COMPUTATIONAL PHOTOGRAPHY

Chapter 10

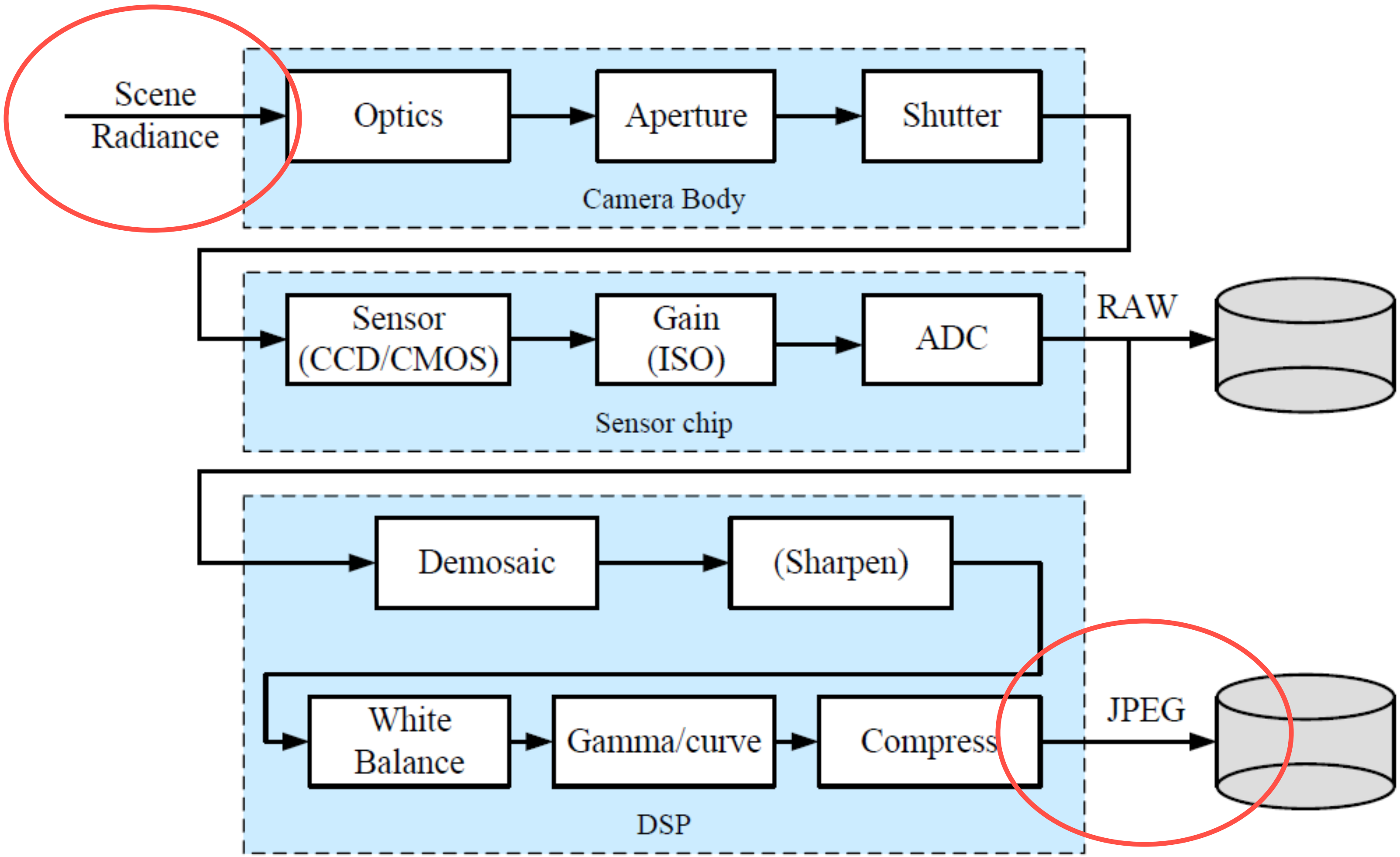
Computational photography

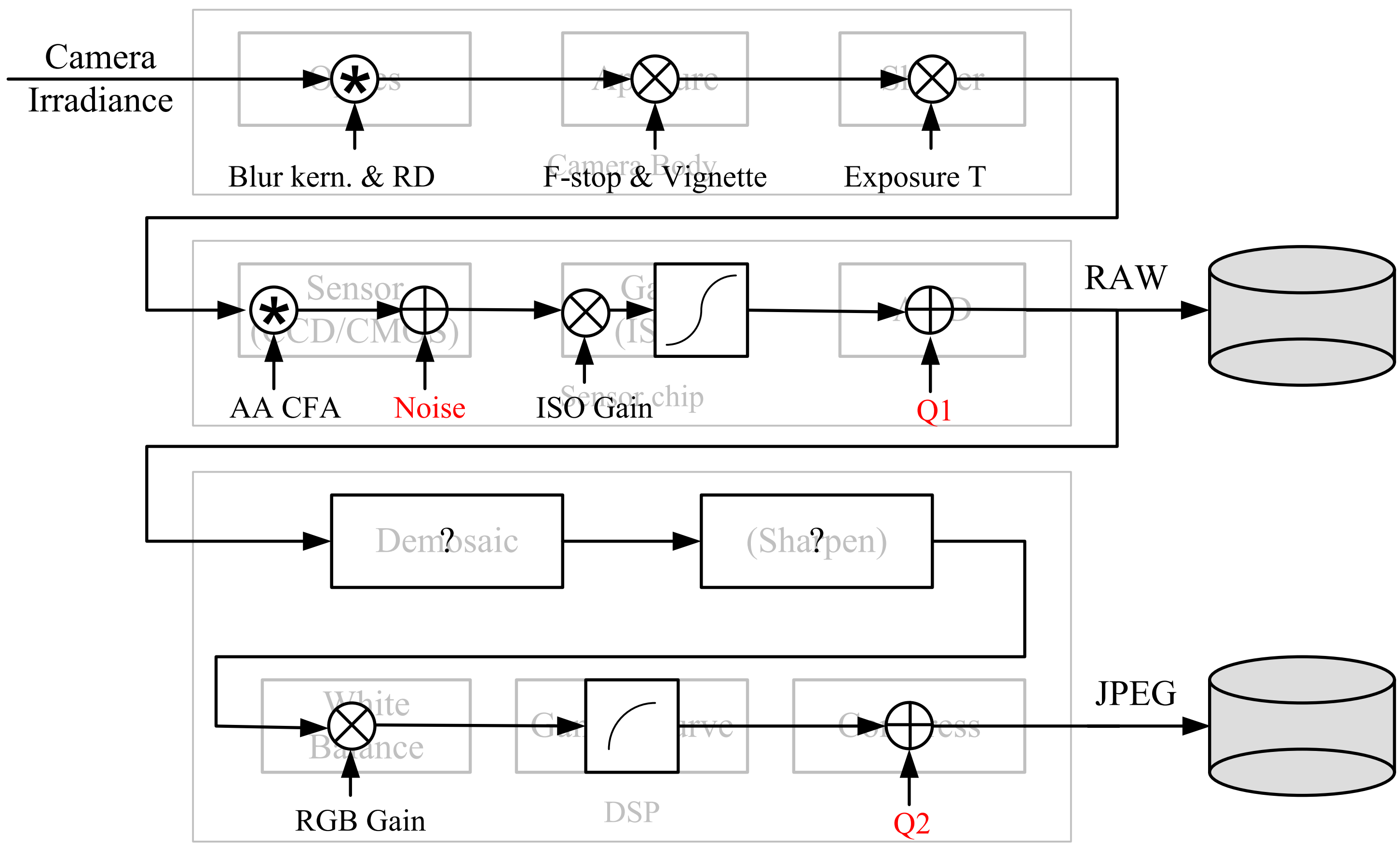
- Computational photography: image analysis and processing algorithms are applied to one or more photographs to create images that go beyond the capabilities of traditional imaging systems

Computational photography

- Photometric calibration: the measurement of camera and lens responses
- High dynamic range imaging: capturing the full range of in a scene through the use of multiple exposures
- Image matting and compositing: algorithms for cutting pieces of images from one photograph and pasting tem into others
- Super-resolution and blur removal: improving the resolution of images
- Texture analysis and synthesis: how to generate novel textures form real-world samples for applications such as holes filling

Image sensing pipeline

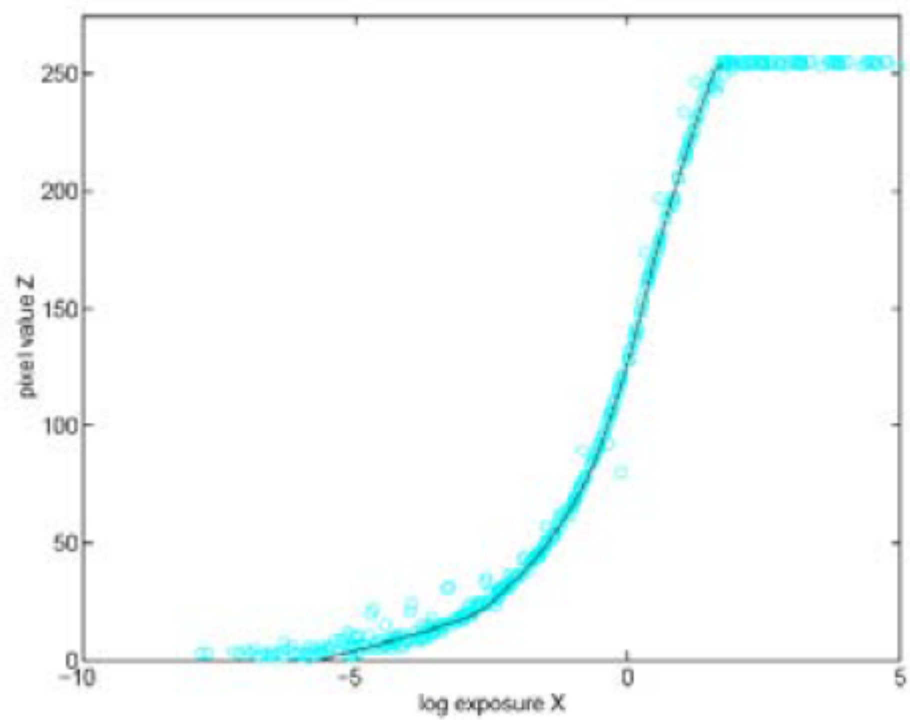



Camera
Irradiance
Blur kern. & RD
F-stop & Vignette
Exposure T
Sensor
AA CFA
Noise
ISO Gain
Q1
RAW
?
?
JPEG
RGB Gain
DSP
Q2

