HW1 High Dynamic Range Imaging

Appendix

陳立得

Mar 22, 2021

Outline

- Grading
  - Implementation
  - Experiment& Free Study
- Addtional Implementation Details
  - Response Calibration
  - Construct Radiance

Grading

Items		Score
Implementation (65%)	Camera Response Calibration	20%
	Global Tone Mapping	10%
	Local Tone Mapping	15%
	Edge-Preserving Filter	15%
	White Balance	5%
Experiment& Free Study (35%)	Experiments	20%
	Free Study	15%

Grading: Implementation

- You will get full score if your result pass the bar
  - same result with TA's implementation

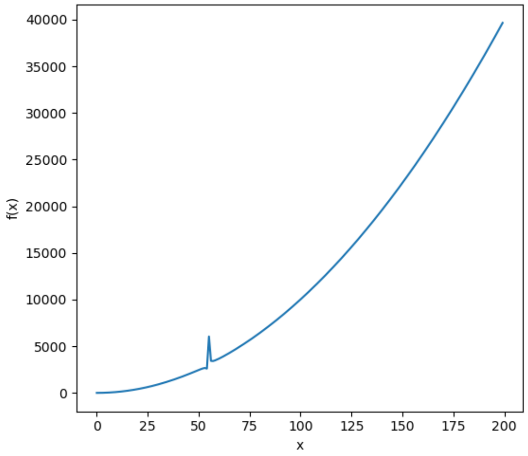
Complete function `globalTM()` in tm.py. Your result for /TestImg/memorial.hdr should be similar to /ref/p2_gtm.png (PSNR>45dB), under the default setting `s=1.0` to get a full score.

Grading: Experiment& Free Study

- Experiment
  - Finish an asked Figure/Curve/Image
  - Discussion
- Free Study
  - Select *Two* topics you want
  - Research and discuss on it
- What should be included in Report?
  1. Assumption
  2. Justification

Example: Do not

- For variable x, sweep from 0.1 ~ 200
- Describe the trend ($f(x)$ v.s. x)
    - which maybe already mentioned in class
- Notice something weird around x in (50~60)
- I guess xxx so, xxx ...



Example: Do

- Keep you sweep for observation
  - Describe the trend if it's important to you
- Assume that: $f(x) = f_{ideal}(x) + \frac{g(y)}{x-55}$
  - Design a experiment to justify your assumption
    - ex1. sweep y
    - ex2. Design a special experiment to eliminate unideal part
- Describe
  - Where the assumption comes from?
  - Why you design the experiment in this way?
  - How your experiment prove your assumption?

You don't need to be "correct"

- It's ok to provide an assumption that fits reality imperfectly
- We will grade the report based on :
  - Correctness of reasoning
  - Rigorousness of justification

Response Calibration

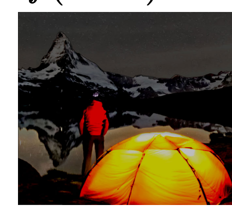
- We want E (radiance) of a scene
- What do we have?
  - Z (Pixel value) and Δt (Exposure time)
- What do we know (or assume)?
  - Z has one-to-one mapping with exposure $E\Delta t$
    - Other setting unchanged
  - The mapping:
    - $g(Z) = \ln E + \ln \Delta t$
- If we have $g(Z)$ for all possible Z ([0:1:256])
  - and exposure time Δt_j for a taken image j
  - We can obtain $\ln E = g(Z) - \ln \Delta t$

E

Δt

$f(E\Delta t) = Z$

Z



What do we want again?

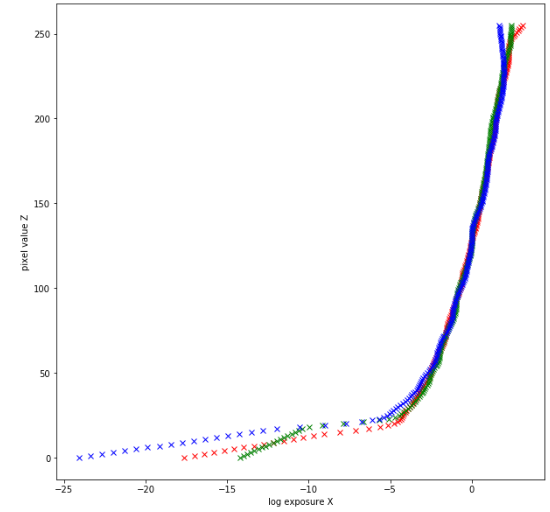
- $g(Z)$ for all possible Z ([0:1:256])
  - 256 variables
- What relation do we have?
  - Exposure Mapping

$$g(Z) - \ln E = \ln \Delta t$$

  - Smoothness Constraint

$$g''(Z) = 0$$

- How to find out $g(z)$?
  - Measuring a lot of samples
  - Measure Z_{ij} on E_i and Δt_j

