Chapter 2: Digital Image Fundamentals

(lecture starts at 16:15)

Outline

Components of a Digital Imaging System

Elements of Visual Perception

Light and the Electromagnetic Spectrum

Image Sensing and Acquisition

Sampling and Quantization

Chapter 1
Introduction

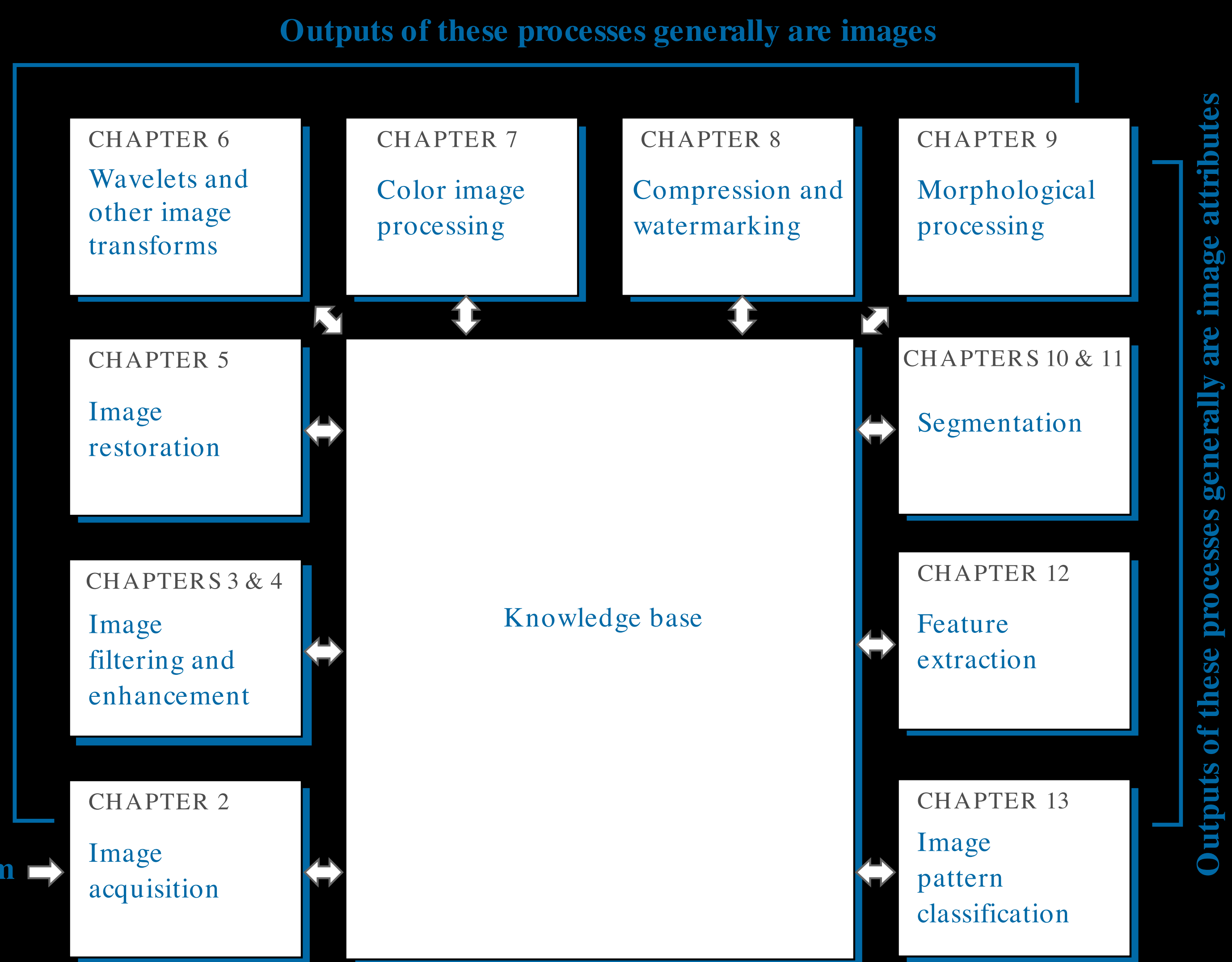
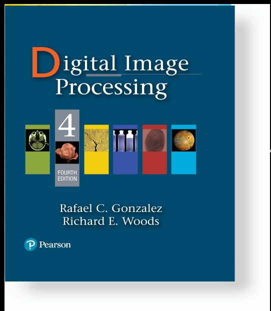


FIGURE 1.23 Fundamental steps in digital image processing. The chapter(s) indicated in the boxes is where the material described in the box is discussed.



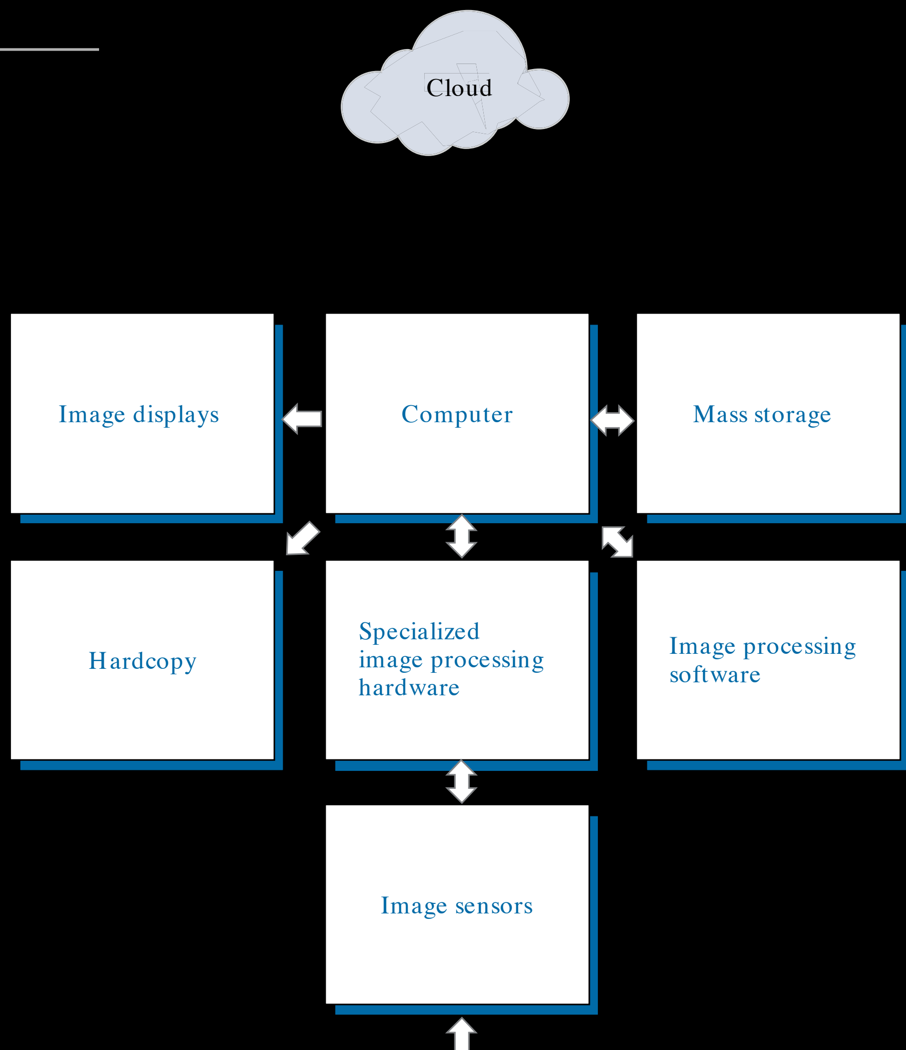


FIGURE 1.24 Components of a general-purpose image processing system.

Types of Image Degradations (1/2)

lack of contrast

image
enhancement

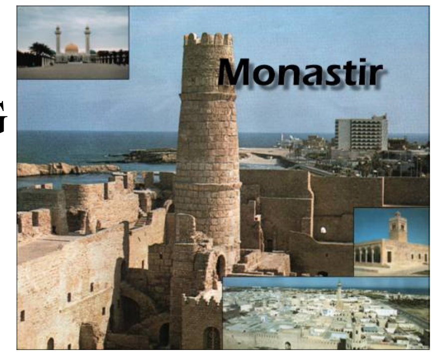
motion blur

image
restoration

Types of Image Degradations (2/2)

BLURRING

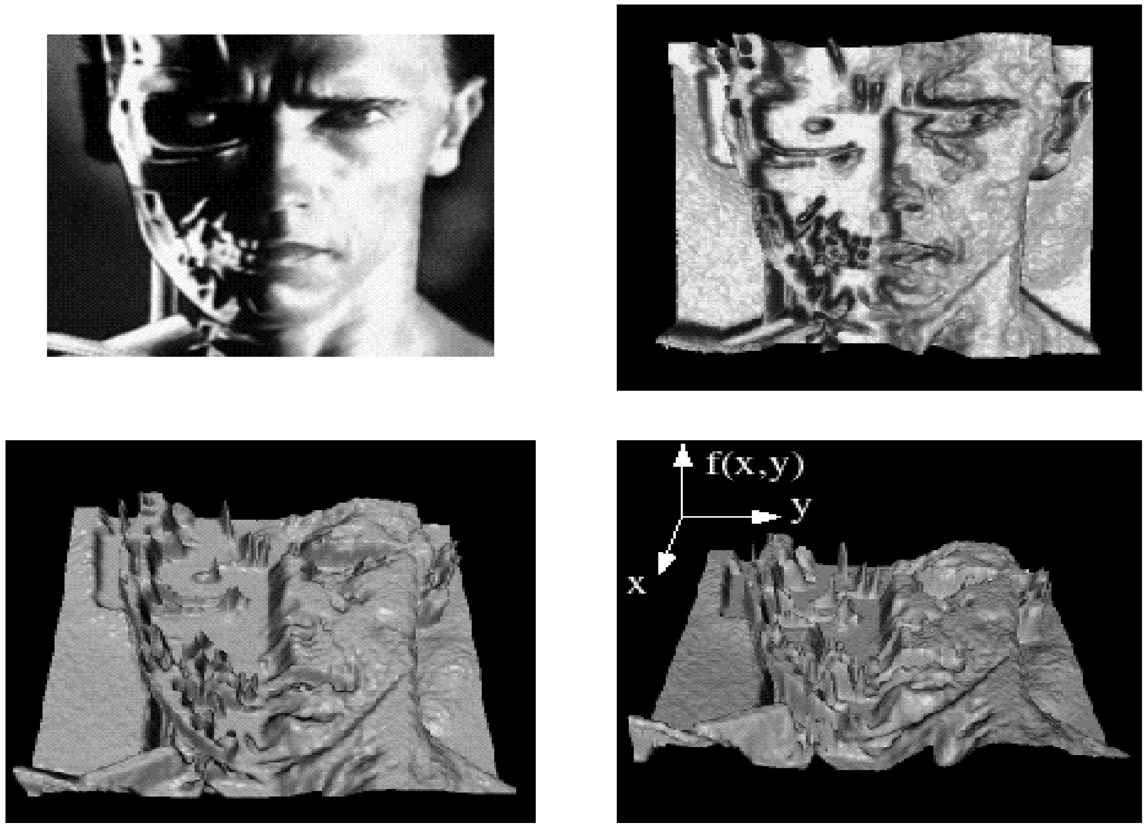
image
restoration



NOISE

image
restoration

Images as functions

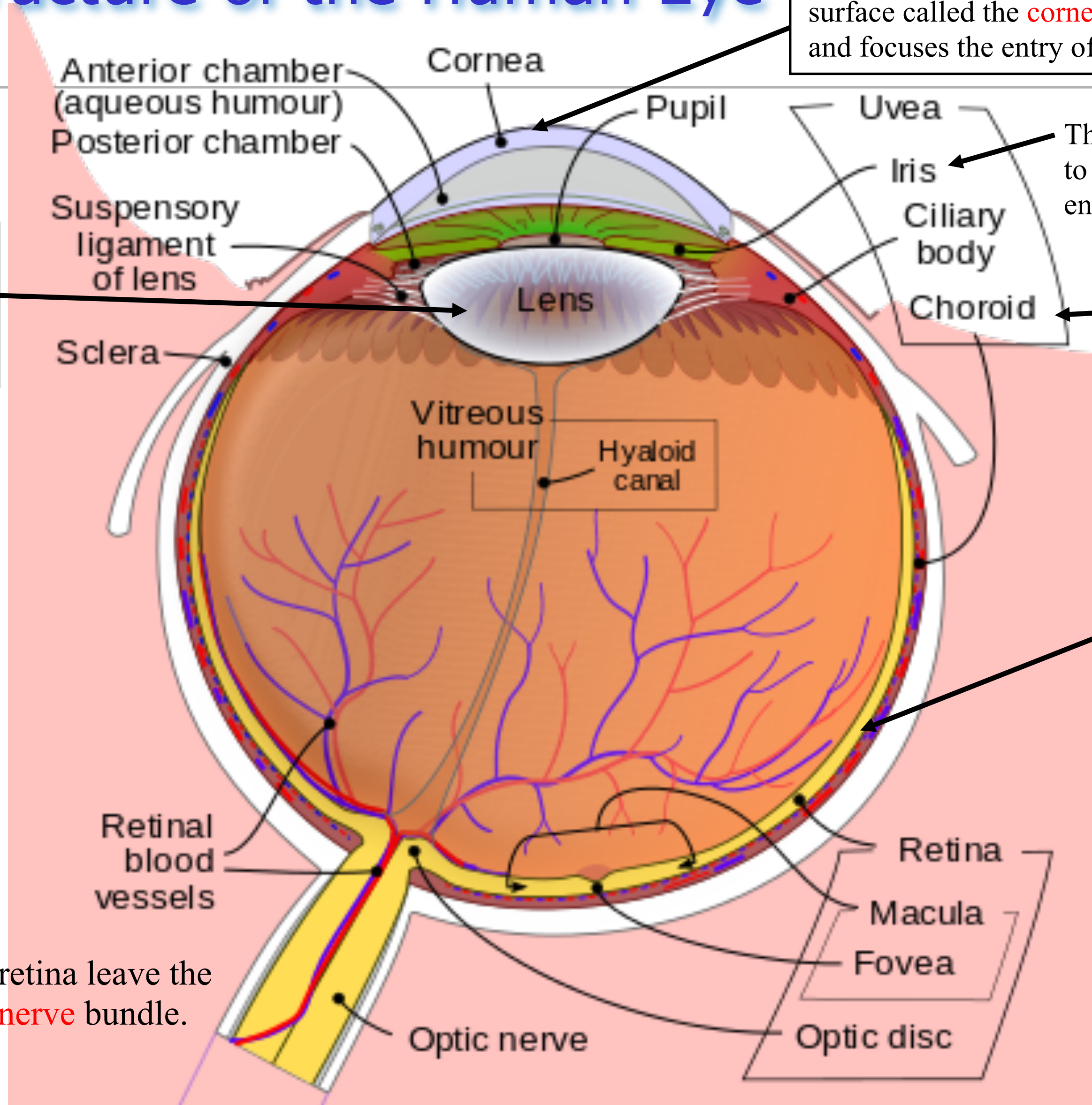


Chapter 2: Digital Image Fundamentals

Structure of the Human Eye

Front of eye is covered by a transparent surface called the cornea (a window that controls and focuses the entry of light into the **eye)**

Light entering the cornea is focused on the retina surface by a Lens



The *iris* acts as a diaphragm to control the amount of light entering the eye.

