

SAIR

Spatial AI & Robotics Lab

CSE 473/573

L7: PYRAMIDS & HISTOGRAM

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Spatial AI & Robotics Lab

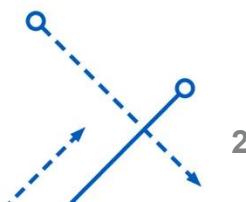
Department of Computer Science and Engineering



University at Buffalo The State University of New York

Content

- Image Pyramids
 - Gaussian, Laplacian
 - Convolution and Transposed Convolution
- Image Histogram
 - Equalization
 - Image Enhancement
 - Histogram Equalization





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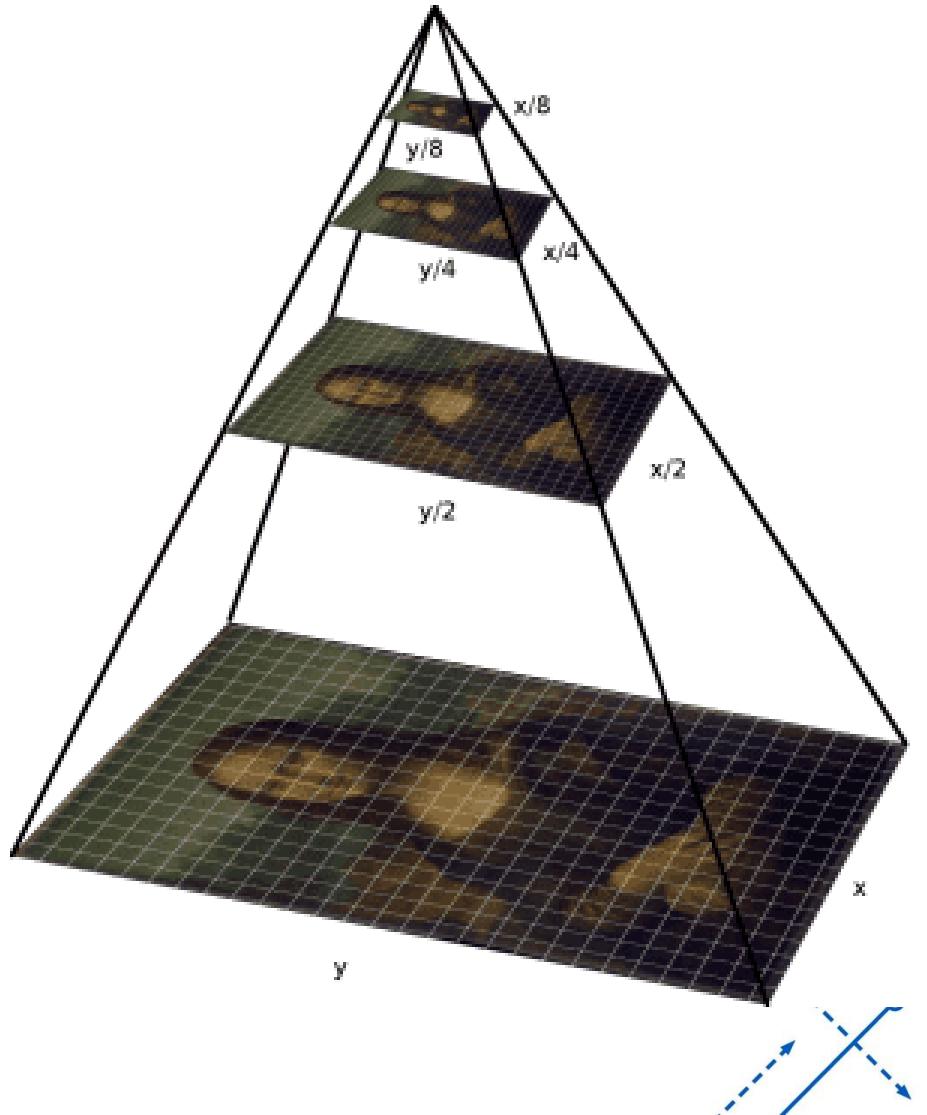
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IMAGE PROCESSING

Pyramids

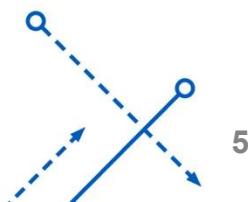
Image Pyramids

- Gaussian pyramid
- Laplacian pyramid
- Transposed Convolution

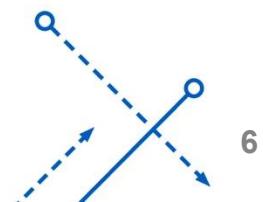
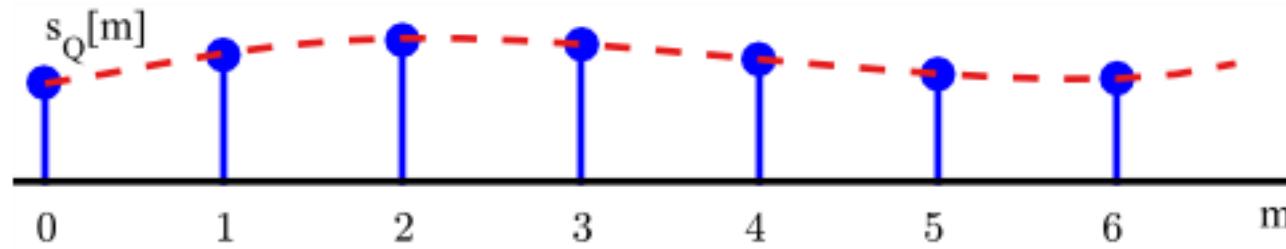
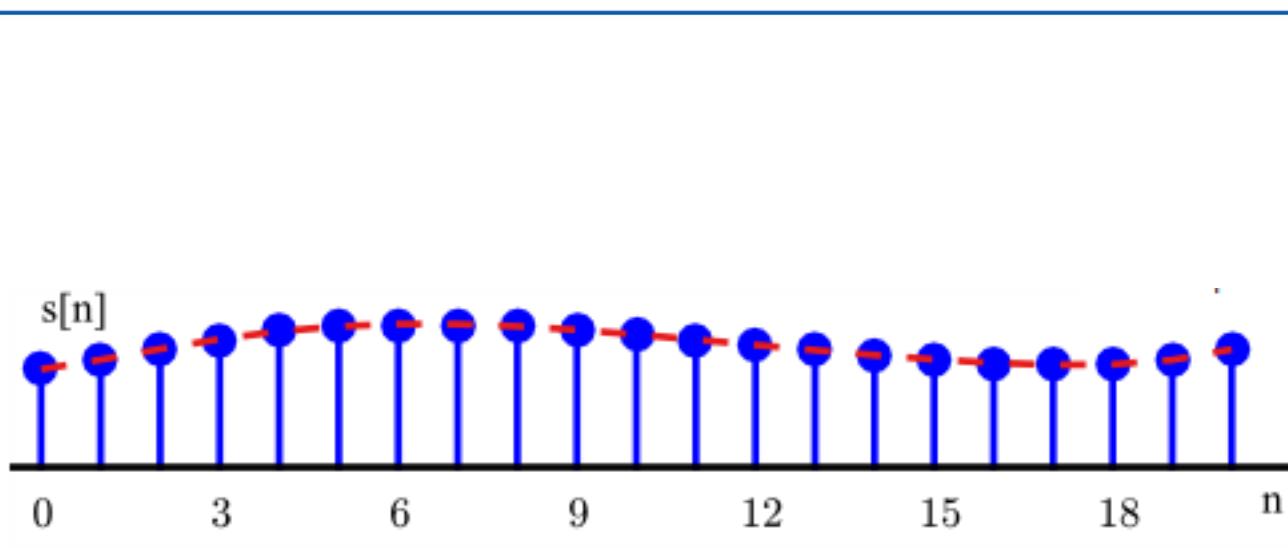


Pyramids applications

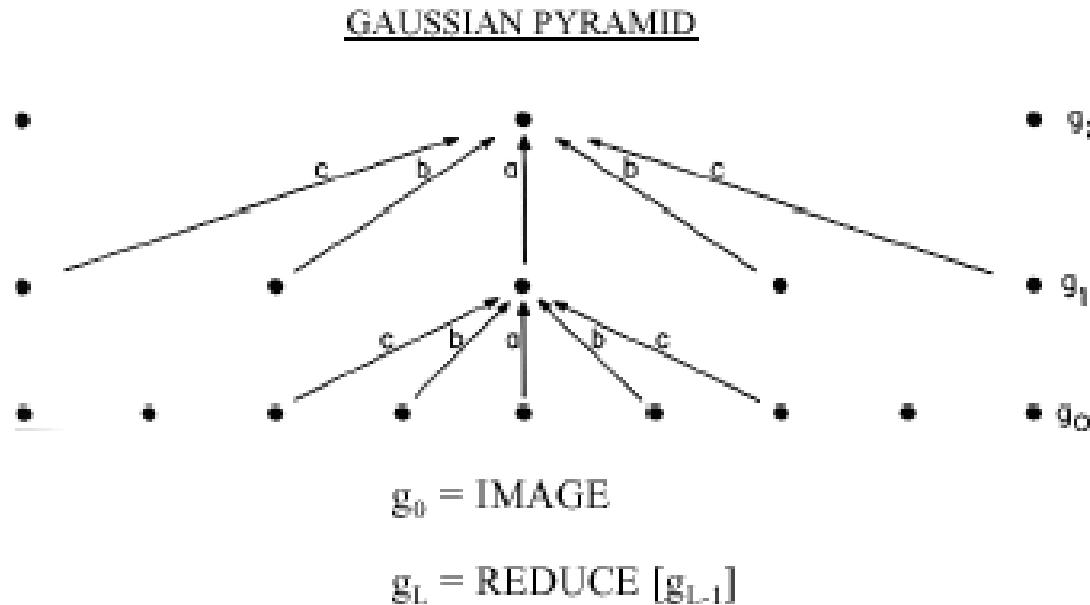
- Up- or Down- sampling images.
- Multi-resolution image analysis
 - Look for an object over various spatial scales
 - Coarse-to-fine image processing
 - form blur estimate or the motion analysis on very low-resolution image, up-sample and repeat.
 - Often a successful strategy for avoiding local minima in complicated estimation tasks.



Down-sampling



The Gaussian pyramid



- A one-dimensional graphic representation of the process of a Gaussian pyramid.
- Each row of dots represents nodes within a level of the pyramid.
- The values in a high level are the weighted average of values in the next lower level.
- Note that node spacing doubles from level to level.

