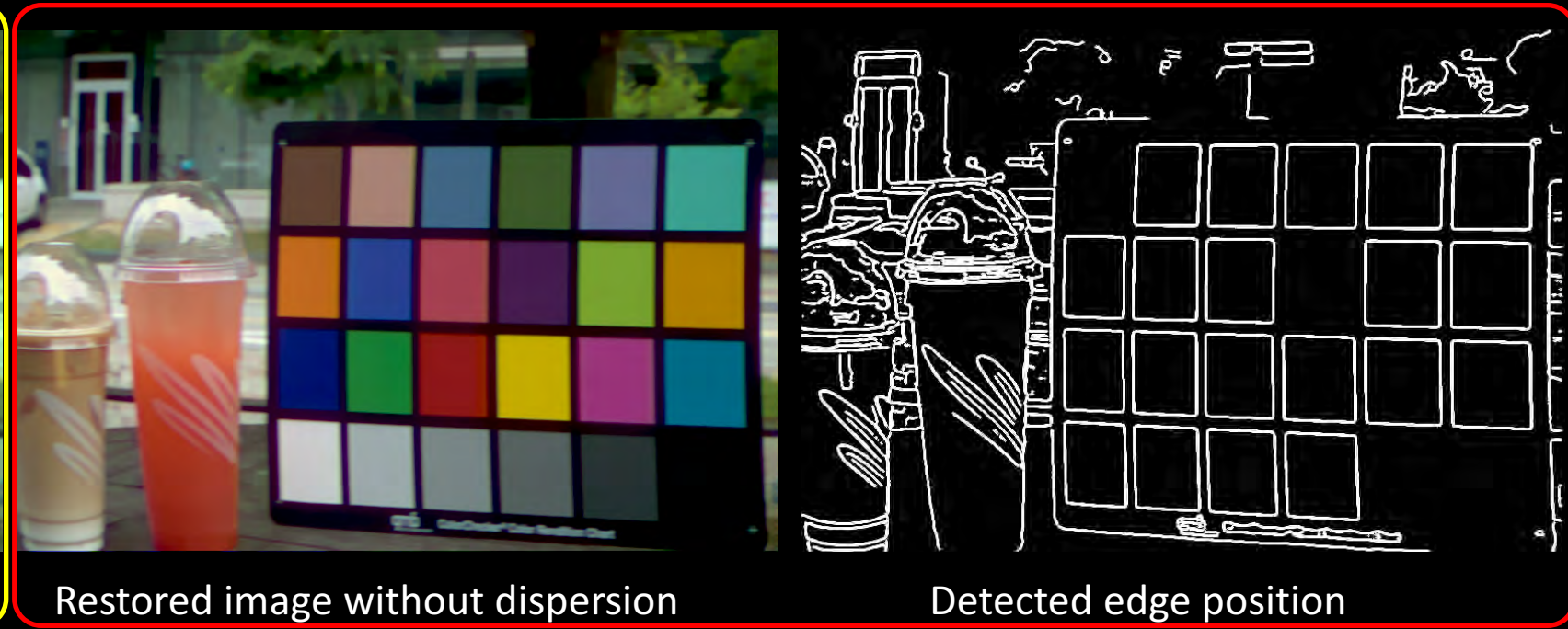
# Edge Restoration for Detecting Region of Interests

Input



Input image with dispersion

Output



Restored image without dispersion

Detected edge position

$$\mathbf{i}_{\text{aligned}} = \arg \min_{\mathbf{i}} \left\| \underbrace{\Omega \Phi \mathbf{i}}_{\text{Data term}} - \mathbf{j} \right\|_2^2$$

