

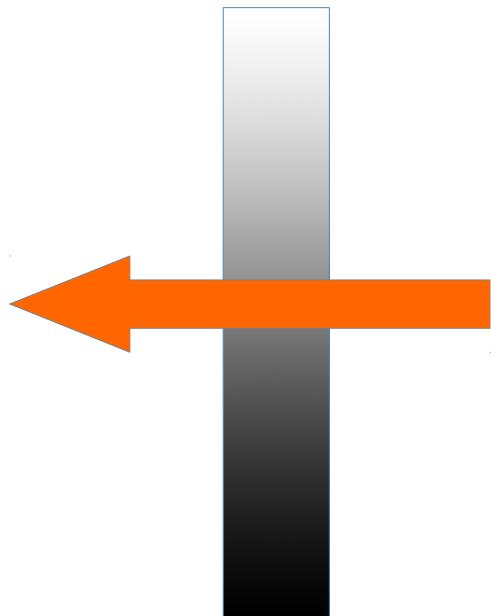
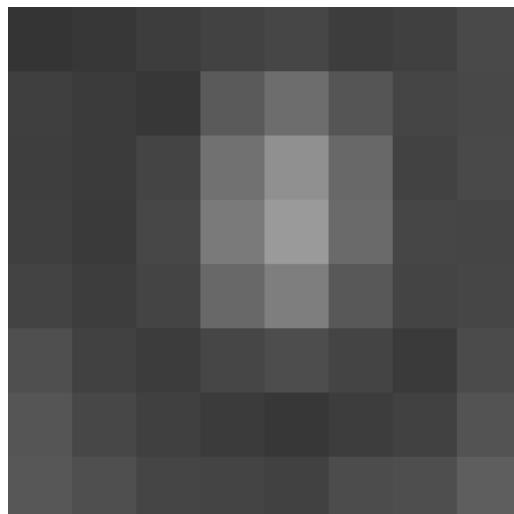
# Digital Image Processing

## Image Enhancement : Gray-Level Transformations

Suyash P. Awate

# Digital Image

- Assumptions
  - 8-bit per pixel
  - 256 intensity levels or gray levels
    - 0, 1, ..., 255 : this is called the grayscale
    - 0 = black
    - 255 = white



52	55	61	66	70	61	64	73
63	59	55	90	109	85	69	72
62	59	68	113	144	104	66	73
63	58	71	122	154	106	70	69
67	61	68	104	126	88	68	70
79	65	60	70	77	68	58	75
85	71	64	59	55	61	65	83
87	79	69	68	65	76	78	94

# Enhancement

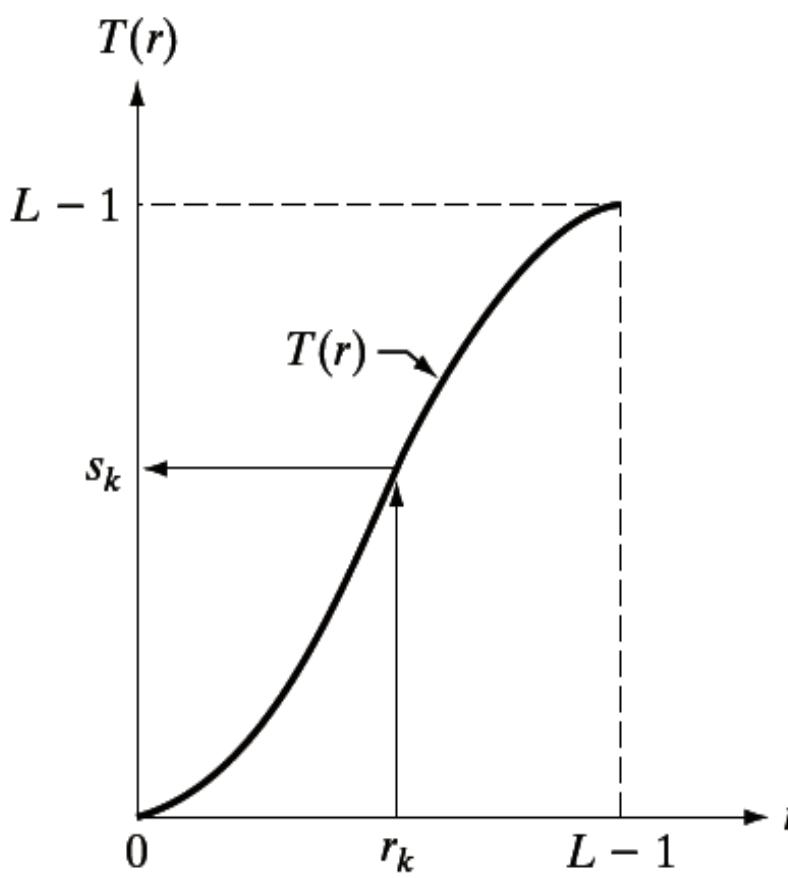
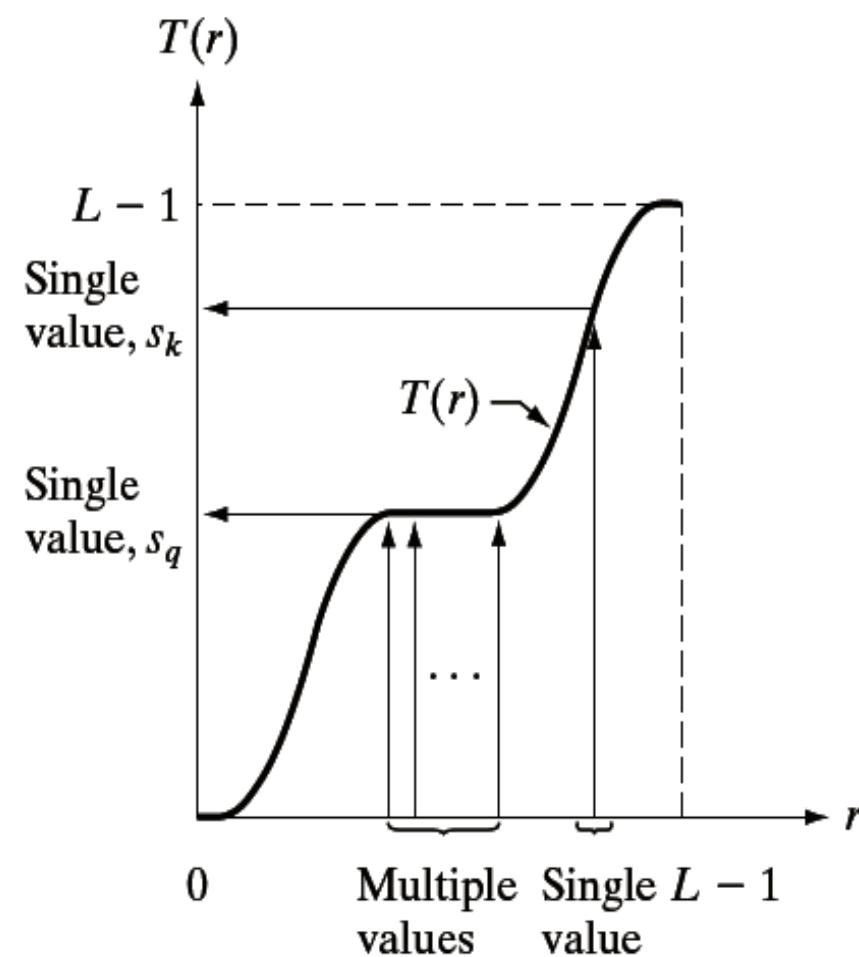
- What does it mean ?
  - Processing an image so that the result is more suitable (compared to the original image) for a **specific** application
- Evaluation
  - Visual, subjective
  - Quantitative

# Gray-Level Transformations

- Design **functions** to transform gray levels within an image by directly operating on them
  - Example
    - Input Image :  $f(x,y)$
    - Transformation :  $T(\cdot)$  operates on individual intensities
    - Output Image :  $g(x,y) = T(f(x,y))$
  - Another example
    - Transformation :  
 $U(\cdot)$  operates on  
intensities in a neighborhood
    - Output Image :  
 $g(x,y) = U(f(x,y), f(x+1,y), f(x-1,y))$

# Gray-Level Transformations

- We'd like transformations to be **monotonic** functions
  - Monotonically increasing function:  $a > b \rightarrow T(a) \geq T(b)$
  - Monotonically decreasing function:  $a > b \rightarrow T(a) \leq T(b)$

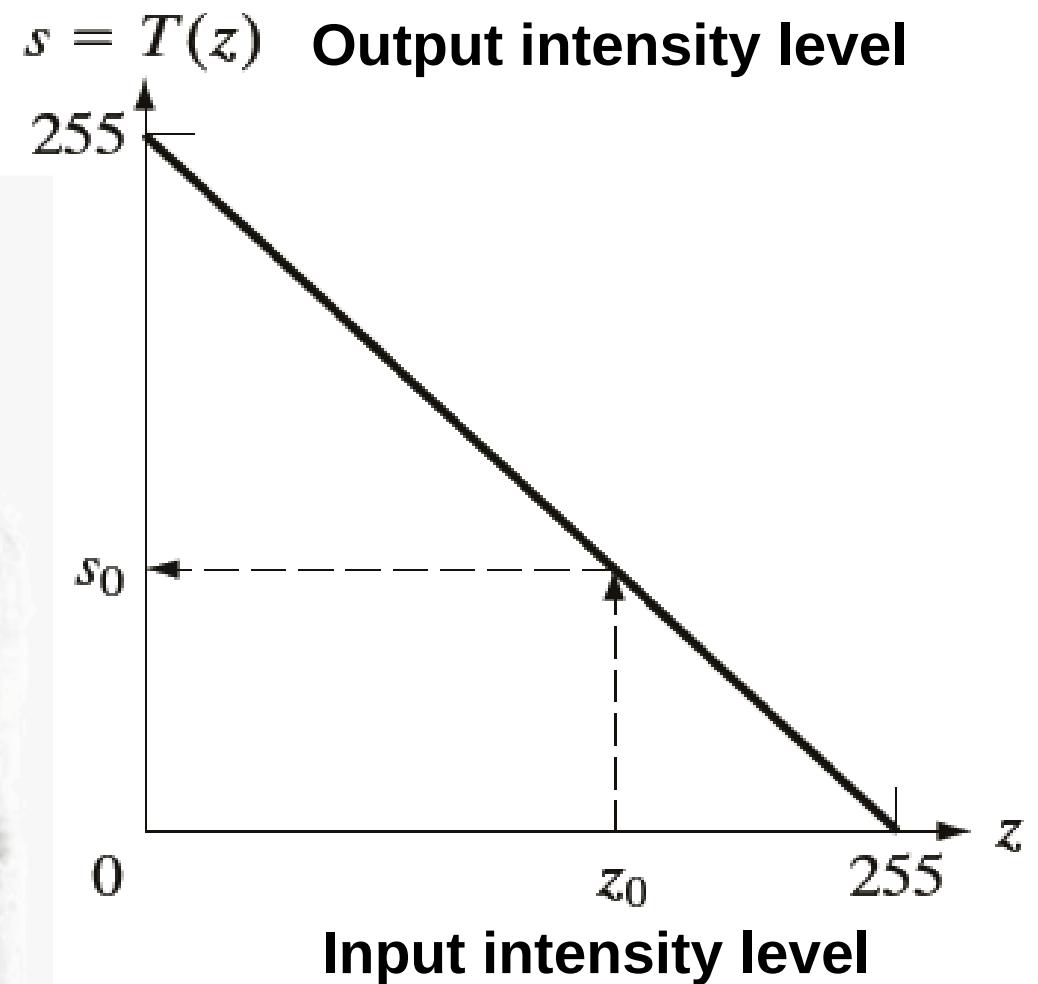
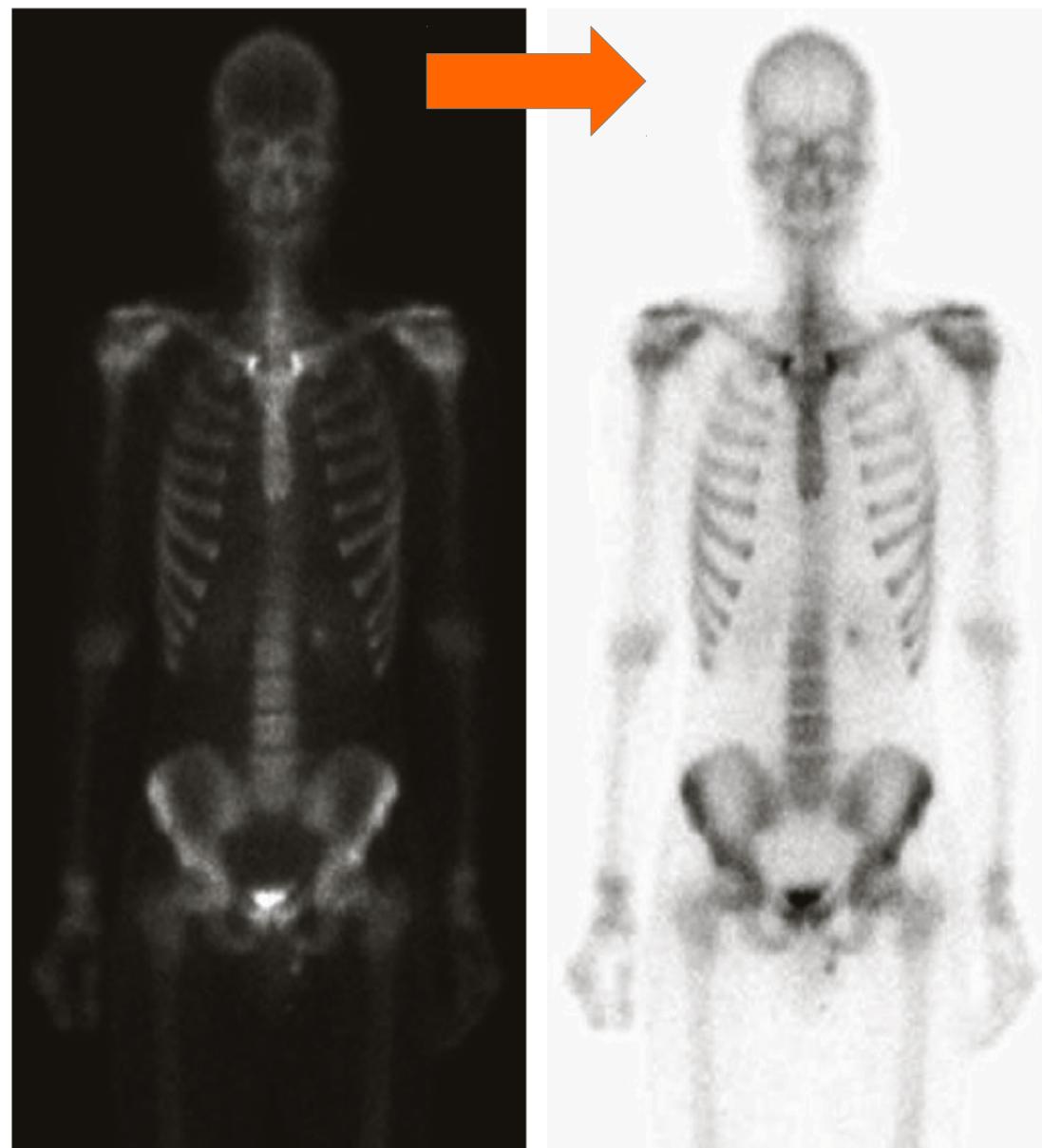


a b

**FIGURE 3.17**  
(a) Monotonically increasing function, showing how multiple values can map to a single value.  
(b) Strictly monotonically increasing function. This is a one-to-one mapping, both ways.

