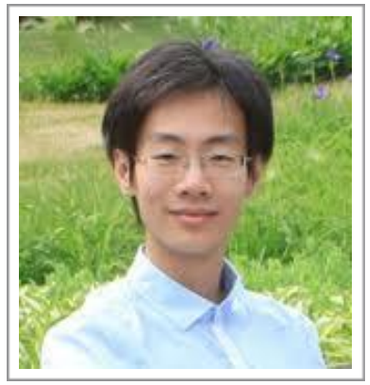
From Pixels to Physics

Probabilistic color de-rendering



Ying Xiong

Kate Saenko

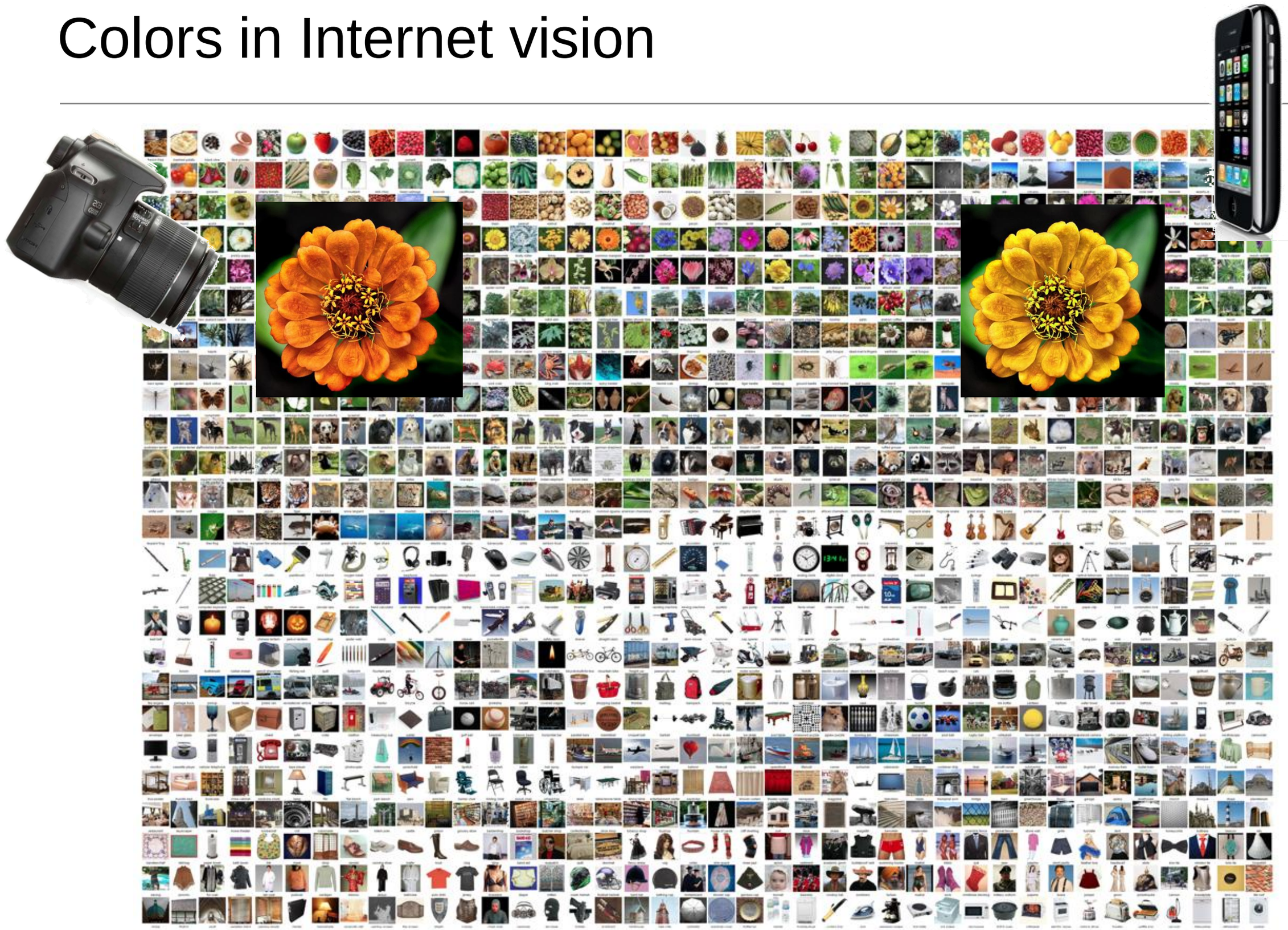
Trevor Darrell

Todd Zickler

Harvard University

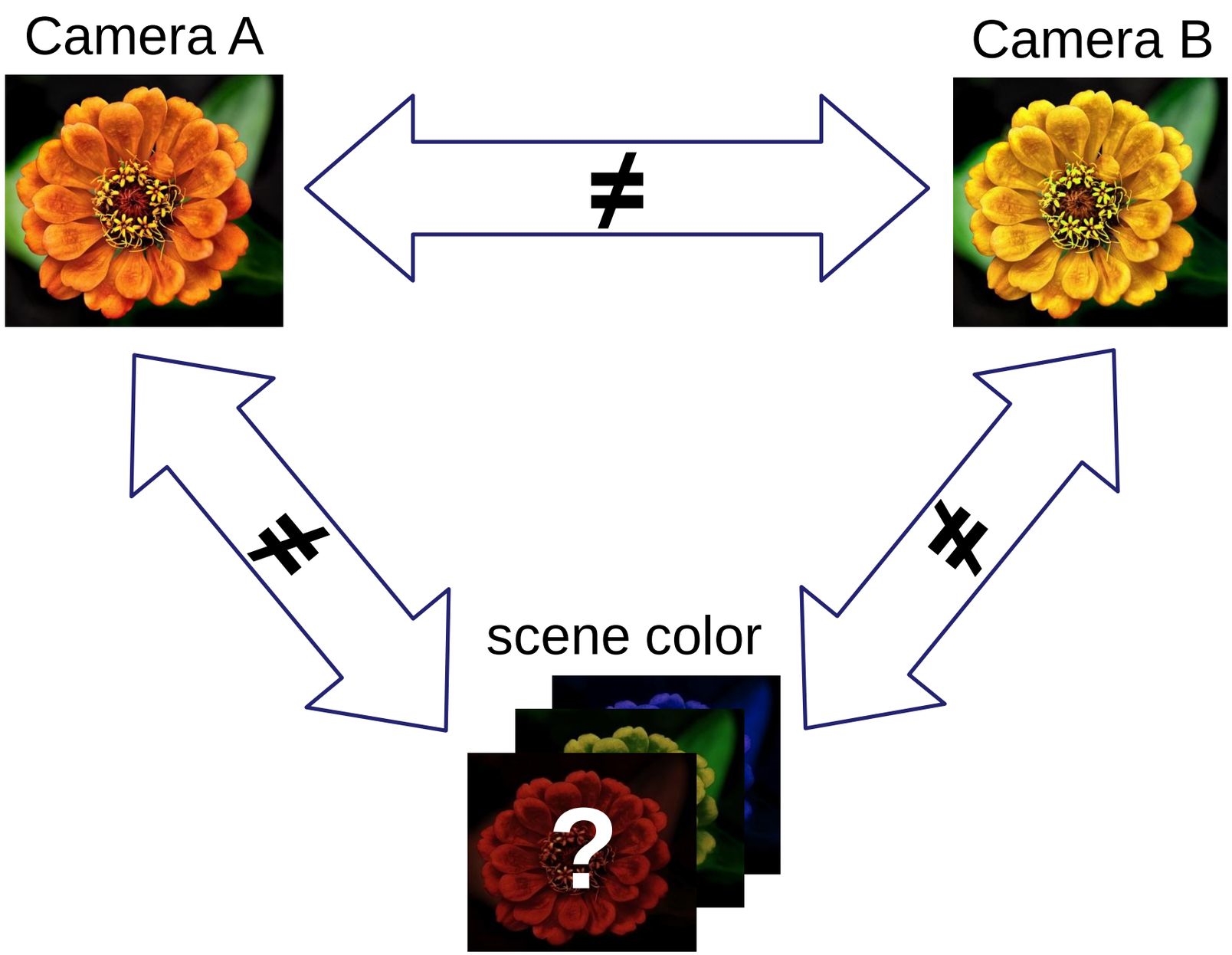
University of California, Berkeley

Colors in Internet vision



Photos courtesy of ImageNet

Colors in Internet vision



An approach: probabilistic derendering

JPG

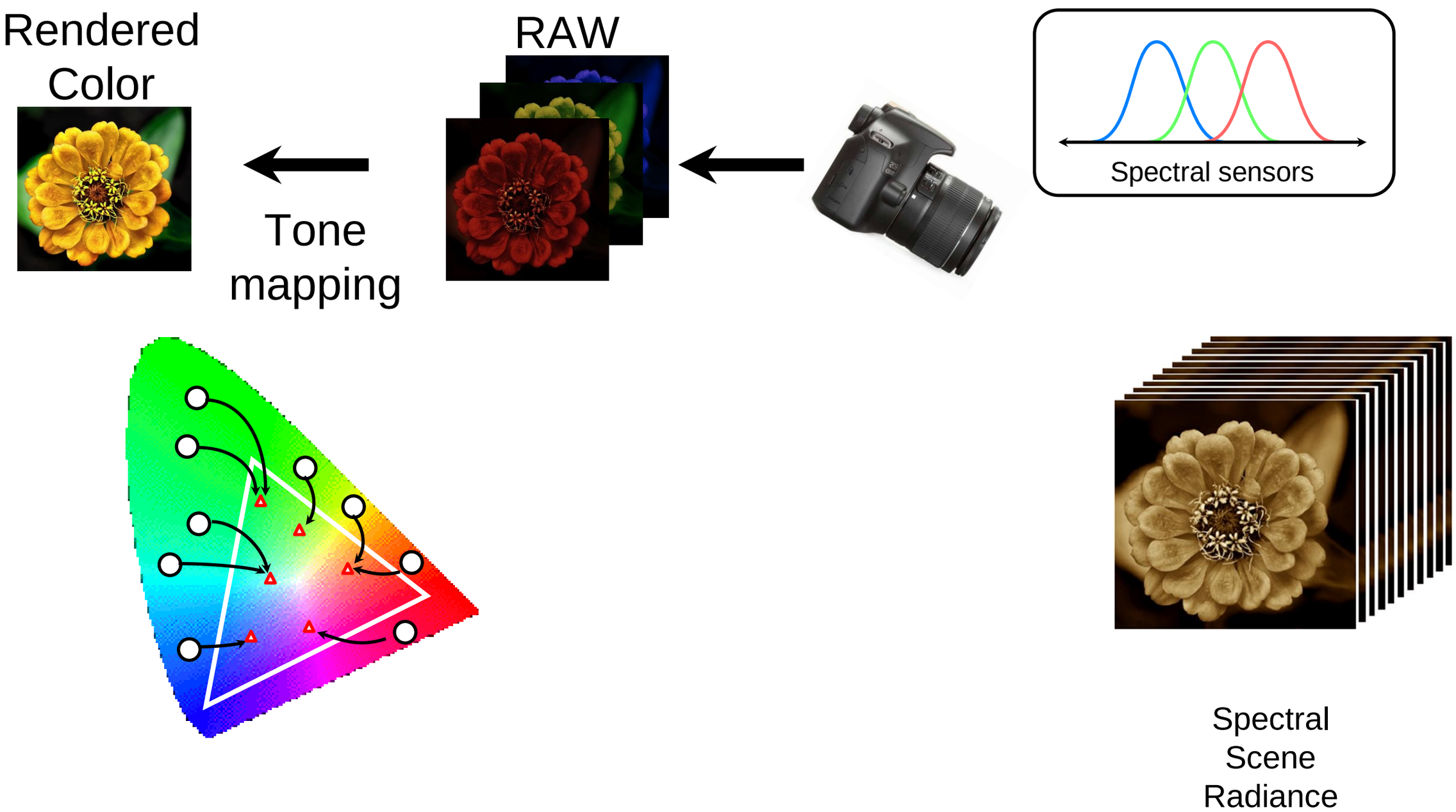
rendered color values (ignoring compression artifacts)

