Digital Image Processing:
Digital Imaging Fundamentals

Chapter 02

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Contents

This lecture will cover:

- The human visual system
- Light and the electromagnetic spectrum
- Image representation
- Image sensing and acquisition
- Sampling, quantisation and resolution
- Some basic relationships between pixels
- Linear and nonlinear operations

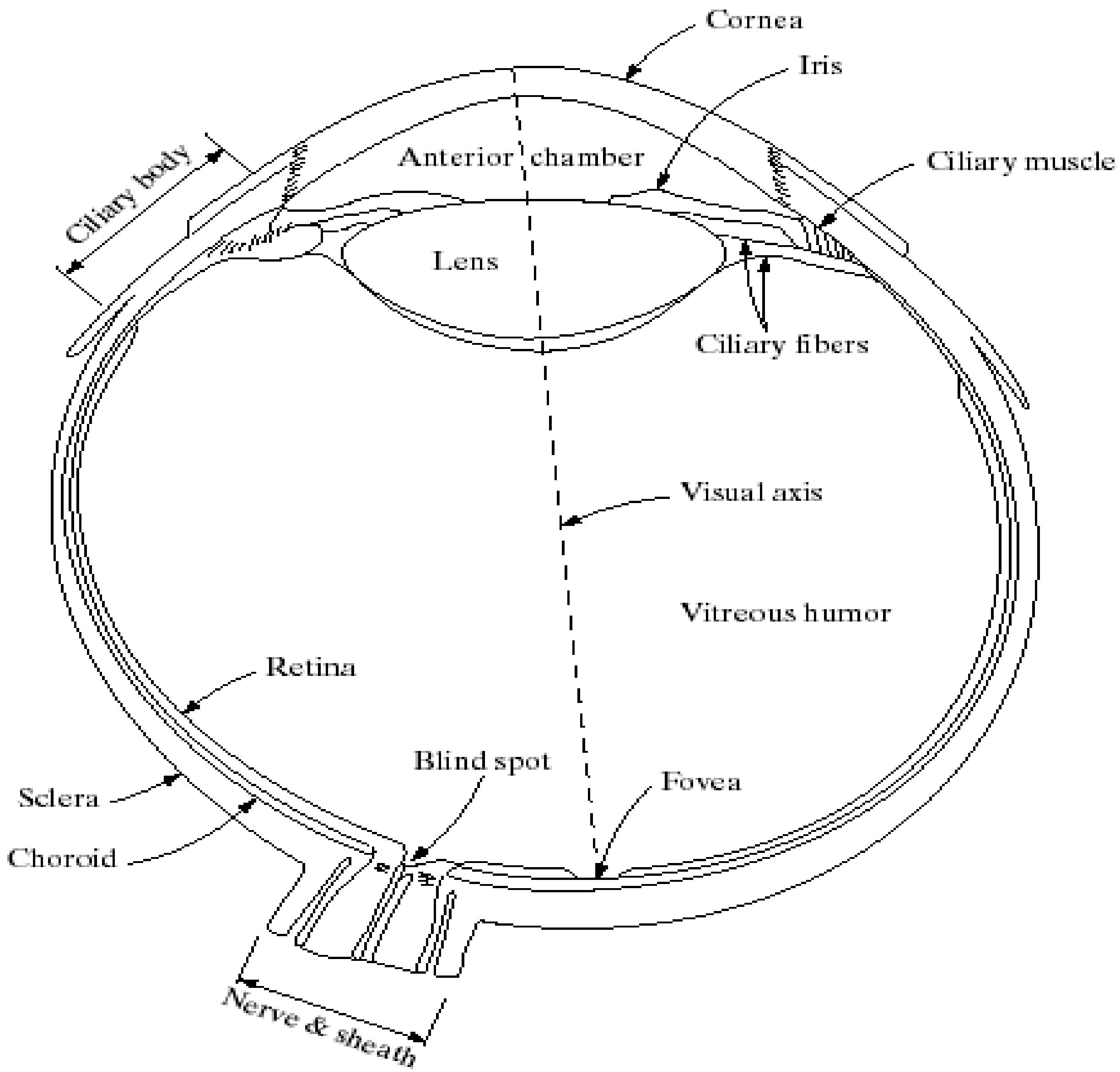
Human Visual System

The **best vision model** we have!

Knowledge of **how images form in the eye** can **help us** with **processing** digital images.

We will take just a **whirlwind tour** of the human visual system.

Structure Of The Human Eye



Structure Of The Human Eye

The lens focuses light from objects onto the retina

The **retina** is covered with **light receptors** called ***cones*** (6-7 million) and ***rods*** (75-150 million)

Cones are concentrated around the fovea and are very sensitive to colour

Rods are more spread out and are sensitive to low levels of illumination

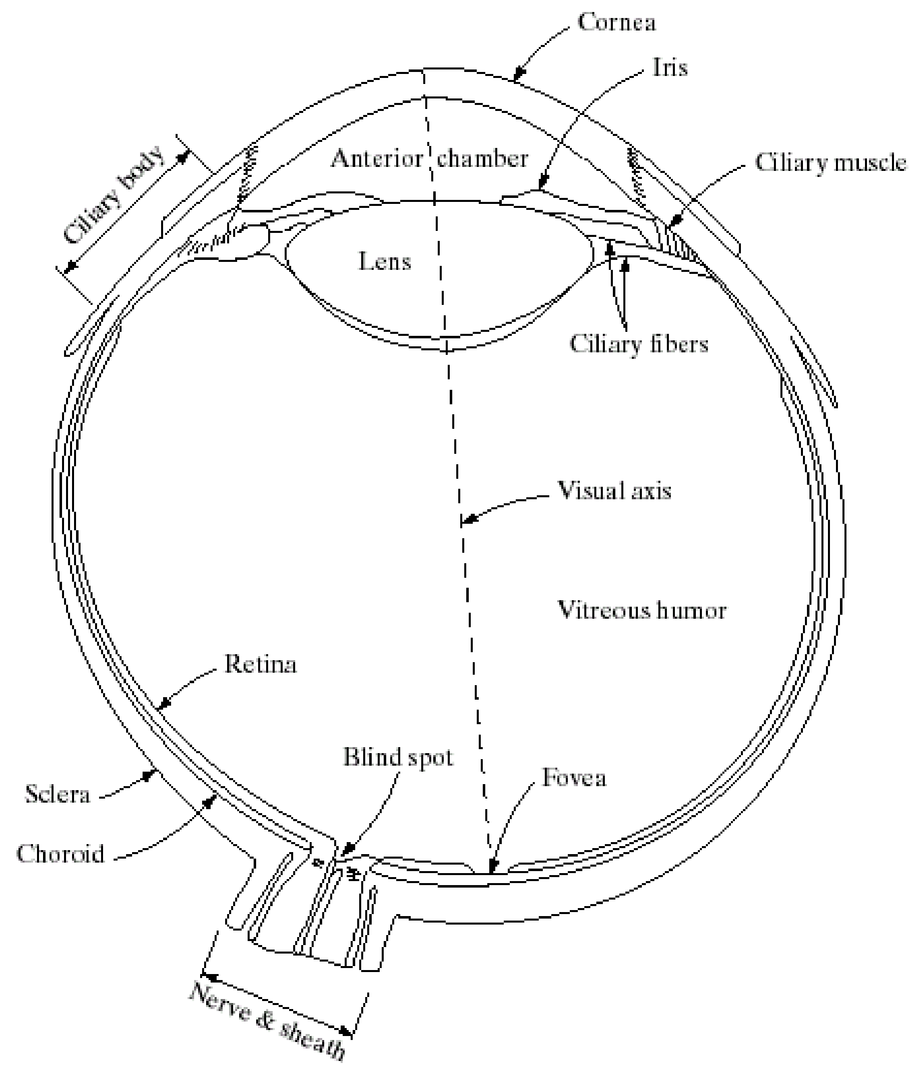
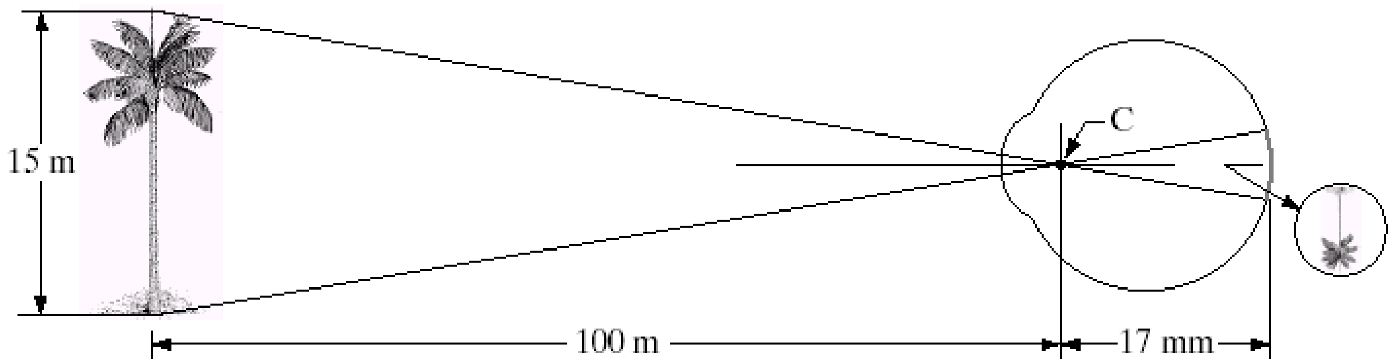


Image Formation In The Eye

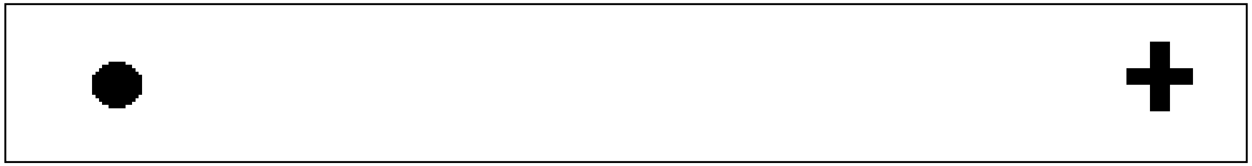
Muscles (Iris) within the eye can be used to change the shape of the lens allowing us focus on objects that are near or far away

An image is **focused** onto the **retina** causing **rods and cones to become excited** which ultimately send signals to the brain



1. Blind-Spot Experiment

Draw an image similar to that below on a piece of paper (the dot and cross are about 6 inches apart)



Close your right eye and focus on the cross with your left eye

Hold the image about 20 inches away from your face and move it slowly towards you

The dot should disappear!

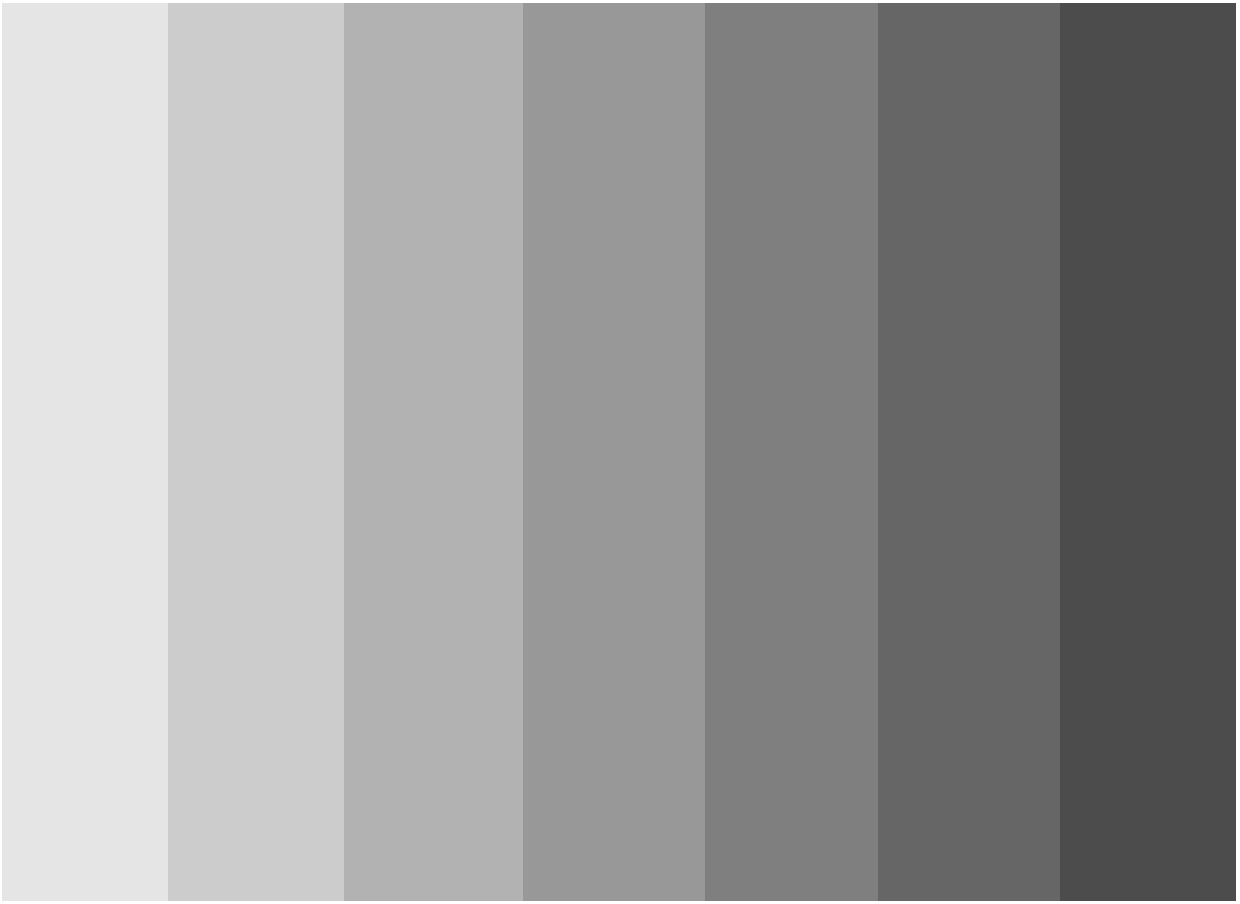
2. Brightness Adaptation & Discrimination

The **human visual system** can perceive approximately **10^{10} different light intensity** levels

However, at **any one time** we can only **discriminate** between **a much smaller** number – ***brightness adaptation***

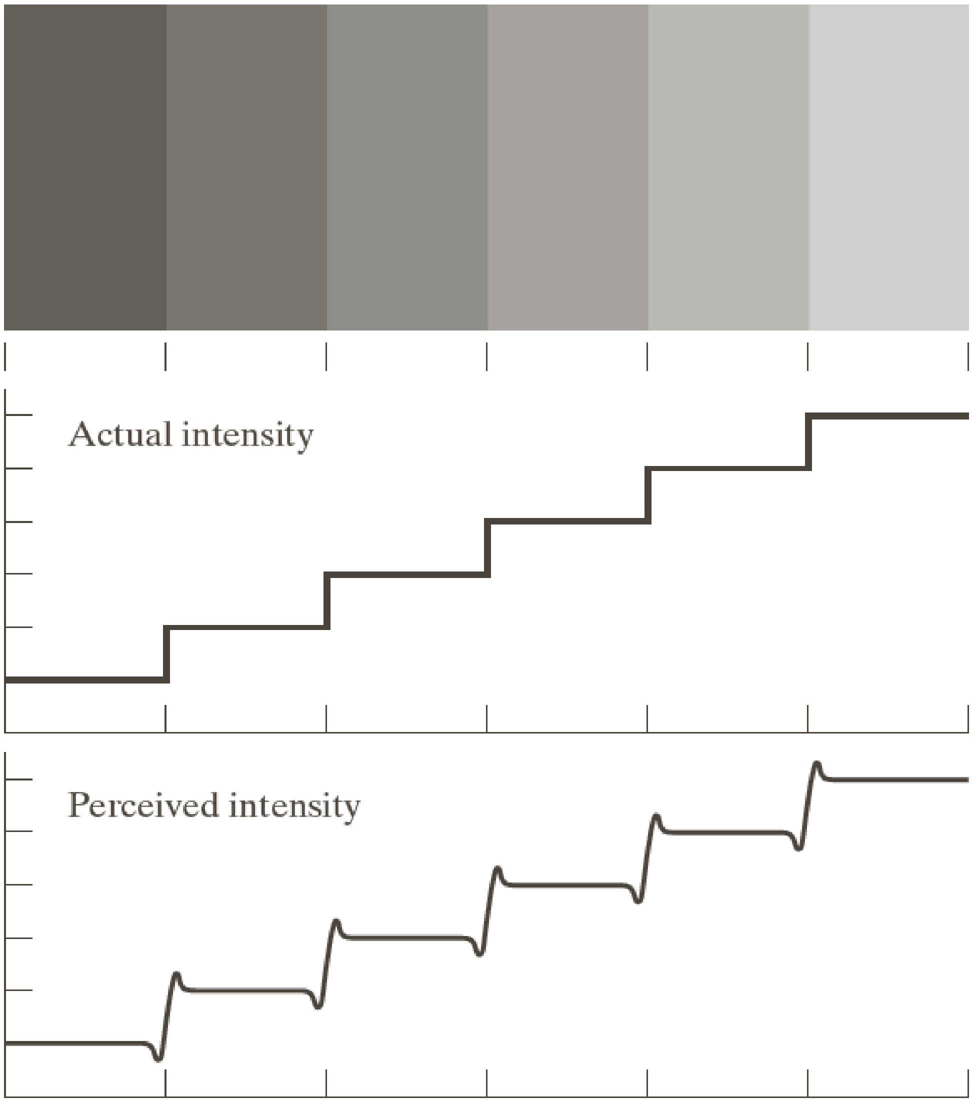
Similarly, the ***perceived intensity*** of a region is **related to the light intensities** of the regions **surrounding** it this is called **Simultaneous contrast**.

2. Brightness Adaptation & Discrimination (cont…)



An example of Mach bands

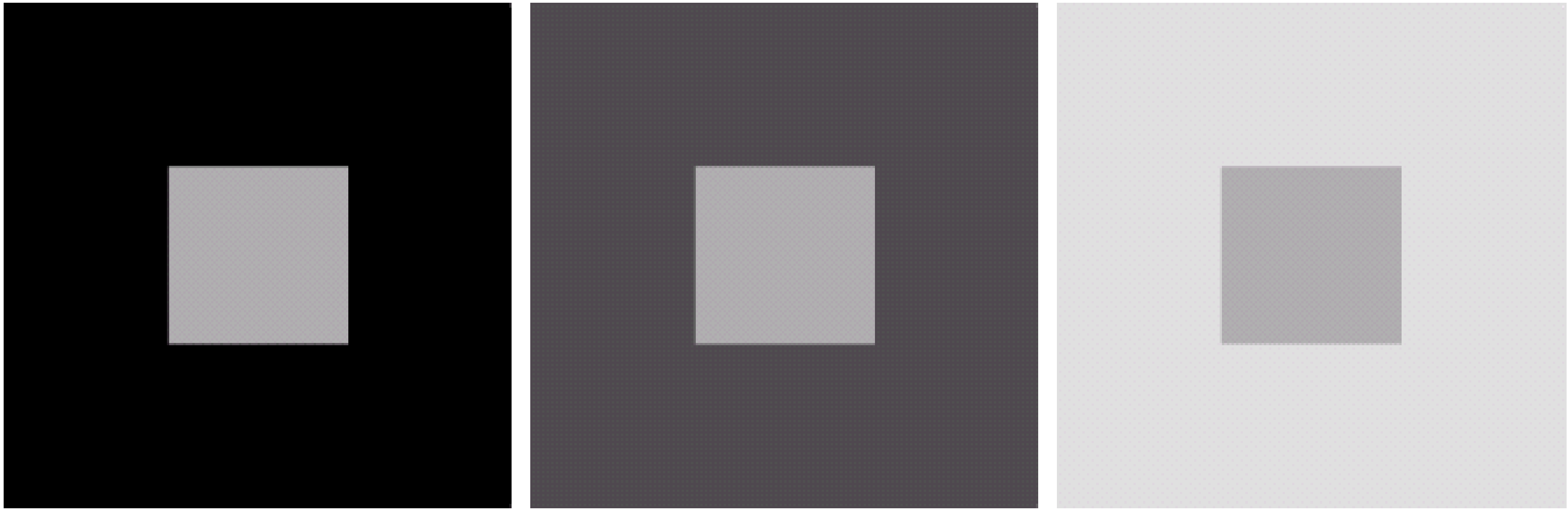
2. Brightness Adaptation & Discrimination (cont…)



For human visual system the **<u>perceived brightness</u>** is not a simple function of intensity.

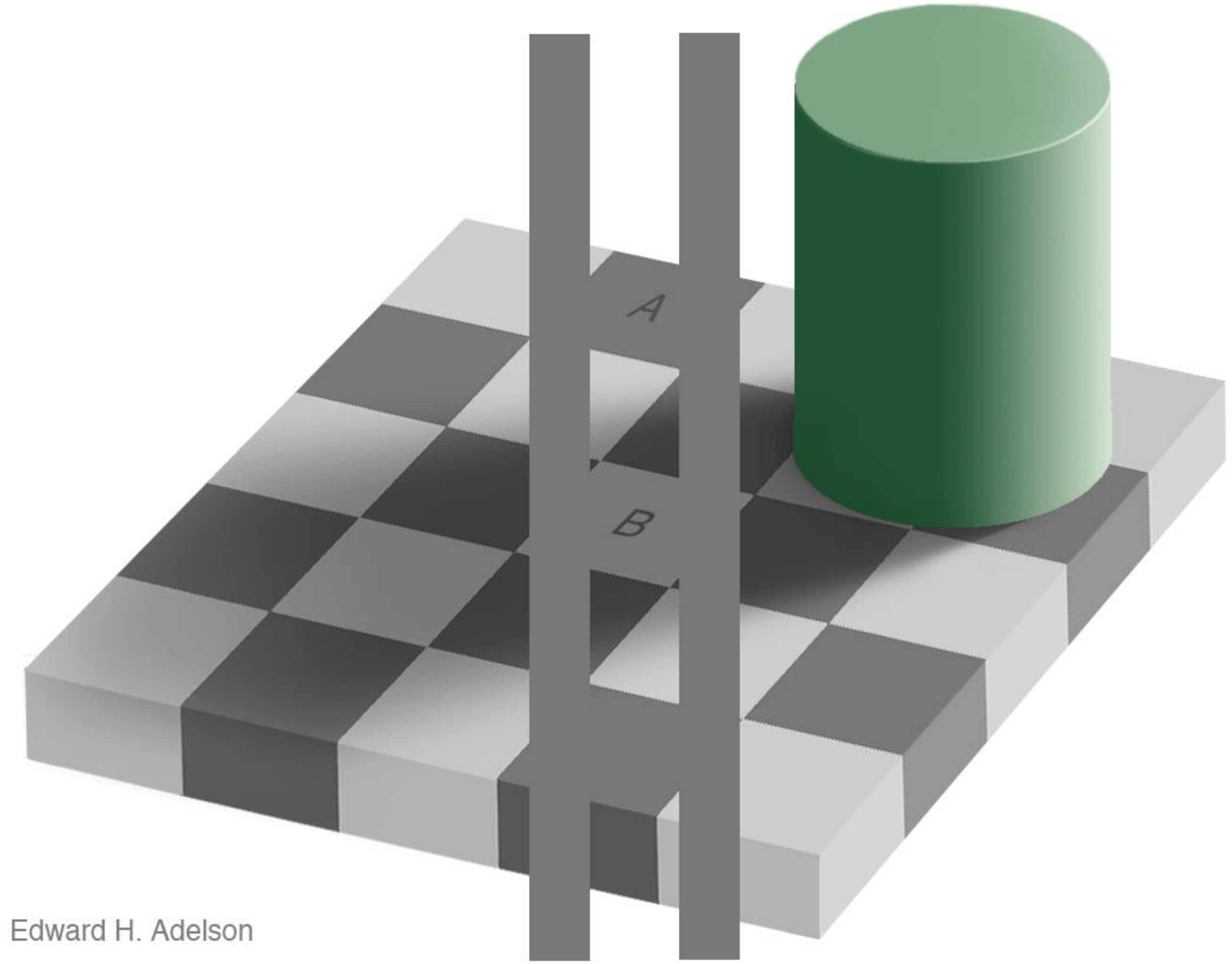
It is based on the fact that the visual system tends to **undershoot** or **overshoot** around the boundary of regions of different intensities.

