High Dynamic Range (HDR)

Topic 3

Week 2 – Jan. 16th, 2019

Topic 3: HDR

- **High Dynamic Range (HDR)**
- Capturing HDR Images
- Computing the Camera Response Function

Dynamic Range

- Our visual perception is markedly different than that we see in photos
- Highlighted by trying to photograph scenes with very bright & very dark areas
- Dynamic range: ratio between the brightest & darkest areas of image visible
- Measured in “stops” (like EV):

$$\log_2(\text{dynamic range})$$

Debevec et al, SIGGRAPH’97

Dynamic Range

- Human: ~14 EV stops
- 8-bit image: ~6 stops
- EV is a log scale!
- We can’t capture HDR well
  - Best sensors capture 14 bits/pixel
  - Most images are 8-bit
- We can’t display HDR well
  - TV/monitors: 6-10 Stops

Debevec et al, SIGGRAPH’97

(T. Borer et al. "A "Display Independent" High Dynamic Range Television System”)

Capturing HDR: The Problem

- Bright pixels: saturate the sensor – no information!
- Dark pixels: are below the threshold required to be represented

Capturing HDR: Multiple Exposures

- Idea: Take photos at multiple EV to capture more dynamic range
  - For low EV, bright areas won't saturate pixels
  - For high EV, dark areas will have give enough light to be representable

Displaying HDR: Tone Mapping

- Idea: Like we use a gamma function to better display linear images, find a mapping function that can display more tones from our HDR image in 8-bit LDR display
- Making this look realistic is perhaps the bigger challenge!

R. Fattal et al., “Gradient Domain High Dynamic Range Compression,” Proc. ACM SIGGRAPH 2002

HDR in 2019

- A lot has changed since Fattal et al. in 2002
- Almost every modern smartphone has an HDR capture mode (of various extent/quality)
- High-end TVs/monitors now sell with “HDR” feature, movies are increasingly captured in HDR (both of these 10-bit, ~10 stops!)

HDR in 2019

- Almost every new smartphone has an HDR capture mode (of various extent/quality)

Burst photography for high dynamic range and low-light imaging on mobile cameras

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Jonathan T. Barron Florian Kainz Jiawen Chen Marc Levoy
Google Research

Figure 1: *A comparison of a conventional camera pipeline (left, middle) and our burst photography pipeline (right) running on the same cell-phone camera. In this low-light setting (about 0.7 lux), the conventional camera pipeline underexposes (left). Brightening the image (middle) reveals heavy spatial denoising, which results in loss of detail and an unpleasantly blotchy appearance. Fusing a burst of images increases the signal-to-noise ratio, making aggressive spatial denoising unnecessary. We encourage the reader to zoom in. While our pipeline excels in low-light and high-dynamic-range scenes (for an example of the latter see figure 10), it is computationally efficient and reliably artifact-free, so it can be deployed on a mobile camera and used as a substitute for the conventional pipeline in almost all circumstances. For readability the figure has been made uniformly brighter than the original photographs.*

HDR in 2019

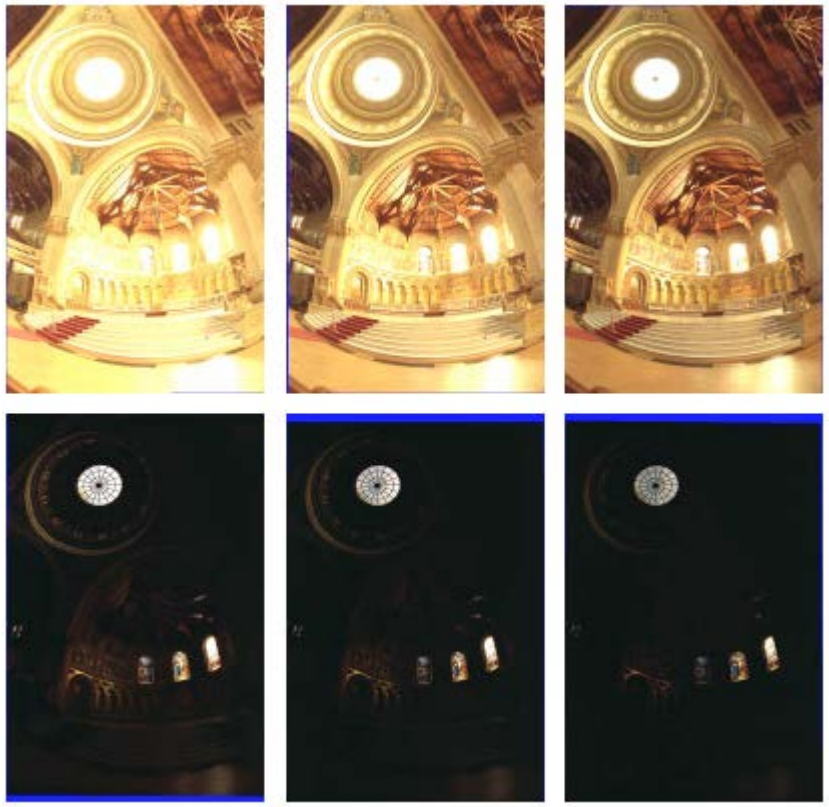
- High-end TVs now sell with “HDR” of varying quality
- Movies are captured in HDR
- Both of these are at best 10-bit, ~10 stops!
- Still far from human DR!

Topic 3: HDR

- High Dynamic Range (HDR)
- **Capturing HDR Images**
- Computing the Camera Response Function

Capturing HDR: Idea

- Problem: Our cameras can only capture a limited representation of the scene irradiance Φ, represented by pixel value Z
- In different exposures, a different dynamic range for each pixel is captured
- The true scene irradiance for each pixel will only be represented within the dynamic range of some of these photos
- Idea: Let's capture many exposures and somehow combine them!

