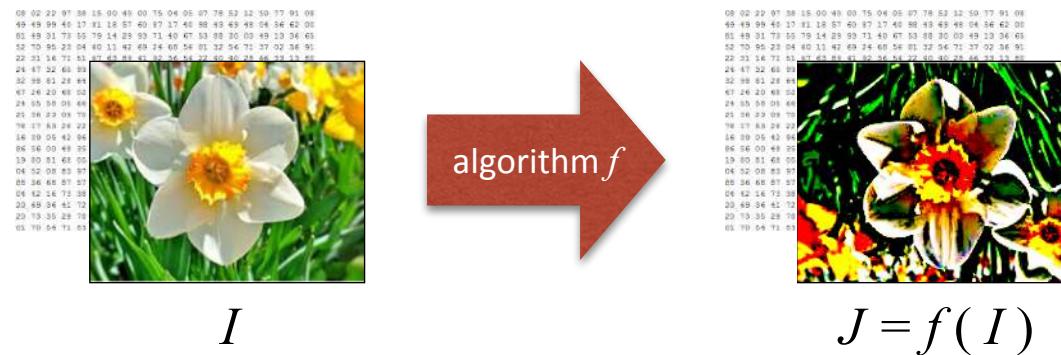
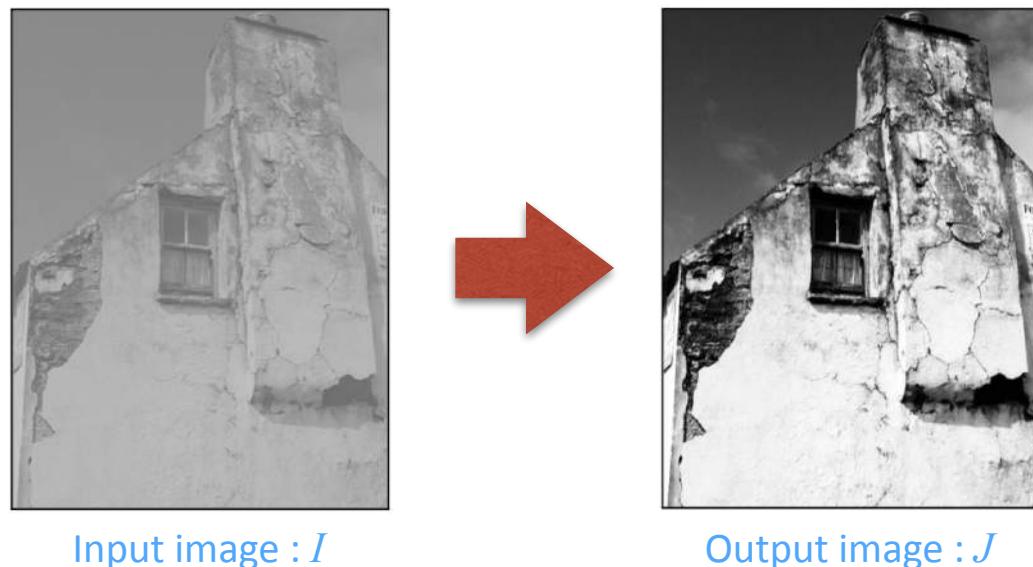


Histogram and point operations

- Image processing is the study of any algorithm that takes an **image as input** and returns an **image as output**



- Example: contrast adjustment



■ Images as functions

- We can think of the *intensity of an image* as a function of position (u, v)
- Let $\Omega \subset \mathbb{N}^2$ be the *image domain*. Then an image is a **discrete function**:

$$I : \Omega \rightarrow \mathbb{R}$$

■ Example



A simple image

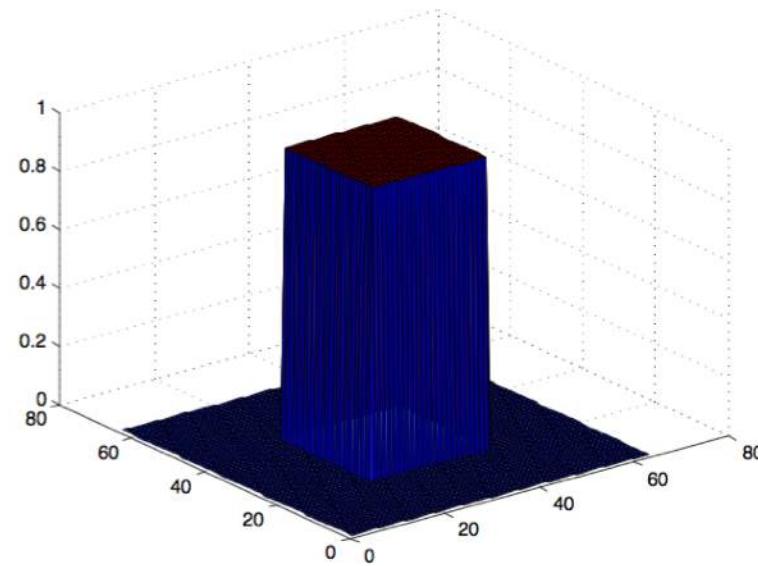
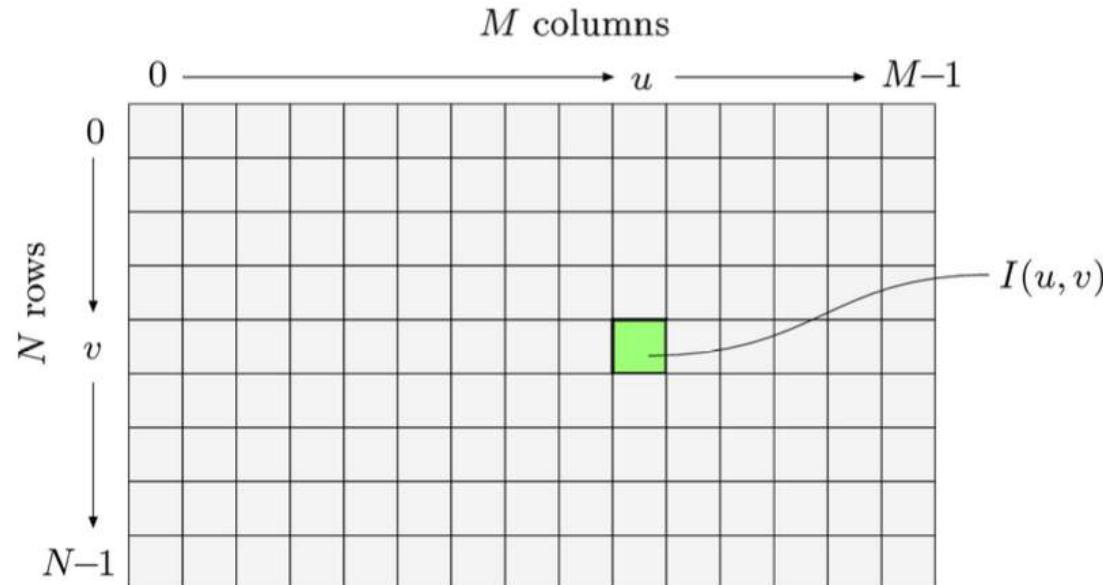