3. Simultaneous Contrast



An example of *simultaneous contrast*

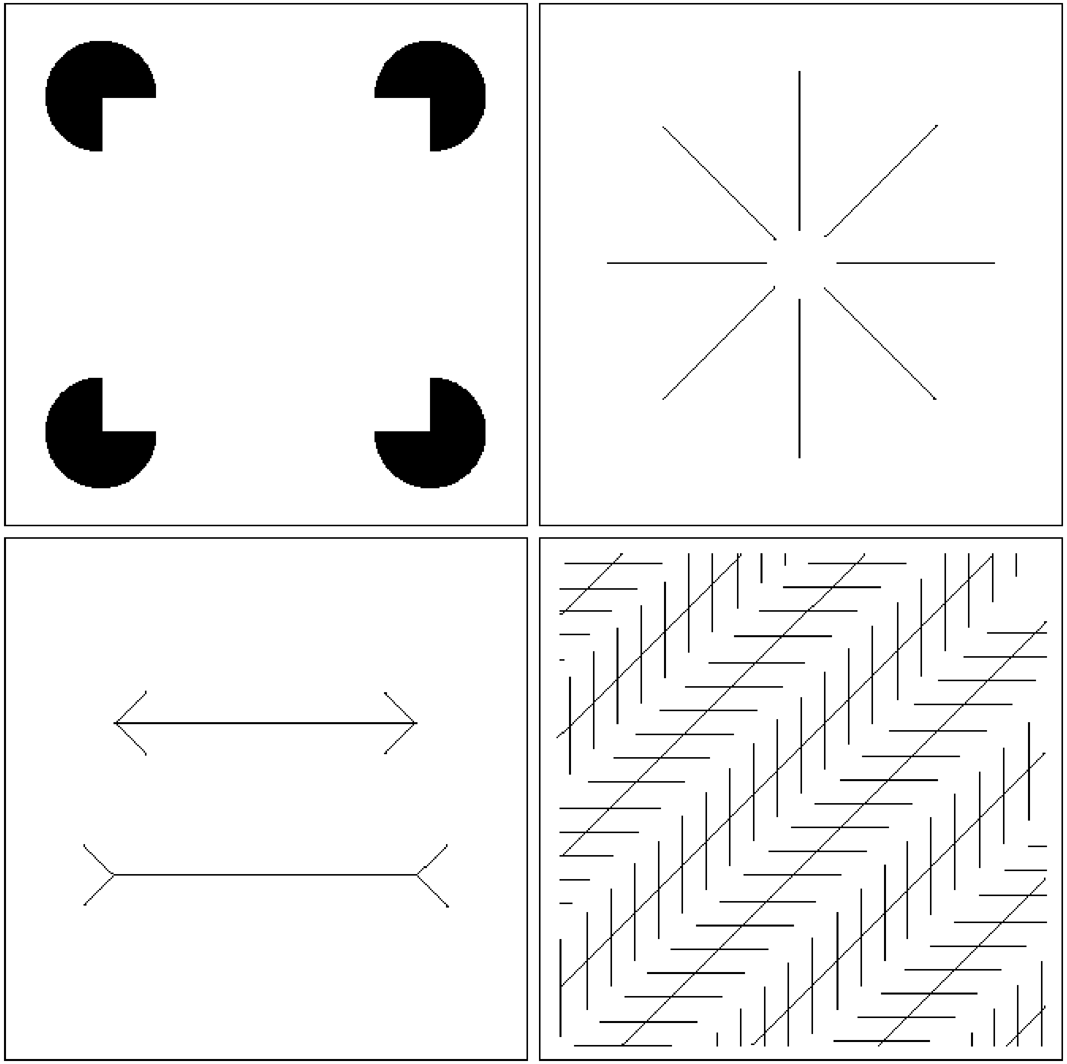
3. Simultaneous Contrast



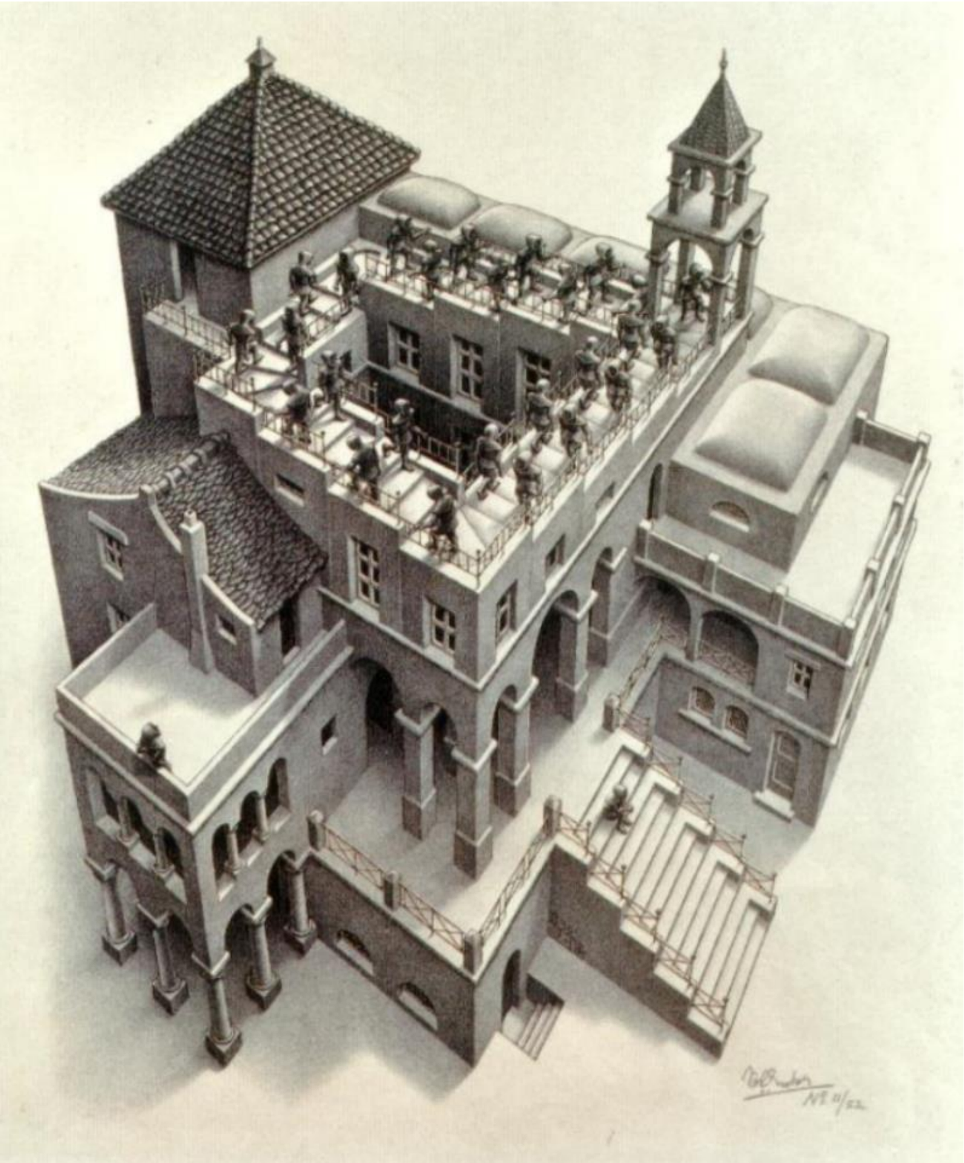
For more great illusion examples take a look at: http://web.mit.edu/persci/gaz/

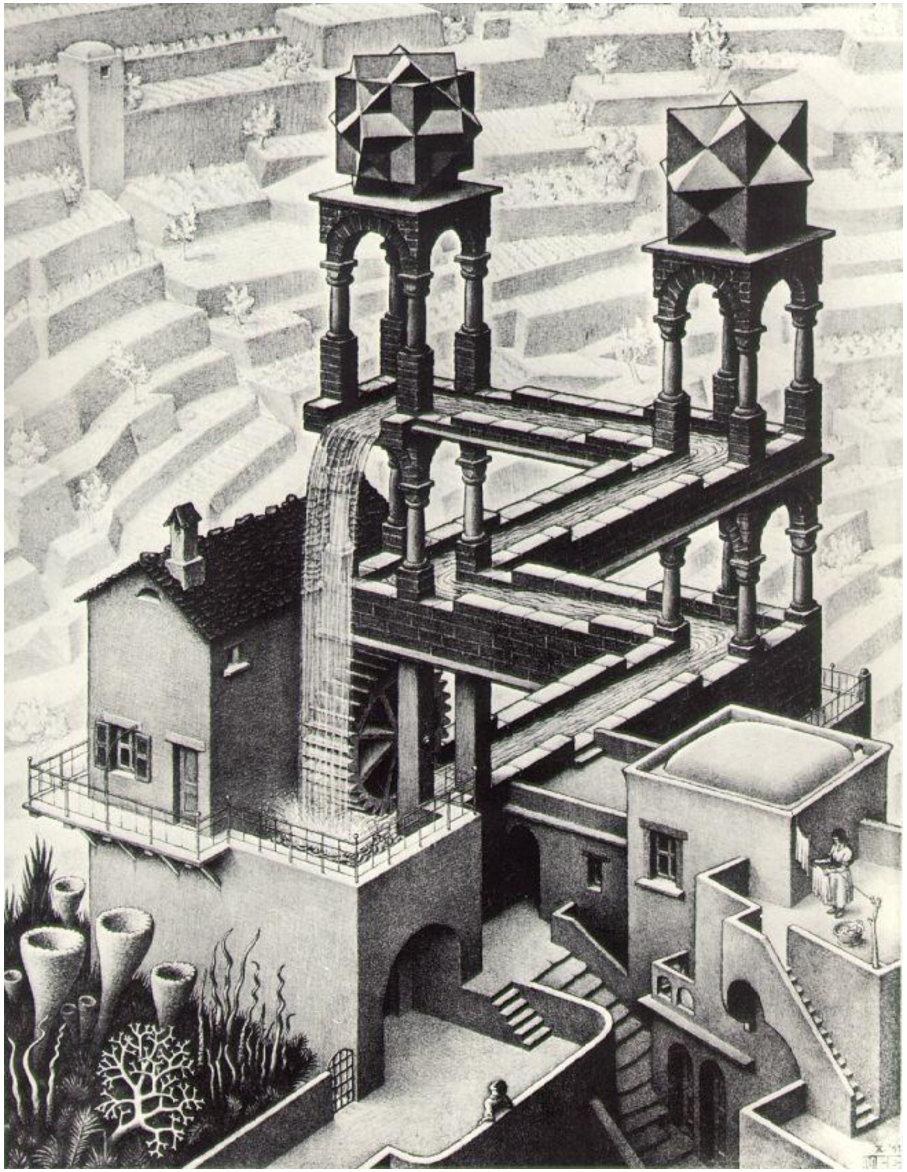
4. Optical Illusions

Our visual systems play lots of interesting tricks on us

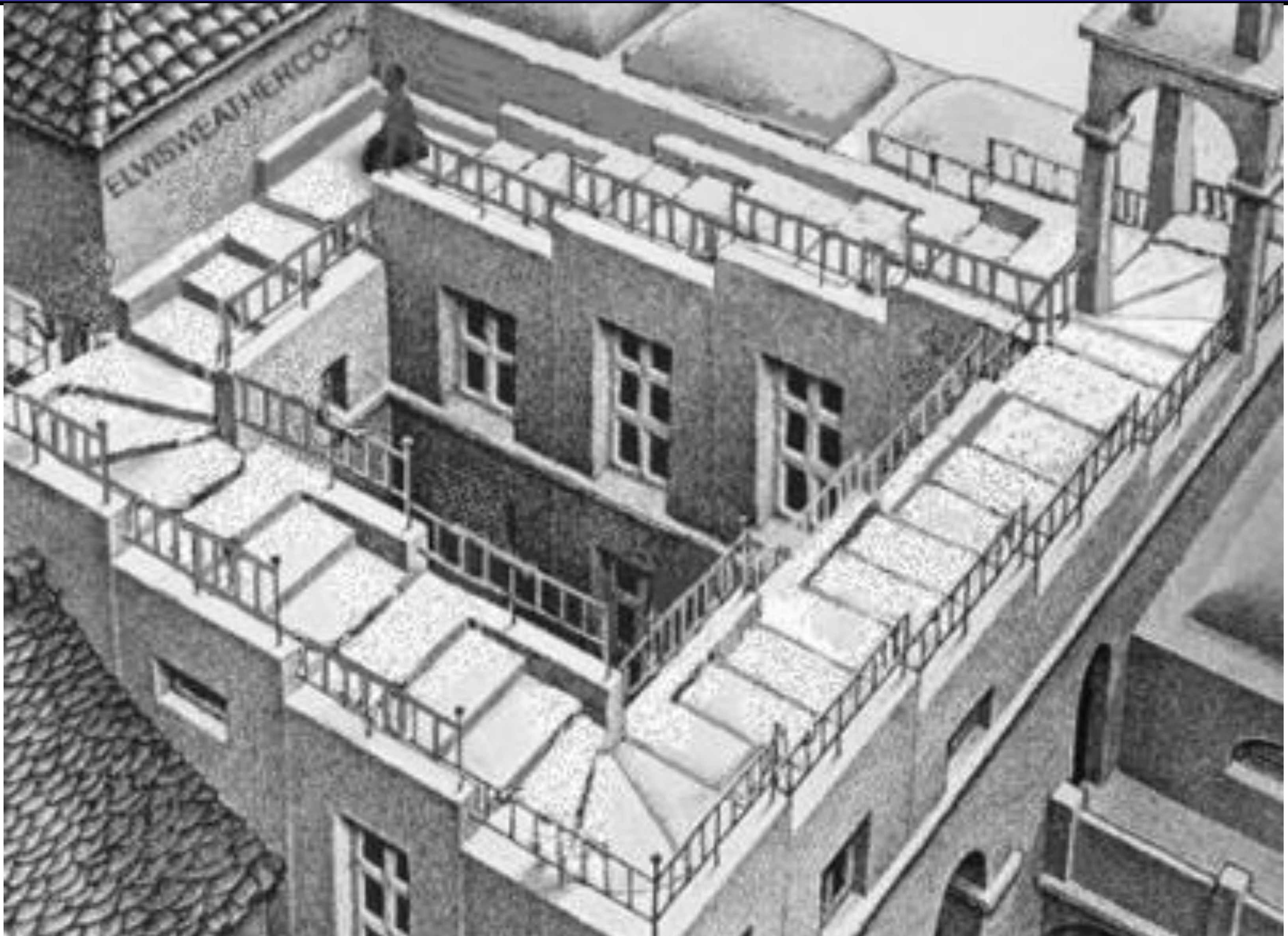


4. Optical Illusions (cont…)

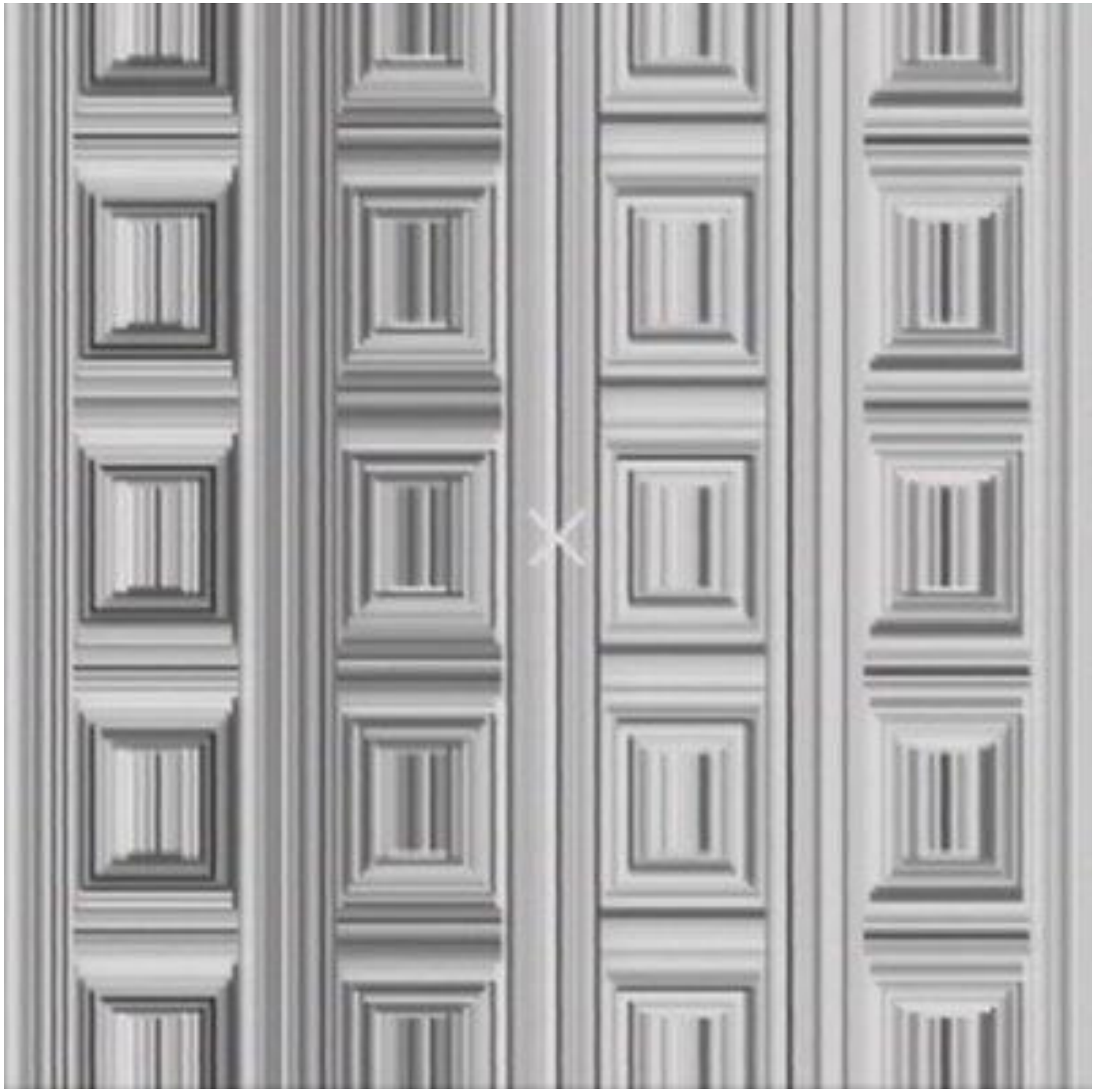




4. Optical Illusions (cont…)



4. Optical Illusions (cont…)



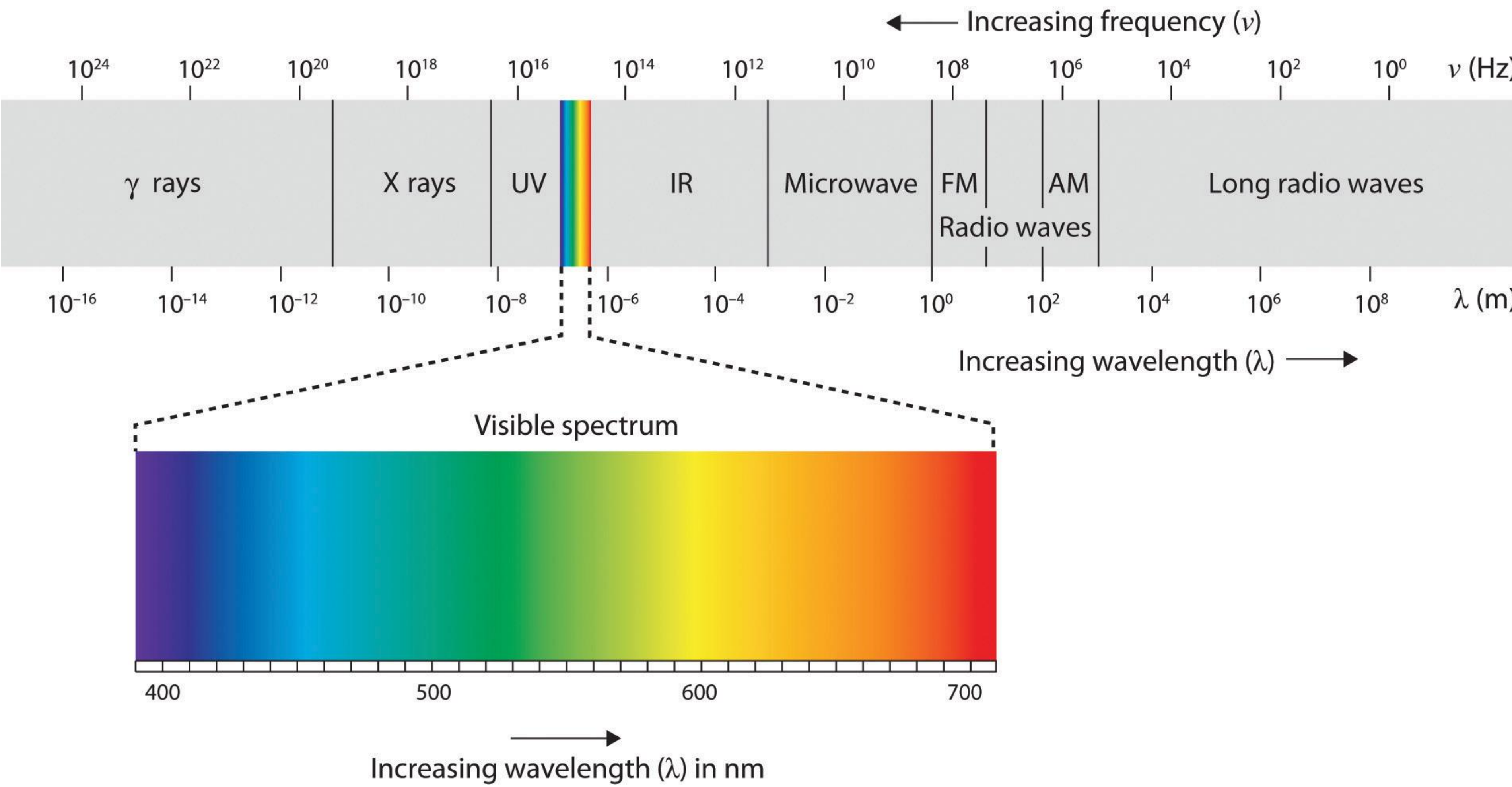
Do at home illusion

Stare at the cross in the middle of the image and think circles

Light And The Electromagnetic Spectrum

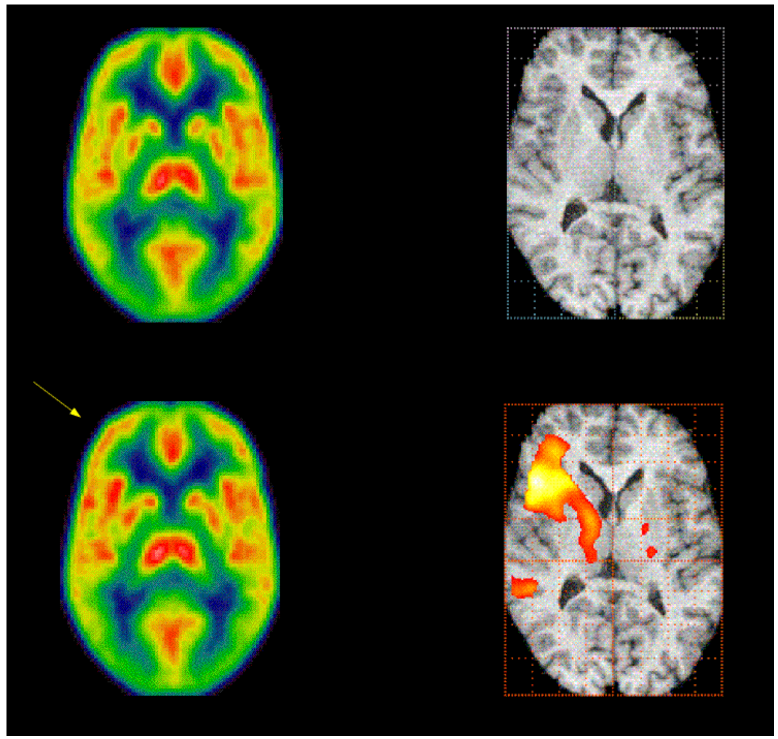
- In 1666 Sir Isaac Newton discovered that **light passed through a prism splits into a continuous spectrum** of colour.
- Many image applications **use electromagnetic radiation** that is far outside the visual spectrum – x-ray images, infra-red images etc.
- Light is just a particular part of the electromagnetic spectrum that can be sensed by the human eye.
- The electromagnetic spectrum is split up according to the wavelengths of different forms of energy.

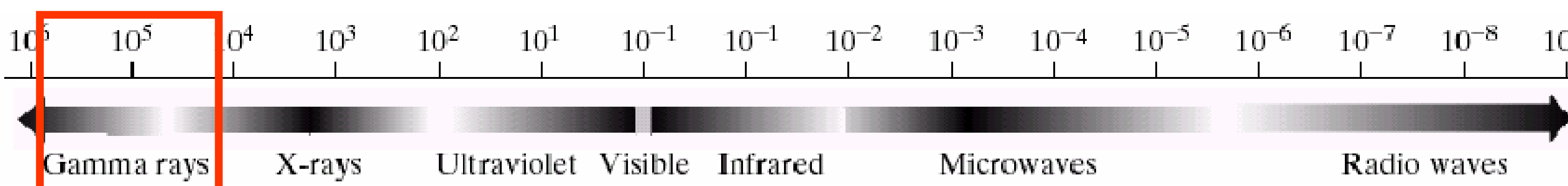
Electromagnetic Spectrum



Positron Emission Tomography (PET) Images

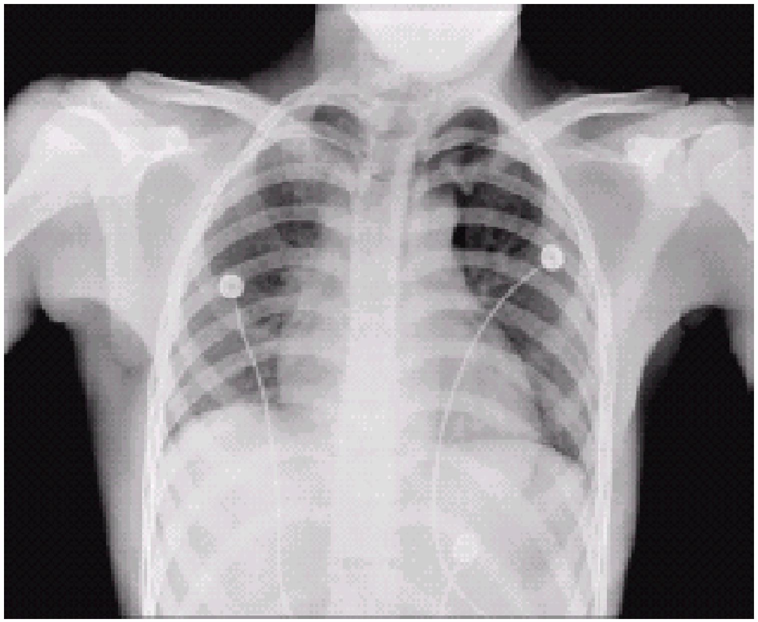
Operate in gamma-ray frequency





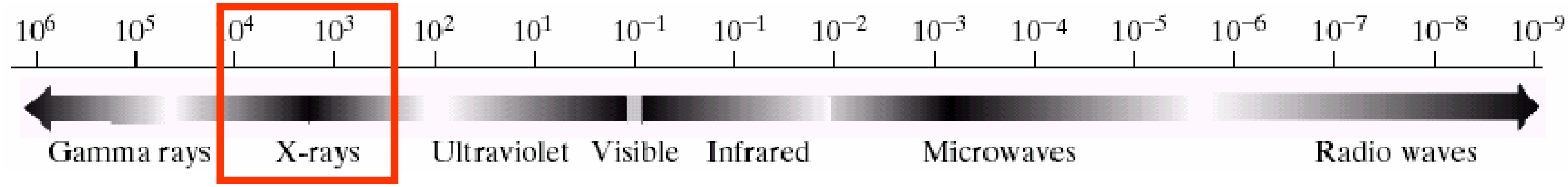
X-RAY Imaging

Operate in X-ray frequency



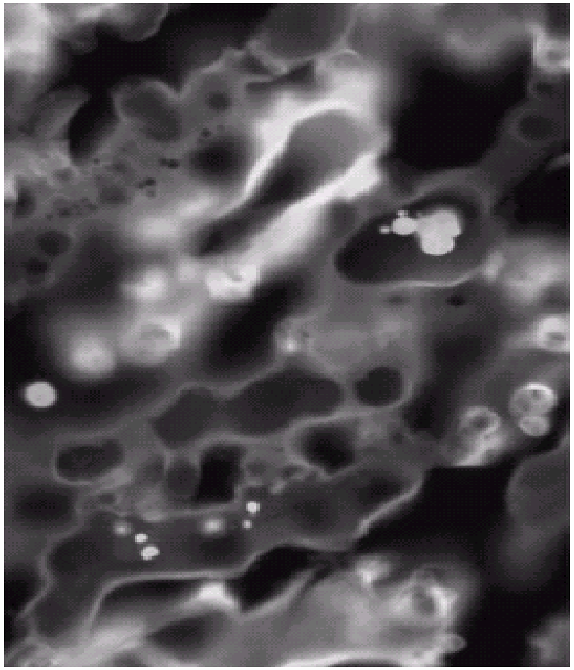
chest

head

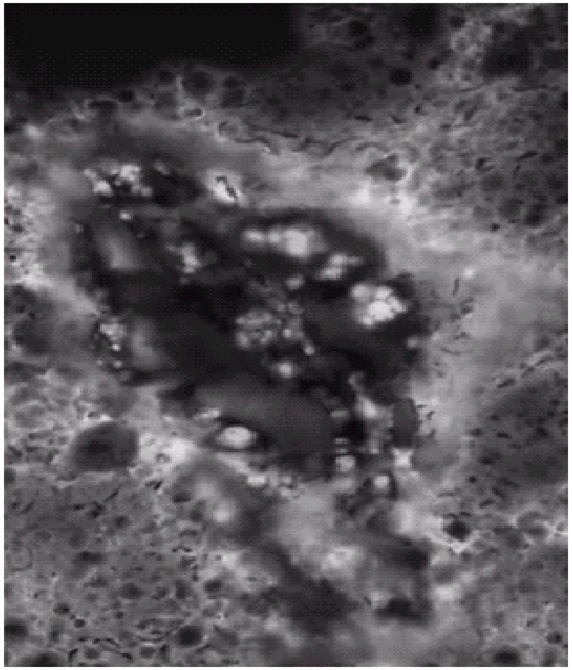


Fluoresense Microscopy

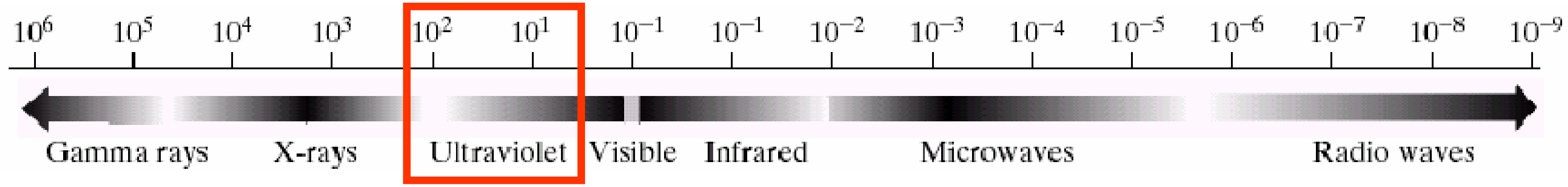
Operate in ultraviolet frequency



normal corn



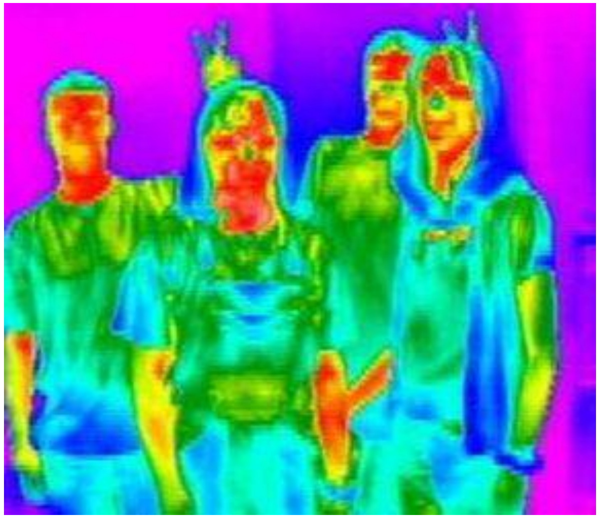
smut corn



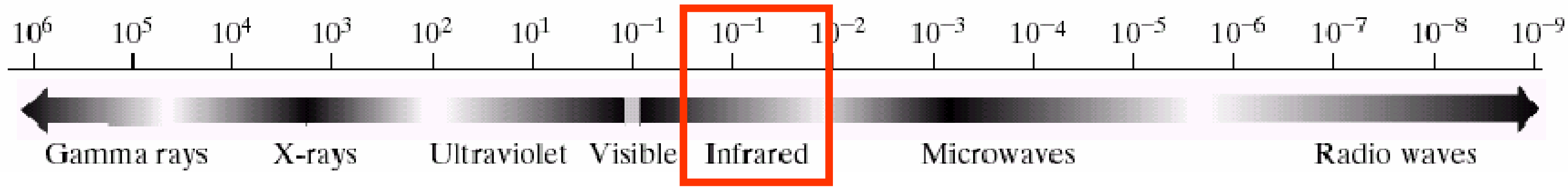
Thermal Imaging

Operate in infrared frequency

Grayscale representation
(bright pixels correlate with
high-temperature regions)