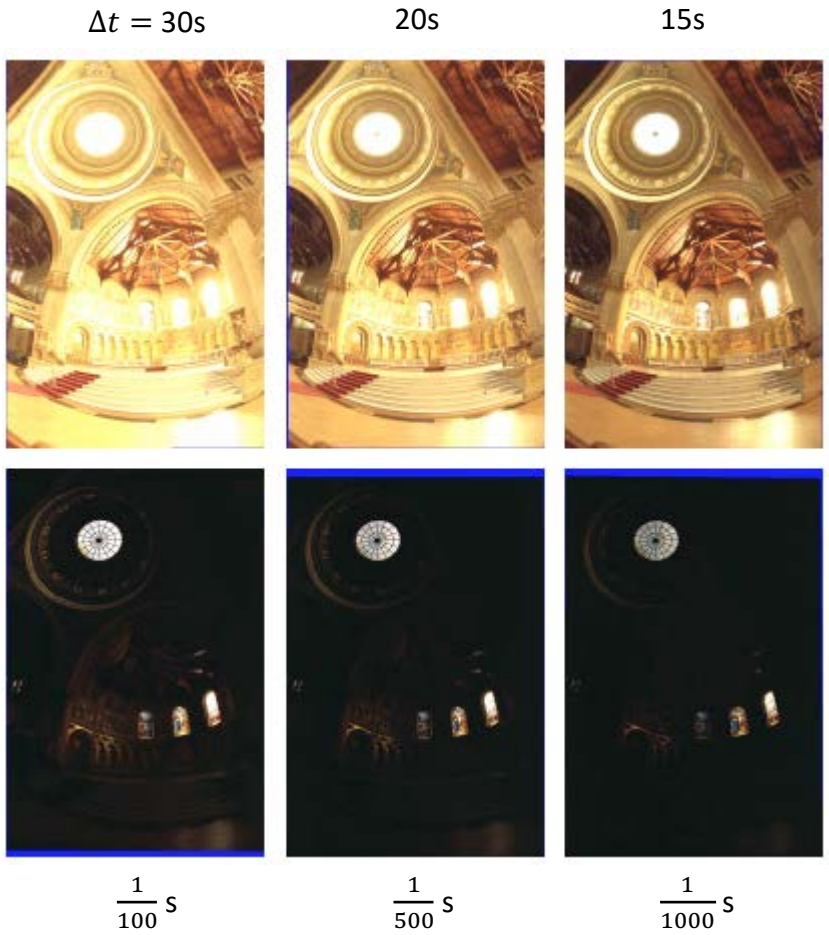


Capturing HDR: Multiple Exposures

- What camera settings should we use capture the different exposures?

Capturing HDR: Multiple Exposures

- Capture with different exposure times Δt
- Assume view doesn't change (i.e. camera is on tripod, or steady), and scene is static
- To combine, we need to know how pixel value in each image is relates!



Capturing HDR: Multiple Exposures

- Assume we have two photos, A and B, where $\Delta t_A = 2\Delta t_B$
- i.e. B has half the exposure duration
- How does each pixel $\mathrm{Z_B}(x, y)$ in B relate to corresponding pixel $\mathrm{Z_A}(x, y)$ in A?

Δt_A Δt_B

A B

Capturing HDR: Multiple Exposures

- $\mathrm{Z_A}(x, y), \mathrm{Z_B}(x, y)$, where $\Delta t_A = 2\Delta t_B$
- If we assume the camera response function is **linear** then,
  - $\mathrm{Z_A}(x, y) = 2\,\mathrm{Z_B}(x, y)$

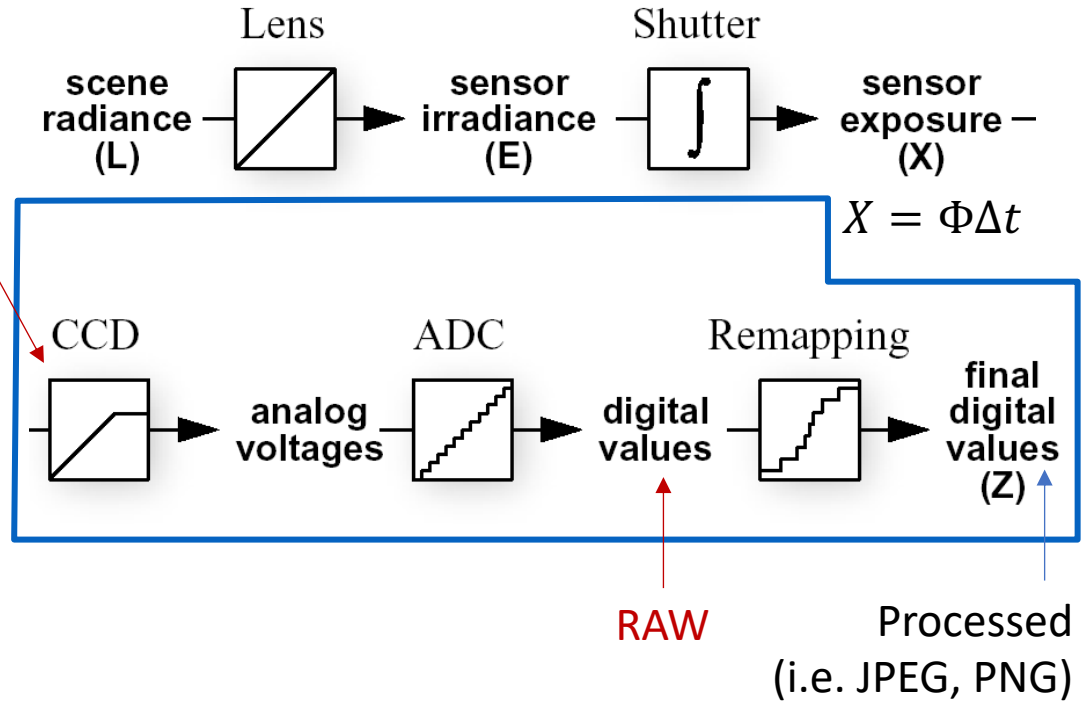
- **However**, we pass the pixel's response through a non-linear gamma function when converting from linear RAW image! (see Topic 1)
  - If we have the RAW photos we are set
  - What if we don't?