Calibration

- Radiometric response function: maps arriving photons into digital values stored in the file
- Noise level estimation

Radiometric response function



- **Affect Factors**:
- 1. Aperture and shutter speed
- 2. A/D converter (controlled by ISO, linear)
- 3. Demosaicing
- 4. …

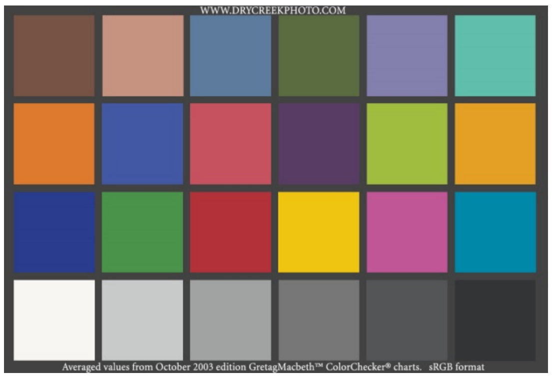
- Hard to model, easier to measure

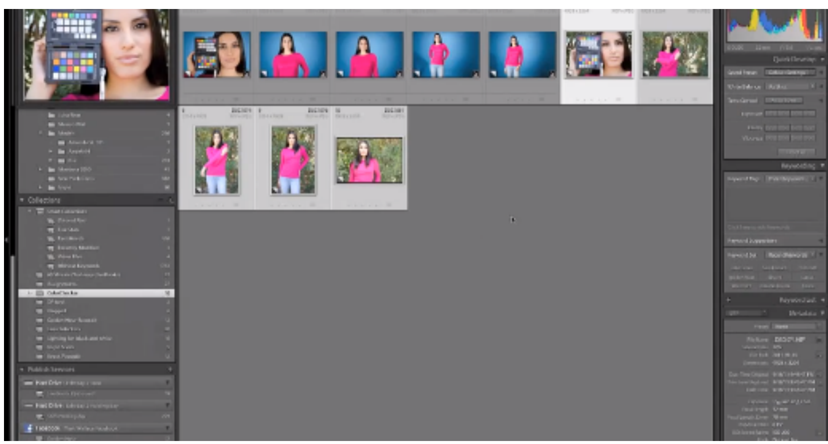
Approaches to measure response function

- Integrating sphere

Approaches to measure response function

- Calibration chart





http://www.adorama.com/alc/0013301/article/Using-the-ColorChecker-Passport-Adorama-TV

Noise level estimation

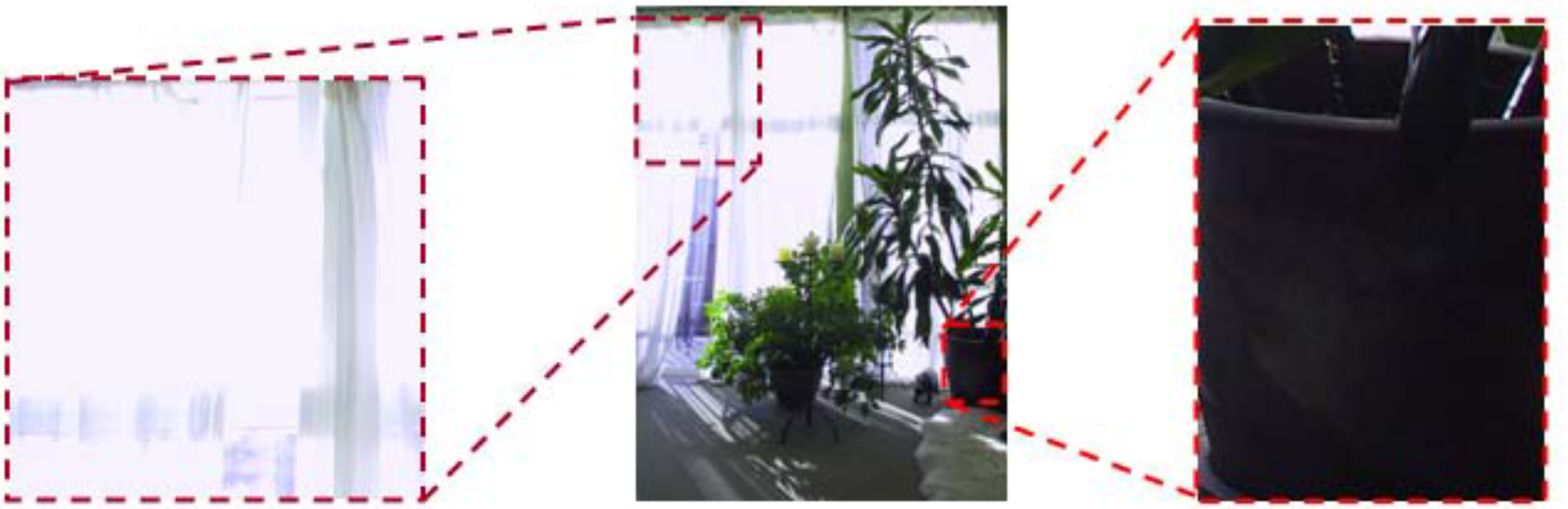
Approaches to measure noise

- Integrating sphere
- Calibration chart
- Taking repeated exposures and computing the variance
- Assuming pixel values should all be the same within some region

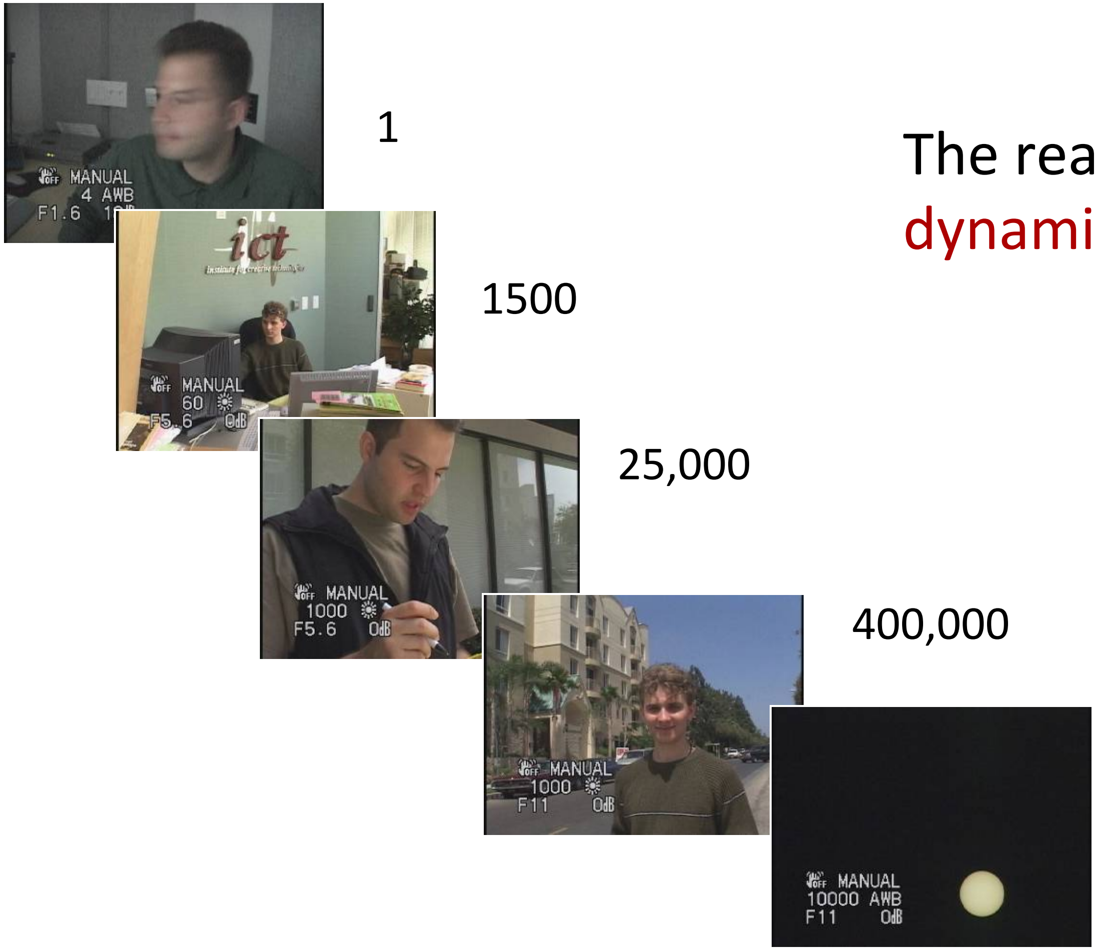
High dynamic range imaging

- Registered images taken at different exposures can be used to calibrate the radiometric response function of a camera
- They can create well-exposed photographs