Data term

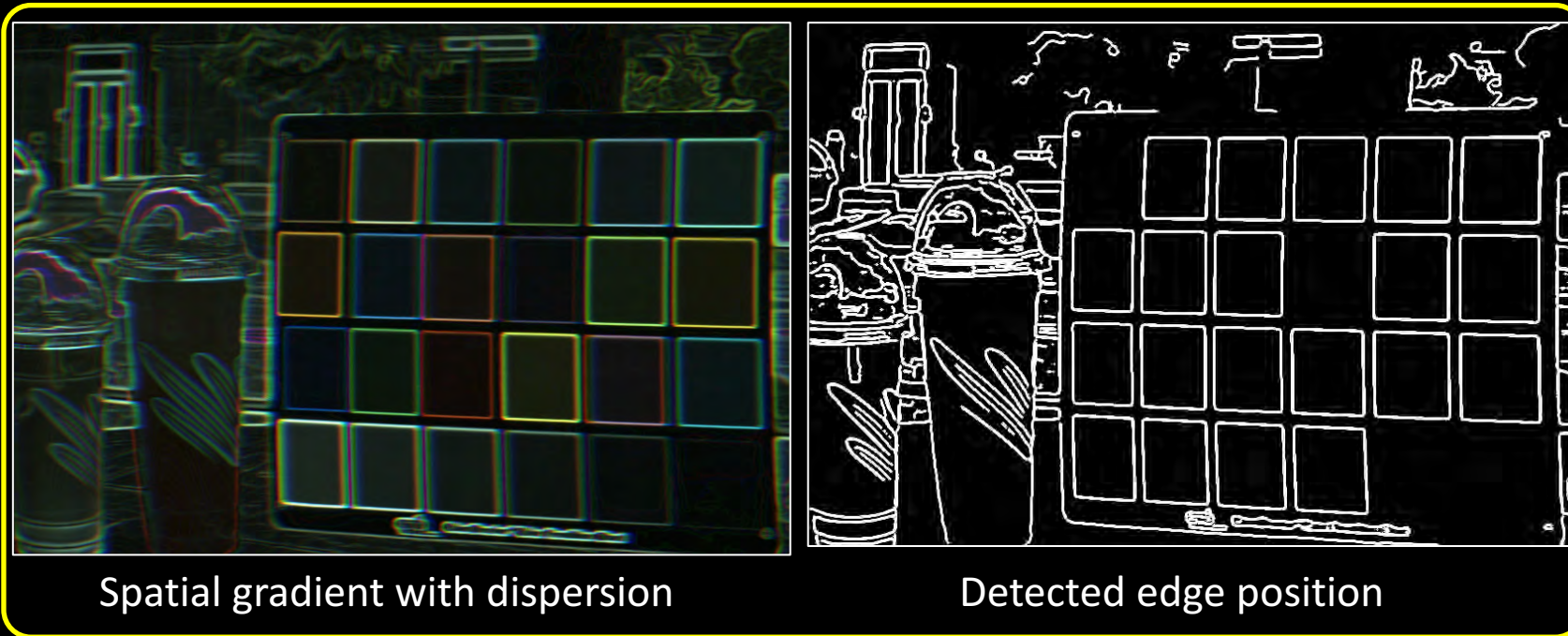
TV prior

Cross-channel prior

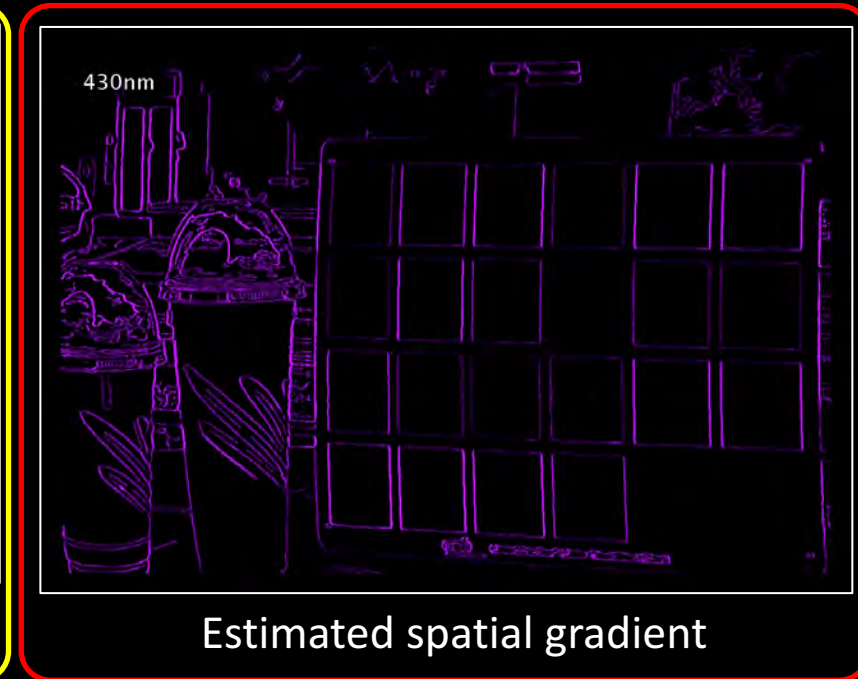
- Remove dispersion around edges
- Cross-channel prior  $\rightarrow$  image without dispersion

# Gradient Reconstruction

Input



Output



$$\hat{\mathbf{g}}_{xy} = \arg \min_{\mathbf{g}_{xy}} \left\| \underbrace{\Omega \Phi}_{\text{Data term in the gradient domain}} \mathbf{g}_{xy} - \underbrace{\nabla_{xy} \mathbf{j}}_{\text{Spectral sparsity of the spatial gradient}} \right\|_2^2$$