Δt_A Δt_B

Inverse Camera Response Function

- With RAW, response is linear (up to I_m)
- Without RAWs, knowing the relative exposure of two photos relies on us knowing the camera response function: f_{camera}
- Recall: f_{camera} gives the pixel value (Z) for a given scene irradiance:

$$Z = f_{\text{camera}}(\Phi \Delta t)$$



Inverse Camera Response Function

- Recall C.R.F. gives the pixel value (Z) for a given scene irradiance:

$$Z = f_{\text{camera}}(\Phi \Delta t)$$

- We want the the scene irradiance given the pixel value (Z), i.e. the inverse C.R.F.:

$$\Phi \Delta t = {f_{\text{camera}}}^{-1}(Z)$$

photons/sec

exposure time

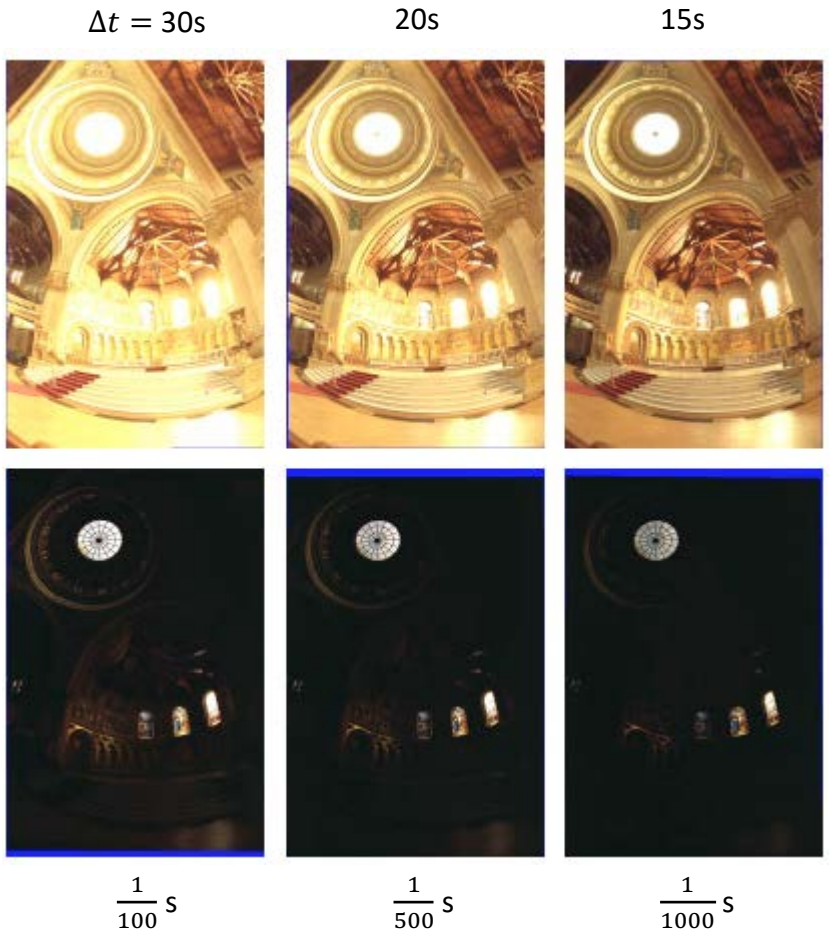
pixel value

Irradiance from Pixel Value

- Assume we have N different exposures
- Each exposure Δt gives us an estimate of the irradiance Φ for the pixel value Z:

$$\Phi \Delta t = {f_{\text{camera}}}^{-1}(Z)$$

- Some of these estimates will be better than others!
  - i.e. estimates from very dark/bright pixels will be poor (why?)



Merging Multiple Exposures: Debevec et al.

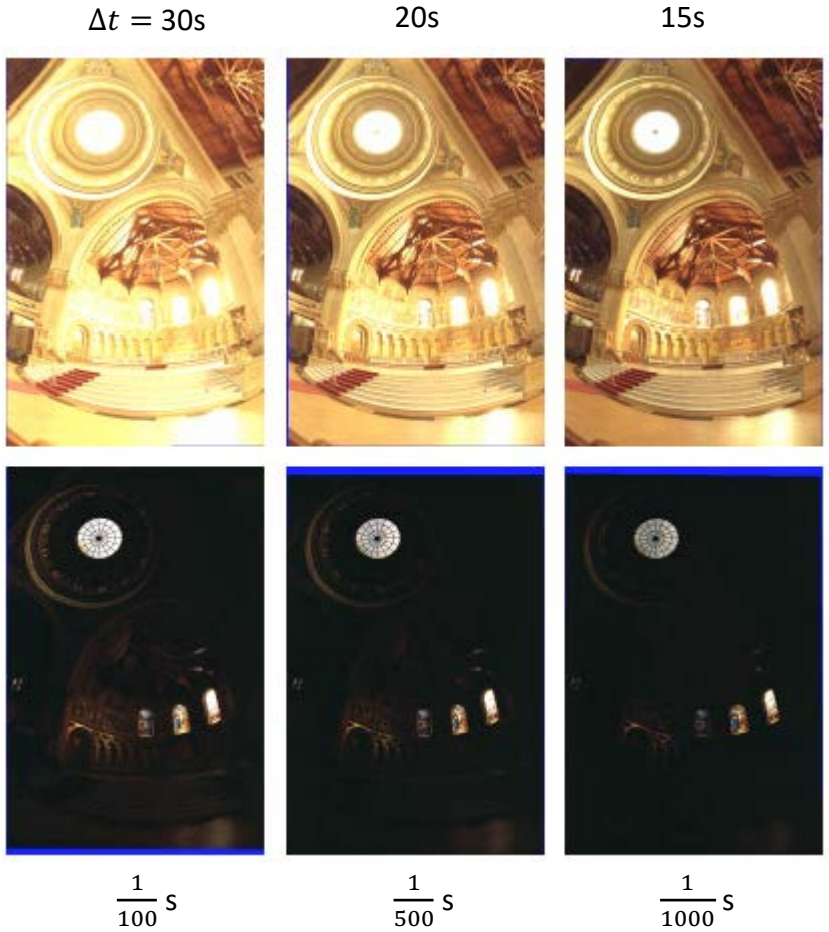
- Algorithm Outline: (see Debevec et al. in readings)

  for each pixel location i and pixel value Z_i:
  for each photo $j = 1, \dots, P$ with exposure time Δt_j:
  estimate Φ_{ij} at pixel location i given Δt_j, Z_i

  combine estimates $\Phi_{ij}, where\ j = 1, \dots, P$ to get Φ_i

  Result: HDR image where each pixel is a float based on our estimate of the scene irradiance Φ_i for each pixel

