

Computational Photography

Prof. Feng Liu

Spring 2022

<http://www.cs.pdx.edu/~fliu/courses/cs510/>

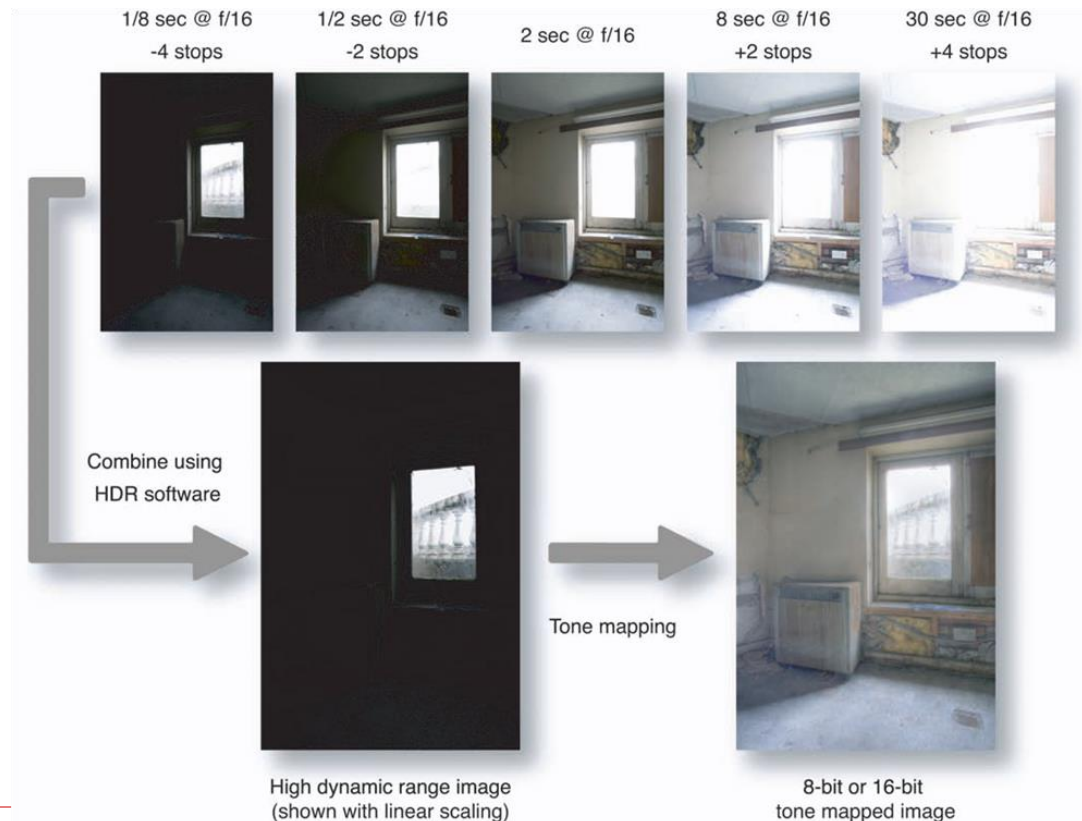
04/19/2022

Last Time

- Re-lighting
 - Tone mapping

Today

- Re-lighting: high dynamic range imaging
- Full presentation schedule is online



High dynamic range imaging

Digital Visual Effects

Yung-Yu Chuang

with slides by Fredo Durand, Brian Curless, Steve Seitz, Paul Debevec and Alexei Efros

The world is high dynamic range



1



1,500



25,000

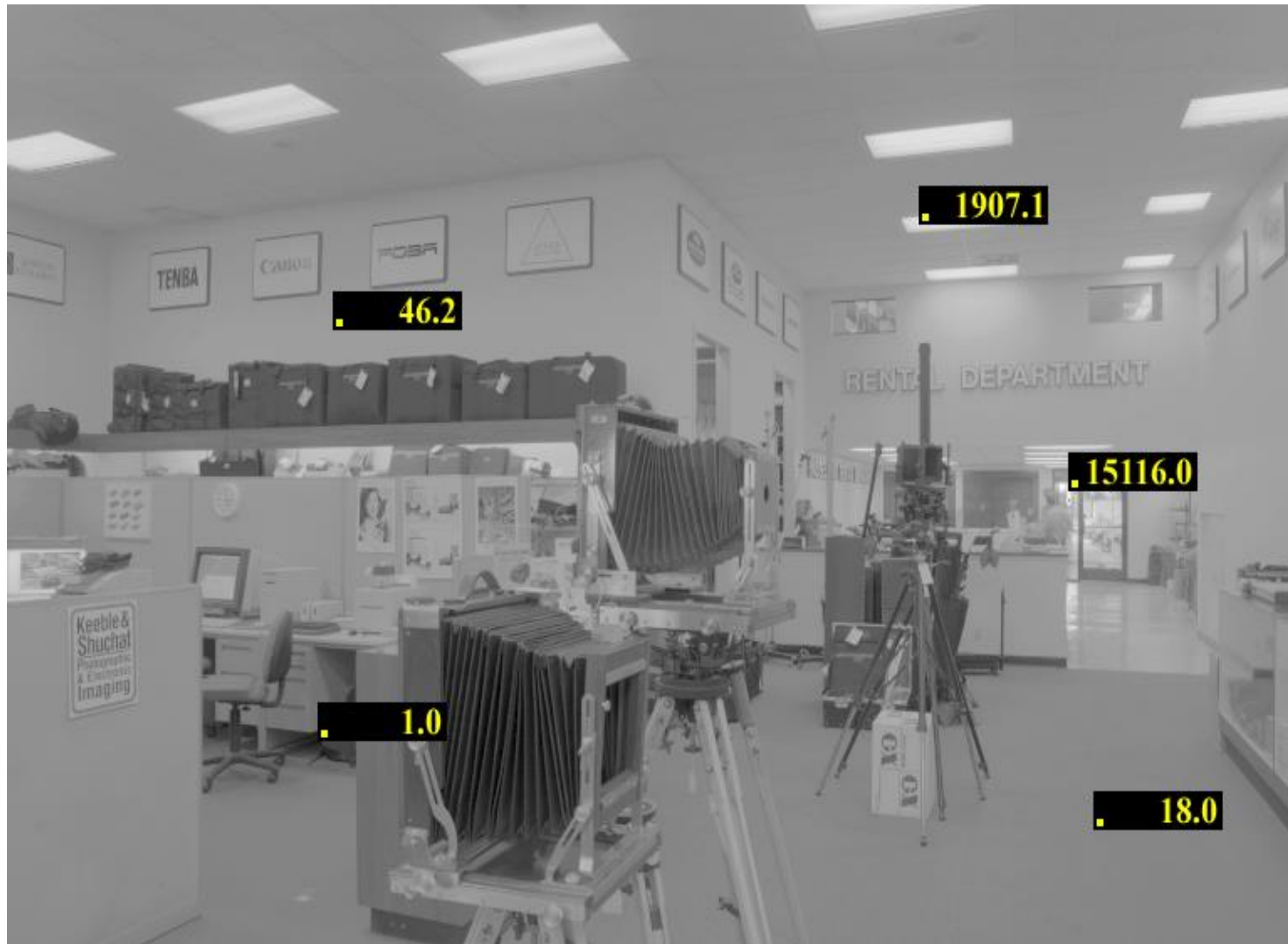


400,000



2,000,000,000

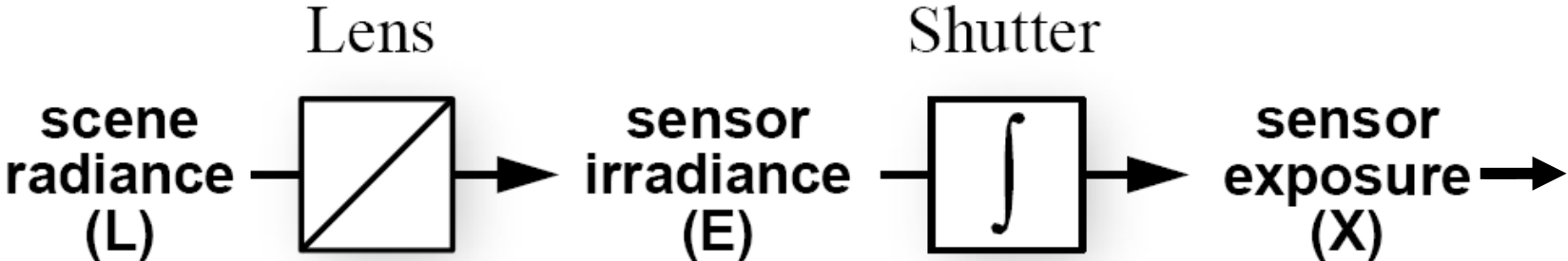
The world is high dynamic range



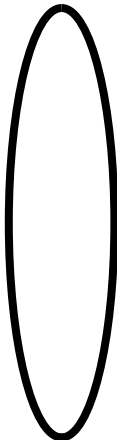
Camera is an imperfect device

- Camera is an imperfect device for measuring the radiance distribution of a scene because it cannot capture the full spectral content and dynamic range.
- Limitations in sensor design prevent cameras from capturing all information passed by lens.