Data term  
in the gradient domain

Spectral sparsity of  
the spatial gradient

Smoothness of  
the spatial gradient

- Estimate spatial gradient which explains the dispersion best
- Restrict reconstruction on the edge pixels only

# Reconstructing the Spectral Images

Input

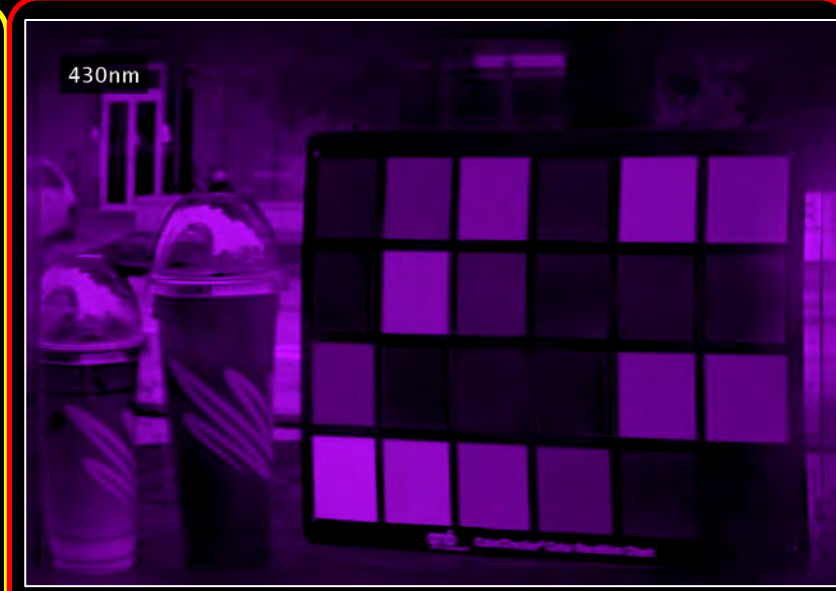


Input image with dispersion



Estimated spatial gradient

Output



Hyperspectral image

$$\mathbf{i}_{\text{opt}} = \arg \min_{\mathbf{i}} \left\| \Omega \Phi \mathbf{i} - \mathbf{j} \right\|_2^2$$

Intensity data term

Gradient data term

Smoothness of  
the spectral curvature

- Gradient-aided hyperspectral reconstruction

# Reconstruction Summary

Edge Restoration

```
graph TD; A[Edge Restoration] --> B[Spectral Gradient Reconstruction]; B --> C[Spectral Image Reconstruction];
```