- i is the pixel location, regarding image as flattened 1D array of pixels



Topic 3: HDR

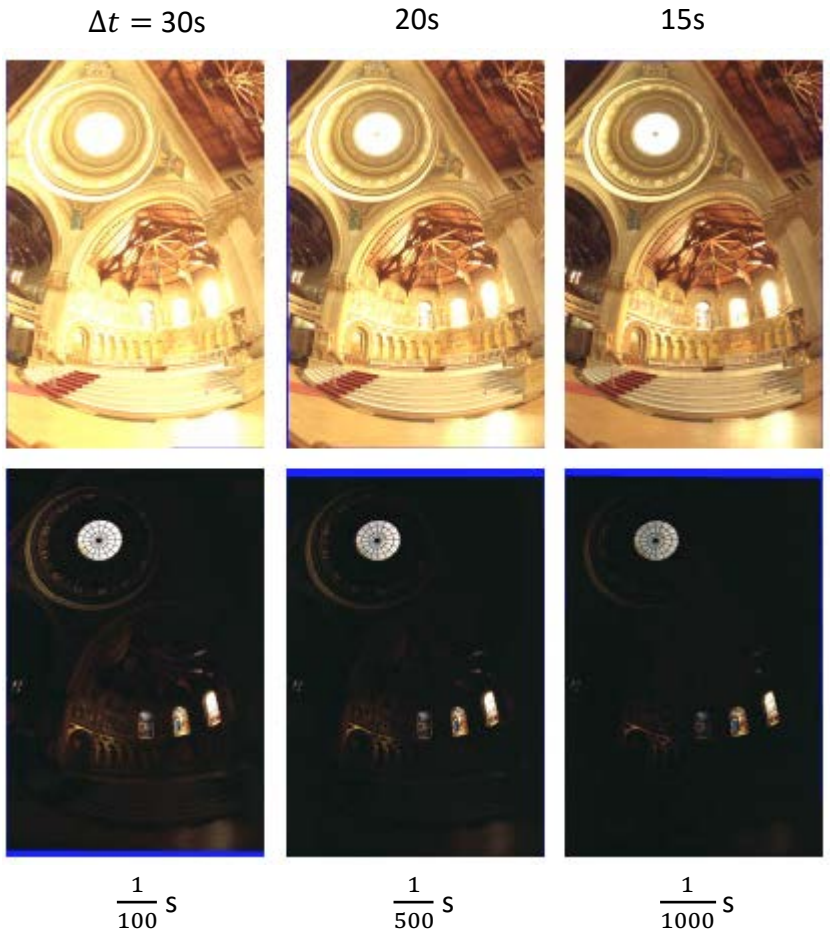
- High Dynamic Range (HDR)
- Capturing HDR Images
- **Computing the Camera Response Function**

Estimating the Camera Response Function

- Want to estimate the function:

$$\Phi\Delta t = {f_{\text{camera}}}^{-1}(Z)$$

- For every photo we take, we get samples of Z and Δt
- **Problem**: we have no way of measuring Φ!
- **Solution**: we have a lot of data, and a couple of tricks!

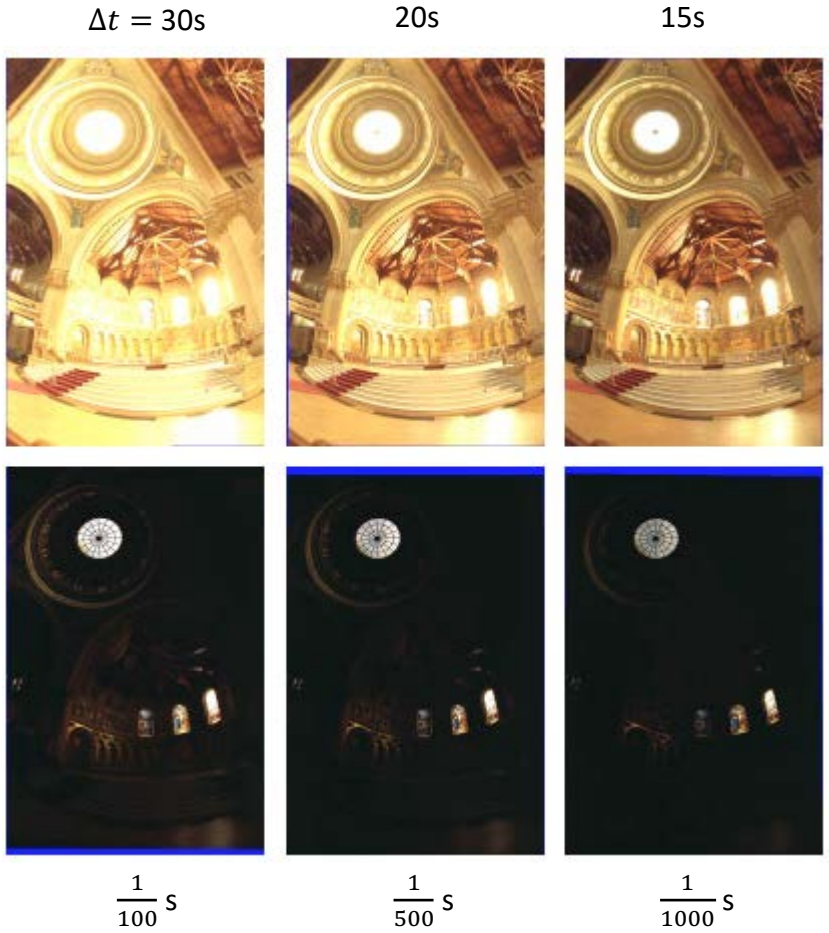


Estimating the Camera Response Function

$$\Phi \Delta t = {f_{\text{camera}}}^{-1}(Z)$$

How do these quantities change by pixel/photo?