Image function as a height field

■ Representing an image

- The data structure for an image is simply a **2D array of values**:



- The values in the array can be any data type (8-bit, 16-bit..., signed/unsigned etc)

■ Note

- Here we work with **grayscale 2D images...**
- ...but in medical imaging they can *have more dimensions and channels!*

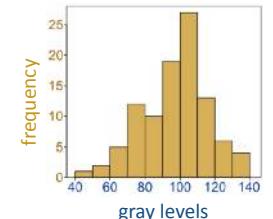
Histogram of an image

(1/2)

- A **histogram** is a function $h(i)$ that gives the *frequency of each intensity i* that occur in an image

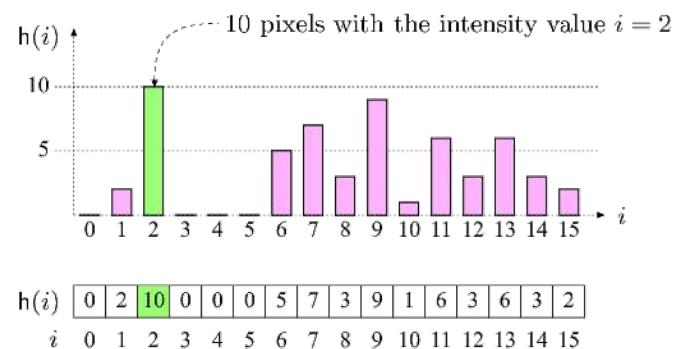
- ▶ Given an image $I : \Omega \rightarrow [0 \dots K - 1]$, its histogram is the function:

$$h(i) = \text{card} \{ (u, v) \mid I(u, v) = i \}$$



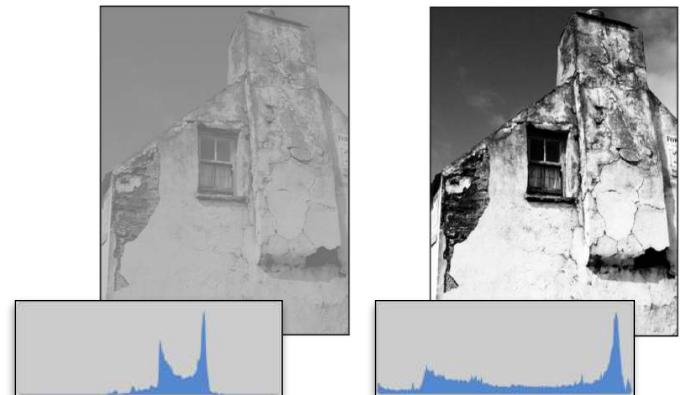
- In other words

- ▶ $h(i)$ = number of pixels with intensity i



- Notes

- ▶ Low-contrast image → histogram is narrow
- ▶ High-contrast image → histogram is spread out
- ▶ In general, *image processing* alters the histogram



Histogram of an image

(2/2)

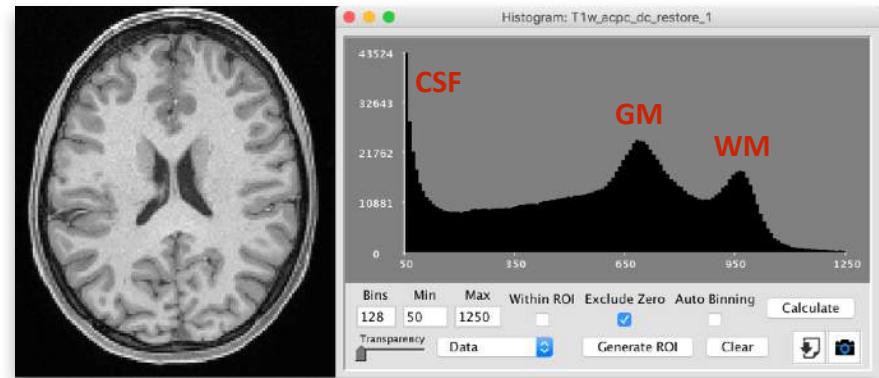
■ Probabilistic interpretation

► Question:

- if we pick a pixel at random, what is the probability that the intensity of this voxel is equal to i ?

► Answer:

- $P(I(u,v)=i) = \# \text{ pixels with value } i / \# \text{ pixels of the image}$
- $P(I(u,v)=i) = h(i) / MN$



■ Generalization: a *binned histogram* gives the frequency of image intensities that fall into *small intervals* (or bins)

- Given an image $I : \Omega \rightarrow [0 \dots K - 1]$, its binned histogram is the function:

$$h(i) = \text{card} \{ (u, v) \mid a_i \leq I(u, v) < a_{i+1} \}$$

where $0 < a_0 < a_1 < \dots < K$

- Typically, we choose equally spaced bins

Definition of “point operation”

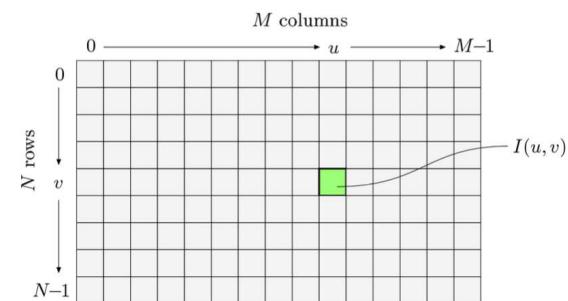
- A **point operation** on an image is an algorithm that *changes each pixel value* according to some function

$$J(u, v) \mapsto f[I(u, v)]$$

- ▶ The function f depends only on the pixel value
- ▶ It is *independent of the spatial location* (u, v)
- ▶ The range of f determines the output datatype, e.g. uint16 or float32

■ Pseudocode

- ▶ **Input:** image $I(u, v)$ defined on $[0 \dots M-1] \times [0 \dots N-1]$
- ▶ **Output:** new image $J(u, v)$
- ▶ $\text{for } v = 0 \dots N-1$
 - $\text{for } u = 0 \dots M-1$
 - $\text{set } J(u, v) = f[I(u, v)]$



Basic examples

(1/3)