Inside the *choroid* is the

The **retina** is composed of two types of receptors: ***rods*** and ***cones***.

Nerves connecting to the retina leave the eyeball through the optic nerve bundle.

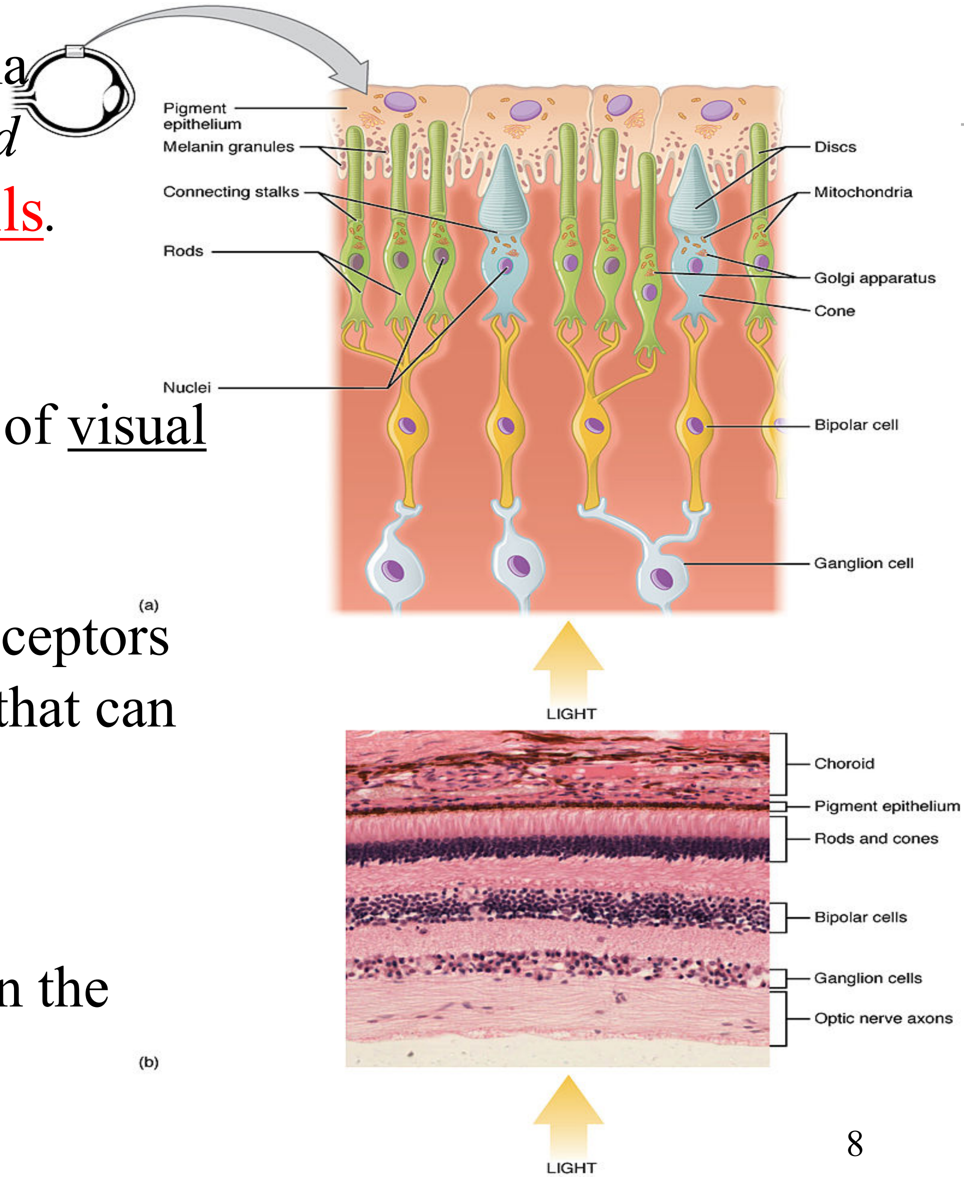
Structure of the Retina

Photoreceptors in mammalian retina consist of three types: *rods, cones and* photosensitive retinal ganglion cells.

A **photoreceptor cell** is a type of neuroepithelial cell that is capable of visual phototransduction.

The biological importance of photoreceptors is that they convert light into signals that can stimulate biological processes.

Photoreceptor proteins in the cell absorb photons, triggering a change in the cell's membrane potential.

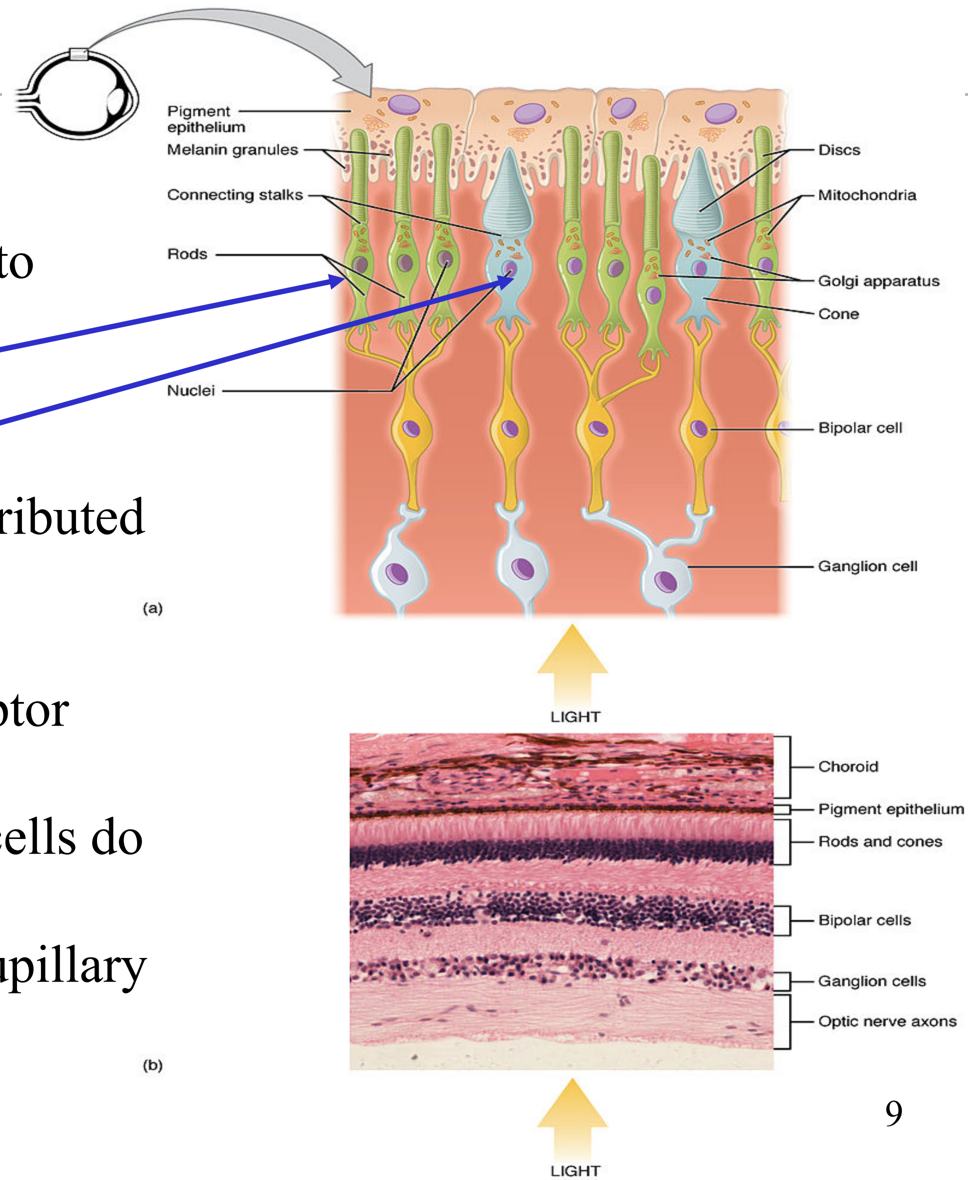


Structure of the Retina

The two classic photoreceptor cells are **rods** and **cones**, each contributing information used by the visual system to form a representation of the visual world, sight.

Rods are narrower than **cones** and distributed differently across the retina.

A third class of mammalian photoreceptor cell, studied during the 1990s, is the **photosensitive ganglion cells**. These cells do not contribute to sight directly, but are thought to support functions such as pupillary light reflex and conscious vision.



Structure of the Retina

Rods are long slender receptors,
75~150 (120) million.

Cones are shorter and thicker,
6~7 (6) million.

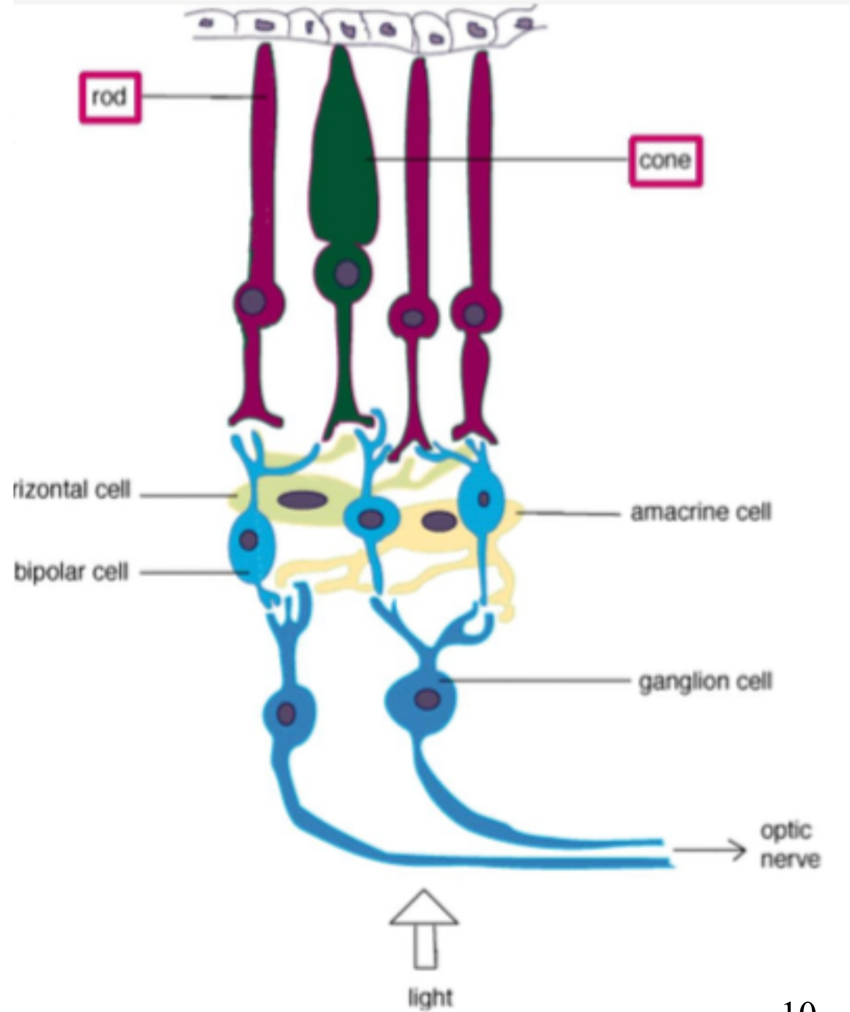


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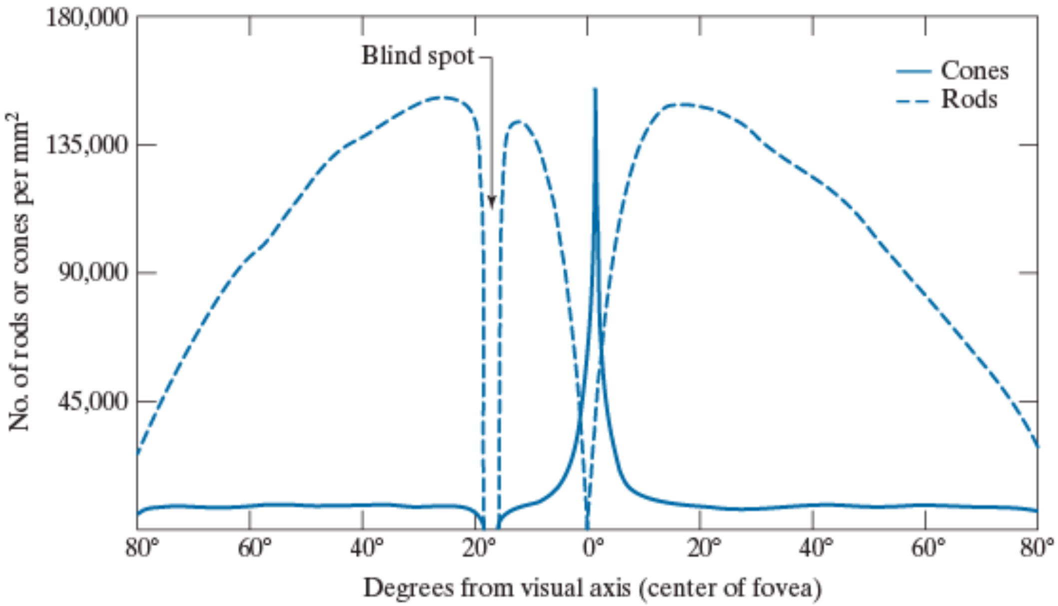
FIGURE 2.2 Distribution of rods and cones in the retina.