High Dynamic Range



The Problem of Dynamic Range



1

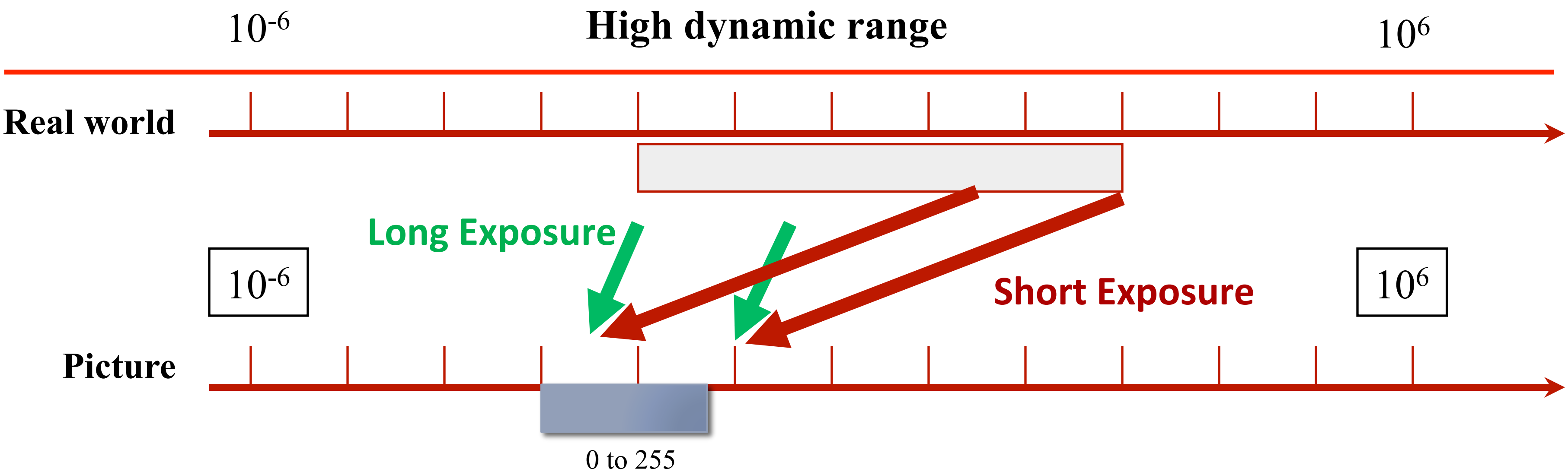
1500

25,000

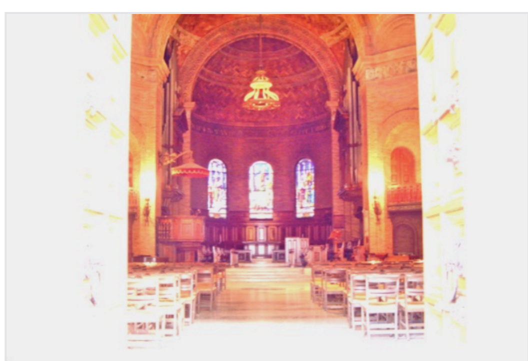
400,000

200,000,000

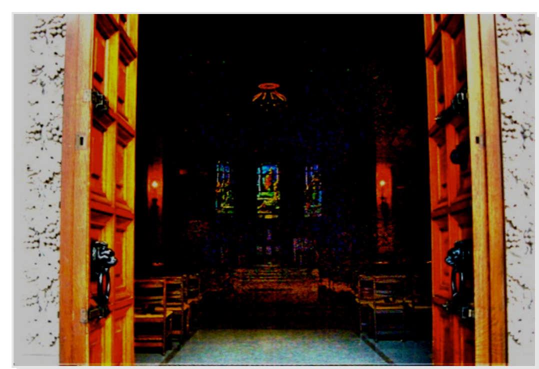
The real world is high dynamic range!



- Today's Cameras: Limited Dynamic Range



High Exposure Image



Low Exposure Image

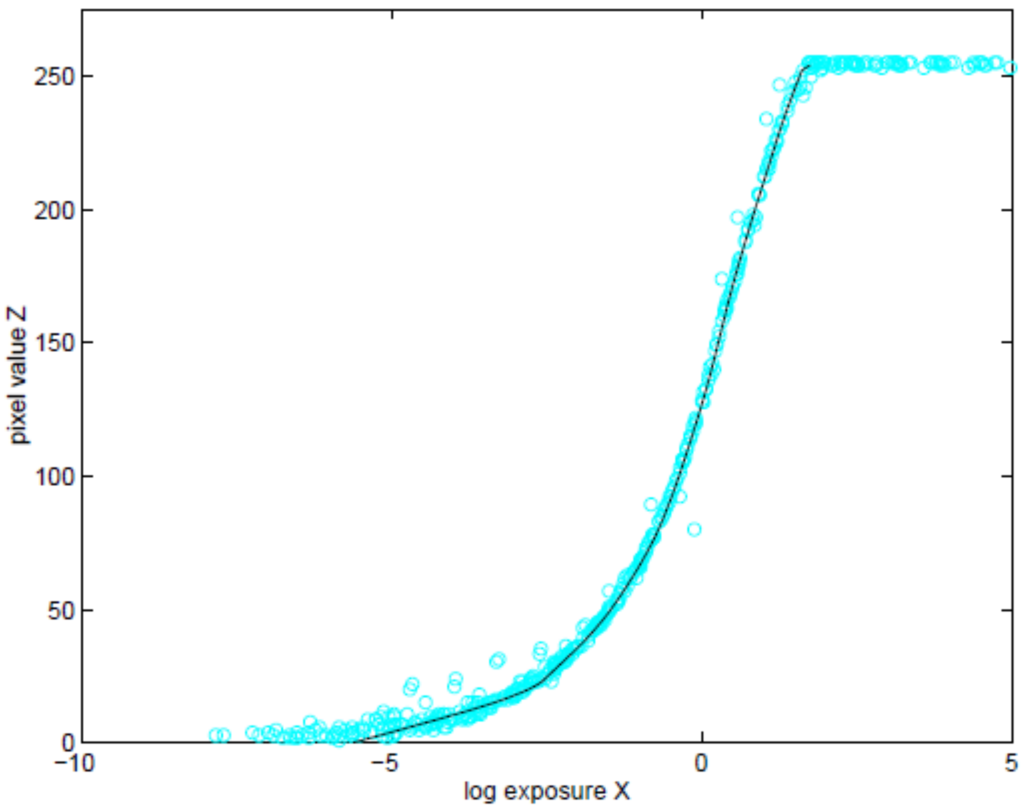
- We need about 5-10 million values to store all brightnesses around us.
- But, typical 8-bit cameras provide **only 256 values**!!

AEB mode and HDR Composite

Recovering HDR

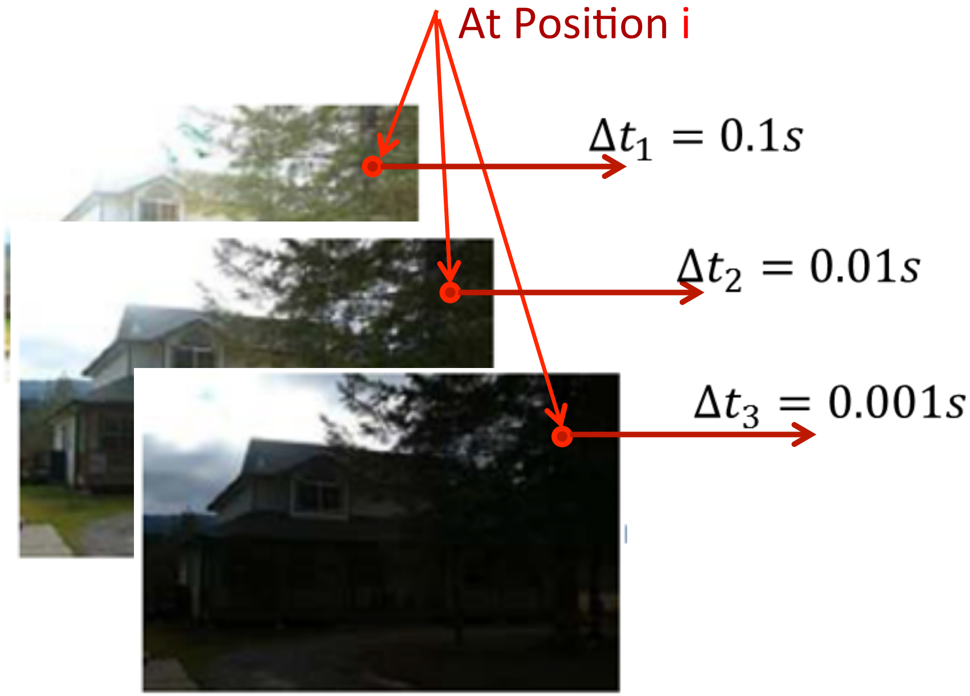
- 1. Extract the radiometric response function from the
- 2. Estimate a radiance map by blending pixels from different exposures
- 3. Tone-map it into a single low dynamic range image

Recover radiometric response



- **Given** multiple exposure pictures
- **Goal**: estimating the radiometric response function(radiance map)

Recover radiance map



- The radiance map can be written as:

$$Z_{ij} = \mathbf{f}(E_i \cdot \Delta t_j)$$

- Where E_i is the radiance at position i.
- Define $E_i \, \Delta t_j$ as the exposure.

- Known: Δt_j , Z_{ij}
- Unknown: E_i, **f**

Recover radiance map

Z_{ij}=**f**($E_i \cdot \Delta t_j$) can be rewrite as:

$f^{-1}(Z_{ij})$=($E_i \cdot \Delta t_j$) , taking the natural logarithm of both sides, we have:

$lnf^{-1}(Z_{ij}) = \ln E_i + ln\Delta t_j$, to simplify notation, let **g=log f^{-1}**

$g(Z_{ij}) = \ln E_i + ln\Delta t_j$

- Note: recovering g only requires recovering finite number of values.(Since the domain of Z is from 0-255)

Recover radiance map

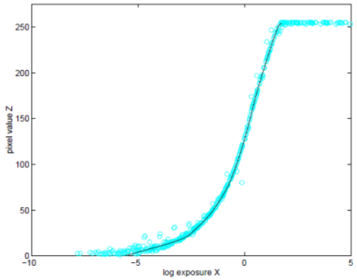
- Objective function:

$$\widehat{Ei}, \widehat{\boldsymbol{g}(\boldsymbol{z})} = \min_{Ei, g(Z)} \sum_{i=1}^{N} \sum_{j=1}^{P} [\boldsymbol{g}\left(Z_{ij}\right) - lnE_i - \ln \Delta t_j]^2 + \lambda \sum_{z=0}^{255} g''(z)$$

Recover radiance map

- **Refine objective function:**
- 1. scalar function: $$g(Z_{mid}) = 0$$
- 2. anticipating the basic shape of the response function:

$$w(z) = \begin{cases} z - Z_{min} & \text{for } z \le \frac{1}{2}(Z_{min} + Z_{max}) \\ Z_{max} - z & \text{for } z > \frac{1}{2}(Z_{min} + Z_{max}) \end{cases}$$



$$\mathcal{O} = \sum_{i=1}^{N} \sum_{j=1}^{P} \{w(Z_{ij})\,[g(Z_{ij}) - \ln E_i - \ln \Delta t_j]\}^2 +$$

$$\lambda \sum_{z=Z_{min}+1}^{Z_{max}-1} [w(z) g''(z)]^2$$

Recover radiance map

- **Refine objective function:**
- 3. How many samples(pixels) do we need to calculate:

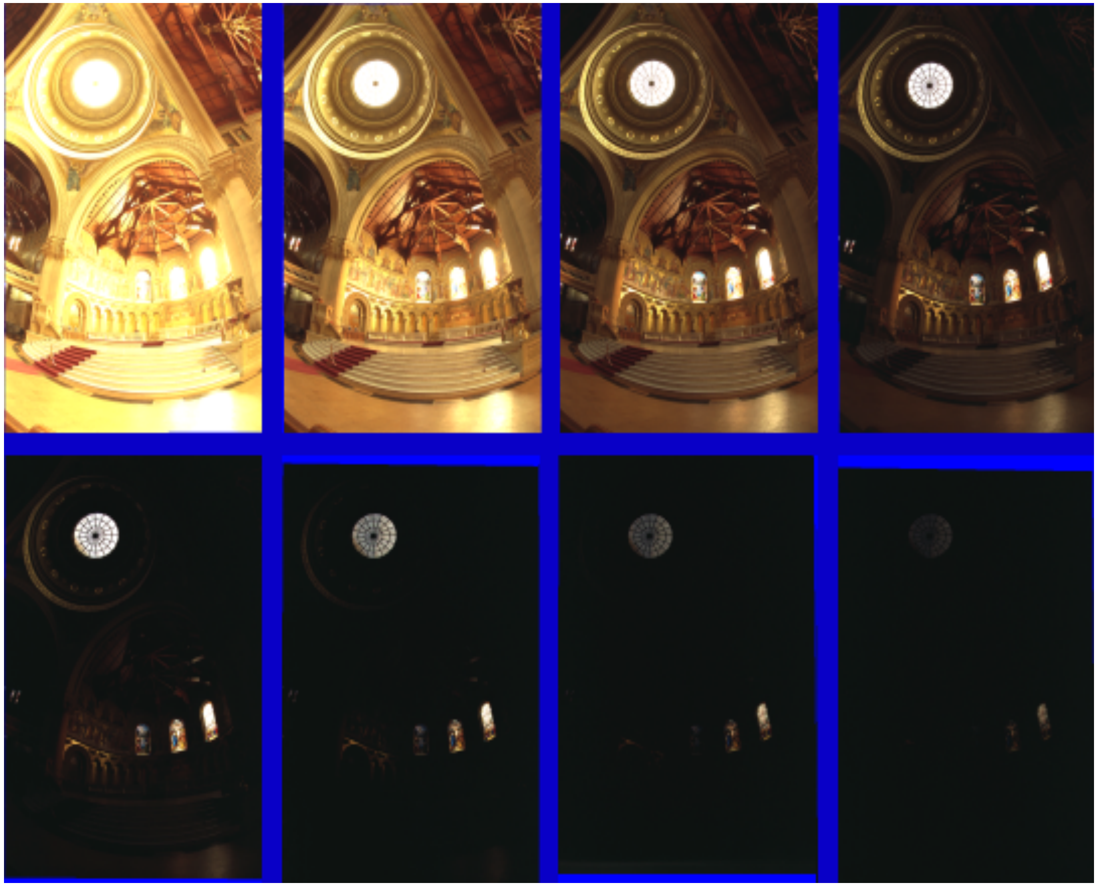
$$\widehat{Ei}, \widehat{\boldsymbol{g}(\mathbf{z})} = \min_{Ei,g(Z)} \sum_{i=1}^{N} \sum_{j=1}^{P} [\boldsymbol{g}(Z_{ij}) - lnE_i - \ln \Delta t_j]^2 + \lambda \sum_{z=0}^{255} g''(z)$$

1.Make sure (# of Ei)*(# of Pictures)>256

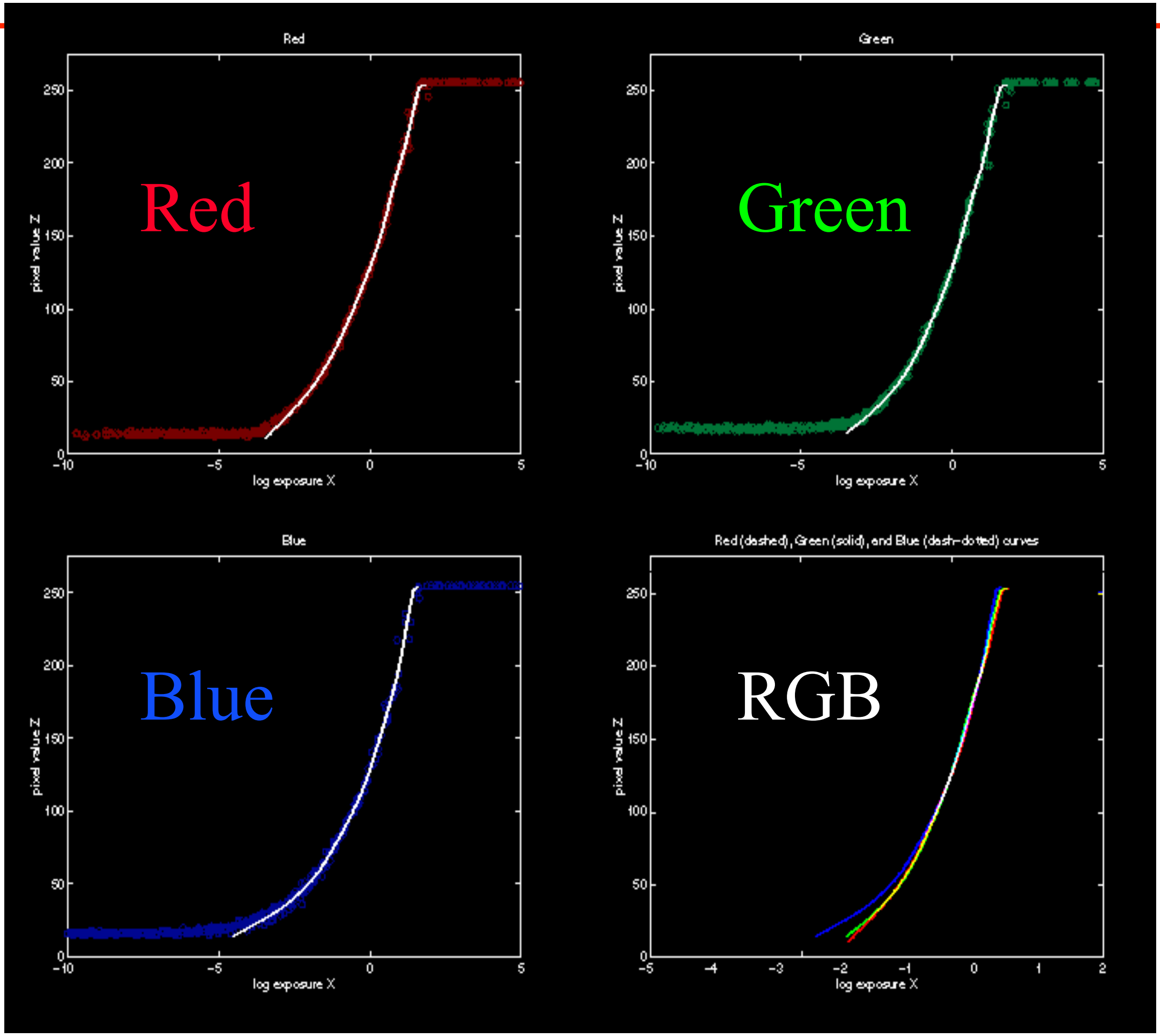
2.The pixel locations should be chosen so that they have a reasonably even distribution of pixel values.