■ Any function can be used, e.g. $f(x)=x^2$, but *not all are useful*

■ Most common

► Addition and multiplication

- $f(p) = p + k$
- $f(p) = p \cdot x$

► Inverse

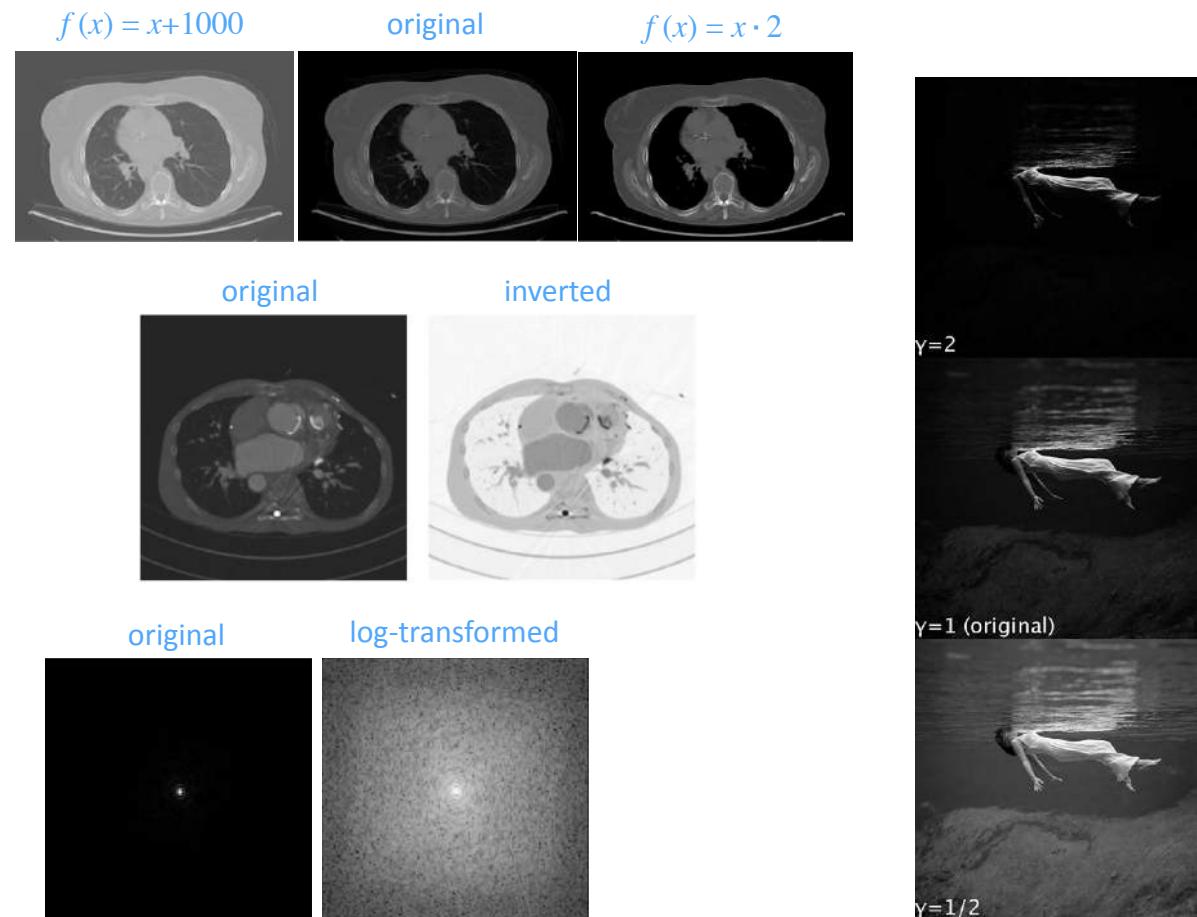
- $f(p) = L - p$

► Log transform

- $f(p) = \log(1+p)$

► Gamma correction

- $f(p) = p^\gamma$



■ Notes

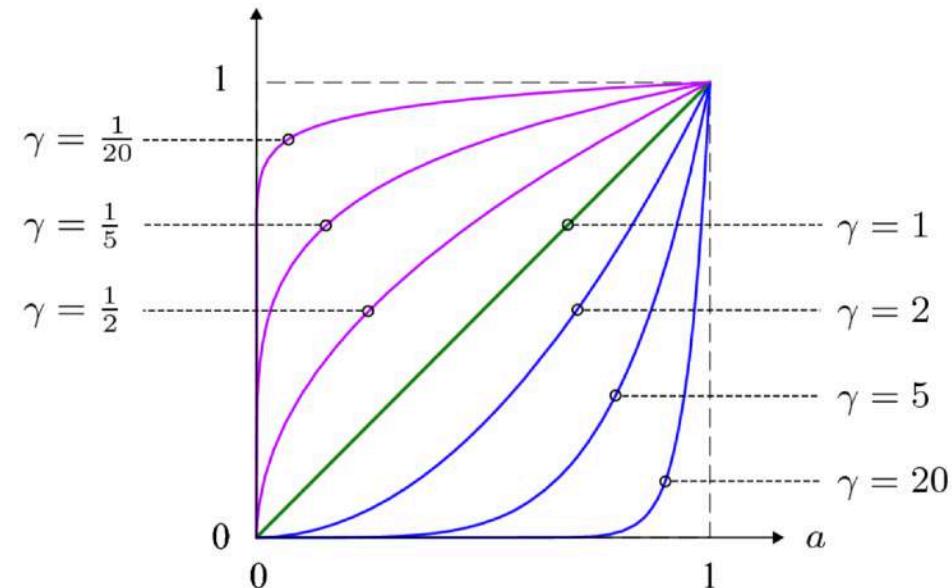
- What happens to their *histograms*?
- Beware of *output data type* (overflow)

■ Gamma correction

- The **human perception** of brightness follows an approximate *power function*

$$f(a) = a^\gamma$$

- **Greater sensitivity** to differences between *darker tones* (than between lighter ones)
- When forming an image, **camera sensors** convert light into an electrical signal
 - NB: different sensors may have different responses to light intensity and produce different signals
- **Display devices** (monitors, printers) turn images into a physical representation (light, ink)