The distributions of **rods** and **cones** are radially symmetric w.r.t. the fovea (central portion of the retina), except at the blind spot which includes no receptors (due to nerve bundle).

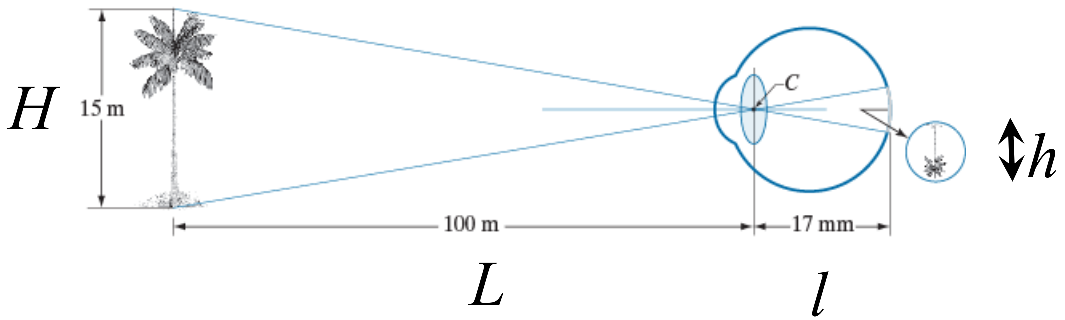
Cones are responsible for **photopic** (color or bright-light) vision; while **rods** are for **scotopic** (dim-light) vision.

Retina is circular with 1.5 mm in diameter with 150 000 cones/mm^2 . This is easily achievable with medium resolution CCD imaging chip of size 5mm x 5mm!

Chapter 2: Digital Image Fundamentals

How's an object seen at the back of the eye?

FIGURE 2.3 Graphical representation of the eye looking at a palm tree. Point C is the focal center of the lens.



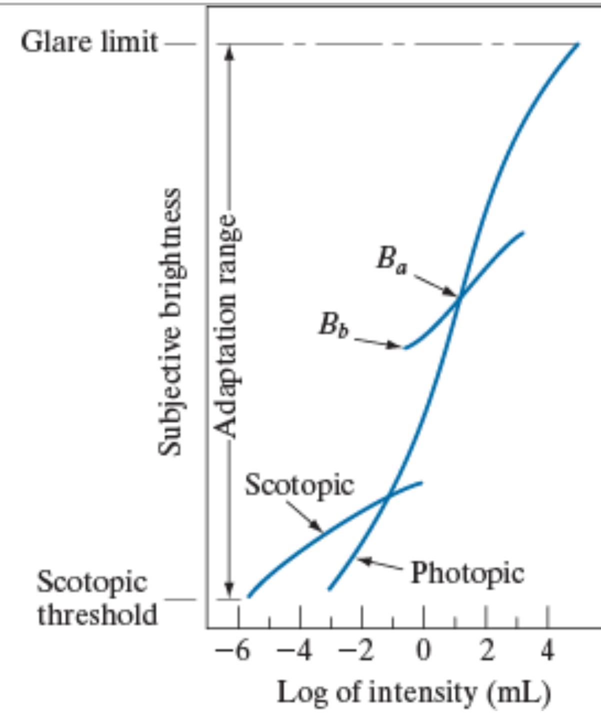
The focal length (distance between the center of the lens and the retina) varies from 17 mm to 14 mm (as the refractive power of the lens increases from its minimum to its maximum). Recall that $H/L = h/l$

Perception takes place by the relative excitation of light receptors, which transform radiant energy into electrical impulses that are ultimately decoded by the brain.

Chapter 2: Digital Image Fundamentals
Subjective Brightness

Human eye can adapt to an enormous range (in the order of 10^{10}) of light intensity levels, from scotopic threshold to the glare limit.

FIGURE 2.4 Range of subjective brightness sensations showing a particular adaptation level, B_a.



Subjective brightness (i.e. perceived intensity) is a logarithmic function of the light intensity incident on the eye.

In photopic vision alone, the range is about 10^6 (-2 to 4 in the log scale). The transition from scotopic to photopic vision is gradual over the range (0.001, 0.1) millilambert[1] (-3 to -1 mL in the log scale).[2]

- [1] Johann H. Lambert 1777, German Physicist,
- [2] see http://www.cns.nyu.edu/~msl/courses/2223/notes.2.pdf

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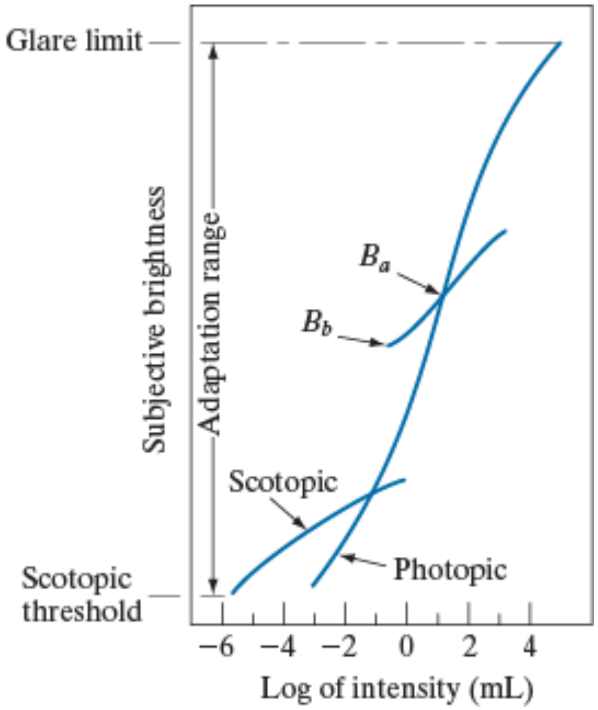
Brightness Adaptation

The visual system is not able to operate over such a huge range simultaneously, instead, it changes its overall sensitivity. This phenomena is called brightness adaptation.

For example, if the eye is adapted to brightness level B_a, the short intersecting curve represents the range of subjective brightness perceived by the eye.

The range is rather restricted, i.e. below level B_b, all stimuli are perceived as indistinguishable black.

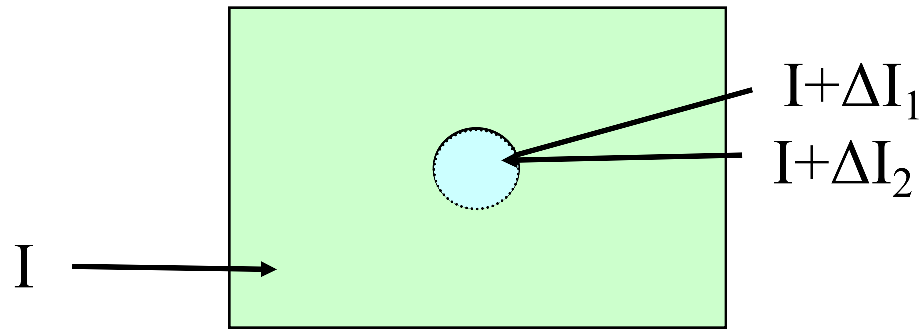
The upper part of the curve (dashed line) is not restricted, but when extended too far, it looses its meaning as it raises the adaptation level higher than B_a.



Eye and Vision video

Experiment for brightness discrimination:

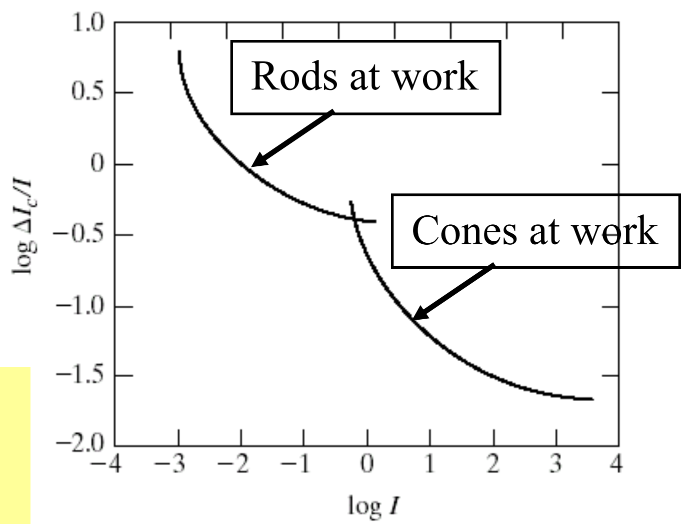
Look at a flat, uniformly illuminated large area, e.g. a large opaque glass illuminated from behind by a light source with intensity I. Add an increment of illumination ΔI, in the form of a short duration flash as a circle in the middle. Vary ΔI and observe the result.



The results should move from ”no perceivable change” to ”perceived change”. The fraction $\Delta I_c/I$ for which ΔI_c produces ”just perceivable change” is called the **Weber ratio**.

A small Weber ratio indicates "good" brightness where a small percentage change in illumination is discriminable. On the other hand, a large Weber ratio represents "poor" brightness indicating that a large percentage change in intensity is needed.

The curve shows that brightness discrimination is poor (large Weber ratio) at low level of illumination, and it improves significantly (Weber ratio decreases) as background illumination increases.



The two branches illustrate the fact that at low levels of illumination, vision is carried out by the rods, whereas at high levels (showing better discrimination), cones are at work.

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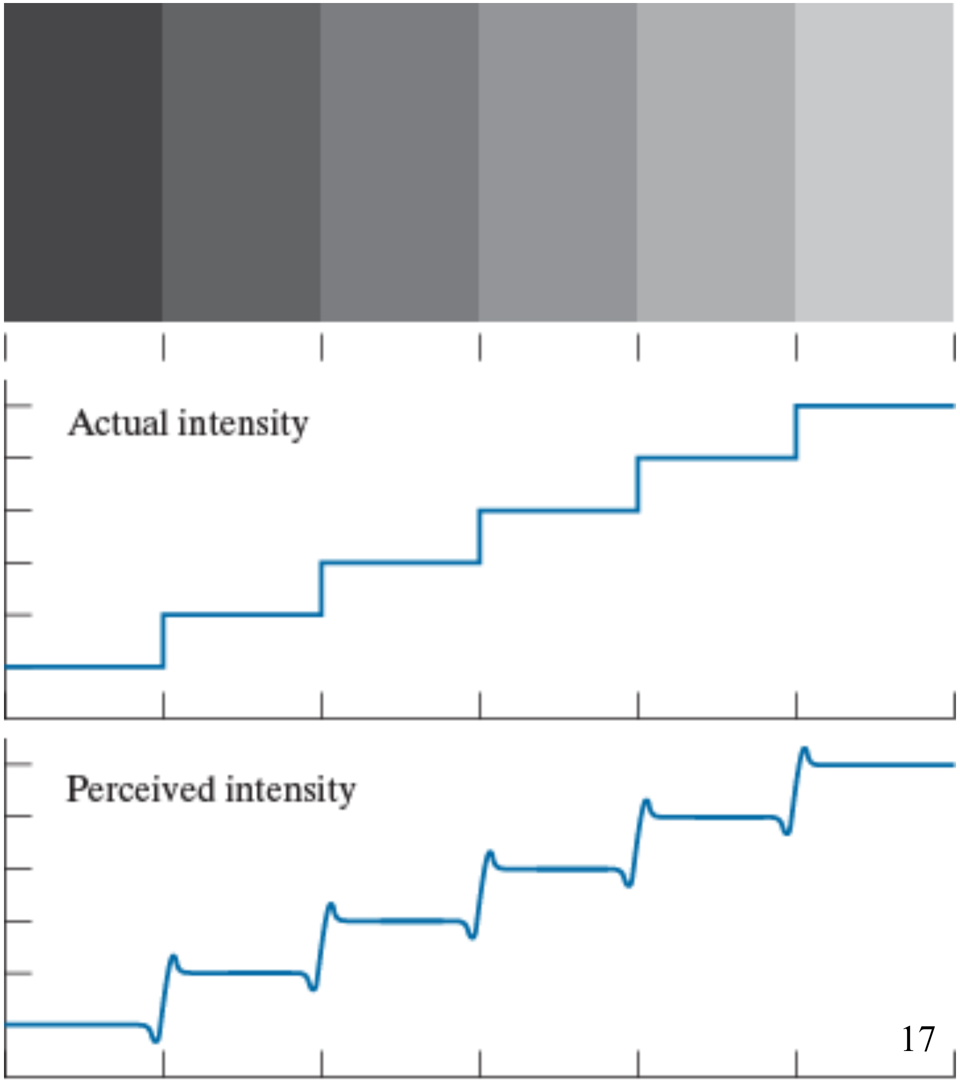
Perceived brightness is NOT a simple function of intensity.