The Gaussian pyramid



GAUSSIAN PYRAMID



0

1

2

3

4

5

- First six levels of the Gaussian pyramid for the "Lady" image.
- The original image at level 0 has 257×257 pixels.
- Each higher level array is roughly half the dimensions of its predecessor.
- Thus, level 5 measures just 9 by 9 pixels.

The Gaussian pyramid



Matrix operation for Down-sampling (1D)

- Assume x_1 is a signal with 16 elements.
- Down-sampled signal x_2 can be expressed as

$$x_2 = G_1 x_1$$

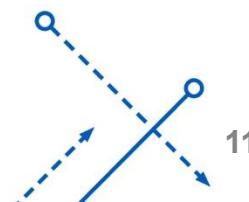
$$G_1 = \begin{matrix} 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 4 & 6 & 4 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 4 & 6 \end{matrix}$$


(Normalization constant of 1/16 omitted for visual clarity.)

Next pyramid level

$$x_3 = G_2 x_2$$

$$G_2 = \begin{matrix} 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 4 & 6 & 4 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 4 \end{matrix}$$

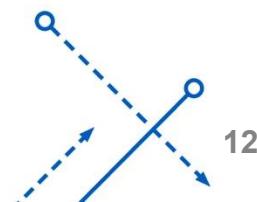
The combined effect of the two pyramid levels

- Smooth with Gaussians, because
 - a Gaussian * Gaussian = another Gaussian

$$x_3 = G_2 G_1 x_1$$

$$G_2 G_1 =$$

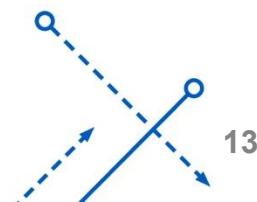
1	4	10	20	31	40	44	40	31	20	10	4	1	0	0	0
0	0	0	0	1	4	10	20	31	40	44	40	31	20	10	4
0	0	0	0	0	0	0	0	1	4	10	20	31	40	44	40
0	0	0	0	0	0	0	0	0	0	0	0	1	4	10	20



Up-sampling

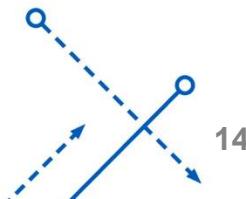
$$y_2 = F_3 x_3$$

$$F_3 = \begin{matrix} 6 & 1 & 0 & 0 \\ 4 & 4 & 0 & 0 \\ 1 & 6 & 1 & 0 \\ 0 & 4 & 4 & 0 \\ 0 & 1 & 6 & 1 \\ 0 & 0 & 4 & 4 \\ 0 & 0 & 1 & 6 \\ 0 & 0 & 0 & 4 \end{matrix}$$

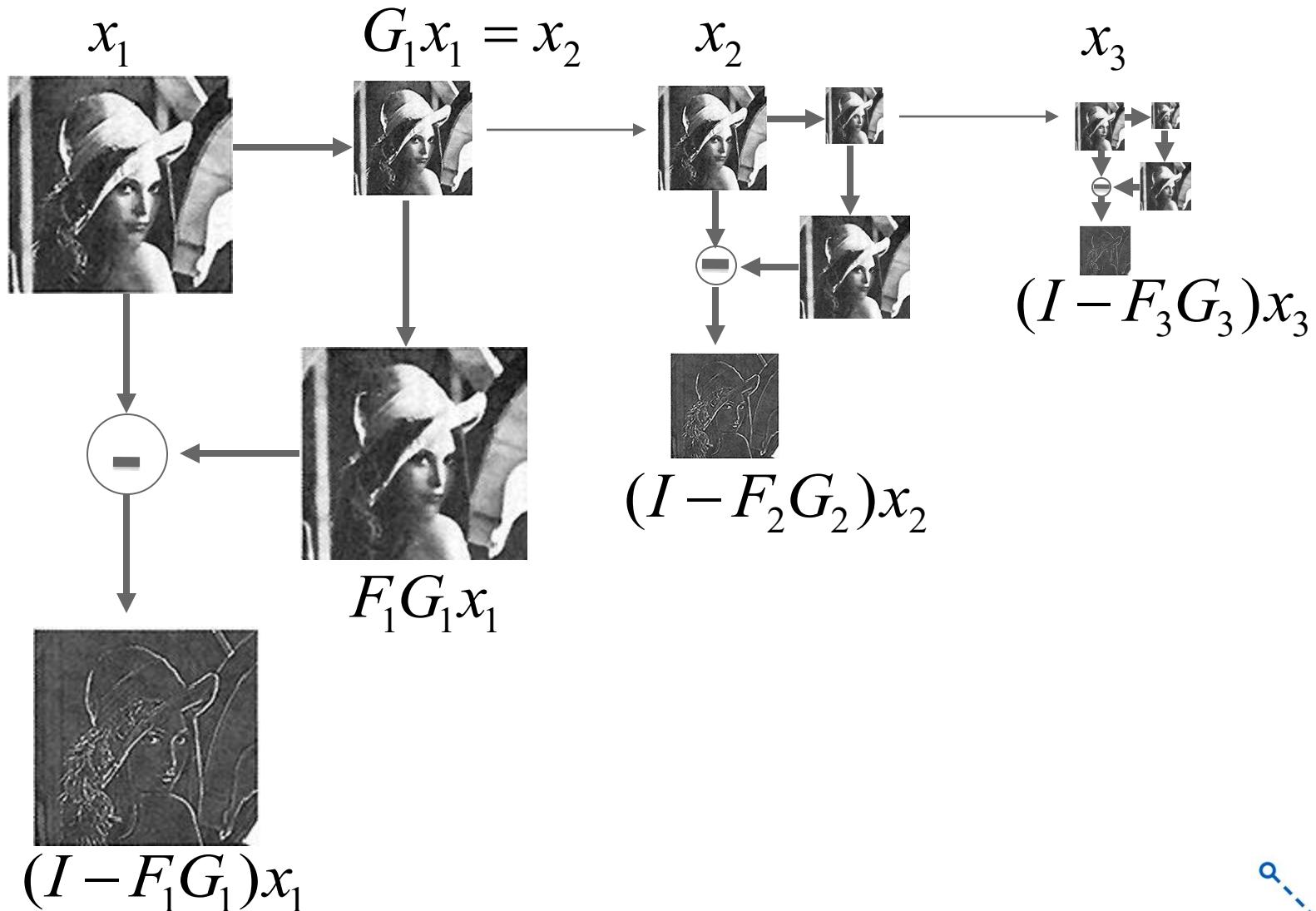


The Laplacian Pyramid

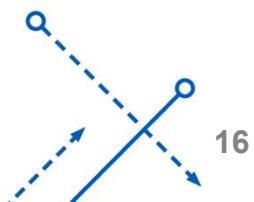
- **Difference between up-sampled Gaussian pyramid and Gaussian pyramid.**
- **Band pass filter** - each level represents spatial frequencies (largely) unrepresented at other level.