Spectral Gradient Reconstruction

Spectral Image Reconstruction

# RESULTS

# Real Scene with a ColorChecker

Input

Output



Input

Reconstructed spectral images

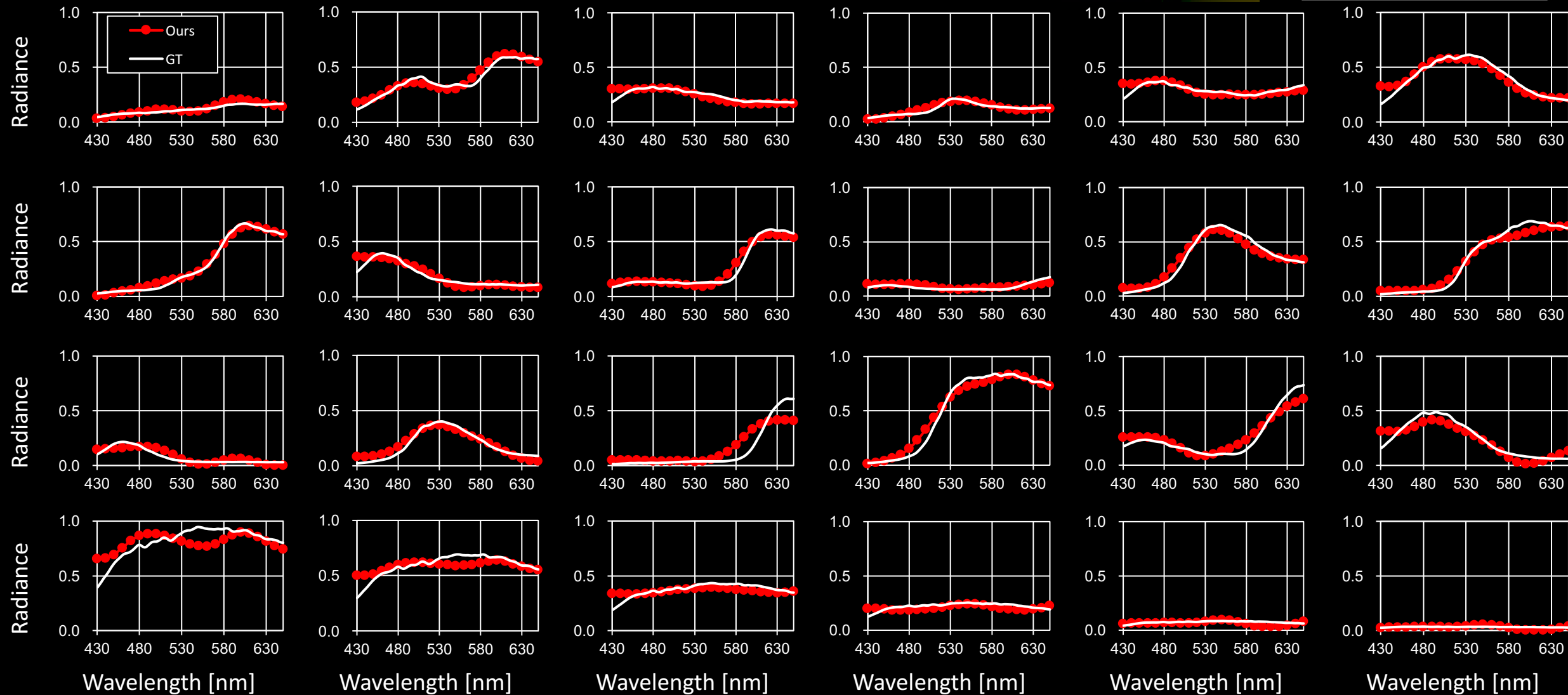
Reconstructed sRGB

- Ground-truth spectrum is measured for each color patch using a spectro-radiometer

# Reconstruction vs. Ground truth

(Red)

(White)





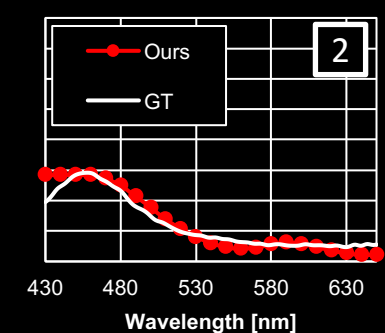
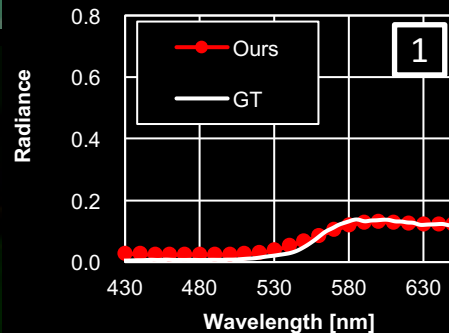
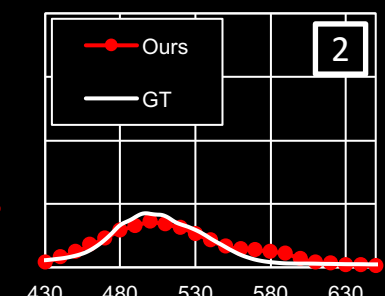
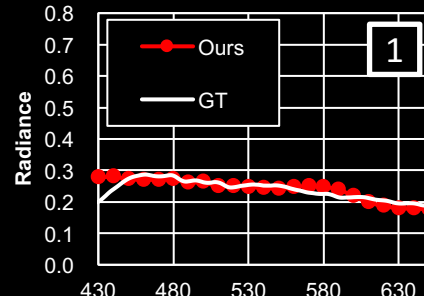
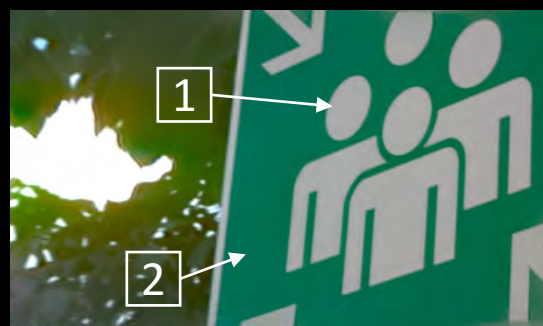
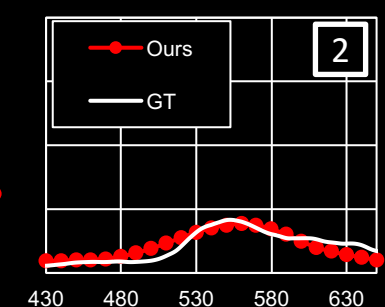
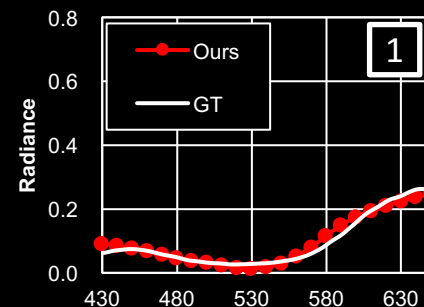
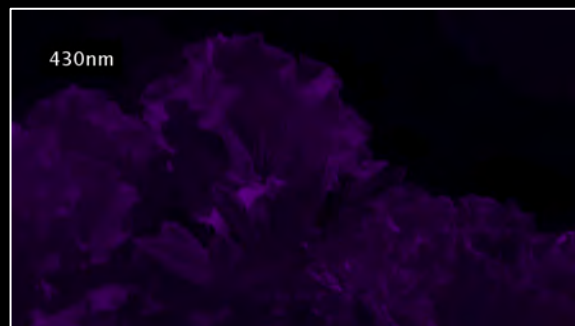
# Results on Various Scenes