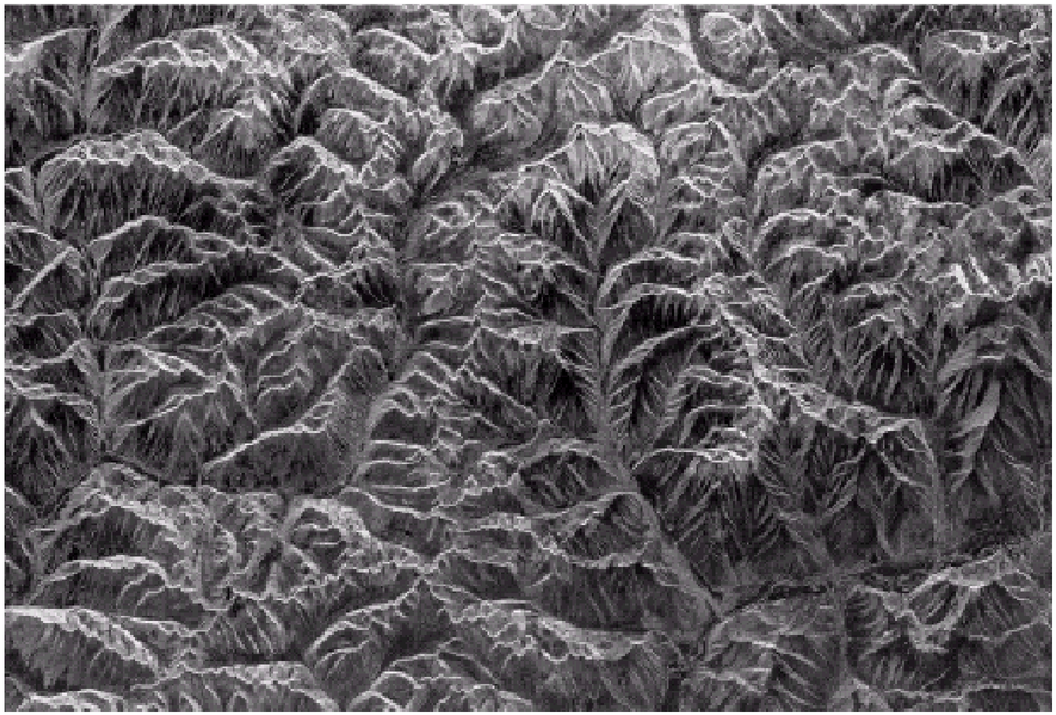


Pseudo-color representation
(Human body dispersing
heat denoted by red)

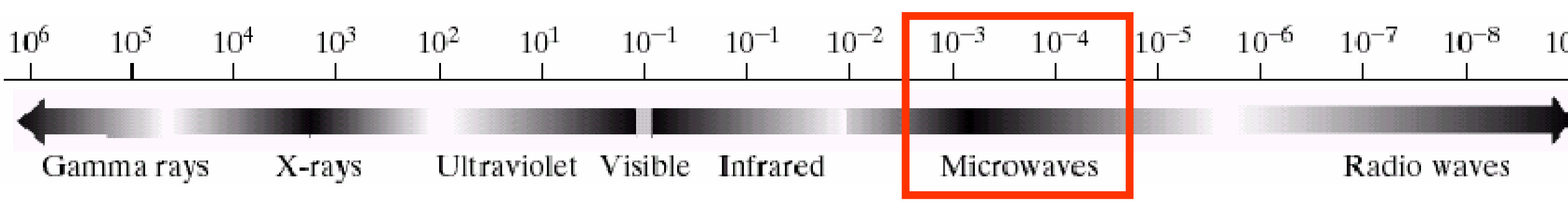


Radar Imaging

Operate in microwave frequency

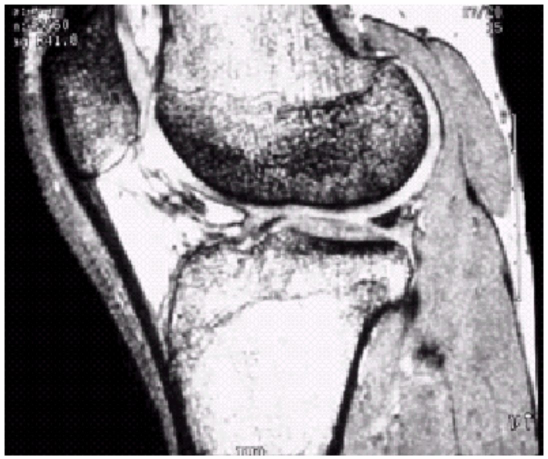


Mountains in Southeast Tibet



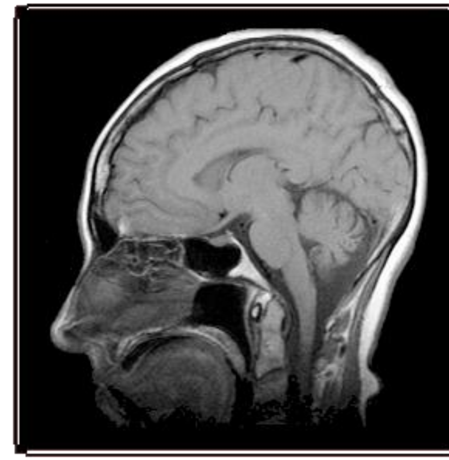
Magnetic Resonance Imaging (MRI)

Operate in radio frequency

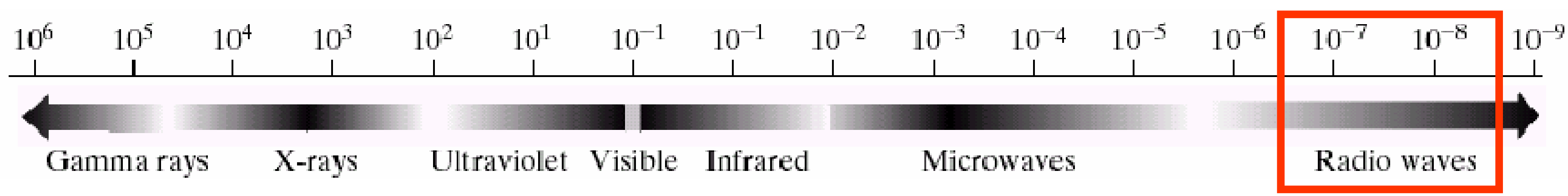


knee

spine



head



Sampling, Quantisation And Resolution

In the following slides we will consider what is involved in capturing a digital image of a real-world scene:

1. **Image sensing and representation**
2. **Sampling and quantisation**
3. **Resolution**

Image Representation

Before we discuss image acquisition recall that a digital image is composed of M rows and N columns of pixels each storing a value.

Pixel values are most often grey levels in the range 0-255(black-white).

We will see later on that images can easily be represented as matrices

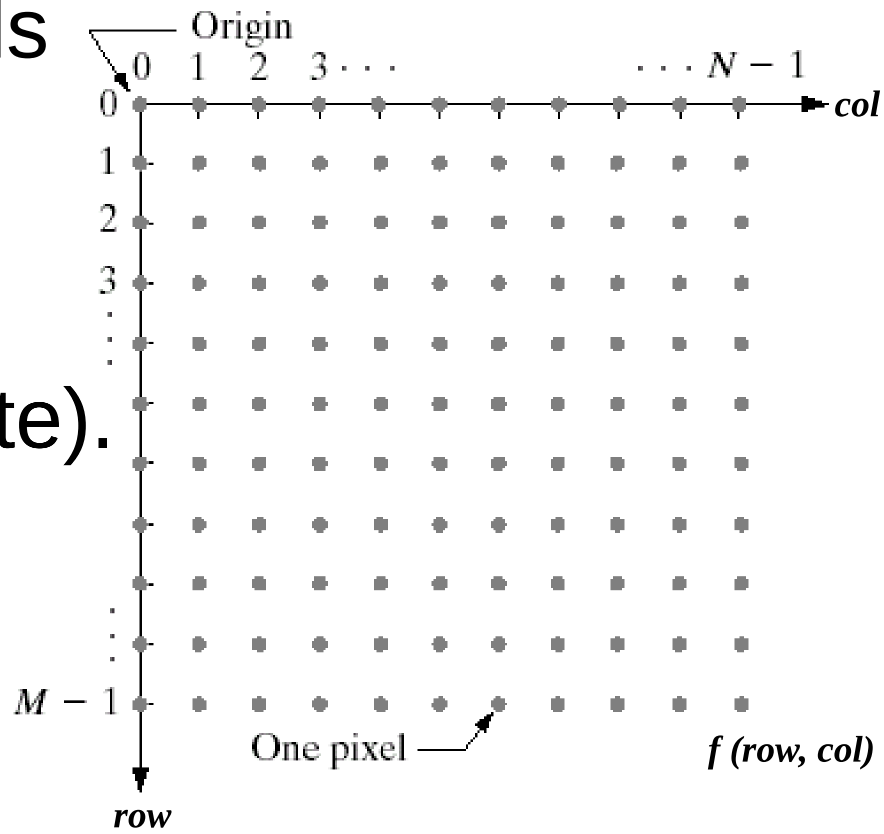
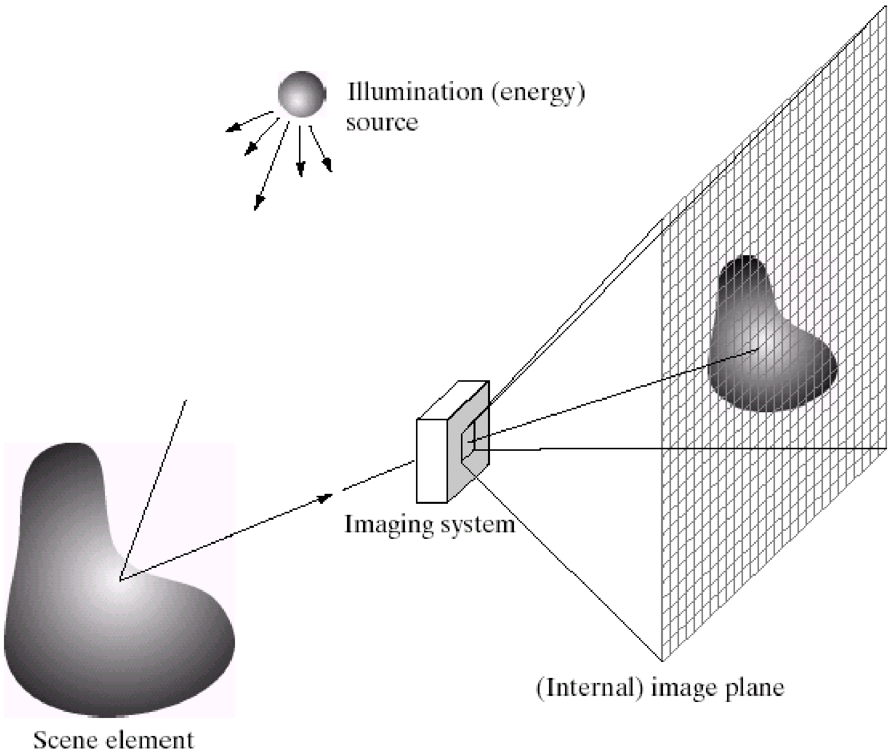


Image Acquisition

Images are typically generated by *illuminating* a *scene* and absorbing the energy reflected by the objects in that scene

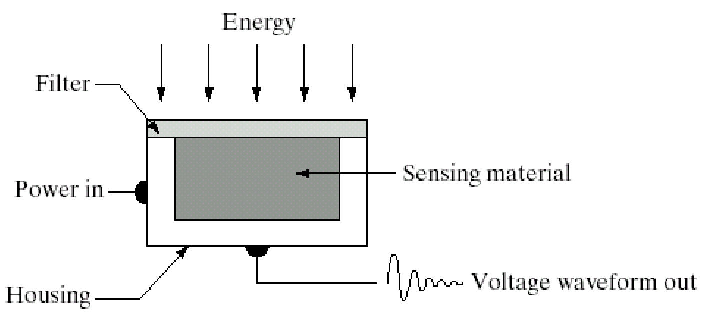


- Typical notions of illumination and scene can be way off:
  - X-rays of a skeleton
  - Ultrasound of an unborn baby
  - Electro-microscopic images of molecules

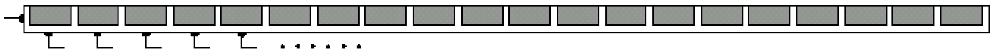
Image Sensing

Incoming energy lands on a sensor material responsive to that type of energy and this generates a voltage

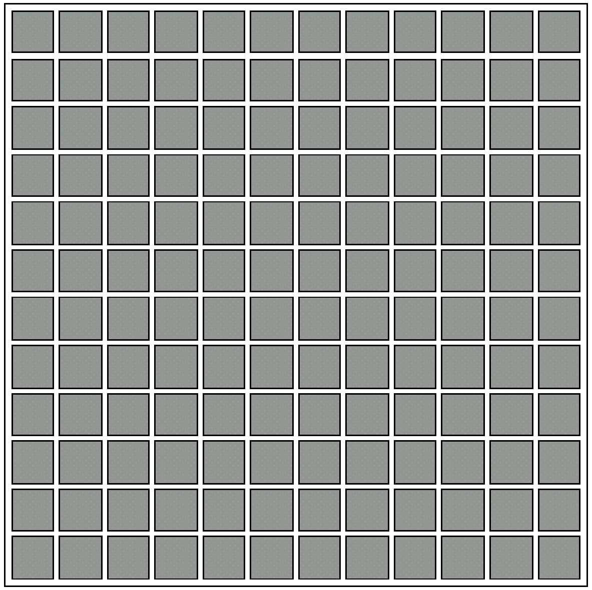
Collections of sensors are arranged to capture images



Imaging Sensor

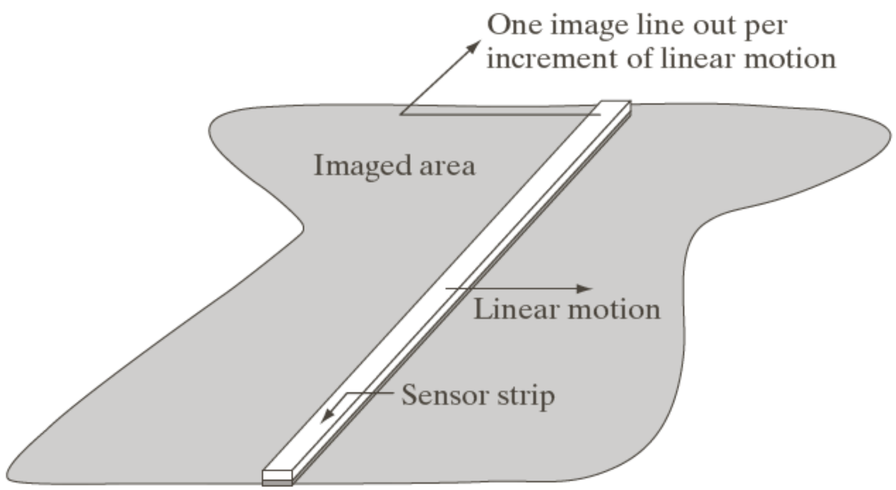


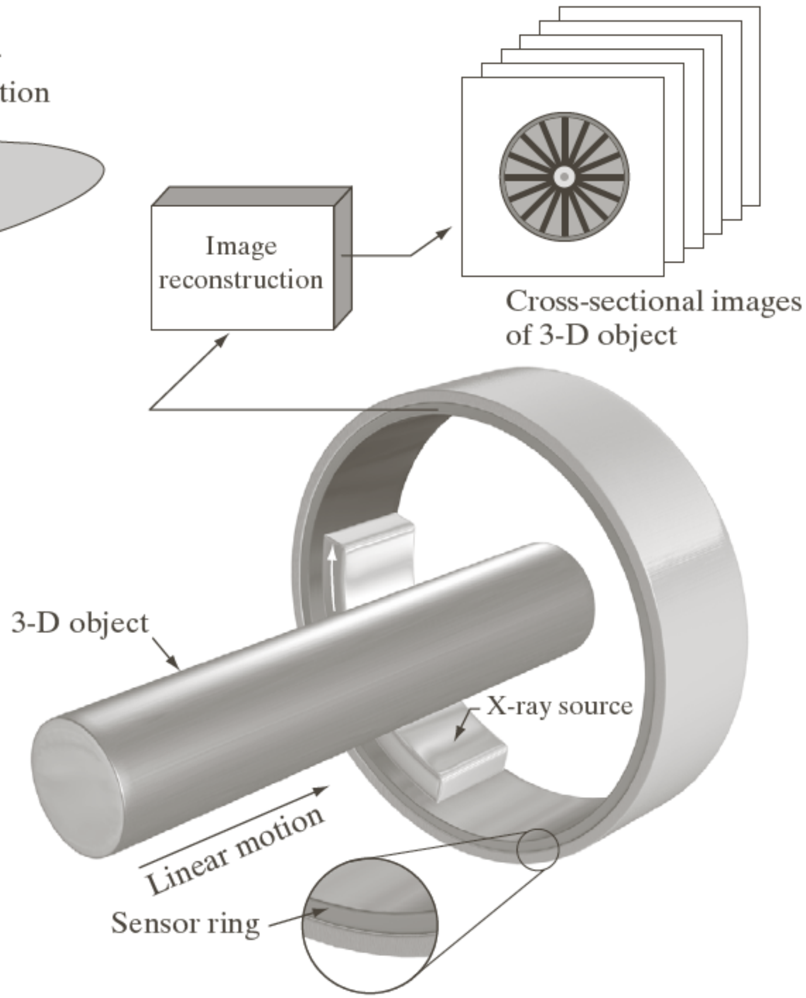
Line of Image Sensors



Array of Image Sensors

Image Sensing

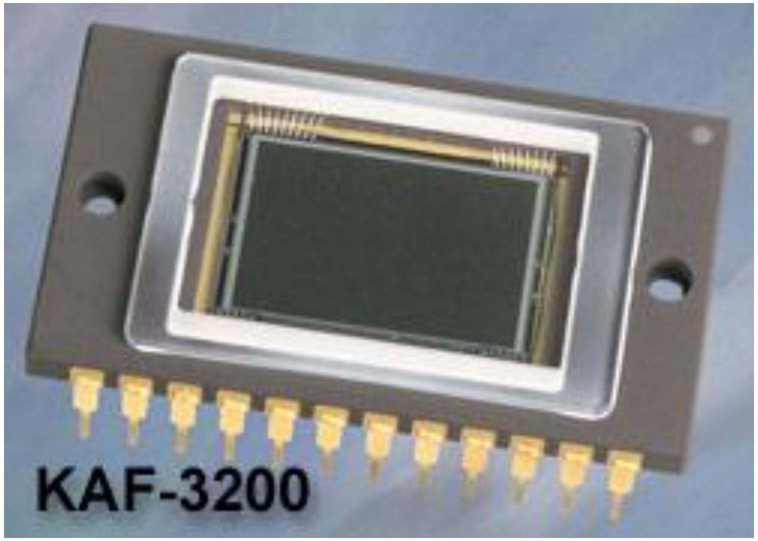




Using Sensor Strips and Rings

Image Sensing

Charge-Coupled Device (CCD)



CCD KAF-3200E from Kodak.
(2184 x 1472 pixels,
Pixel size 6.8 **microns²**)
(1 micron= 10^{-6}m)

- Used to convert a continuous image into a digital image
- Contains an array of light sensors
- Converts photon into electric charges accumulated in each sensor unit

$E = h * f$

Plank's Constant

$h = 6.62606957 \times 10^{-34}$

Image Sampling And Quantization

A digital sensor can only measure a limited number of **samples** at a **discrete** set of energy levels

Sampling & Quantization are the processes of converting a continuous **analogue** signal into a digital representation of this signal

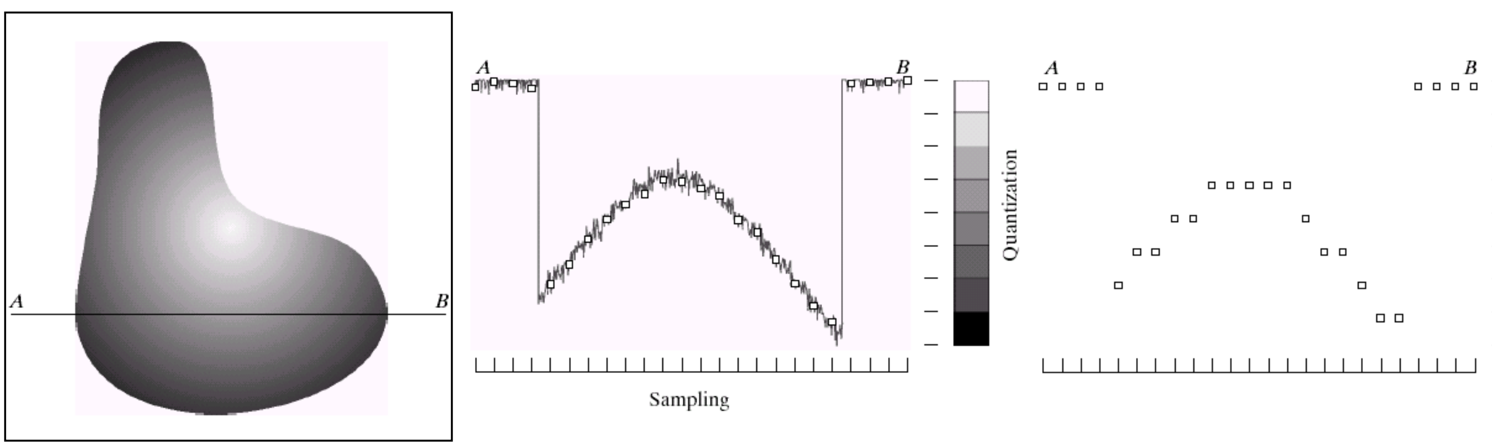
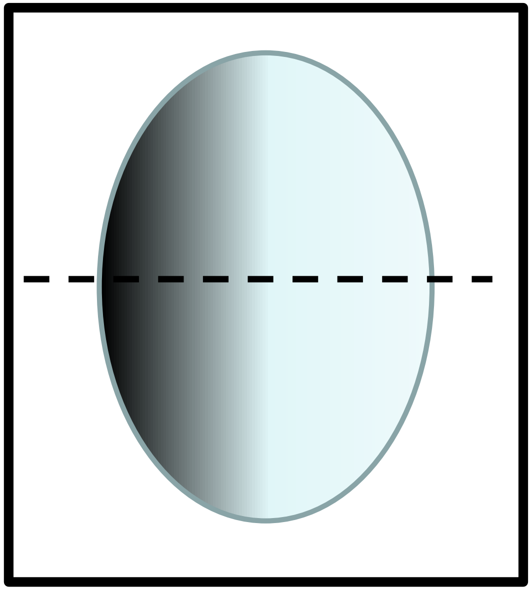


Image Sampling And Quantization



Billion of frequencies are falling on the object and we sample to get only few

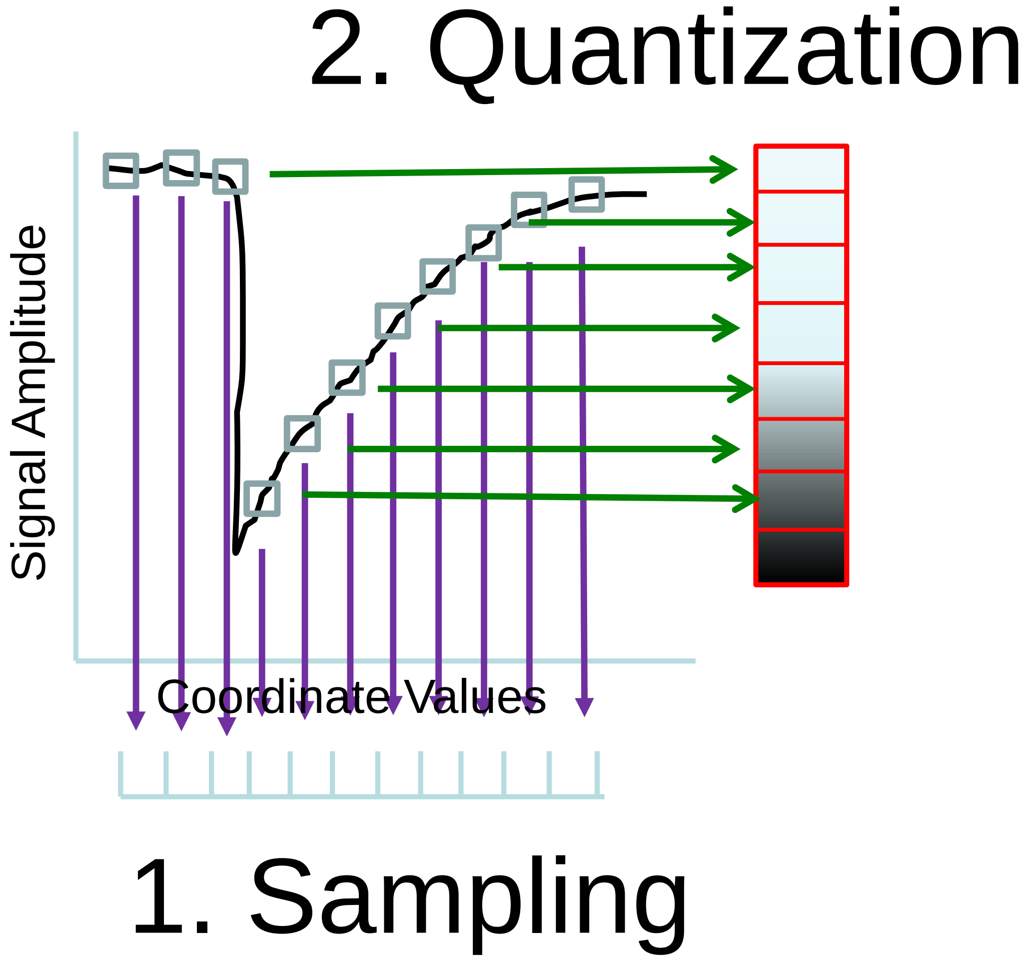


Image Sampling And Quantization

An image may be continuous with respect to the x- and y-coordinates, and also in amplitude. To convert it to digital form, we have to sample the function in both coordinates and in amplitude. Digitizing the coordinate values is called ***sampling***. Digitizing the amplitude values is called ***quantization***.