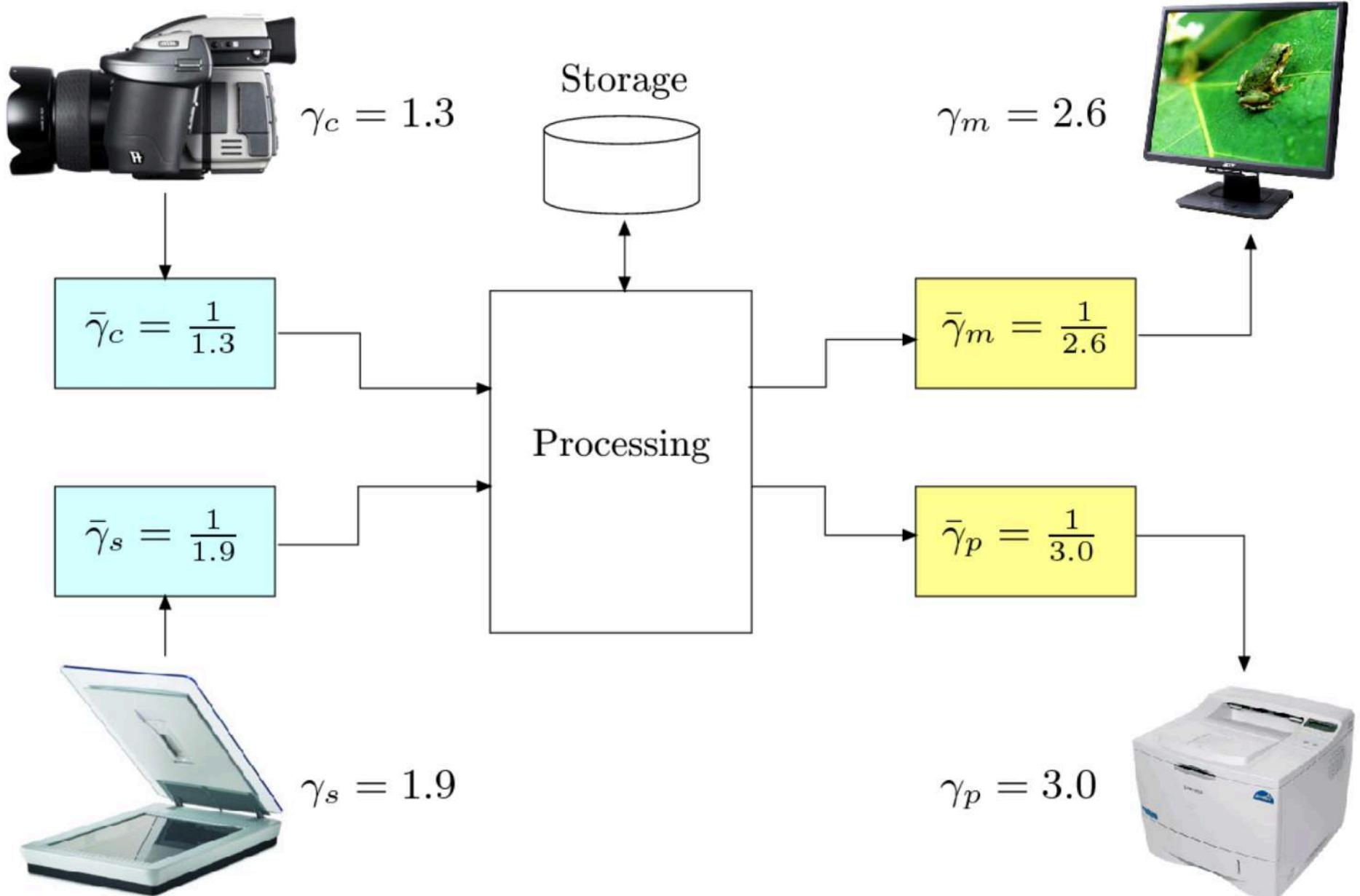


■ Q: how do we make sure there is **consistency**?

■ A: hardware manufacturers **specify the gamma value** to properly *record* or *reproduce* the colors

Basic examples

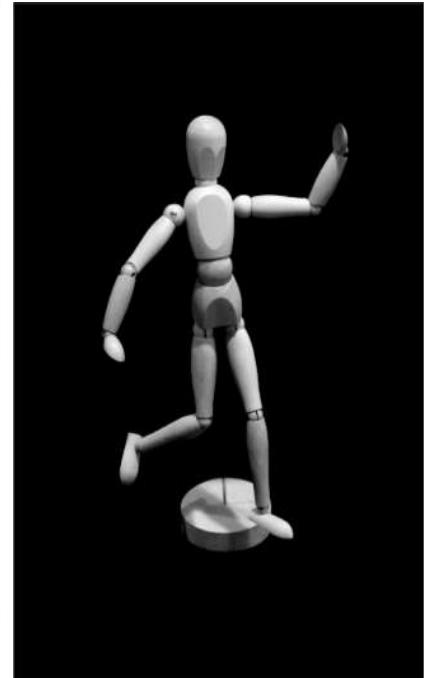
(3/3)



■ Clamping (or clipping)

- *Limit intensities to a given interval $[a, b]$*

$$f(p) = \begin{cases} a & \text{if } p < a \\ p & \text{if } a \leq p \leq b \\ b & \text{if } p > b \end{cases}$$



■ Windowing

- *Clamping followed by intensity stretching to fill the full possible range $[0, M]$*

$$f(p) = \begin{cases} 0 & \text{if } p < a \\ M \times \frac{p-a}{b-a} & \text{if } a \leq p \leq b \\ M & \text{if } p > b \end{cases}$$

■ Thresholding

- ▶ Also called *image binarization*

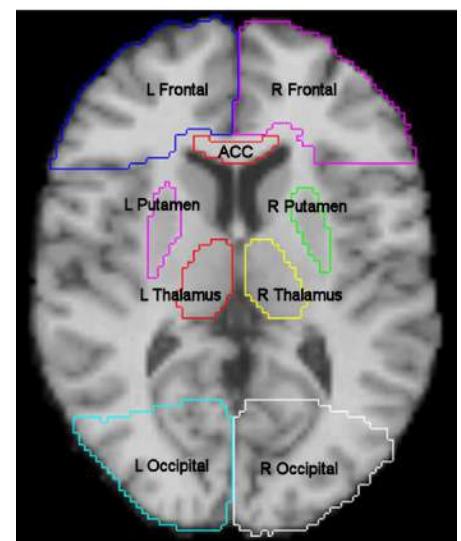
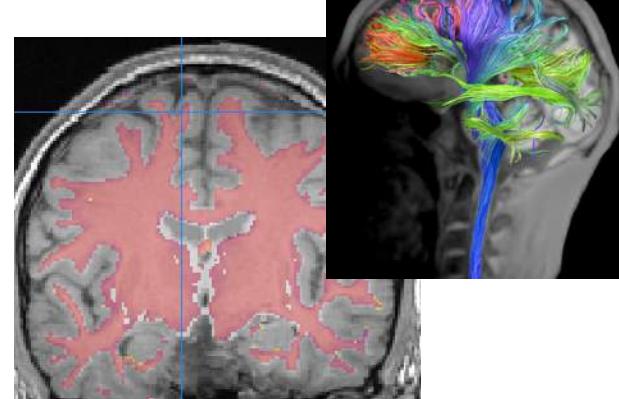
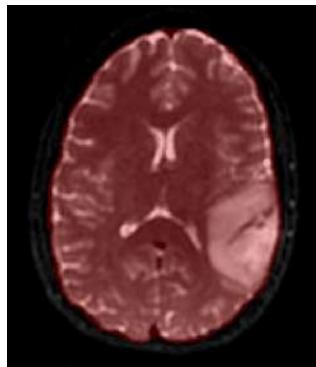
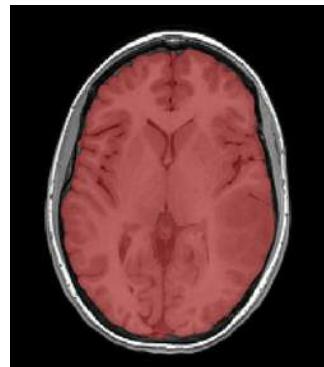
$$f(p) = \begin{cases} 0 & \text{if } p \leq a \\ 1 & \text{if } p > a \end{cases}$$



■ Notes

- ▶ Despite their simplicity, **binary images** are widely used in medical image processing
- ▶ Examples

- Constrain the processing to a given portion of the image, e.g brain
- Regions-of-interest (ROI) analysis