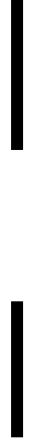
Camera pipeline



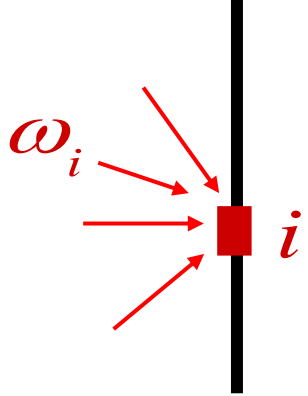
$L(p, \omega)$
 ω p
 Assume a static scene, Thus, L is not a function of time.



lens



shutter

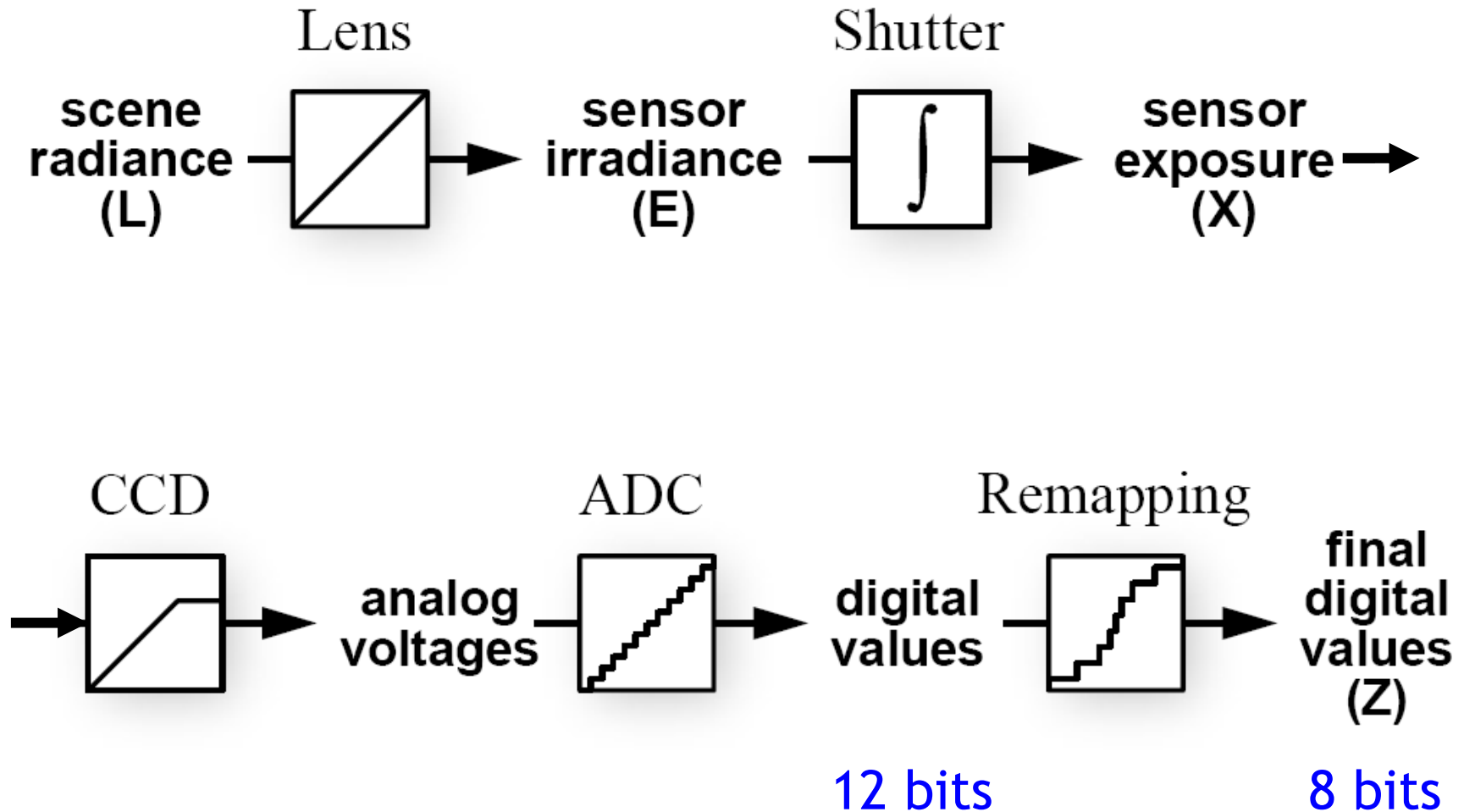


sensor

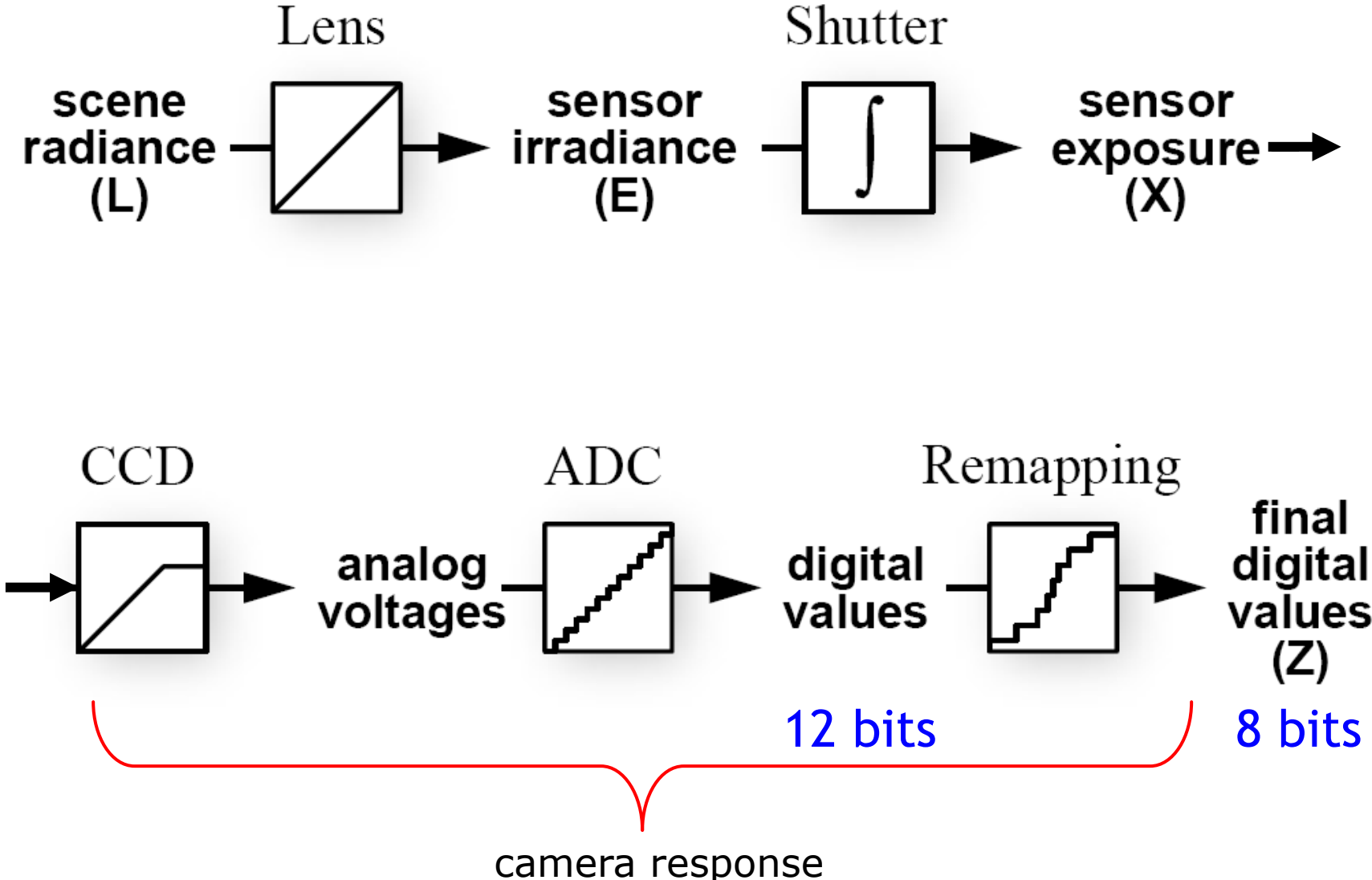
$$E_i = \int_{\Omega} L(i, \omega_i) d\omega$$