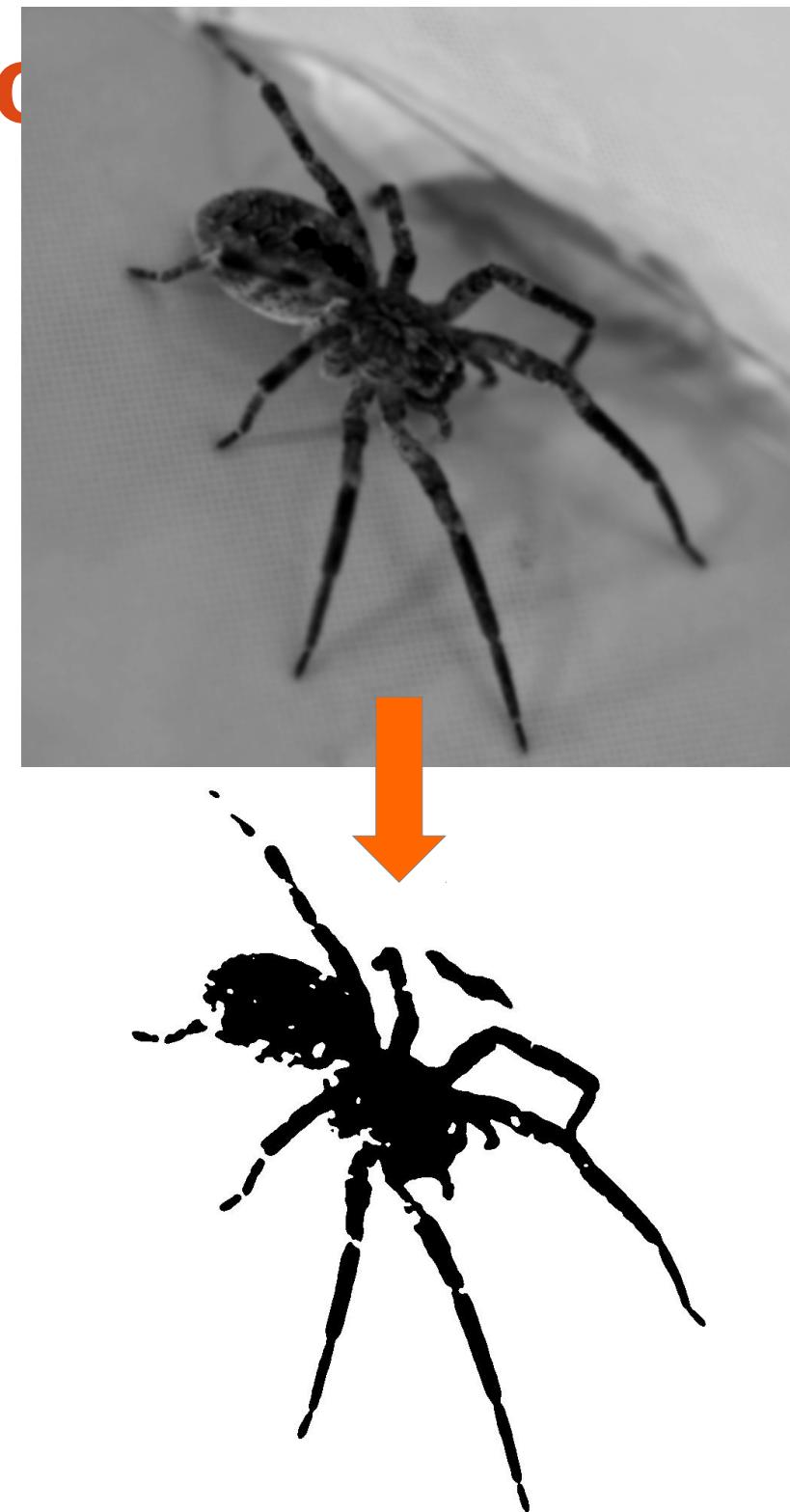
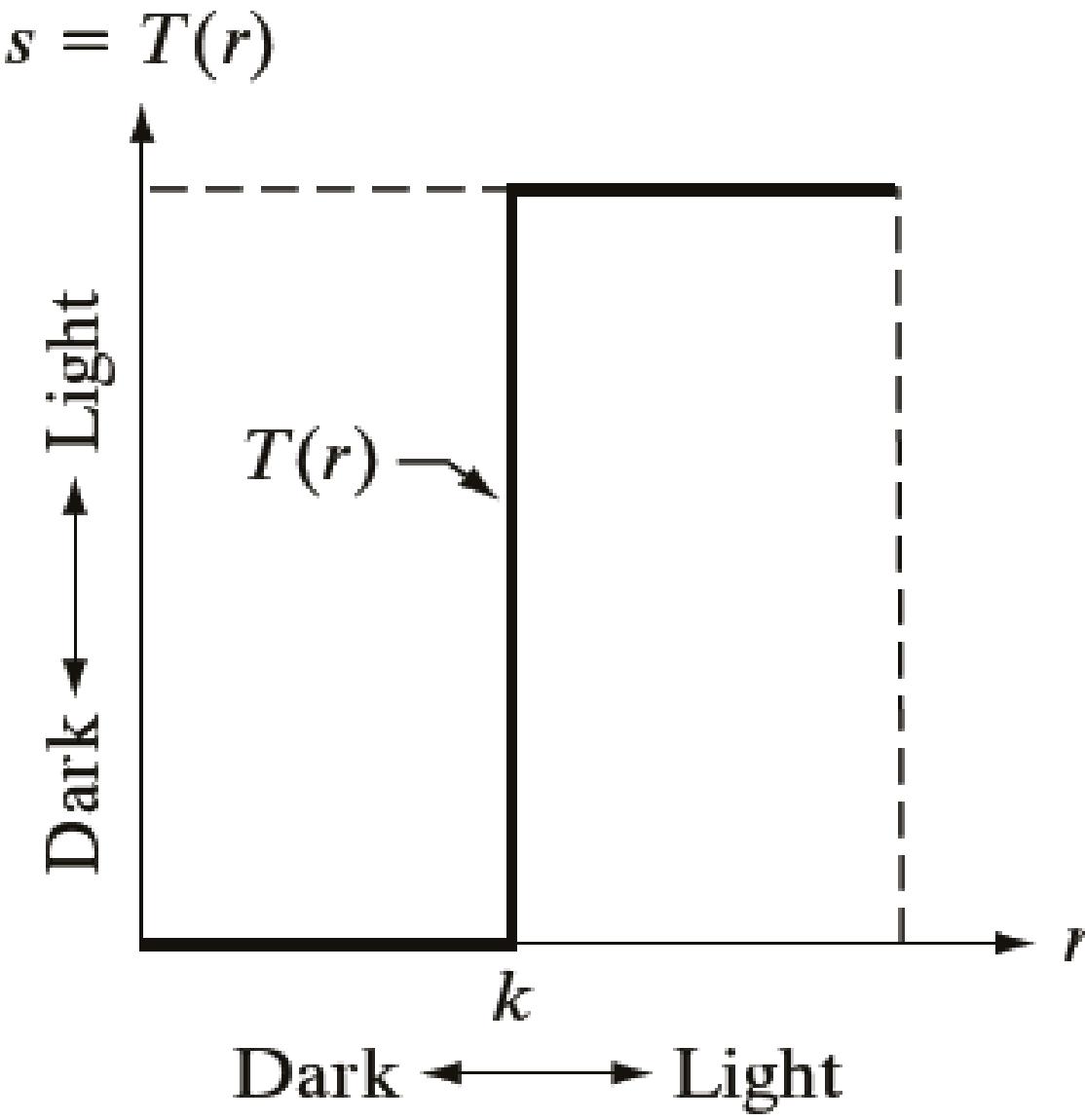
# Gray-Level Transformations

- “Negative”