Example 1: Mach bands

The reflected light intensity from each strip is uniform over its width and differs from its neighbors by a constant amount; nevertheless, the virtual appearance is that transitions at each bar appear brighter on the left side and darker on the right side.

The Mach band* effect can be used to estimate the impulse response of the visual system.

*Mach 1906.



a b c

FIGURE 2.7 Illustration of the Mach band effect. Perceived intensity is not a simple function of actual intensity.

Example 2: Simultaneous Contrast

Each small square is actually the same intensity, but because of different intensities of the surrounding, the small squares do not appear equally bright.

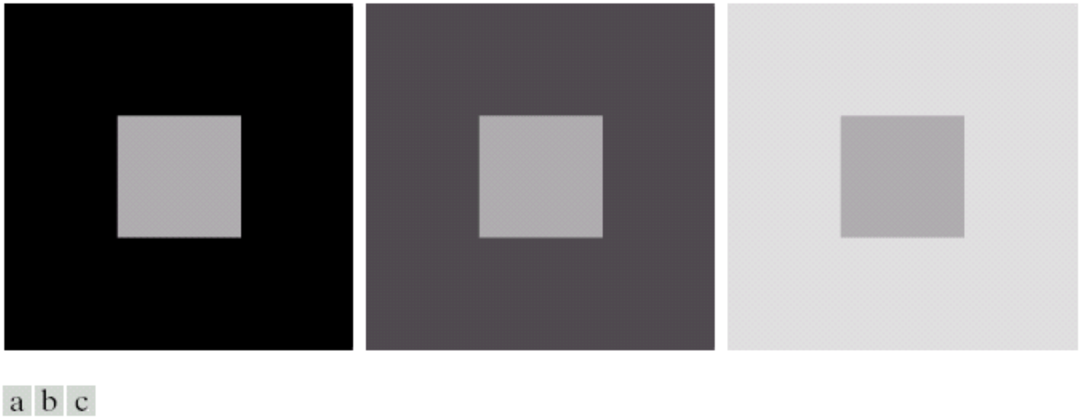
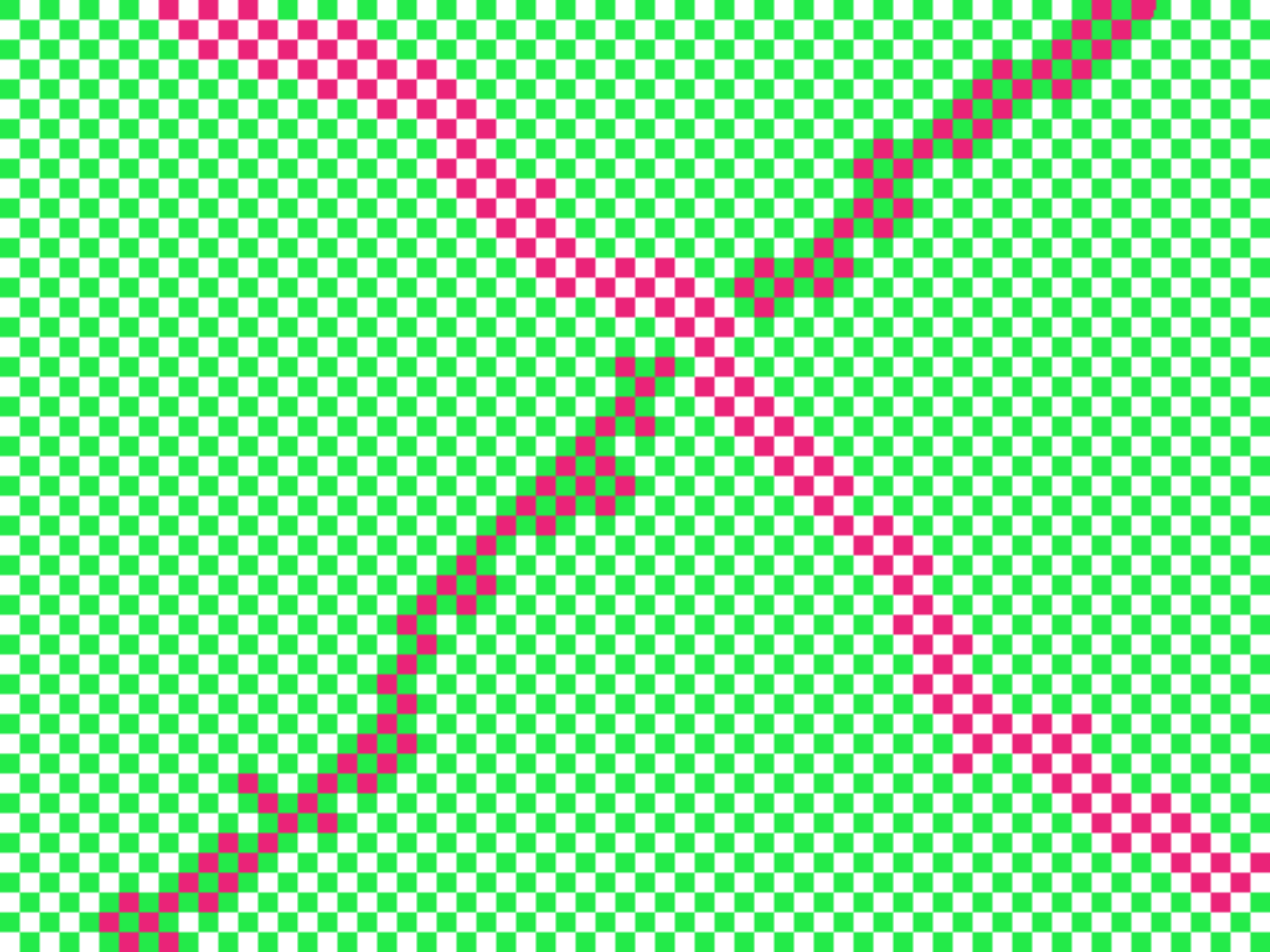
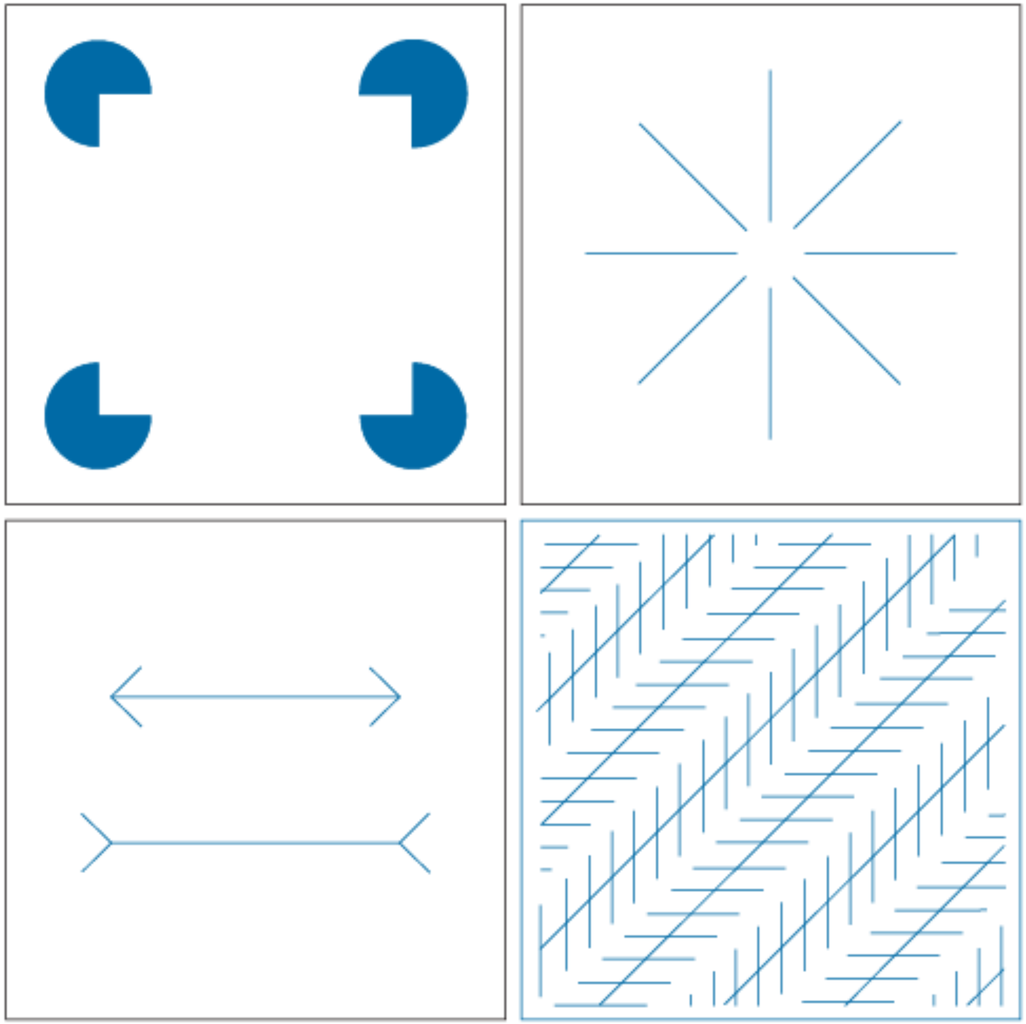


FIGURE 2.8 Examples of simultaneous contrast. All the inner squares have the same intensity, but they appear progressively darker as the background becomes lighter.

Example 3: Metameric Pairs

Any two objects which appear equally bright, even though, their intensities are different are called metameric pairs.





a b
c d

FIGURE 2.9 Some well-known optical illusions.

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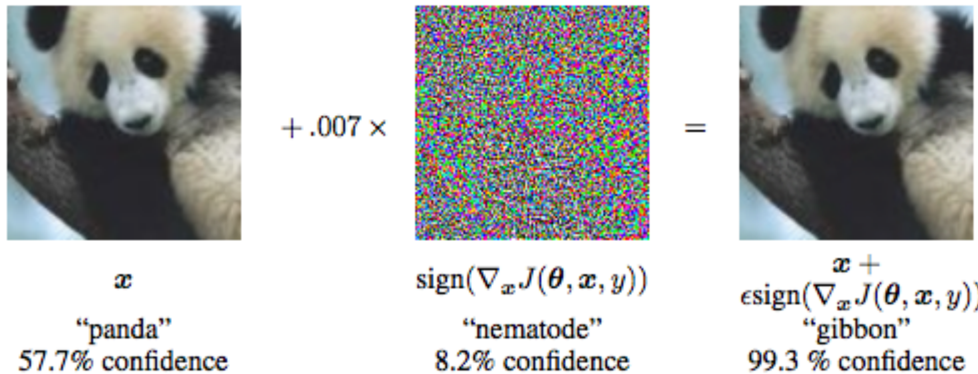
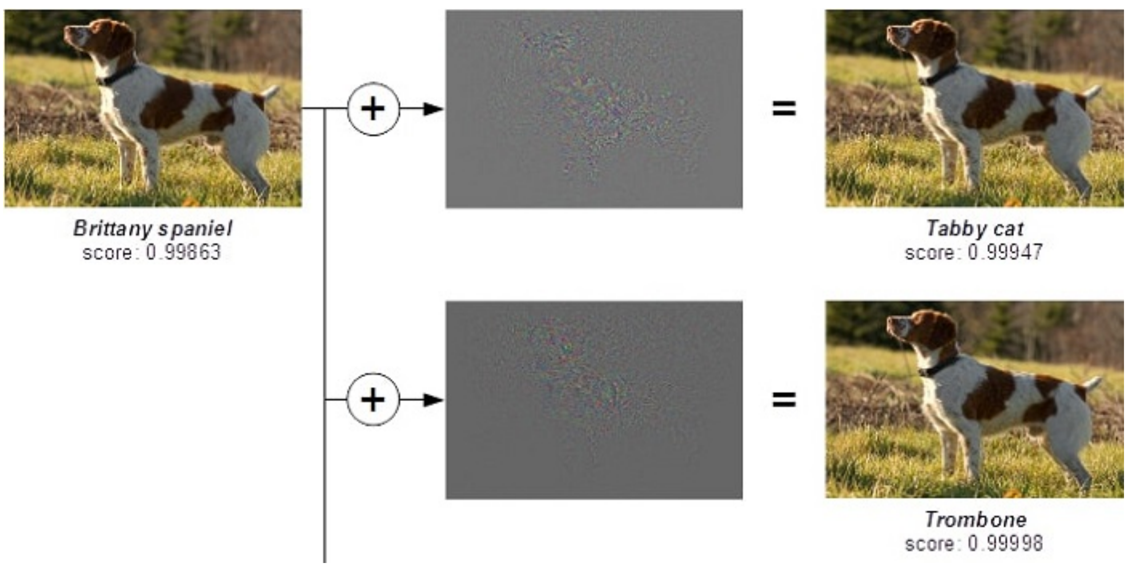
Optical illusions are not just for humans!



Misclassified as a Gibbon (ape)



Misclassified as a cat

Misclassified as a trombone (music instrument)

https://arxiv.org/abs/1412.6572

https://www.kdnuggets.com/2018/10/adversarial-examples-explained.html

Definition:

Light is an electromagnetic radiation which, by simulation, arouses a sensation on the visual receptors making sight possible

Isaac Newton (1666) discovered that when a beam of sunlight is passed through a glass prism, the emerging beam of light is not white but consists instead of a continuous spectrum of colors ranging from violet to red. This is called the visible region of the spectrum, see next figure.