- f_{camera}: same for all pixels & photos
- Z: different for each pixel and image
- Δt: different for each photo, same for pixels in the same photo
- Φ: same for corresponding pixel location across different photos (same scene irradiance), different across pixel locations



Trick #1: Log-Inverse Response Function

- We know how to solve linear systems of equations, however,

$$f^{-1}(Z) = \Phi \cdot \Delta t$$

isn't linear, i.e.:

$$a_1 x_1 + a_2 x_2 + \ \ldots + a_N x_N = b$$

- Instead we can represent it using log as:

$$\log f^{-1}(Z) = \log \Phi + \log \Delta t$$

- We will denote $g(Z) = \log f^{-1}(Z)$ as the **log-inverse response function:**

$$g(Z) = \log \Phi + \log \Delta t$$

Trick #2: Discrete Function Approximation

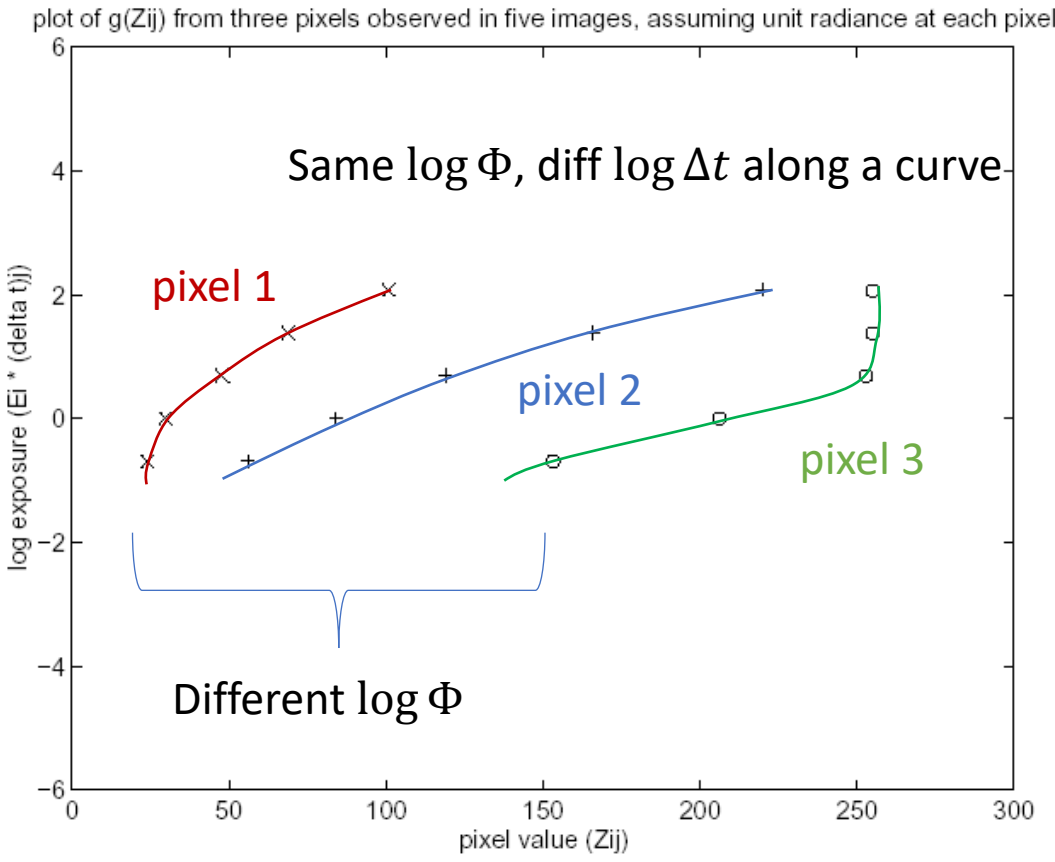
- Our pixels only have 256 **discrete** values, i.e. $Z \in \mathbb{Z}: 0 \leq Z \leq 255$
- Thus we can treat each value of Z as a different equation, i.e.:

$$
\begin{aligned}
g(Z = 0) &= \log \Phi + \log \Delta t \\
g(Z = 1) &= \log \Phi + \log \Delta t \\
&\vdots \\
g(Z = 255) &= \log \Phi + \log \Delta t
\end{aligned}
$$

Computing the Log-Inverse Response Fcn.

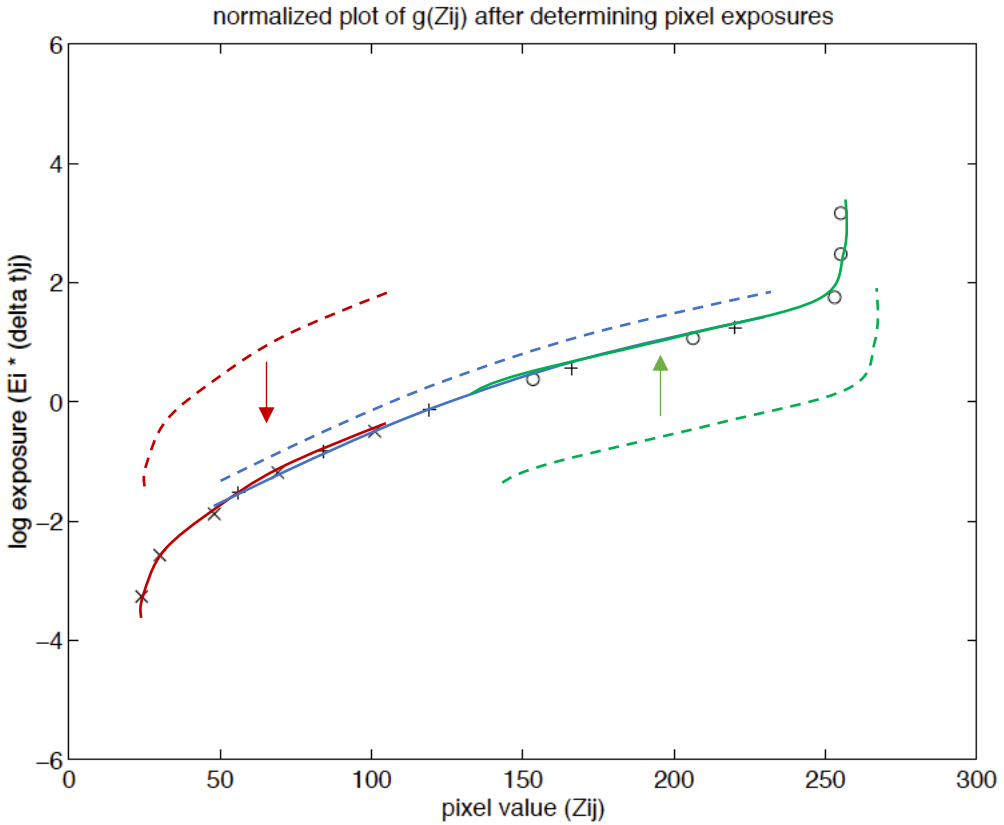
- Plot samples of pixel values Z v.s. $\log \Delta t + \log \Phi$ for 3 different pixel locations
- However, we know different pixel locations have a different $\log \Phi$!
- How will the samples change with different values of $\log \Phi$?

$$g(Z) = \log \Phi + \log \Delta t$$



Computing the Log-Inverse Response Fcn.