$$X_i = \int_{t=0}^{\Delta t} E_i dt = E_i \Delta t$$

Camera pipeline

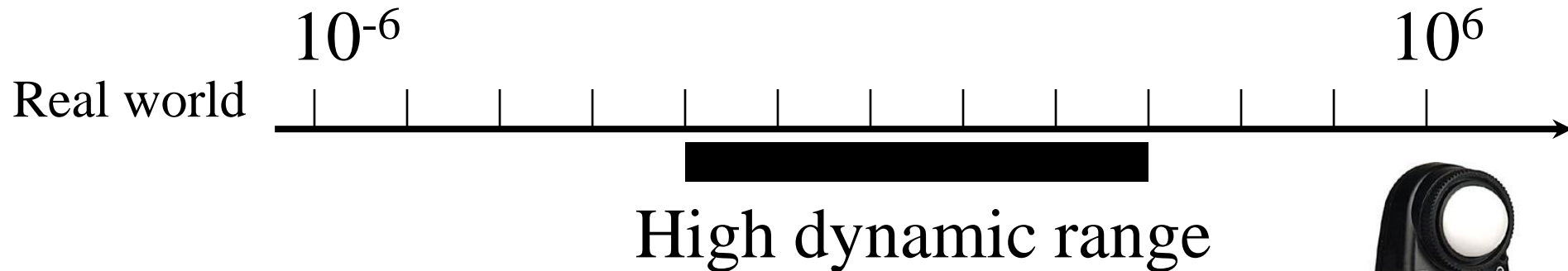


Camera pipeline



Real world dynamic range

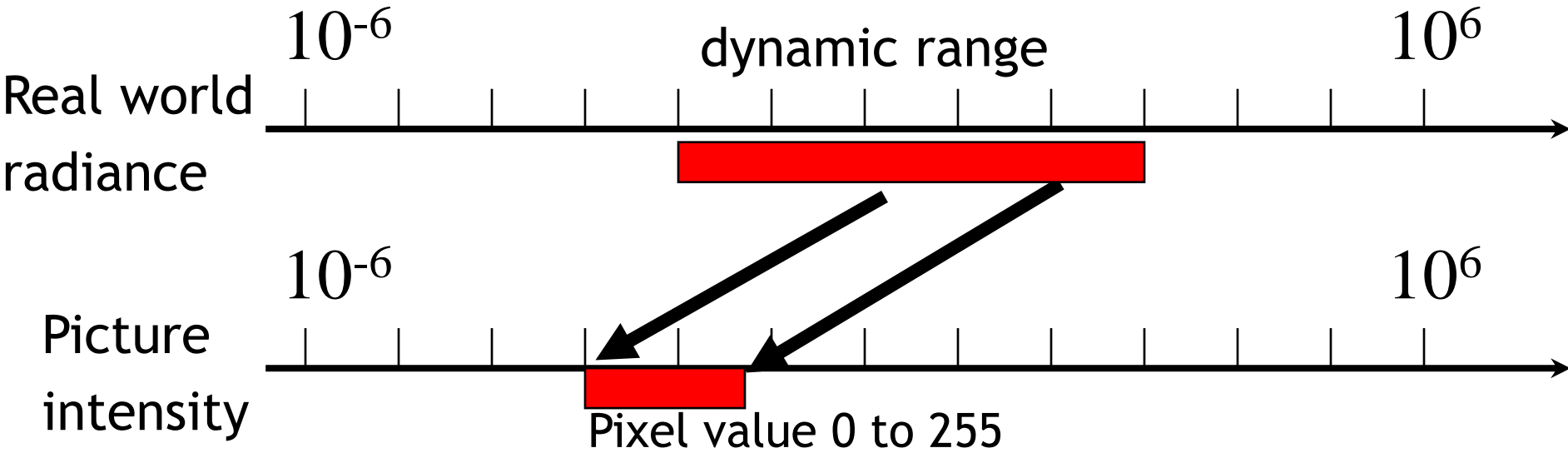
- Eye can adapt from $\sim 10^{-6}$ to 10^6 cd/m²
- Often 1 : 100,000 in a scene
- Typical 1:50, max 1:500 for pictures



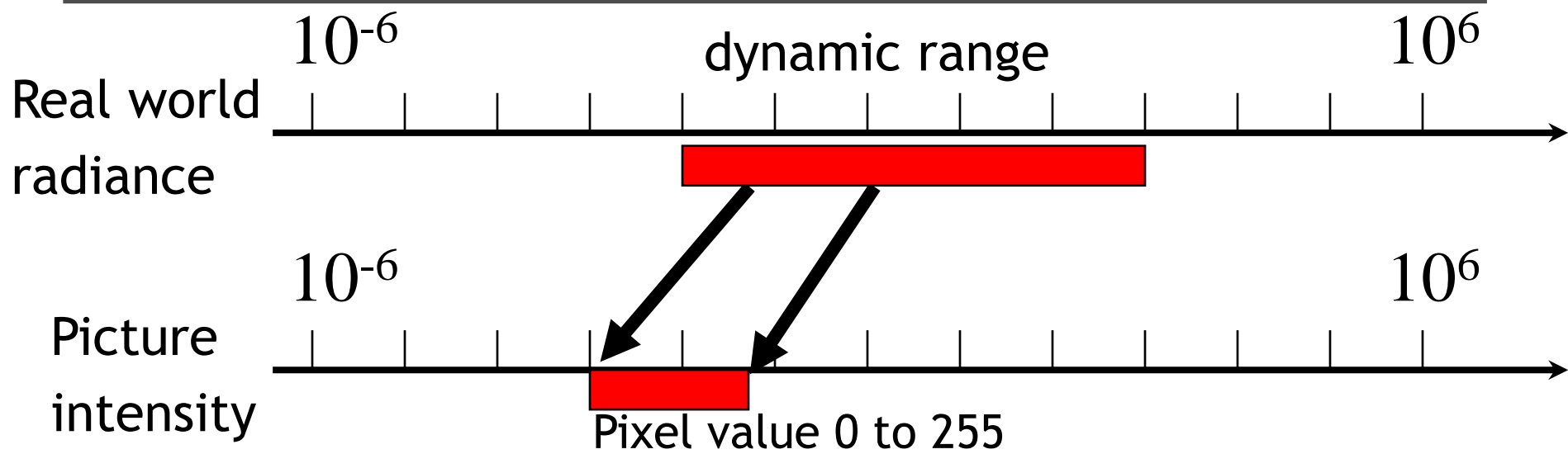
spotmeter



Short exposure



Long exposure

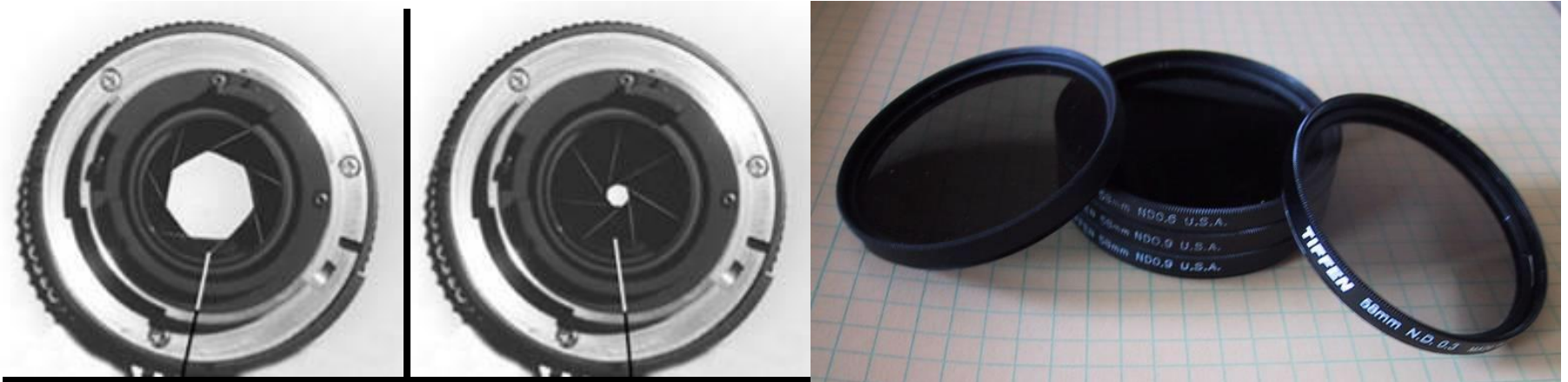


Camera is not a photometer

- Limited dynamic range
 - ⇒ Perhaps use multiple exposures?
- Unknown, nonlinear response
 - ⇒ Not possible to convert pixel values to radiance
- Solution:
 - Recover response curve from multiple exposures, then reconstruct the *radiance map*

Varying exposure

- Ways to change exposure
 - Shutter speed
 - Aperture
 - Neutral density filters



Shutter speed

- Note: shutter times usually obey a power series - each “stop” is a factor of 2

$\frac{1}{4}$, $\frac{1}{8}$, $\frac{1}{16}$, $\frac{1}{32}$, $\frac{1}{64}$, $\frac{1}{128}$, $\frac{1}{256}$, $\frac{1}{512}$,
 $\frac{1}{1024}$ sec

Varying shutter speeds

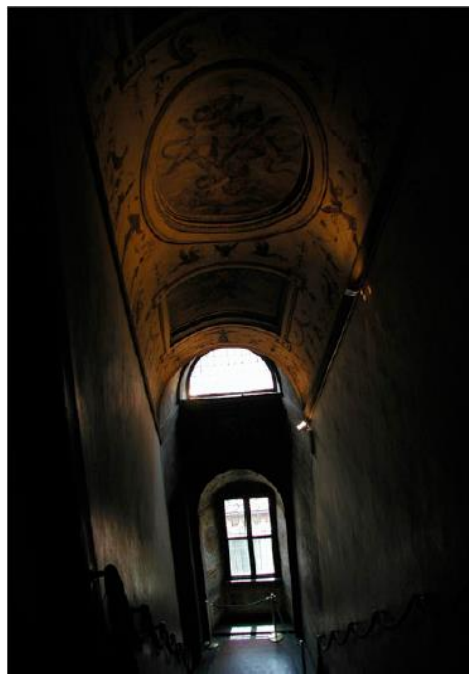
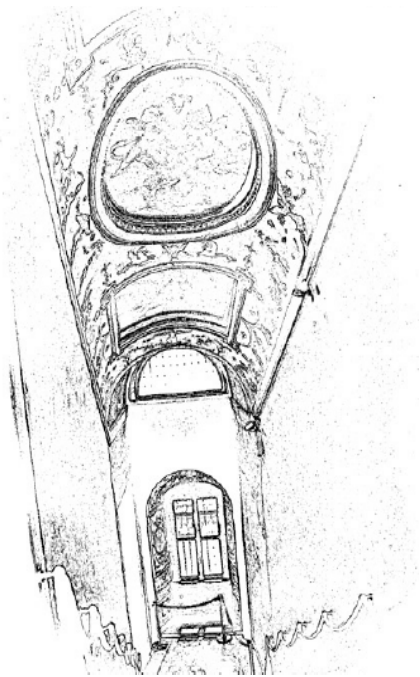
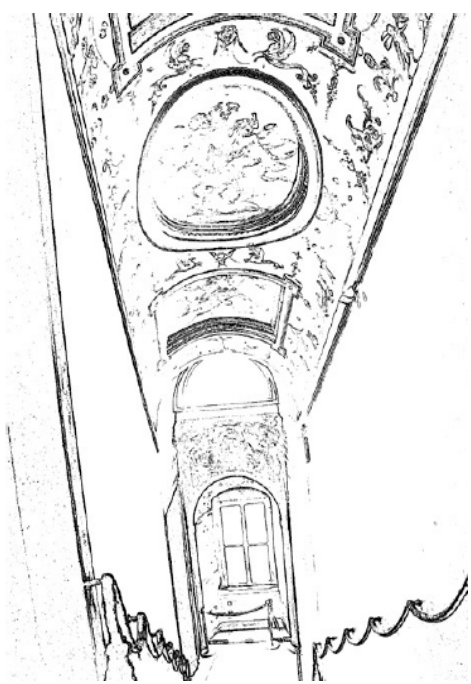