Results: Color Film

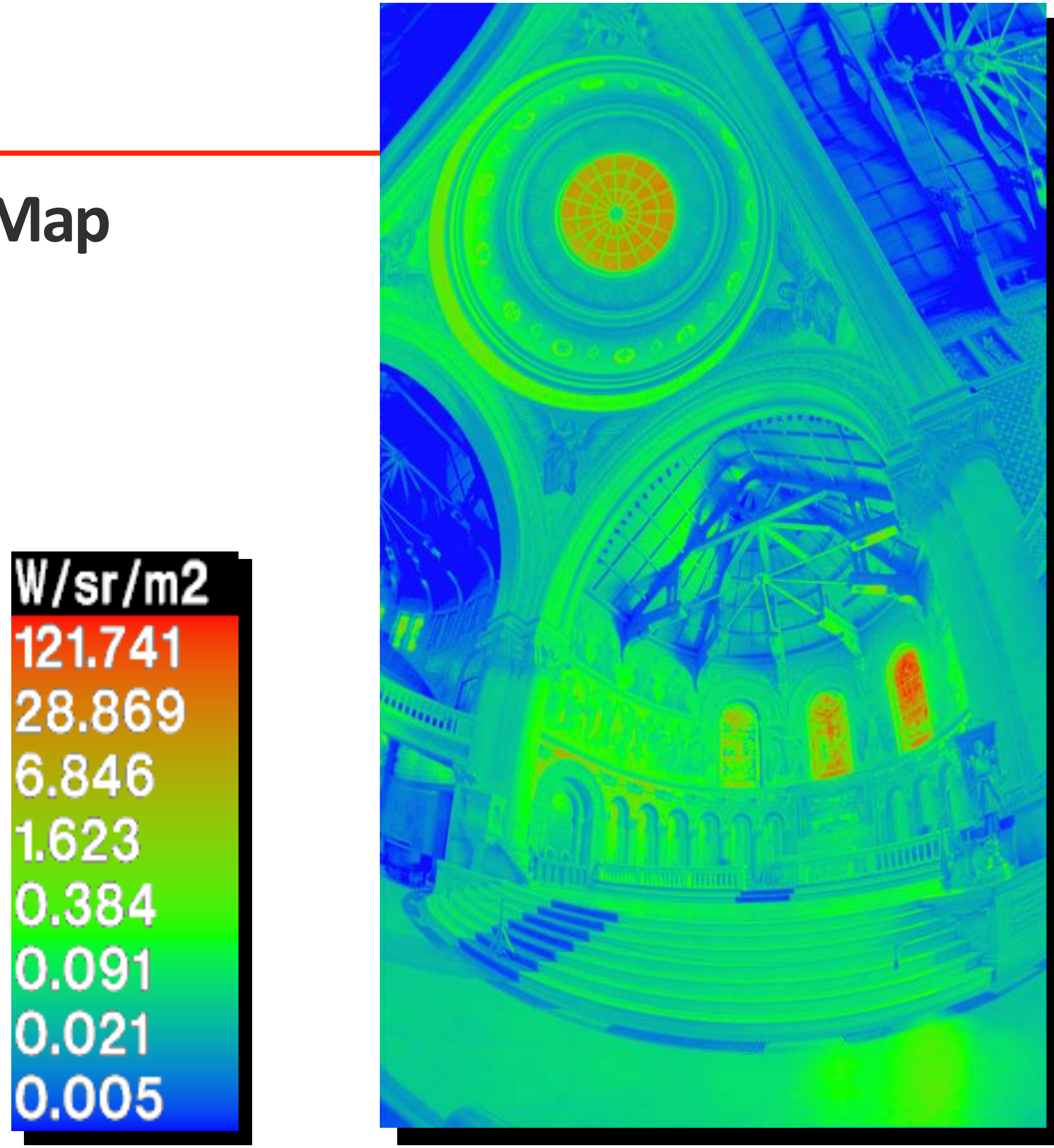
- Kodak Gold ASA 100, PhotoCD



Recovered Response Curves



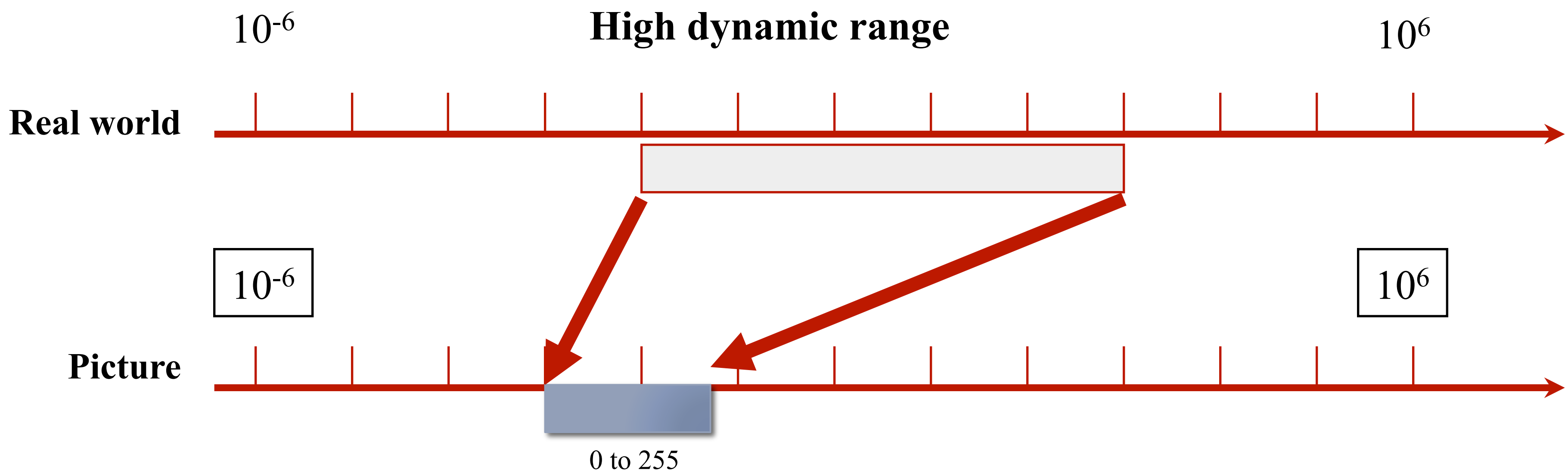
The Radiance Map



Tone-mapping

- Once a radiance map has been computed, it is usually necessary to display it on a lower gamut (i.e., 8-bit) screen or printer

Tone mapping

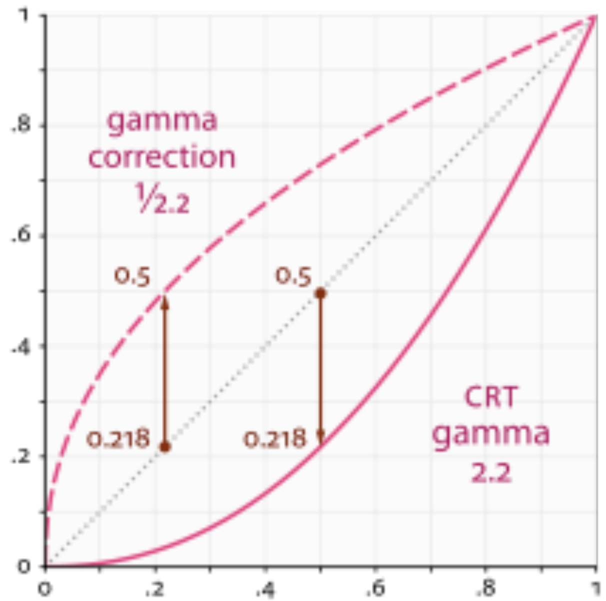


- **Given** radiance map
- **Goal**: build a reasonable mapping function of radiance to pixel values

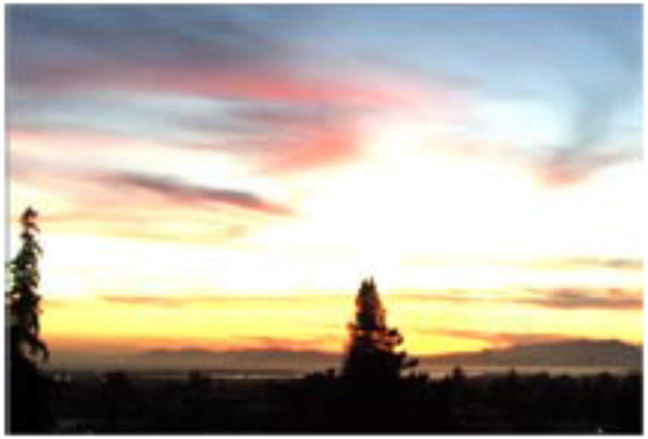
Tone mapping Methods

- **Simple Gamma tone mapping**

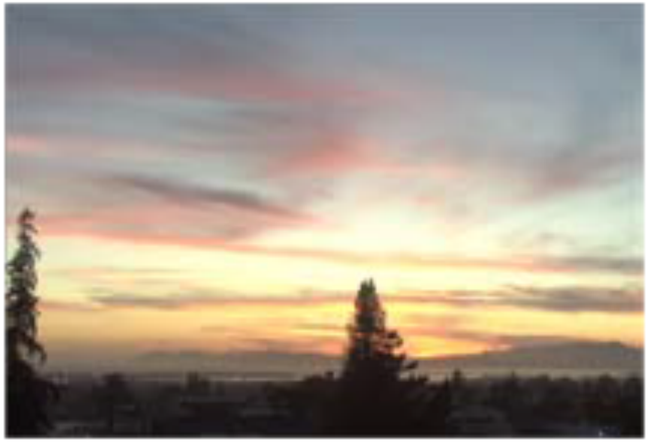
Gamma applied to each color channel independently



Gamma compression



Input Image

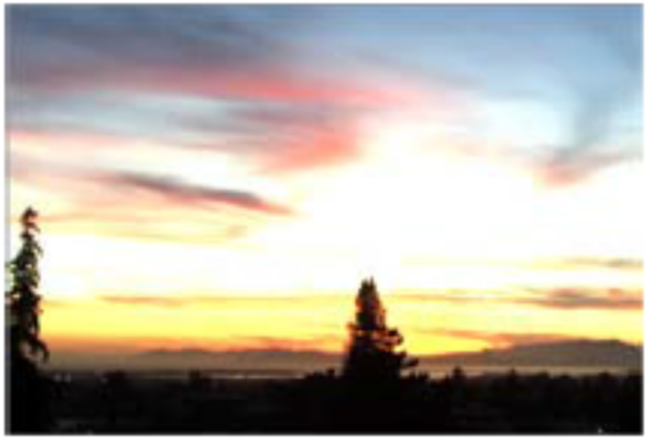


Gamma applied to each channel

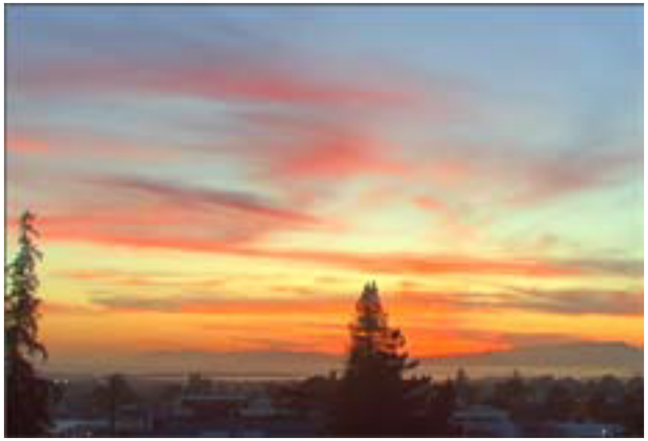
Tone mapping Methods

- **Intensity Gamma tone mapping**

- Splitting the image up into luminance and chrominance(L*a*b) components, and applying the mapping to the luminance channel



Input Image



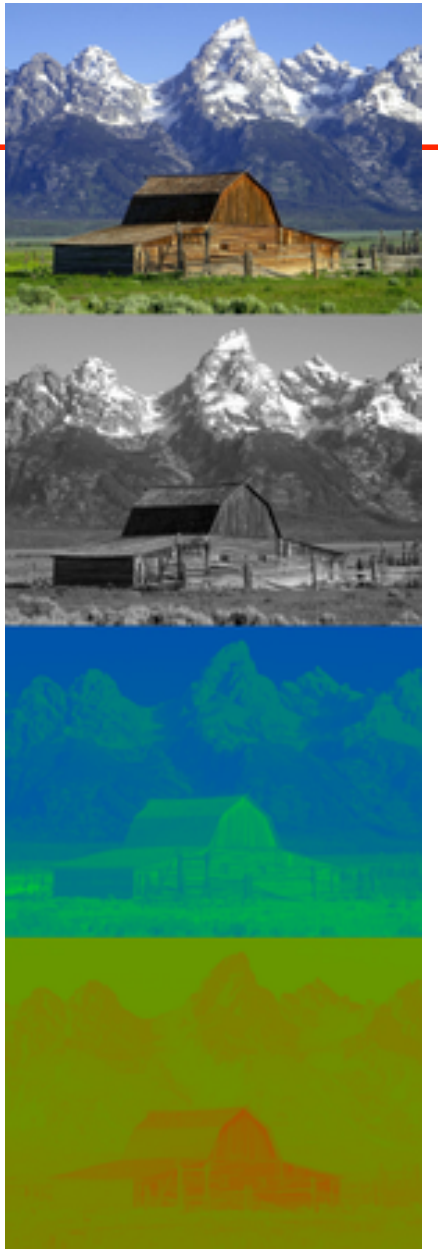
Gamma applied to luminance

Chrominance and luminance

- **YUV** color space

$$\begin{bmatrix} Y' \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.14713 & -0.28886 & 0.436 \\ 0.615 & -0.51499 & -0.10001 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1.13983 \\ 1 & -0.39465 & -0.58060 \\ 1 & 2.03211 & 0 \end{bmatrix} \begin{bmatrix} Y' \\ U \\ V \end{bmatrix}$$