Difficult to find the proper threshold

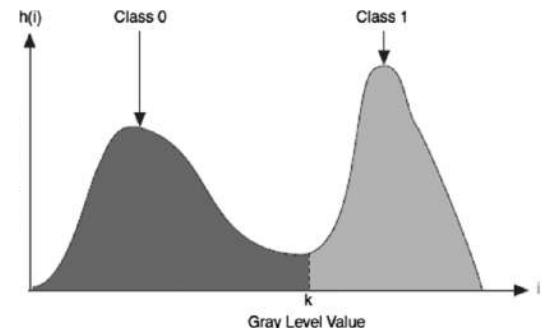
- ▶ Usually, there are **not only two regions**, e.g. foreground and background
- ▶ We will see **advanced segmentation tools** for the more general case

OTSU's method

- ▶ *Very basic* algorithm to **automatically binarize an image**
- ▶ Assumes that the image contains *exactly two regions* (i.e. bimodal histogram)
 - Actually, extensions exist for multiple regions
- ▶ Searches for the threshold that **minimizes the intra-class variance**:

$$\sigma_w^2(t) = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(t)$$

- ω_0 and ω_1 are the *probabilities of the two classes* separated by a *threshold t*
 - σ_0^2 and σ_1^2 are *variances* of these two classes
- ▶ **NB:** iterates through all the possible threshold values



$$\omega_0(t) = \sum_{i=0}^{t-1} p(i)$$

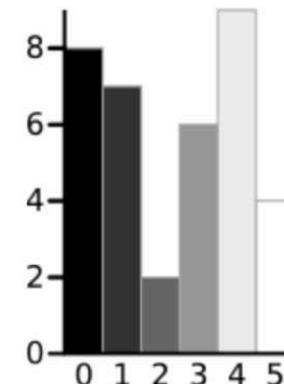
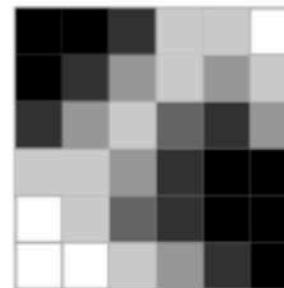
$$\omega_1(t) = \sum_{i=t}^{L-1} p(i)$$

Automatic thresholding

(2/4)

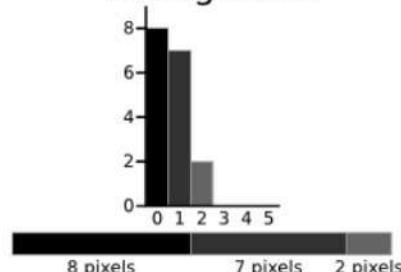
Toy example

- ▶ 6x6 image
- ▶ 6 gray levels



Calculations for the case $t=3$

Background

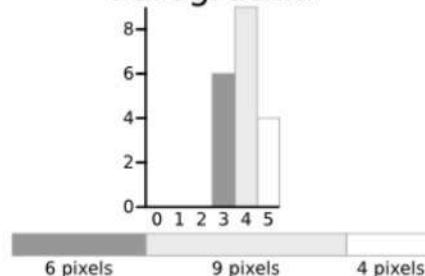


$$\text{Weight } W_b = \frac{8 + 7 + 2}{36} = 0.4722$$

$$\text{Mean } \mu_b = \frac{(0 \times 8) + (1 \times 7) + (2 \times 2)}{17} = 0.6471$$

$$\begin{aligned} \text{Variance } \sigma_b^2 &= \frac{((0 - 0.6471)^2 \times 8) + ((1 - 0.6471)^2 \times 7) + ((2 - 0.6471)^2 \times 2)}{17} \\ &= \frac{(0.4187 \times 8) + (0.1246 \times 7) + (1.8304 \times 2)}{17} \\ &= 0.4637 \end{aligned}$$

Foreground



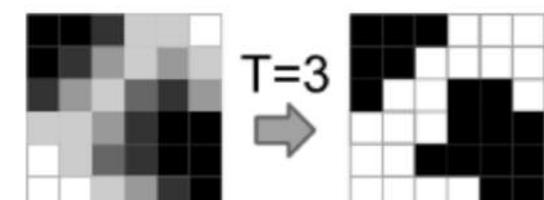
$$\text{Weight } W_f = \frac{6 + 9 + 4}{36} = 0.5278$$

$$\text{Mean } \mu_f = \frac{(3 \times 6) + (4 \times 9) + (5 \times 4)}{19} = 3.8947$$

$$\begin{aligned} \text{Variance } \sigma_f^2 &= \frac{((3 - 3.8947)^2 \times 6) + ((4 - 3.8947)^2 \times 9) + ((5 - 3.8947)^2 \times 4)}{19} \\ &= \frac{(4.8033 \times 6) + (0.0997 \times 9) + (4.8864 \times 4)}{19} \\ &= 0.5152 \end{aligned}$$

Within-class
variance

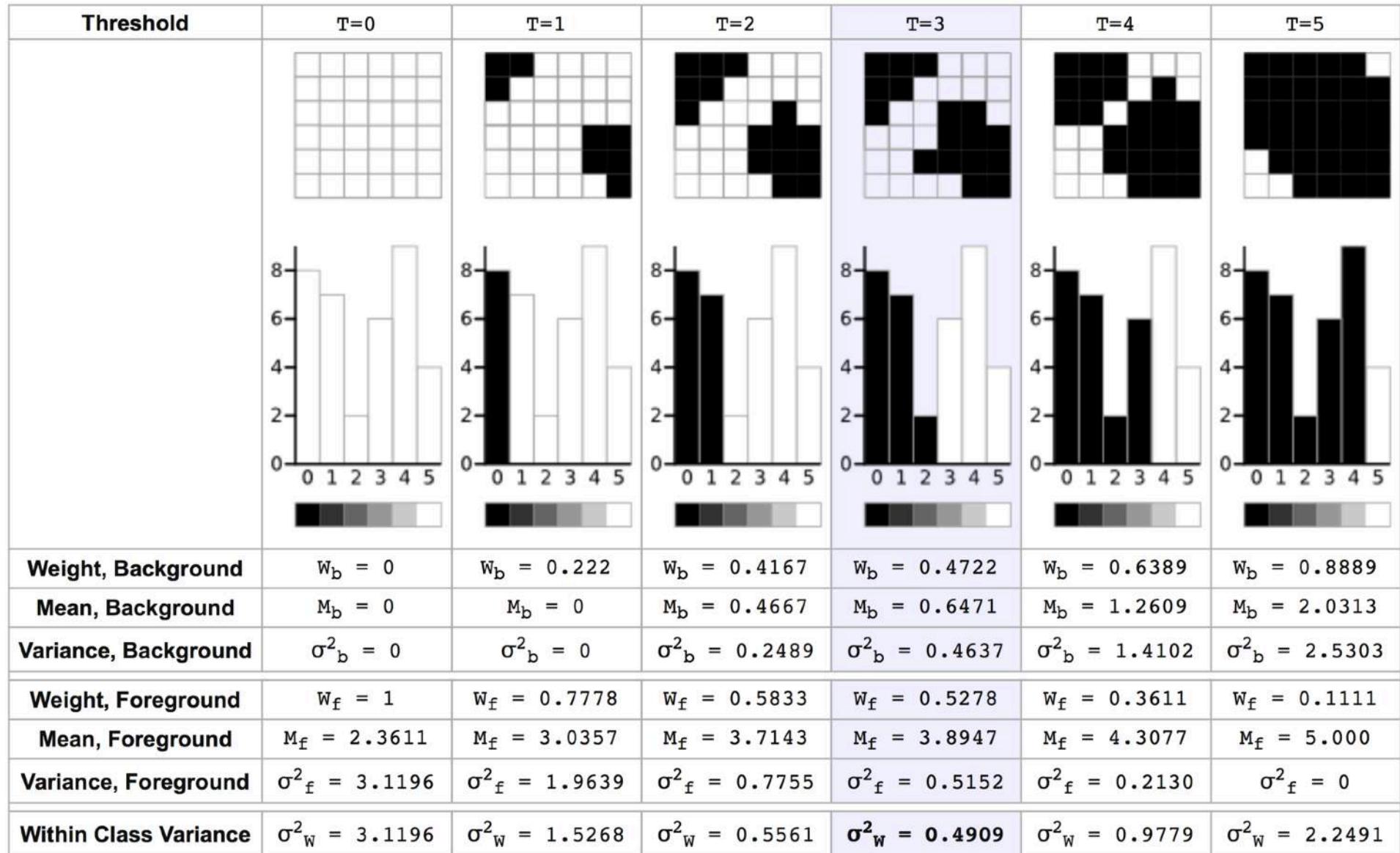
$$\begin{aligned} \sigma_W^2 &= W_b \sigma_b^2 + W_f \sigma_f^2 = 0.4722 * 0.4637 + 0.5278 * 0.5152 \\ &= 0.4909 \end{aligned}$$