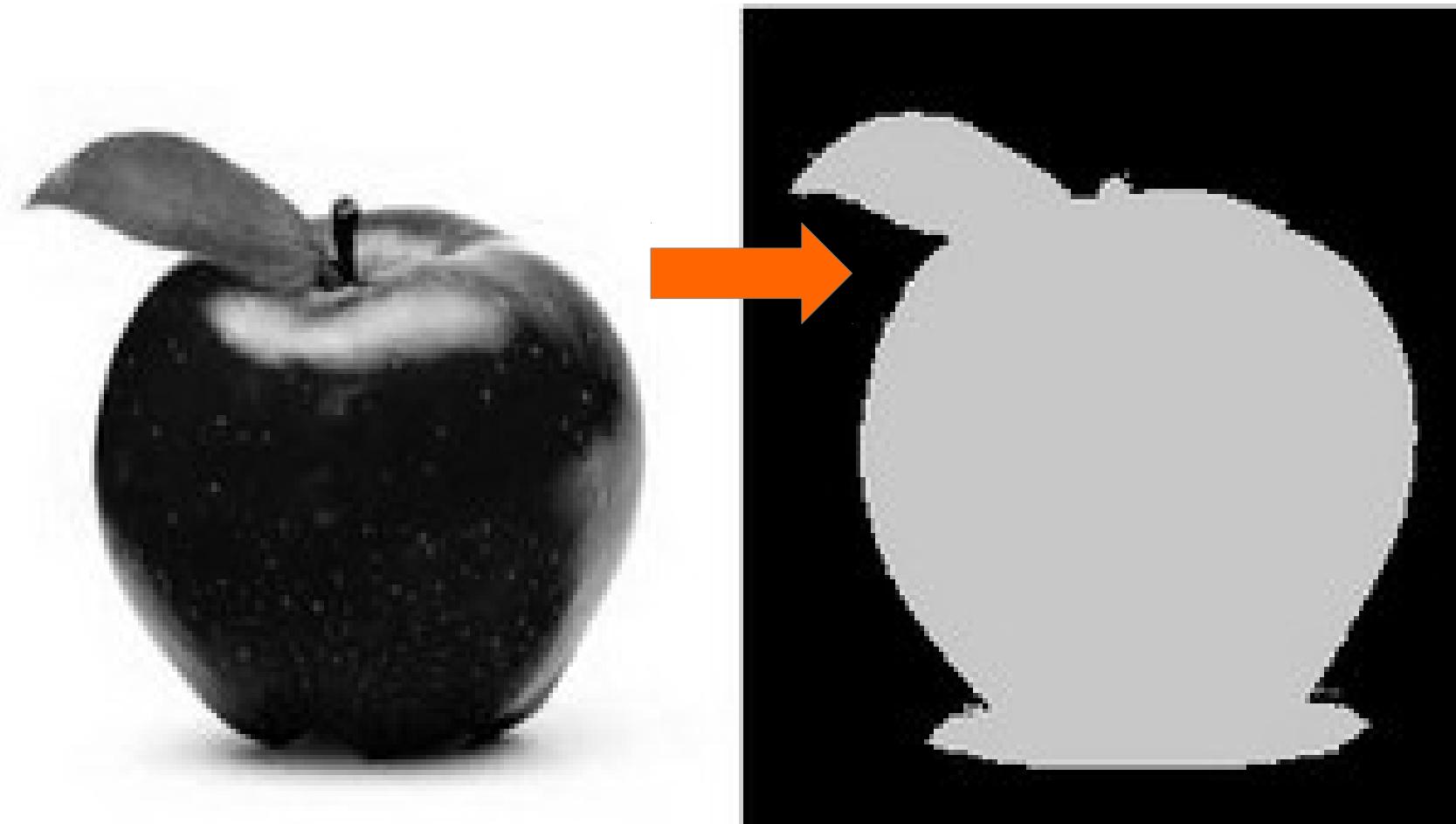
# Gray-Level Transformation

- Thresholding



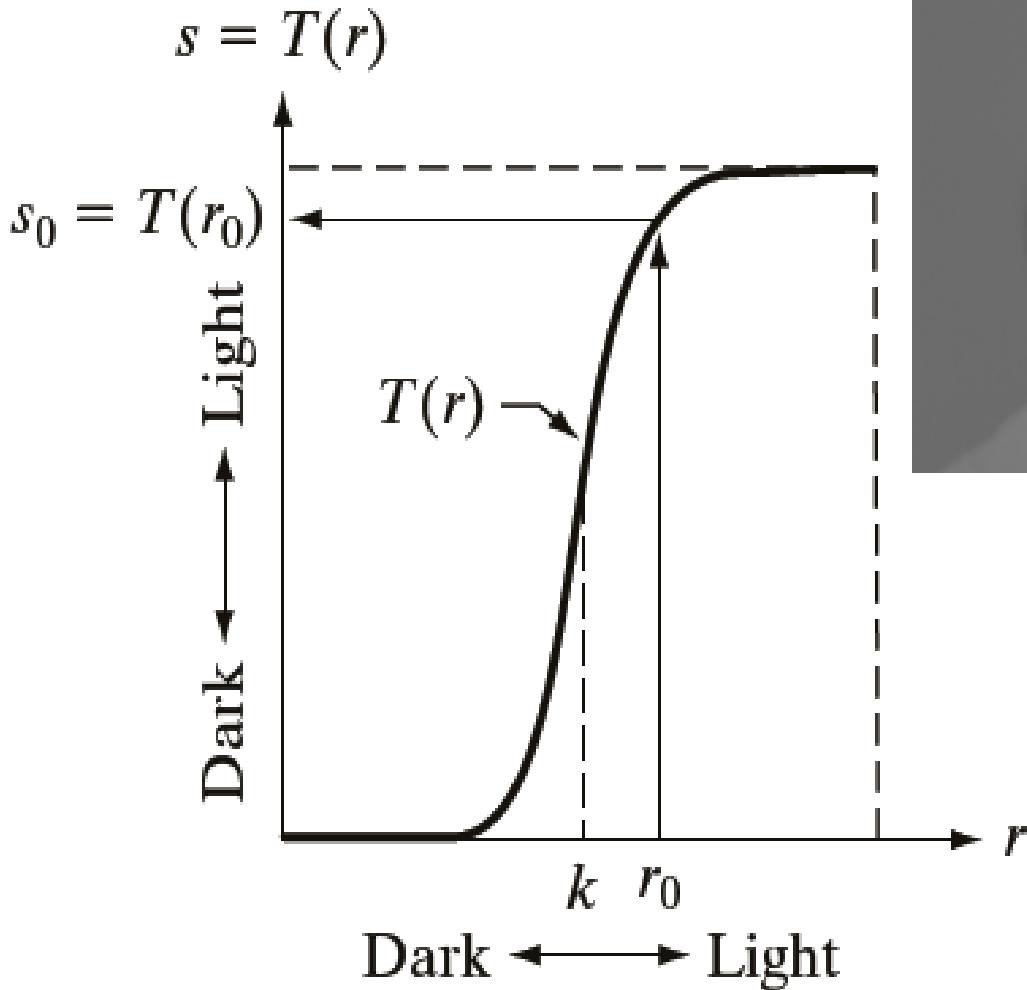
# Gray-Level Transformations

- Thresholding
  - What is the transformation function for this ?



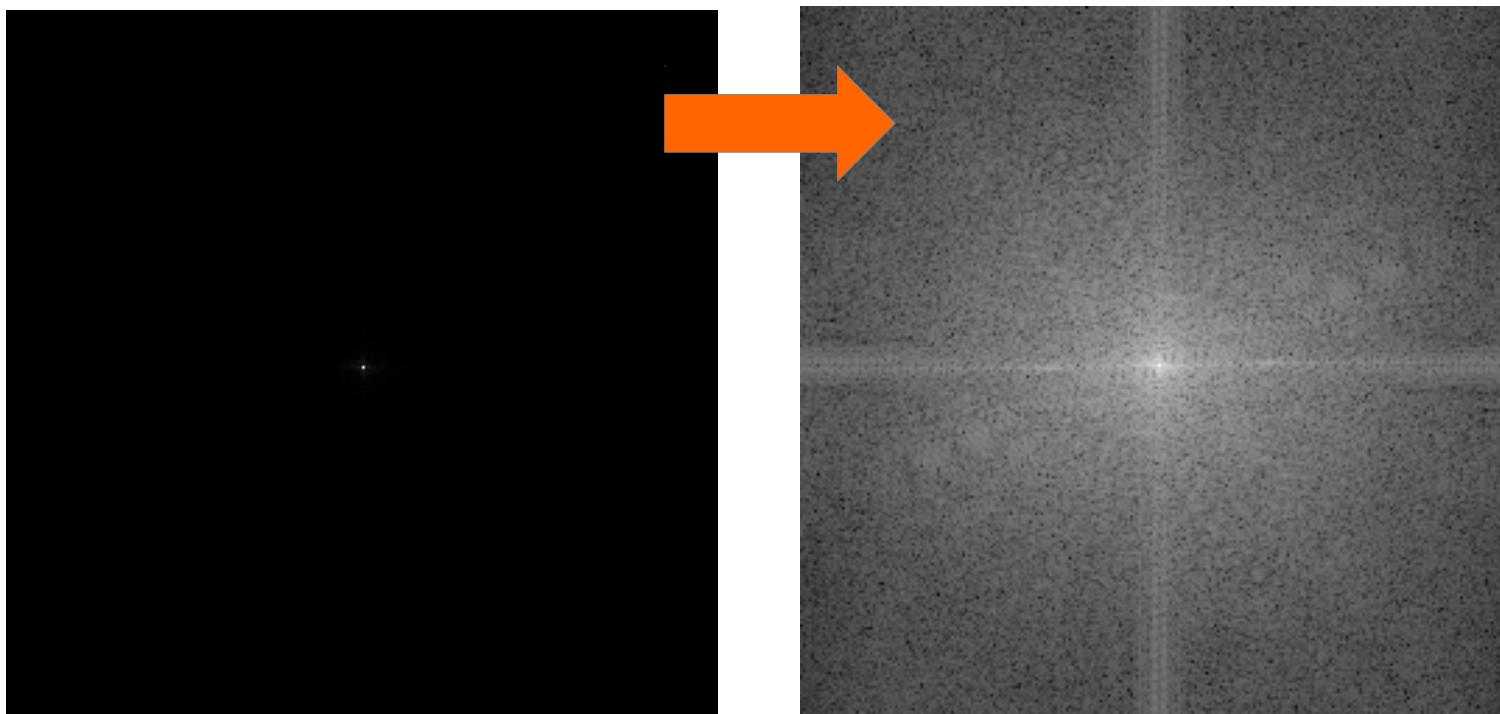
# Gray-Level Transformations

- Contrast stretching



# Gray-Level Transformations

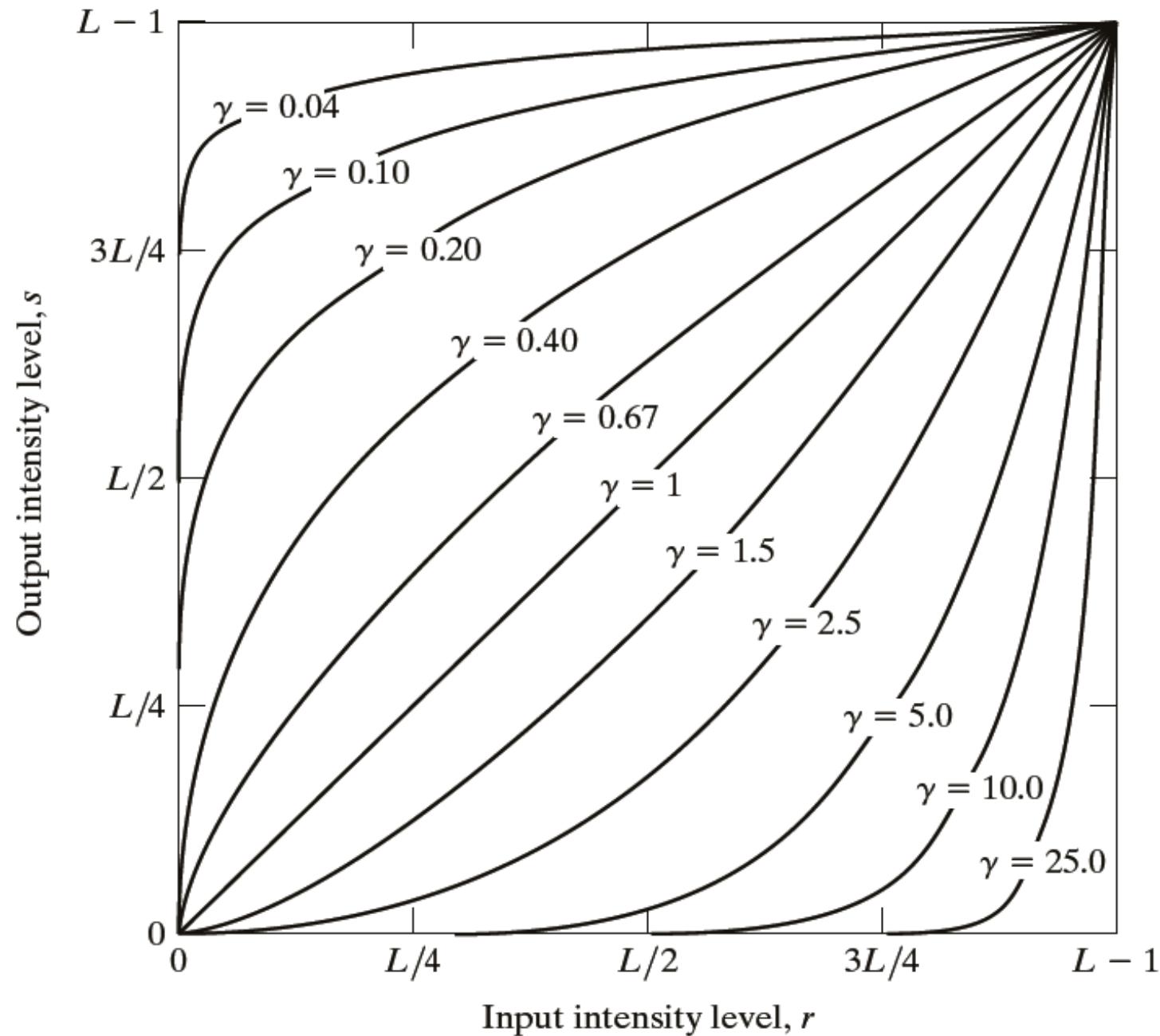
- Logarithm
  - $g(x,y) = c \log [ 1 + f(x,y) ]$ , where  $c = \text{constant}$
  - Input image has some values very large
    - Remaining values map to few colors (left)  $\rightarrow$  details lost
  - Log  $\rightarrow$  compress large values, spread small values



# Gray-Level Transformations

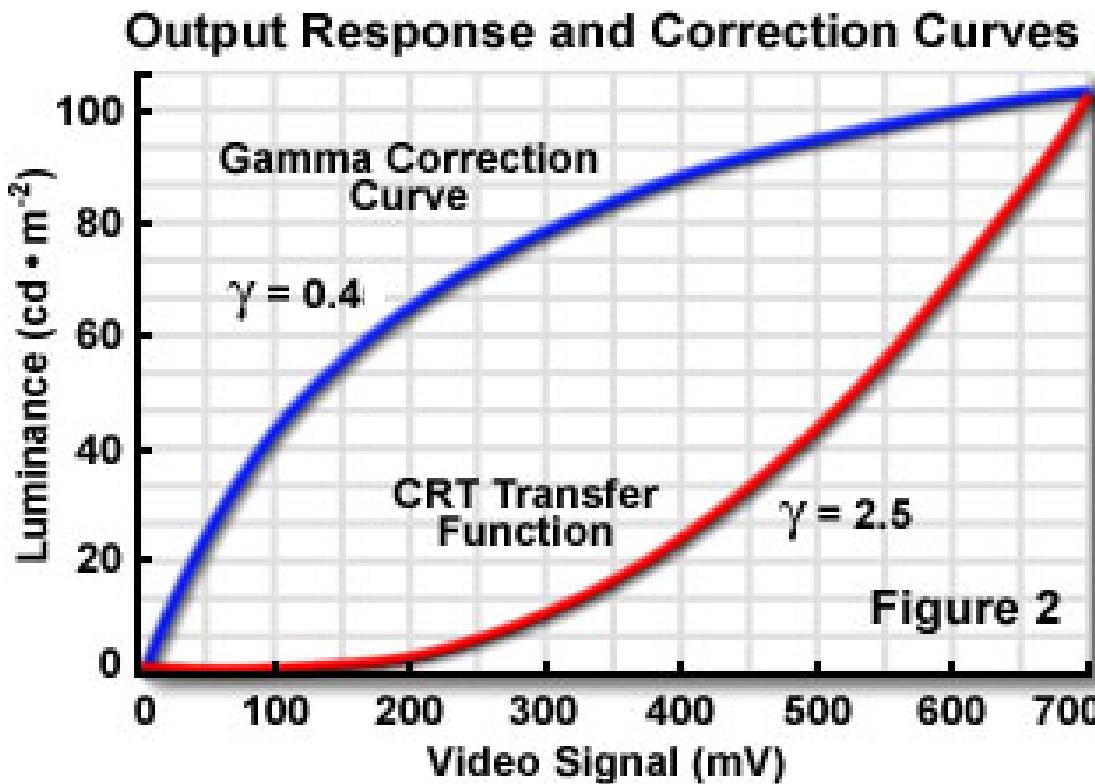
- Power and root transformations

- $s(x,y) = d \left( r(x,y) / c \right)^\gamma$
- For graph →
  - $r$  in  $[0, L-1]$
  - $c = L-1$
  - $d = L-1$



# Gray-Level Transformations

- Gamma correction for display monitors
  - Mapping function from intensity (data) to voltage (screen appearance) is a power function
    - gamma within [1.8, 2.5]
  - Correction applies power transform:  $\text{gamma}' = 1 / \text{gamma}$