Input

Each spectral channel

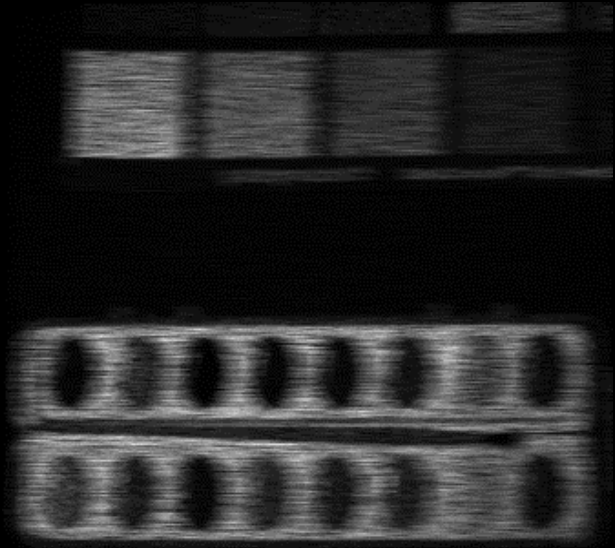
Reconstructed sRGB

Spectral power distribution

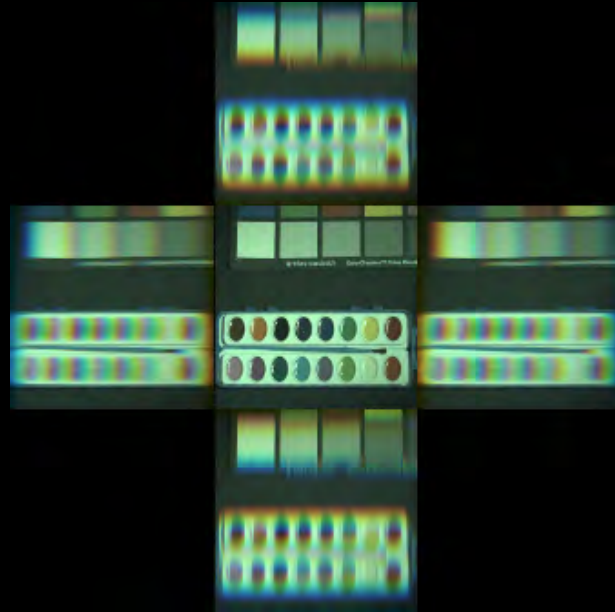


# Comparison with Other Hyperspectral Imaging Systems

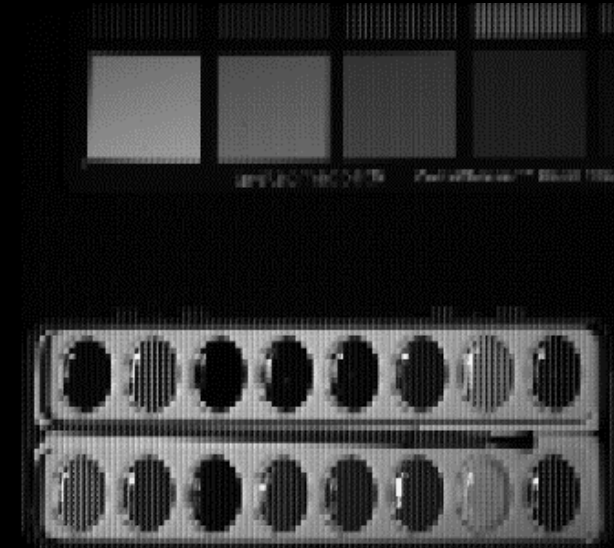
CASSI