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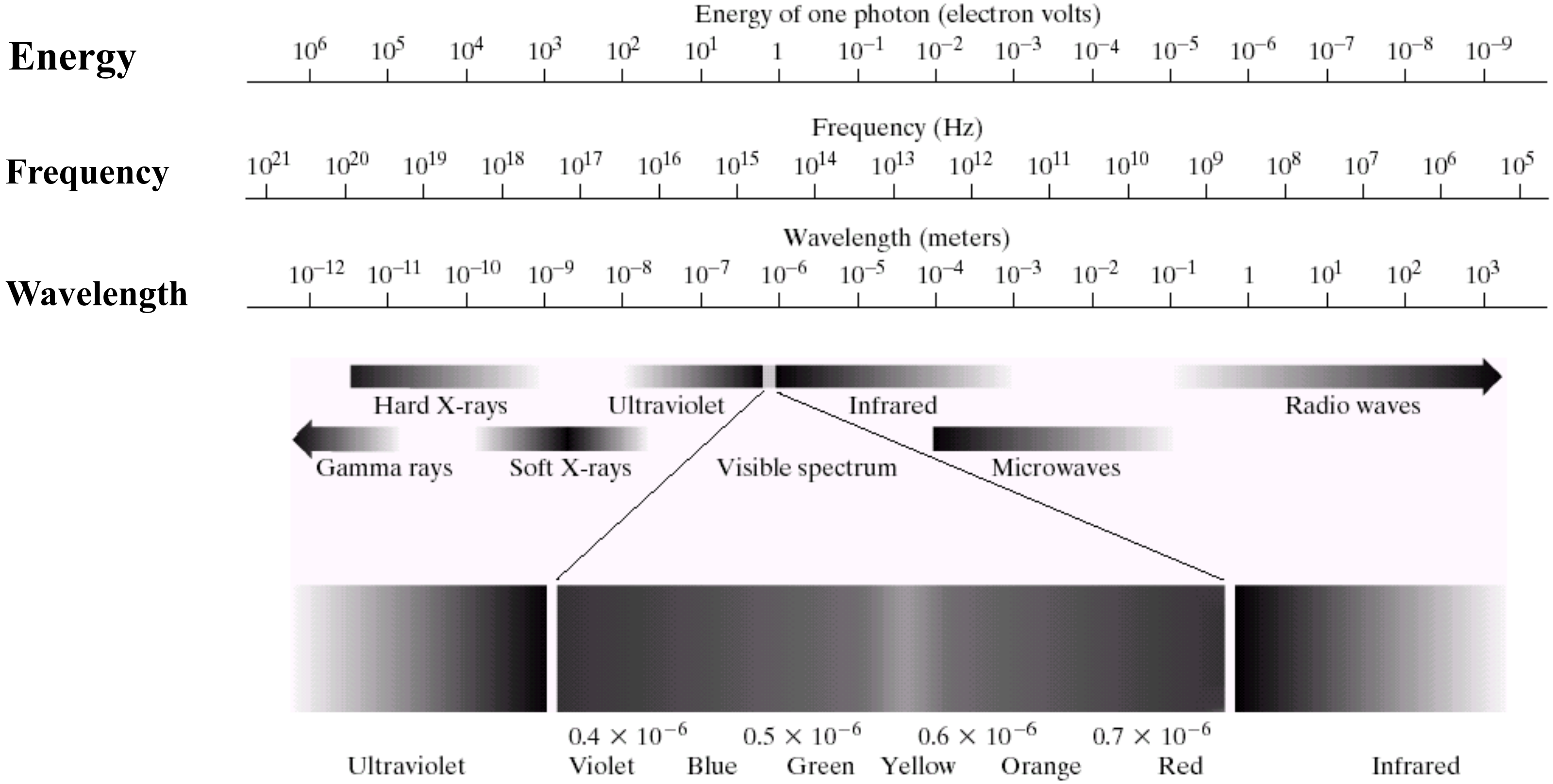


FIGURE 2.10 The electromagnetic spectrum. The visible spectrum is shown zoomed to facilitate explanation, but note that the visible spectrum is a rather narrow portion of the EM spectrum.

The electromagnetic spectrum can be expressed in terms of wavelength (λ), frequency (v), or energy (E). Recall that

$$\lambda = c/v$$

where c is the speed of light (2.998×10^8 m/s).

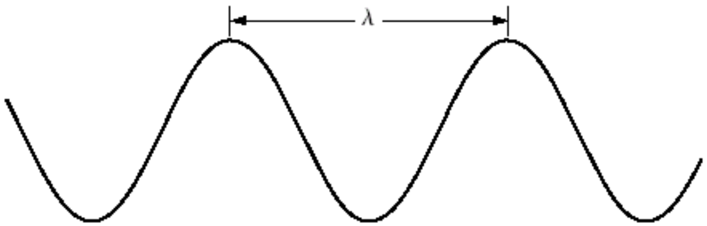
The energy of the various components is given by:

$$E = hv$$

where h is Planck's constant ($6.62606891 \times 10^{-34}$ Joule-seconds (or m^2kg/s)). E is measured in electron-volt.

Electromagnetic waves can be visualized as propagating sinusoidal waves of varying wavelengths (λ) or as a stream of massless particles, each traveling in a wavelike pattern and moving at the speed of light. Each massless particle contains a certain amount (or bundle) of energy. Each bundle of energy is called a **photon**. VIDEO (play)

FIGURE 2.11 Graphical representation of one wavelength.



λ is measured in meters (or km for radio waves), microns (visible) or nanometers (for X-ray).

Image Sensing and Acquisition

The types of images considered are generated by a combination of an ”illumination” source and the reflection or absorption of energy from the ”scene” being imaged.

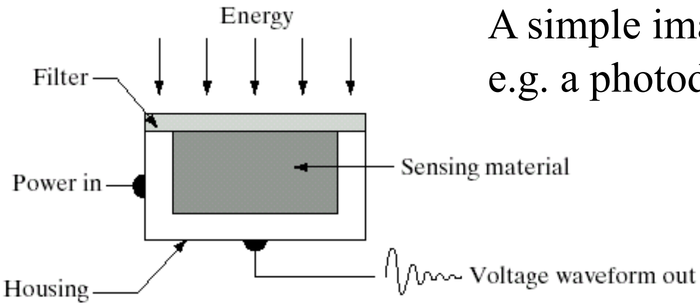
”Illumination” includes visible light, radar, infrared, X-ray, or ultrasound.

”Scene” may be any familiar 3D object, underground, human internal organs.

How to transform illumination energy into digital images?

a
b
c

FIGURE 2.12
(a) Single imaging sensor.
(b) Line sensor.
(c) Array sensor.

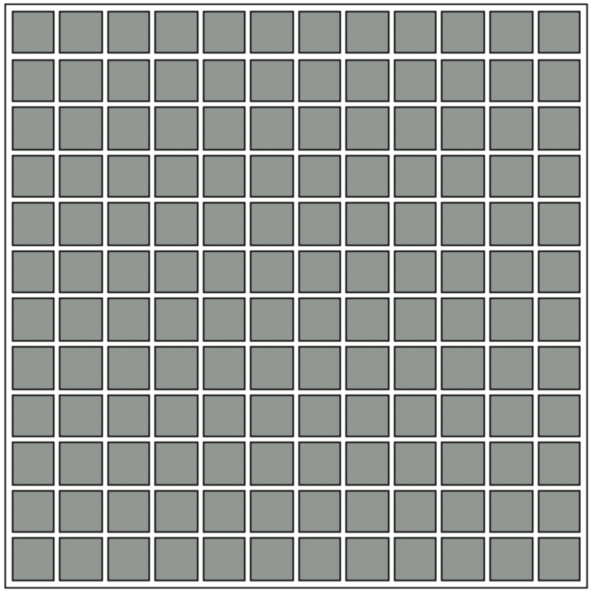


A simple imaging sensor, e.g. a photodiode

voltage output is then digitized to produce a digital image

A line sensor

An array sensor



Generating a 2-D image using a single sensor.

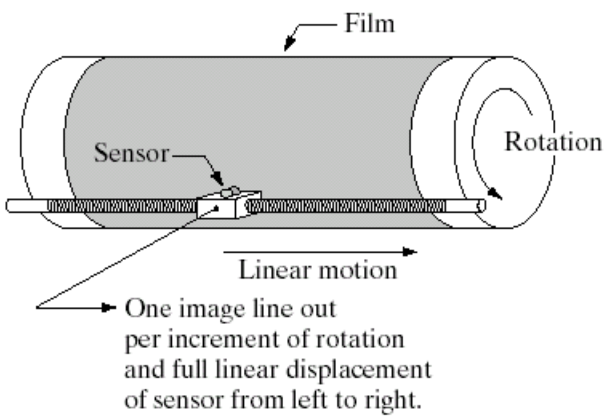
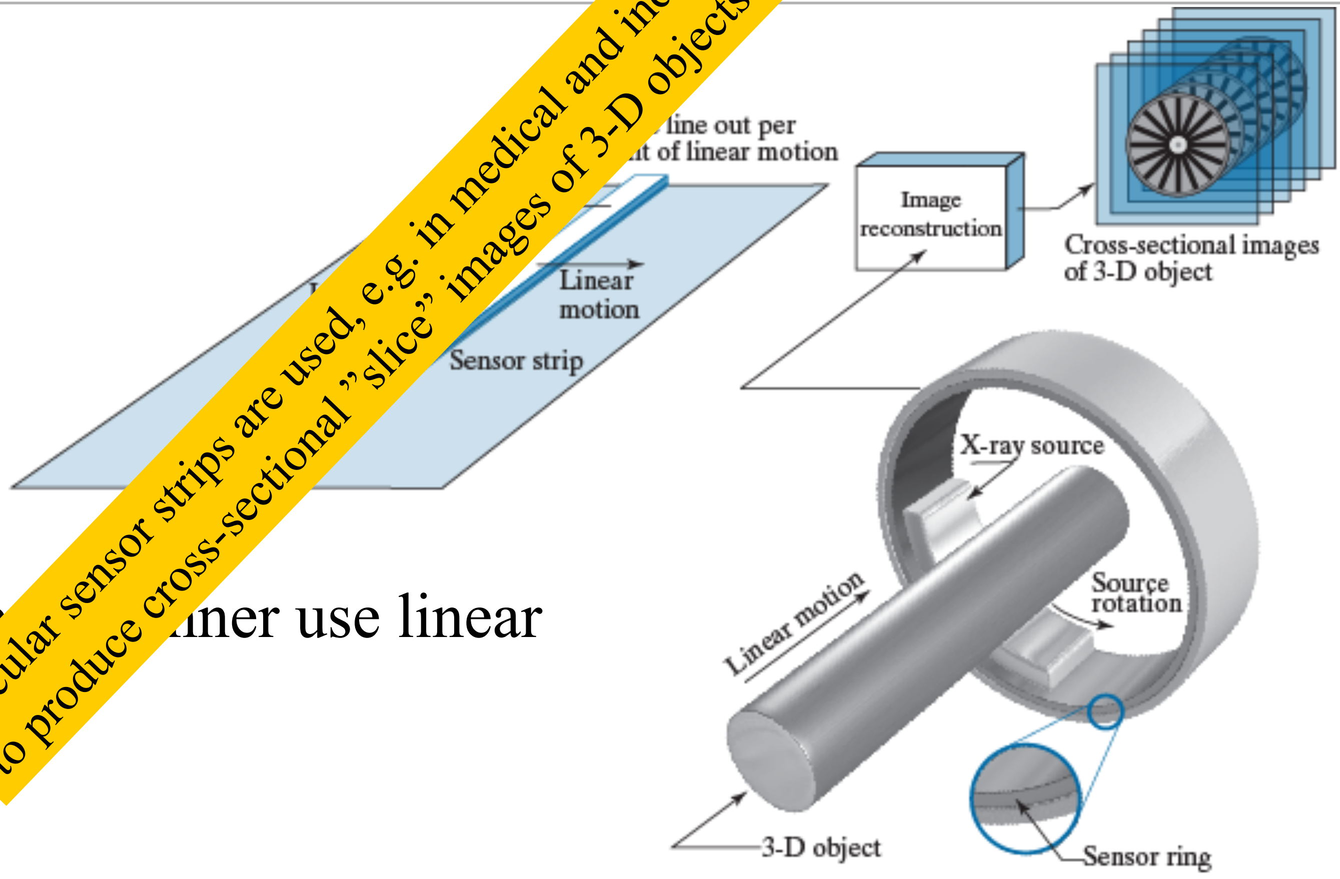


FIGURE 2.13 Combining a single sensor with motion to generate a 2-D image.

This type of mechanical digitizers is called a **microdensitometer** and is used in high-precision scanning (but slow).