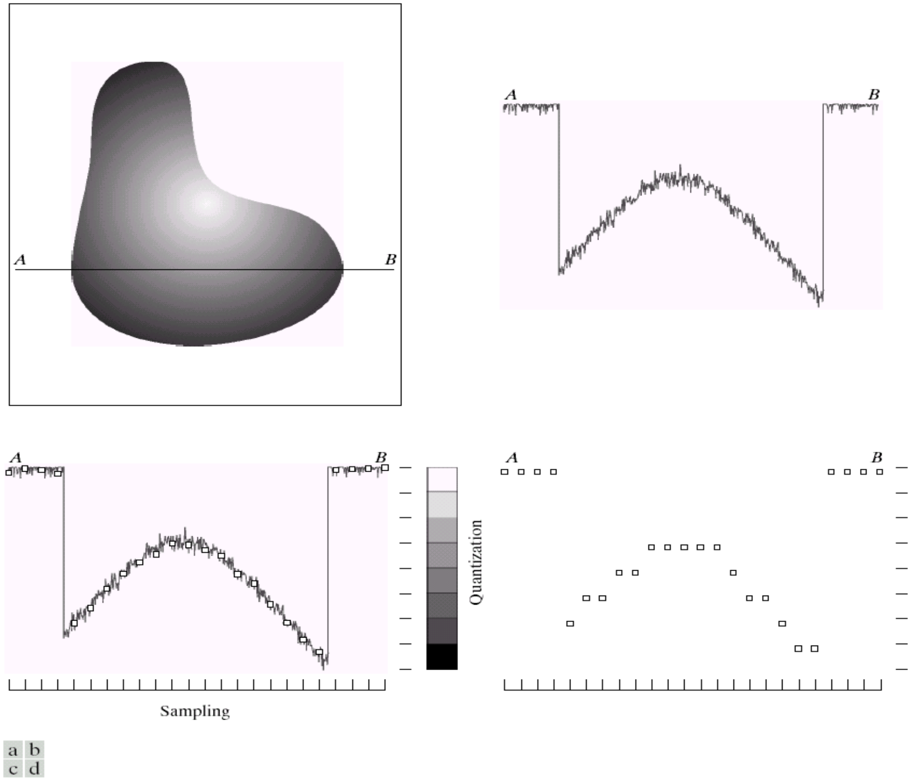


FIGURE 2.16 Generating a digital image. (a) Continuous image. (b) A scan line from A to B in the continuous image, used to illustrate the concepts of sampling and quantization. (c) Sampling and quantization. (d) Digital scan line.

Image Sampling And Quantization (cont…)

Remember that a digital image is always only an **approximation** of a real world scene

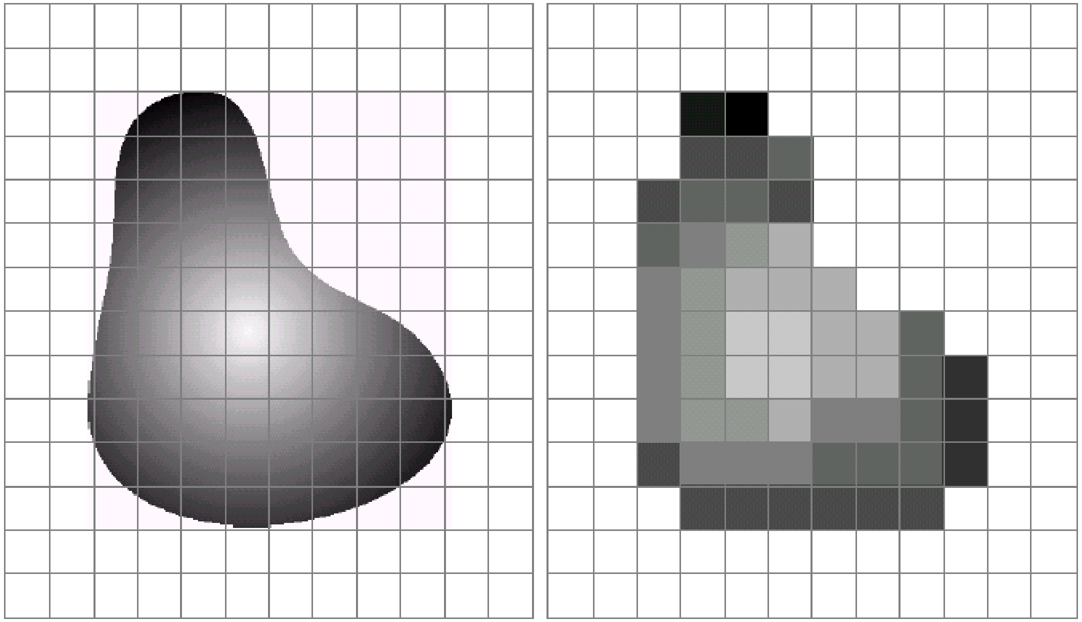


Image Representation

Images taken from Gonzalez & Woods, Digital Image Processing (2002)

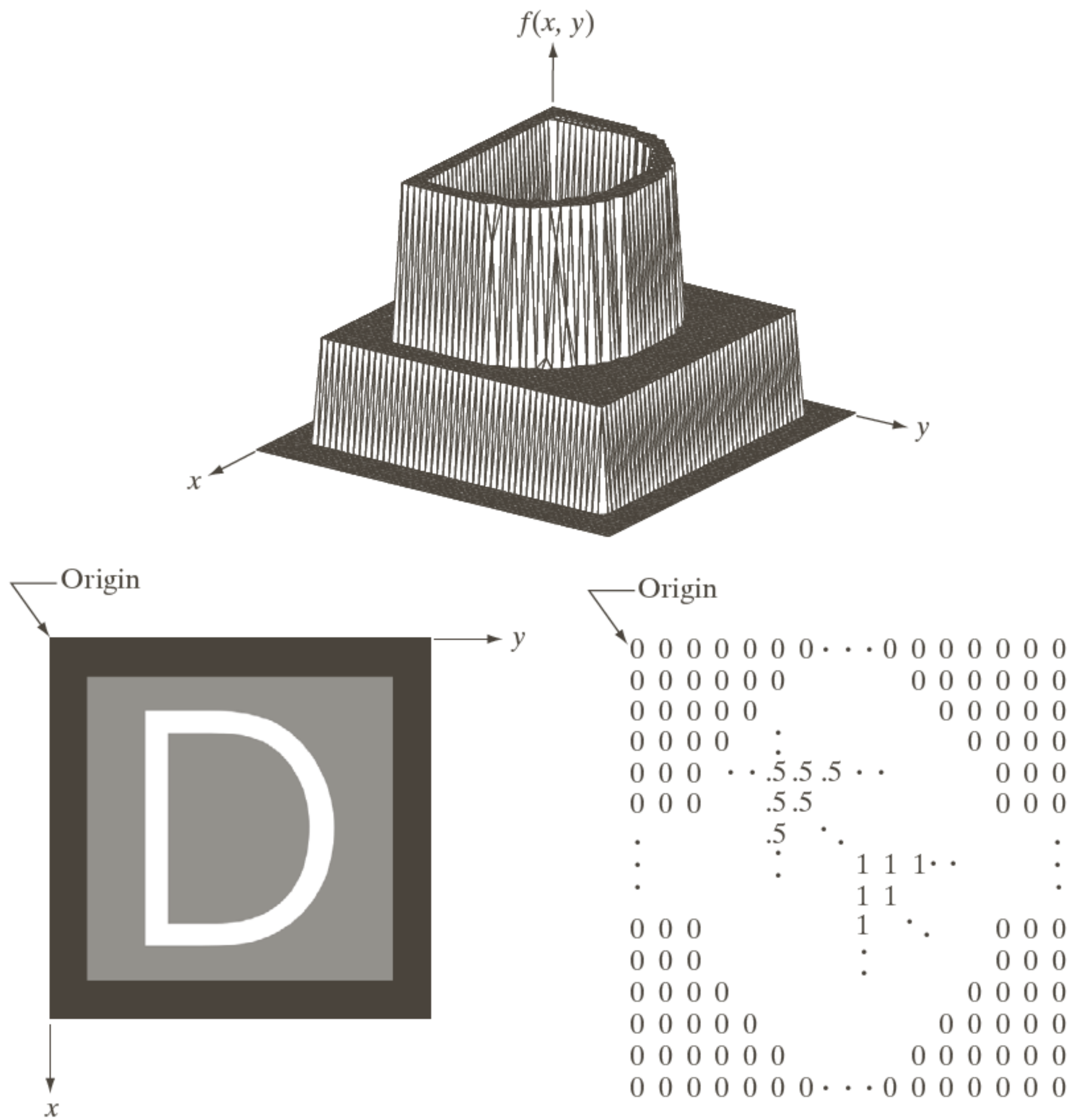


Image Representation

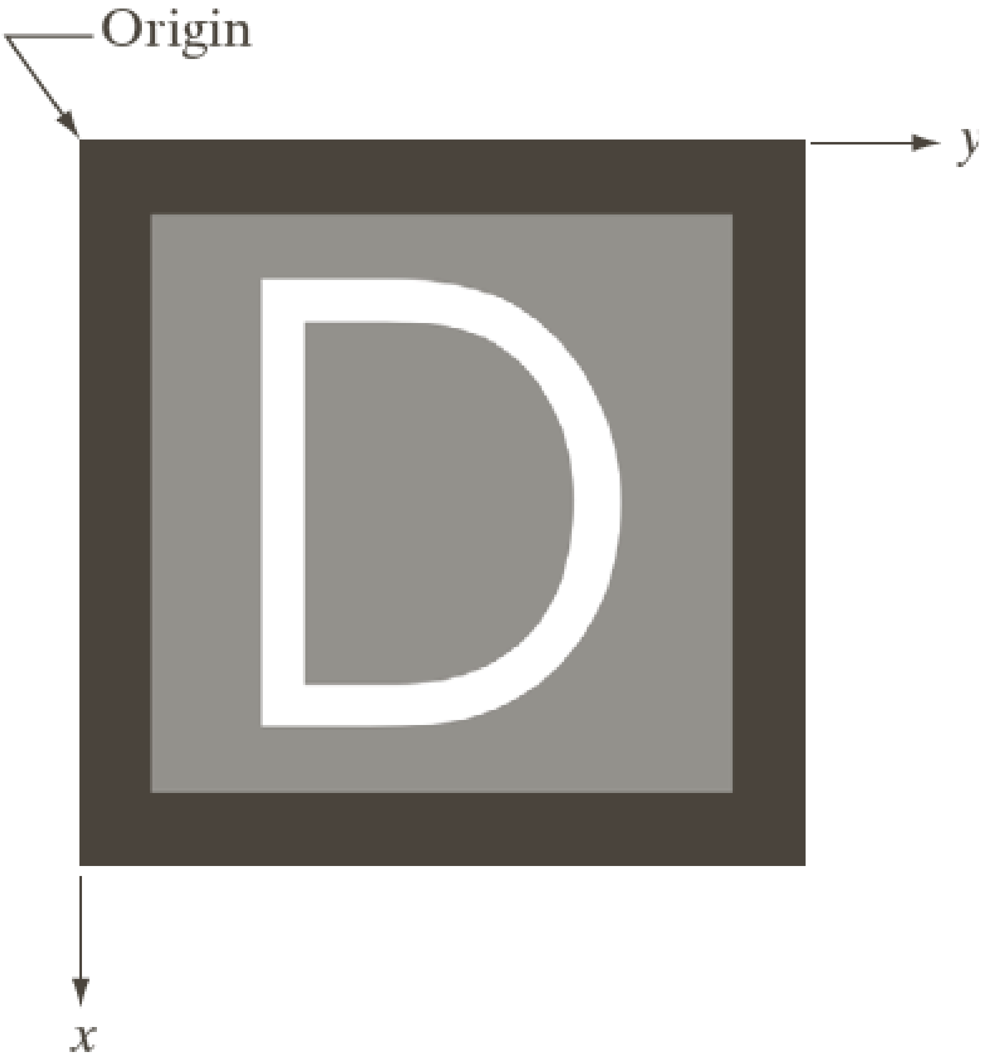


Image Representation

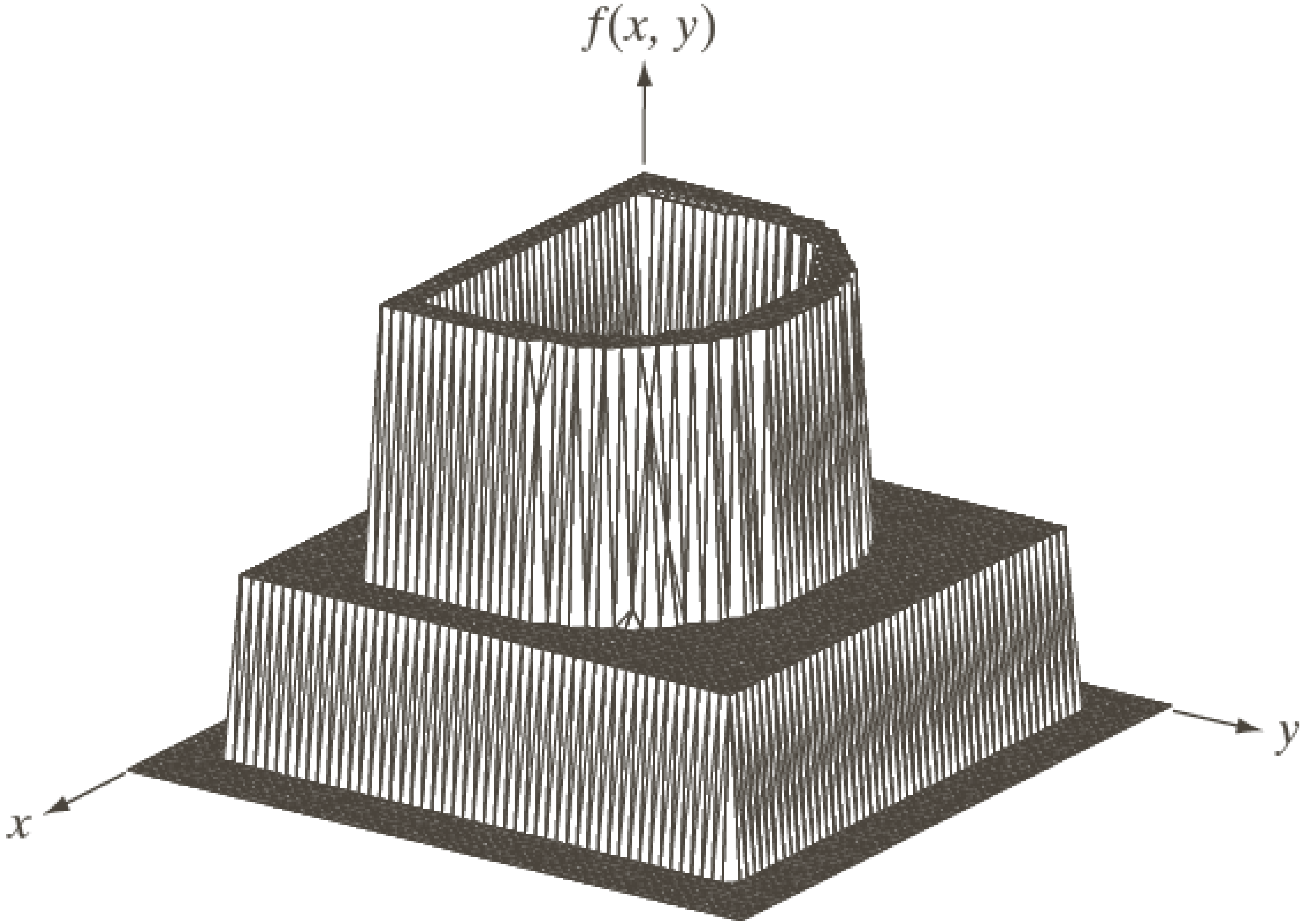
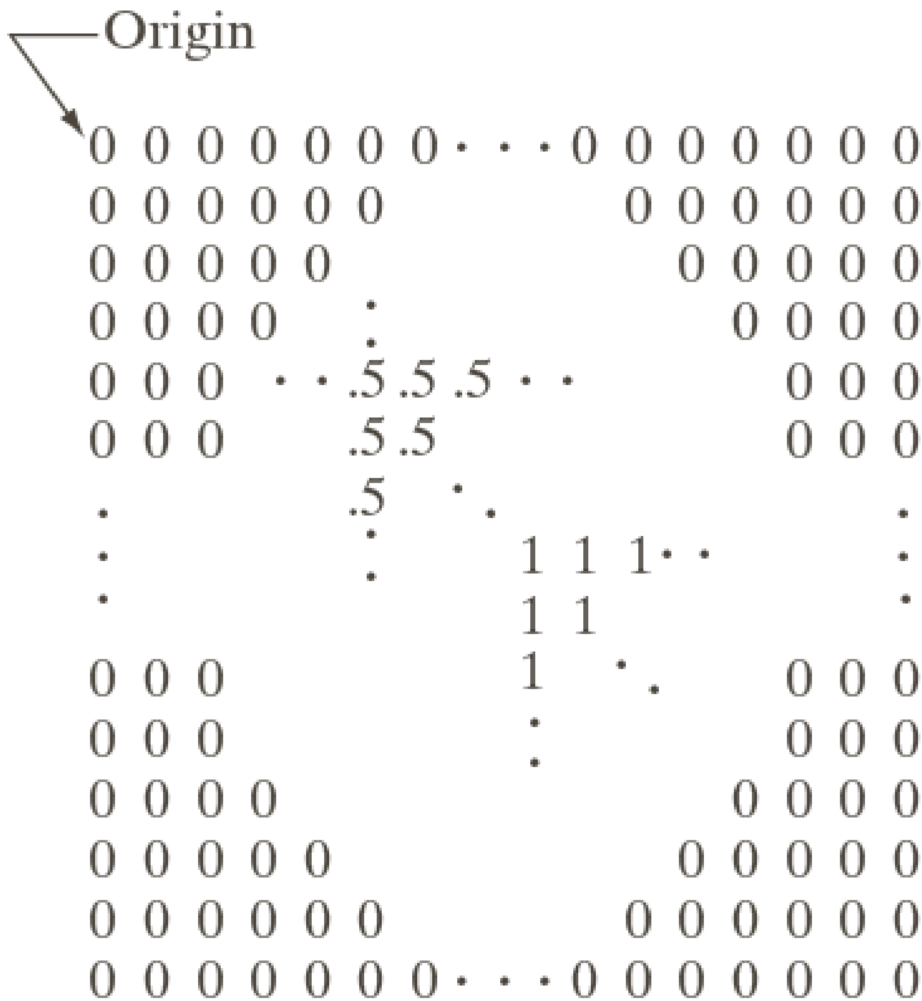


Image Representation



Spatial Resolution

The ***spatial resolution*** of an image is determined by how sampling was carried out.

Spatial resolution simply refers to the smallest discernable detail in an image

- Vision specialists will often talk about pixel size
- Graphic designers will talk about *dots per inch* (DPI)

Spatial Resolution (cont…)

Images taken from Gonzalez & Woods, Digital Image Processing (2002)

Spatial Resolution (cont…)

Resolution:
1024x1024

Spatial Resolution (cont…)

Resolution:
512x512

Spatial Resolution (cont…)

Resolution:
256x256

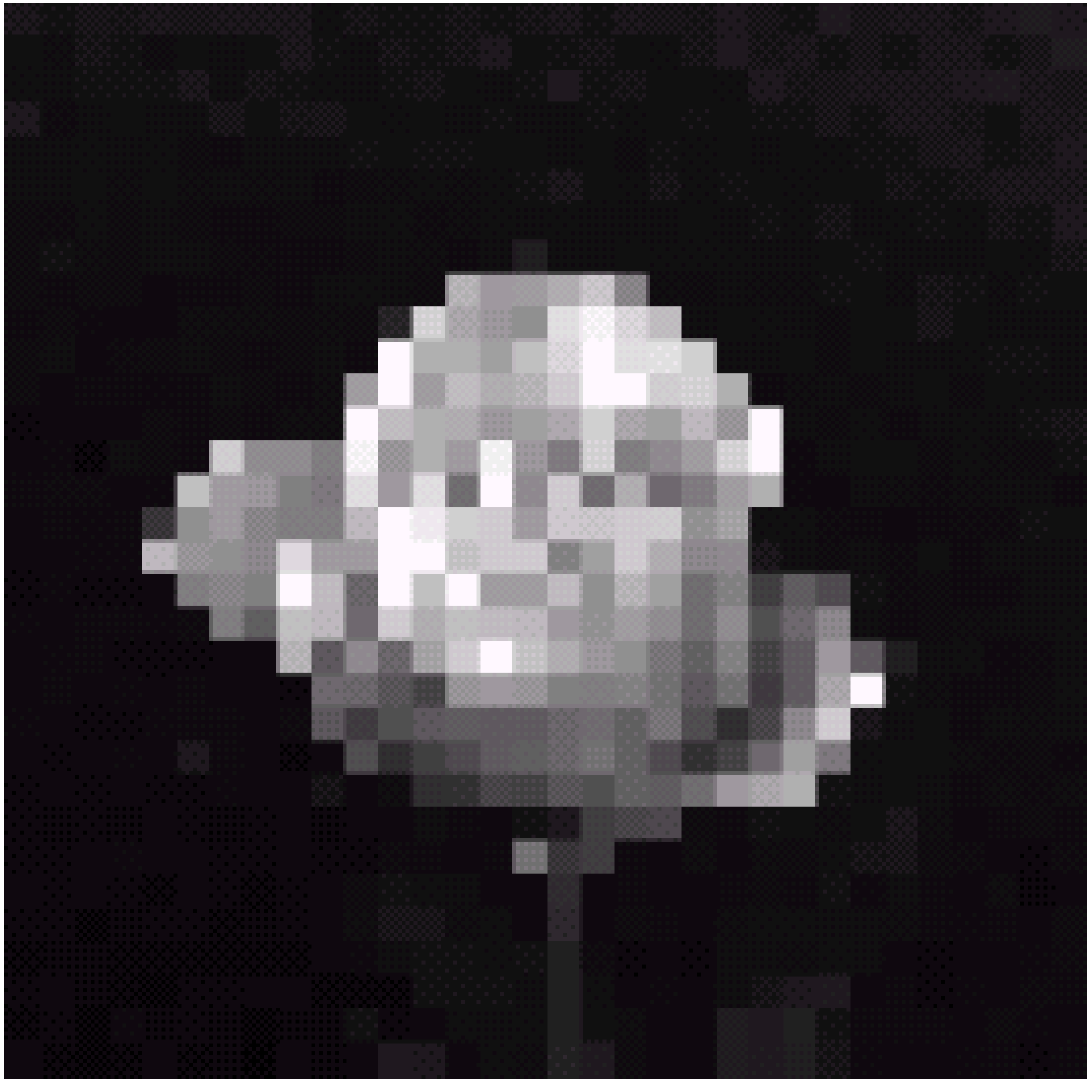
Spatial Resolution (cont…)

Resolution: 128x128

Spatial Resolution (cont…)

Resolution: 64x64

Spatial Resolution (cont…)



Resolution:
32x32

Spatial Resolution (cont…)

Resolution: dots (pixels) per unit distance

***dpi*: dots per inch**

a b
c d

FIGURE 2.20 Typical effects of reducing spatial resolution. Images shown at: (a) 1250 dpi, (b) 300 dpi, (c) 150 dpi, and (d) 72 dpi. The thin black borders were added for clarity. They are not part of the data.