Automatic thresholding

(3/4)

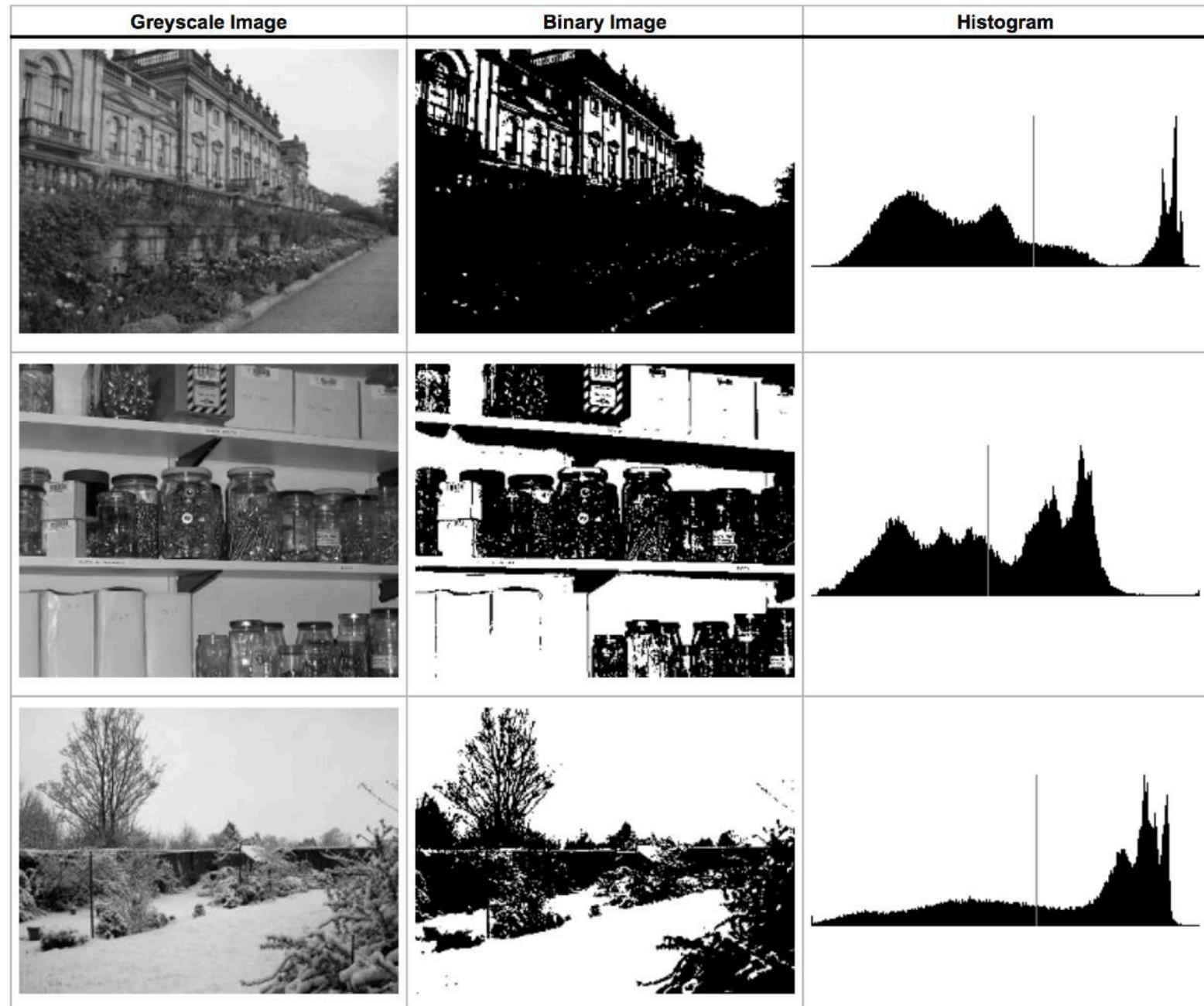
■ Iterate over all threshold values T



Automatic thresholding

(4/4)