Tone mapping Methods

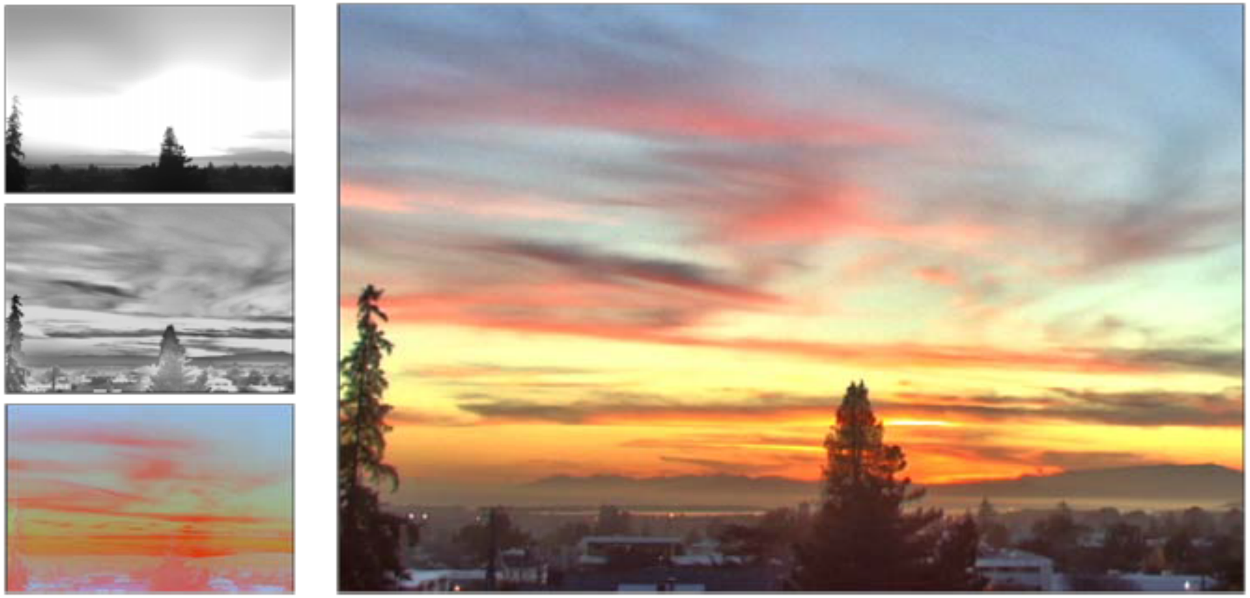
- Advanced mapping method

(a) (b)

Figure 10.21 Local tone mapping using linear filters: (a) low-pass and high-pass filtered log luminance images and color (chrominance) image; (b) resulting tone-mapped image (after attenuating the low-pass log luminance image) shows visible halos around the trees. Processed images courtesy of Frédo Durand, MIT 6.815/6.865 course on Computational Photography.

Tone mapping Methods

- Advanced mapping method (using Edge-preserving filter)



(a) (b)

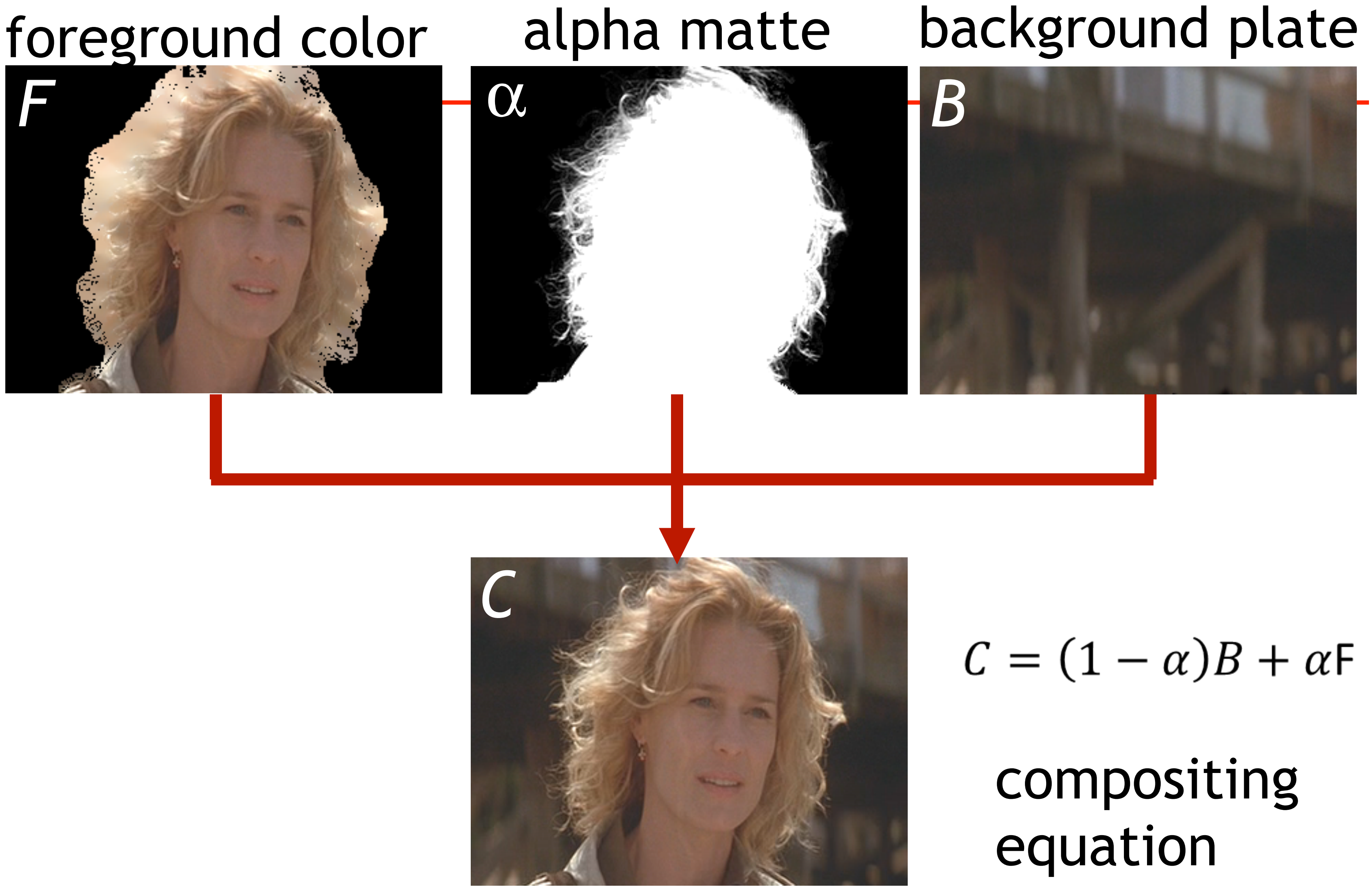
Figure 10.22 Local tone mapping using bilateral filter (Durand and Dorsey 2002): (a) low-pass and high-pass bilateral filtered log luminance images and color (chrominance) image; (b) resulting tone-mapped image (after attenuating the low-pass log luminance image) shows no halos. Processed images courtesy of Frédo Durand, MIT 6.815/6.865 course on Computational Photography.

Image matting and compositing

Compositing Equation

$$C = (1-\alpha)B + \alpha \mathrm{F}$$

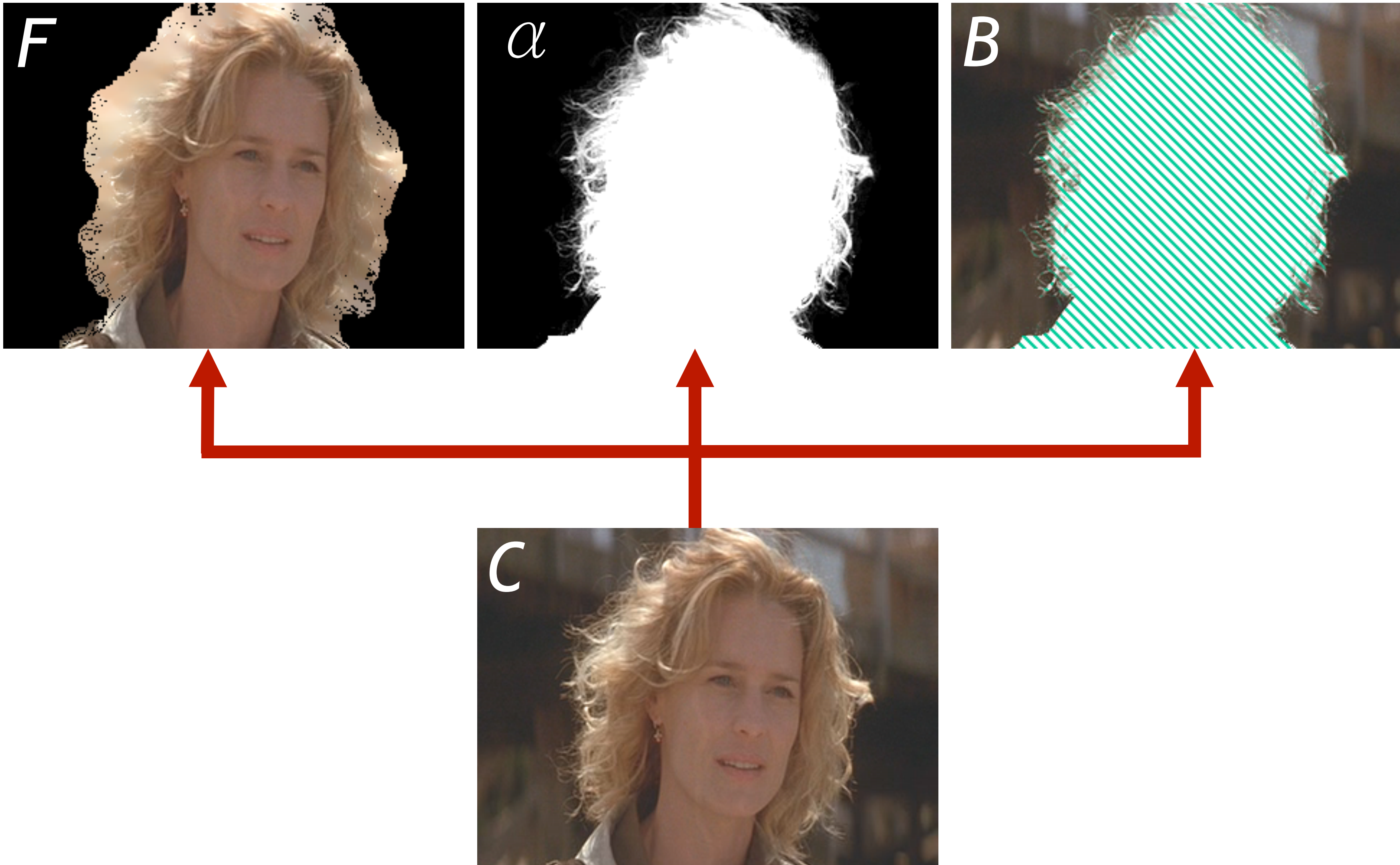
- B: background image
- F: foreground image
- C: composite image