Intensity Level Resolution

Intensity level resolution refers to the number of intensity levels used to represent the image

- The more intensity levels used, the **finer the level of detail discernable** in an image
- Intensity level resolution is usually given in terms of the number of bits used to store each intensity level

Number of Bits	Number of Intensity Levels	Examples
1	2	0, 1
2	4	00, 01, 10, 11
4	16	0000, 0101, 1111
8	256	00110011, 01010101
16	65,536	1010101010101010

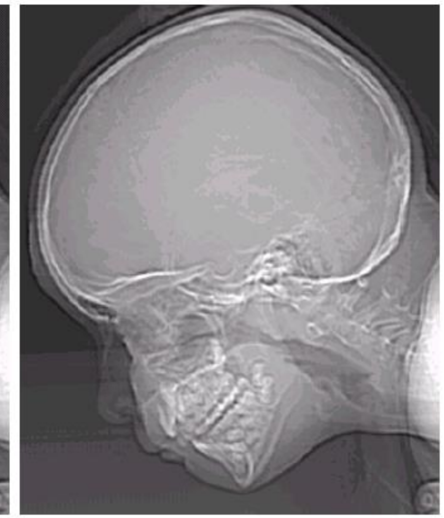
Intensity Level Resolution (cont…)

256 grey levels (8 bits per pixel)

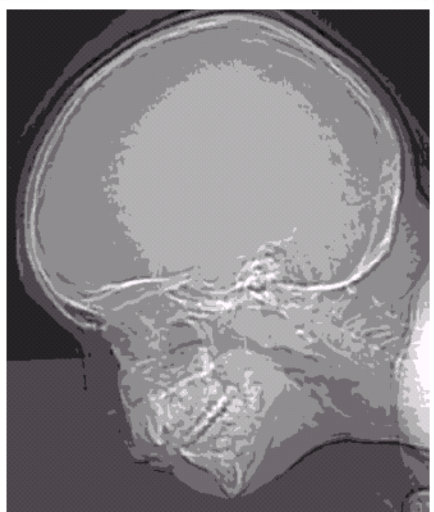
128 grey levels (7 bpp)

64 grey levels (6 bpp)

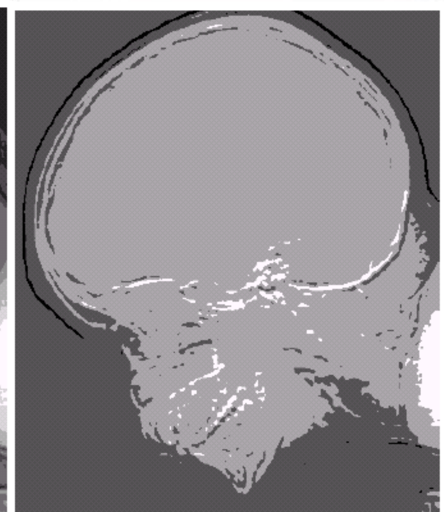
32 grey levels (5 bpp)



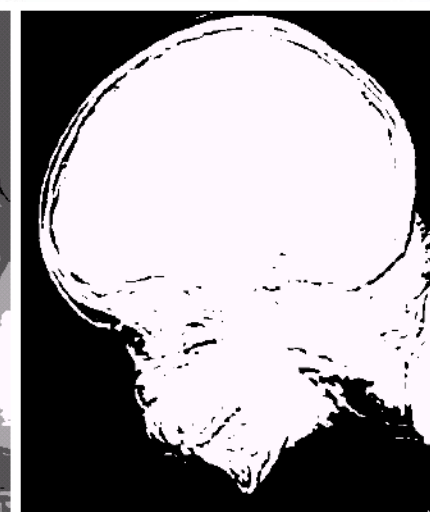
16 grey levels (4 bpp)



8 grey levels (3 bpp)



4 grey levels (2 bpp)



2 grey levels (1 bpp)

Images taken from Gonzalez & Woods, Digital Image Processing (2002)

Intensity Level Resolution (cont…)

Resolution: 8bpp (i.e., 256 Grey Levels)

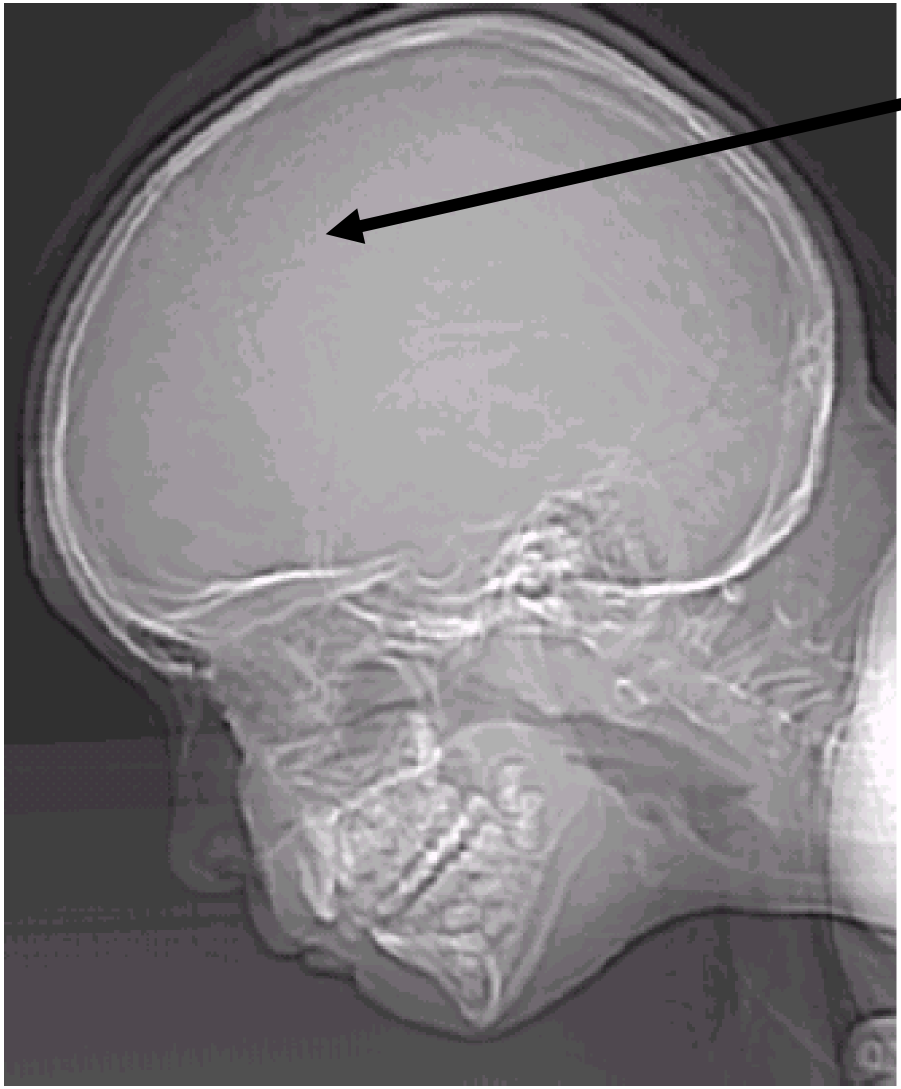
Intensity Level Resolution (cont…)

Resolution: 7bpp
(i.e., 128 Grey
Levels)

Intensity Level Resolution (cont…)

Resolution: 6bpp
(i.e., 64 Grey
Levels)

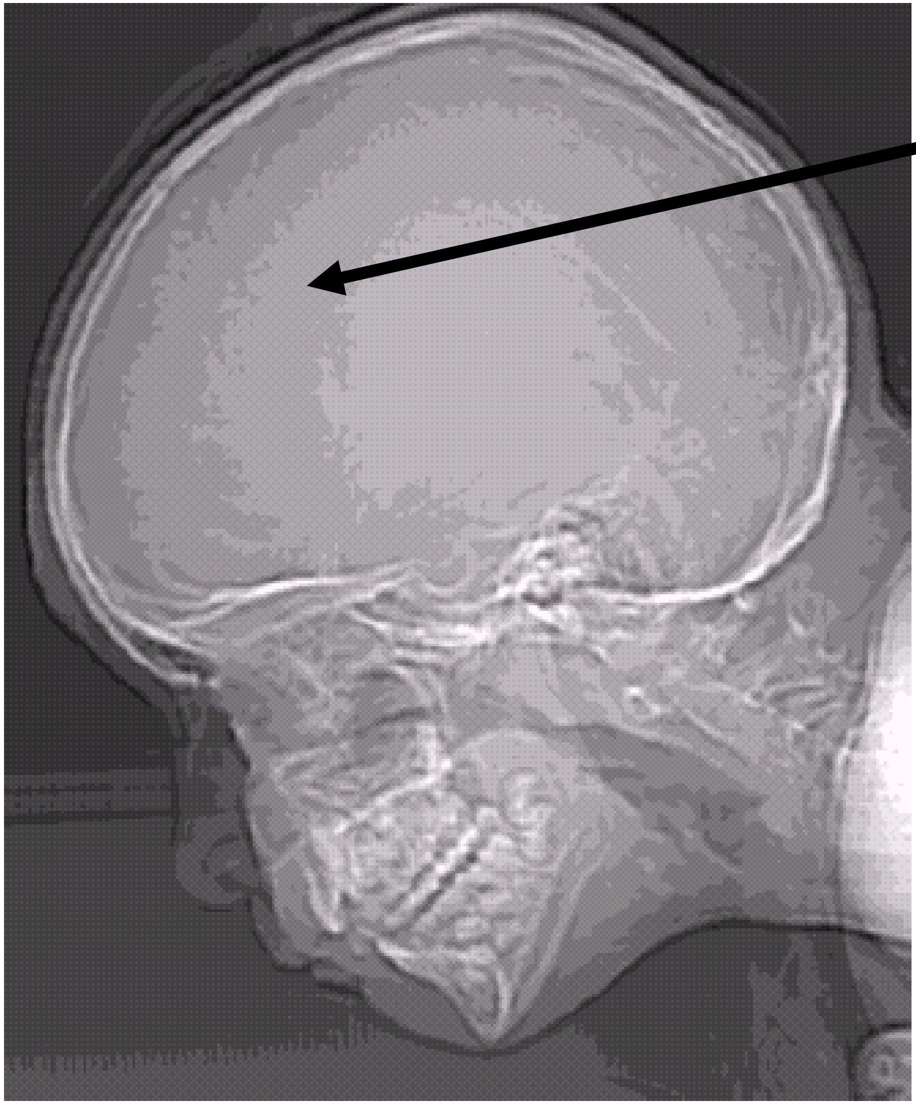
Intensity Level Resolution (cont…)



Notice False Contouring

Resolution: 5bpp (i.e., 32 Grey Levels)

Intensity Level Resolution (cont…)



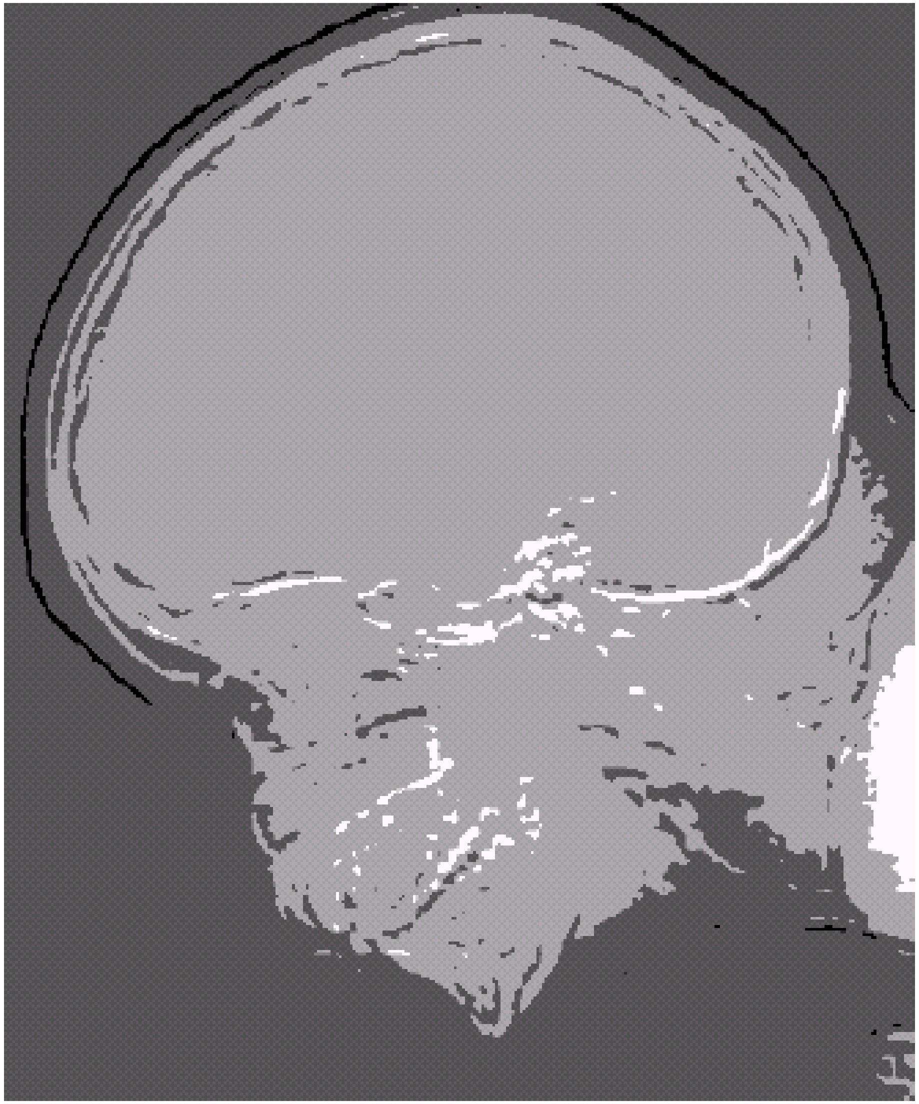
False Contouring becomes more prominent as you decrease bit levels

Resolution: 4bpp (i.e., 16 Grey Levels)

Intensity Level Resolution (cont…)

Resolution: 3bpp (i.e., 8 Grey Levels)

Intensity Level Resolution (cont…)



Resolution: 2bpp (i.e., 4 Grey Levels)

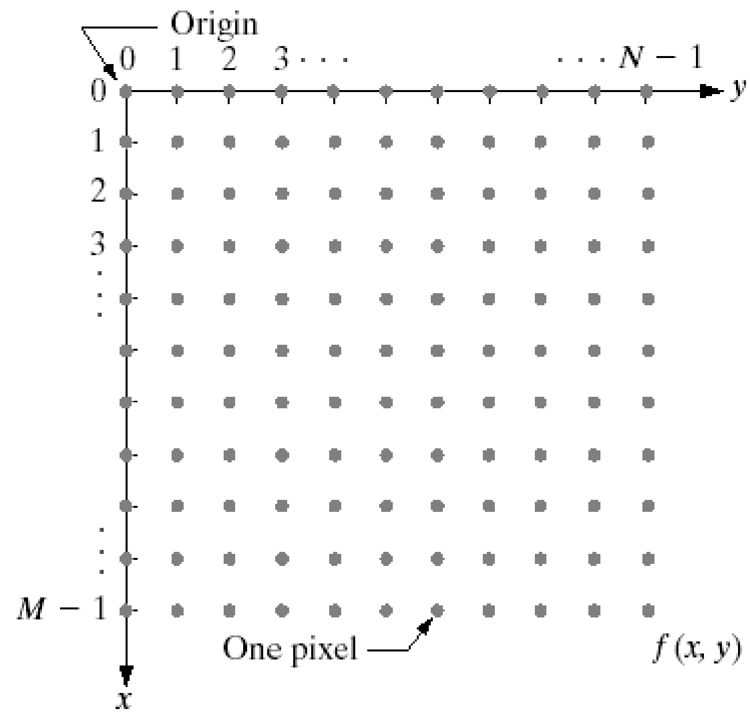
Intensity Level Resolution (cont…)

Resolution: 1bpp (i.e., 2 Grey Levels) also called a binary image.

Image Representation

Digital image

- ***M*** $\times$ ***N*** array
- \# bits to store : ***b* = *M*** $\times$ ***N*** $\times$ ***k bits***
- ***L*** discrete intensities – power of 2
  - ***L* = 2*^k^*** — $L = 2^k$
  - Integers in the interval [**0, *L* - 1**]
  - **Dynamic range** is the range of tonal difference between the lightest and darkest light of an image.
    - **If low**: image has a dull, washed-out gray look.
  - **Contrast**: difference between highest and lowest intensity
    - **If high**: Images are visually appealing.



Brightness & Contrast

Brightness is a relative term. It depends on your visual perception. Brightness comes into picture when we try to compare with a reference.

Contrast is the **variation in intensity levels** of an image. When the **Dynamic range** of an image **covers all available range** of the imaging system then the image exhibits **high contrast**.

$$Brightness(B) = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i,j)$$

$$Contrast = \sqrt{\frac{1}{MN} (f(i,j) - B)^2}$$

Contrast Examples

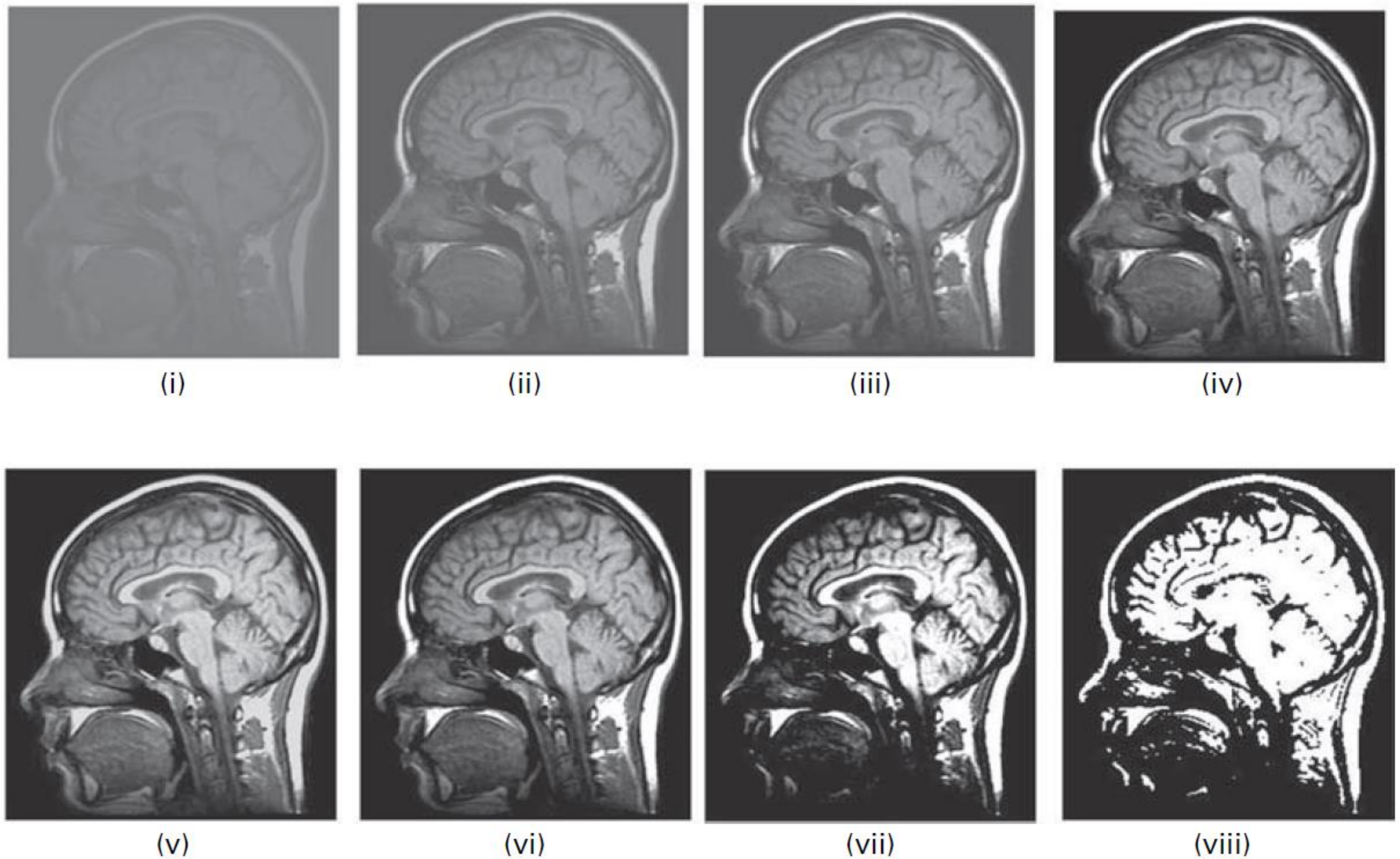
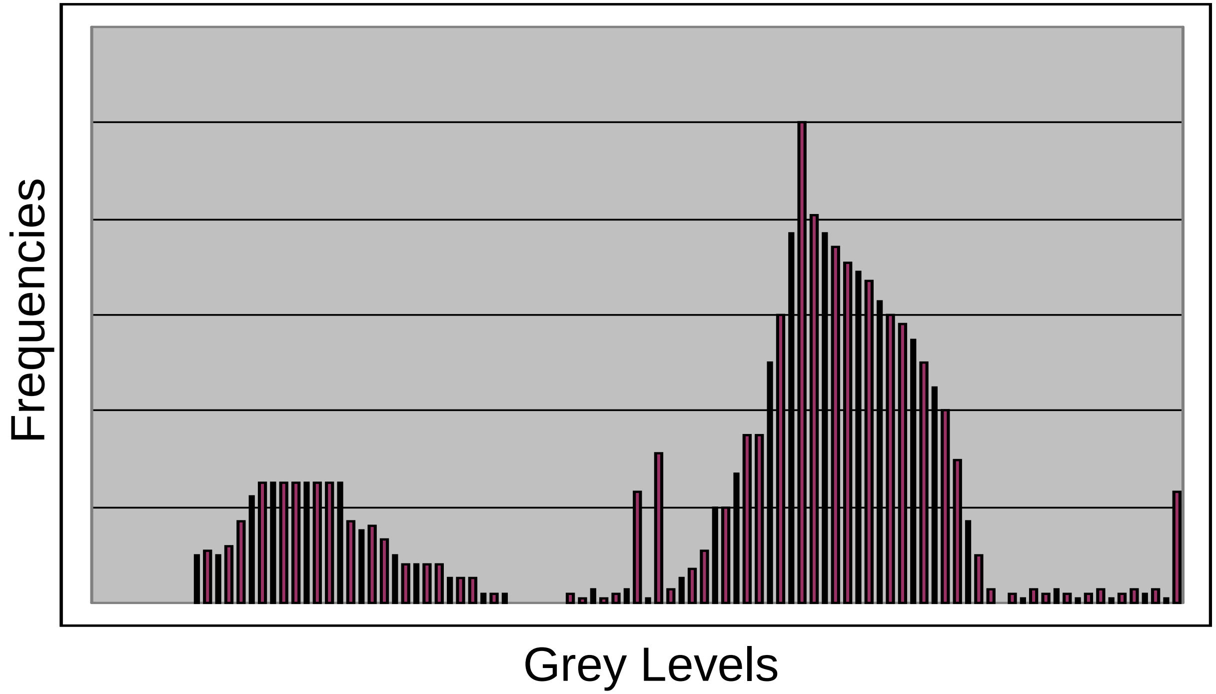


Figure 5.4 A series of images showing different contrasts. (The lowest contrast image is (i), and the highest contrast image is (viii).)

Image Histograms

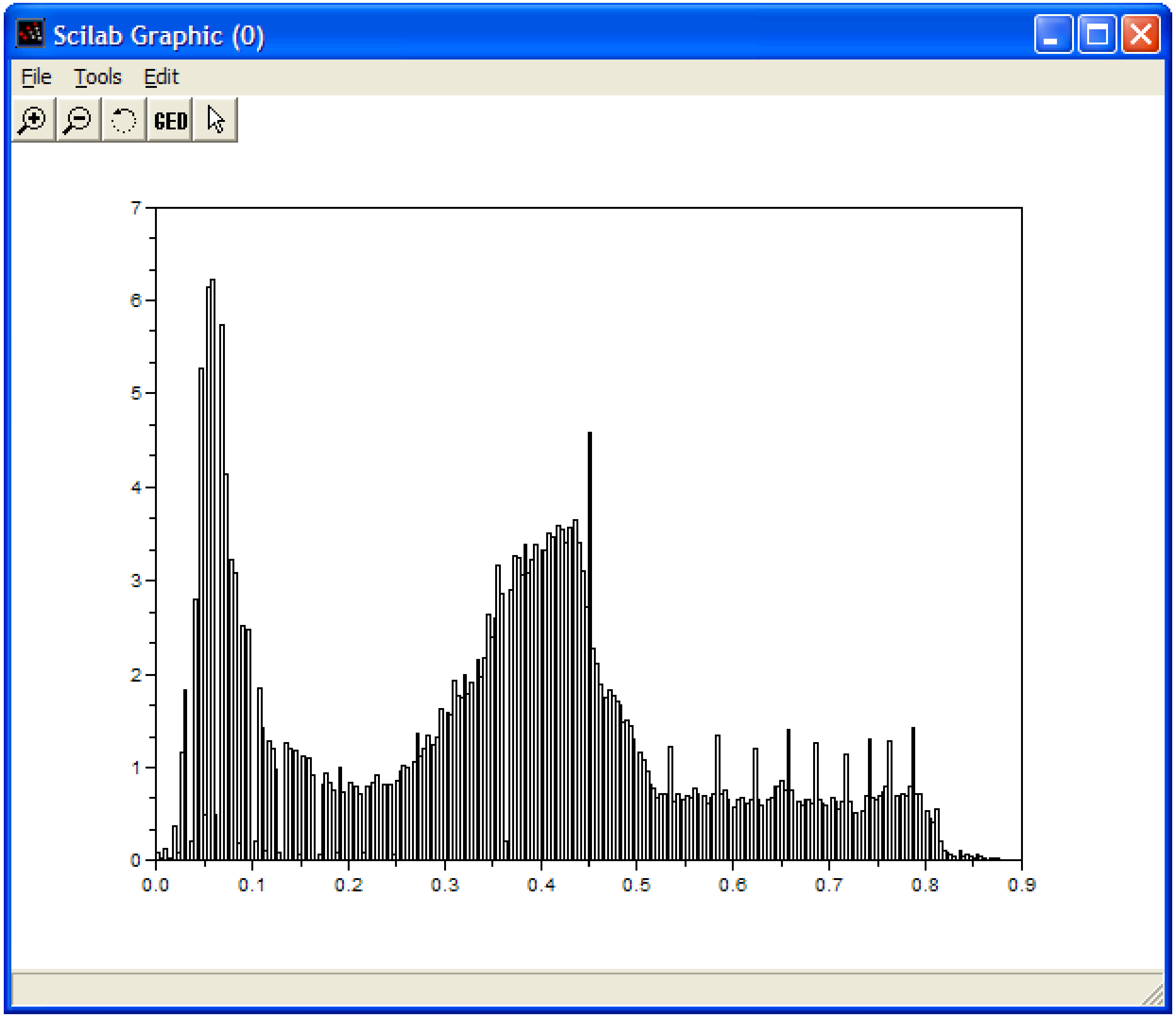
The histogram of an image shows us the distribution of grey levels in the image