scene color

$p\Big($  $\Big)$

values linearly proportional to physical scene colors

Problem: tone mapping is many-to-one

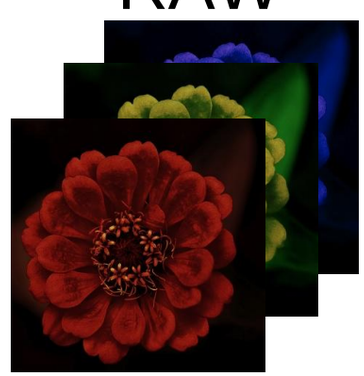


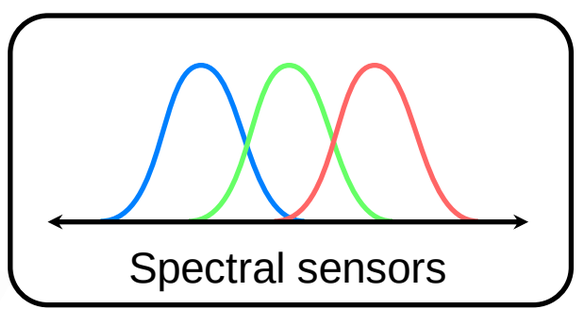
Problem: tone mapping is many-to-one

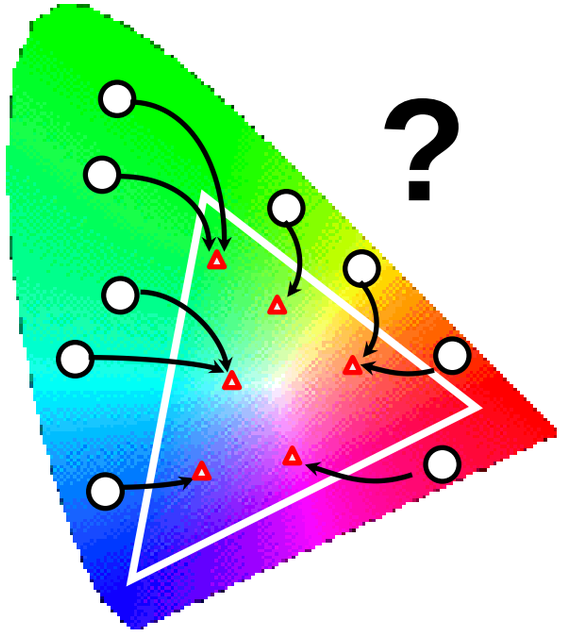
Rendered Color

Tone mapping

RAW







A Standard Default Color Space for the Internet - sRGB

Michael Stokes (Hewlett-Packard), Matthew Anderson (Microsoft),

Srinivasan Chandrasekar (Microsoft), Ricardo Motta (Hewlett-Packard)

Version 1.10, November 5, 1996

Introduction

Hewlett-Packard and Microsoft propose the addition of support for a standard color space, sRGB, within the Microsoft operating systems, HP products, the Internet, and all other interested vendors. The aim of this color space is to complement the current color management strategies by enabling a third method of handling color in the operating systems, device drivers