■ Examples

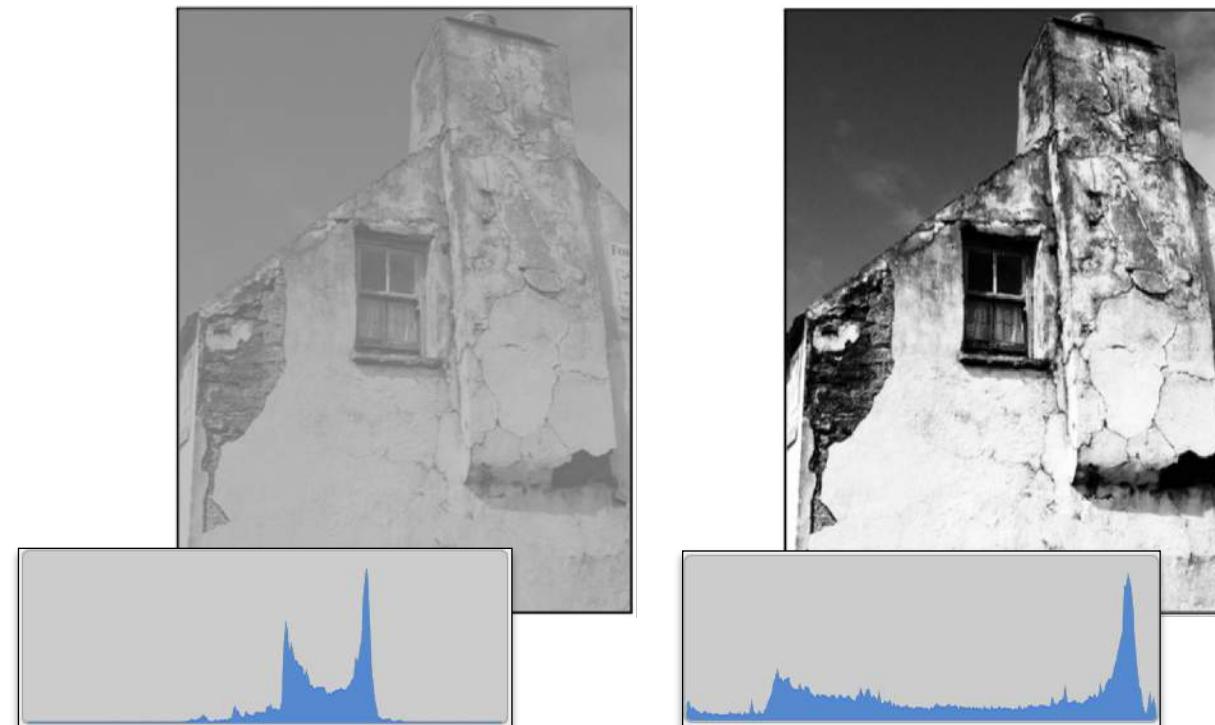
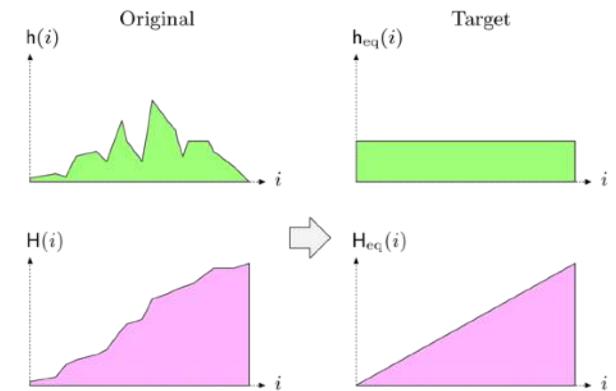


Automatic contrast adjustment

(1/2)

■ **Histogram equalization** aims at improving the contrast by *rescaling the histogram*

- ▶ Low-contrast images use only portion of the available gray levels, i.e. narrow histogram
- ▶ After *equalization*, histogram is *spread out*
- ▶ The intensities now range over *all possible gray levels*

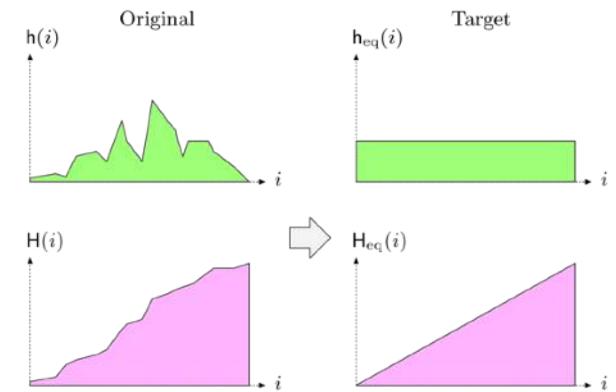


Automatic contrast adjustment

(1/2)

■ Histogram equalization aims at improving the contrast by *rescaling the histogram*

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- ▶ After *equalization*, histogram is *spread out*
- ▶ The intensities now range over *all possible gray levels*



■ Based on the *cumulative distribution function* of $h(i)$ (also called **cumulative histogram**)

- ▶ $H(i)$ = number of pixels with an *intensity less than or equal* to i

$$H(i) = \sum_{j=0}^i h(j)$$

Automatic contrast adjustment

(2/2)

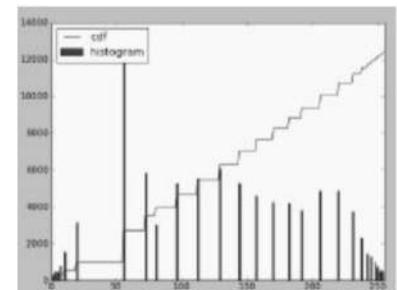
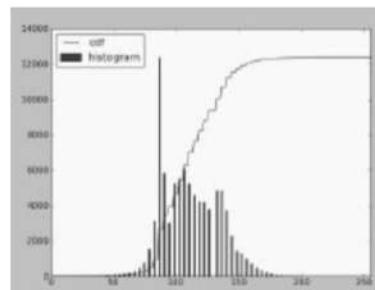
Procedure

- (1) Compute the *histogram* $h(i)$ of the image
- (2) *Normalize* $h(i)$ s.t. its range is $[0, 1]$ (i.e. divide by the total number of pixels)
- (3) Calculate the *cumulative histogram* $H(i)$
- (4) Apply the following *point operation function* to every pixel p :

$$f(p) = \text{round} \left(\frac{H(p) - H_{\min}}{1 - H_{\min}} \cdot (L - 1) \right)$$

where L is the number of gray levels of the image (i.e. $[0, L-1]$ range)

Example



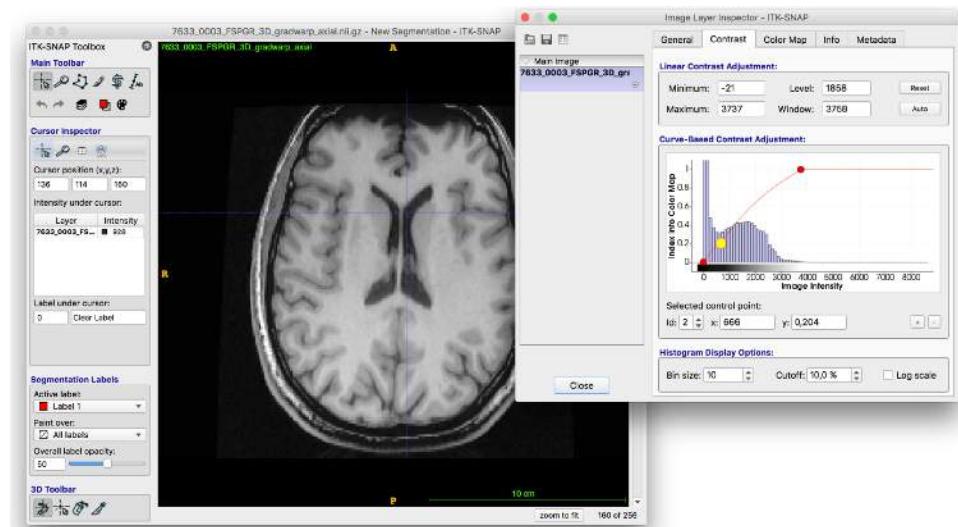
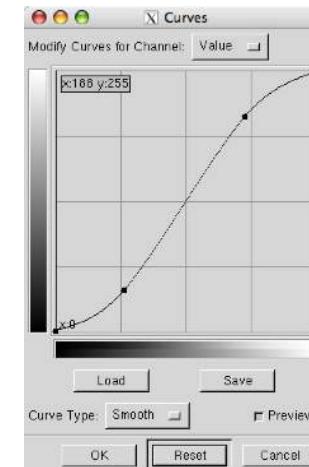
“Curves” operation