Without Correction



With Correction



# Gray-Level Transformations

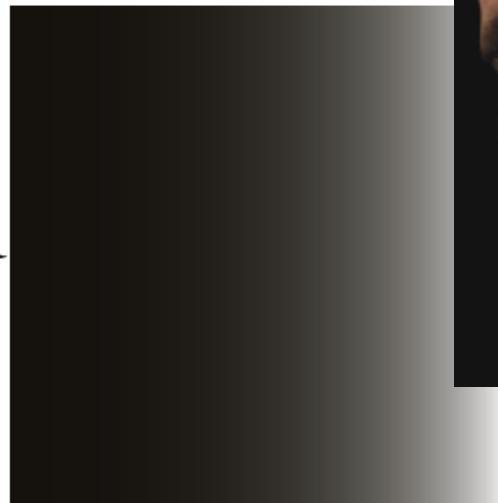
Without Correction

With Correction

- Gamma correction



Original image

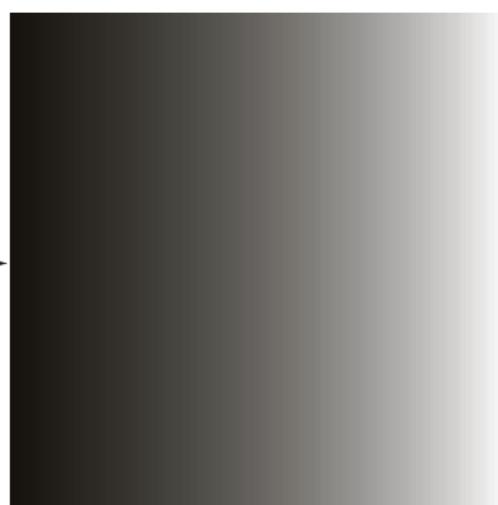


Gamma  
correction

Original image as viewed  
on monitor



Gamma-corrected image

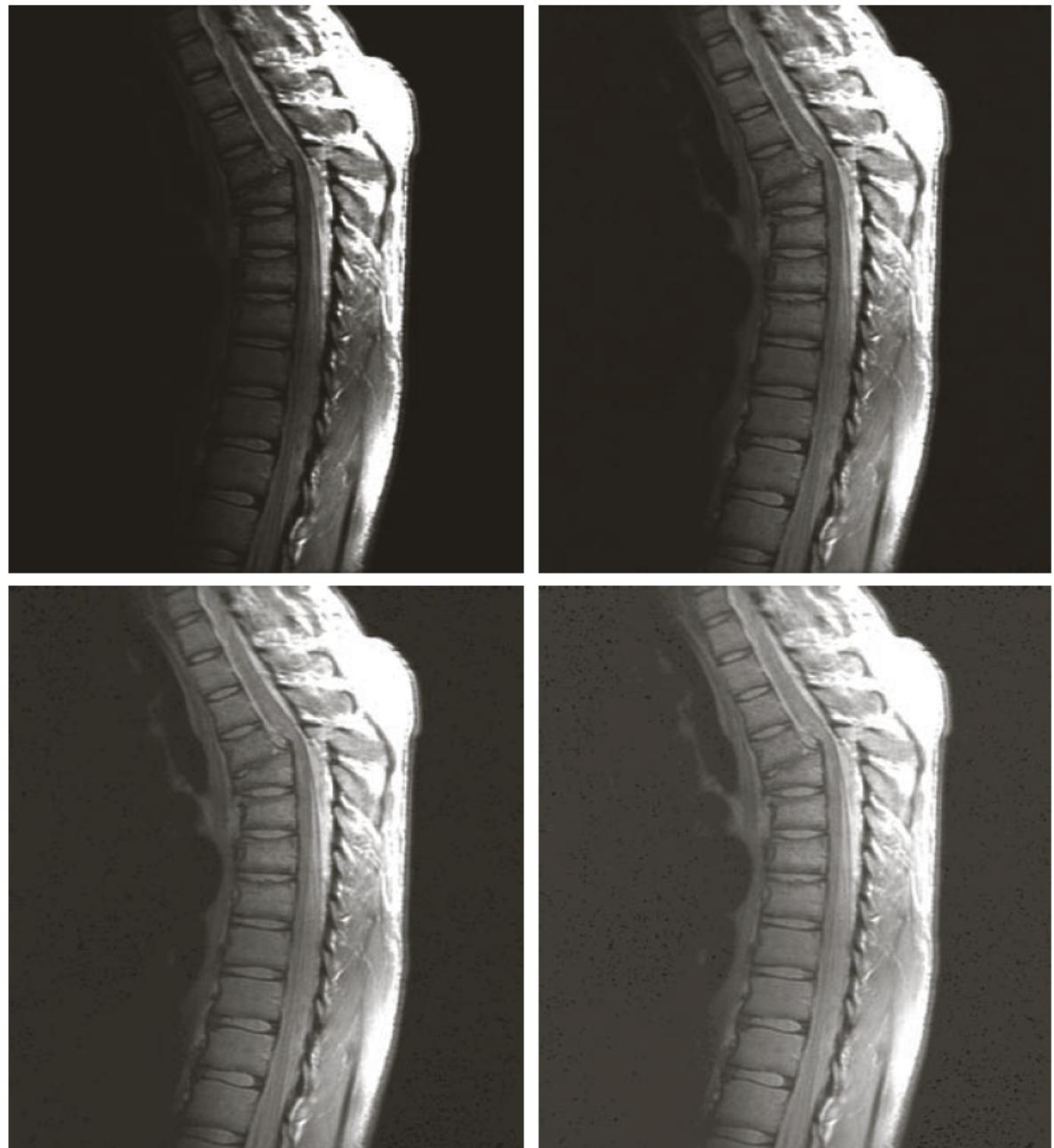


Gamma-corrected image as  
viewed on the same monitor

# Gray-Level Transformations

- Gamma correction in medical imaging (e.g., MRI)

- gamma =  
1.0 , 0.6  
0.4 , 0.3



# Gray-Level Transformations

- Gamma correction to improve washed-out images

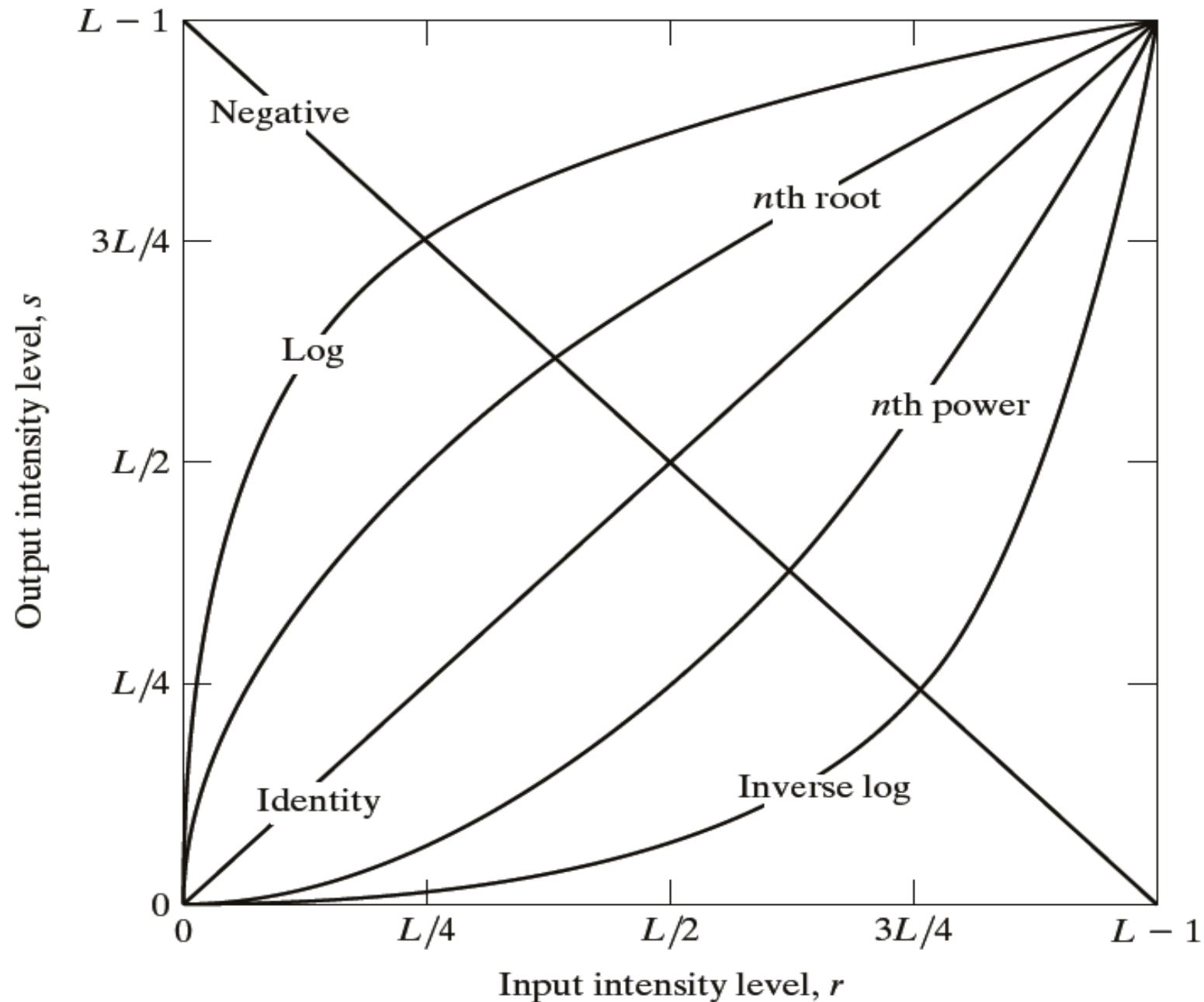
- Input image  
= top left
- For other images,  
is gamma  
more than 1 or  
less than 1 ?



# Gray-Level Transformations

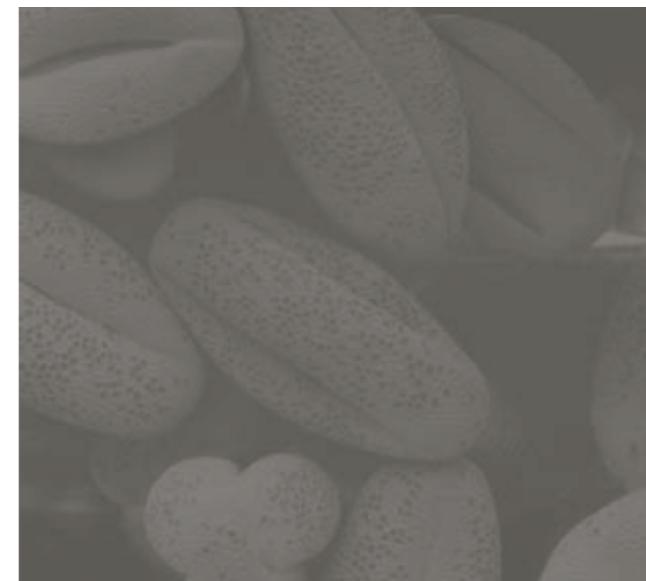
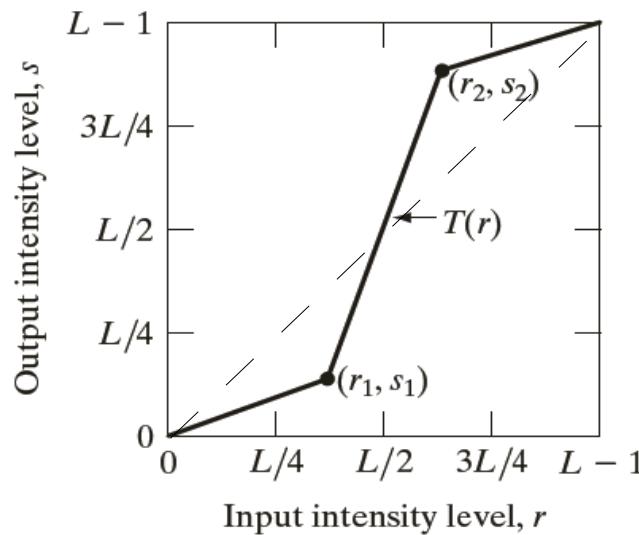
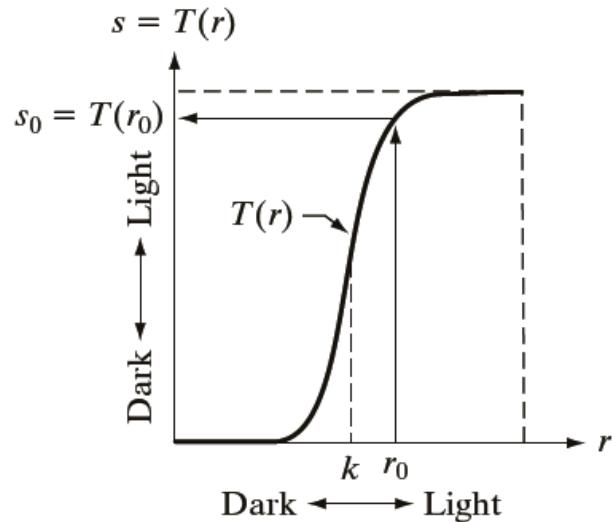
- Typical transformation functions

- Log, exp
- Power, root
  - $n > 1$



# Gray-Level Transformations

- Piecewise-linear transformation functions
  - Easier to design than complex nonlinear functions