Problem: tone mapping is many-to-one

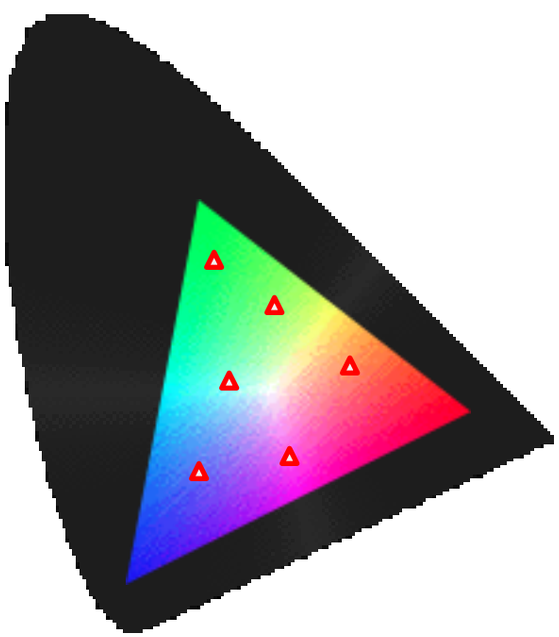
Our approach

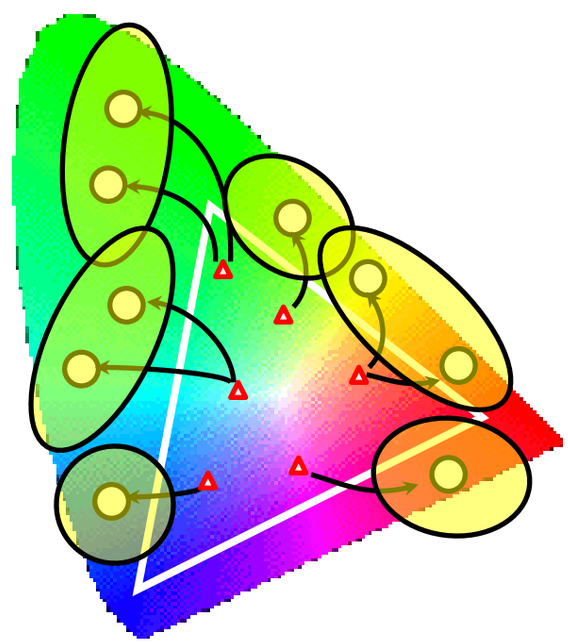
Rendered Color

De-rendering

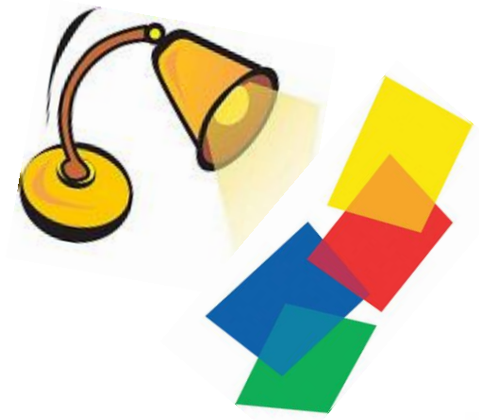
RAW

$p($  $)$





Some data



RAW $\mathbf{x}$ ←

JPEG $\mathbf{y}$ ←

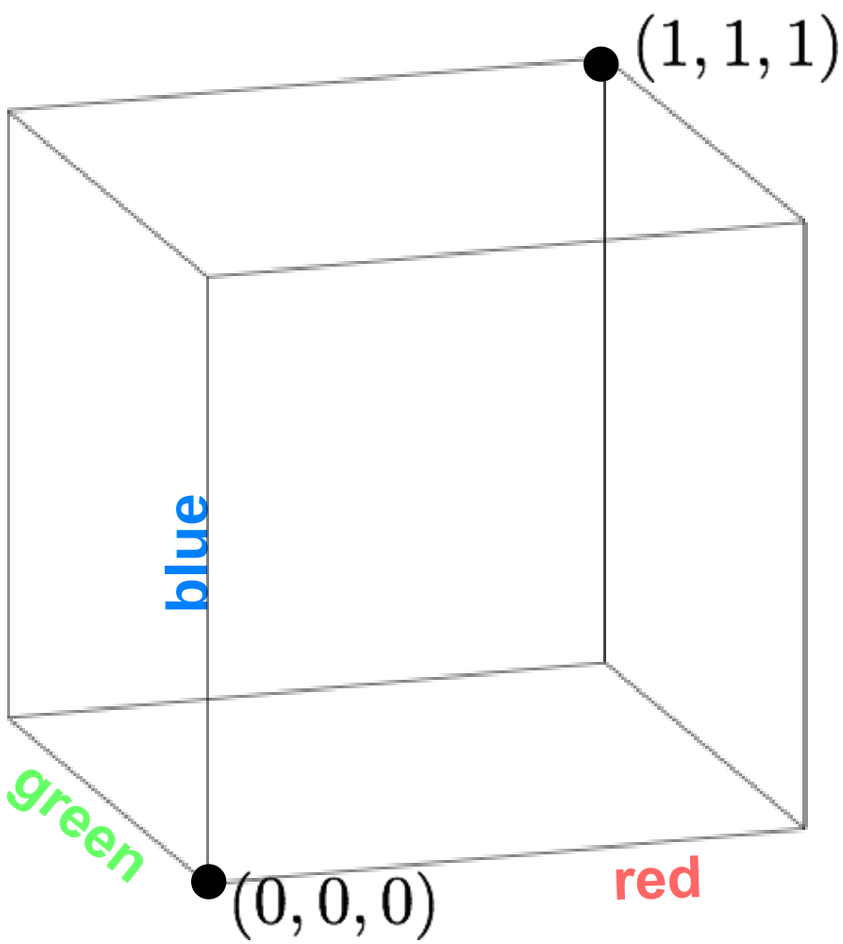
Panasonic DMC-LX3

Some data

RAW ←

JPEG ←

Panasonic DMC-LX3



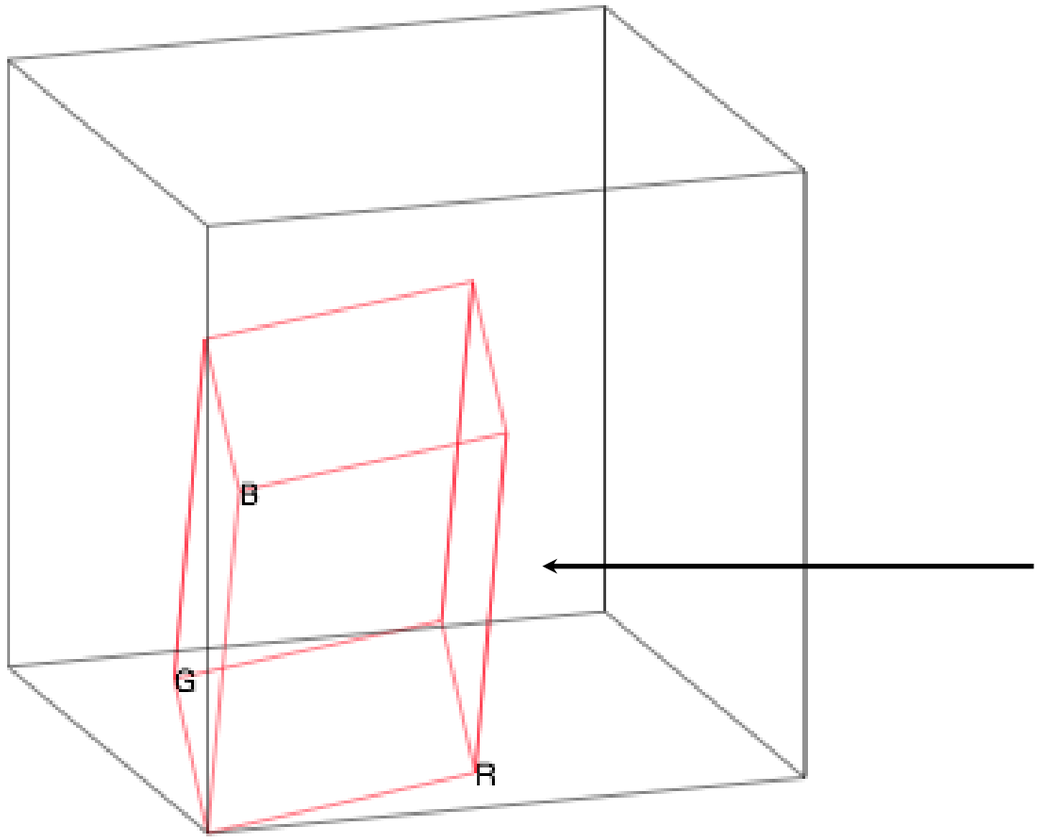
← Possible RAW colors

Some data

RAW ←

JPEG ←

Panasonic DMC-LX3



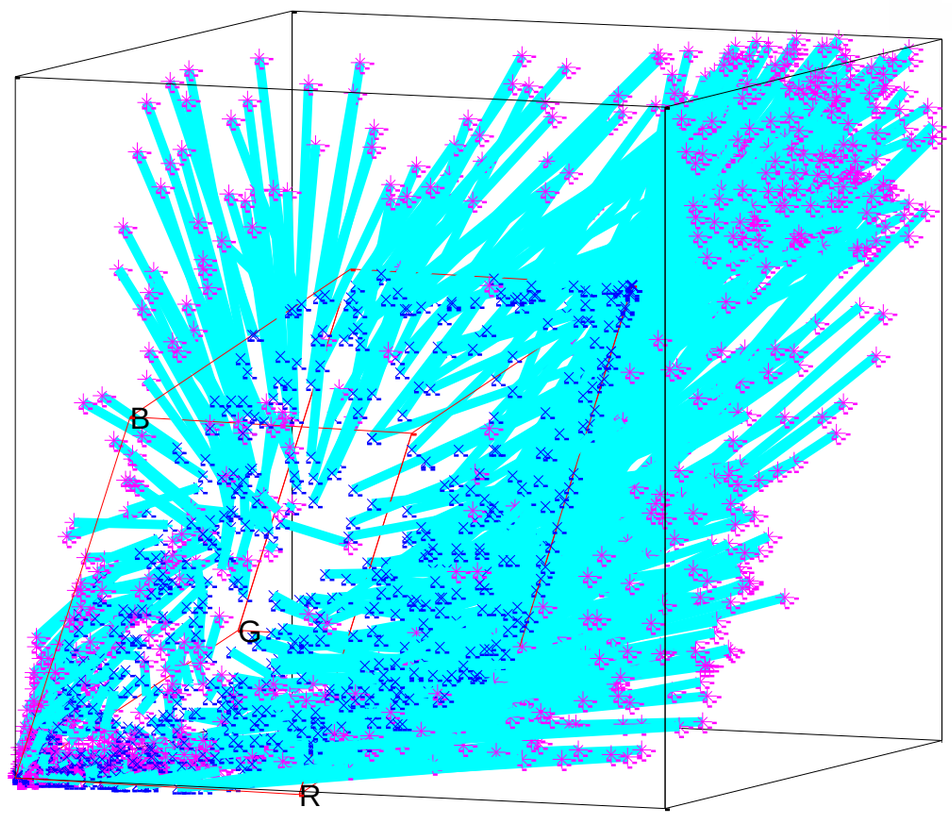
sRGB output gamut

Some data

RAW ←

JPEG ←

Panasonic DMC-LX3

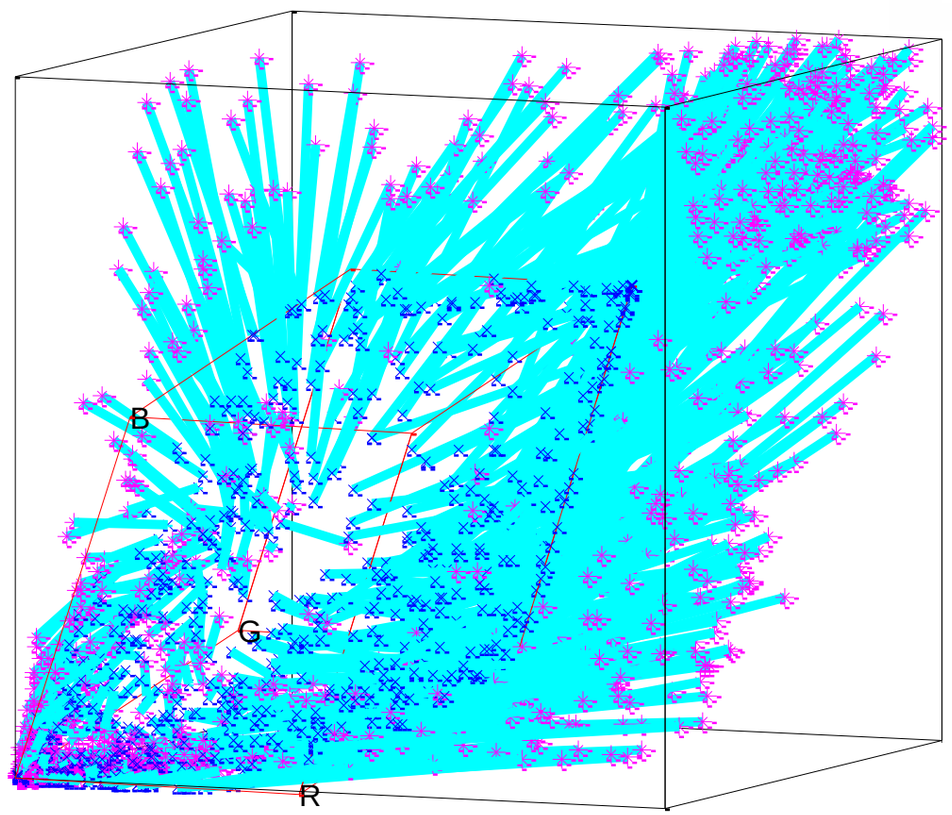


Some data

RAW ←

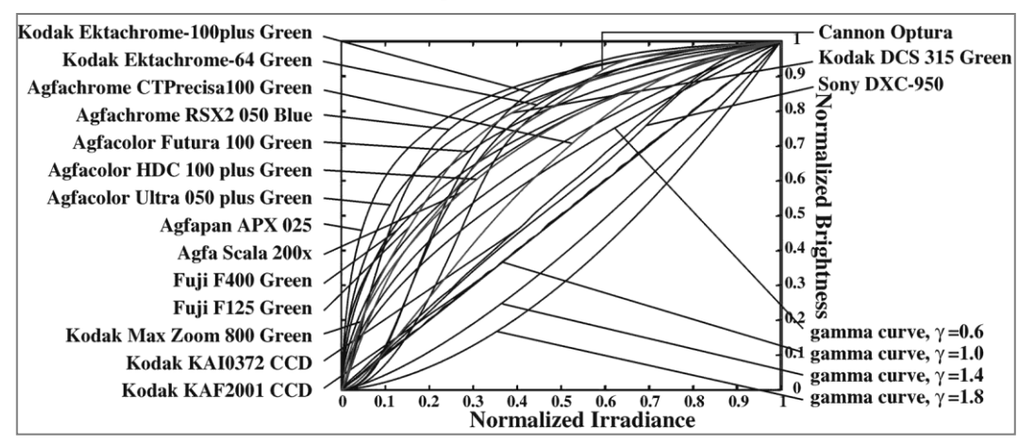
JPEG ←

Panasonic DMC-LX3



Related Work:

Per-channel
"radiometric response functions"



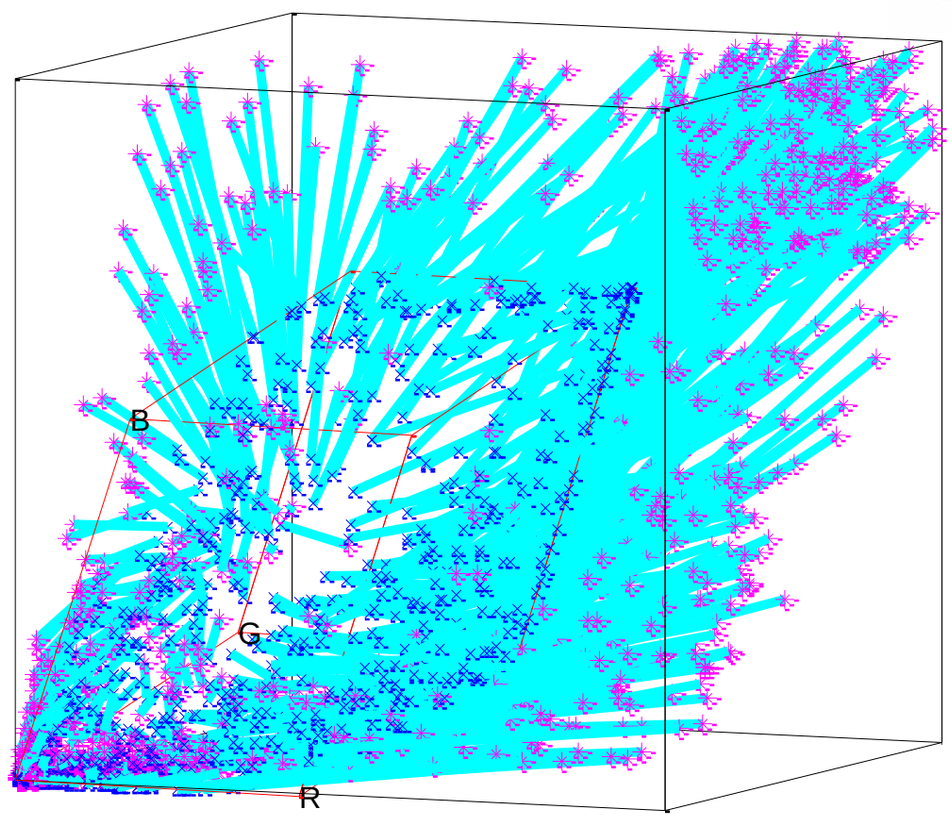
[Mann & Picard, 1995; Debevec & Malik, 1997; Mitsunaga & Nayar, 1999; Grossberg & Nayar, 2004; Pal et al., 2004; …]

Some data

RAW ←

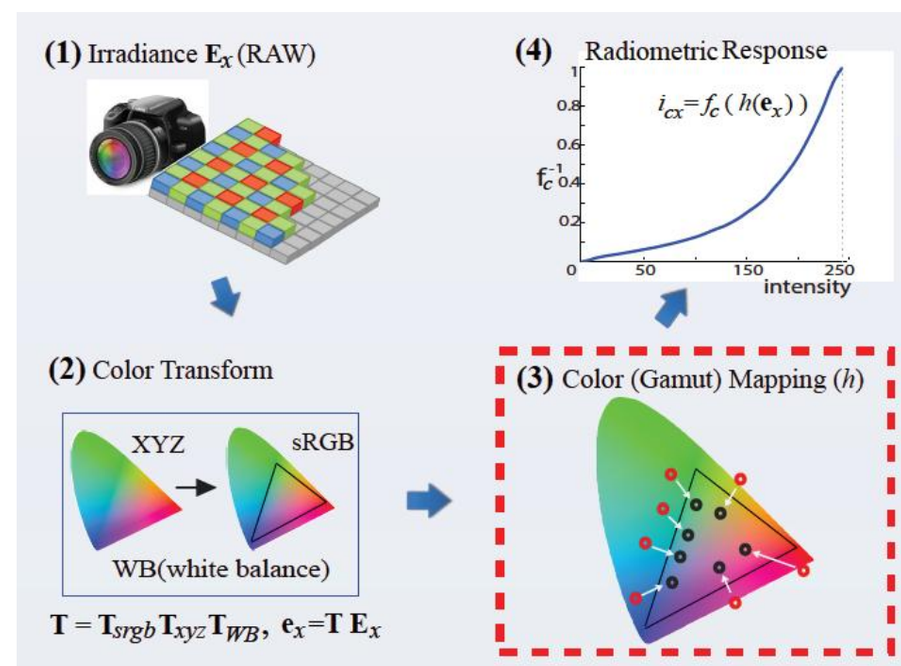
JPEG ←

Panasonic DMC-LX3



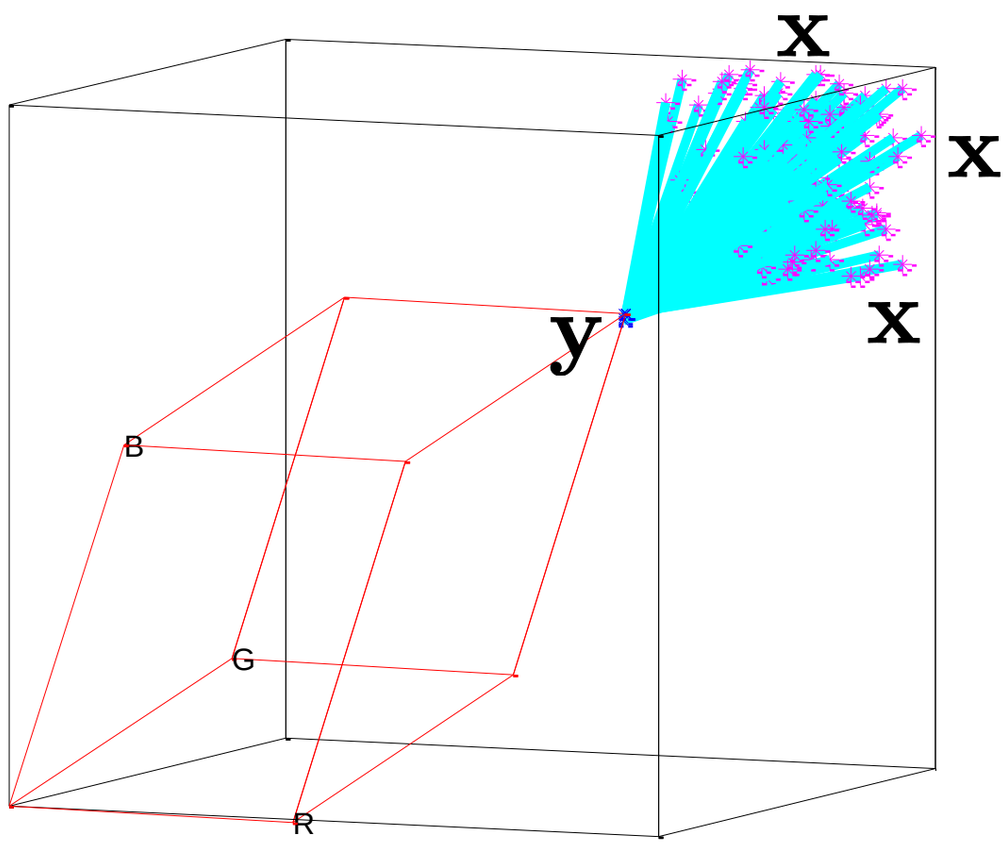
Related Work:

Cross-channel deterministic maps

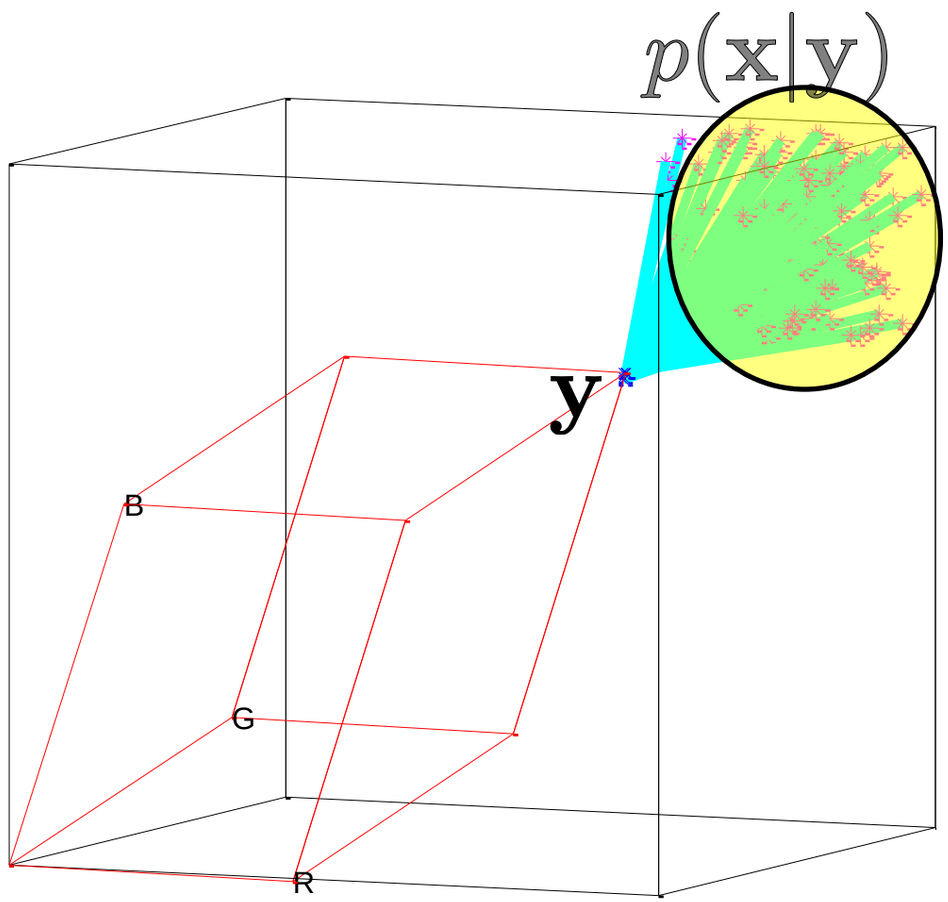


[Chakrabarti et al, 2009; Lin et al., 2011]

Our approach: local GP regression



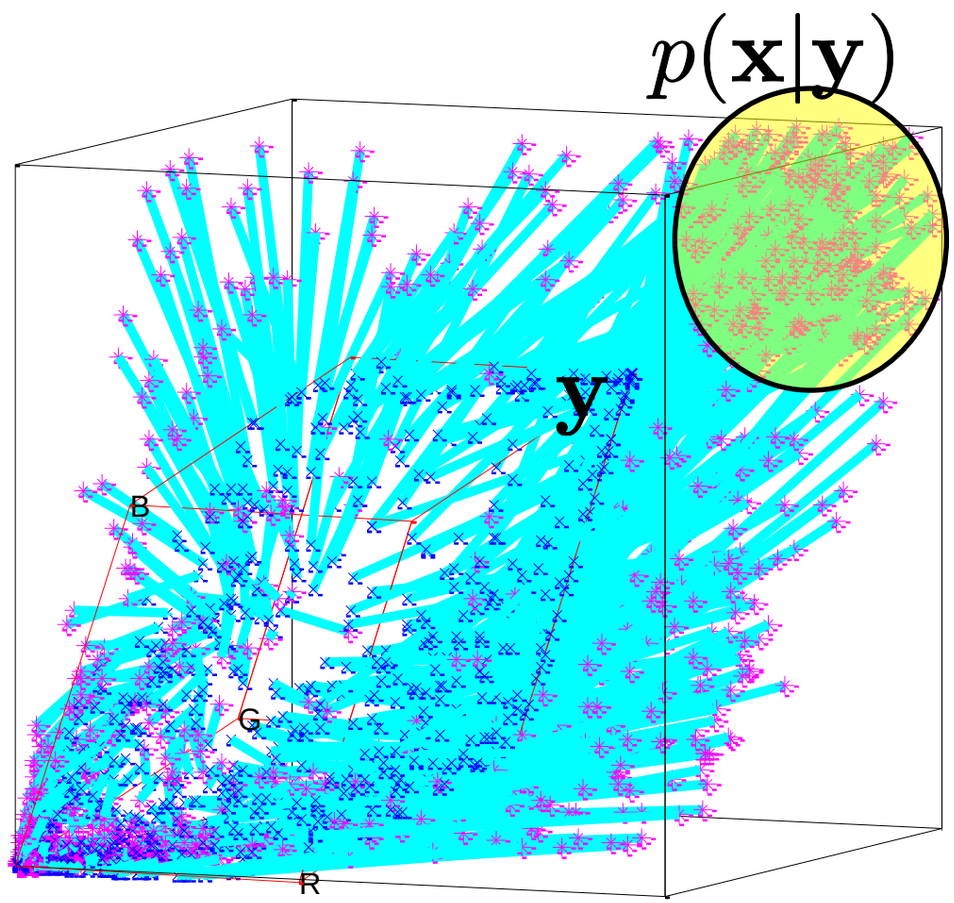
Our approach: local GP regression



Our approach: local GP regression

Training set:

$$\mathcal{D} = \{(\mathbf{x}_i, \mathbf{y}_i), i = 1 \ldots N\}$$



$$\mathbb{R}^1 \longleftarrow \mathbb{R}^3$$

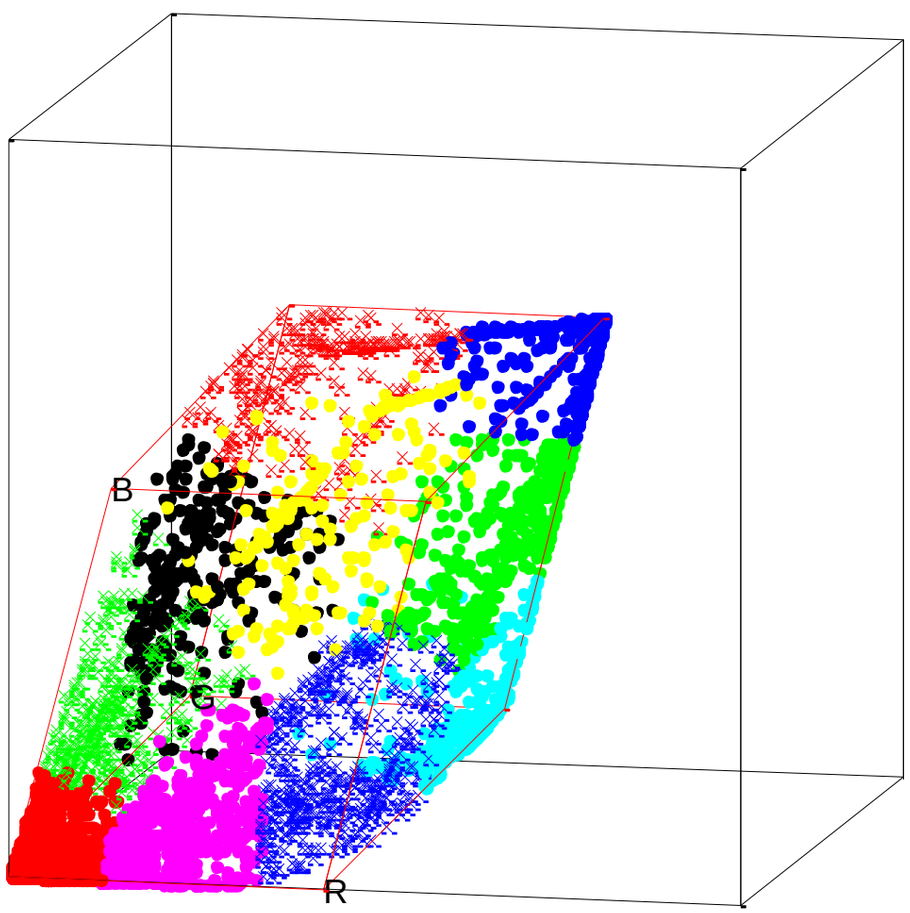
$$x_i^{\mathrm{red}} = z^{\mathrm{red}}(\mathbf{y}_i) + \epsilon_i, \quad \epsilon_i \propto \mathcal{N}(0, \sigma^2)$$

$$p(\mathbf{x}|\mathbf{y}) = \prod_{\mathrm{c=r,g,b}} p_{\mathrm{GP}}(x^c|\mathcal{D}, \mathbf{y})$$

Our approach: local GP regression

Training set:

$$\mathcal{D} = \{(\mathbf{x}_i, \mathbf{y}_i), i = 1 \ldots N\}$$



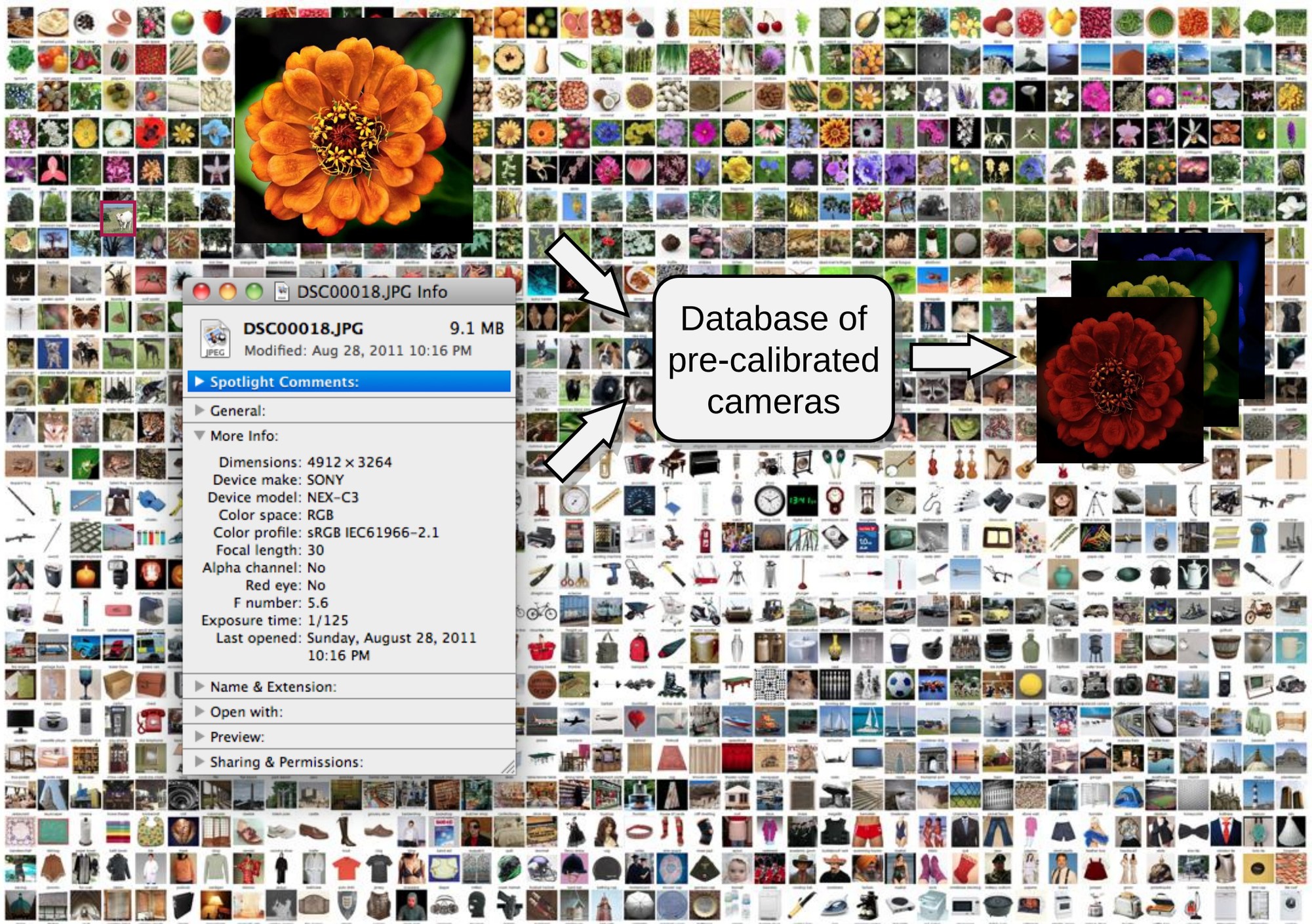
$$\mathbb{R}^1 \longleftarrow \mathbb{R}^3$$

$$x_i^{\text{red}} = z^{\text{red}}(\mathbf{y}_i) + \epsilon_i, \quad \epsilon_i \propto \mathcal{N}(0, \sigma^2)$$

$$p(\mathbf{x}|\mathbf{y}) = \prod_{\text{c=r,g,b}} p_{\text{GP}}(x^c | \mathcal{D}_{N(\mathbf{y})}, \mathbf{y})$$

[Urtasan & Darrell, 2008]
[Rasmussen and Z. Ghahramani, 2002]
[McHutchon and Rasmussen, 2011]

Potential Applications



Potential Applications

Recognition

[Nilsback and Zisserman, 2006]

Intrinsic images

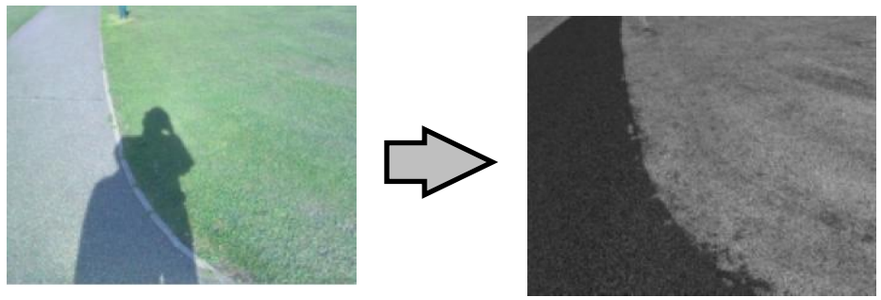
[Sunkavalli et al., 2008]

Deblurring (blind or non-blind)

[Whyte et al., 2011]

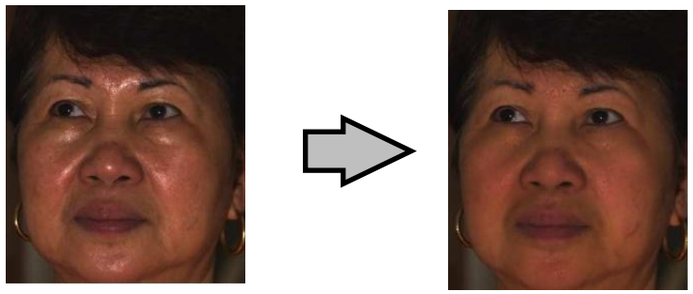
Potential Applications

Shadow removal



[Finlayson et al., 2002]

Glare removal

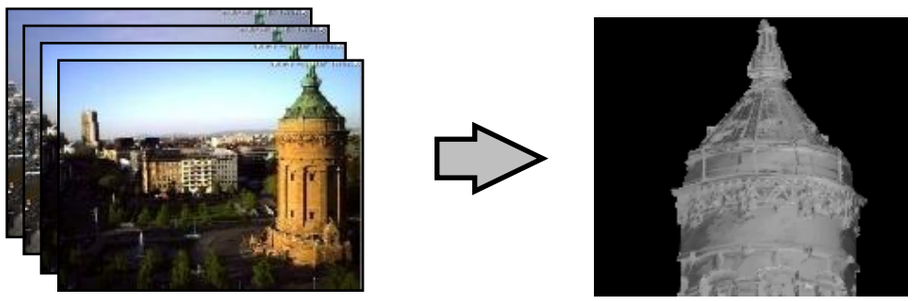


[Mallick et al., 2006]

Multi-exposure HDR imaging

[Debevec and Malik, 1997]

Photometric stereo



[Ackerman et al., 2010]

Probabilistic multi-exposure imaging

Multi-exposure imaging

Conventional approach:
weight all measurements equally

$$\mathbf{x}_0 = \frac{1}{n}\sum_i \frac{\alpha_0}{\alpha_i}\mathbf{x}_i$$
$$= \frac{1}{n}\sum_i \frac{\alpha_0}{\alpha_i} f^{-1}(\mathbf{y}_i)$$

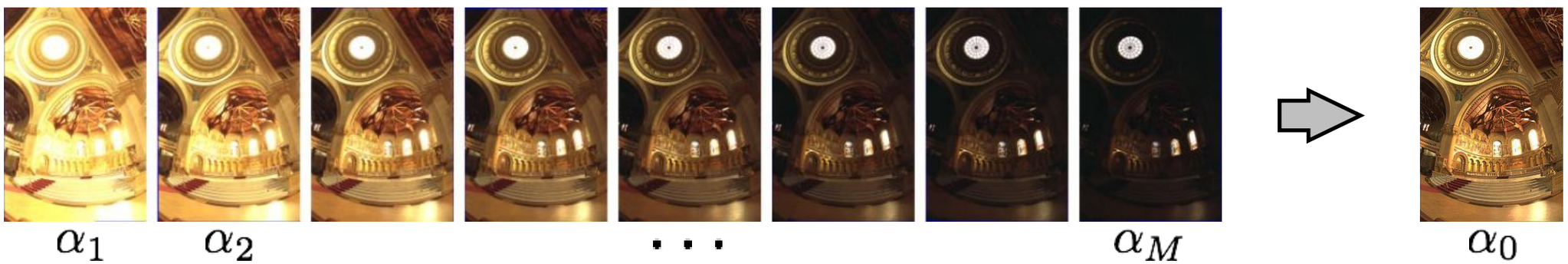
[Debevec and Malic, 1997]
[Mitsunaga and Nayar, 1999]
[Robertson et al. 2003]
……

Probabilistic approach:
combine estimates according to variance

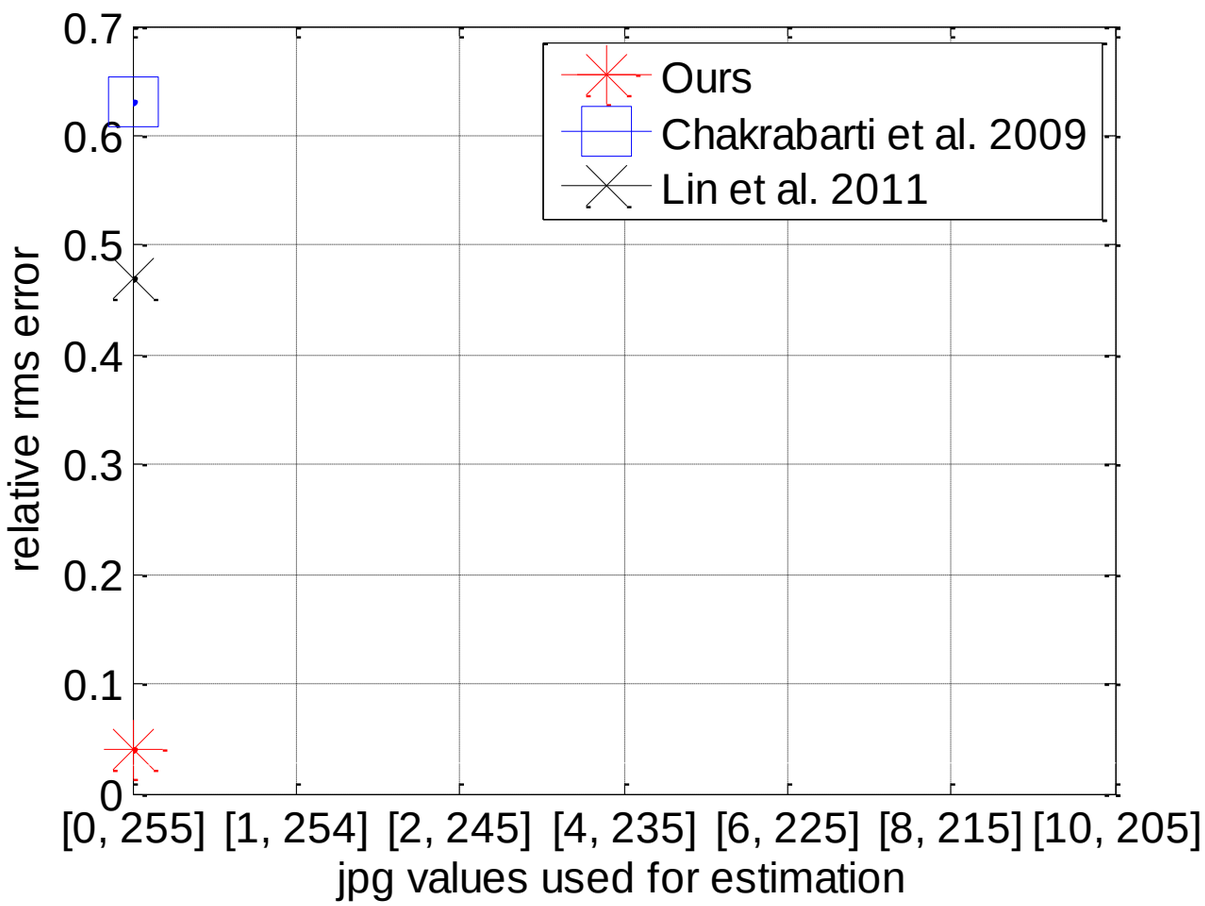
$$p(\mathbf{x}_0|\mathbf{y}_1 \ldots \mathbf{y}_N) = \prod_i p_{x_0|y_i}(\mathbf{x}_0|\mathbf{y}_i)$$
$$= \prod_i \frac{\alpha_i}{\alpha_0} p_{x_i|y_i}\left(\frac{\alpha_i}{\alpha_0}\mathbf{x}_0|\mathbf{y}_i\right)$$