Massively useful in image processing, especially in segmentation

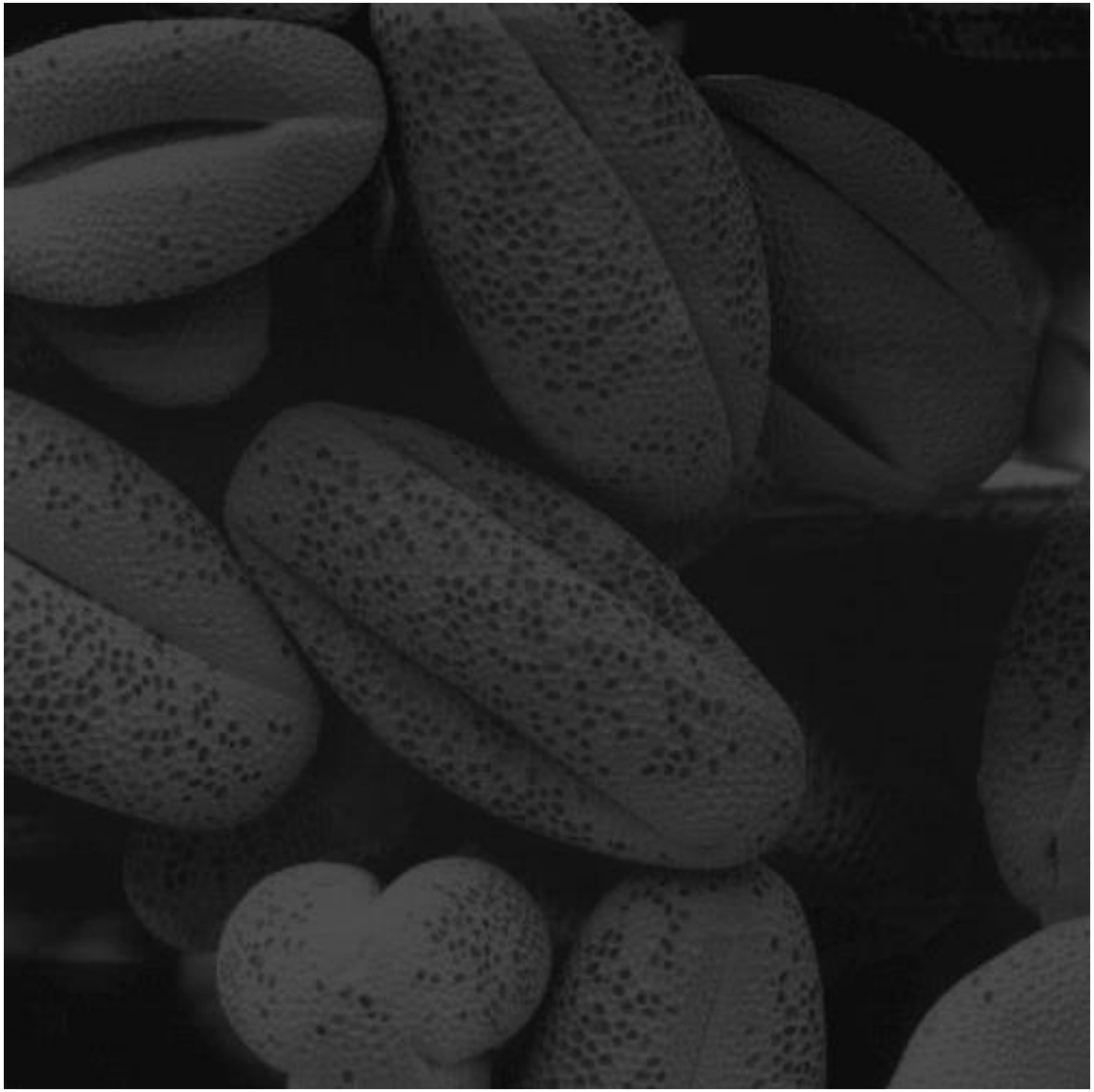


Histogram Examples

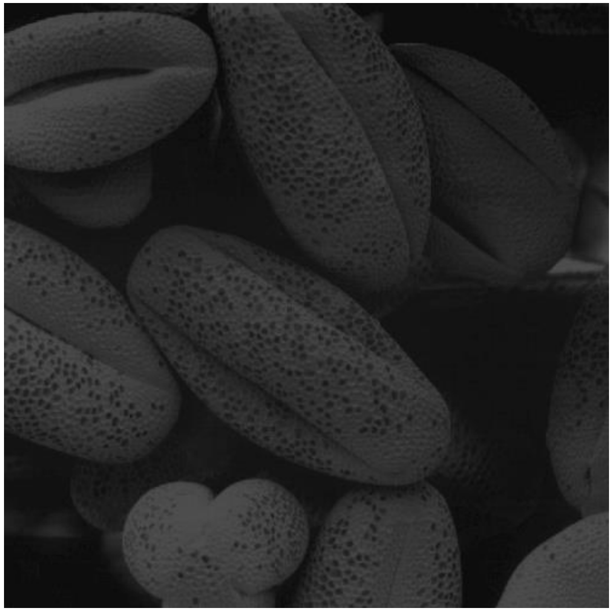
Histogram Examples (cont…)

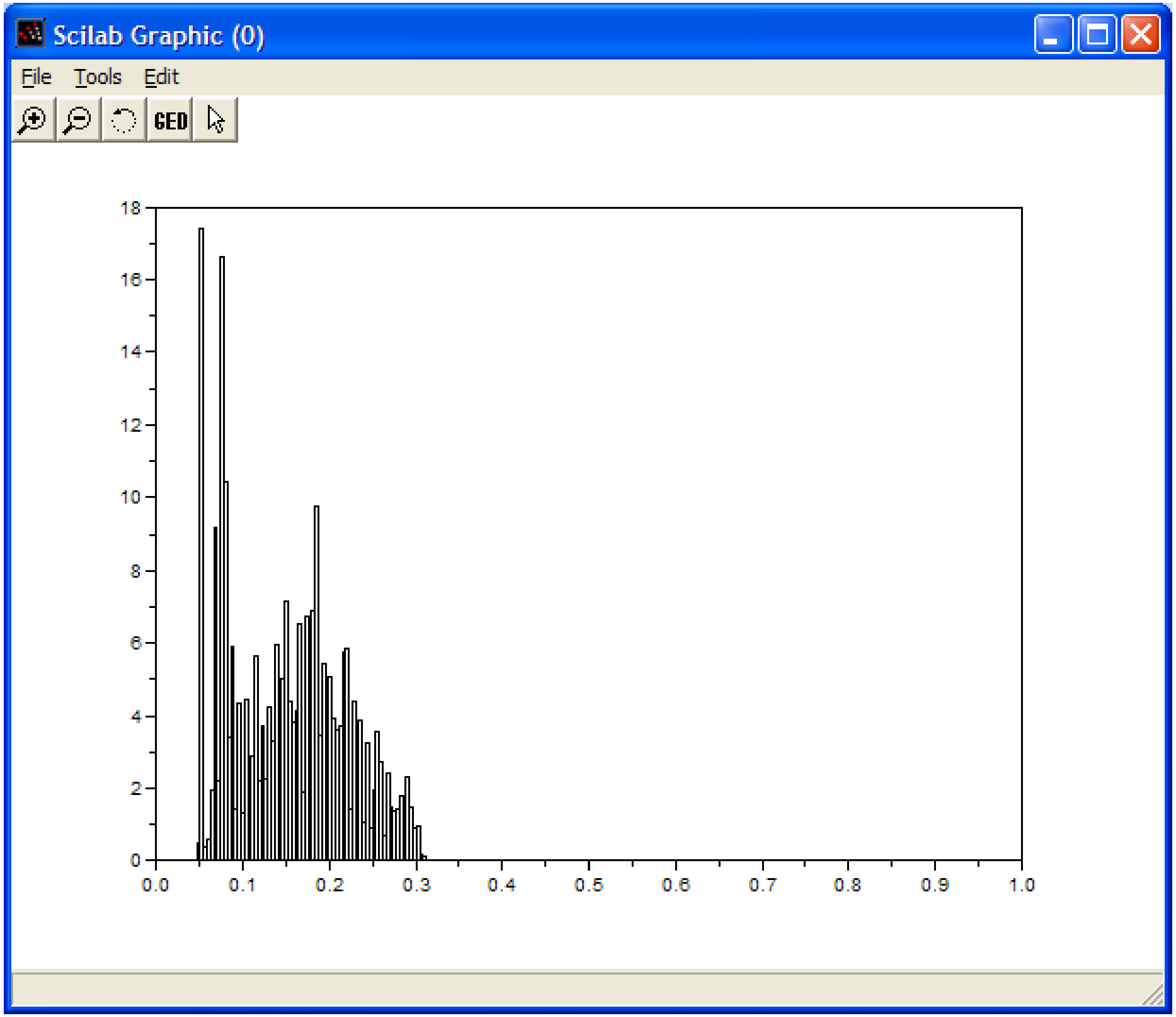


Histogram Examples (cont…)



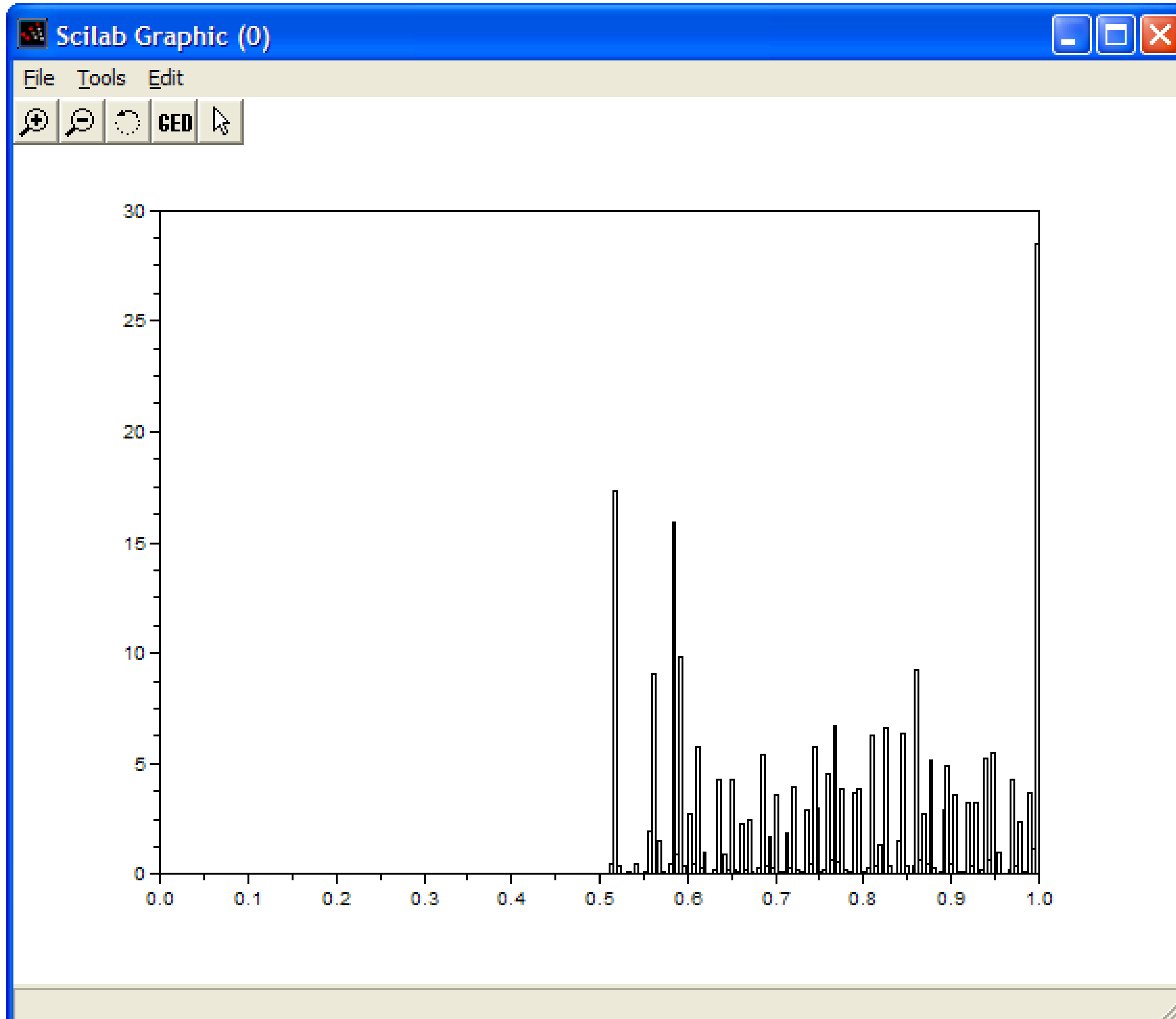
Histogram Examples (cont…)



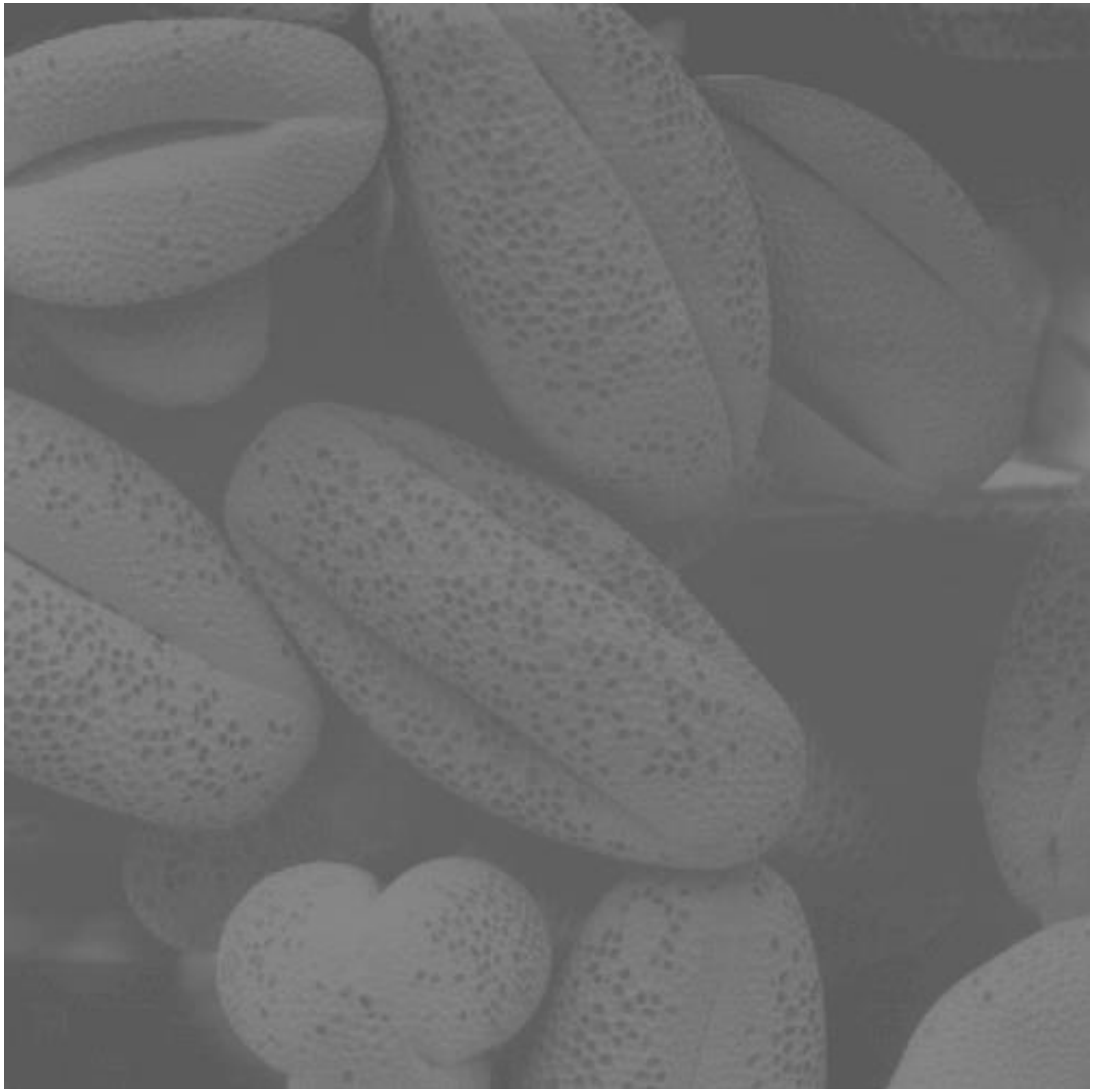


Histogram Examples (cont…)

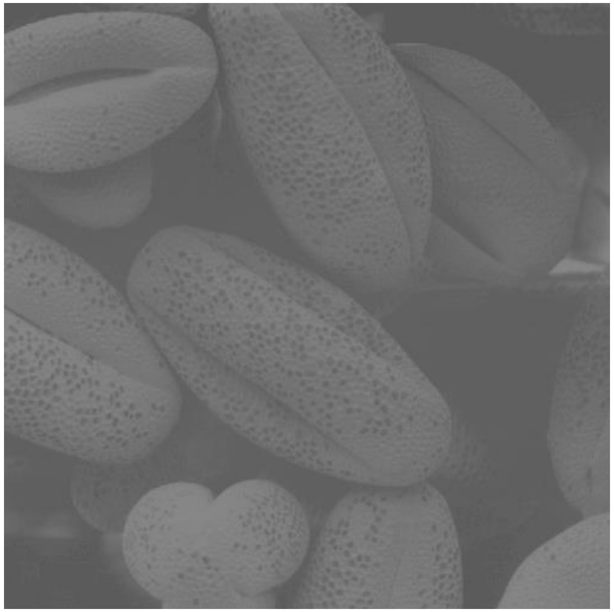
Histogram Examples (cont…)

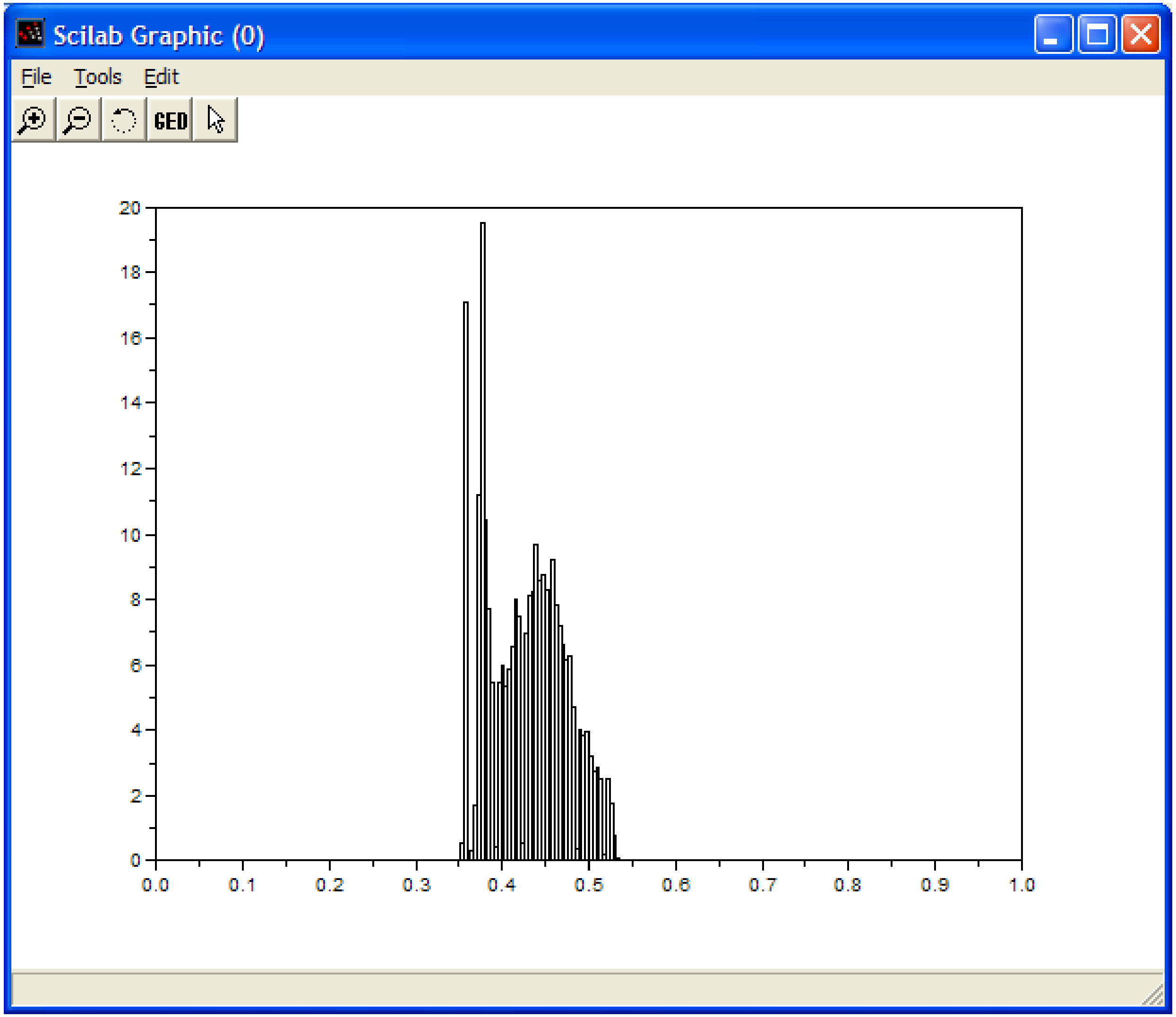


Histogram Examples (cont…)



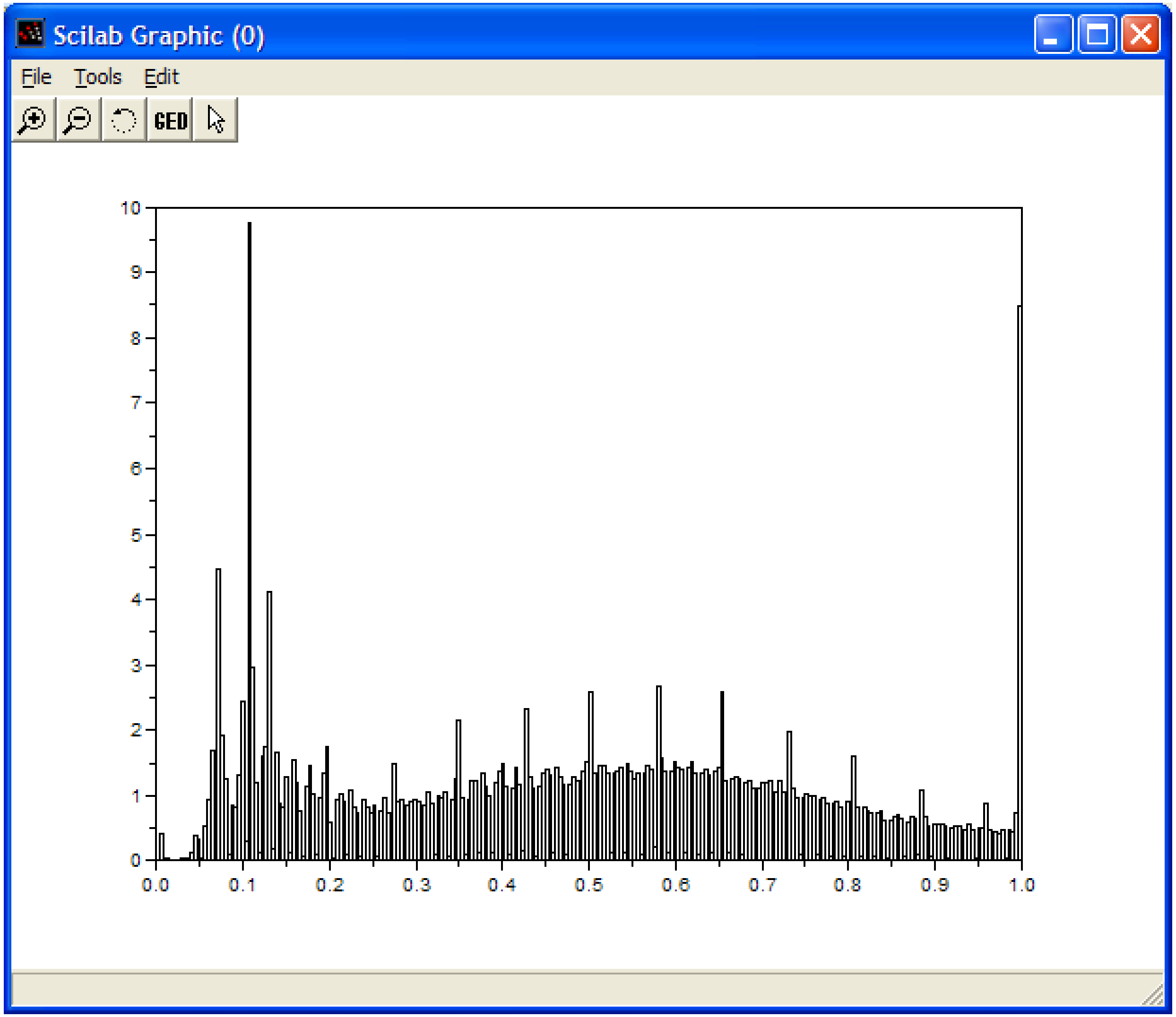
Histogram Examples (cont…)





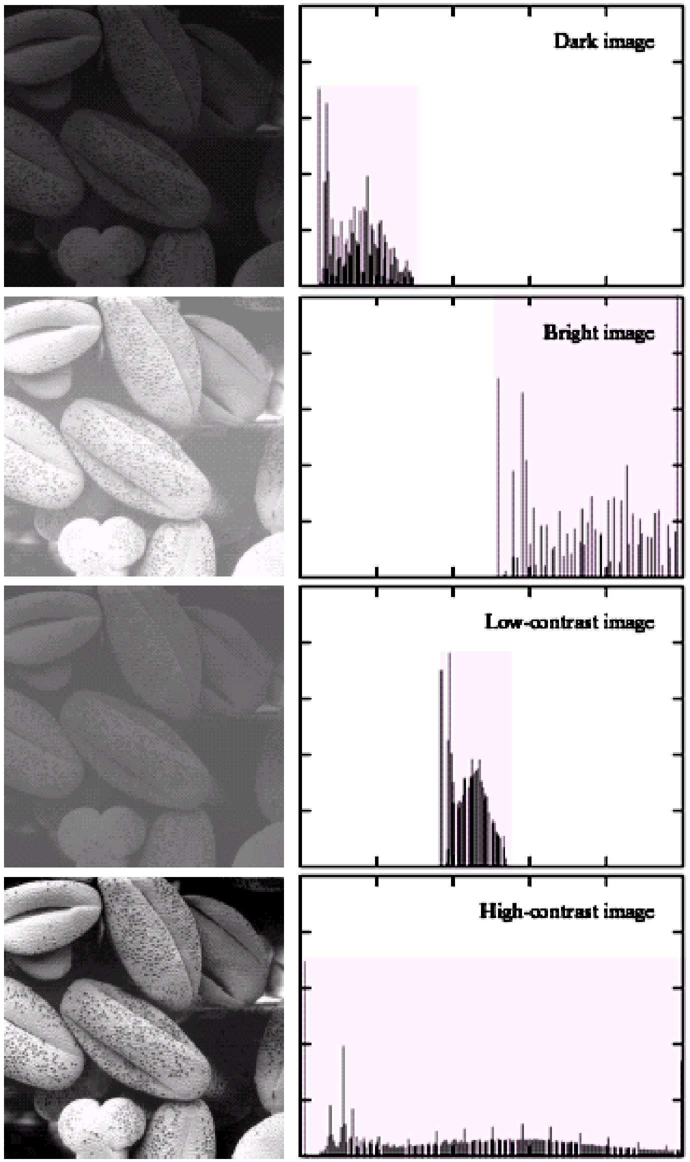
Histogram Examples (cont…)