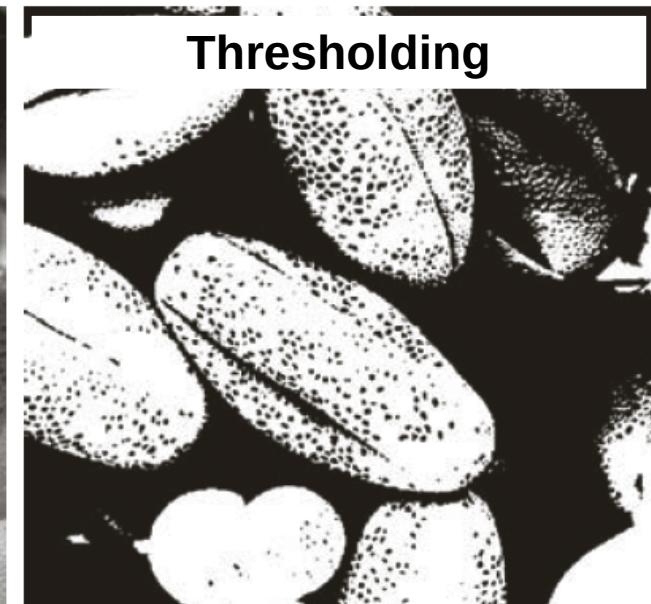


Contrast stretching

- Can model complex transformations
- Contrast stretching



Thresholding

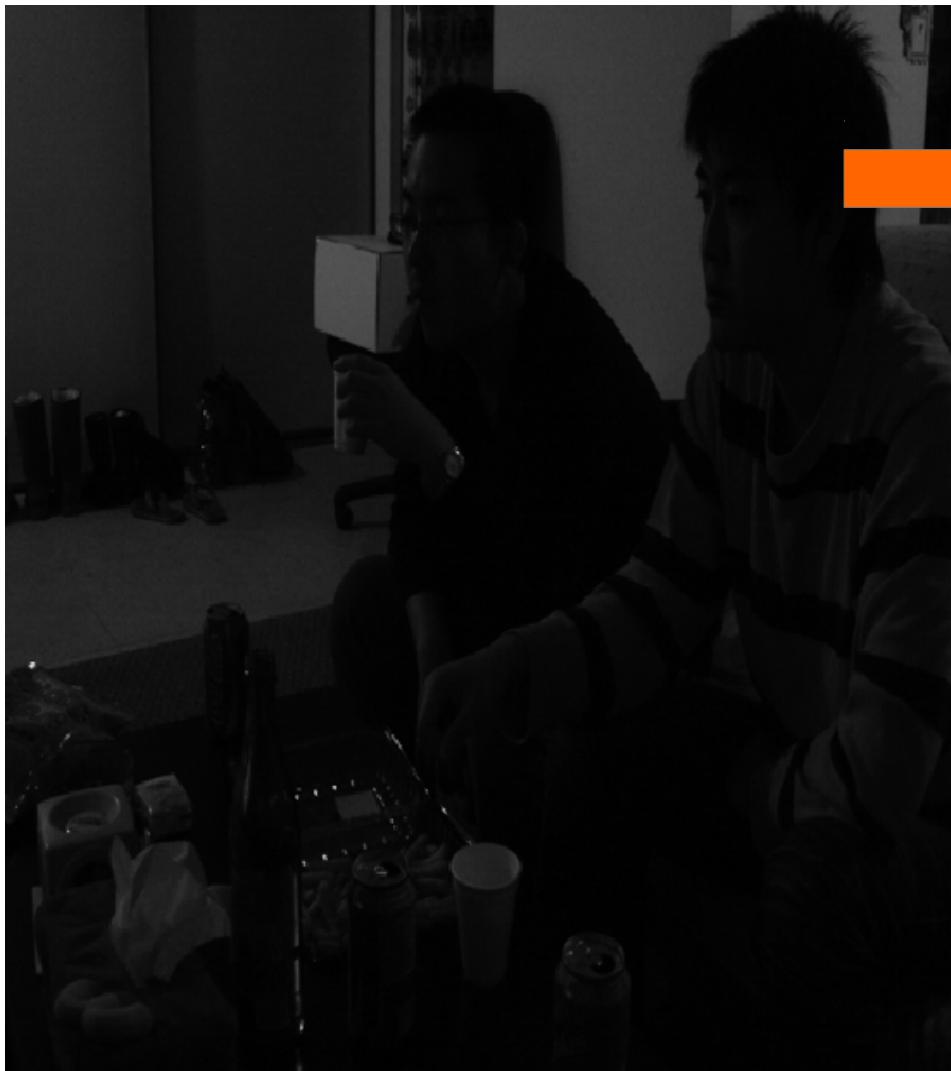


# Gray-Level Transformations

- Histogram processing
  - What is a histogram ?
    - Probability theory refresher
  - What can it achieve ?
    - Contrast enhancement
    - Automatic, without tuning parameters

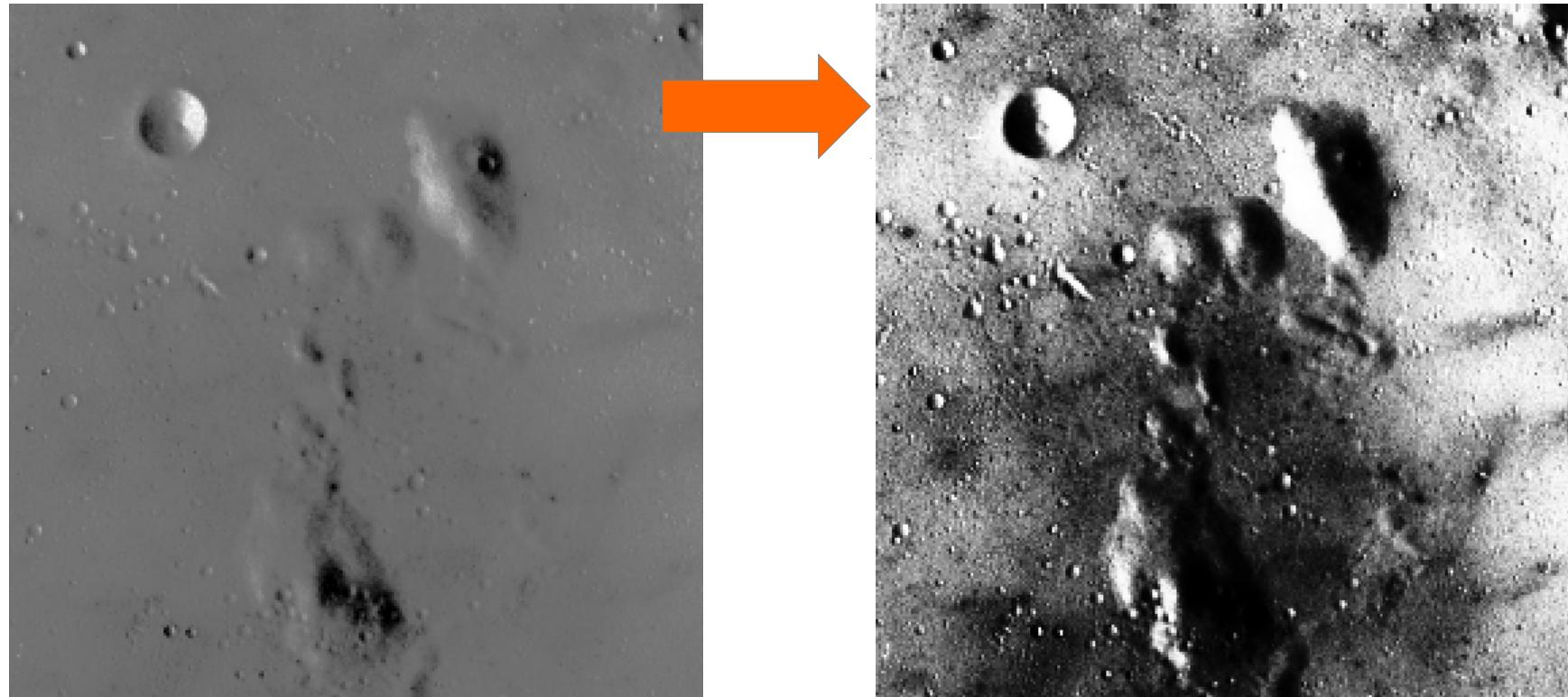
# Gray-Level Transformations

- Histogram processing
  - What can it achieve ?



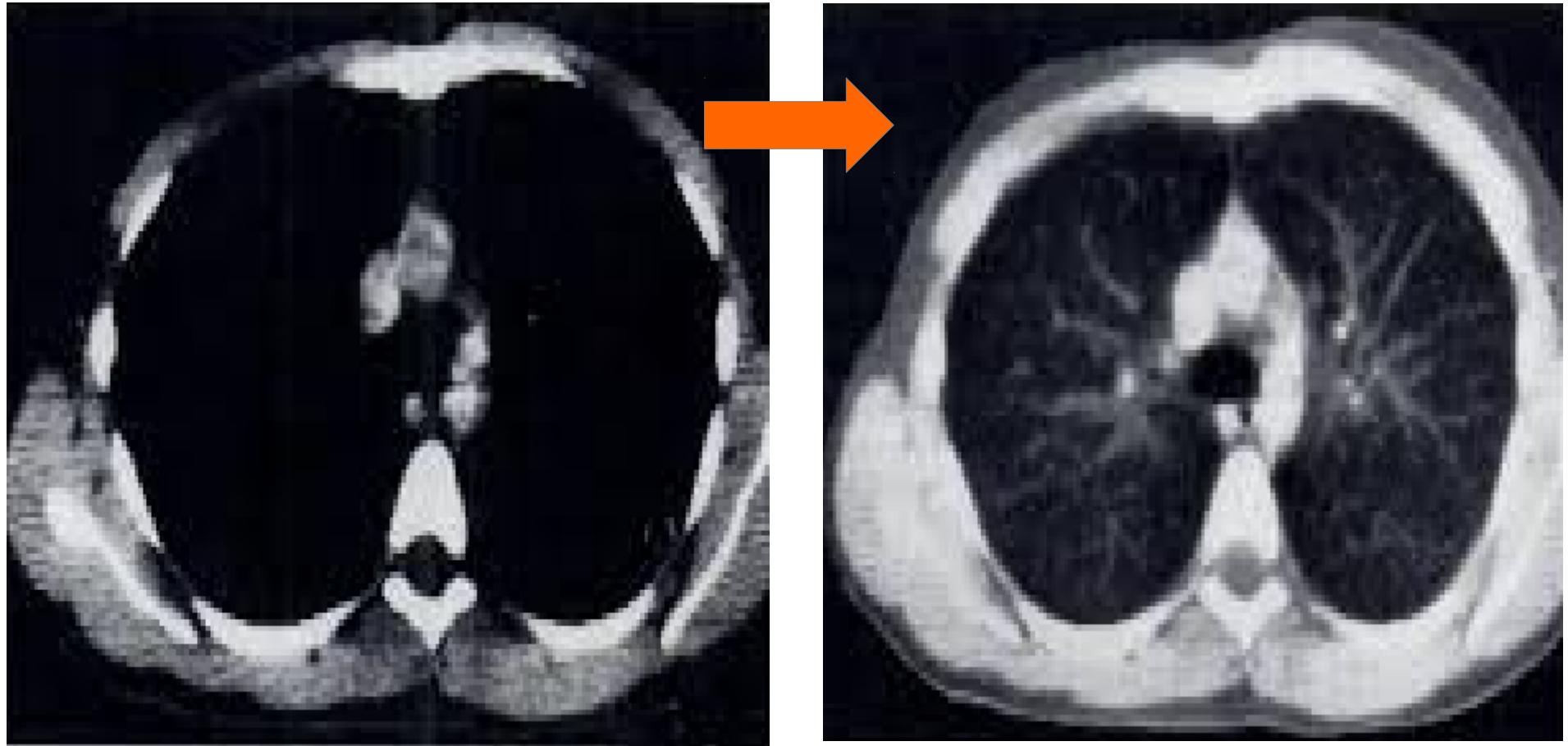
# Gray-Level Transformations

- Histogram processing
  - What can it achieve ?



# Gray-Level Transformations

- Histogram processing
  - What can it achieve ?



# Gray-Level Transformations

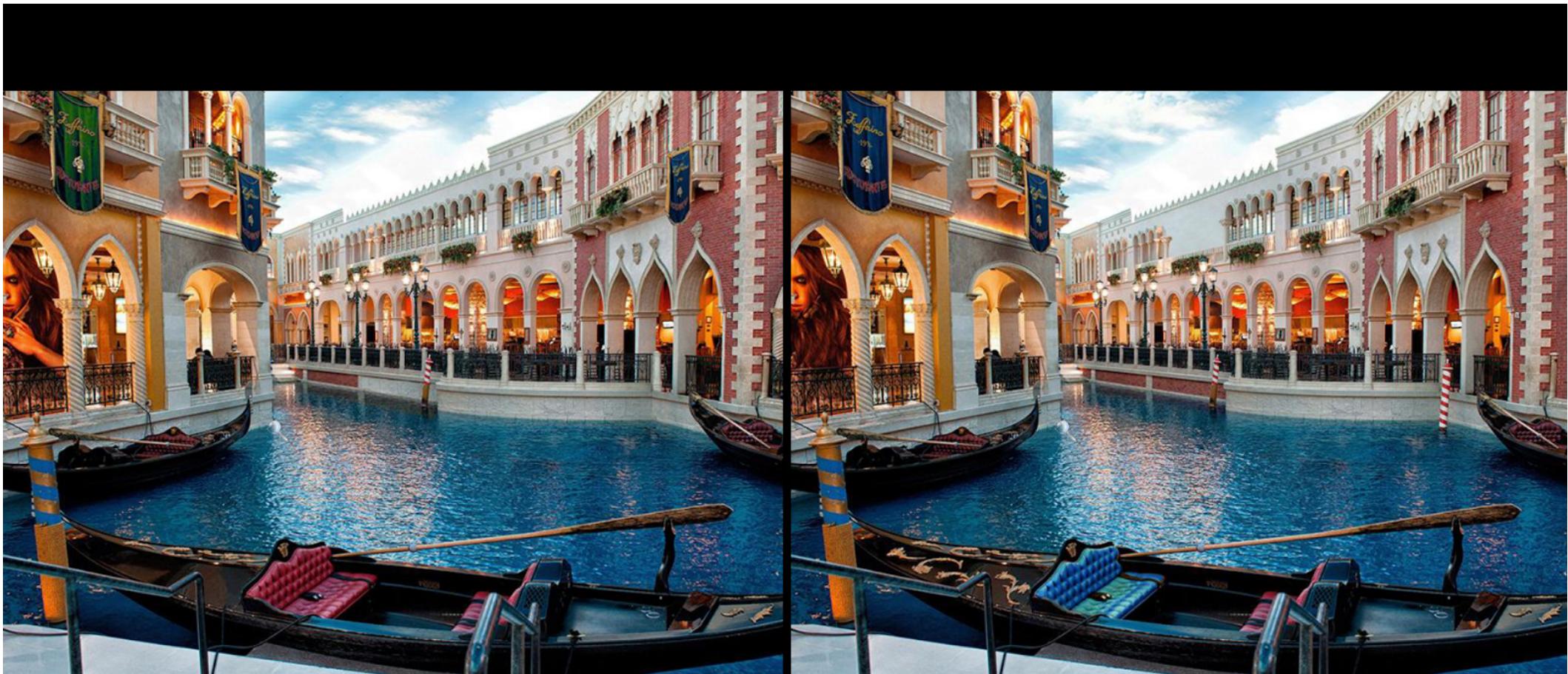
- Histogram processing
  - What can it achieve ?