Laplacian pyramid algorithm



Gaussian pyramid



Laplacian pyramid



512

256

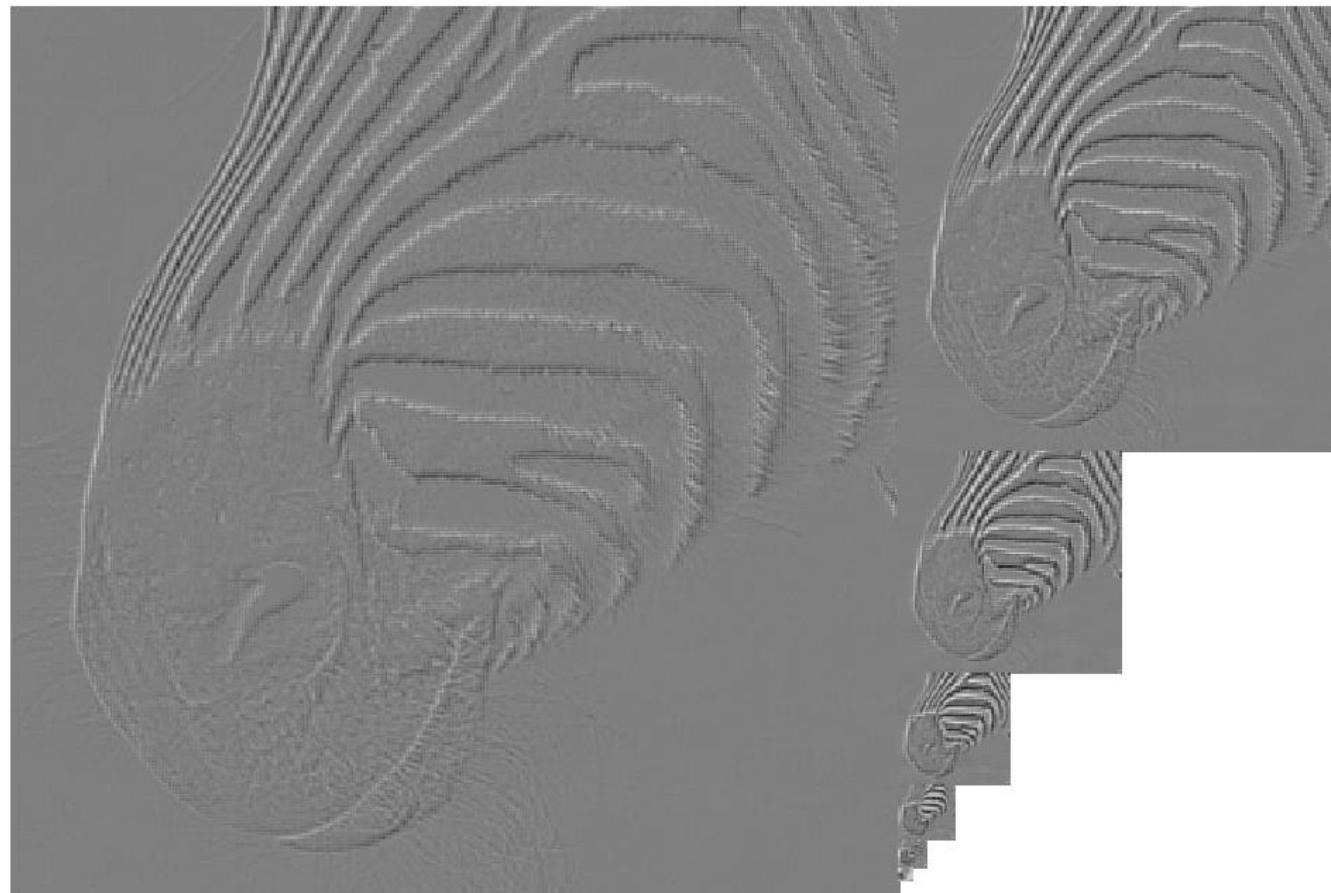
128

64

32

16

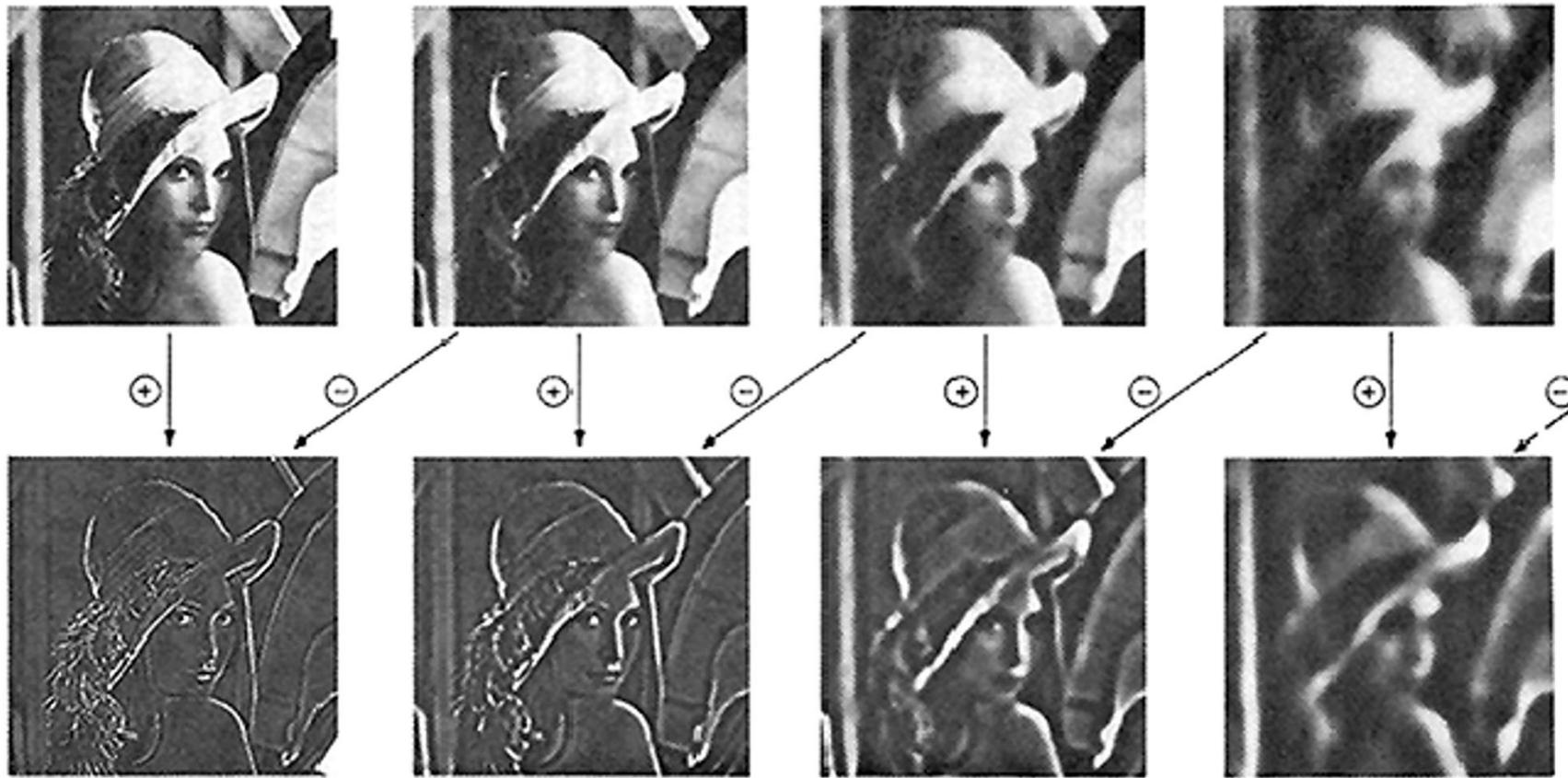
8



17

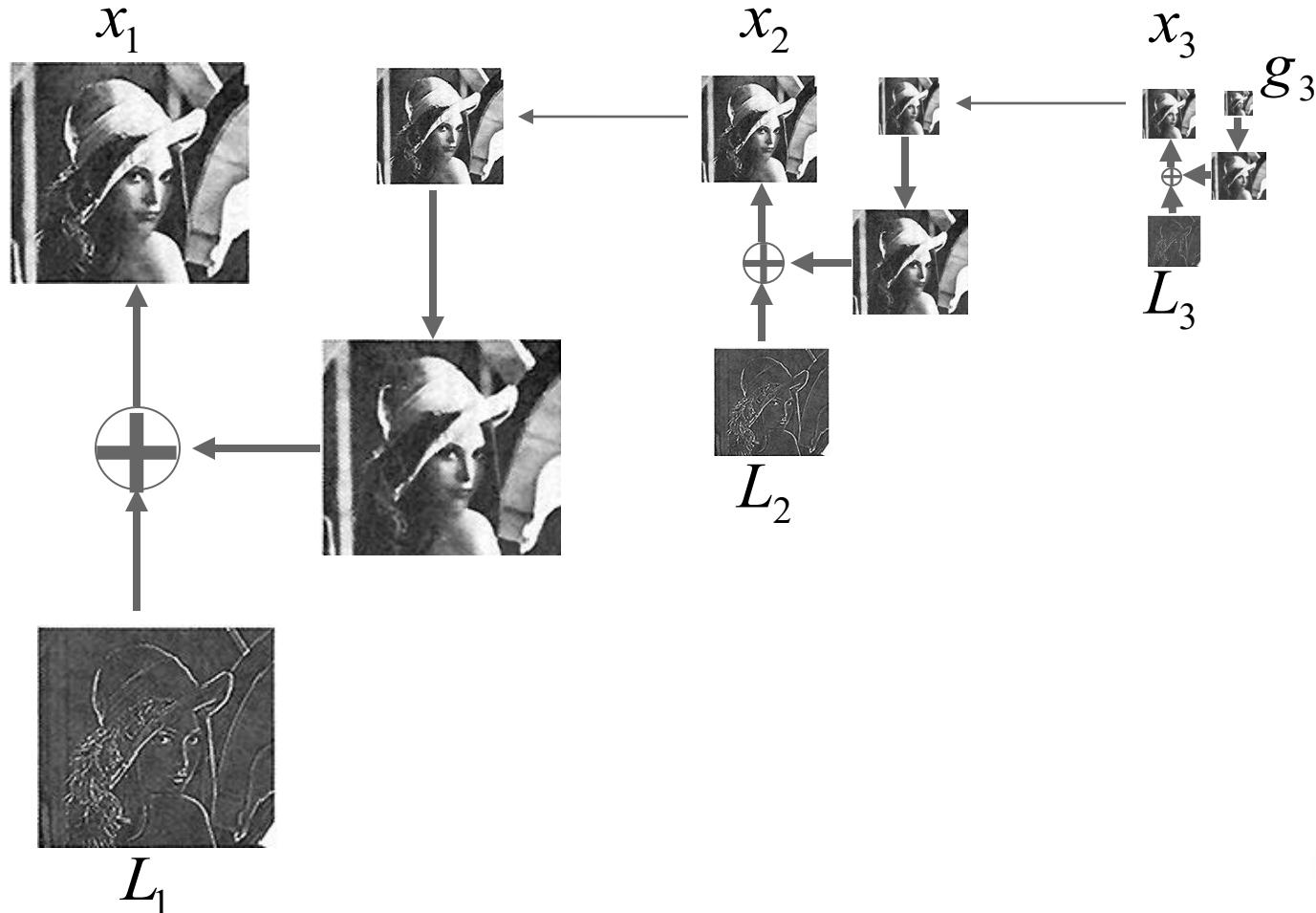
Laplacian Pyramid

- Information captured at each level of a Gaussian (top) and Laplacian (bottom) pyramid
 - showing full resolution.



Laplacian Pyramid

- Reconstruction: recover x_1 from L_1 , L_2 , L_3 and g_3



Laplacian Pyramid Reconstruction algorithm

G# is the blur-and-downsample operator at pyramid level #

F# is the blur-and-upsample operator at pyramid level #

Laplacian pyramid elements:

$$L_1 = (I - F_1 G_1) x_1$$

$$x_2 = G_1 x_1$$

$$L_2 = (I - F_2 G_2) x_2$$

$$x_3 = G_2 x_2$$

$$L_3 = (I - F_3 G_3) x_3$$

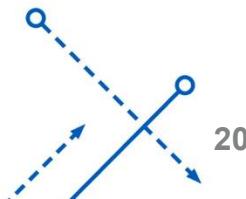
$$x_4 = G_3 x_3$$

Reconstruction of original image (x_1) from Laplacian pyramid elements:

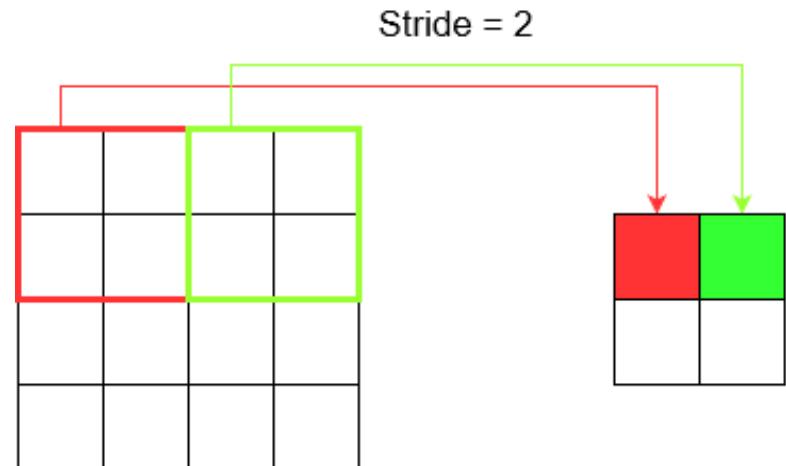
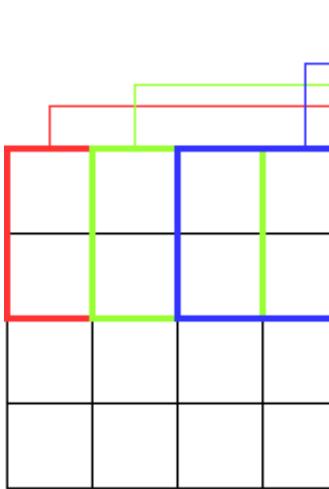
$$x_3 = L_3 + F_3 x_4$$

$$x_2 = L_2 + F_2 x_3$$

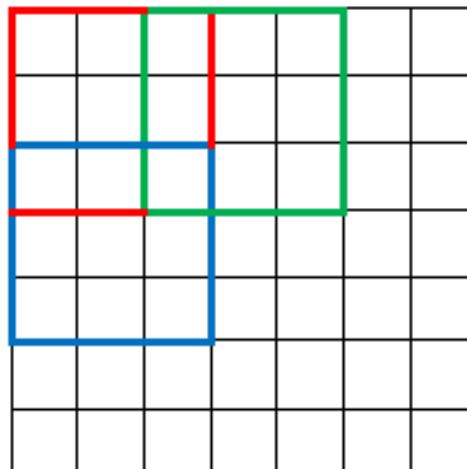
$$x_1 = L_1 + F_1 x_2$$



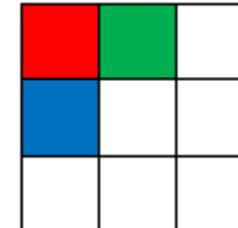
Convolution for Down-sampling



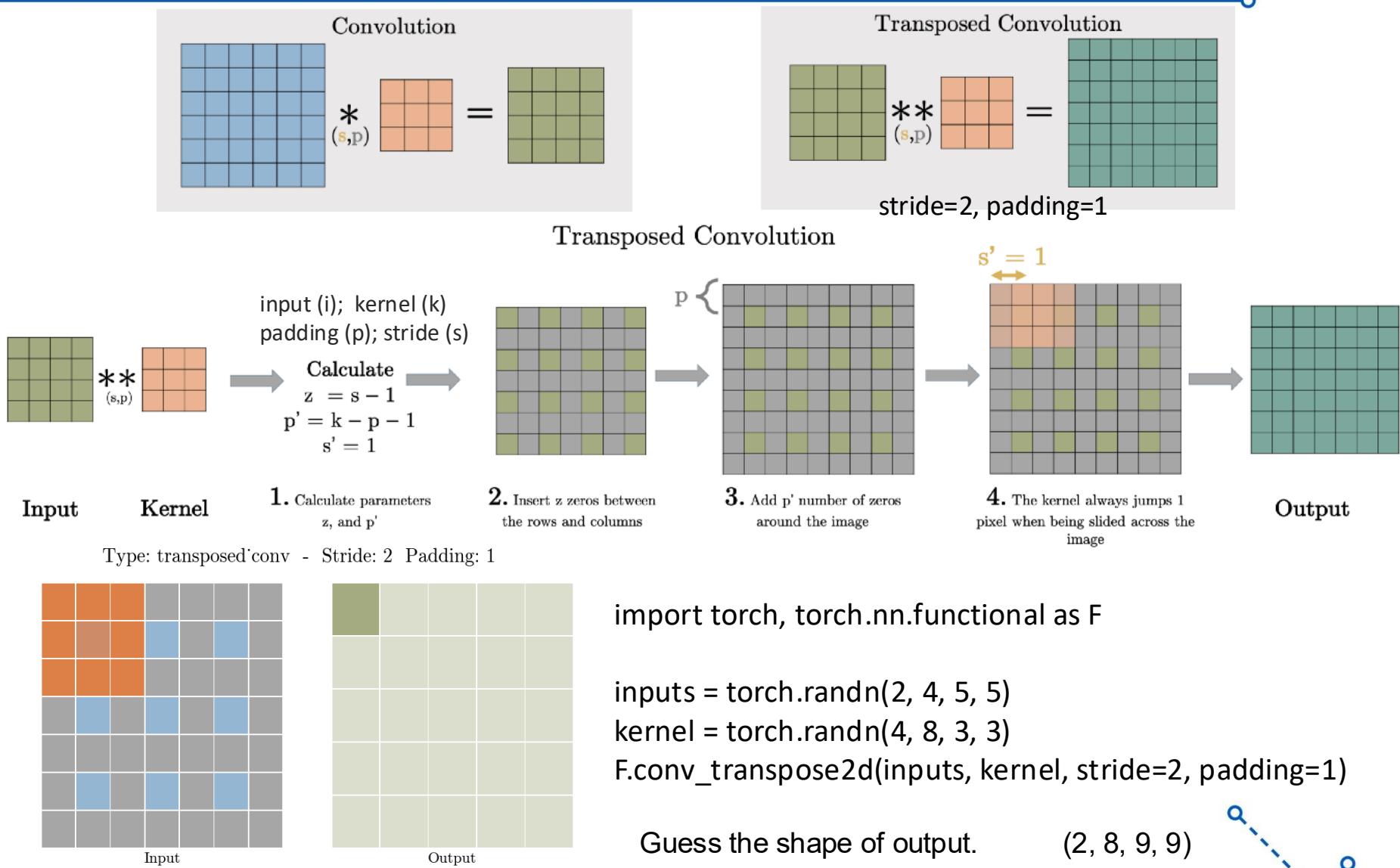
7 x 7 Input Volume



3 x 3 Output Volume

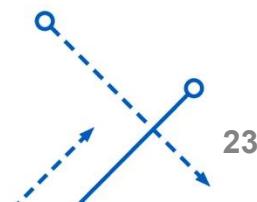


Transposed Convolution for Up-sampling



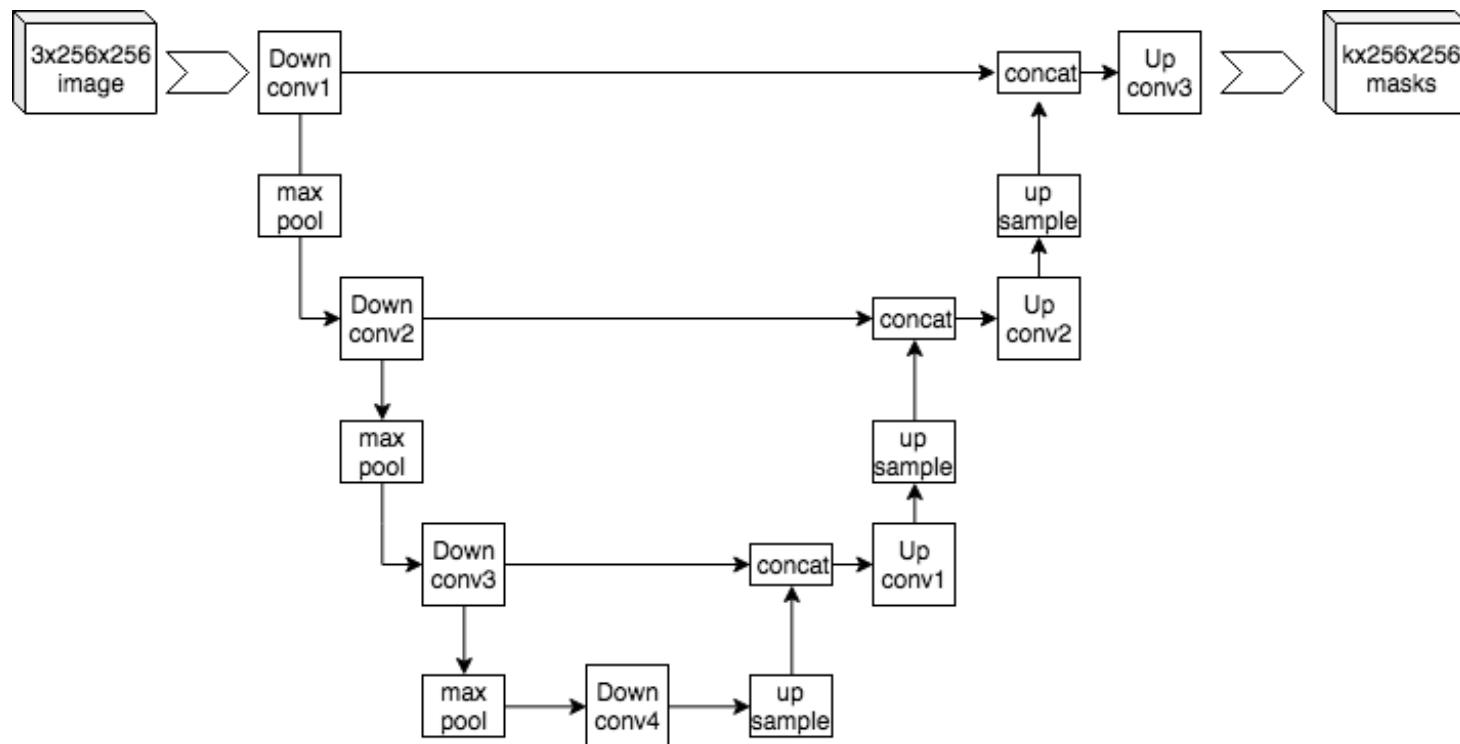
Transposed Convolution & Deconvolution

- The two terms are often used interchangeably.
- Deconvolution can be a misnomer:
 - As it mathematically implies the precise inverse of a convolution,
 - But this is not true.