HDRI capturing from multiple exposures

- Capture images with multiple exposures
- Image alignment (even if you use tripod, it is suggested to run alignment)
- Response curve recovery
- Ghost/flare removal

Image alignment

- We will introduce a fast and easy-to-implement method for this task, called Median Threshold Bitmap (MTB) alignment technique.
- Consider only integral translations. It is enough empirically.
- The inputs are N grayscale images. (You can either use the green channel or convert into grayscale by $Y=(54R+183G+19B)/256$)
- MTB is a binary image formed by thresholding the input image using the median of intensities.



Edge map

Input

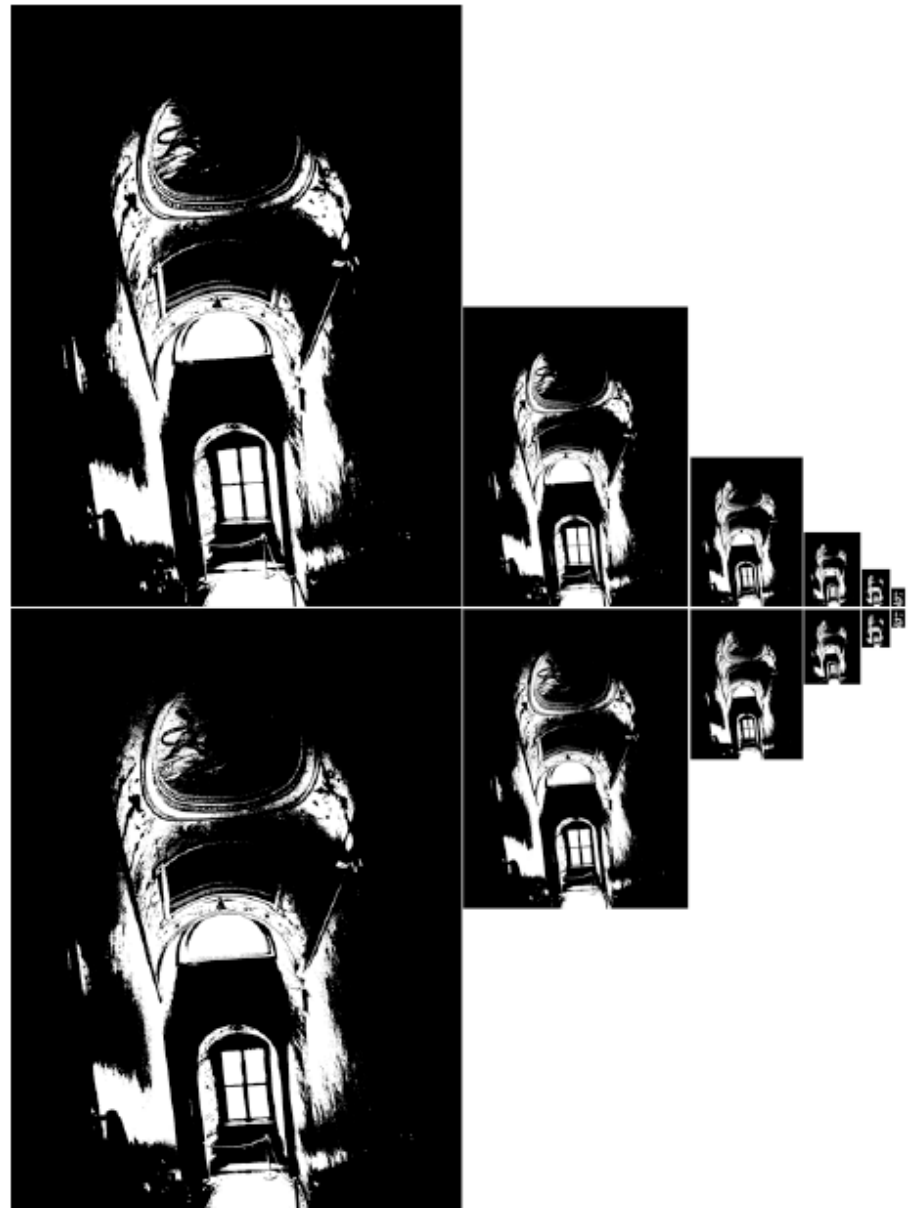
MTB

Why is MTB better than gradient?

- Edge-detection filters are dependent on image exposures
- Taking the difference of two edge bitmaps would not give a good indication of where the edges are misaligned.

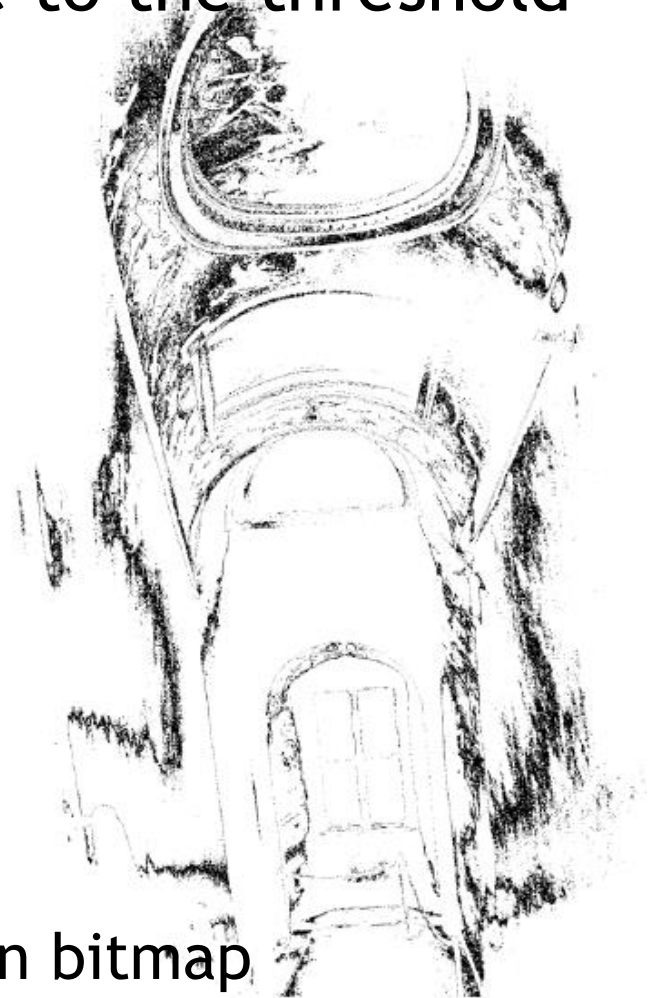
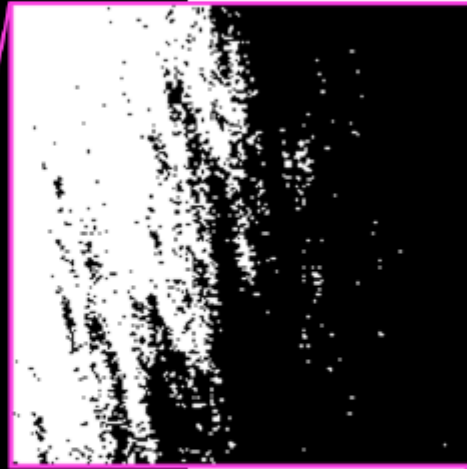
Search for the optimal offset

- Try all possible offsets.
- Gradient descent
- Multiscale technique
- $\log(\text{max_offset})$ levels
- Try 9 possibilities for the top level
- Scale by 2 when passing down; try its 9 neighbors



Threshold noise

ignore pixels that are close to the threshold



exclusion bitmap

Results

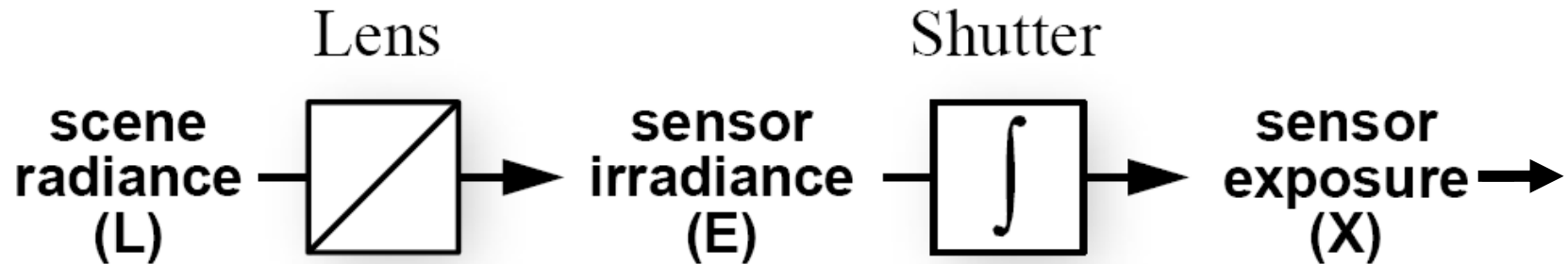
Success rate = 84%. 10% failure due to rotation.
3% for excessive motion and 3% for too much high-frequency content.