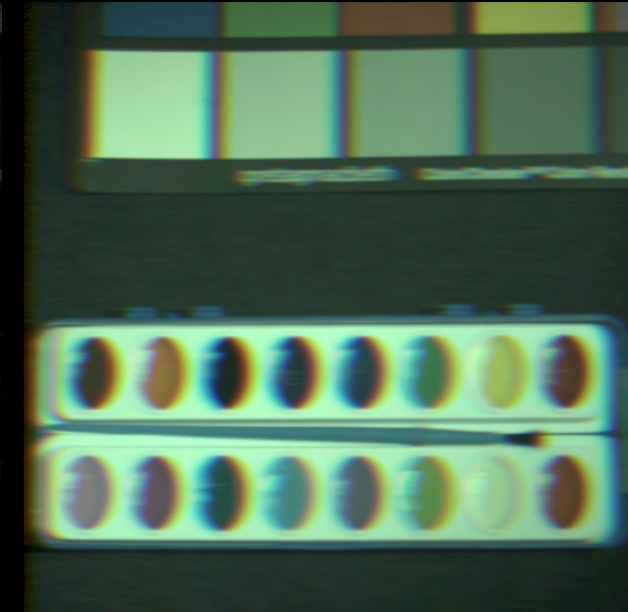
CTIS



PMVIS



Ours



# Comparison with Other Hyperspectral Imaging Systems

CASSI



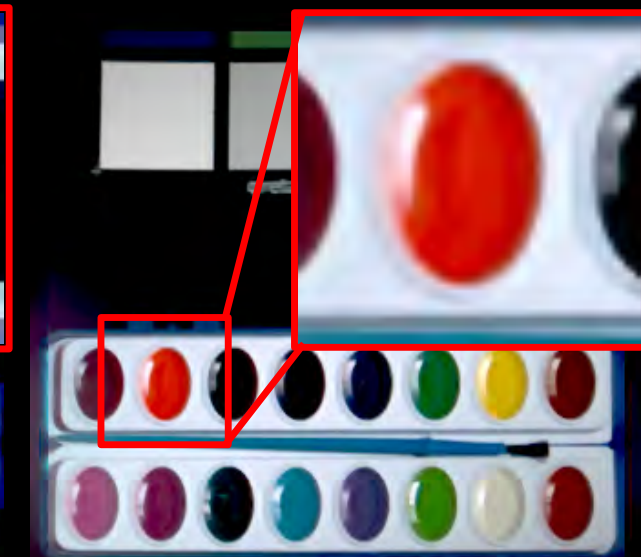
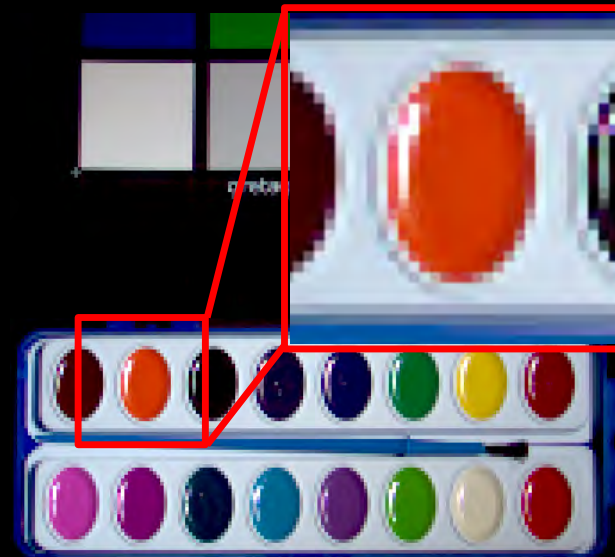
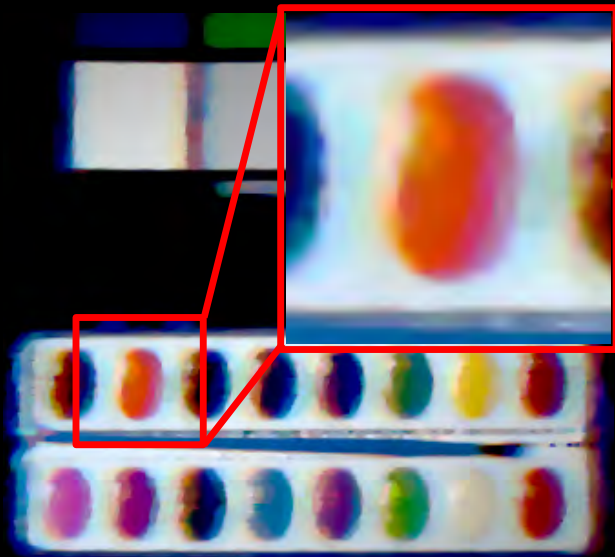
CTIS