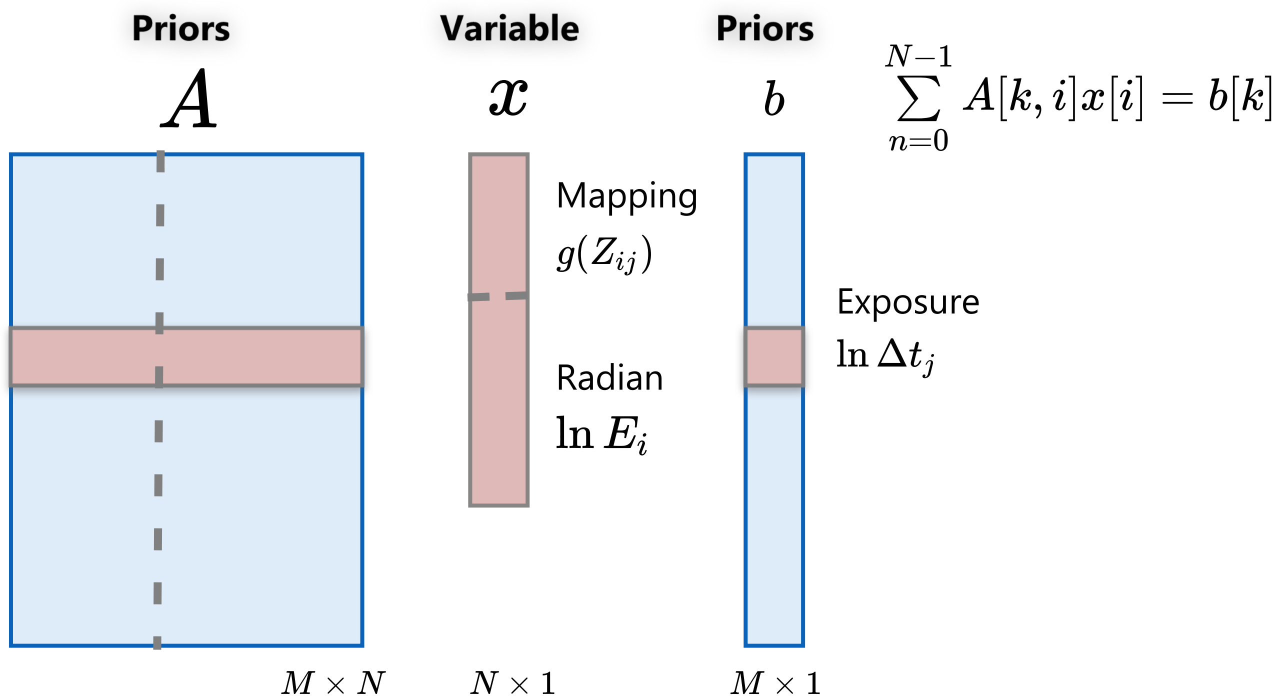


Solving Objective Function

$$O = \sum_i \sum_j [g(Z_{ij}) - \ln E_i - \ln \Delta t_j]^2 + \lambda \sum_z [g''(z)]^2$$

- The objective function describes a relation (we want) between
  - **variables** and **measurements**
- What are variables?
  - The unknown terms $g(z)$ and $\ln E_i$
- What are measurements?
  - The known terms Z_{ij} and Δt_j

Objective Function in Matrix Form



- M {#(euqations)}: number of measurements($\Delta t_j, Z_{ij}$) -> $I \times J$
- N {#(variables)}: 256 + #(E_i) -> 256 + I