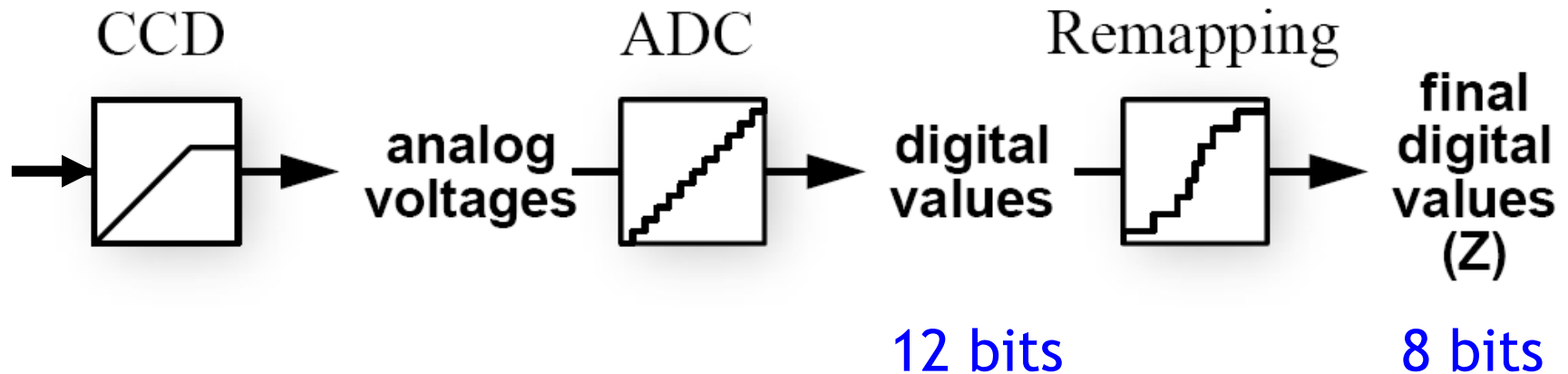
Unaligned HDR

Aligned HDR

Recovering response curve



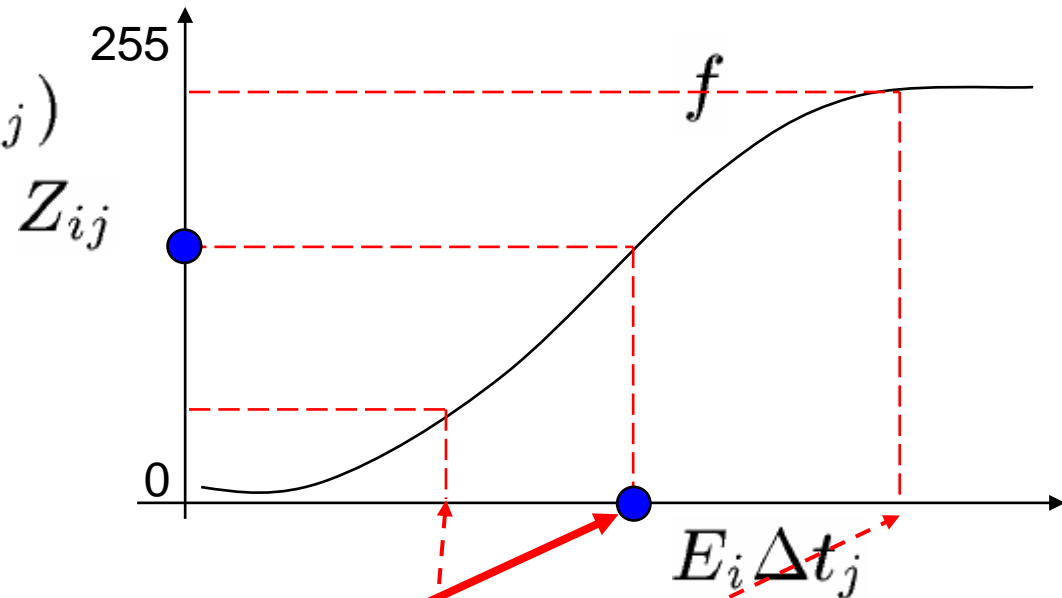
$$Z_{ij} = f(E_i \Delta t_j)$$



Recovering response curve

- We want to obtain the inverse of the response curve

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

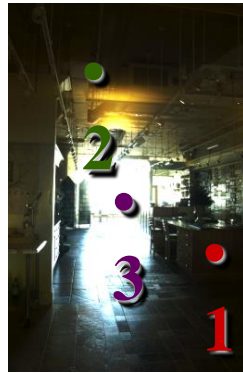


Recovering response curve

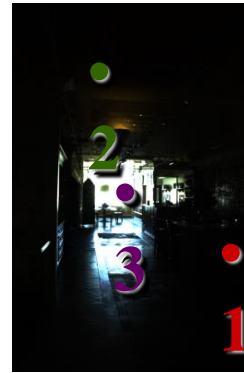
Image series



$\Delta t =$
2 sec



$\Delta t =$
1 sec



$\Delta t =$
1/2 sec

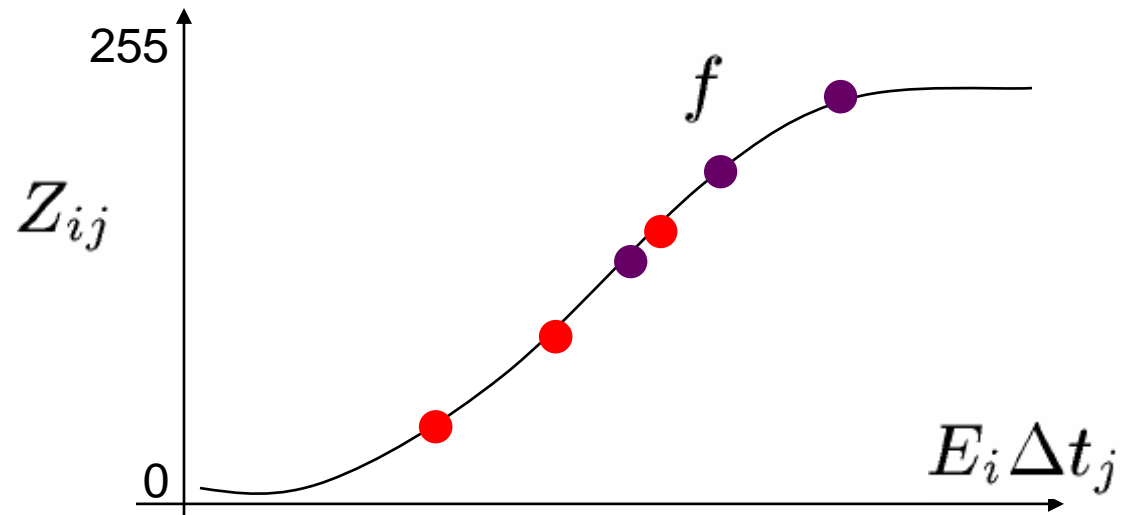


$\Delta t =$
1/4 sec



$\Delta t =$
1/8 sec

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