Image Acquisition Usin… sor Strips

circular sensor strips are used, e.g. in medical and industrial imaging
to produce cross-sectional ”slice” images of 3-D objects.



most flat b… …ner use linear
sensor s…

a b

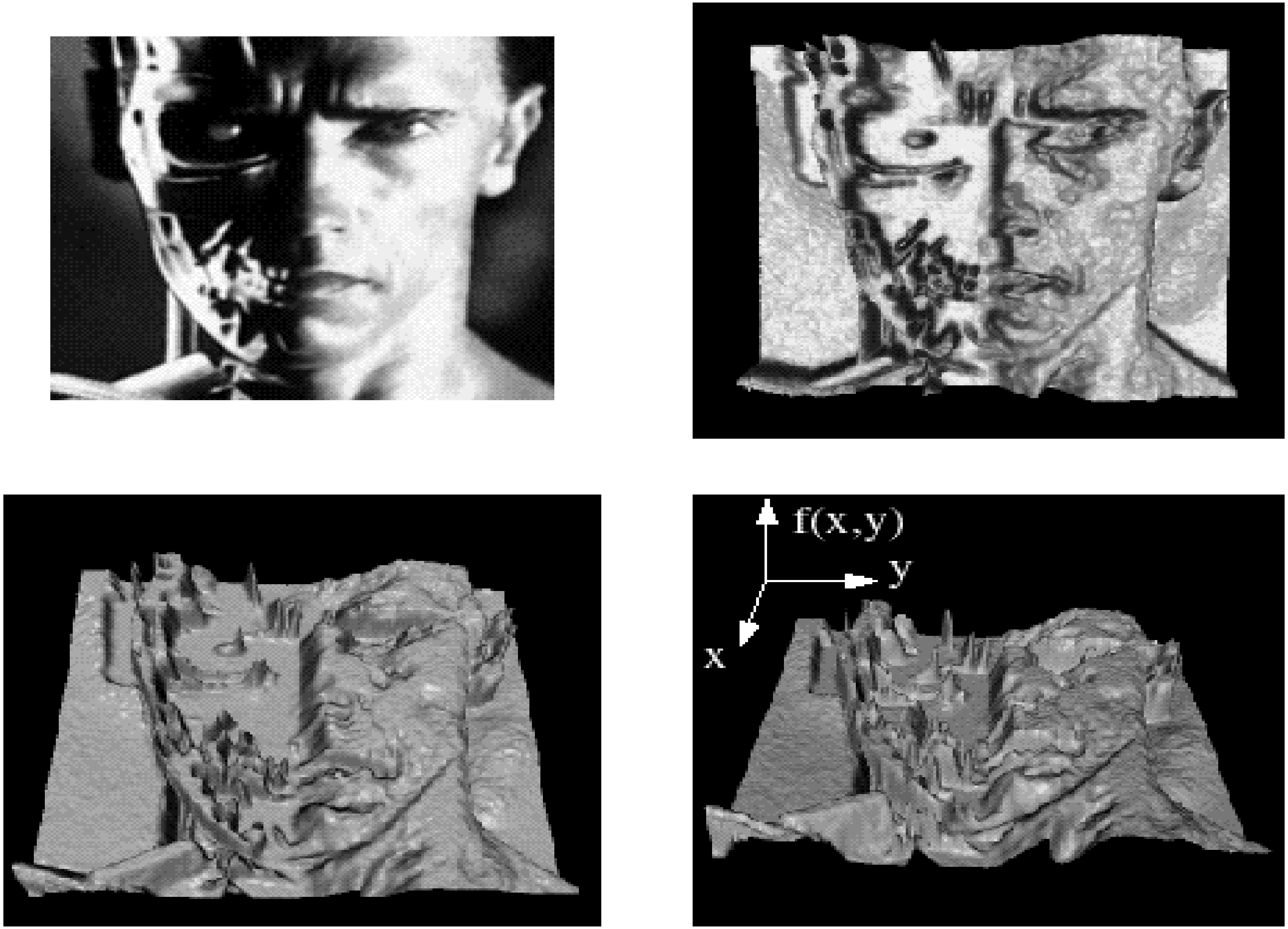
FIGURE 2.14 (a) Image acquisition using a linear sensor strip. (b) Image acquisition using a circular sensor strip.

Principles of Image Acquisition, Sampling and Quantization

A Simple Image Model

- Image: a 2-D light-intensity function $f(x, y)$
- The value of f at (x, y) → the intensity (brightness) of the image at that point
- $0 < f(x, y) < \infty$

Images as functions



A Simple Image Formation Model

Consider the monochrome case, e.g., black and white images

Represent the spectral intensity distribution of the image by a continuous function $f(x,y)$, *i.e.*, for fixed value of (x,y), $f(x,y)$ is proportional to the grey level of the image at that point.

Of course,

$$\text{(black) } 0 \leq f(x,y) \leq f_{max} \text{ (white)}$$

Why such limits?

Lower bound is because light intensity is a real positive quantity (recall that intensity f is proportional to $|E|^2$, where E is the electric field).

Upper bound is due to the fact that in all practical imaging systems, the physical system imposes some restrictions on the maximum intensity level of an image, e.g., film saturation and cathode ray tube phosphor heating.

Intermediate values between 0 and f_{max} are called shades of gray varying from black to white.

Digital Image Acquisition

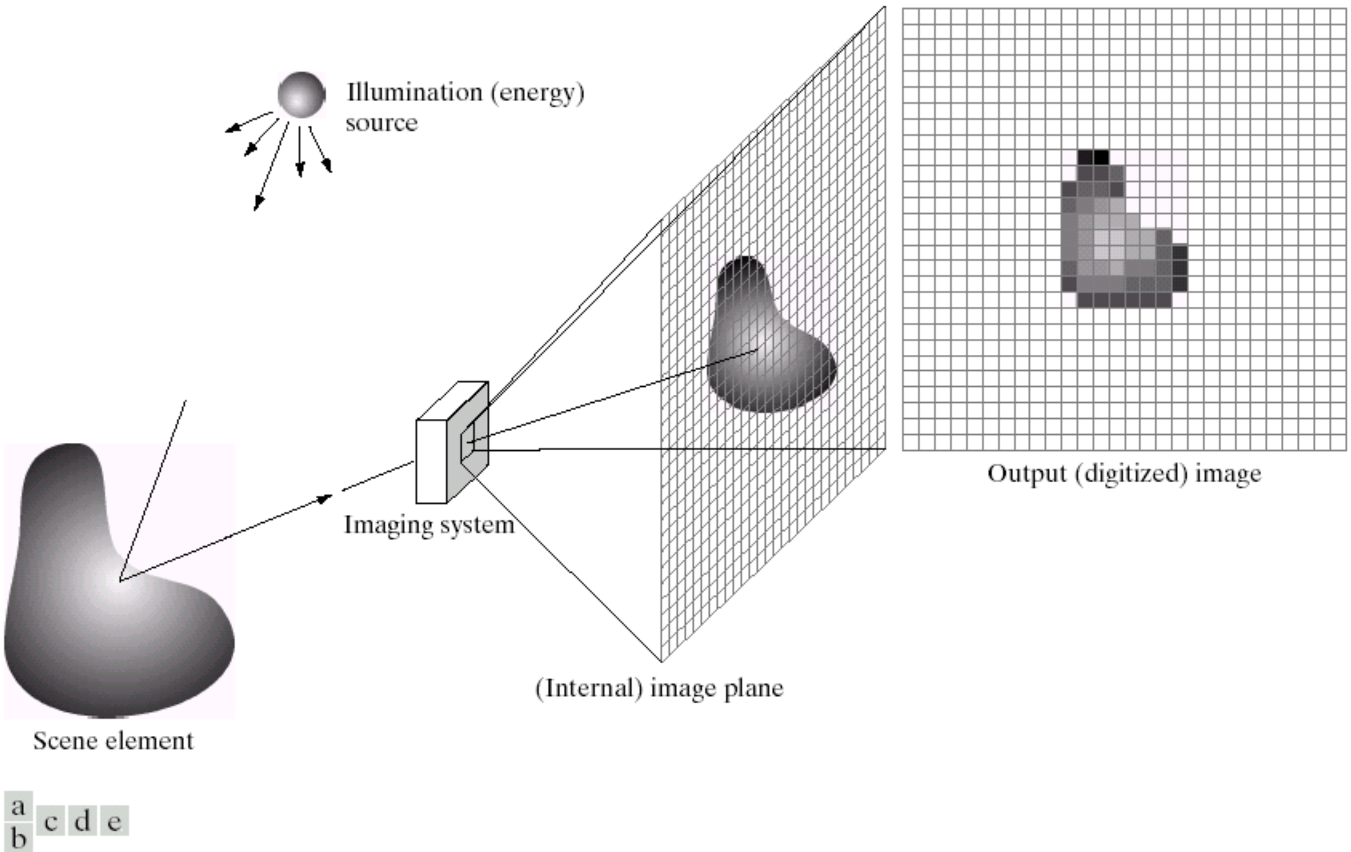


FIGURE 2.15 An example of the digital image acquisition process. (a) Energy ("illumination") source. (b) An element of a scene. (c) Imaging system. (d) Projection of the scene onto the image plane. (e) Digitized image.

A Simple Image Model

- Nature of $f(x, y)$:
  - The amount of source light incident on the scene being viewed, **illumination component**
  - The amount of light reflected by the objects in the scene, **reflectance component**

A Simple Image Model

- Illumination & reflectance components:

  – Illumination: $i(x, y)$
  – Reflectance: $r(x, y)$

  – $f(x, y) = i(x, y) \cdot r(x, y)$

  – $0 < i(x, y) < \infty$ and $0 < r(x, y) < 1$

  (from total absorption to total reflectance)

A Simple Image Model

- Sample values of $r(x, y)$:
  - 0.01: black velvet
  - 0.93: snow

- Sample values of $i(x, y)$:
  - 90,000 lx: sunny day
  - 10,000 lx: cloudy day
  - 0,1 lx: evening, full moon
  - 1000 lx: typical office

  1 lux = 1 lm (lumen) / m^2

A Simple Image Model

- Intensity of a monochrome image f at (x_o, y_o): gray level l of the image at that point

$$l = f(x_o, y_o)$$

- $L_{min} \leq l \leq L_{max}$
  - Where L_{min}: positive
    L_{max}: finite

A Simple Image Model

- In practice:
  - $L_{min} = i_{min} r_{min}$ and
  - $L_{max} = i_{max} r_{max}$
- E.g. for indoor image processing:
  - $L_{min} \approx 10$ $L_{max} \approx 1000$
- $[L_{min}, L_{max}]$: gray scale
  - Often shifted to $[0,\ L-1]$ → $l = 0$: black
    $l = L-1$: white

Sampling & Quantization

- The spatial and amplitude digitization of f(x,y) are called:
  - image sampling when it refers to spatial coordinates (x, y) and
  - gray-level quantization when it refers to the amplitude.

Digital Image

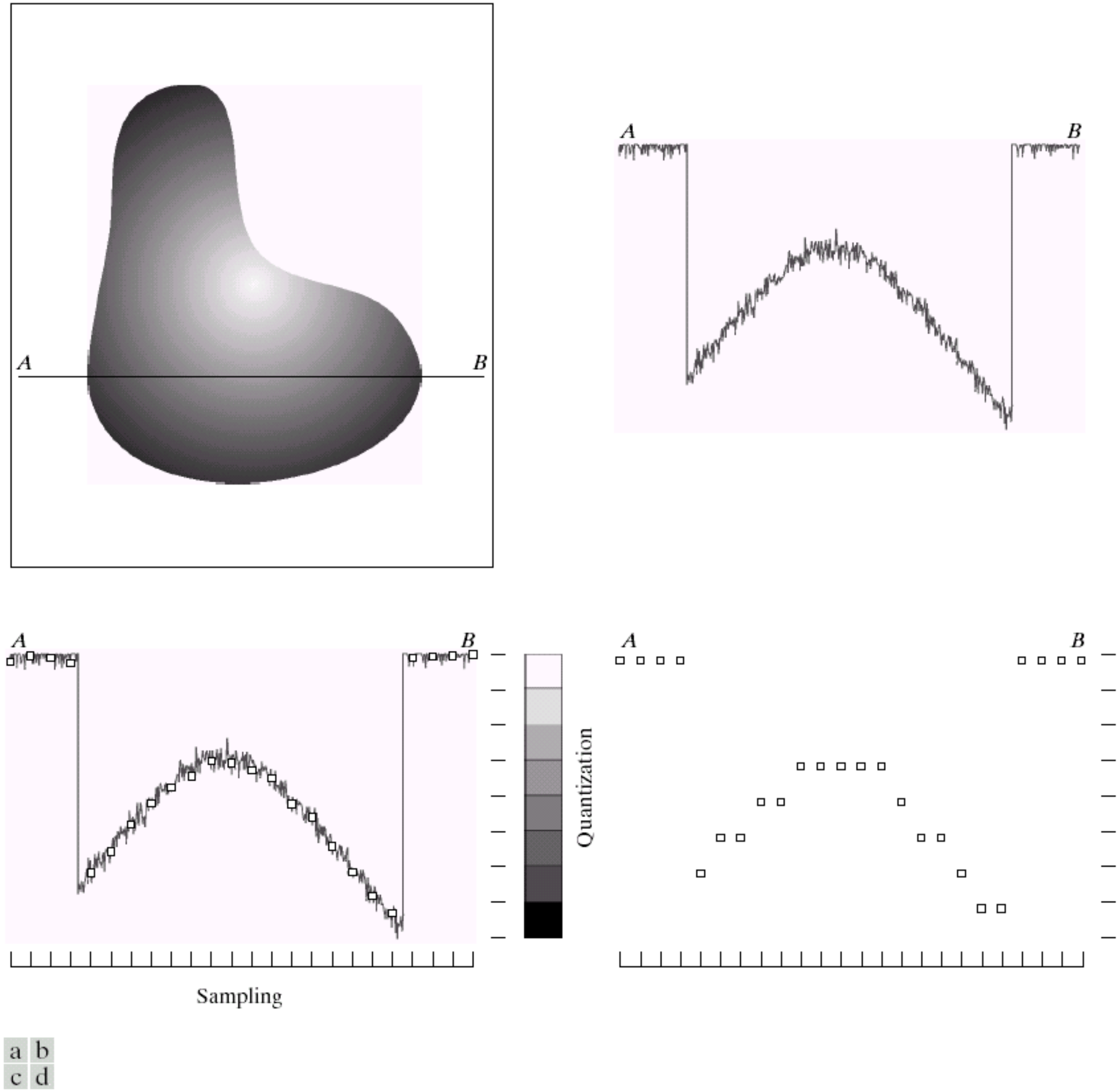
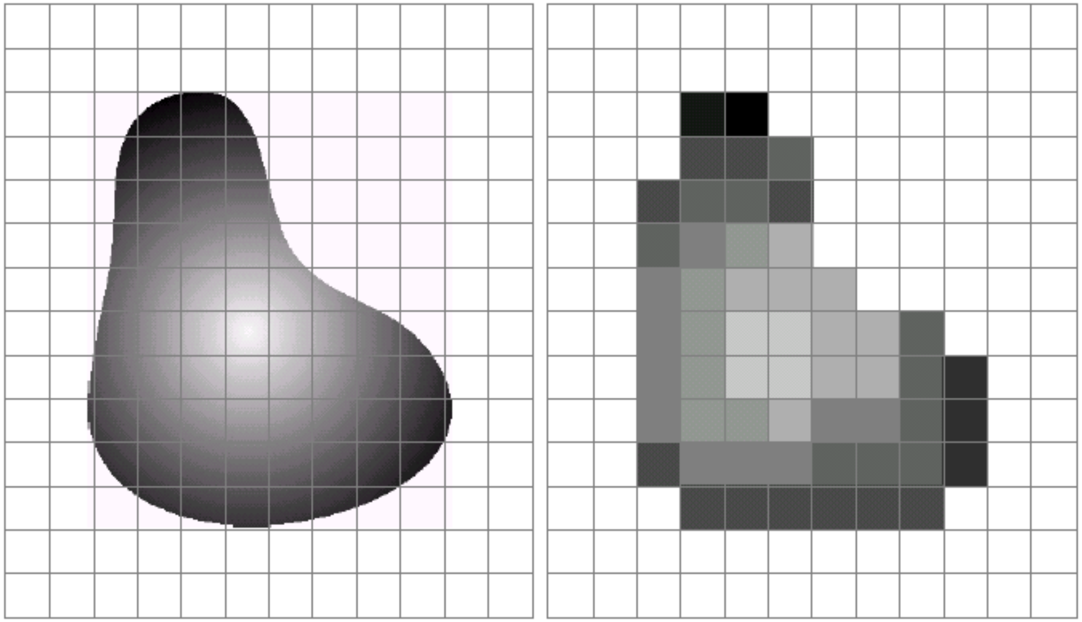