# Find All Differences



0/10







# Gray-Level Transformations

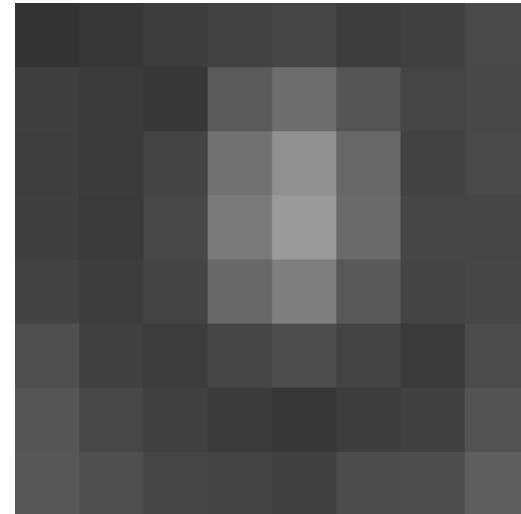
- Histogram processing
  - What is a histogram ?
    - Probability theory refresher (very brief)
      - Probability mass/density function
      - Random variables
      - Random experiments
      - Sample space, events, probability functions
      - Transformation of a random variable

# Gray-Level Transformations

- **Random experiment** = an experiment whose outcome isn't certain
  - Flip of a coin
  - Throw of a die
- **Sample space** = set of all possible outcomes of a random experiment
  - Coin flip : { head, tail }
  - Die throw : { 1, 2, 3, 4, 5, 6 }

# Gray-Level Transformations

- Random experiment
  - Select a pixel location in an image
- Sample space
  - Set of all pixel locations $\{ (1,1), (1,2), \dots, (1,8), (2,1), (2,2), \dots, (2,8), \dots, (8,1), (8,2), \dots, (8,8) \}$



52	55	61	66	70	61	64	73
63	59	55	90	109	85	69	72
62	59	68	113	144	104	66	73
63	58	71	122	154	106	70	69
67	61	68	104	126	88	68	70
79	65	60	70	77	68	58	75
85	71	64	59	55	61	65	83
87	79	69	68	65	76	78	94



# Gray-Level Transformations

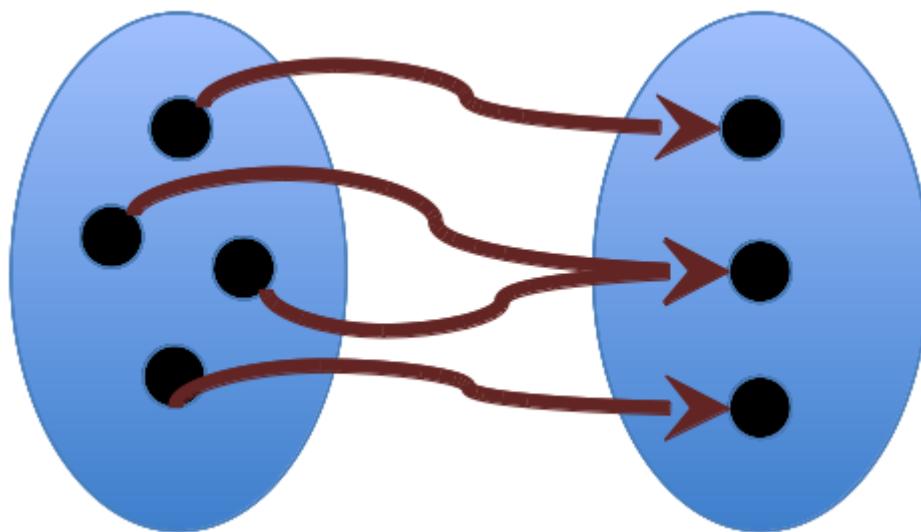
- **Event** is a subset of a sample space
  - Event of getting a head on a coin toss = { head }
  - Event of getting an even number on a die roll = ?  
= { 2, 4, 6 }
  - Event of getting a pixel in the left half of the image
- **Event space** = set of all possible events

# Gray-Level Transformations

- **Probability function  $P(\cdot)$** 
  - A probability function on **sample space  $\Omega$**  assigns every event  $A$  in  $\Omega$  a number in  $[0,1]$  s.t.
    - $P(\Omega) = 1$
    - $P(A \cup B) = P(A) + P(B)$  when  $A \cap B = \emptyset$
  - $P(A)$  is the **probability** that **event A occurs**
  - Examples
    - Probability function for coin toss = ?
    - Probability function for die roll = ?

# Gray-Level Transformations

- **Random variable** = a function
  - $X : \Omega \rightarrow \mathbb{R}$
  - Domain = sample space
  - Range = set of real numbers



# Gray-Level Transformations

- Random variable is an **abstraction**
  - We don't care about outcomes (directly)
  - We only care about values mapped to outcomes
  - Die example
    - We don't care about die value, just even or odd
  - Image example
    - We don't care about pixel location, just pixel intensity

# Gray-Level Transformations

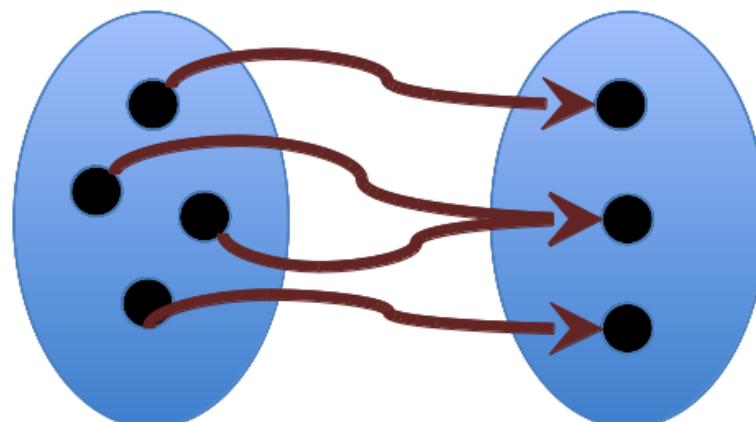
- Defining events using random variables
  - Example: Sum of a pair of dice
  - Sample Space:  $\Omega = \{ (i,j) : 1 \leq i,j \leq 6 \}$
  - Probability function:  $P((i,j)) = 1/36$
  - Random variable:  $X((i,j)) = i + j$
  - Event  $\{ X=a \} = \{ w \in \Omega : X(w)=a \}$ 
    - $P(X=5)$   
=  $P(\{(1,4), (2,3), (3,2), (4,1)\})$   
=  $P((1,4)) + P((2,3)) + P((3,2)) + P((4,1))$   
=  $4 / 36$

# Gray-Level Transformations

- Defining events using random variables
  - Example:
    - Intensity at a randomly-chosen pixel in 8x8 image  $f(x,y)$
  - Sample Space:  $\Omega = \{ (x,y) : 1 \leq x, y \leq 8 \}$
  - Probability function:  $P((x,y)) = 1/64$
  - Random variable:  $Z((x,y)) = f(x,y)$
  - Event  $\{ Z > 100 \} = \{ w \in \Omega : Z(w) > 100 \}$

# Gray-Level Transformations

- **Discrete random variable (RV)**
  - Maps outcomes to values in a countable set
  - **Probability mass function**  $p : R \rightarrow [0,1]$ 
    - Probability that the RV takes a value 'a'
    - $p(a) = p(X=a) = \sum_{w : X(w)=a} P(w)$
  - **Cumulative distribution function**  $F : R \rightarrow [0,1]$ 
    - Probability that the RV takes a value **less than** x
    - $F(a) = p(X \leq a) = \sum_{w : X(w) \leq a} P(w)$
    - $F(a) = p(X \leq a) = \sum_{b : b \leq a} p(X=b)$



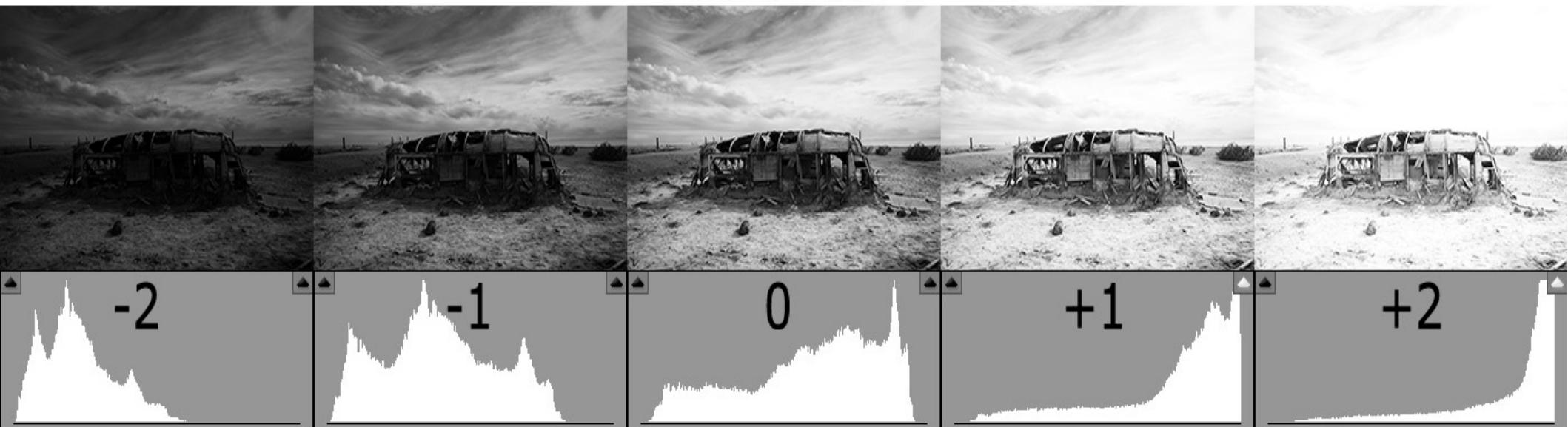
# Gray-Level Transformations

- **Continuous random variable (RV)**
  - Maps outcomes to values in an uncountable set
    - Sample space itself is uncountable
      - e.g., continuous image function  $X(\cdot)$  defined on  $[0,1] \times [0,1]$
  - **Cumulative distribution function**  $F : \mathbb{R} \rightarrow [0,1]$ 
    - Probability that the RV takes a value less than  $c$ 
      - $F(c) = p(x < c) = \int_{w : X(w) \leq c} P(w) dw$
      - $F(c) = p(x < c) = \int_{x < c} p(x) dx$
  - **Probability density function**  $p : \mathbb{R} \rightarrow \mathbb{R}$ 
    - $p(\cdot)$  is derivative of  $F(\cdot)$
    - $p(x)$  is NOT probability of event ‘ $x$ ’ ( $p(x)$  can be  $> 1$ )
    - Events, of interest, are subsets of the form  $\{x : a < x < b\}$
    - $p(a < x < b) = \int_{a < x < b} p(x) dx$

# Gray-Level Transformations

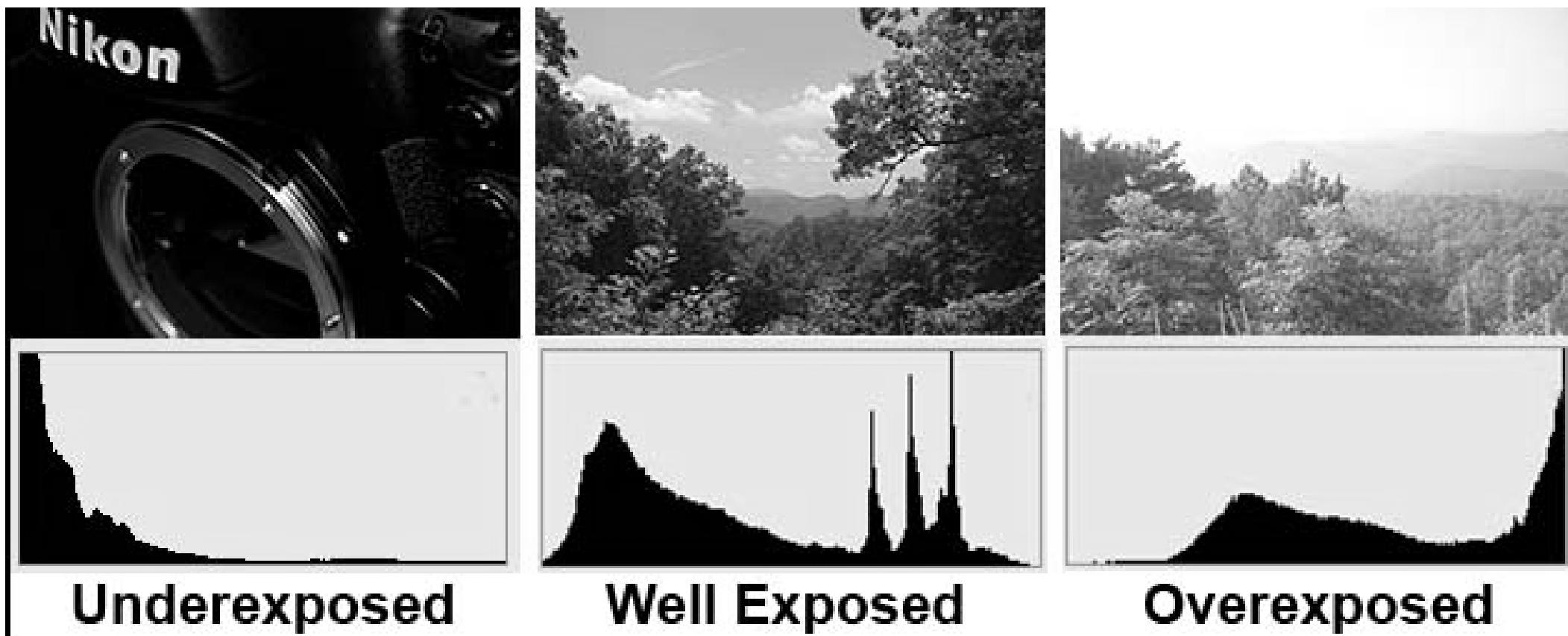
- Histograms are related to photograph exposure
  - Aperture size (amount of light per unit time)
  - Shutter speed (time of exposure)