Histogram Examples (cont…)



Histogram Examples (cont…)

- A selection of images and their histograms
- Notice the relationships between the images and their histograms
- Note that the **high contrast image** has the most **evenly spaced histogram**



Dynamic Range (Scene vs Detector)

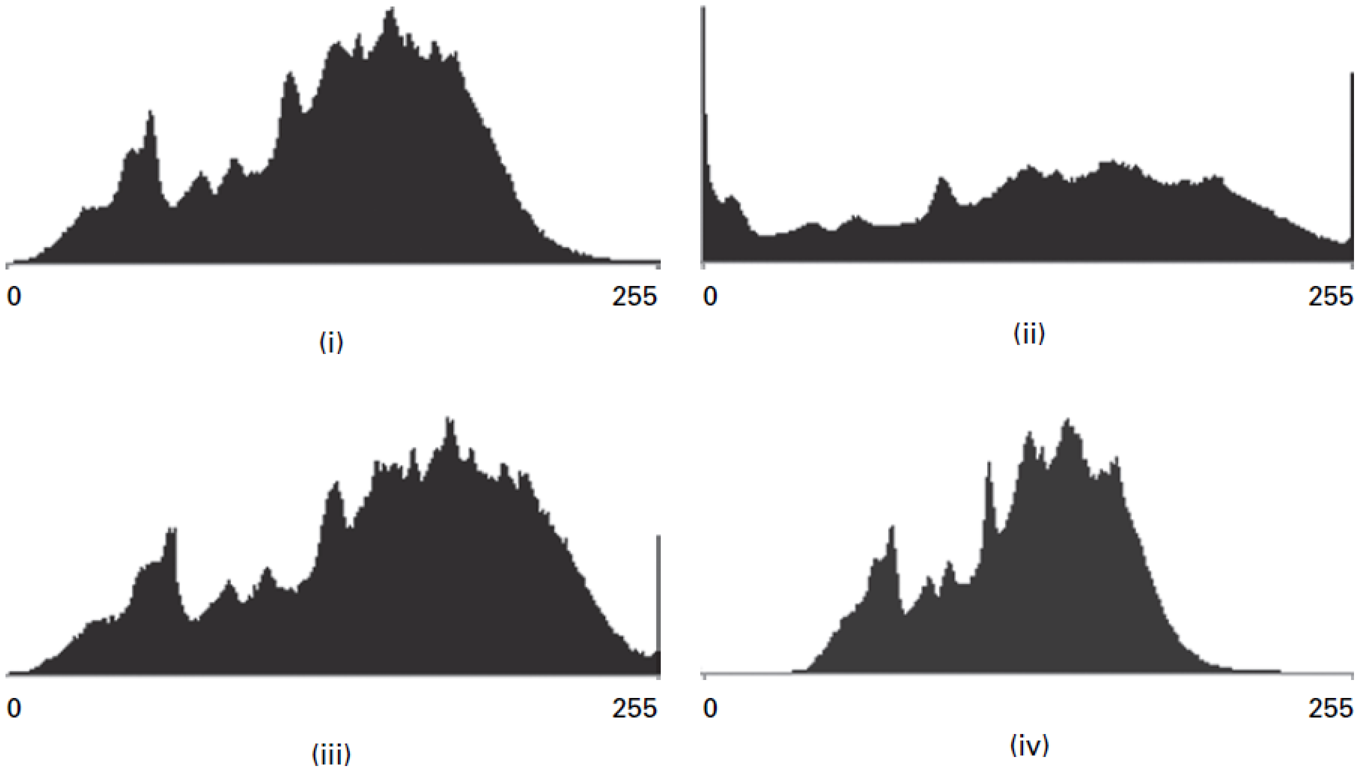
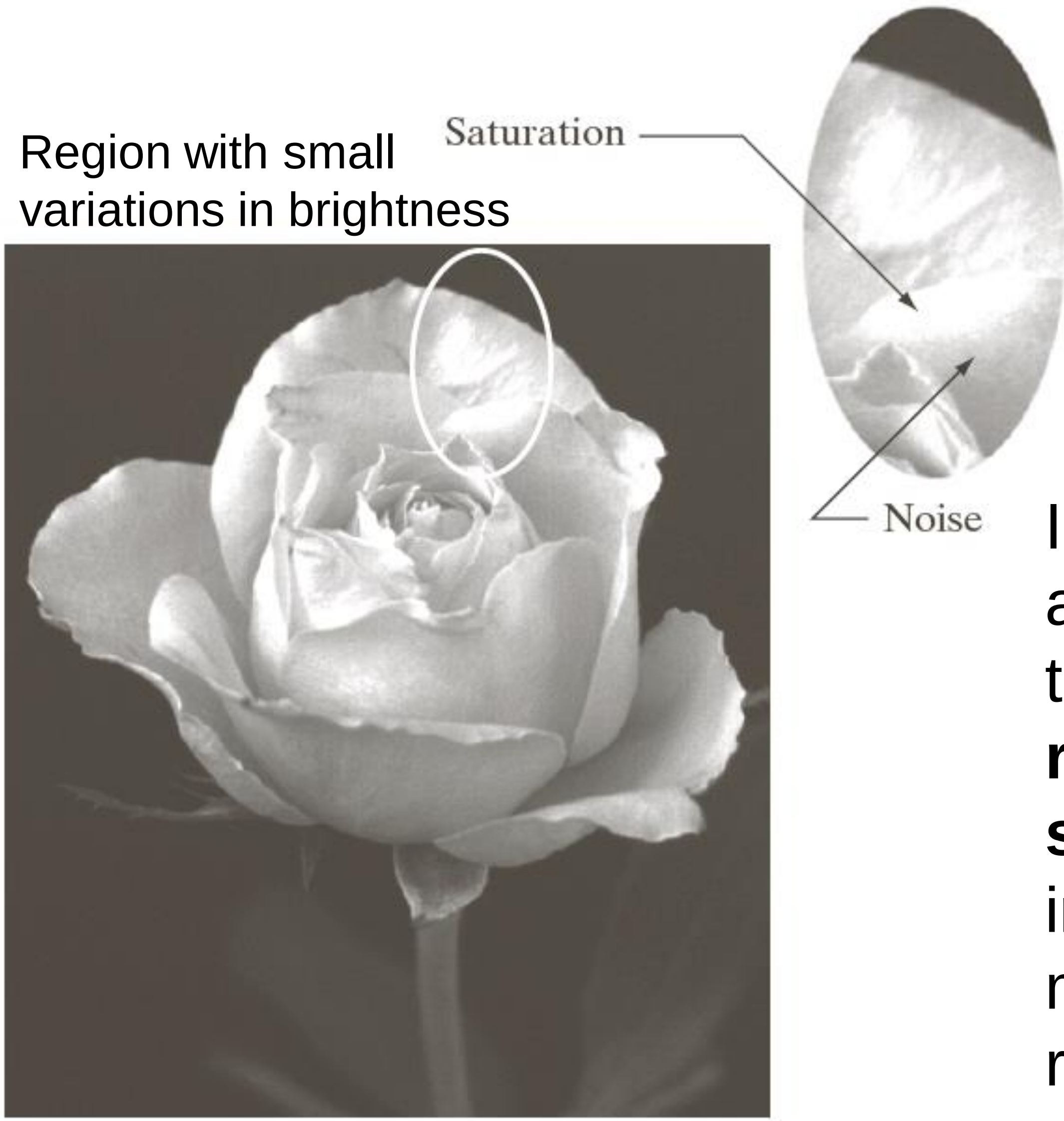


Figure 5.3 Gray-level histograms which indicate: (i) the full dynamic range of the scene is optimally captured by the detector; (ii) the dynamic range of the scene is larger than the dynamic range of the detector, resulting in overflow at the top end of the histogram and underflow at the bottom end of the histogram; (iii) the dynamic ranges of the scene and the detector are matched, but incorrect exposure has resulted in the recorded pixel values being too large and overflowing at the top end of the histogram; (iv) the dynamic range of the scene is lower than the dynamic range of the detector.

Saturation & Noise



Noise is an unwanted signal that exists in electronic systems

In imaging, **saturation** is a type of distortion where the **recorded image (or region) is limited to some maximum value**, interfering with the measurement of bright regions of the scene.

Images taken from Gonzalez & Woods, Digital Image Processing (2002)

Entropy

Entropy is a measure of the amount of disorder or randomness in a system.

For images entropy measures the average global information content of the image in bits per pixel.

In information theory the **information content** of a single message state in units of information is given by:

$$I(E) = \log(1/P(E)) = -\log P(E)$$

Where $P(E)$ is the prior probability of the occurrence of a message and $I(E)$ is the amount of information in the message.

Entropy (cont..)

In an image, the pixel values, a_i, occur with probabilities $P(a_i)$, which are given by the bin heights of the normalized histogram; the available pixel values run from 0 *to* $2^n–1$.

A first-order estimate of the entropy, *H*, of an image is given by the sum of the information content of each pixel:

$$H = -\sum_{i=0}^{2^n-1} P(a_i)\, I(a_i) = -\sum_{i=0}^{2^n-1} P(a_i) \log_2 P(a_i)$$

$$H = -\sum_{i=0}^{2^n-1} P(a_i)\ \log_2 P(a_i) = -\Sigma(1/2^n)\cdot \log_2(1/2^n) = +\Sigma(1/2^n)\cdot n = n$$

Entropy Example

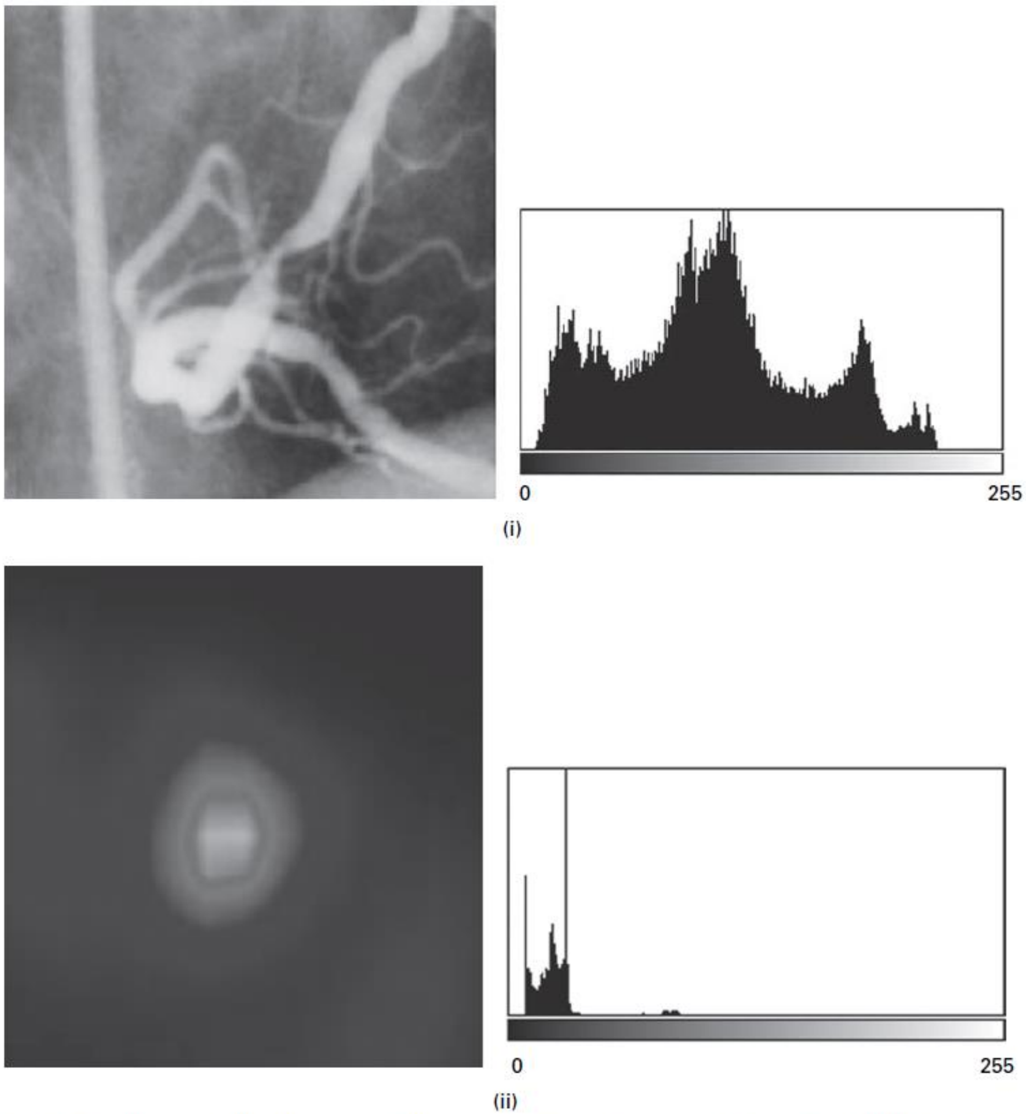


Figure 5.7 Images and their histograms. The corresponding entropies are (i) 7.50 and (ii) 4.95 bits pixel^{-1}.

High Contrast and High Entropy

Low Contrast and Low Entropy

Resolution: How Much Is Enough?

The big question with resolution is always *how much is enough*?

- This all depends on what is in the image and what you would like to do with it
- Key questions include
  - Does the image look aesthetically pleasing?
  - Can you see what you need to see within the image?

Resolution: How Much Is Enough? (cont…)

The picture on the right is fine for counting the number of cars, but not for reading the number plate

Intensity Level Resolution (cont…)

Low Detail | Medium Detail | High Detail

a b c

FIGURE 2.22 (a) Image with a low level of detail. (b) Image with a medium level of detail. (c) Image with a relatively large amount of detail. (Image (b) courtesy of the Massachusetts Institute of Technology.)

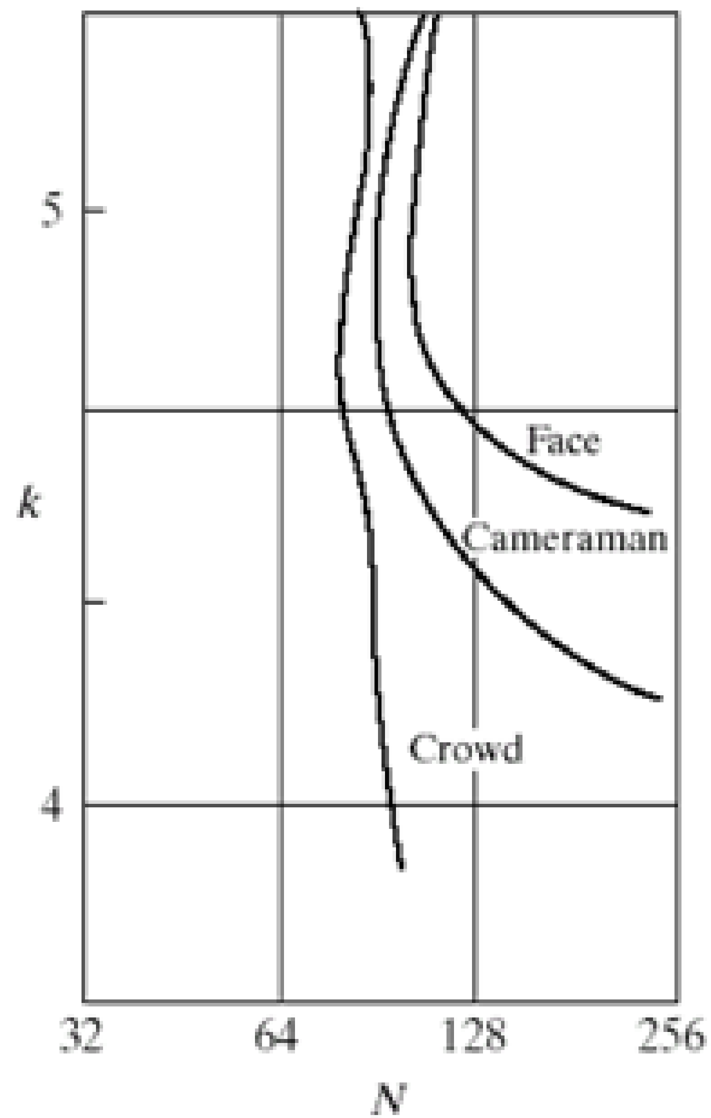
Huang Experiment [1965] attempt to quantify experimentally the effects on image quality produced by varying *N* and *k* simultaneously.

Intensity Level Resolution (cont…)

Isopreference curves tend to become more vertical as the detail in the image increase.

As the detail in the image decrease the perceived quality remained the same in some intervals in which the spatial resolution was increased, but the number of gray levels actually decreased.

A possible explanation is that a decrease in *k* tends to increase the apparent *contrast* of an image, a visual effect that human often perceive as improved quality in an image.



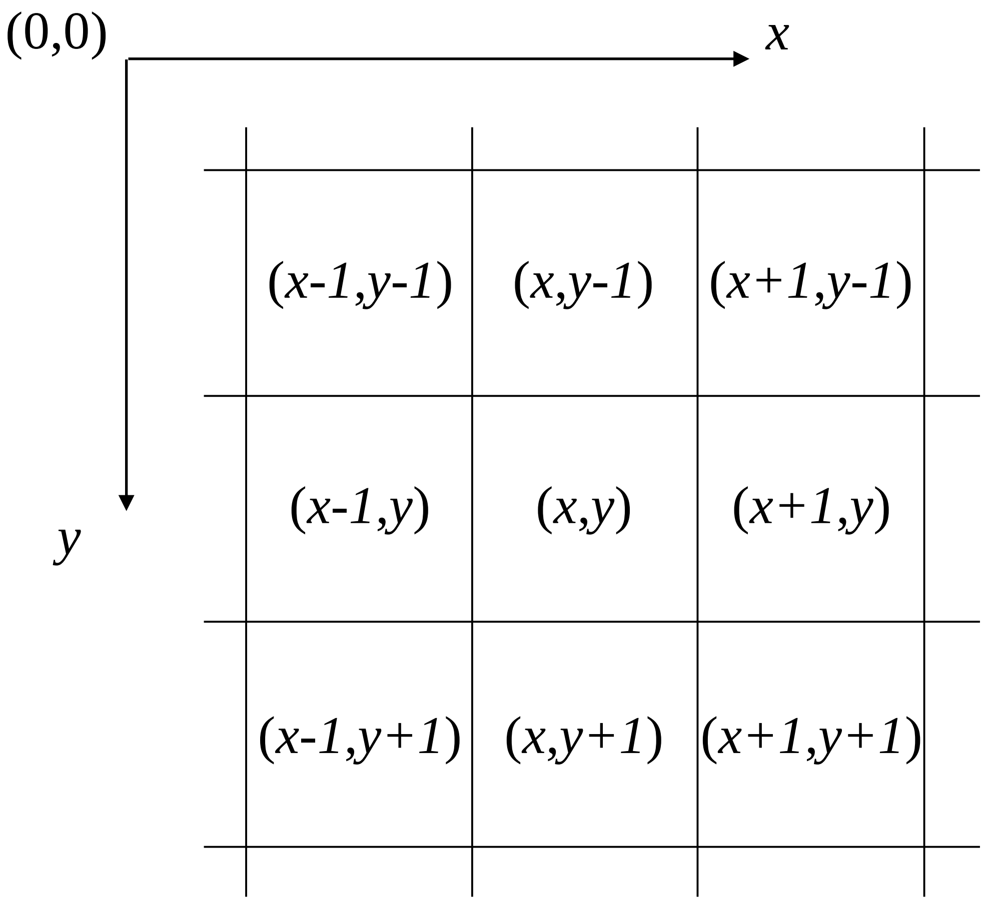
Summary

We have looked at:

- Human visual system
- Light and the electromagnetic spectrum
- Image representation
- Image sensing and acquisition
- Sampling, quantisation and resolution

Next slides we start to look at basic image operations

Basic Relationship of Pixels

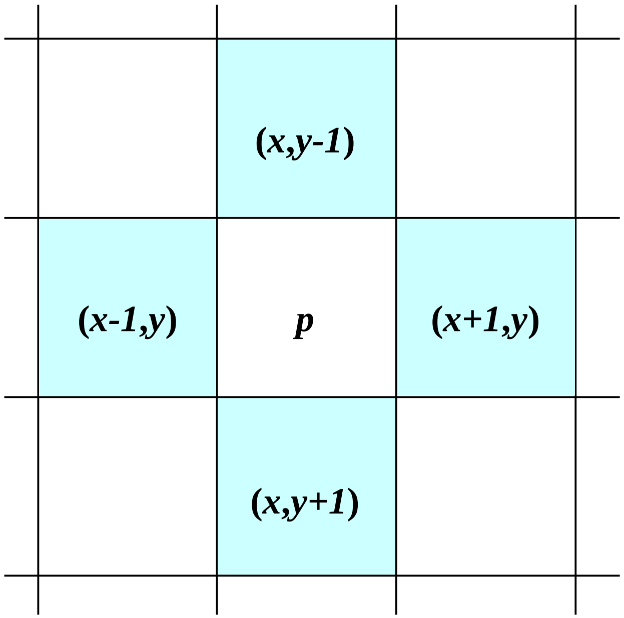


$f(x,y)$ is the reference pixel

Conventional indexing method

Neighbors of a Pixel

Neighborhood relation is used to tell adjacent pixels. It is useful for analyzing regions.



4-neighbors of *p*:

$$N_4(p) = \left\{ \begin{array}{c} (x-1,y) \\ (x+1,y) \\ (x,y-1) \\ (x,y+1) \end{array} \right\}$$

4-neighborhood relation considers only vertical and horizontal neighbors.

Note: $q \in N_4(p)$ implies $p \in N_4(q)$

Neighbors of a Pixel (cont.)

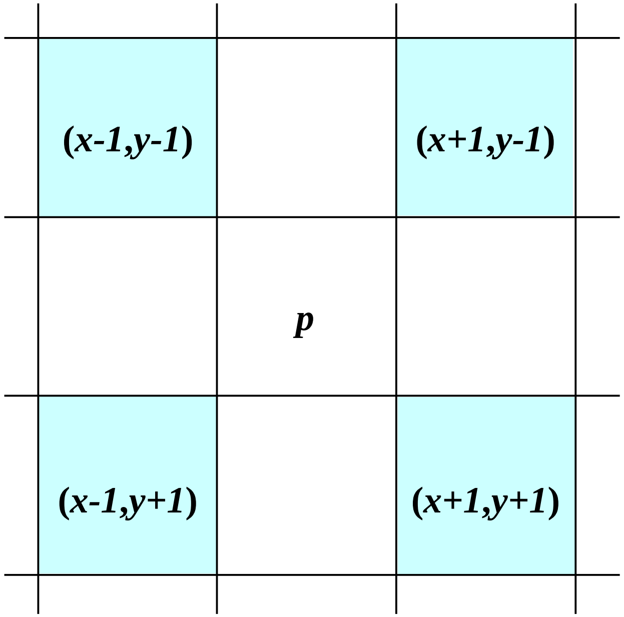
(*x*-*1*,*y*-*1*)	**(*x*,*y*-*1*)**	**(*x*+*1*,*y*-*1*)**
(*x*-*1*,*y*)	***p***	**(*x*+*1*,*y*)**
(*x*-*1*,*y*+*1*)	**(*x*,*y*+*1*)**	**(*x*+*1*,*y*+*1*)**

8-neighbors of *p*:

$$N_8(p) = \left\{ \begin{matrix} (x-1,y-1) \\ (x,y-1) \\ (x+1,y-1) \\ (x-1,y) \\ (x+1,y) \\ (x-1,y+1) \\ (x,y+1) \\ (x+1,y+1) \end{matrix} \right\}$$

8-neighborhood relation considers all neighbor pixels.

Neighbors of a Pixel (cont.)



Diagonal neighbors of *p*:

$$N_D(p) = \left\{ \begin{matrix} (x-1,y-1) \\ (x+1,y-1) \\ (x-1,y+1) \\ (x+1,y+1) \end{matrix} \right\}$$

Diagonal -neighborhood relation considers only diagonal neighbor pixels.

Connectivity

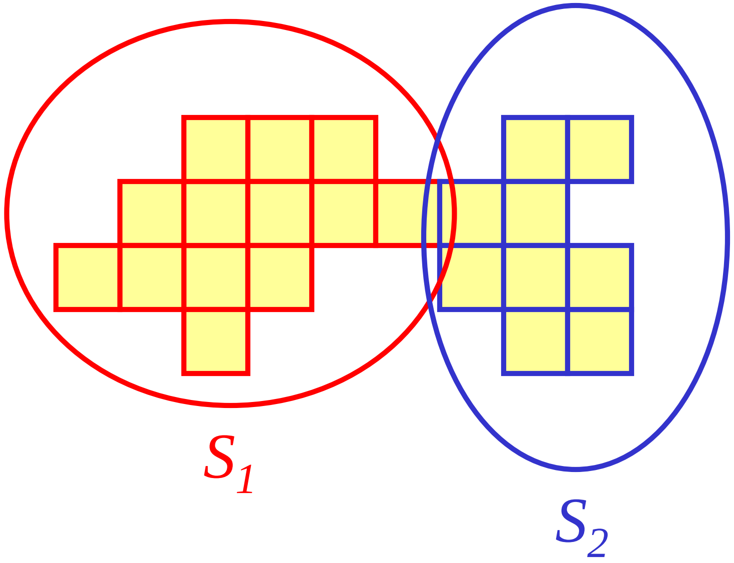
Connectivity is adapted from neighborhood relation.
Two pixels are connected if they are in the same class (i.e. the same color or the same range of intensity) and they are neighbors of one another.

For p and q from the same class

- 4-connectivity: p and q are 4-connected if $q \in N_4(p)$
- 8-connectivity: p and q are 8-connected if $q \in N_8(p)$
- mixed-connectivity (m-connectivity):
  p and q are m-connected if $q \in N_4(p)$ or
  $q \in N_D(p)$ and $N_4(p) \cap N_4(q) = \varnothing$

Adjacency

A pixel p is *adjacent* to pixel q if they are **connected**.
Two **image subsets (or regions)** S_1 and S_2 are adjacent if at least one pixel in S_1 is **connected** to some pixel in S_2



We can define type of adjacency: 4-adjacency, 8-adjacency or m-adjacency depending on type of connectivity.