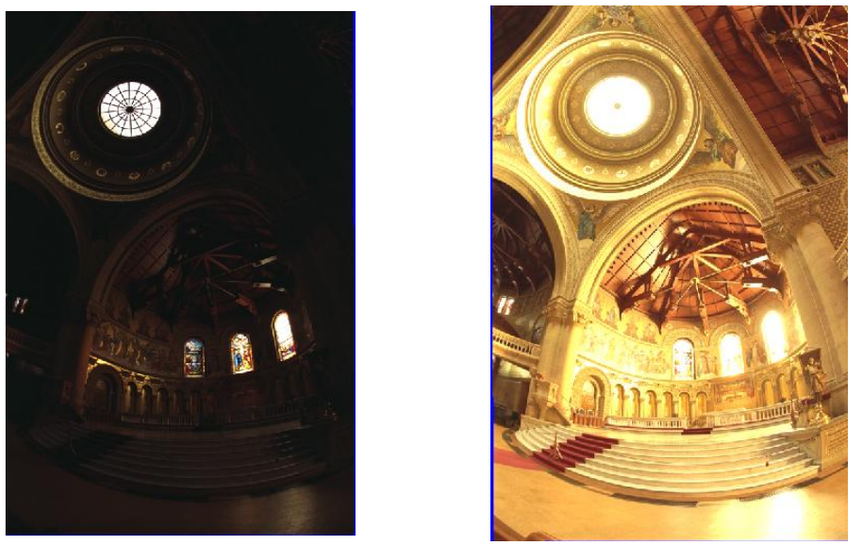
Probabilistic multi-exposure imaging

Multi-exposure imaging



Panasonic DMC-LX3

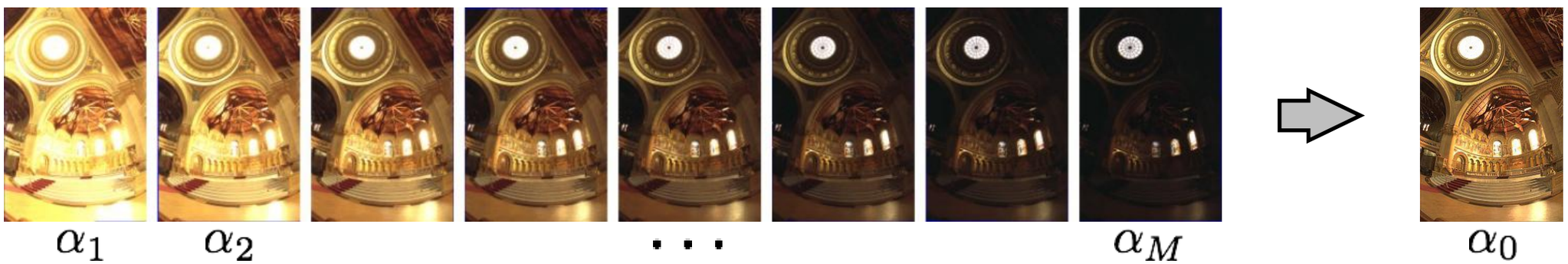




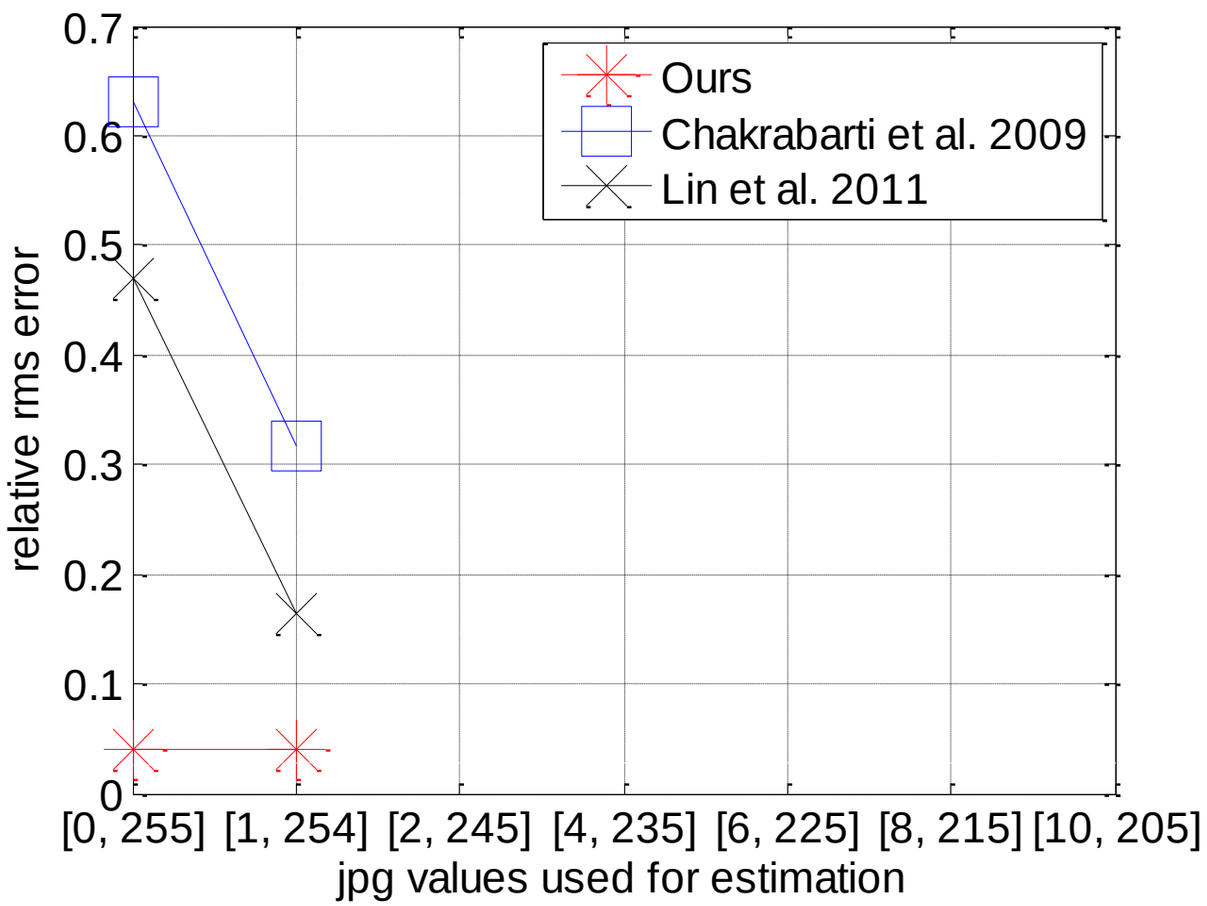
[0 , 255]

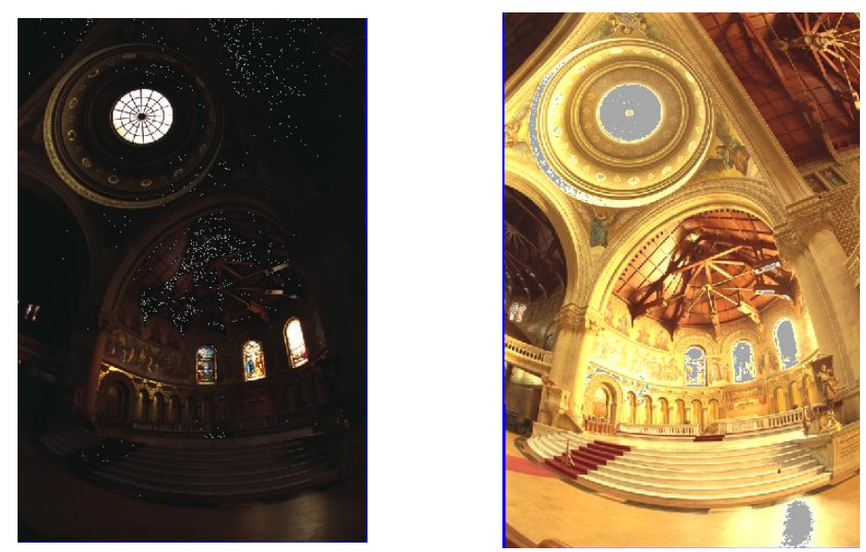
Probabilistic multi-exposure imaging

Multi-exposure imaging



Panasonic DMC-LX3



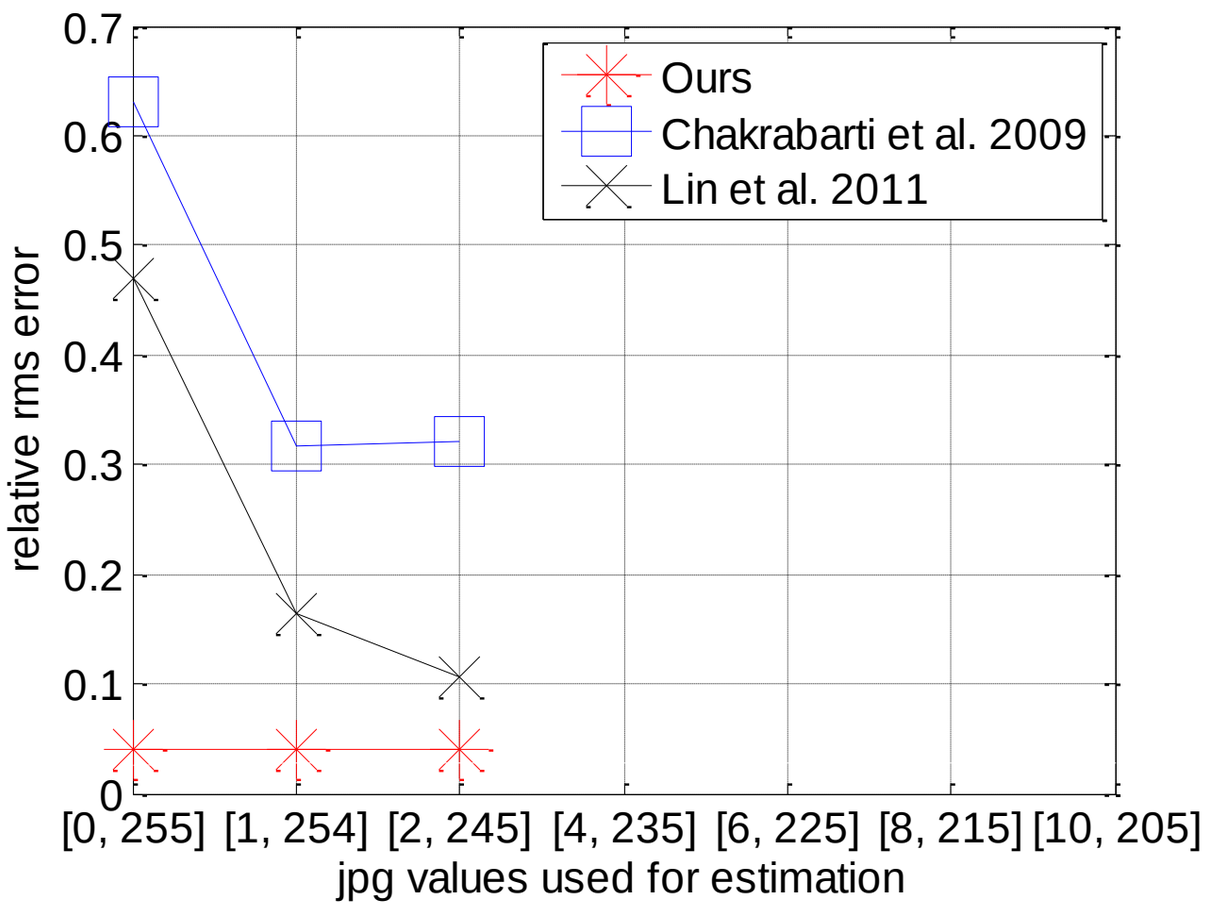


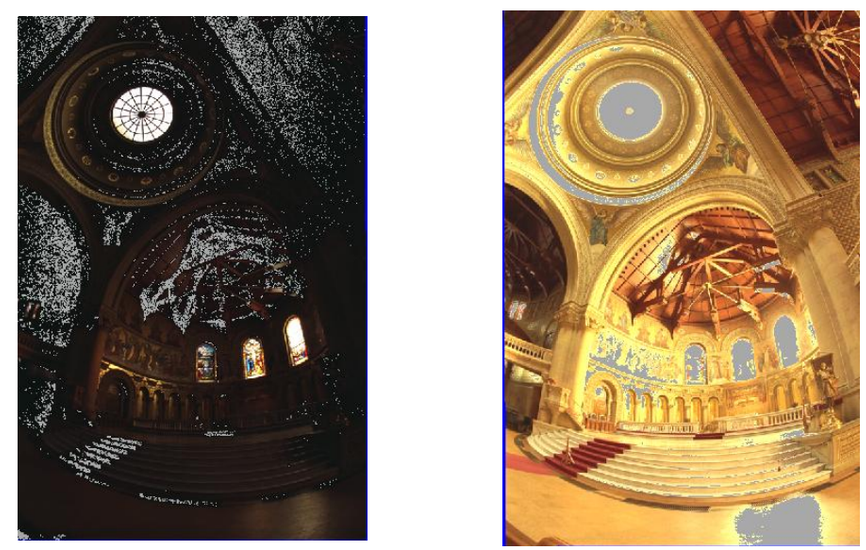
[1 , 254]