EXPOSURE



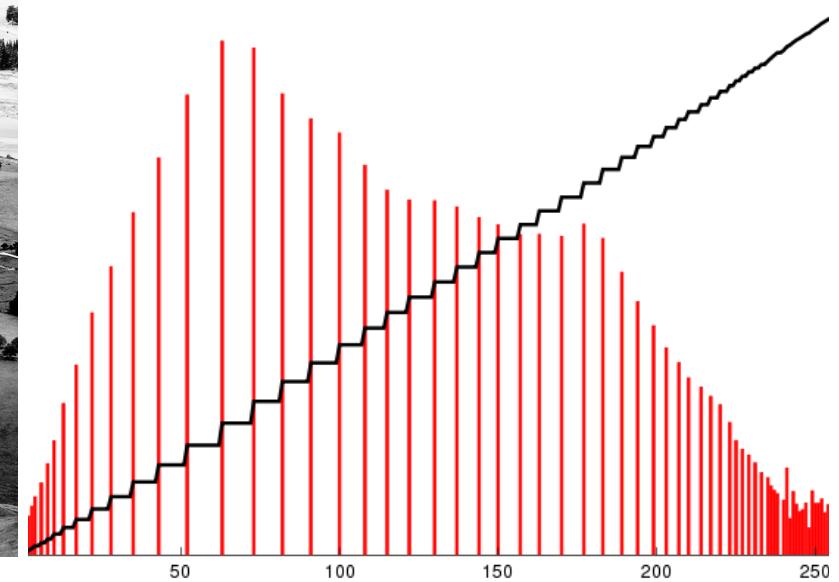
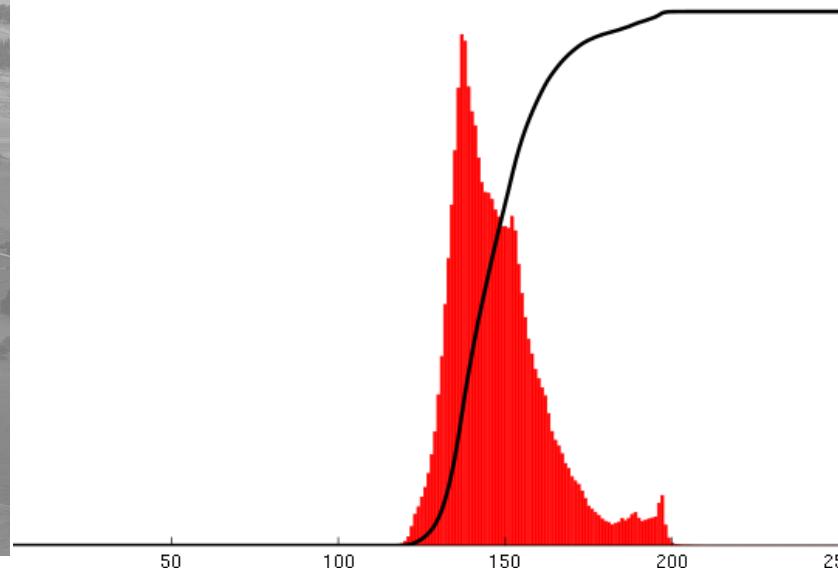
# Gray-Level Transformations

- Histograms are related to photograph exposure
  - Aperture size
  - Shutter speed



# Gray-Level Transformations

- Histogram equalization : Motivation

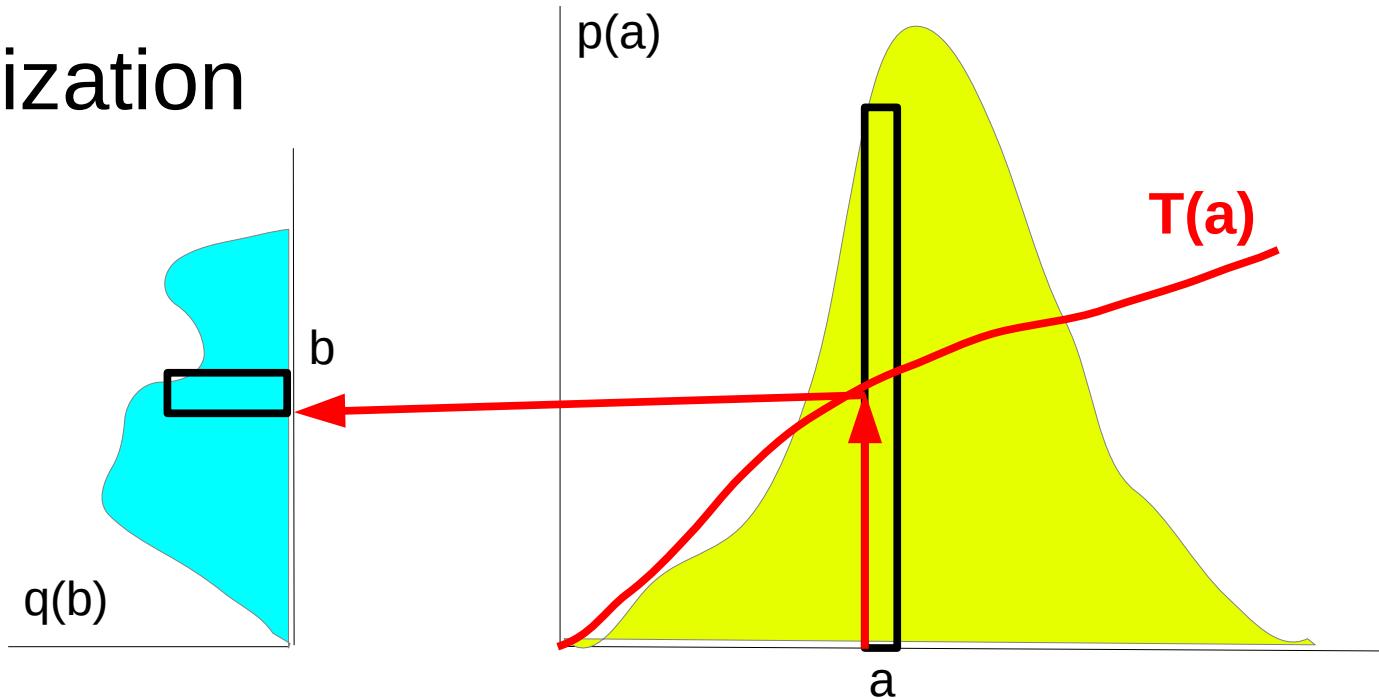


# Gray-Level Transformations

- Histogram equalization
  - Assume **continuous** distributions (and image)
  - Given histogram  $p(a)$
  - **Design function  $T(a) = b$  such that  $q(b) = \text{uniform distribution}$**
  - Assume  $0 < a < 1, 0 < b < 1$
  - Then, we want  $q(b) = 1$
  - Consider a **monotonically increasing** intensity-transformation function  $T(\cdot)$

# Gray-Level Transformations

- Histogram equalization



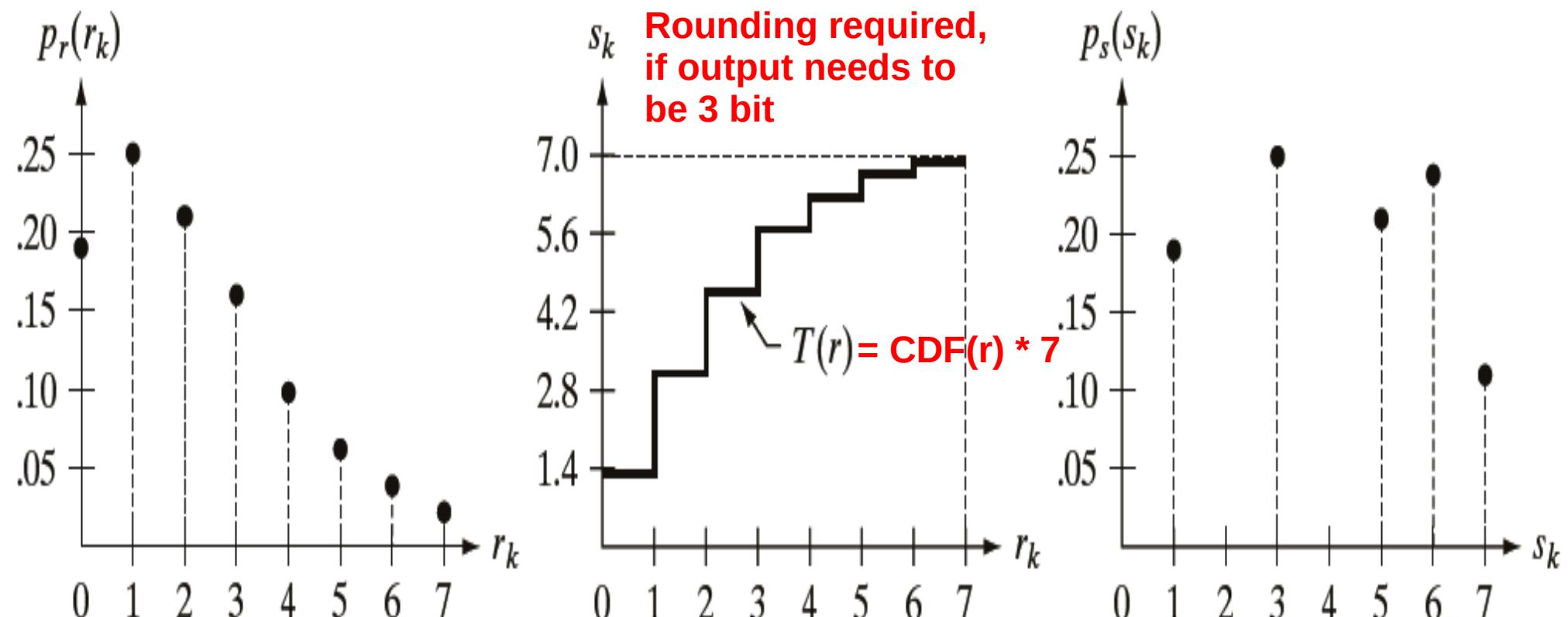
- Let  $b = T(a)$
- **Mass conservation** implies:  $p(a) da = q(b) db$
- Integrate left hand side from 0 to  $a'$
- Integrate right hand side from  $0 = T(a') = b'$
- Left hand side =  $CDF_a(a')$
- Right hand side =  $CDF_b(b')$

# Gray-Level Transformations

- Histogram equalization
  - If we want  $q(b) = 1$ , then  $CDF_b(b') = b'$
  - So,  $CDF_a(a') = CDF_b(b') = b'$
  - So, transformation function  $T(.) =$   
CDF of intensities in original image  $CDF_a(.)$

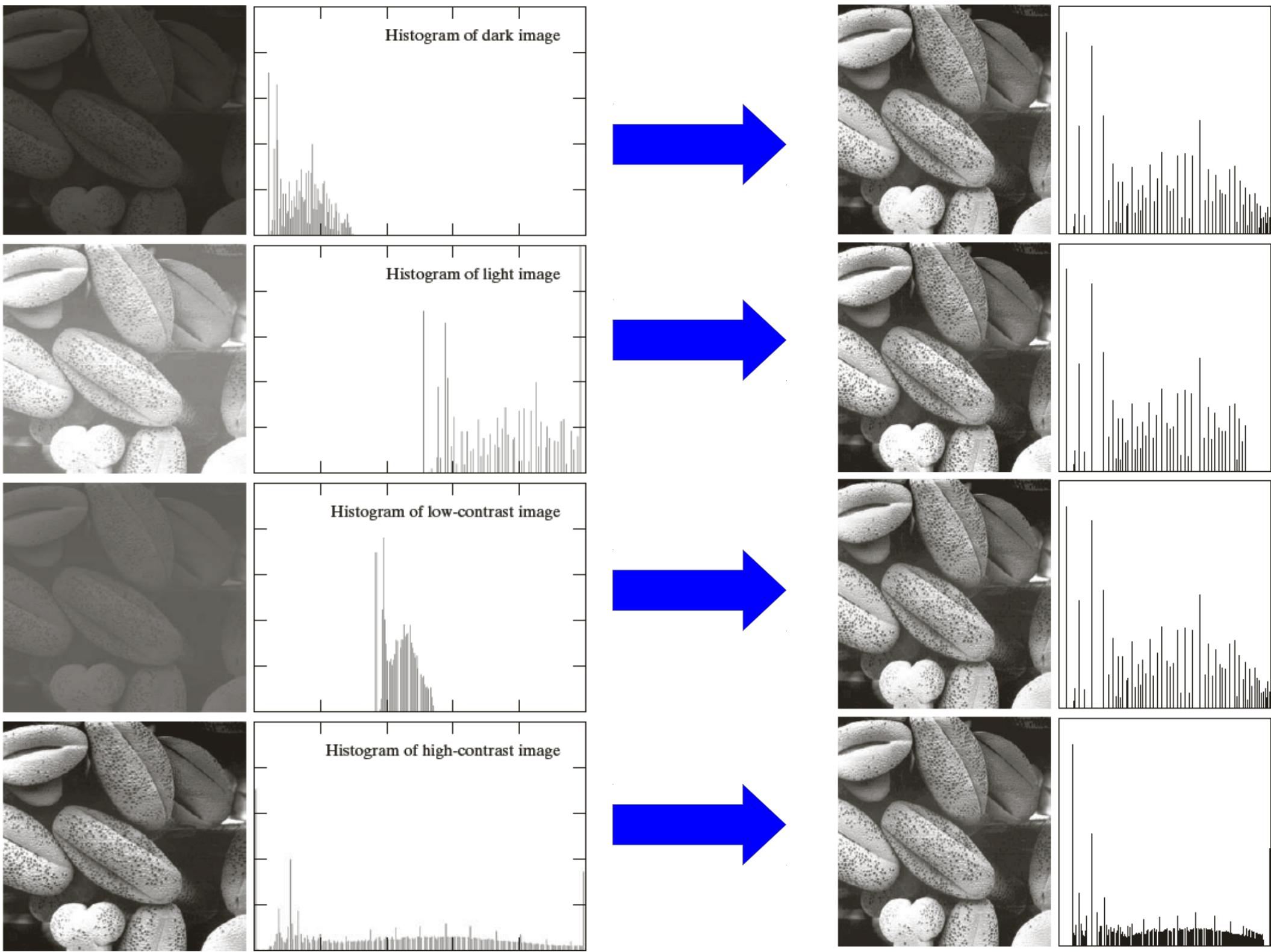
# Gray-Level Transformations

- Histogram equalization example (3-bit image)