Path

A ***path*** from pixel p at (x,y) to pixel q at (s,t) is a sequence of distinct pixels:

$$(x_0,y_0), (x_1,y_1), (x_2,y_2),\ldots, (x_n,y_n)$$

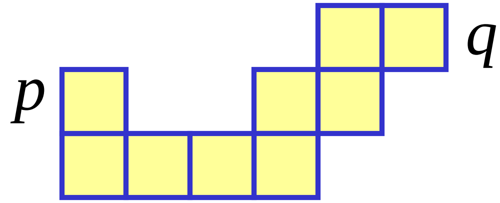
such that

$$(x_0,y_0) = (x,y) \text{ and } (x_n,y_n) = (s,t)$$

and

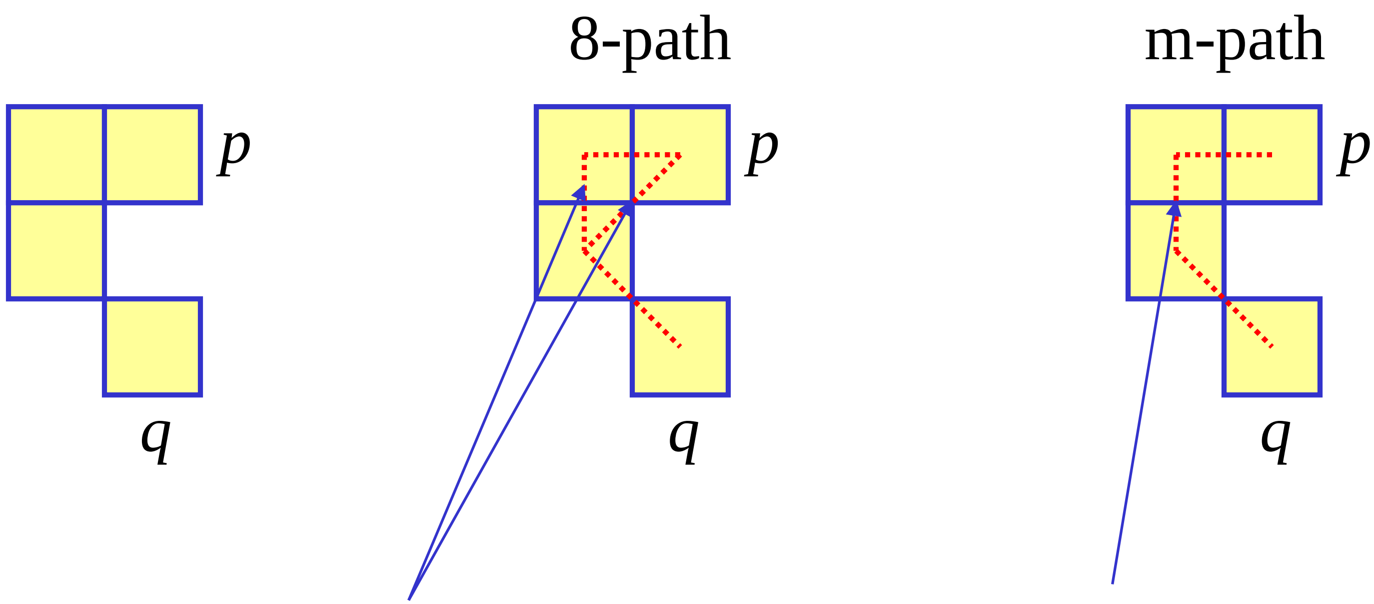
$$(x_i,y_i) \text{ is } \textbf{connected} \text{ to } (x_{i-1},y_{i-1}), \qquad i = 1,\ldots,n$$

e.g.,



We can define type of path: 4-path, 8-path or m-path depending on type of connectivity.

Path (cont.)



8-path from p to q
results in some ambiguity

m-path from p to q
solves this ambiguity

- Recall mixed-connectivity (m-connectivity):
  p and q are m-connected if $q \in N_4(p)$ or
  $q \in N_D(p)$ and $N_4(p) \cap N_4(q) = \varnothing$

Distance

For pixel p, q, and z with coordinates (x,y), (s,t) and (u,v), D is a ***distance function*** or ***metric*** if

- $D(p,q) \geq 0$ $\quad$ ($D(p,q) = 0$ if and only if $p = q$)
- $D(p,q) = D(q,p)$
- $D(p,z) \leq D(p,q) + D(q,z)$

Example: Euclidean distance

$$D_e(p,q) = \sqrt{(x-s)^2 + (y-t)^2}$$

Arithmetic Operations

- Array operations between images
- Carried out between corresponding pixel pairs
- Four arithmetic

$$s(x, y) = f(x, y) + g(x, y)$$

$$d(x, y) = f(x, y) - g(x, y)$$

$$p(x, y) = f(x, y) \times g(x, y)$$

$$v(x, y) = f(x, y) \div g(x, y)$$

- e.g. Averaging K different noisy images can decrease noise
  - Used in the field of astronomy

Averaging K different noisy images can decrease noise. Used in astronomy

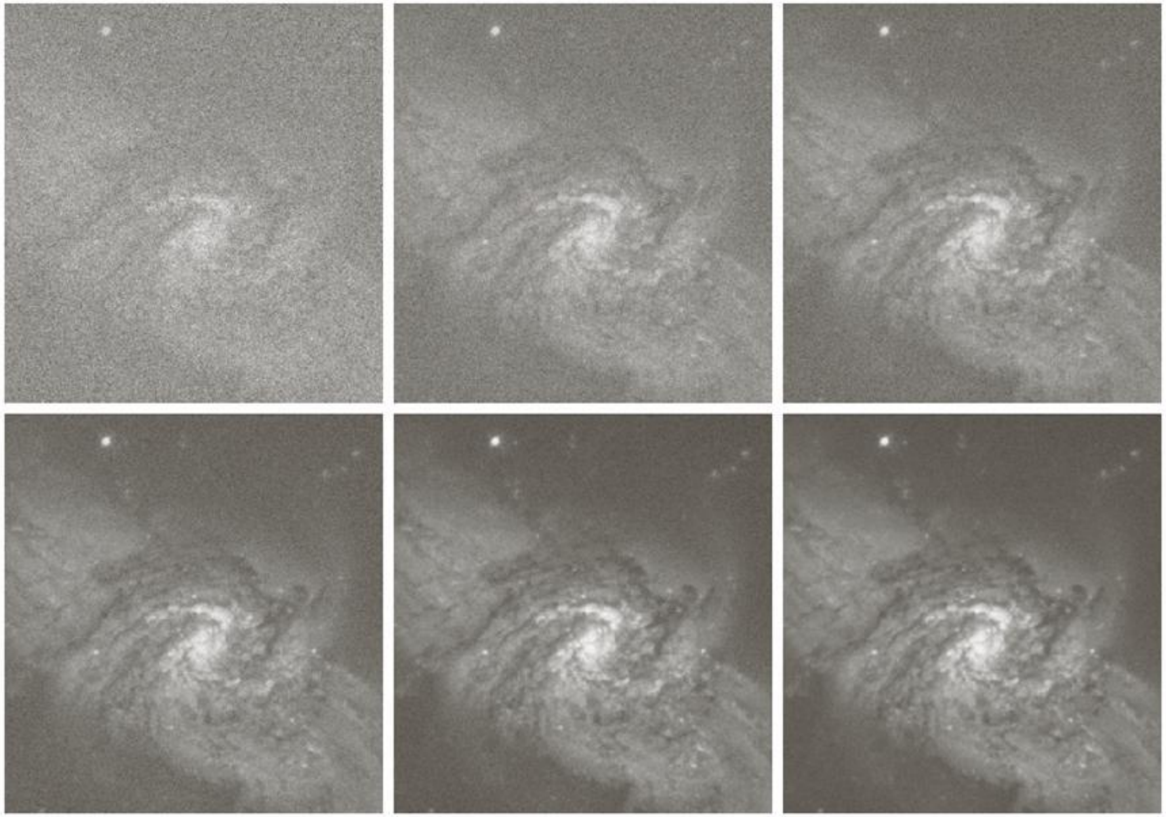
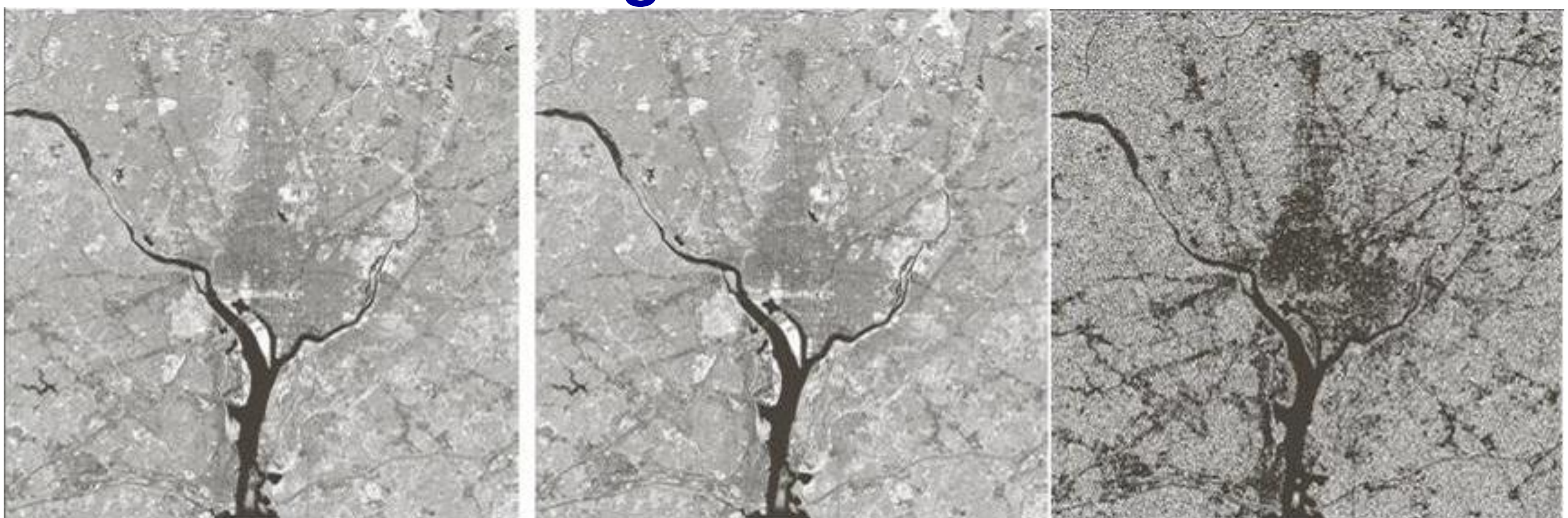


FIGURE 2.26 (a) Image of Galaxy Pair NGC 3314 corrupted by additive Gaussian noise. (b)–(f) Results of averaging 5, 10, 20, 50, and 100 noisy images, respectively. (Original image courtesy of NASA.)

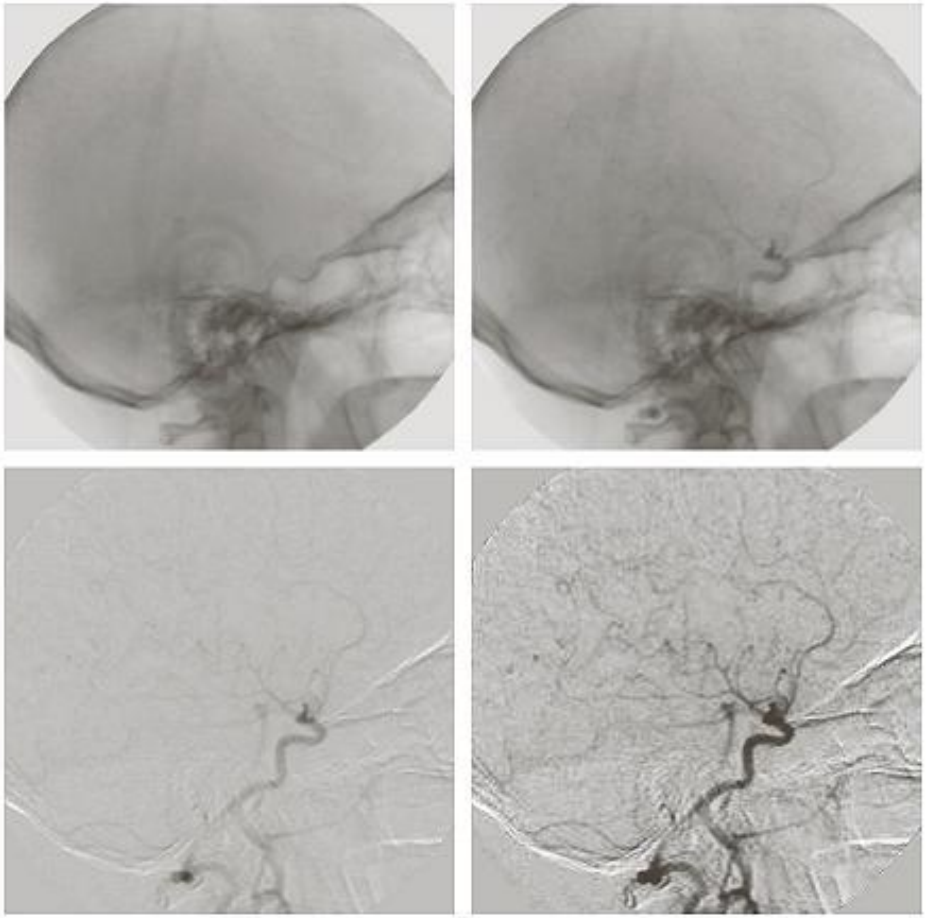
Enhancement of difference between images using **image subtraction**



a b c

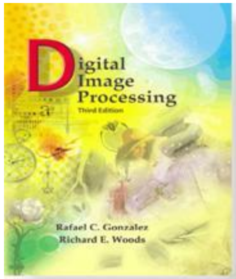
FIGURE 2.27 (a) Infrared image of the Washington, D.C. area. (b) Image obtained by setting to zero the least significant bit of every pixel in (a). (c) Difference of the two images, scaled to the range [0, 255] for clarity.

Mask mode radiography- Image Subtraction



a	b
c	d

FIGURE 2.28 Digital subtraction angiography. (a) Mask image. (b) A live image. (c) Difference between (a) and (b). (d) Enhanced difference image. (Figures (a) and (b) courtesy of The Image Sciences Institute, University Medical Center, Utrecht, The Netherlands.)

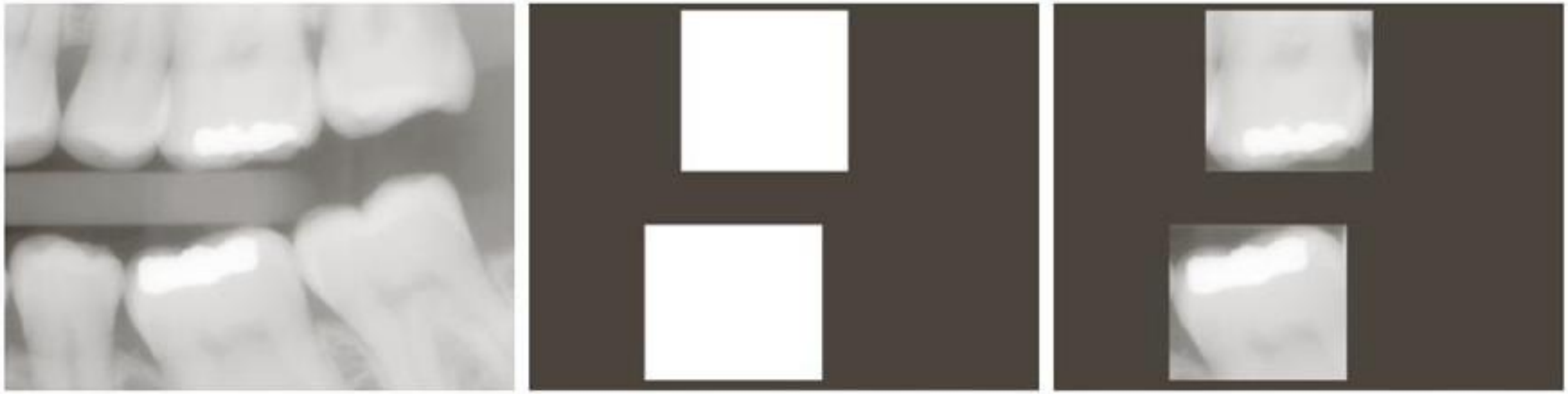


Shading correction by image multiplication (and division)

a b c

FIGURE 2.29 Shading correction. (a) Shaded SEM image of a tungsten filament and support, magnified approximately 130 times. (b) The shading pattern. (c) Product of (a) by the reciprocal of (b). (Original image courtesy of Mr. Michael Shaffer, Department of Geological Sciences, University of Oregon, Eugene.)

Masking (ROI) using image multiplication



a b c

FIGURE 2.30 (a) Digital dental X-ray image. (b) ROI mask for isolating teeth with fillings (white corresponds to 1 and black corresponds to 0). (c) Product of (a) and (b).

Arithmetic Operations

- To guarantee that the full range of an arithmetic operation between images is captured into a fixed number of bits, the following approach is performed on image f

$$f_m = f - \min(f)$$

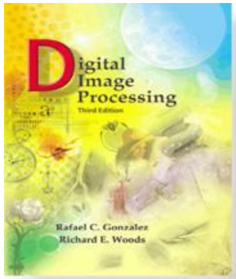
which creates an image whose minimum value is 0. Then the scaled image is

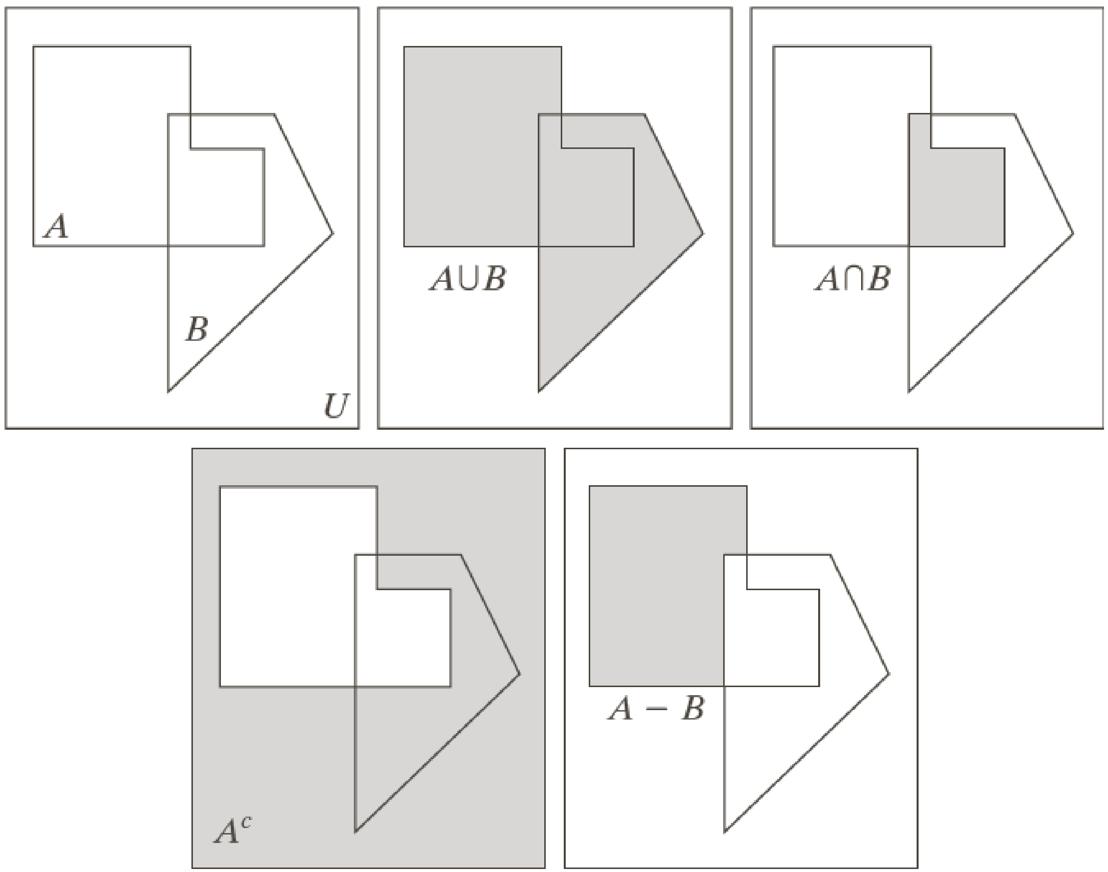
$$f_s = K\,[\,f_m / max(f_m)]$$

whose value is in the range [0, K]

Set and Logical Operations

- Sets can be used to represent the regions of an image i.e., elements of sets be the coordinates of pixels (ordered pairs of integers) representing regions (objects) in an image
  - Union
  - Intersection
  - Complement
  - Difference
- Logical operations
  - OR
  - AND
  - NOT
  - XOR

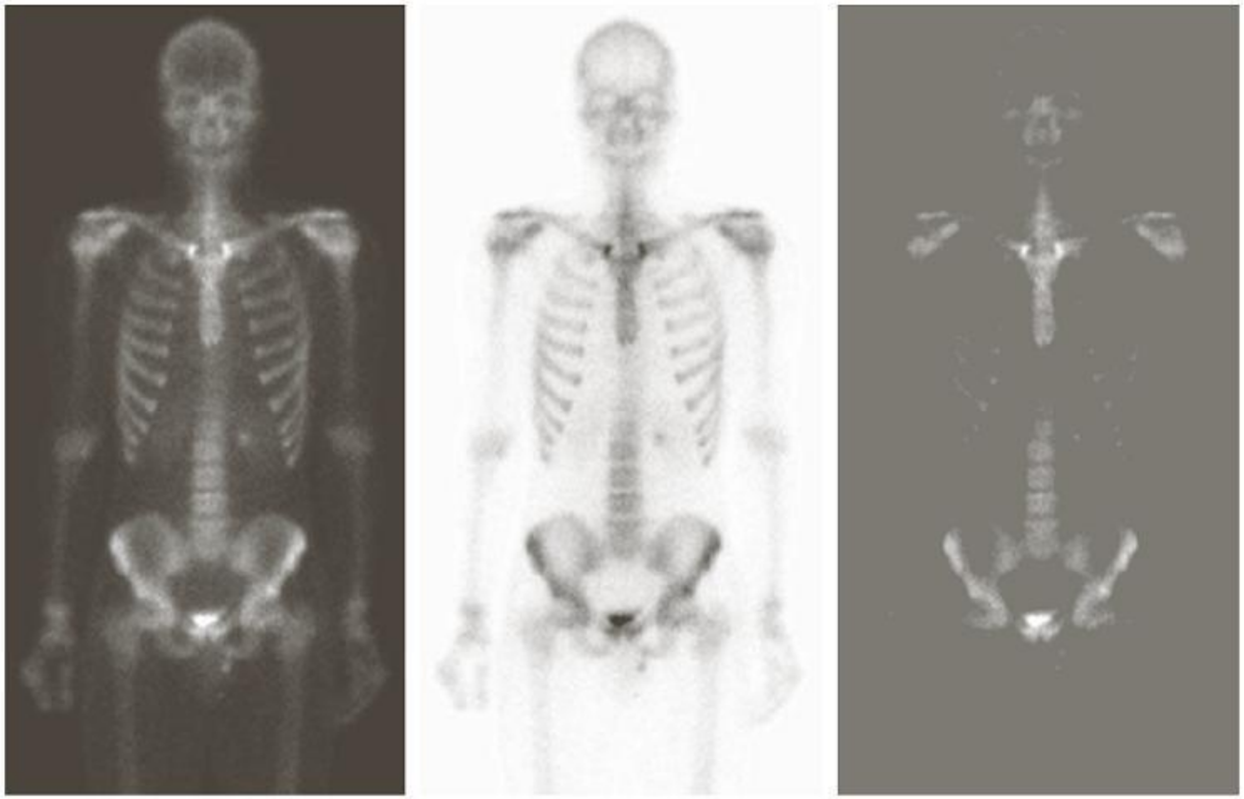




a b c
d e

FIGURE 2.31
(a) Two sets of coordinates, A and B, in 2-D space. (b) The union of A and B. (c) The intersection of A and B. (d) The complement of A. (e) The difference between A and B. In (b)–(e) the shaded areas represent the member of the set operation indicated.

Set Operations on images are unconventional



a b c

FIGURE 2.32 Set operations involving gray-scale images. (a) Original image. (b) Image negative obtained using set complementation. (c) The union of (a) and a constant image. (Original image courtesy of G.E. Medical Systems.)

Application of Set Operations

Logical Operations on Images (binary images only)

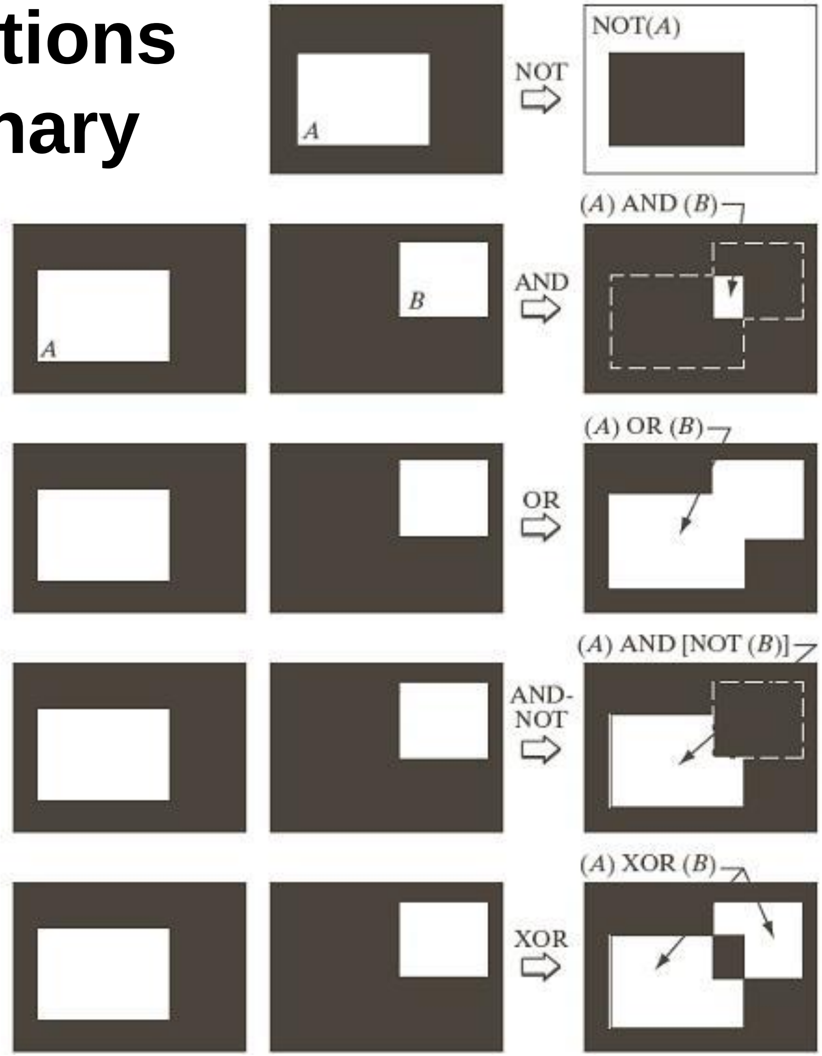


FIGURE 2.33 Illustration of logical operations involving foreground (white) pixels. Black represents binary 0s and white binary 1s. The dashed lines are shown for reference only. They are not part of the result.