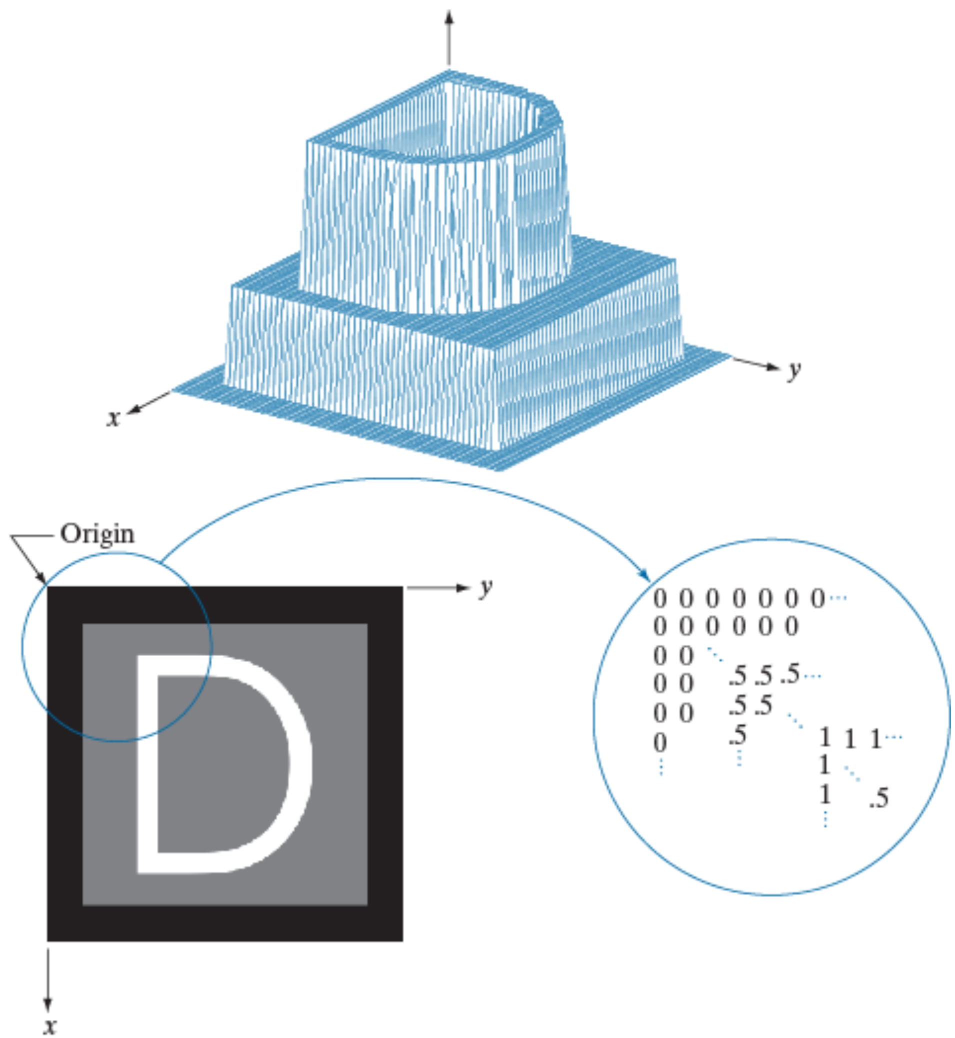
FIGURE 2.16 Generating a digital image. (a) Continuous image. (b) A scan line from A to B in the continuous image, used to illustrate the concepts of sampling and quantization. (c) Sampling and quantization. (d) Digital scan line.

Sampling and Quantization



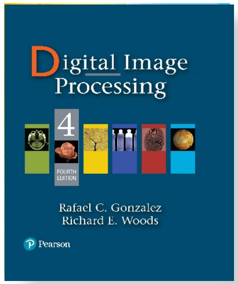
a b

FIGURE 2.17 (a) Continuos image projected onto a sensor array. (b) Result of image sampling and quantization.



a
b c

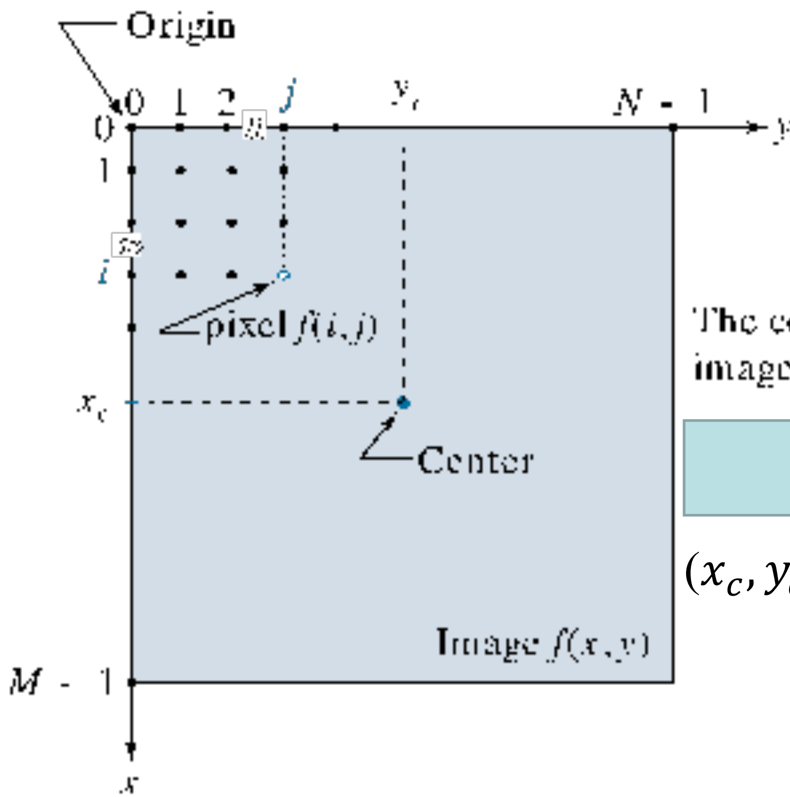
FIGURE 2.18 (a) Image plotted as a surface. (b) Image displayed as a visual intensity array. (c) Image shown as a 2-D numerical array. (The numbers 0, .5, and 1 represent black, gray, and white, respectively.)



Chapter 2

Digital Image Fundamentals

FIGURE 2.19 Coordinate convention used to represent digital images. Because coordinate values are integers, there is a one-to-one correspondence between x and y and the rows (r) and columns (c) of a matrix.



The coordinates of the image center are

$$(x_c, y_c) = \left(floor\left(\frac{M}{2}\right), floor\left(\frac{N}{2}\right)\right)$$

Sampling & Quantization

$$f(x,y)=\begin{bmatrix} f(0,0) & f(0,1) & \dots & f(0,M-1) \\ f(1,0) & \dots & \dots & f(1,M-1) \\ \dots & \dots & \dots & \dots \\ f(N-1,0) & f(N-1,1) & \dots & f(N-1,M-1) \end{bmatrix}$$

Digital Image

Image Elements
(Pixels)

Sampling & Quantization

- The digitization process requires decisions about:
  - values for N, M (where N x M: the image array)

and

  - the number of discrete gray levels (quantization levels) allowed for each pixel.

Sampling & Quantization

- Usually, in DIP these quantities are integer powers of two:

$$N = 2^n \qquad M = 2^m \qquad \underbrace{L}_{\text{number of gray levels}} = 2^k$$

- Another assumption is that the discrete levels are equally spaced between 0 and L-1 in the gray scale.

Sampling & Quantization

- If b is the number of bits required to store a digitized image then:
  - $b = N \text{ x } M \text{ x } k$ (if M=N, then b=N^2k)

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The number of bits required to store an image is $b=M\text{x}N\text{x}k$ and when $M=N$, b becomes N^2k.

TABLE 2.1
Number of storage bits for various values of N and k.

N/k	1 (L = 2)	2 (L = 4)	3 (L = 8)	4 (L = 16)	5 (L = 32)	6 (L = 64)	7 (L = 128)	8 (L = 256)
32	1,024	2,048	3,072	4,096	5,120	6,144	7,168	8,192
64	4,096	8,192	12,288	16,384	20,480	24,576	28,672	32,768
128	16,384	32,768	49,152	65,536	81,920	98,304	114,688	131,072
256	65,536	131,072	196,608	262,144	327,680	393,216	458,752	524,288
512	262,144	524,288	786,432	1,048,576	1,310,720	1,572,864	1,835,008	2,097,152
1024	1,048,576	2,097,152	3,145,728	4,194,304	5,242,880	6,291,456	7,340,032	8,388,608
2048	4,194,304	8,388,608	12,582,912	16,777,216	20,971,520	25,165,824	29,369,128	33,554,432
4096	16,777,216	33,554,432	50,331,648	67,108,864	83,886,080	100,663,296	117,440,512	134,217,728
8192	67,108,864	134,217,728	201,326,592	268,435,456	335,544,320	402,653,184	469,762,048	536,870,912

Ex. 8-bit images of size 1024 by 1024 and higher require a significant storage space!

How do these parameters (N and k) affect the image?

Sampling & Quantization

- How many samples and gray levels are required for a good approximation?
  - Resolution (the degree of discernible detail) of an image depends on the number of samples and the number of gray levels.
  - i.e. the more these parameters are increased, the closer the digitized array approximates the original image.
  - But: storage & processing requirements increase rapidly as a function of N, M, and k

Sampling & Quantization

- Different versions (images) of the same object can be generated through:
  - Varying the image size M and N,
  - Varying k (number of bits)
  - Varying both