- With the correct relative $\log \Phi$ for each pixel location, the samples line up



Putting it all together

For each pixel location $1 \leq i \leq N$, photo $1 \leq j \leq P$:

pixel value for ith pixel, jth image (**known**)

pixel scene irradiance for for ith pixel (**unknown**)

$$g(Z_{ij}) = \log \Phi_i + \log \Delta t_j$$

inverse log C.R.F. (**unknown**)

exposure time of jth image (**known**)

We want to compute:

- $g(0), g(1), \ldots, g(255)$
- $\log \Phi_i$

We are given:

- N pixel locations + intensity in P images, with known Δt_j

Putting it all together: Equations + Unknowns

For each pixel location $1 \leq i \leq N$, photo $1 \leq j \leq P$:

pixel value for i[th] pixel, j[th] image (**known**)

pixel scene irradiance for for i[th] pixel (**unknown**)

$$g(Z_{ij}) = \log \Phi_i + \log \Delta t_j$$

inverse log C.R.F. (**unknown**)

exposure time of j[th] image (**known**)

We are given:

- **N pixels** in **P images**, with known Δt_j

We know:

$$\forall_{ij}\ , g(Z_{ij}) - \log \Phi_i = \log \Delta t_j$$

Idea:

- Each pixel in each photo is one equation, so we have $\boldsymbol{N \cdot P}$ **equations**!
- Unknowns: Φ_i, g ➔ $\boldsymbol{N + 256}$ **unknowns**

Equations

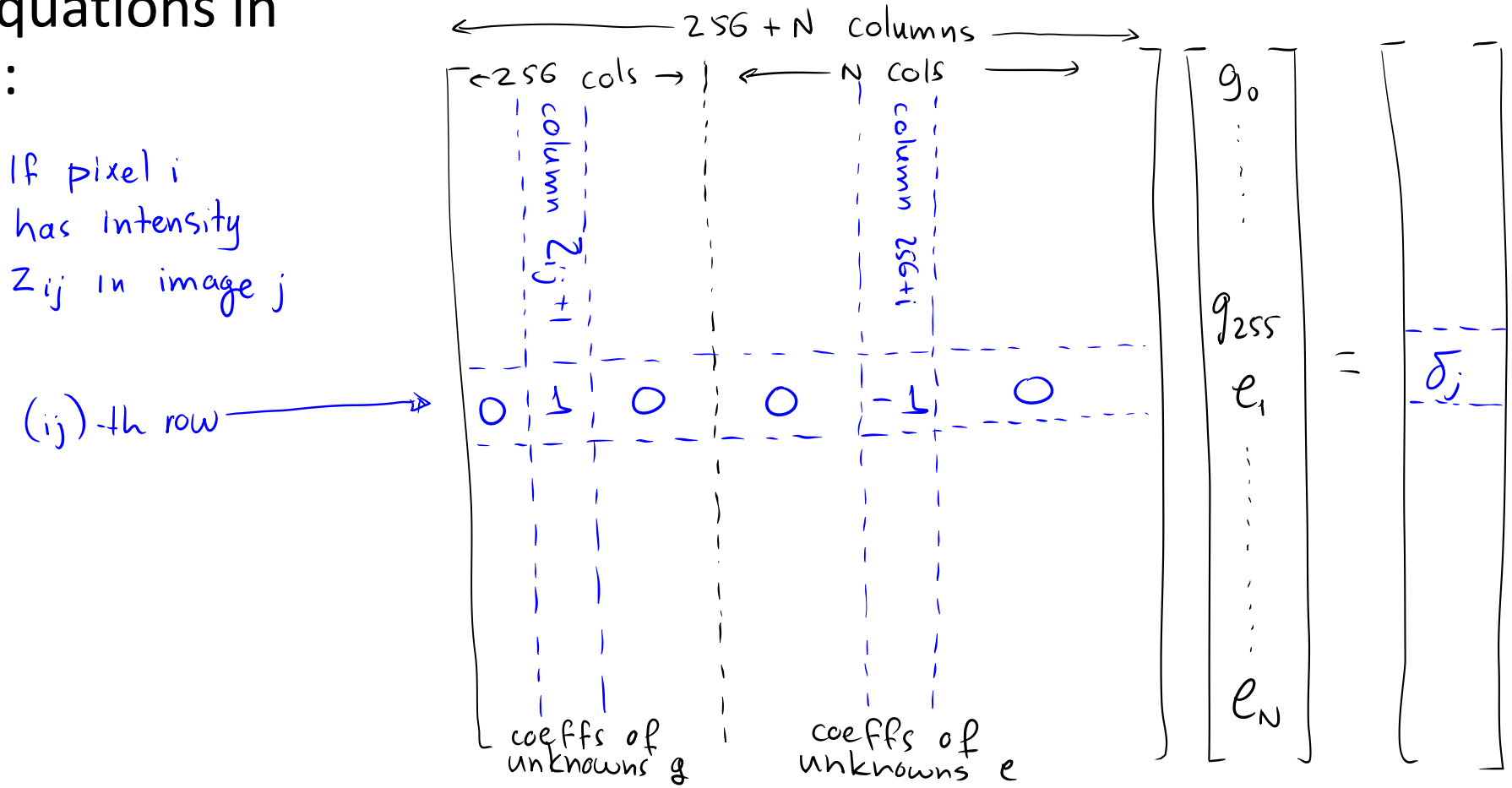
- Each pixel: $g(Z_{ij}) - \log \Phi_i = \log \Delta t_j$
- Let (to simplify notation):
  - $g_{Z_{ij}} \equiv g(Z_{ij})$,
  - $e_i \equiv \log \Phi_i$
  - $\delta_j \equiv \log \Delta t_j$
- Then, for each pixel:
  - $g_{ij} - e_i = \delta_j$
- Single eqn. in matrix form:

$$\begin{bmatrix} 0 \cdots 0 & 1 & 0 \cdots 0 & -1 \cdots 0 \end{bmatrix} \begin{bmatrix} g_0 \\ \vdots \\ g_{255} \\ e_1 \\ \vdots \\ e_N \end{bmatrix} = \delta_j$$