Recovering response curve

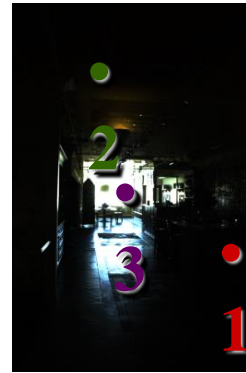
Image series



$\Delta t =$
2 sec



$\Delta t =$
1 sec



$\Delta t =$
1/2 sec



$\Delta t =$
1/4 sec



$\Delta t =$
1/8 sec

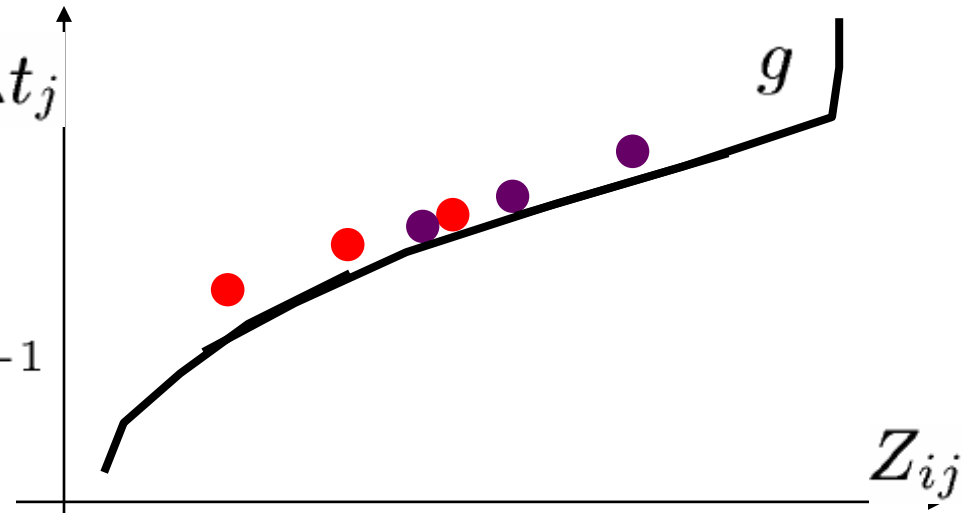
$$\ln E_i + \ln \Delta t_j$$

$$f^{-1}(Z_{ij}) = E_i \Delta t_j$$

$$\ln f^{-1}(Z_{ij}) = \ln E_i + \ln \Delta t_j$$

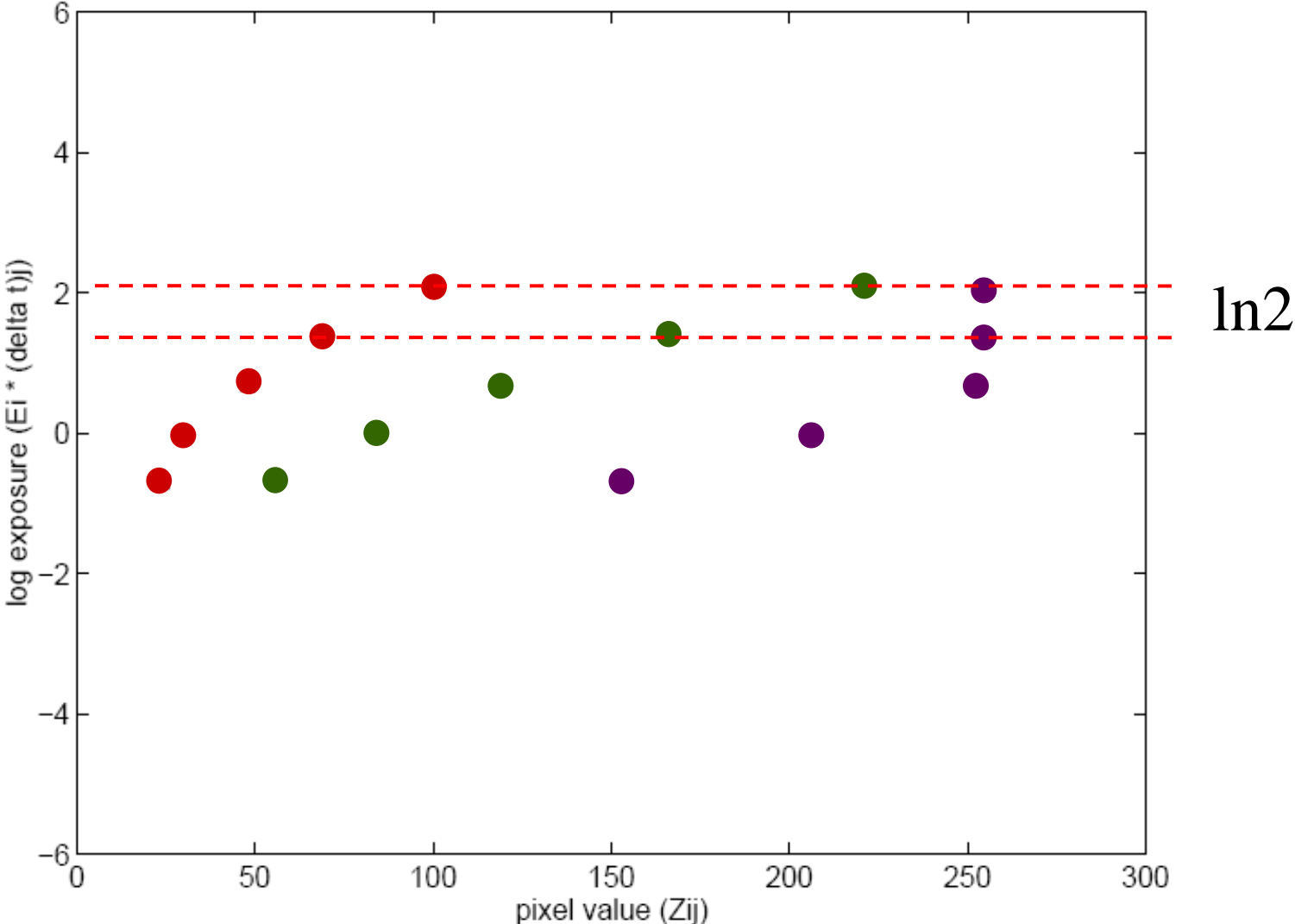
let us define function $g = \ln f^{-1}$

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



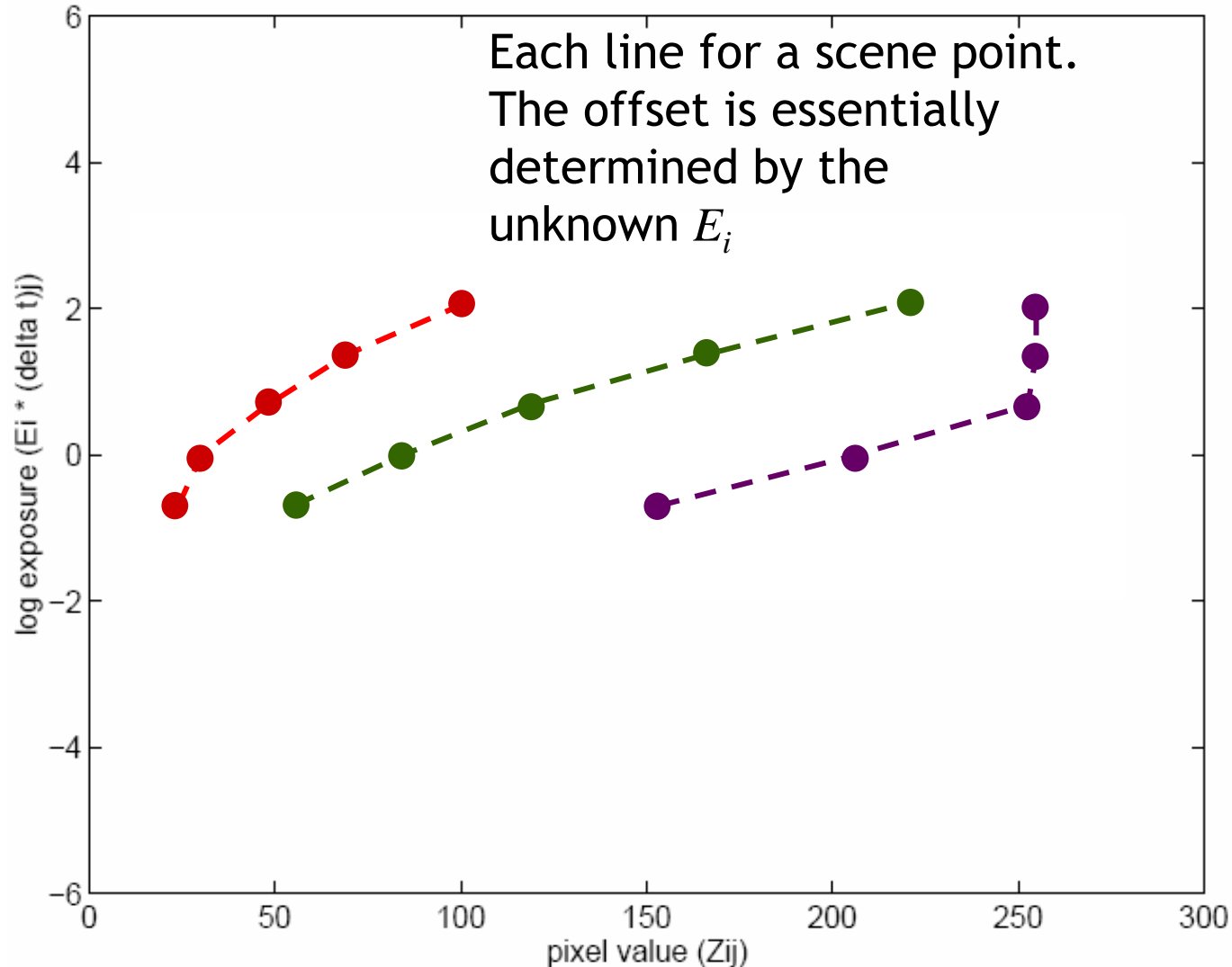
Idea behind the math

plot of $g(Z_{ij})$ from three pixels observed in five images, assuming unit radiance at each pixel