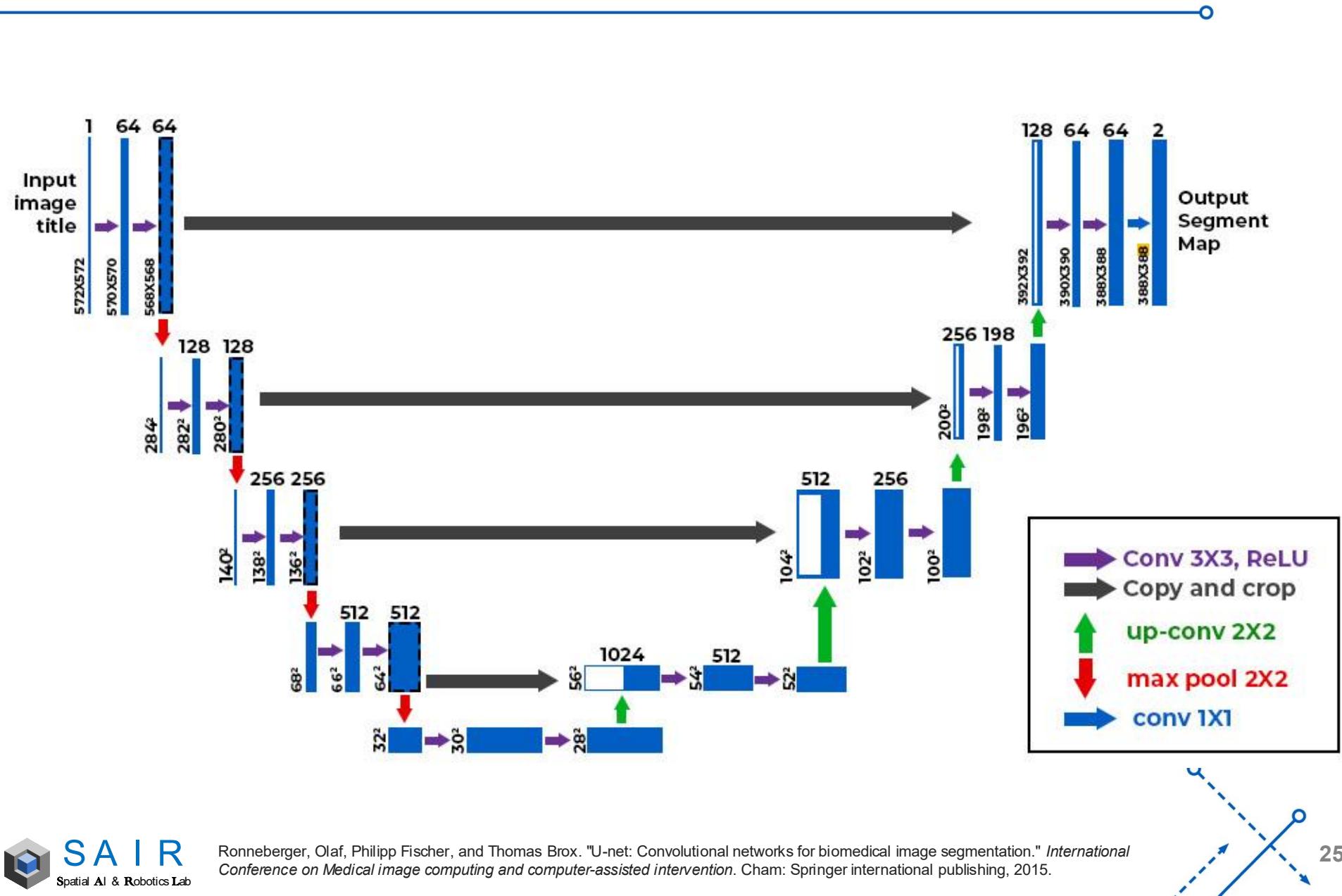
Why use these representations?

- Handle real-world size variations
- Remove noise, Analyze texture
- Recognize objects, Label image features



Shelhamer E, Long J, Darrell T (April 2017). "Fully Convolutional Networks for Semantic Segmentation". *IEEE Transactions on Pattern Analysis and Machine Intelligence*. **39** (4): 640–651

U-Net Structure





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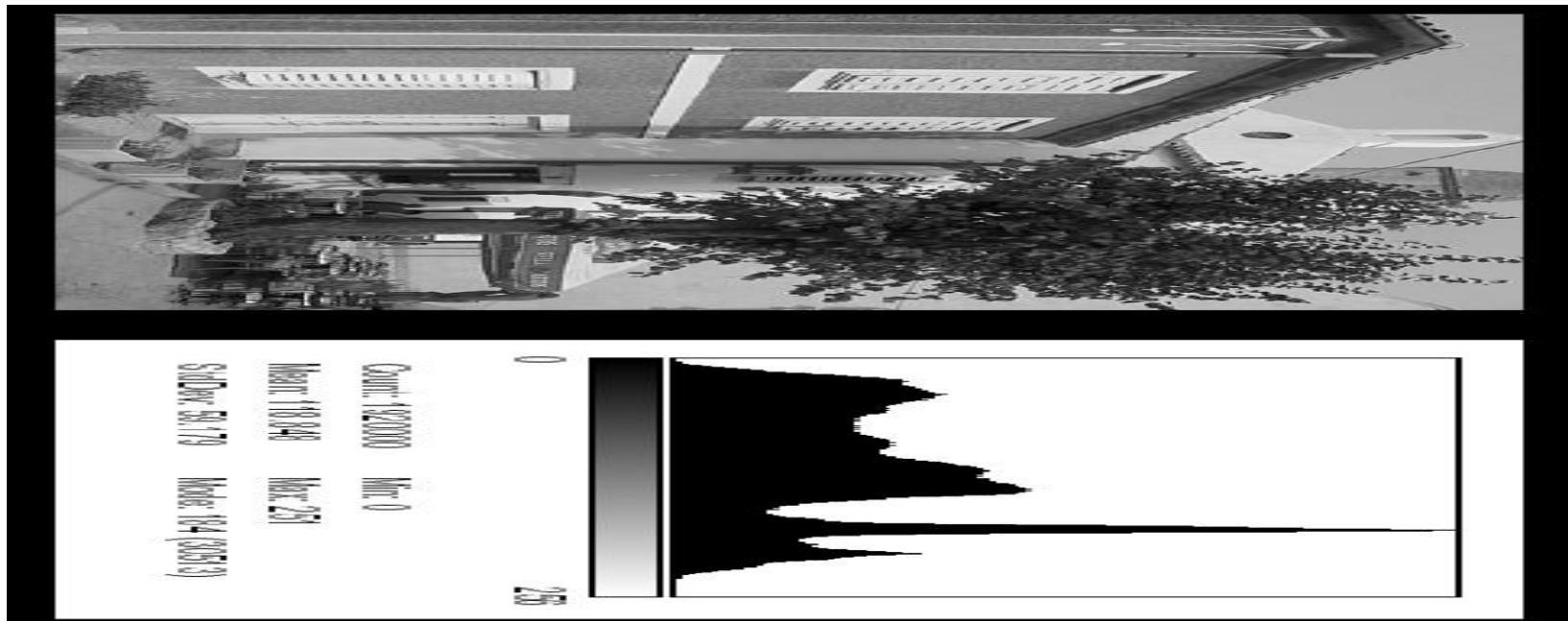
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IMAGE PROCESSING

Histogram

Histogram

- Histograms plots how many times (frequency) each intensity value in image occurs
 - Image (left) has 256 distinct gray levels (8 bits)
 - Histogram (right) shows frequency (how many times) each gray level occurs



Histogram

- Many cameras display real time histograms of scene
 - Helps avoid taking over-exposed pictures



A Digital Single Lens Reflex Camera

Histogram

- A histogram for a grayscale image with intensity values in range

$$I(u, v) \in [0, K - 1]$$

- would contain exactly K entries
- For 8-bit grayscale image, $K = 2^8 = 256$
- Each histogram entry is defined as:
 - $h(i)$ = number of pixels with intensity i ($0 < i < K$).
 - $h(255)$ = number of pixels with intensity $i = 255$.

Formal definition

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

Number (size of set) of pixels

such that

Normalized Histogram

Histogram $h(r_k) = n_k$

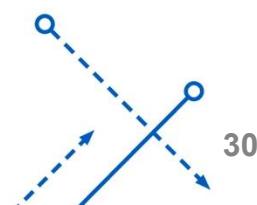
r_k is the k^{th} intensity value

n_k is the number of pixels in the image with intensity r_k

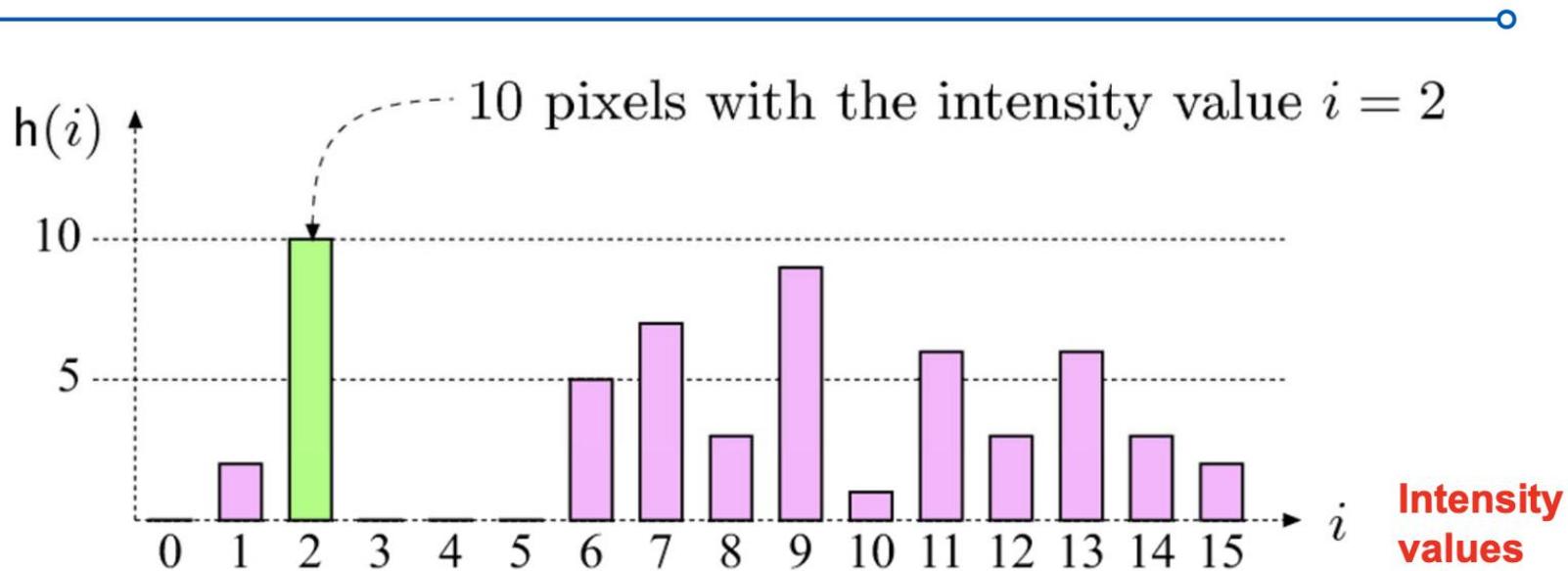
Normalized histogram $p(r_k) = \frac{n_k}{MN}$