$(Z_{ij}+1)$-th column ↑ $(256-i)$-th column

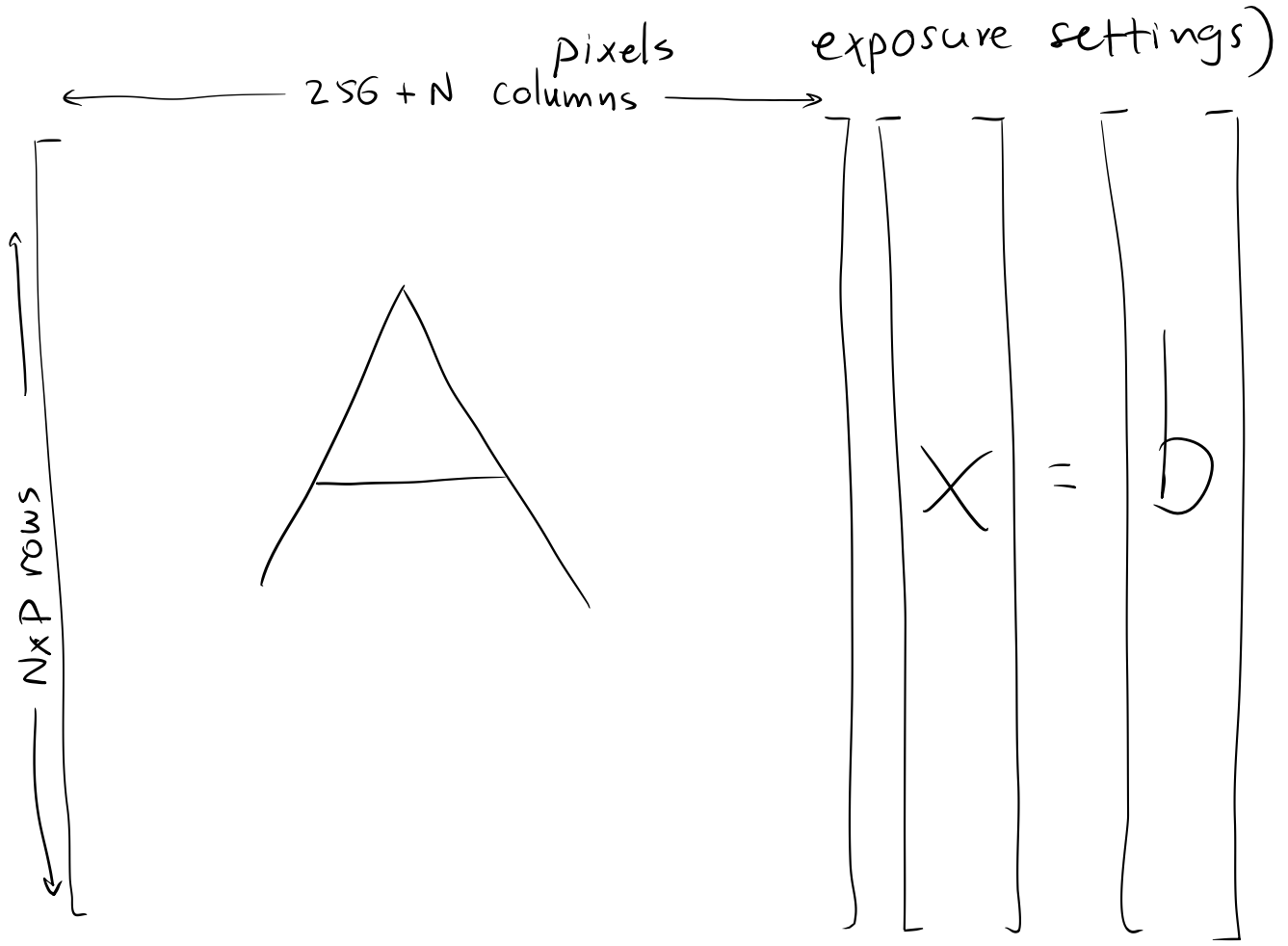
Equations

- System of equations in matrix form:



Solving The System of Equations

- To solve this system, matrix A must be non-singular
- We can help ensure this by choosing N, P such that $NP \gg 256 + N$
- e.g. N=1000 pixels from P = 20 photos (20 exposure settings)



Smoothness Constrains

Idea: The camera response function smoothly in real cameras

So we add more equations to enforce smoothness

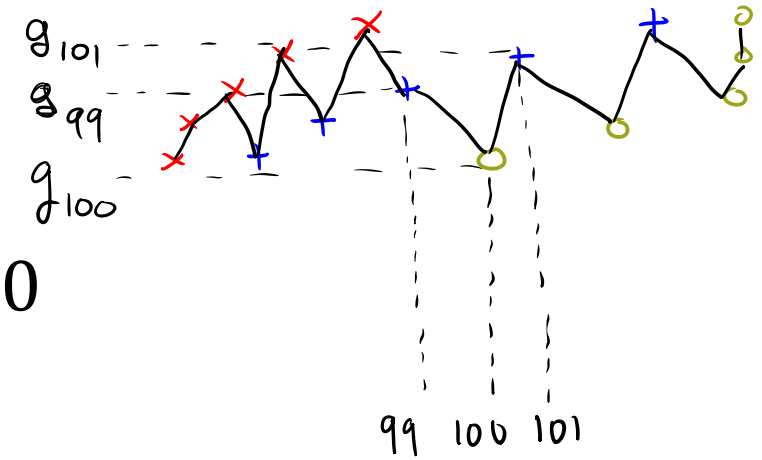
Intuition: Force near-constant rate of change:

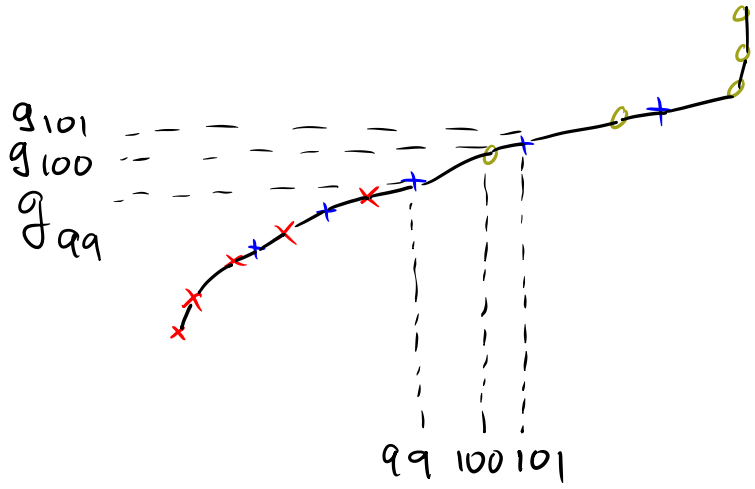
$$g_{100} - g_{99} \approx g_{101} - g_{100} \iff 2g_{100} - g_{101} - g_{99} \approx 0$$

Add these equations to the system:

$2g_l - g_{l+1} - g_{l-1} = 0$

$(l = 1,2, \dots 254)$





Smoothness Constraints

- Original equations

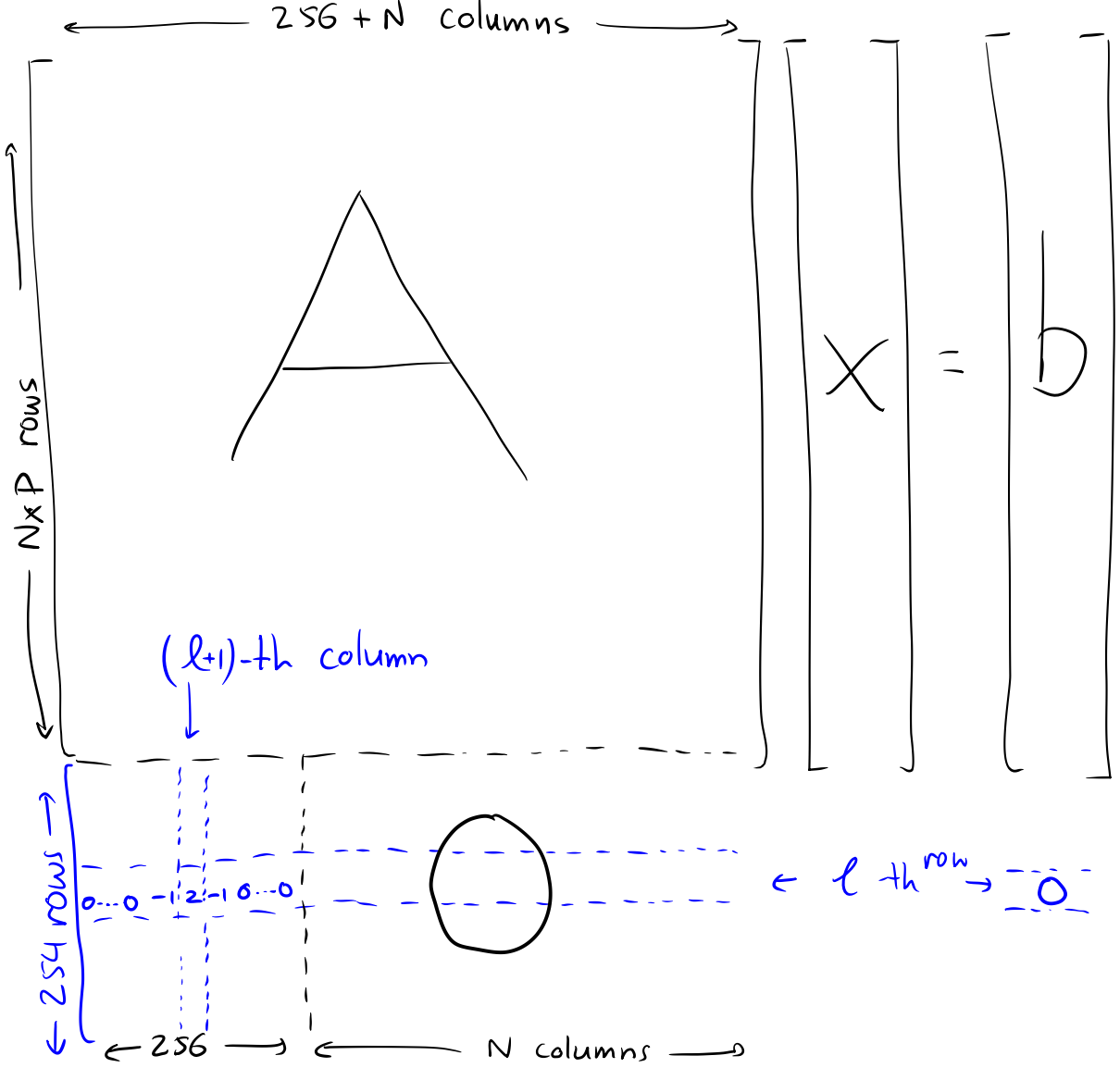
$g_{ij} - e_i = \delta_j$

$(1 \leq i \leq N, 1 \leq j \leq P)$

- Smoothness equations

$2g_l - g_{l+1} - g_{l-1} = 0$

$(l = 1,2, \ldots 254)$



Finally: Merging Multiple Exposures

- Algorithm HDR: (see Debevec et al. in readings)

  for each pixel location i and pixel value Z_{i}:

  for each photo $j = 1, \ldots, P$:

$$\log \Phi_{\mathrm{ij}} = g(Z_{ij}) - \log \Delta t_{\mathrm{j}}$$

$$\log \Phi_{\mathrm{i}} = \frac{\sum_{j=1}^{P} w(Z_{ij}) \log \Phi_{\mathrm{ij}}}{\sum_{j=1}^{P} w(Z_{ij})}$$

  Where $w(Z_{ij})$ is a weighting factor that depends on the pixel value. Pixels close to saturation (255), or close to the black level (0) are weighted lower.

  (Note: in the paper $\mathrm{E} \equiv \Phi$)