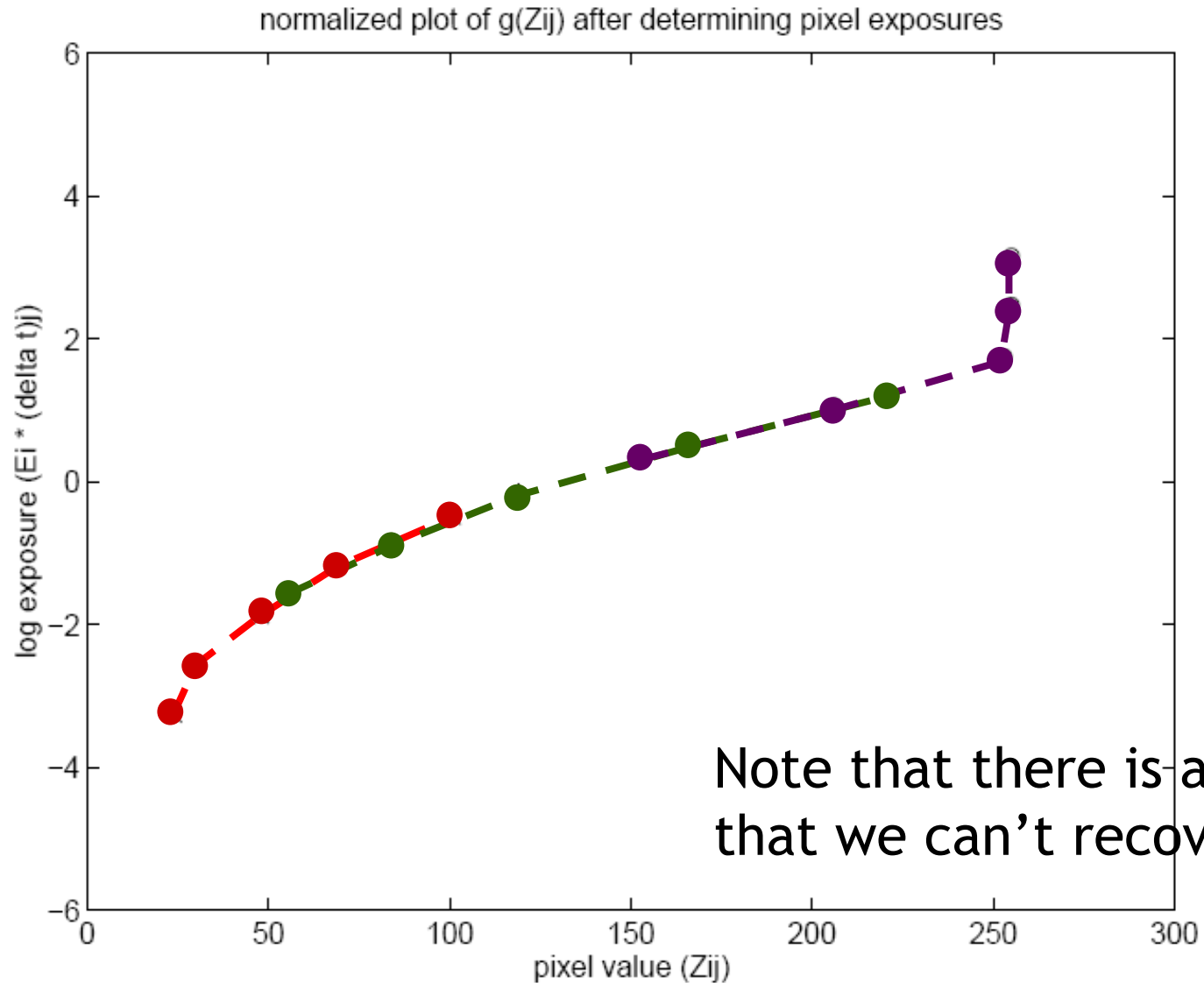


Idea behind the math

plot of $g(Z_{ij})$ from three pixels observed in five images, assuming unit radiance at each pixel



Idea behind the math



Basic idea

- Design an objective function
- Optimize it

Math for recovering response curve

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

f is monotonic, it is invertible

$$\ln f^{-1}(Z_{ij}) = \ln E_i + \ln \Delta t_j$$

let us define function $g = \ln f^{-1}$

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

minimize the following

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

$$g''(z) = g(z-1) - 2g(z) + g(z+1)$$

Recovering response curve

- The solution can be only up to a scale, add a constraint

$$g(Z_{mid}) = 0, \text{ where } Z_{mid} = \frac{1}{2}(Z_{min} + Z_{max})$$

- Add a hat weighting function

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

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

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

Recovering response curve

- We want $N(P - 1) > (Z_{max} - Z_{min})$
If $P=11$, $N \sim 25$ (typically 50 is used)
- We prefer that selected pixels are well distributed and sampled from constant regions. They picked points by hand.
- It is an overdetermined system of linear equations and can be solved using SVD

How to optimize?

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

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

1. Set partial derivatives zero
- 2.

$$\min \sum_{i=1}^N (\mathbf{a}_i \mathbf{x} - \mathbf{b}_i)^2 \rightarrow \text{least - square solution of } \begin{bmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \\ \vdots \\ \mathbf{a}_N \end{bmatrix} \mathbf{x} = \begin{bmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \\ \vdots \\ \mathbf{b}_N \end{bmatrix}$$

Matlab code

```
%  
% gsolve.m - Solve for imaging system response function  
%  
% Given a set of pixel values observed for several pixels in several  
% images with different exposure times, this function returns the  
% imaging system's response function g as well as the log film irradiance  
% values for the observed pixels.  
%  
% Assumes:  
%  
%   Zmin = 0  
%   Zmax = 255  
%  
% Arguments:  
%  
%   Z(i,j) is the pixel values of pixel location number i in image j  
%   B(j)   is the log delta t, or log shutter speed, for image j  
%   l      is lambda, the constant that determines the amount of smoothness  
%   w(z)   is the weighting function value for pixel value z  
%  
% Returns:  
%  
%   g(z)   is the log exposure corresponding to pixel value z  
%   lE(i)  is the log film irradiance at pixel location i  
%
```

Matlab code

```

function [g,lE]=gsolve(Z,B,l,w)

n = 256;
A = zeros(size(Z,1)*size(Z,2)+n+1,n+size(Z,1));
b = zeros(size(A,1),1);

k = 1;           %% Include the data-fitting equations
for i=1:size(Z,1)
    for j=1:size(Z,2)
        wij = w(Z(i,j)+1);
        A(k,Z(i,j)+1) = wij; A(k,n+i) = -wij; b(k,1) = wij * B( j);
        k=k+1;
    end
end

A(k,129) = 1;    %% Fix the curve by setting its middle value to 0
k=k+1;

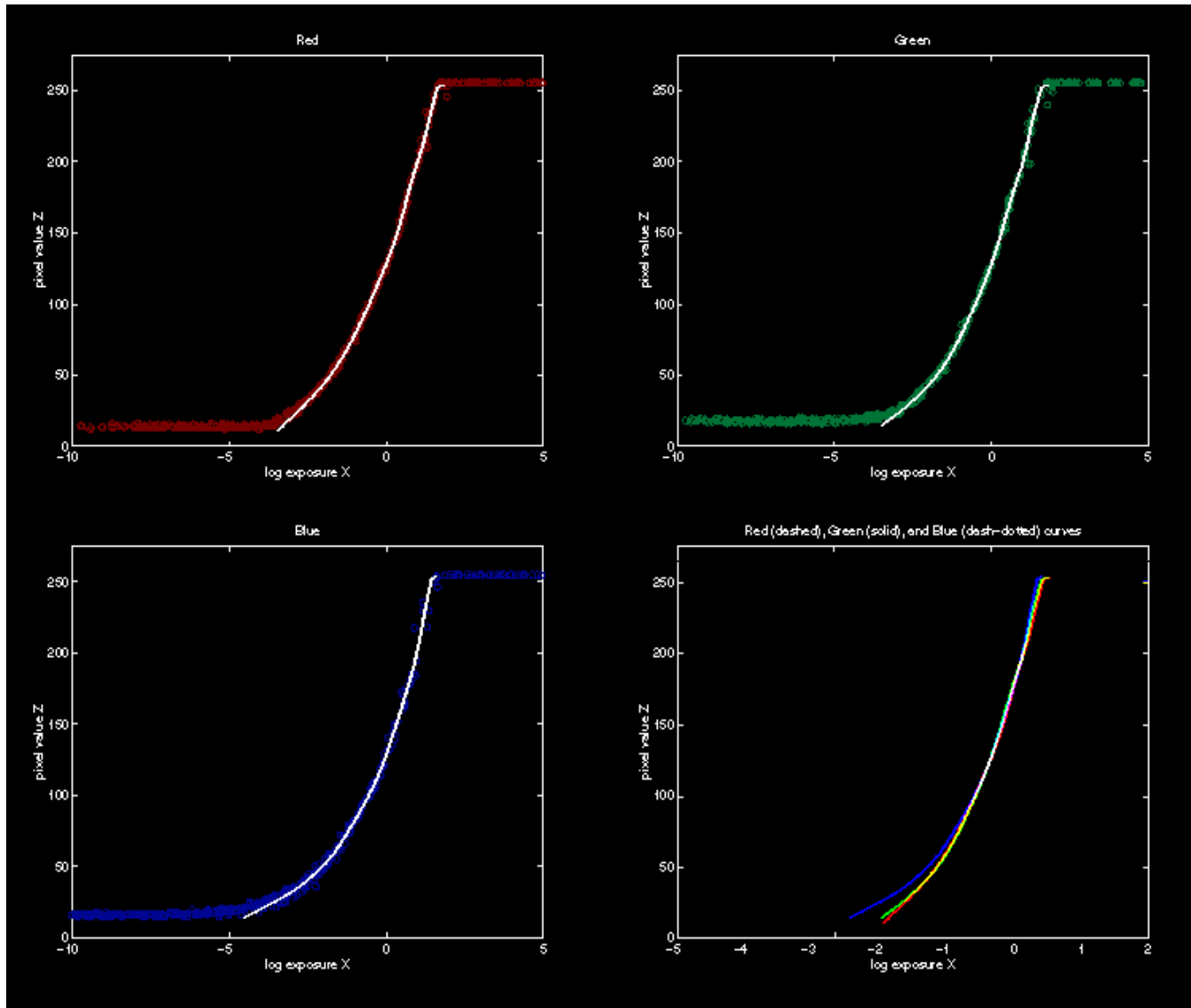
for i=1:n-2      %% Include the smoothness equations
    A(k,i)=l*w(i+1); A(k,i+1)=-2*l*w(i+1); A(k,i+2)=l*w(i+1);
    k=k+1;
end

x = A\b;        %% Solve the system using SVD

g = x(1:n);
lE = x(n+1:size(x,1));