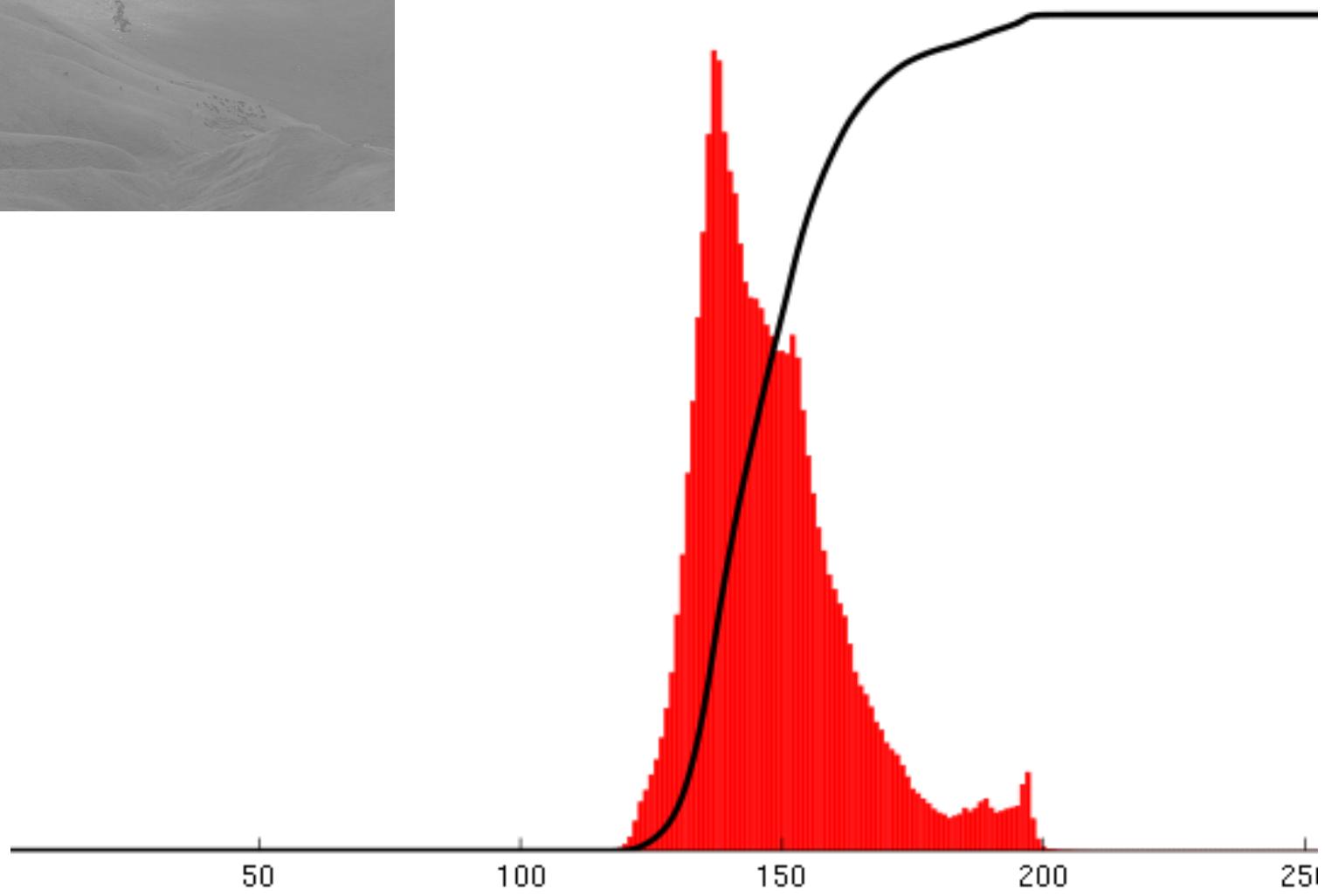
a b c

**FIGURE 3.19** Illustration of histogram equalization of a 3-bit (8 intensity levels) image. (a) Original histogram. (b) Transformation function. (c) Equalized histogram.



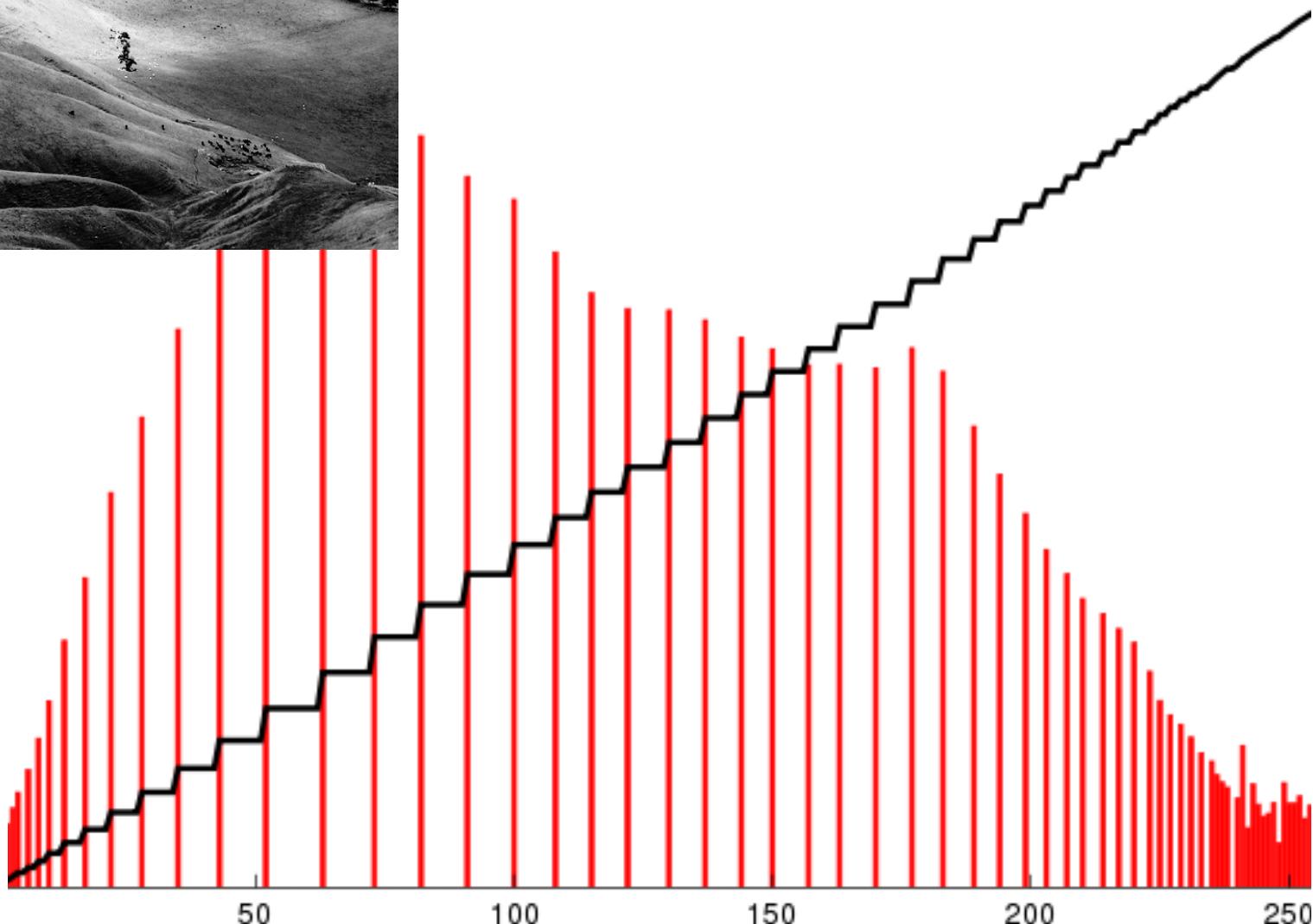


# Transformations





# Transformations



# Gray-Level Transformations

- Why is the output histogram NOT exactly uniform ?
  - Because of discretization of space and intensity
  - Theoretically
    - Contradicts the assumption of continuous distributions (i.e., continuous spatial domain, continuous intensities)
    - We used that to derive transformation for histogram equalization
  - Practical problem (1 of 2)
    - Imagine 8-bit images → 256 intensities ( $B=256$  bins)
    - Imagine an input image containing only  $N=100$  unique intensities (unique upto bin-width)
    - For output image, uniform histogram must contain **some** pixels for each intensity (bin)
    - How can we map  $N=100$  values to  $B=256$  bins ?
      - No systematic straightforward way to map  $N$  unique values to  $B (> N)$  bins

# Gray-Level Transformations

- Why is the output histogram NOT exactly uniform ?
  - Because the set of intensities in digital images is discrete
  - Practical problem (2 of 2)
    - Imagine 8-bit images → 256 intensities ( $B = 256$  bins)
    - Imagine an input image containing  $N=256$  unique intensities (some mass exists in each bin) and  $M=2560$  pixels
    - For output image, uniform histogram must contain **an equal number of ( $M/N=10$ )** pixels for each intensity
    - If some intensity “a” in input image has 20 pixels, then intensity  $b=T(a)$  in output image will have  $\geq 20$  pixels
    - How can we decide which 10 of those  $\geq 20$  pixels should be assigned intensity “b” ?
      - No systematic and straightforward way to do that

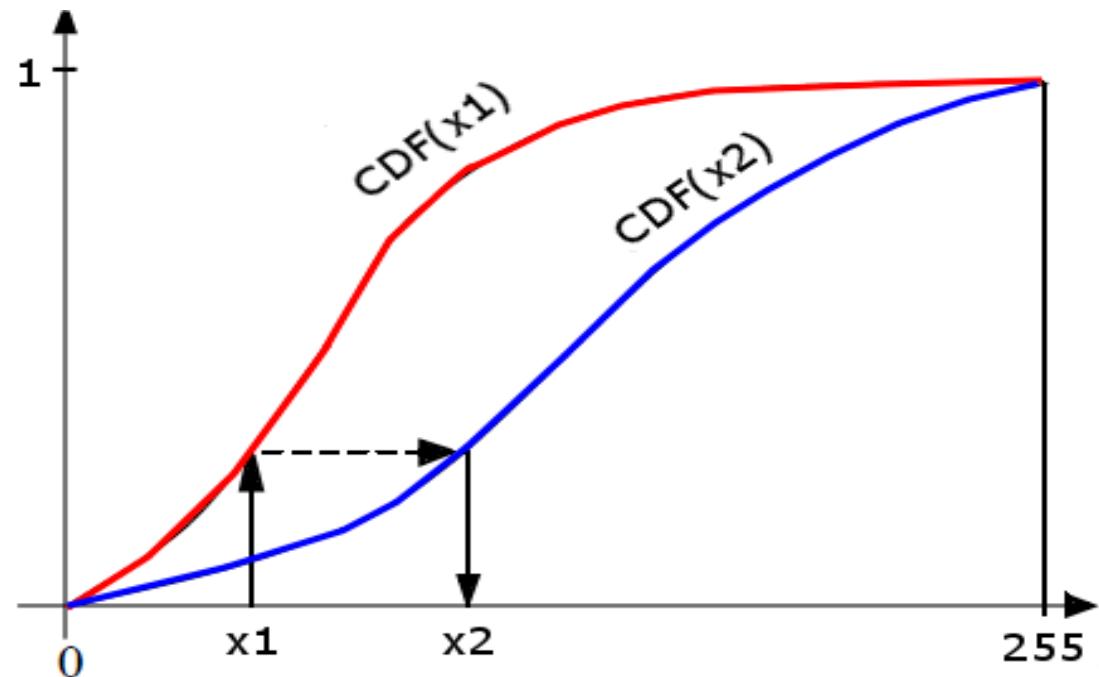
# Gray-Level Transformations

- Histogram matching
  - Sometimes, we don't want to equalize
  - But, we want to match the histogram of one image to another chosen histogram (NOT uniform)
    - e.g., for standardizing the intensity
  - In that case,

$$CDF_a(a) = CDF_b(b)$$

implies

$$b = CDF_b^{-1}(CDF_a(a))$$



# Gray-Level Transformations

- Histogram matching