$$C = (1 - \alpha)B + \alpha \mathrm{F}$$

compositing equation

Matting



Matting ambiguity

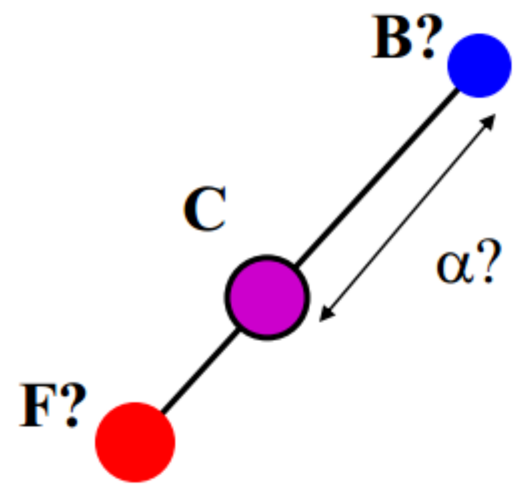
$$C = (1 - \alpha)B + \alpha F$$

Known: C

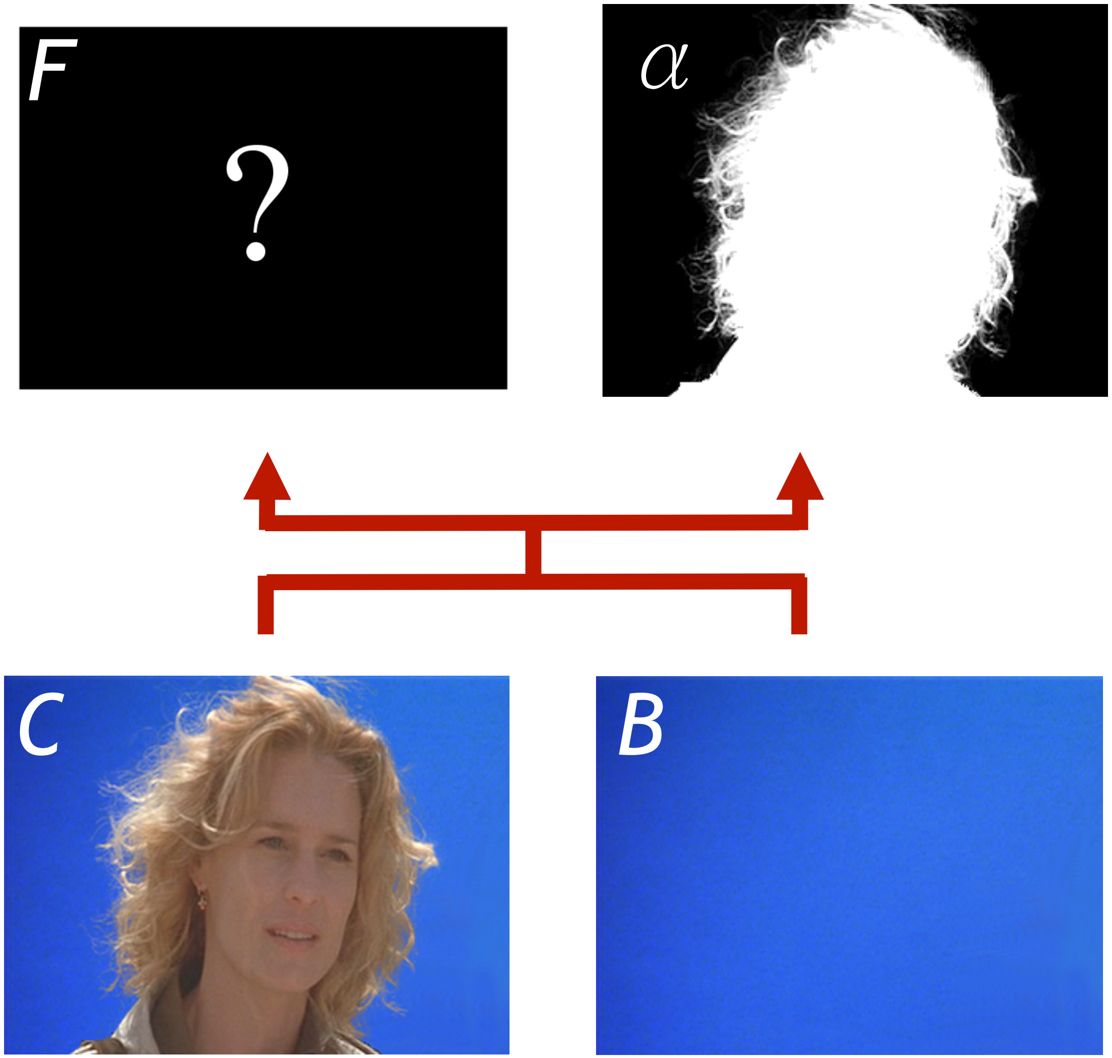
Unknown: α, B, F

7 unknowns: α and triplets for F and B

3 equations, one per color channel



Blue screen matting



$$C = (1 - \alpha)B + \alpha F$$

Known: C, B
Unknown: α, F

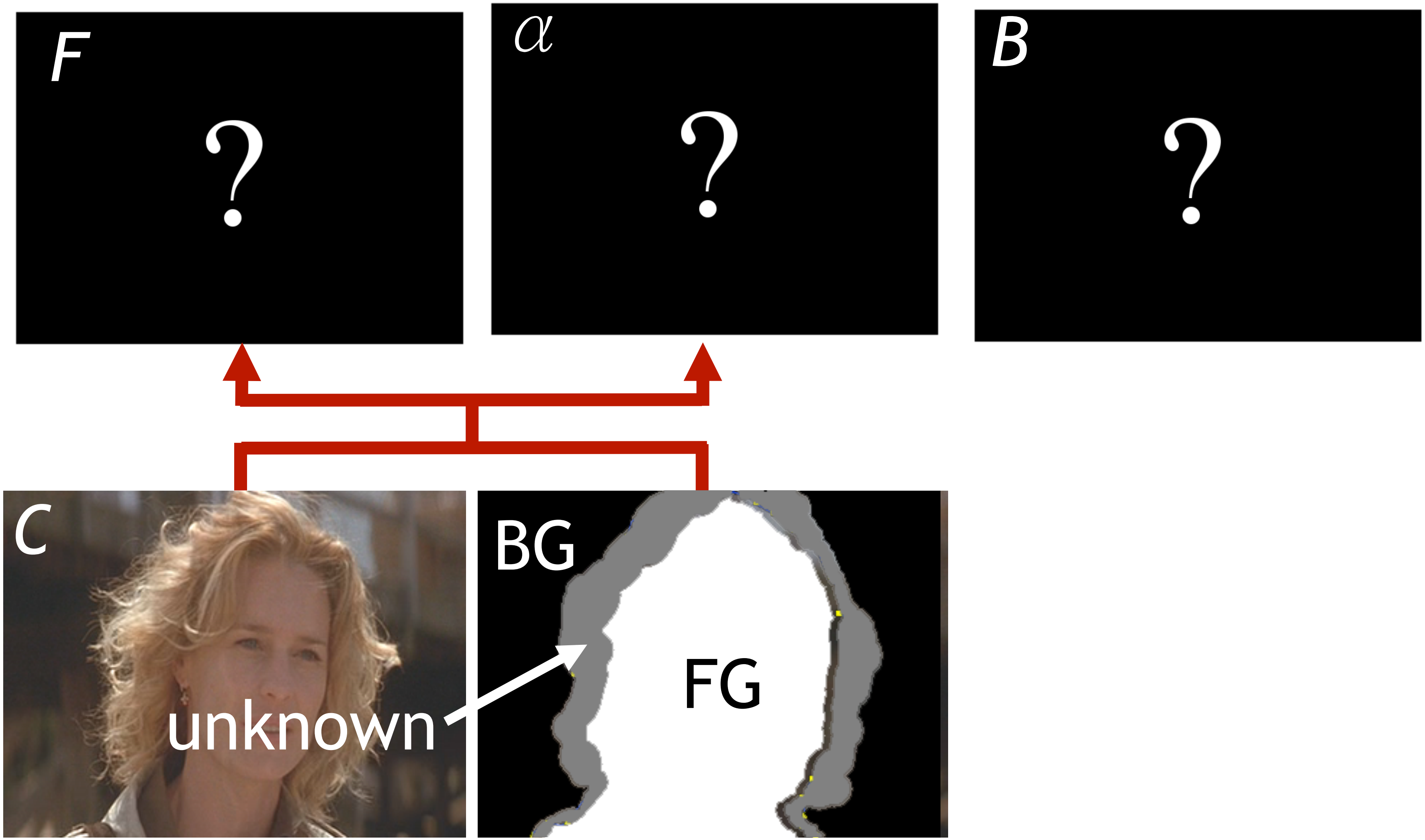
4 unknowns: α and triplets for F
3 equations, one per color channel

Blue screen matting issues

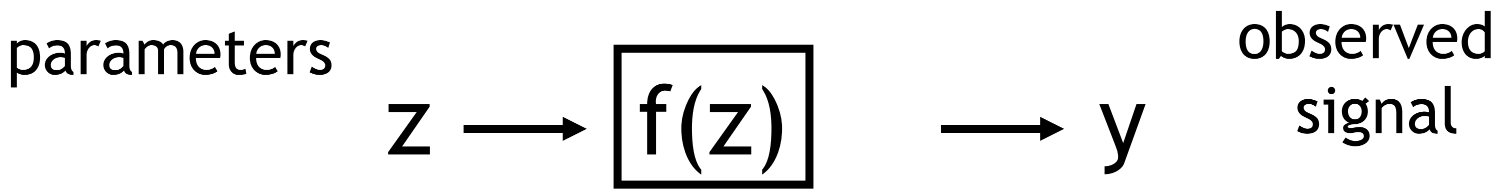
- **Color limitation**
- – Annoying for blue-eyed people

  adapt screen color (in particular green)
- **Shadows**
- – How to extract shadows cast on background

Natural image matting



Bayesian framework



$$z^* = \max_z P(z \mid y)$$

$$= \max_z \frac{P(y \mid z) P(z)}{P(y)}$$

$$= \max_z L(y \mid z) + L(z)$$

Example:
super-resolution
de-blurring
de-blocking
...

Bayesian matting approach(Chuang 2001)

$$P(\mathbf{F},\mathbf{B},\alpha|C) = P(C|\mathbf{F},\mathbf{B},\alpha)\, P(\mathbf{F},\mathbf{B},\alpha) \,/\, P(C)$$

Foreground, background, transparency you want to estimate

Color you observe

Likelihood function

Prior probability

Constant w.r.t. parameters x.