```

Recovered response function



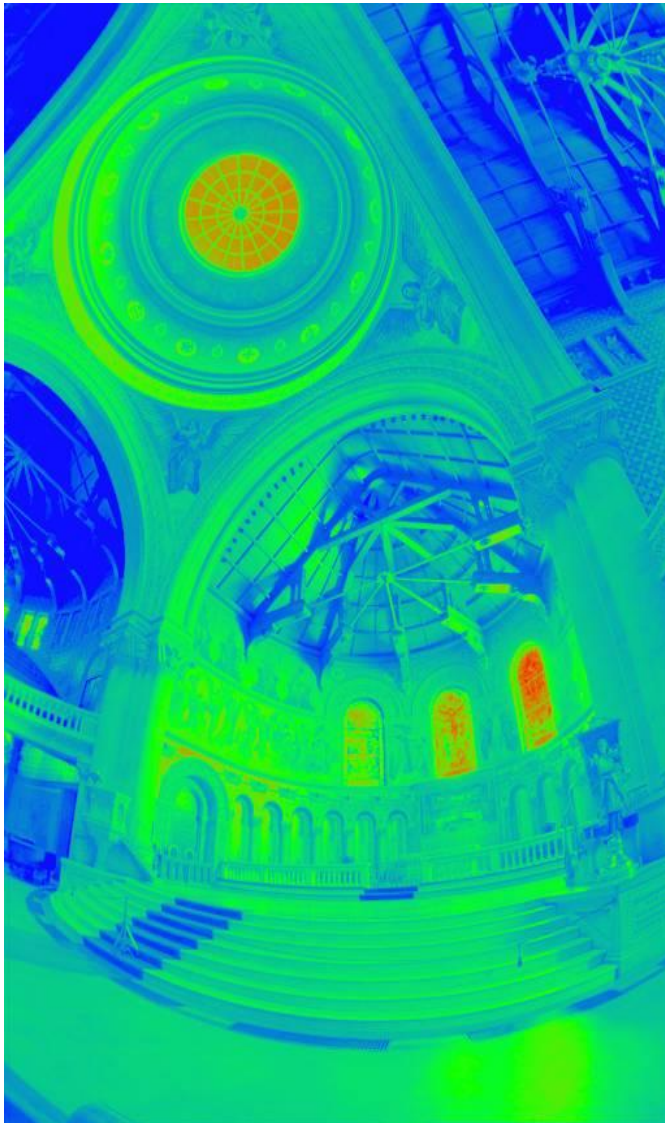
Constructing HDR radiance map

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

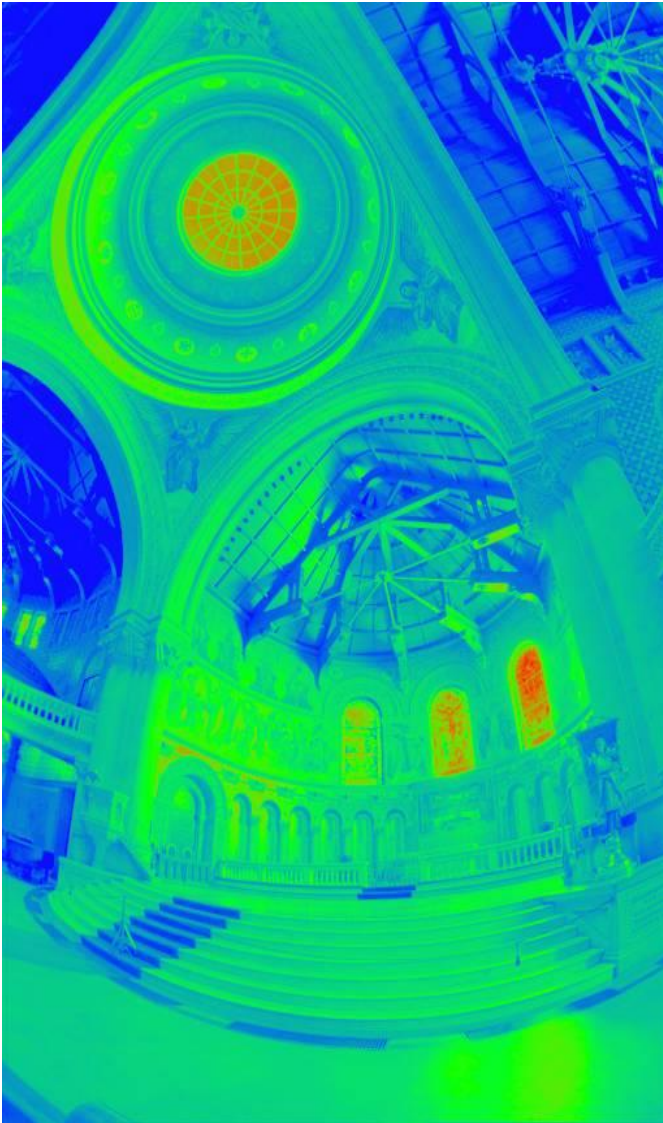
combine pixels to reduce noise and obtain a more reliable estimation

$$\ln E_i = \frac{\sum_{j=1}^P w(Z_{ij})(g(Z_{ij}) - \ln \Delta t_j)}{\sum_{j=1}^P w(Z_{ij})}$$

Reconstructed radiance map

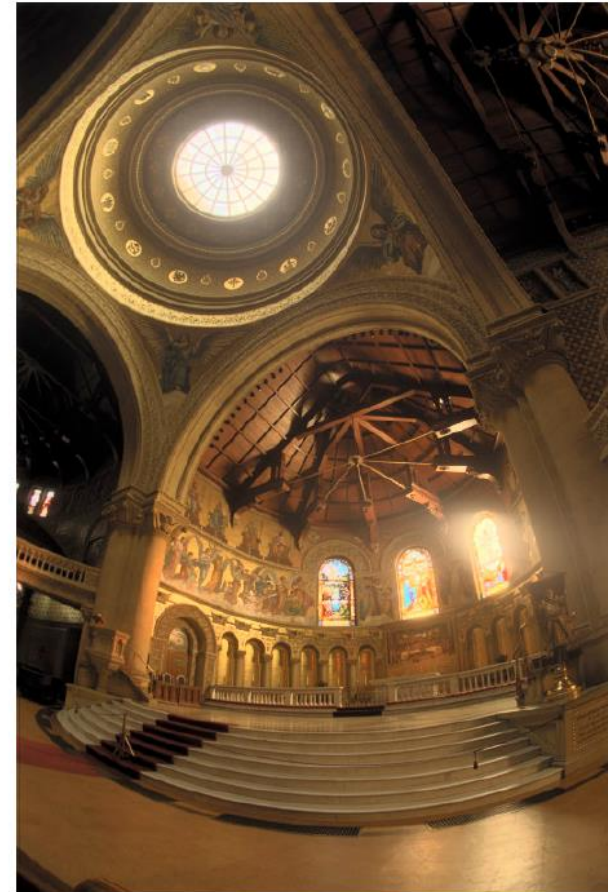
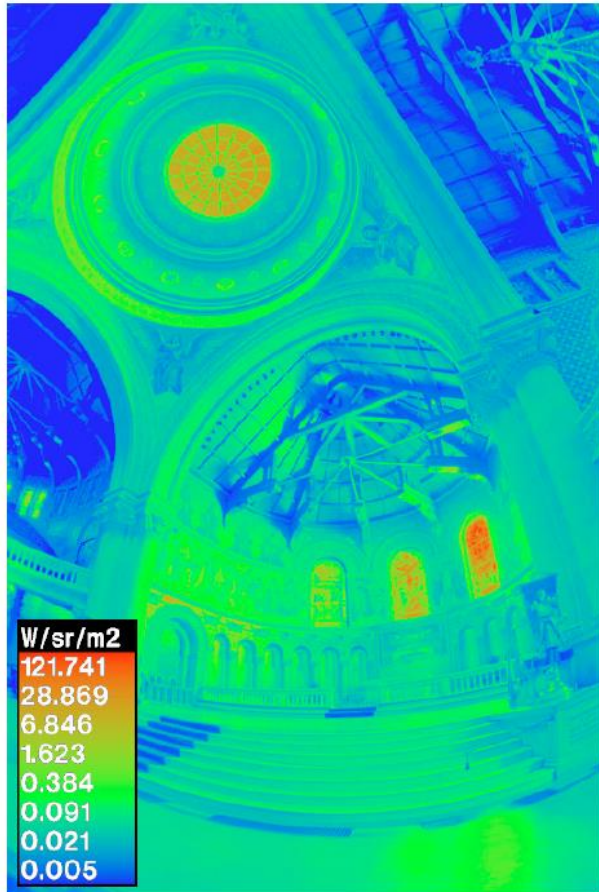


What is this for?



- Human perception
- Vision/graphics applications

Tone Mapping



Reprint from [Debevec and Malik 97]

Student paper presentation

Robust color-to-gray via nonlinear global mapping

Yongjin Kim, Cheolhun Jang
Julien Demouth, and Seungyong Lee
SIGGRAPH ASIA 2009

Presenter: Chen, Ray

Next Time

- Panorama
- Student paper presentations
 - 04/21: Nguyen, Henry
 - Colorization Using Optimization
A. Levin, D. Lischinski, and Y. Weiss
SIGGRAPH 2004
 - 04/21: Gerendasy, Daniel R.
 - Color harmonization
D. Cohen-Or, O. Sorkine, R. Gal, T. Leyv, and, Y. Xu
ACM SIGGRAPH 2006