Data Term Assignment

$$\sum_i \sum_j [g(Z_{ij}) - \ln E_i - ln\Delta t_j]^2$$

That's say in k-th measurement, image 3($\Delta t_3 = 2$),
pixel 12 has intensity $Z_{12,3} = 127$.
We want the variables $\ln E_{12}$ and $g(127)$ has the following relationship

$$g(127) - \ln E_{12} = \ln 2$$

Then we should set row k as

- $A(k, 127) = 1$
- $A(k, 256 + 12) = -1$
- $b(k) = \ln 2$

Smoothness Term Assignment

$$g''(z) = g(z-1) - 2g(z) + g(z+1) = 0$$

That's say in k-th experiments

Intensity $z = 16$ should have 0 second order derivatives

$$g''(16) = g(15) - 2g(16) + g(17) = 0$$

Then we should set row k as

- $A(k, 15) = 1$
- $A(k, 16) = -2$
- $A(k, 17) = 1$
- $b(k) = 0$

Bring back Reliability Weight

$$O = \sum_i \sum_j w(Z_{ij})[g(Z_{ij}) - \ln E_i - ln\Delta t_j]^2 + \lambda \sum_z [w(z)g''(z)]^2$$

That's say in k-th measurement, image 3($\Delta t_3 = 2$),

pixel 12 has intensity $Z_{12,3} = 127$.

We want the variables $\ln E_{12}$ and $g(127)$ has the following relationship

$$w(127)g(127) - w(127)\ln E_{12} = w(127)\ln 2$$

Bring back Reliability Weight

We want the variables $\ln E_{12}$ and $g(127)$ has the following relationship

$$w(127)g(127) - w(127)\ln E_{12} = w(127)\ln 2$$

Then we should set row k as

- $A(k, 127) = w(127)$
- $A(k, 256 + 12) = -w(127)$
- $b(k) = w(127)\ln 2$

Solve Least Square Problems

- $||Ax - b||^2$
- A is usaully not square matrix
  - We want more measurements(equations) to reduce the measurement error
- If we can find $A^\dagger$ (pseudo inverse of A)
- We can obtain
  - $x = A^\dagger b$
  - Which minimize the square error $||Ax - b||^2$

Solve Least Square Problems

- $||Ax - b||^2$
- In Numpy, we can solve the least square problem with
  - `linalg.lstsq(a, b, rcond='warn')`
  - `a` : (M, N) array_like "Coefficient" matrix.
  - `b` : {(M,), (M, K)} array_like
- Returns: `x` {(N,), (N, K)} ndarray
  - Least-squares solution. If b is two-dimensional, the solutions are in the K columns of x.

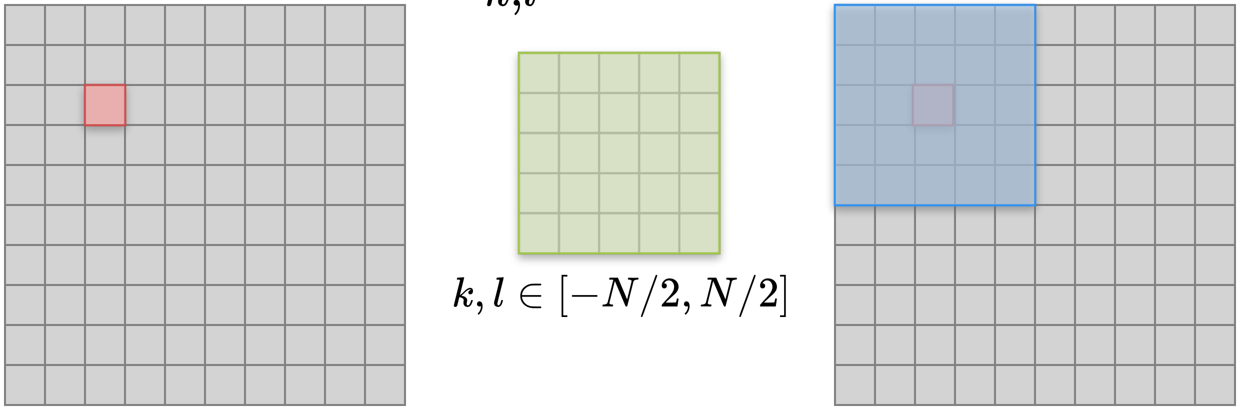
Construct Radiance

- For an image j with exposure time (Δt_j)
- The radiance is simplely
  - $E_i = \exp\left(g(Z_{ij}) - \ln \Delta t_j\right)$
- But why don't we use all availabe images?
  - $\ln E_i = \frac{\sum_j w(Z_{ij})[g(Z_{ij}) - \ln \Delta t_j]}{\sum_j w(Z_{ij})}$
  - $E_i = \exp(\ln E_i)$

Image Filtering

- Covolution between $w_{K \times L}$ and $L_{I \times J}$
- LTI, Symmetric Filter

$$L'(i,j) = \sum_{k,l} w(k,l)\, L(i+k, j+l)$$



$k, l \in [-N/2, N/2]$