n_k : the number of pixels in the image of size $M \times N$ with intensity r_k

Probability density function



Histogram

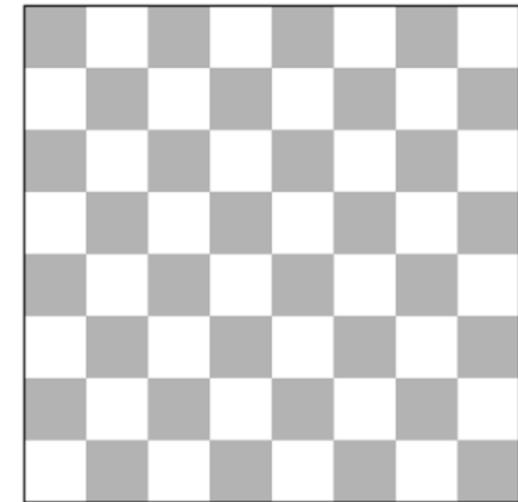
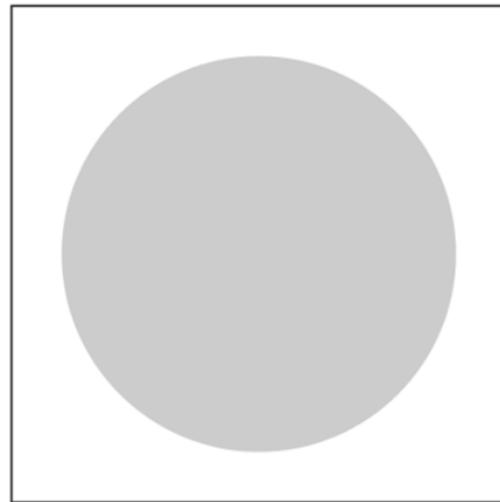
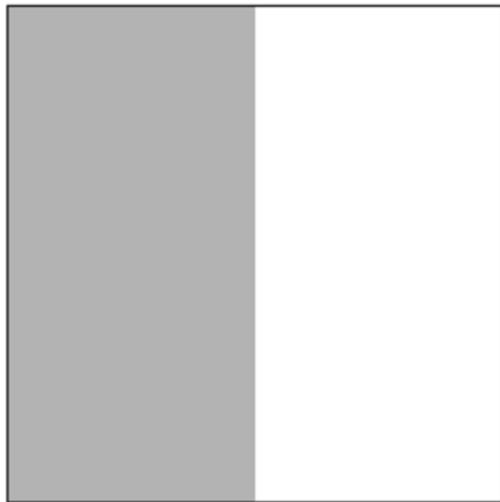


$h(i)$	0	2	10	0	0	0	5	7	3	9	1	6	3	6	3	2
i	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

- E.g., $K = 16$, 10 pixels have intensity value = 2
- Histograms: only statistical information
- No indication of location of pixels

Histogram

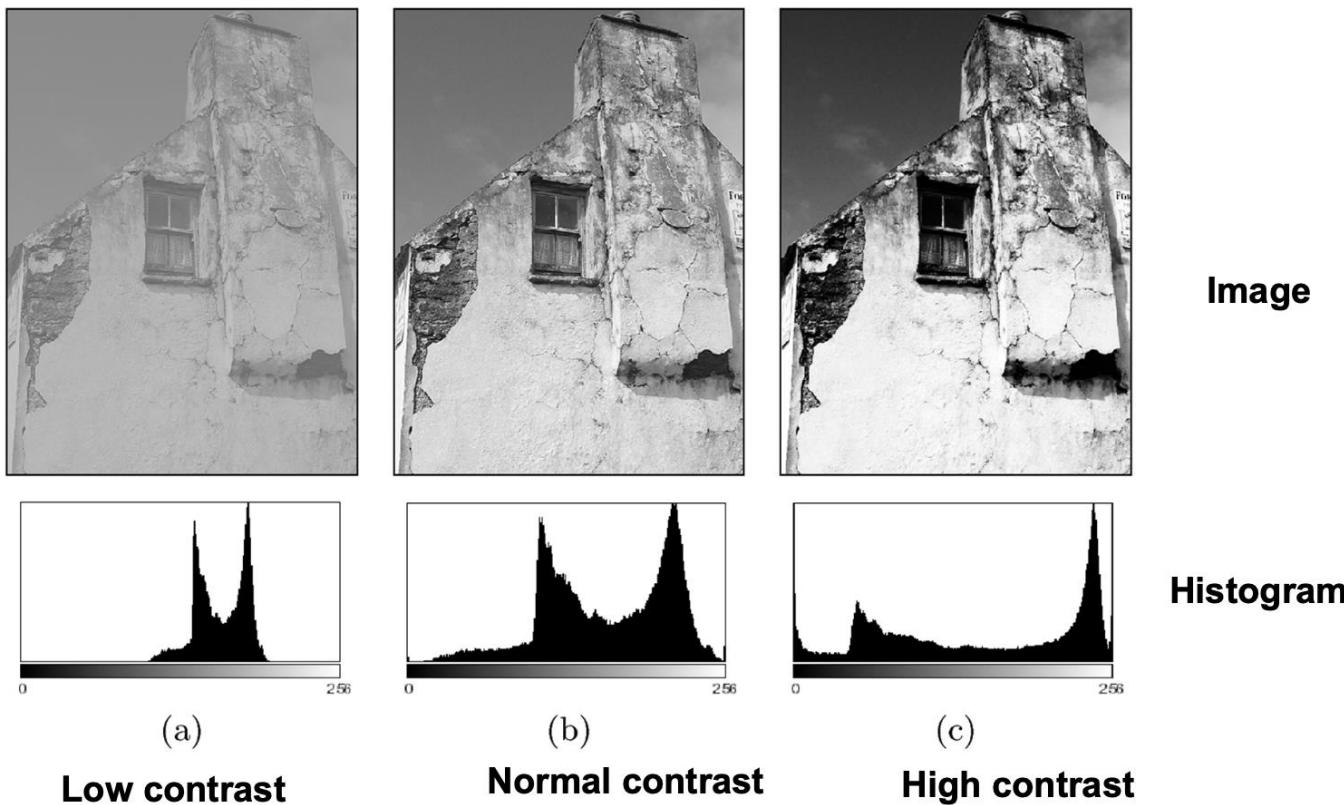
- Different images can have same histogram
- 3 images below have same histogram



- Half of pixels are gray, half are white
 - Same histogram = same statistics
 - Distribution of intensities could be different
- Can we reconstruct image from histogram? No!

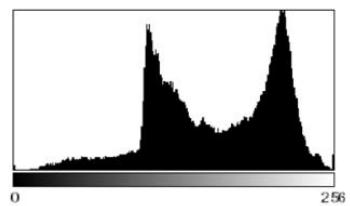
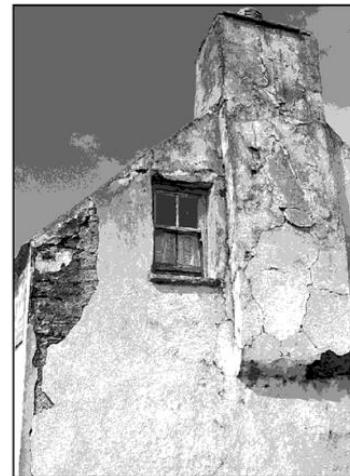
Histogram V.S. Contrast

- What is Good Contrast?
 - Widely spread intensity values
 - Large difference between min and max intensity



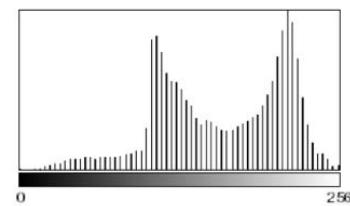
Histogram and Dynamic Range

- Dynamic Range: number of distinct pixels in image
 - High dynamic range (HDR) means very bright and very dark parts in a single image (many distinct values)



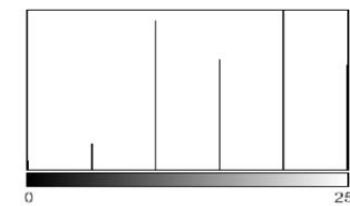
(a)

High Dynamic Range



(b)

**Low Dynamic Range
(64 intensities)**



(c)

**Extremely low
Dynamic Range
(6 intensity values)**

Large Histograms: Binning

- High resolution image can yield very large histogram
- E.g., 32-bit image = $2^{32} = 4,294,967,296$ columns
 - Such a large histogram impractical to display
- Solution is Binning
 - Combine ranges of values into histogram columns

So, given the image $I : \Omega \rightarrow [0, K - 1]$, the binned histogram for I is the function

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

$$\text{where } 0 = a_0 < a_1 < \dots < a_B = K.$$

Number (size of set) of pixels

such that

Pixel's intensity is
between a_i and a_{i+1}

Cumulative Histogram

- Useful for histogram equalization (introducing later)
- Similar to the Cumulative Density Function (CDF)
- Definition

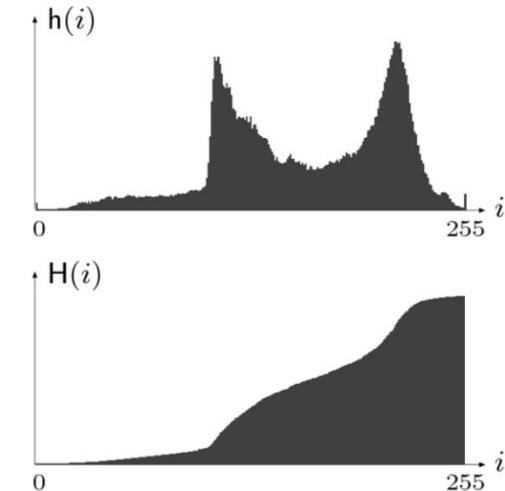
$$H(i) = \sum_{j=0}^i h(j) \quad \text{for } 0 \leq i < K$$

- Monotonically increasing

$$H(K-1) = \sum_{j=0}^{K-1} h(j) = M \cdot N$$

Last entry of
Cum. histogram

Total number of
pixels in image



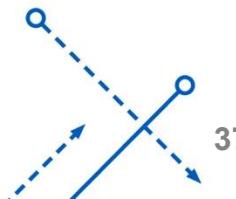
Point Operation

- Point operations changes a pixel's intensity value.