PMVIS



Ours



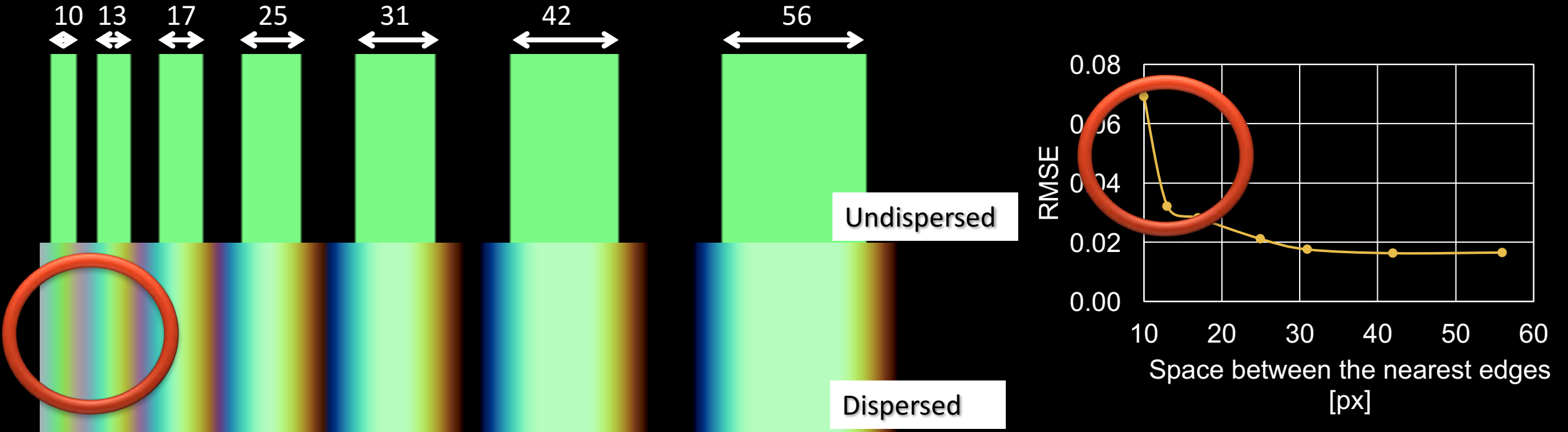
PSNR: 22.99dB/ SSIM: 0.82

PSNR: 24.41dB/ SSIM: 0.70

PSNR: 19.98dB/ SSIM: 0.73

**PSNR: 27.63dB/ SSIM: 0.88**

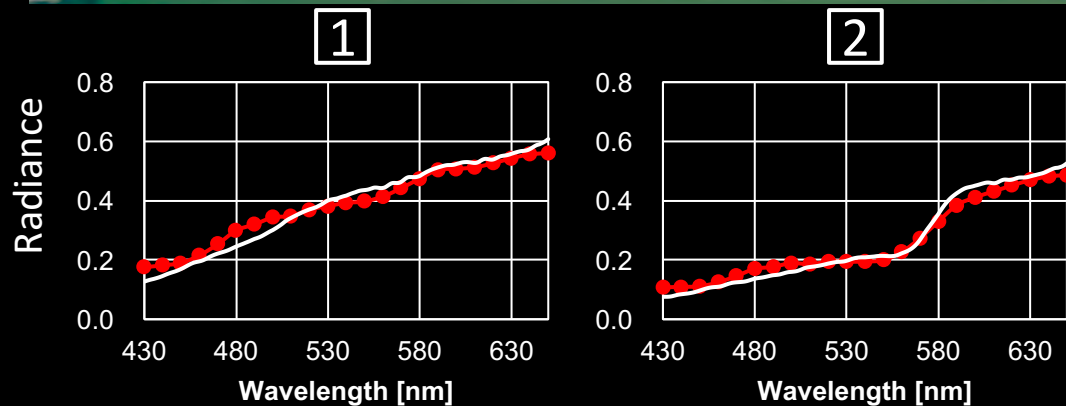
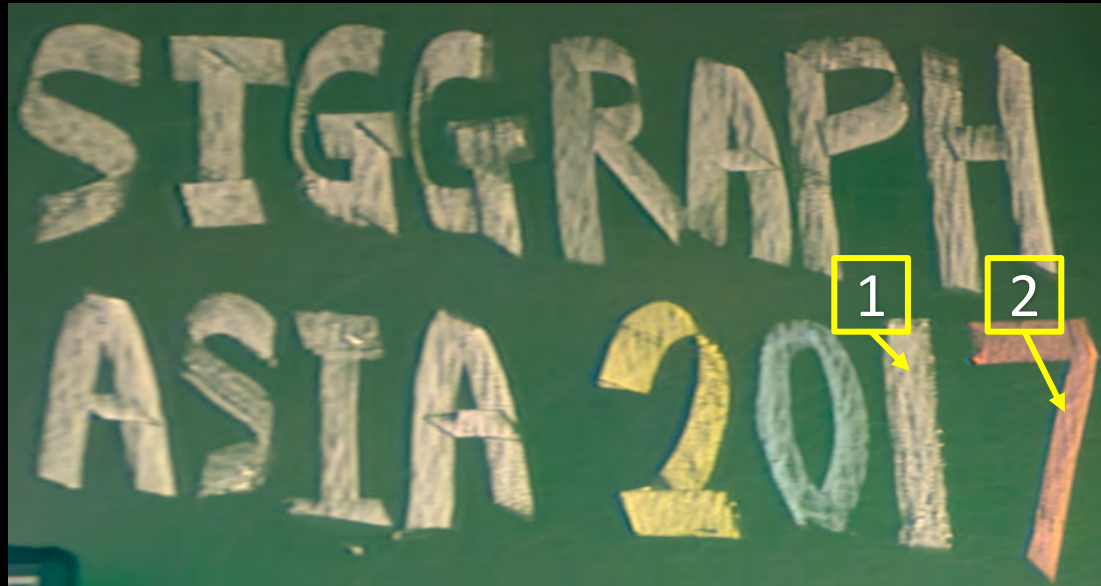
# Limitations: High-frequency Spatial Structures