Probabilistic multi-exposure imaging

Multi-exposure imaging

Panasonic DMC-LX3



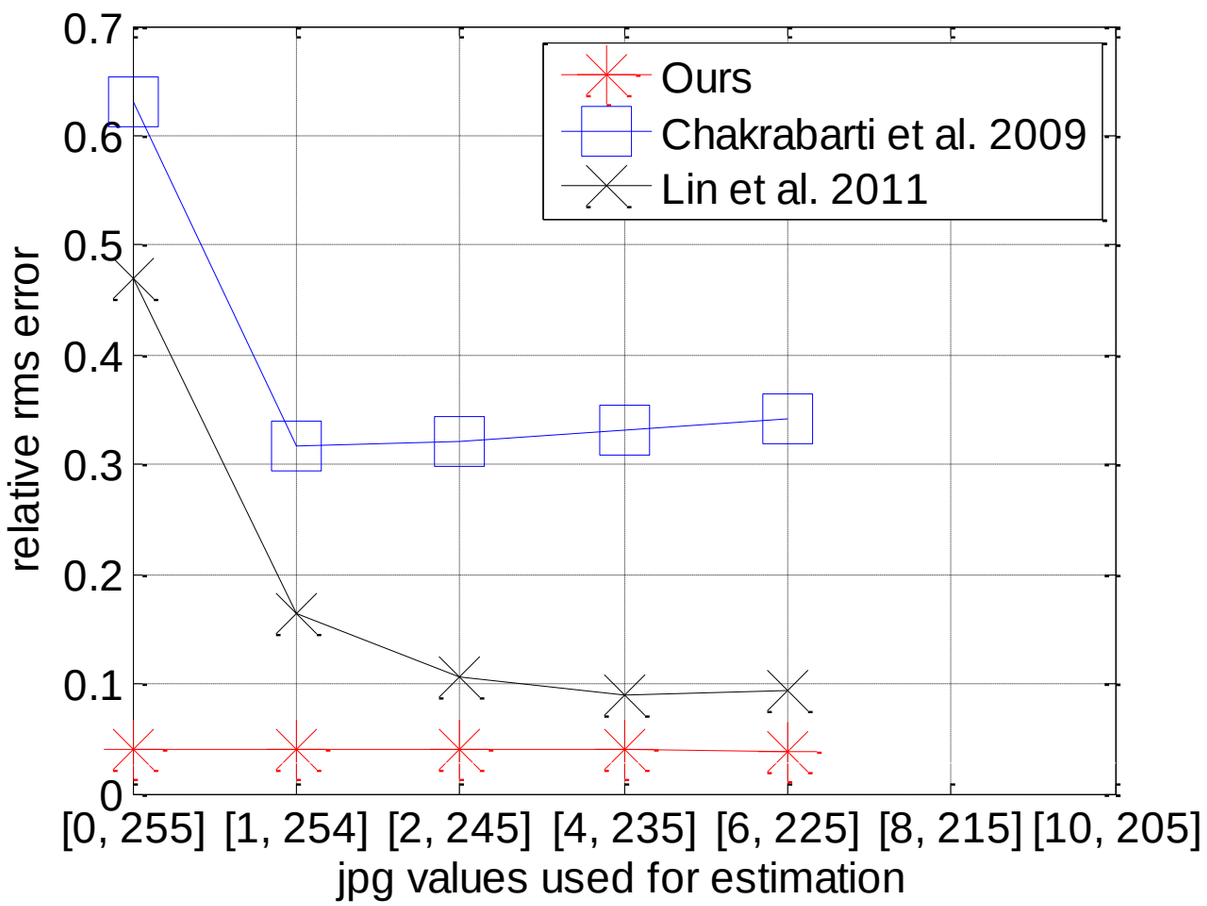


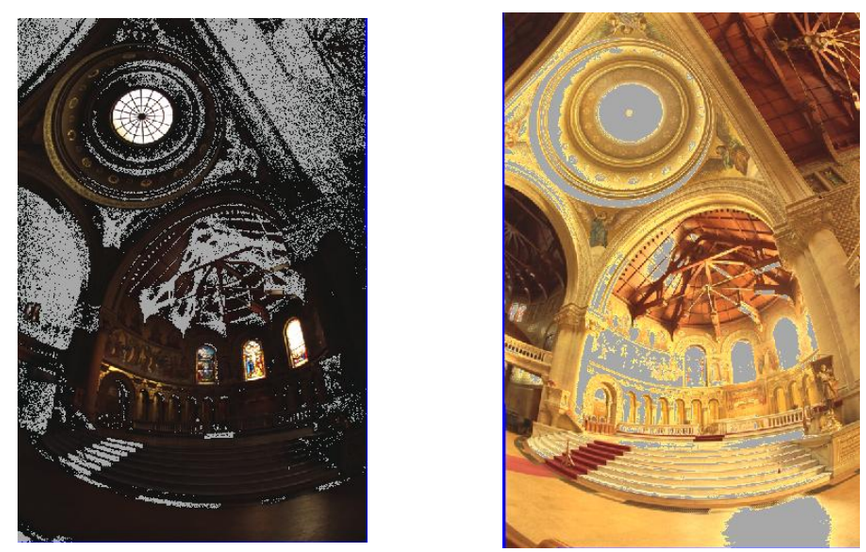
[2 , 245]

Probabilistic multi-exposure imaging

Multi-exposure imaging

Panasonic DMC-LX3



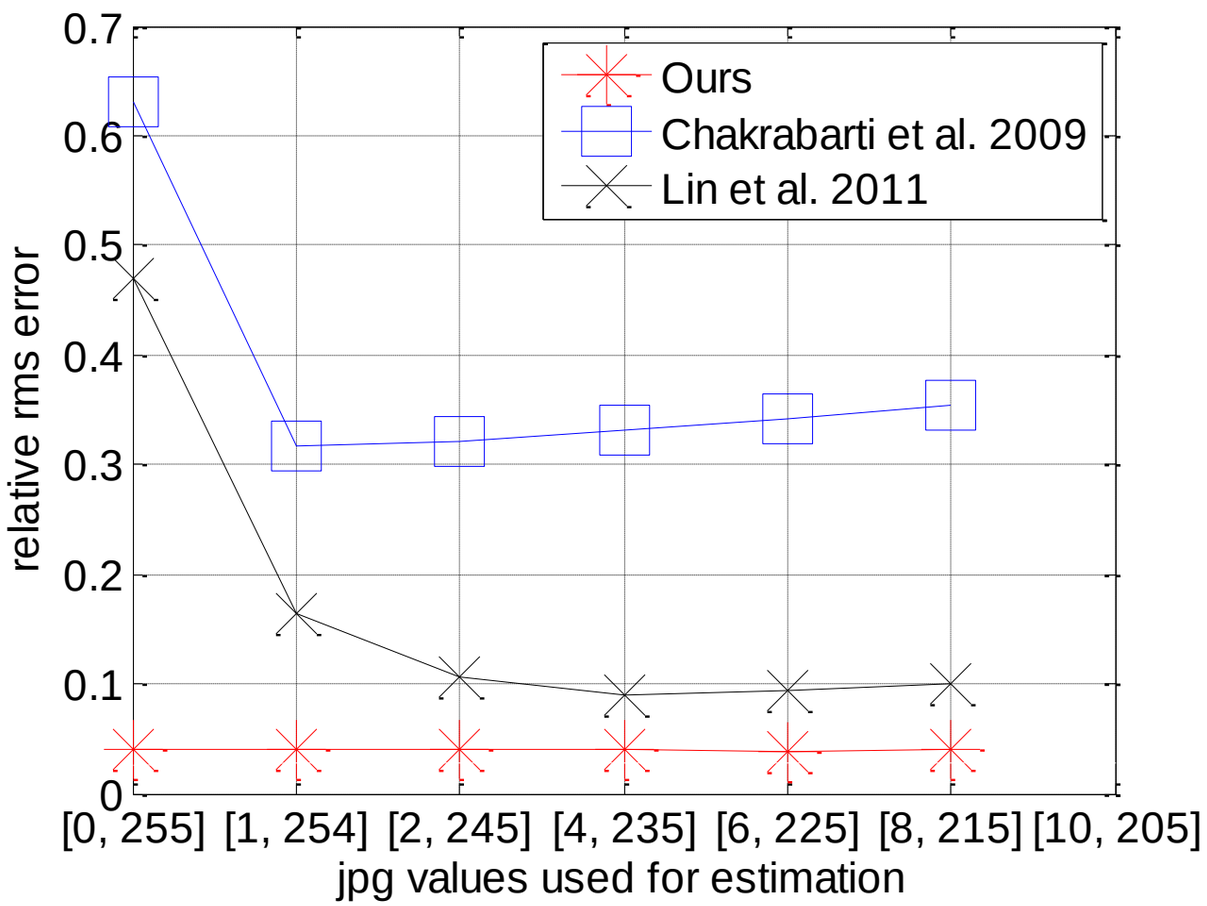


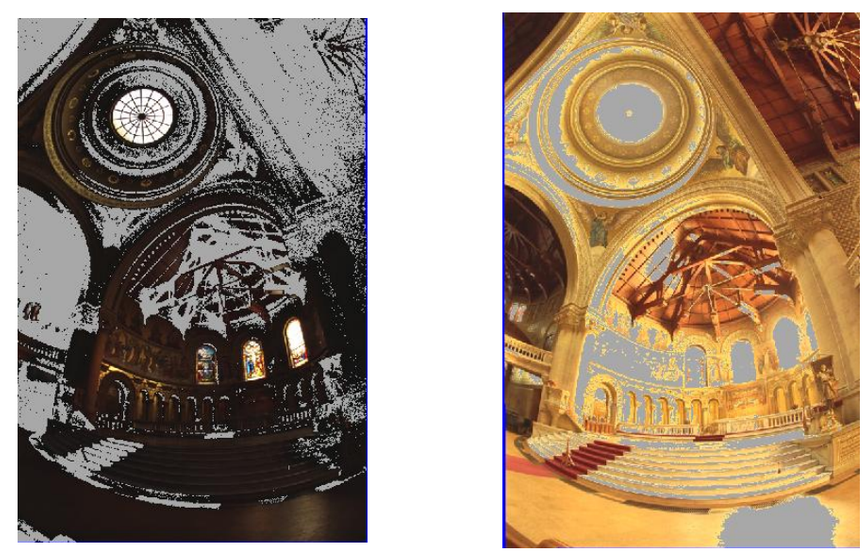
[6 , 225]