$$a' \leftarrow f(a)$$

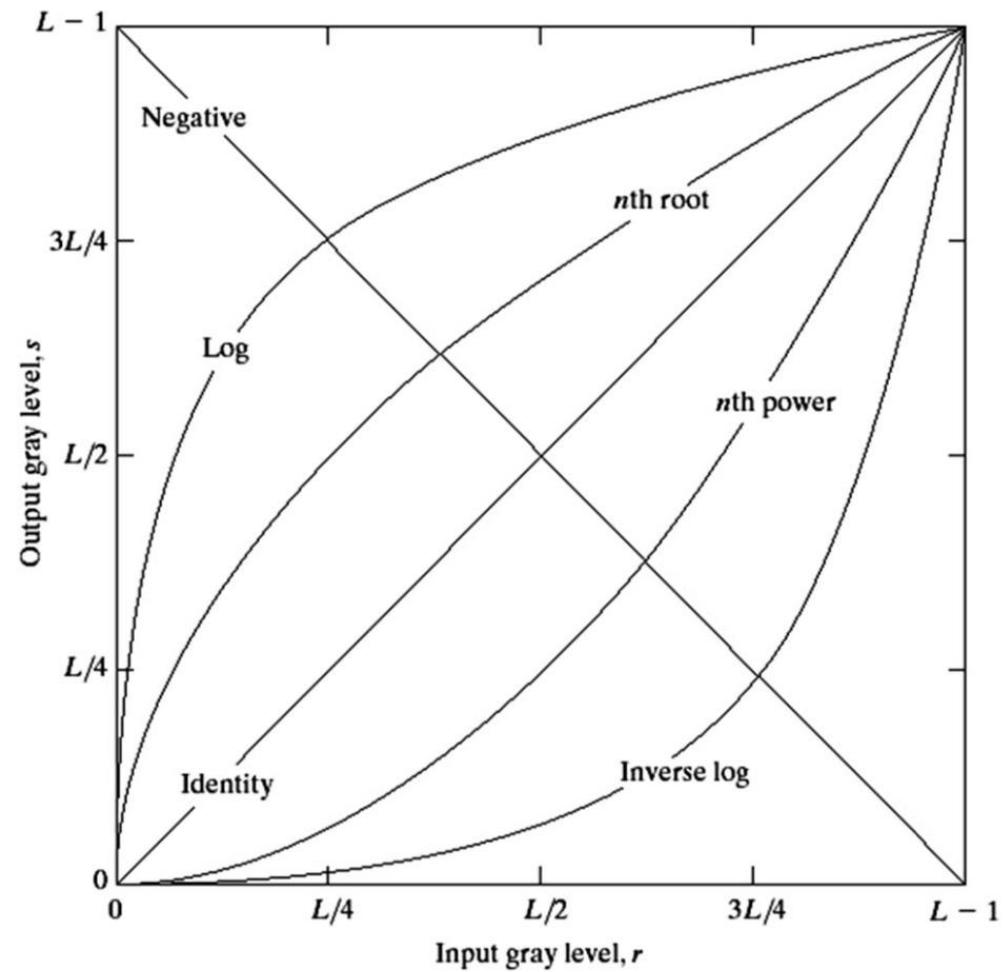
$$I'(u, v) \leftarrow f(I(u, v))$$

- New pixel intensity depends on
 - Pixel's previous intensity $I(u, v)$
 - Mapping function $f()$
- Does not depend on
 - Pixel's location (u, v)
 - Intensities of neighboring pixels



Basic Grey Level Point Operation

- 3 most common gray level operation
 - Linear
 - Negative/Identity
 - Logarithmic
 - Log/Inverse log
 - Power law
 - nth power/nth root



Power Law Transformations

- Power law transformations have the form

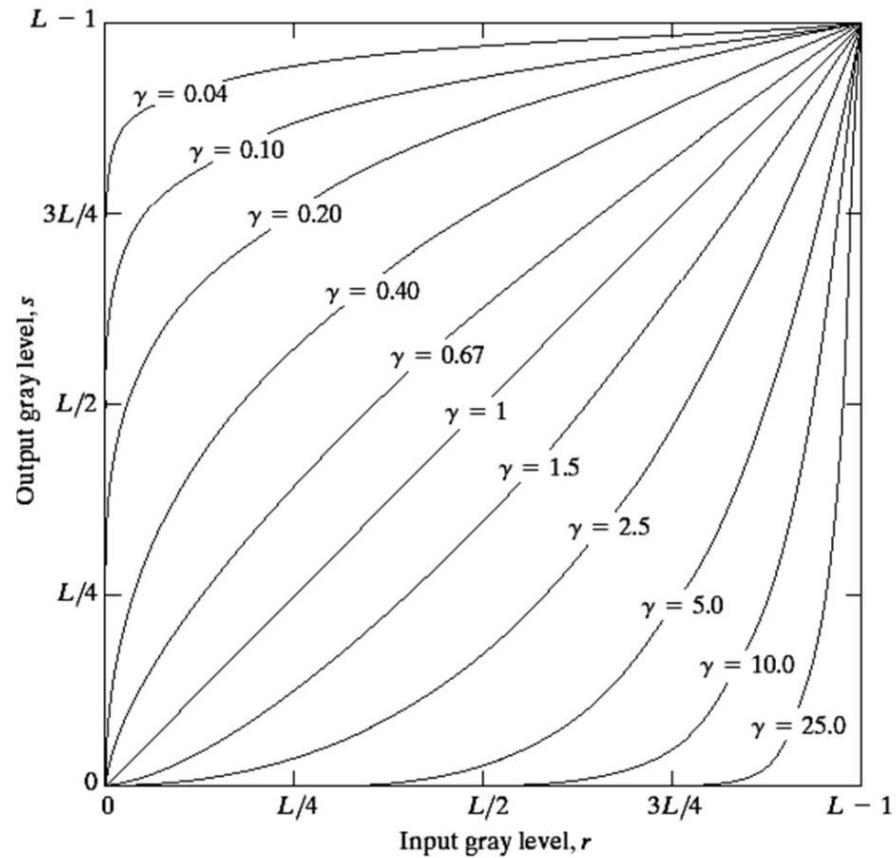
$$s = c * r^\gamma$$

Annotations:

- New pixel value (s)
- Constant (c)
- Old pixel value (r)
- Power (γ)

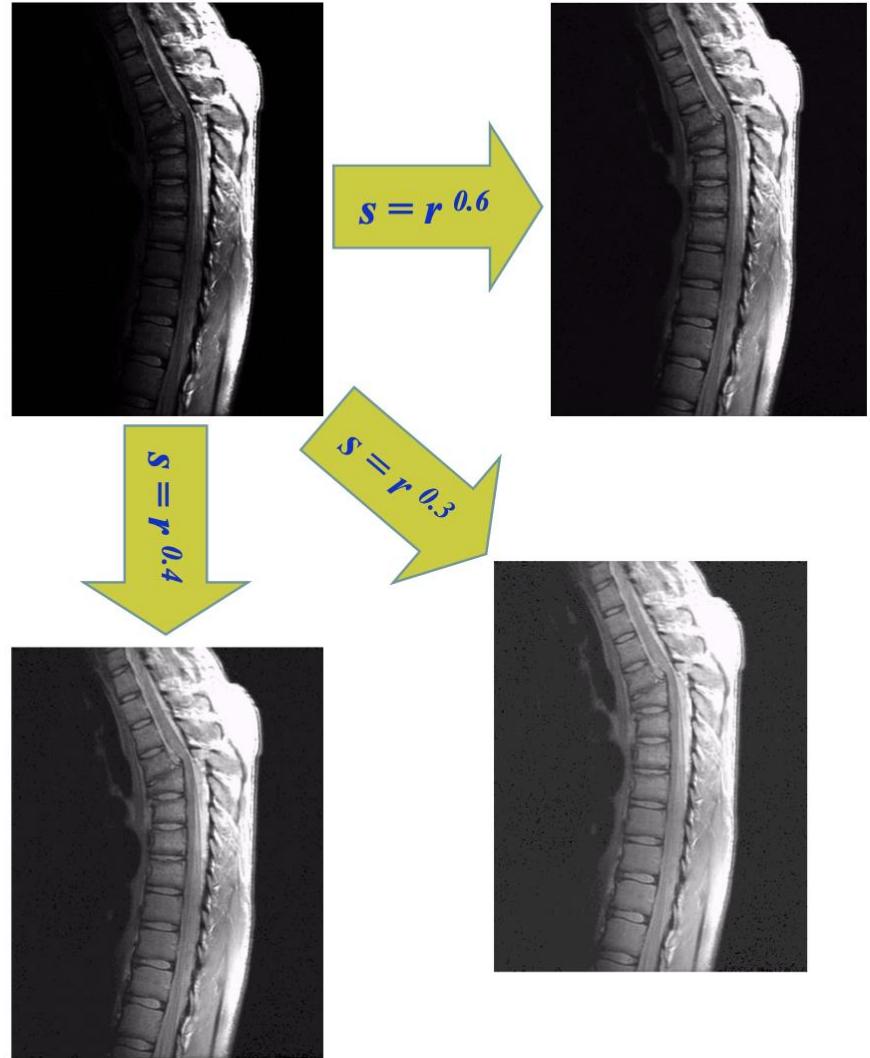
- Map narrow range of dark input values into wider range of output values or vice versa

- Varying γ gives a whole family of curves



Power Law Example

- Magnetic Resonance (MR) image of fractured human spine



- Different power values highlight different details

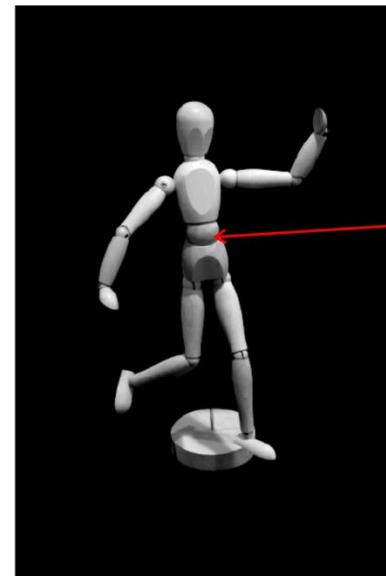
Intensity Windowing

- A clamp operation, then linearly stretching image intensities to fill possible range
- To window an image in $[a,b]$ with max intensity M

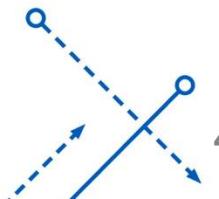
$$f(p) = \begin{cases} 0 & \text{if } p < a \\ M \times \frac{p-a}{b-a} & \text{if } a \leq p \leq b \\ M & \text{if } p > b \end{cases}$$



Original Image



Windowed Image



Automatic Contrast Adjustment

- Modify pixel intensities such that the available range of range of pixels is full covered.
- Algorithm
 - Find high and lowest pixel intensities, a_{low} and a_{high}
 - Linear stretching the intensity range.