- Most *software packages* allow us to manually alter histograms by adjusting the contrast with a **continuous curve**

■ **Continuous** point-operation functions

- ▶ Let's assume for simplicity:
 - That the image has *continuous pixel type* (floating point)
 - The *intensity range* is in the interval $[0, 1]$, i.e. $I : \Omega \rightarrow [0, 1]$
- ▶ A *continuous point-operation* is any function

$$f : [0, 1] \rightarrow [0, 1]$$



■ The contrast is changed as...

- ▶ slope = 1 → no contrast change
- ▶ slope < 1 → contrast is decreased
(wide range of values mapped to *smaller range* of values)
- ▶ slope > 1 → contrast is increased
(stretches small range of values to *larger range* of values)

High Dynamic Range (HDR) imaging

(1/8)

- **FACT:** sensors in digital cameras capture *much less dynamic range* than the human eye
 - ▶ **Dynamic Range** = *ratio* between *maximum* and *minimum* measurable light intensities

■ Examples

your eyes



High Dynamic Range (HDR) imaging

(1/8)

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■ Examples

your camera



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■ Examples

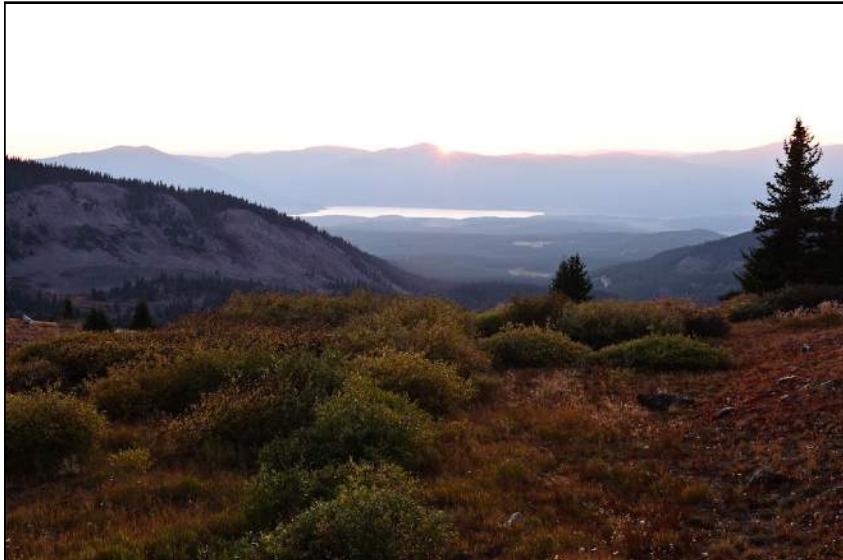
your camera



High Dynamic Range (HDR) imaging

(2/8)

■ What is the problem?



Try to **correctly expose the ground**,
but end up completely blowing out the sky



Try to **correctly expose the sky**,
but the ground becomes too dark to see any detail

■ Clearly, camera is unable to capture such a **large dynamic range**

High Dynamic Range (HDR) imaging

(2/8)

■ What is the problem?



Try to **correctly expose**
but end up completely b

Try to **expose the sky**,
it's too dark to see any detail

■ Clearly, camera is not able to handle **large dynamic range**

■ HDR imaging is a way to **capture all the dynamic range of a scene** by combining multiple exposures

- This resembles **what our eyes do**: they adapt the “exposure” when looking at different portions of the scene having different light intensities

High Dynamic Range (HDR) imaging

(3/8)

- There are **many different techniques** for HDR photography
 - e.g. *Tone Mapping, Digital Blending, Dynamic Range Increase, Luminance Masking...*

■ The **basic idea** is:

- Capture the same scene with different exposures
 - **Normal:** standard exposure
 - **Under-exposed:** to get details in the *lightest* areas
 - **Over-exposed:** to get details in the *darkest* areas



- Combine them together into one image to obtain contrast in each area of the image

■ This way, all areas of the image will be **properly exposed!**

High Dynamic Range (HDR) imaging

(4/8)

■ Examples of different functions

EV: +2



EV: 0



EV: -2



Natural

High Dynamic Range (HDR) imaging

(4/8)

■ Examples of different functions

EV: +2



EV: 0



EV: -2



Balanced

High Dynamic Range (HDR) imaging

(4/8)

■ Examples of different functions

EV: +2



EV: 0



EV: -2



Painterly

High Dynamic Range (HDR) imaging

(4/8)

■ Examples of different functions

EV: +2



EV: 0



EV: -2



Surreal

High Dynamic Range (HDR) imaging

(5/8)

- HDR photography has become a **photographic phenomenon**
- **Most cameras** (also phones) offer the possibility to shoot in HDR

- ▶ This function is usually called ***Auto Exposure Bracketing*** (AEB)
- ▶ Automatically *acquire multiple exposures* with a single click
- ▶ Multiple images are saved



- *Moving objects create “ghosts”*

- ▶ **NB:** use the tripod!



- Same love it, some hate it

- ▶ It relies heavily on *post-processing*
- ▶ So, the output image can really be *whatever you want it to be!!!*

High Dynamic Range (HDR) imaging

(6/8)

■ Some good examples



High Dynamic Range (HDR) imaging

(6/8)

■ Some good examples



High Dynamic Range (HDR) imaging

(6/8)

■ Some good examples



High Dynamic Range (HDR) imaging

(6/8)

■ Some good examples



High Dynamic Range (HDR) imaging

(7/8)

■ Some extreme examples



High Dynamic Range (HDR) imaging

(7/8)

■ Some **extreme** examples



High Dynamic Range (HDR) imaging

(7/8)

■ Some **extreme** examples



High Dynamic Range (HDR) imaging

(7/8)

■ Some **extreme** examples



High Dynamic Range (HDR) imaging

(8/8)

- Definitely, **too much** post processing...



High Dynamic Range (HDR) imaging

(8/8)

- Definitely, **too much** post processing...



High Dynamic Range (HDR) imaging

(8/8)

- Definitely, **too much** post processing...



High Dynamic Range (HDR) imaging

(8/8)

- Definitely, **too much** post processing...



Limitations of point operations

■ Main limitations

- ▶ They don't know *where they are* in an image
- ▶ They don't know anything about their *neighbors*

■ Most image features (e.g. edges) involve a **spatial neighborhood** of pixels



Requires derivatives (i.e. spatial information)

■ If we want to enhance these features we need to **go beyond point operations**