Probabilistic multi-exposure imaging

Multi-exposure imaging

Panasonic DMC-LX3

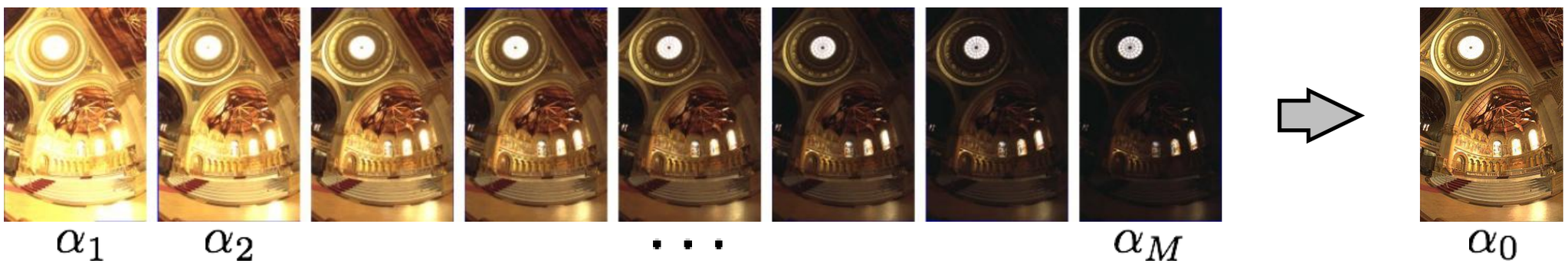




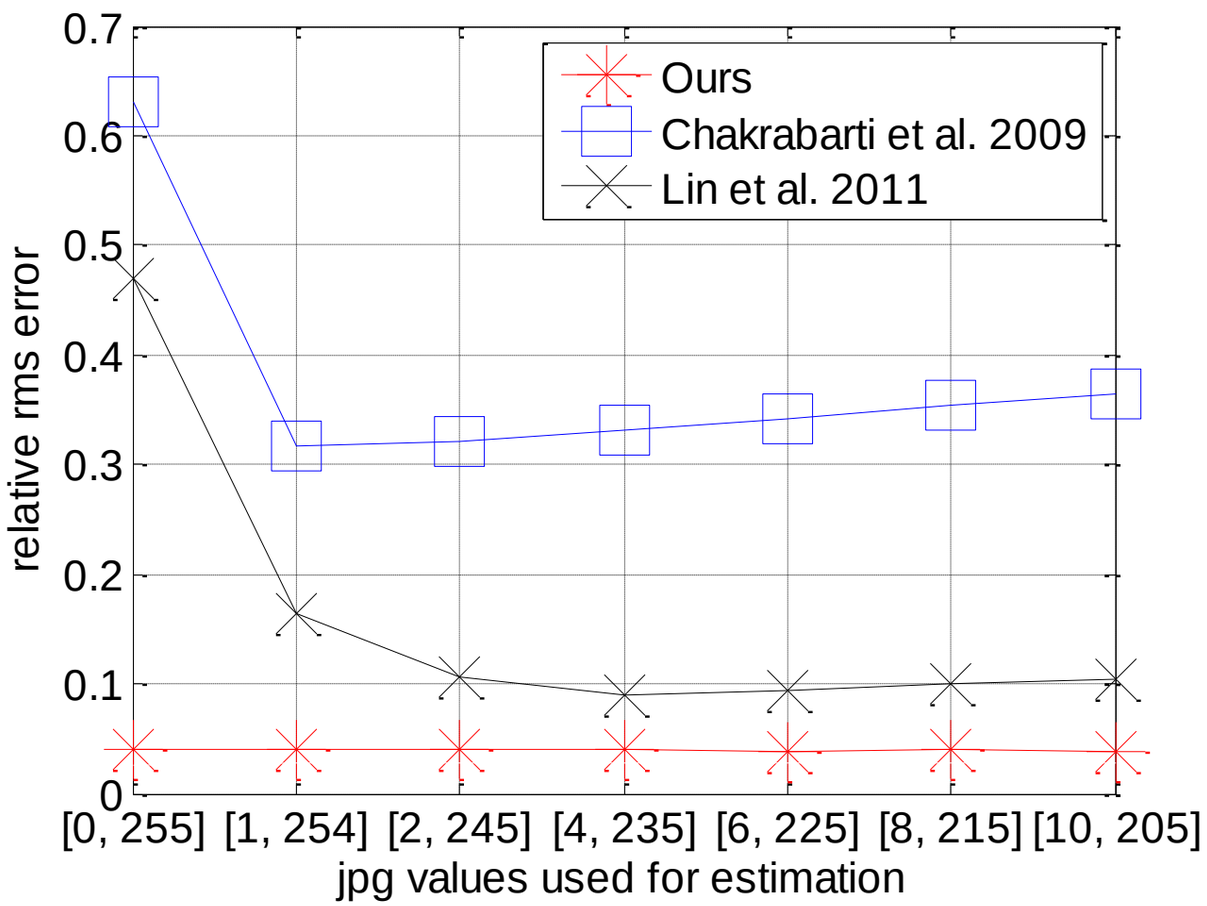
[8 , 215]

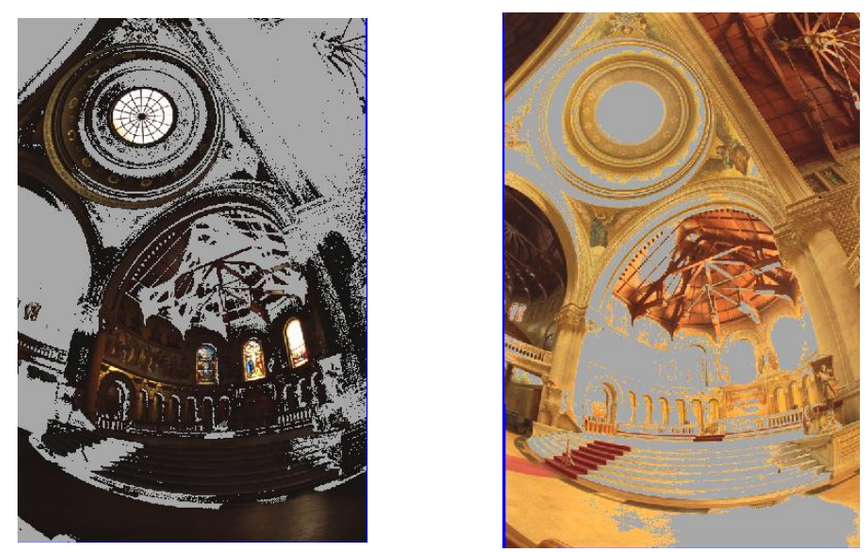
Probabilistic multi-exposure imaging

Multi-exposure imaging



Panasonic DMC-LX3

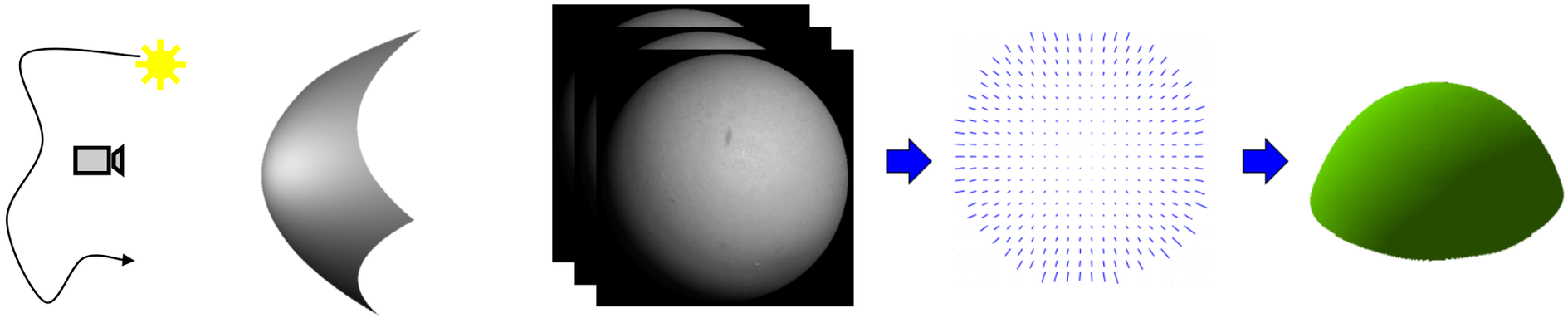




[10 , 205]

Probabilistic photometric stereo

(Calibrated, Lambertian) Photometric stereo



Conventional approach:
weight all measurements equally

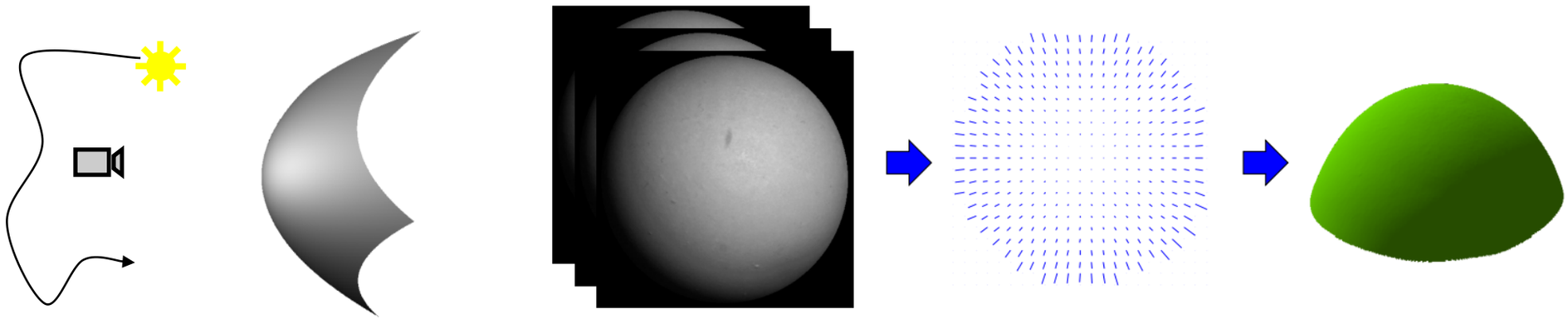
$$\mathbf{l}_j^\top \mathbf{b} = E_j$$
$$\mathbf{b} = (\mathbf{L}^\top \mathbf{L})^{-1} \mathbf{L}^\top \mathbf{E}$$

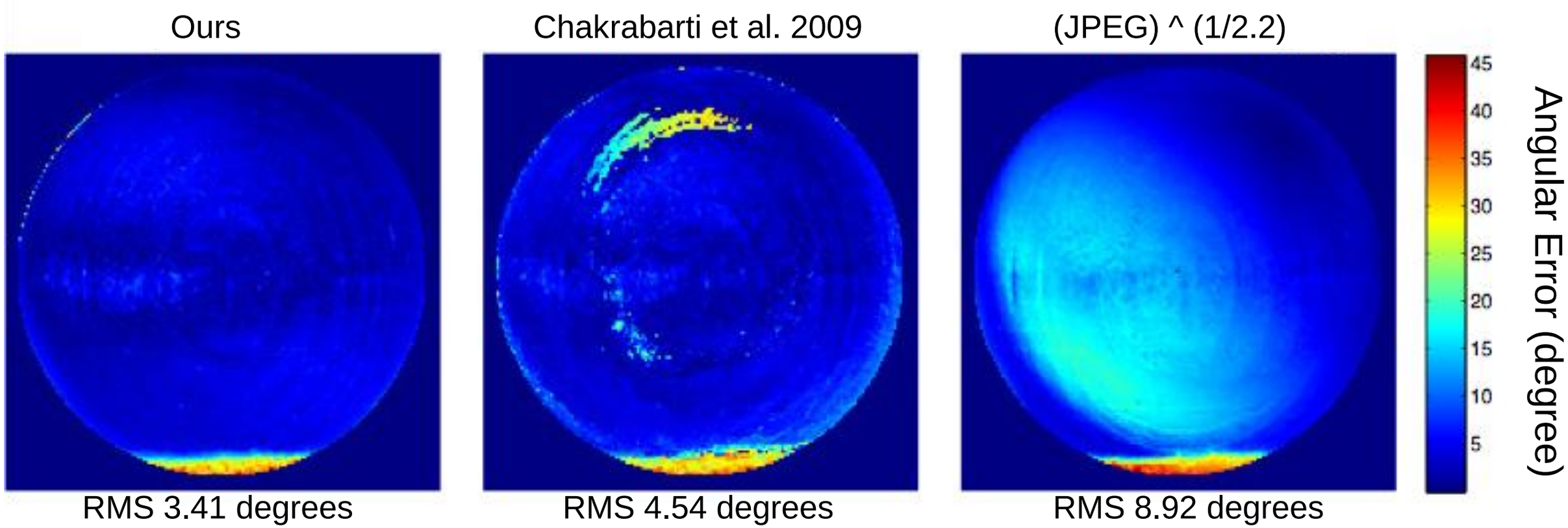
Probabilistic approach:
combine estimates according to variance

$$\mathbf{l}_j^\top \mathbf{b} = E_j, \quad E_j \sim \mathcal{N}(\mu_j, \sigma_j^2)$$
$$\mathbf{b} = (\mathbf{L}^\top \mathbf{W} \mathbf{L})^{-1} \mathbf{L}^\top \mathbf{W} \mathbf{E}$$

Probabilistic photometric stereo

(Calibrated, Lambertian) Photometric stereo





Summary

- Color-derendering with a measure of uncertainty
- Improves performance for probabilistic adaptations of HDR imaging and photometric stereo
- Should be useful for probabilistic adaptations of other tasks as well (deblurring, dehazing, intrinsic images, stitching and matching, color constancy, etc.)