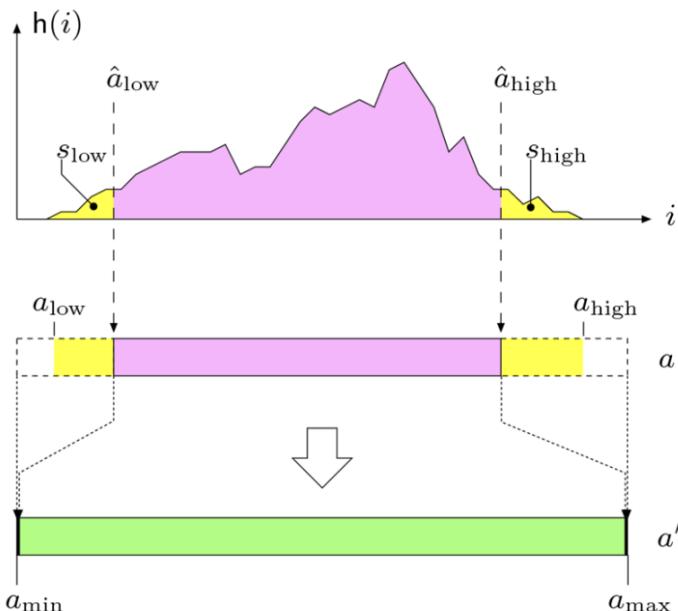
$$f_{\text{ac}}(a) = a_{\text{min}} + (a - a_{\text{low}}) \cdot \frac{a_{\text{max}} - a_{\text{min}}}{a_{\text{high}} - a_{\text{low}}}$$

If $a_{\text{min}} = 0$ and $a_{\text{max}} = 255$

$$f_{\text{ac}}(a) = (a - a_{\text{low}}) \cdot \frac{255}{a_{\text{high}} - a_{\text{low}}}$$

Modified Contrast Adjustment

- Better to map only certain range of values.
- Get rid of tails (usually noises), with predefined percentiles s_{low} and s_{high}

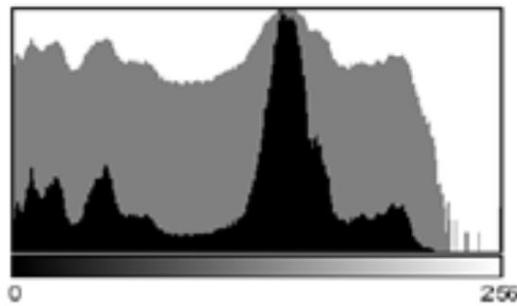


$$\hat{a}_{\text{low}} = \min\{ i \mid H(i) \geq M \cdot N \cdot s_{\text{low}} \}$$

$$\hat{a}_{\text{high}} = \max\{ i \mid H(i) \leq M \cdot N \cdot (1 - s_{\text{high}}) \}$$

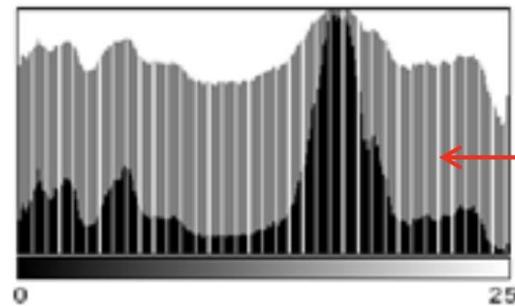
$$f_{\text{mac}}(a) = \begin{cases} a_{\min} & \text{for } a \leq \hat{a}_{\text{low}} \\ a_{\min} + (a - \hat{a}_{\text{low}}) \cdot \frac{a_{\max} - a_{\min}}{\hat{a}_{\text{high}} - \hat{a}_{\text{low}}} & \text{for } \hat{a}_{\text{low}} < a < \hat{a}_{\text{high}} \\ a_{\max} & \text{for } a \geq \hat{a}_{\text{high}} \end{cases}$$

Effects of Automatic Contrast Adjustment



(a)

Original



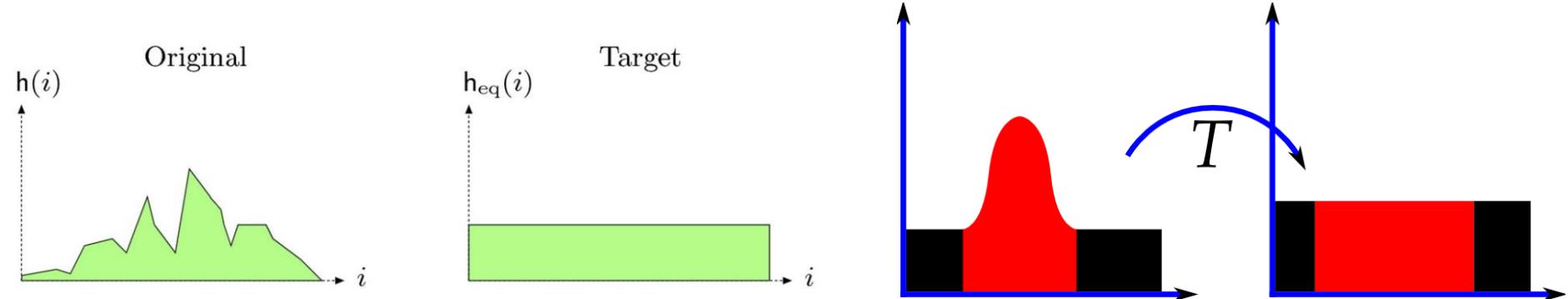
(b)

Result of automatic
Contrast Adjustment

Linearly stretching
range causes gaps
in histogram

Histogram Equalization

- Adjust 2 different images to make their histograms (intensity distributions) similar
- Apply a point operation that changes histogram of modified image into uniform distribution.



Histogram Equalization: Algorithm

- Normalized Histogram

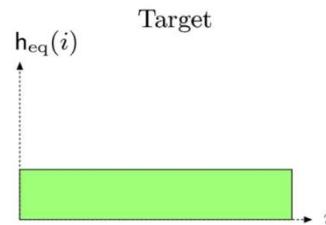
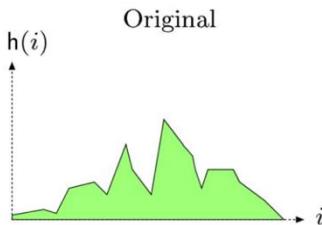
$$p_x(i) = p(x = i) = \frac{n_i}{n}, \quad 0 \leq i < L$$

- Cumulated Normalized Histogram

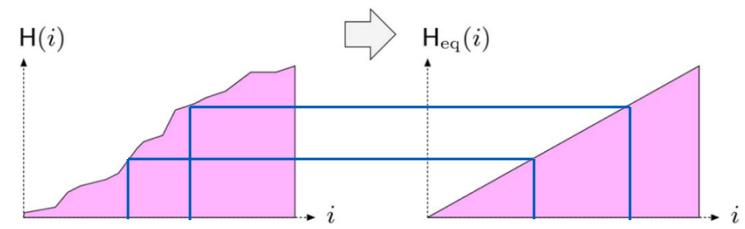
$$\text{cdf}_x(i) = \sum_{j=0}^i p_x(x = j),$$

- A transform for histogram equalization, WHY?

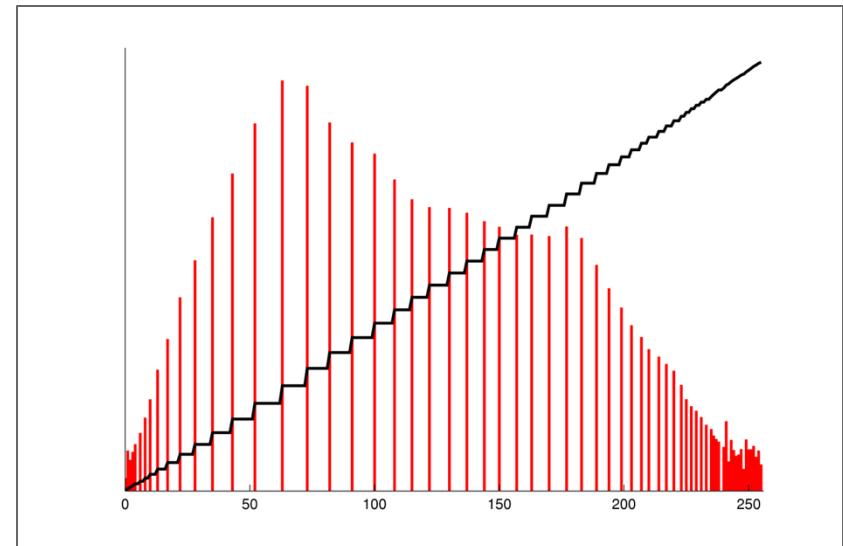
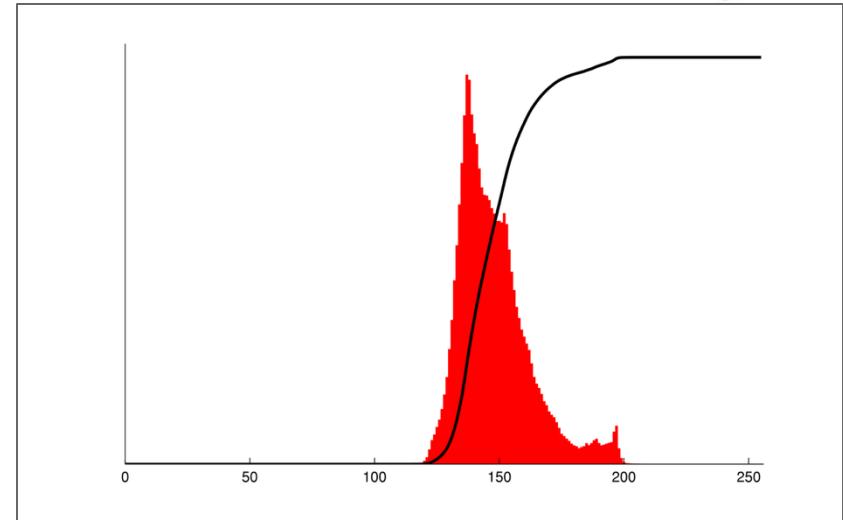
$$y = T(k) = \text{cdf}_x(k)$$



Cumulative Histogram



Histogram Equalization Example



Content

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 - Gaussian, Laplacian
 - Convolution and Transposed Convolution
- Image Histogram
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