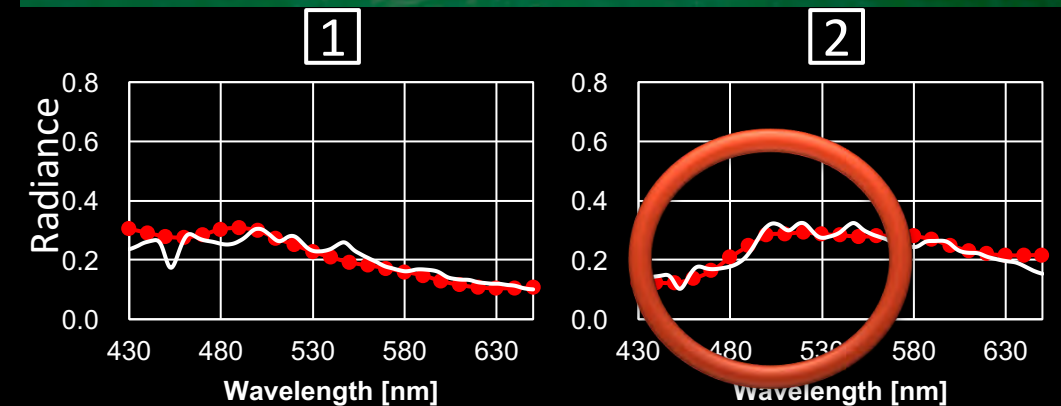
- Reconstruction accuracy degrades severely when the dispersion profiles of neighboring edges become overlapped

# Limitations: High-frequency Spectral Information

Tungsten light



Xenon light



- Our method cannot capture the high-frequency spectral details

# Future Work

- Reconstruction algorithm for various edge structures
  - Deep priors for hyperspectral images
- Depth from dispersion
  - Estimate depth from dispersion
- Integration with CTIS
  - Better reconstruction algorithm for CTIS

# Compact Single-Shot Hyperspectral Imaging using a Prism

Seung-Hwan Baek

Incheol Kim

Diego Gutierrez

Min H. Kim



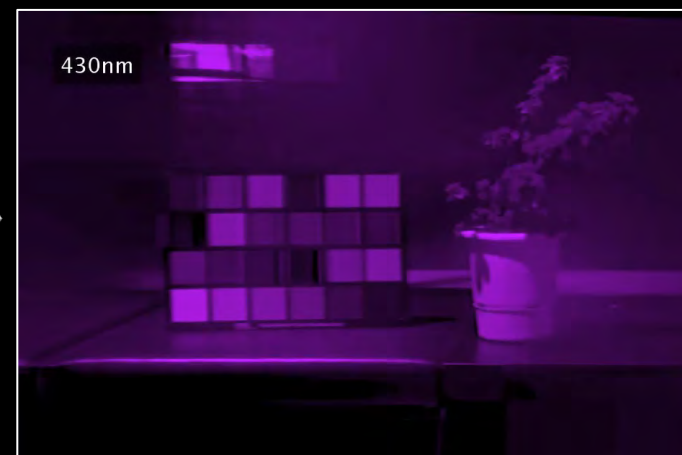
Simple camera setup

+

Dispersion modeling

Reconstruction algorithm

Computational method



Hyperspectral image

## Acknowledgements

- VCLAB members, Adrian Jarabo, Belen Masia and anonymous reviewers