Bayesian matting approach(Chuang 2001)

- We must try to build a probability distribution for the unknown regions.

$$\boldsymbol{max}\, L(F,B,\alpha|C) = \boldsymbol{max}\, L(C|F,B,\alpha) + L(F,B,\alpha) - L(C)$$

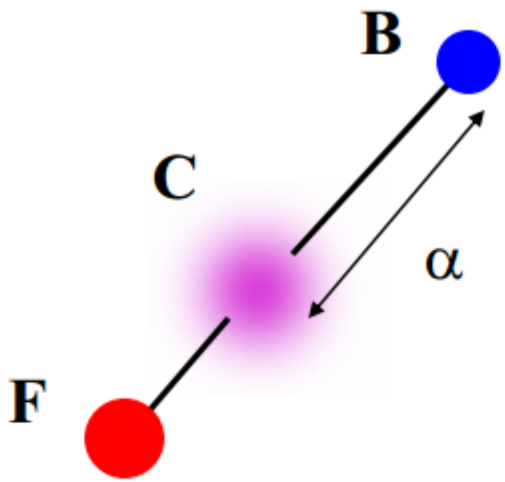
$$= \boldsymbol{max}\, L(C|F,B,\alpha) + L(F,B,\alpha)$$

$$= \boldsymbol{max}\, L(C|F,B,\alpha) + L(F) + L(B) + L(\alpha)$$

Bayesian matting approach(Chuang 2001)

- **Log likelihood** $\mathbf{L}(C|F,B,\alpha)$

$$\mathbf{L}(C|F,B,\alpha) = -\|C - \alpha F - (1-\alpha)B\|^2 / \sigma^2$$



Bayesian matting approach(Chuang 2001)

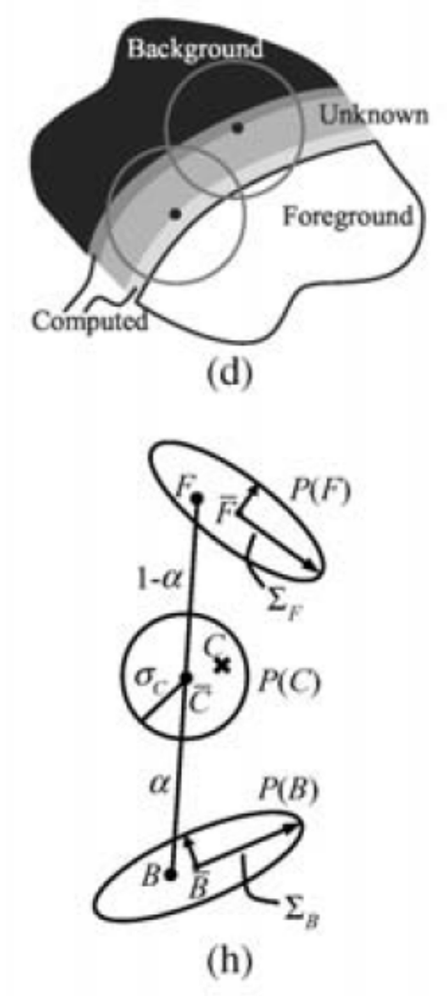
- **Prior probabilities** $L(F), L(B)$

$$\mathbf{L}(F) = -(\mathrm{F} - \boldsymbol{\overline{F}})^T \Sigma_F^{-1} (\mathrm{F} - \boldsymbol{\overline{F}})/\mathbf{2}$$

$$\overline{F} = \frac{1}{W} \sum_{i \in N} w_i F_i$$

$$\Sigma_F = \frac{1}{W} \sum_{i \in N} w_i (F_i - \overline{F})(F_i - \overline{F})^T$$

- **SAME for B**



Bayesian matting approach(Chuang 2001)

- **Prior probabilities** $L(\alpha)$
- In this work, we assume that log likelihood for the opacity $L(\alpha)$ is constant.
- Ignort it.

Bayesian matting approach(Chuang 2001)

$$\boldsymbol{max}\, L(F,B,\alpha|C) \;=\boldsymbol{max}\, L(C|F,B,\alpha) + L(F) + L(B)$$

$$\mathbf{L}(C|F,B,\alpha) = -\|C-\alpha F-(1-\alpha)B\|^{2}/\sigma^{2}$$

$$\mathbf{L}(F) = -(\mathrm{F}-\overline{\boldsymbol{F}})^{T}\Sigma_{F}{}^{-1}(\mathrm{F}-\overline{\boldsymbol{F}})/\mathbf{2}$$

$$\mathbf{L}(B) = -(\mathrm{B}-\bar{B})^{T}\Sigma_{B}{}^{-1}(\mathrm{B}-\overline{\boldsymbol{B}})/\mathbf{2}$$

Bayesian matting approach(Chuang 2001)

- Solve math problem: (for α constant)

- **Derive L(C|F,B,α) + L(F) +L(B)+L(α) wrt F & B, and set to zero gives**

$$\begin{bmatrix} \Sigma_F^{-1} + I\alpha^2/\sigma_C^2 & I\alpha(1-\alpha)/\sigma_C^2 \\ I\alpha(1-\alpha)/\sigma_C^2 & \Sigma_B^{-1} + I(1-\alpha)^2/\sigma_C^2 \end{bmatrix} \begin{bmatrix} F \\ B \end{bmatrix} = \begin{bmatrix} \Sigma_F^{-1}\overline{F} + C\alpha/\sigma_C^2 \\ \Sigma_B^{-1}\overline{B} + C(1-\alpha)/\sigma_C^2 \end{bmatrix},$$

Bayesian matting approach(Chuang 2001)

- Solve math problem: for $F\&B$ constant

- **Derive L(C|F,B,α) + L(F) +L(B)+L(α) wrt α, and set to zero gives**

$$\alpha = \frac{(C-B)\cdot(F-B)}{\|F-B\|^2}$$

Bayesian matting approach(Chuang 2001)

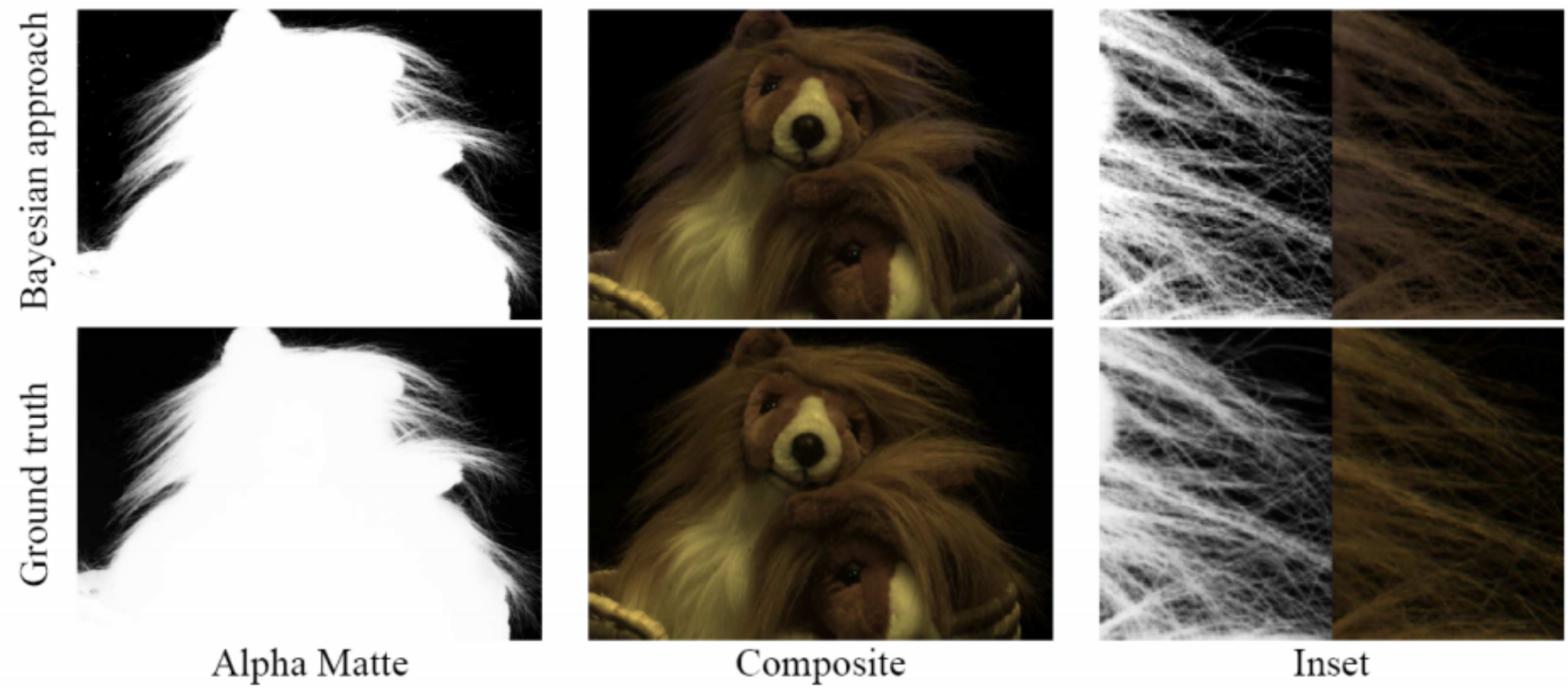
- **Solve math problem:**

- 1. The user specifies a trimap
- 2. Compute Gaussian distributions for foreground and background regions
- 3. **Iterate**
  - – Keep α constant, solve for F & B (for each pixel)
  - – Keep F & B constant, solve for α (for each pixel)

- Note that pixels are treated independently

Bayesian matting approach(Chuang 2001)

- Results:



Super-resolution and blur removal

How to increase resolution

- Possible ways for increasing an image resolution:
  - – Reducing pixel size.
  - – Increase the chip-size.
  - – Super-resolution.

How to increase resolution

- **Reduce pixel size:**
  - Increase the number of pixels per unit area.
- Advantage:
  - Increases spatial resolution.
- Disadvantage:
  - Noise introduced.
  - As the pixel size decreases, the amount of light decreases.

How to increase resolution

- **Increase the chip size (HW):**
- Advantage:
  - Enhances spatial resolution.
- Disadvantage:
  - High cost for high precision optics.

How to increase resolution

- **Superresolution (SR):**
  - Process of combining multiple low resolution images to form a high resolution image.
- Advantages:
  - Cost less than comparable approaches.
  - LR imaging systems can still be utilized.

Super resolution

$$o_k(\mathbf{x}) = D\{b(\mathbf{x}) * s(\hat{h}_k(\mathbf{x})\} + n_k(\mathbf{x})$$

$$\sum_k ||o_k(\mathbf{x}) - D\{b(\mathbf{x}) * s(\hat{h}_k(\mathbf{x})\}||^2$$

$$\sum_k ||o_k - DB_K W_K s||^2$$

Super-resolution

- Obtaining a HR image from one or multiple LR images .

zoom

apply super-resolution technique

Super-resolution