Example 1: An image may exhibit Noise and Saturation

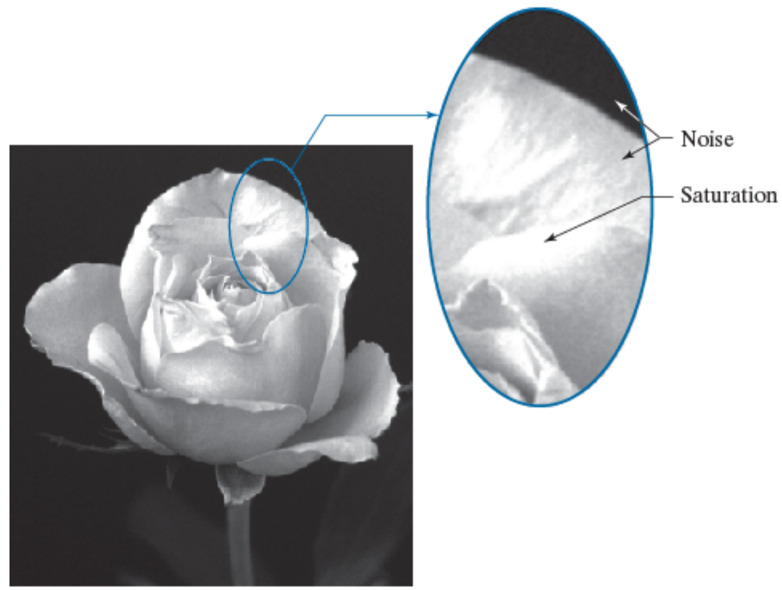


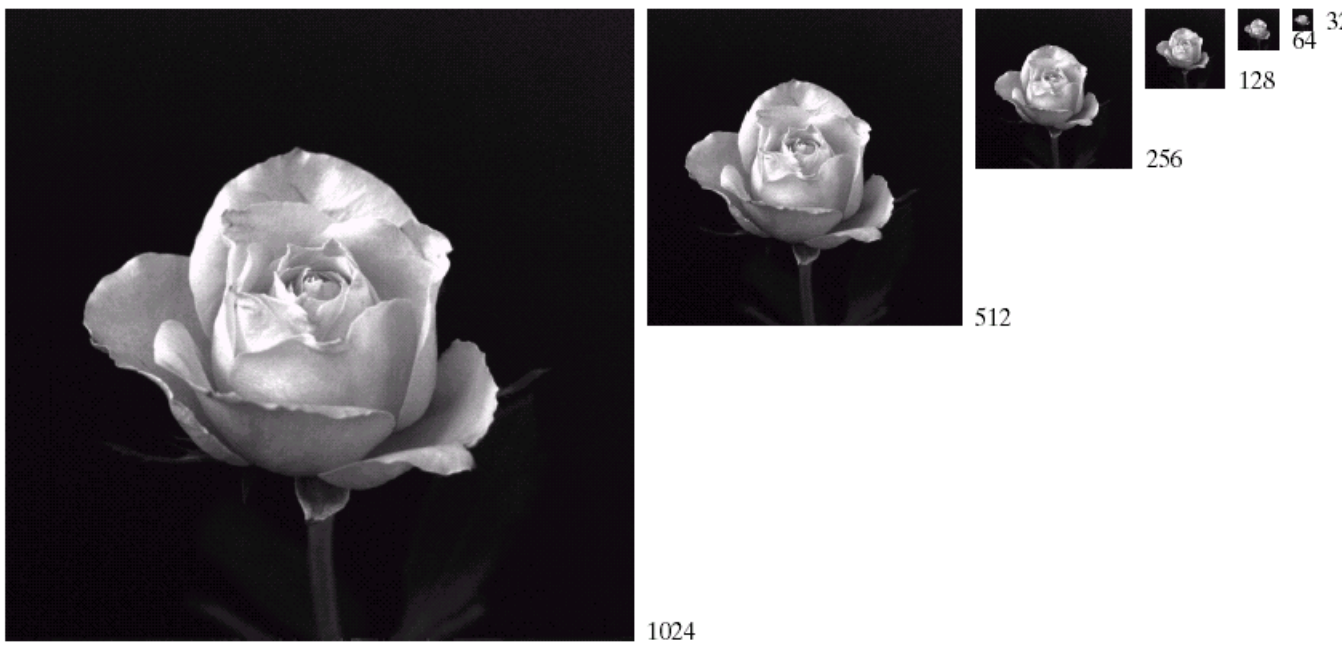
FIGURE 2.20 An image exhibiting saturation and noise. Saturation is the highest value beyond which all intensity values are clipped (note how the entire saturated area has a high, constant intensity level). Visible noise in this case appears as a grainy texture pattern. The dark background is noisier, but the noise is difficult to see.

Saturation: highest value beyond which all intensity values are clipped (saturation area has a high constant intensity level

Visible noise: Grainy texture patterns (more difficult to see in the dark background)

Chapter 2: Digital Image Fundamentals

Example 2a: Spatial Resolution: we keep k constant at 8 bits and we vary N from 1024 to 32.



~~FIGURE 2.19~~ A 1024 × 1024, 8-bit image subsampled down to size 32 × 32 pixels. The number of allowable gray levels was kept at 256.

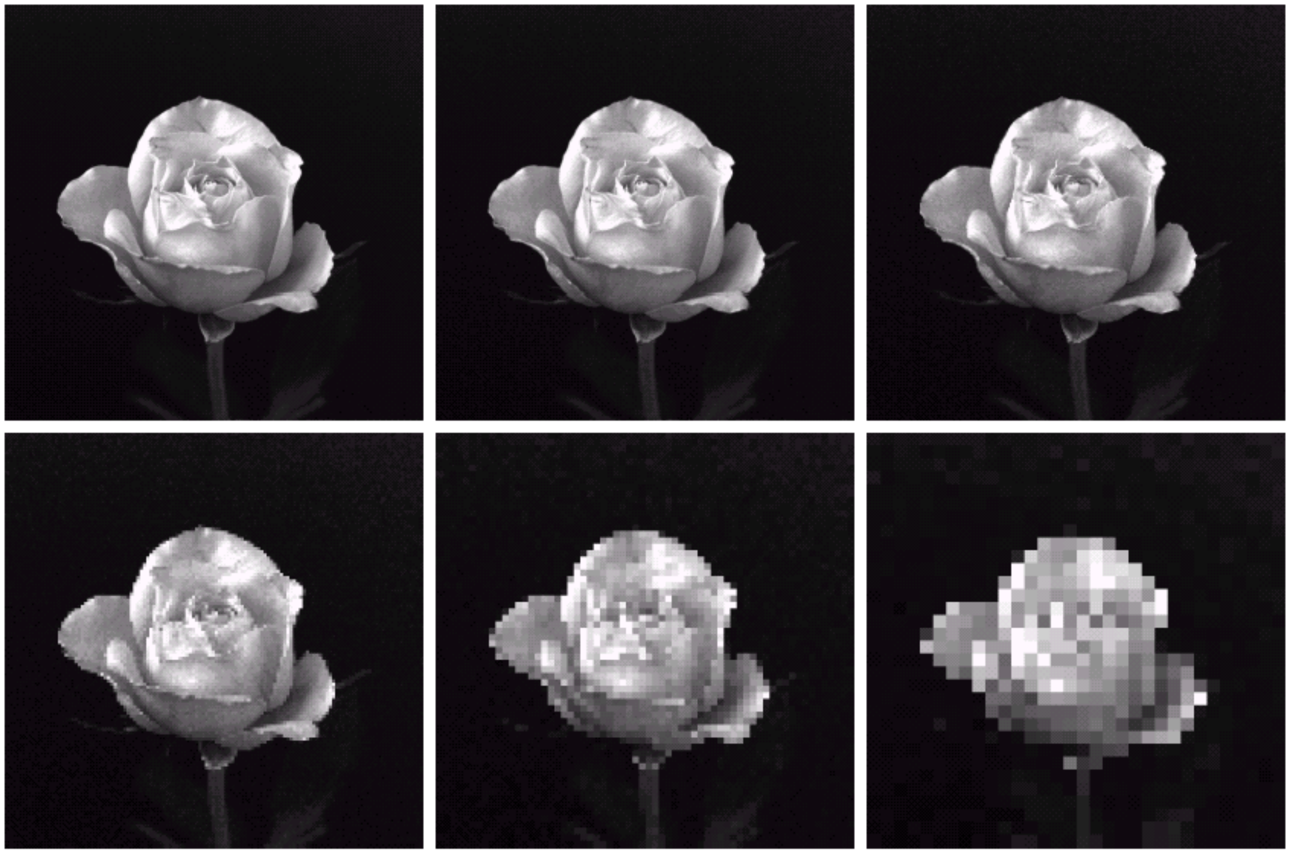
How? The original 1024 by 1024 image is subsampled by removing every other column and every other row to produce the 512 by 512 image.

Image Resampling:

To visualize the difference, we up-sample (by duplication) to the original size of 1024 by 1024.

1024x1024

256x256



128x128

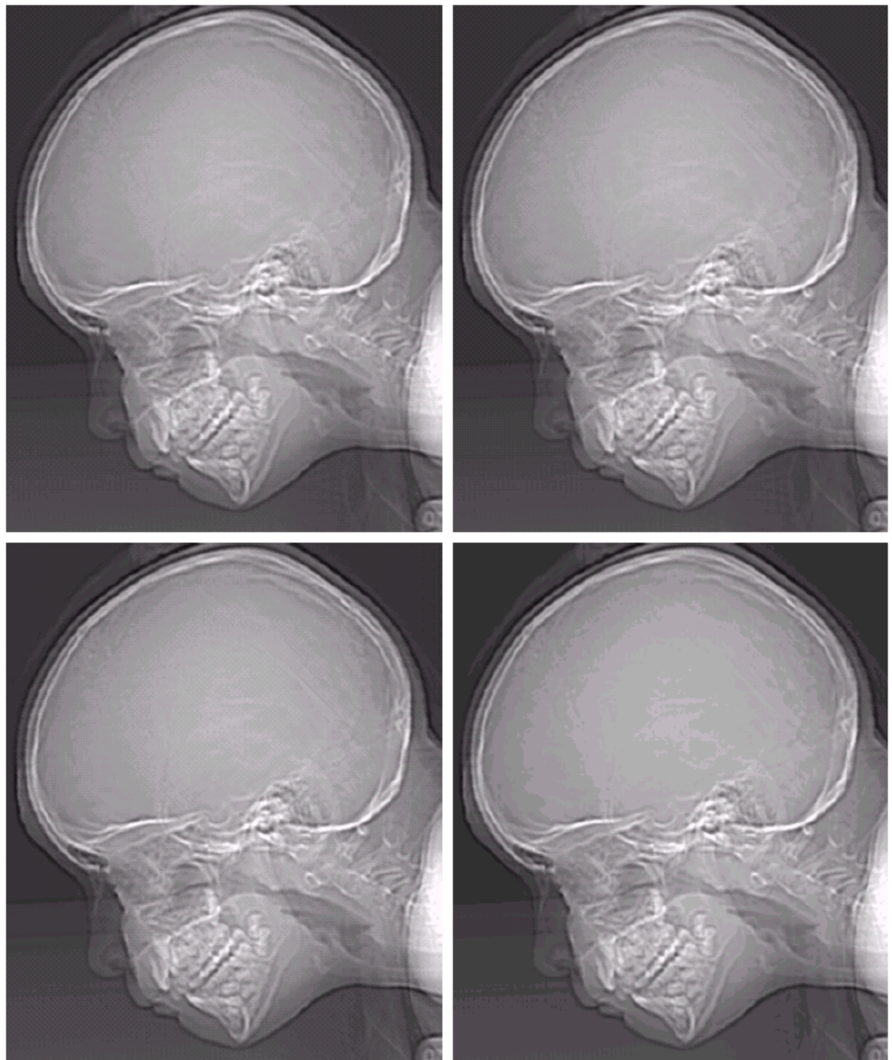
32x32

a b c
d e f

[redacted] (a) 1024 × 1024, 8-bit image. (b) 512 × 512 image resampled into 1024 × 1024 pixels by row and column duplication. (c) through (f) 256 × 256, 128 × 128, 64 × 64, and 32 × 32 images resampled into 1024 × 1024 pixels.

Example 2b: we keep the image size constant at 452x374 and reduce the number of gray levels $L=2^k$ from 256 to 2 (i.e. reduce k from 8 to 1)

256 levels



a b
c d

[redacted]
(a) 452 × 374, 256-level image. (b)–(d) Image displayed in 128, 64, and 32 gray levels, while keeping the spatial resolution constant.

128 levels

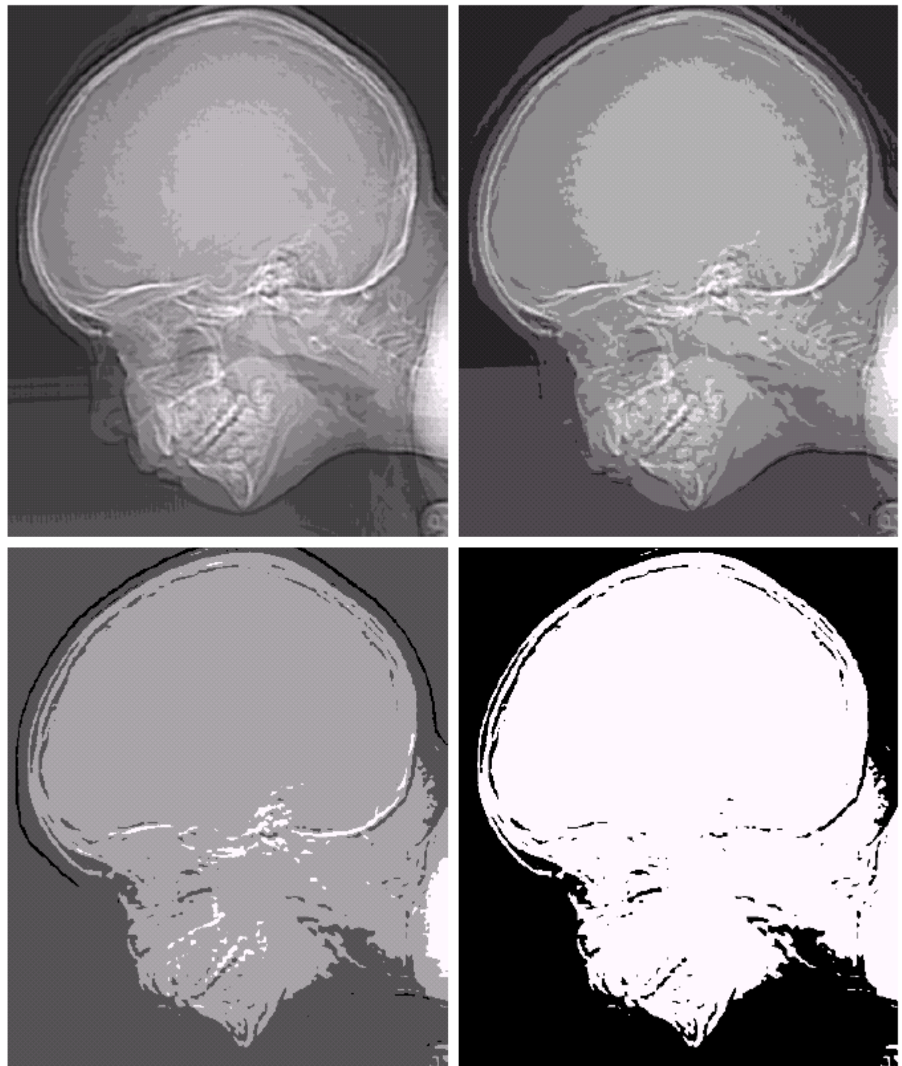
64 levels

in this 32-level image, note the appearance of very fine ridge-like structures in the areas of smooth gray levels, e.g. skull.

Due to insufficient number of gray levels, this artifact is more visible below and it is called false contouring.

e f
g h

[redacted]
(Continued)
(e)–(h) Image displayed in 16, 8, 4, and 2 gray levels. (Original courtesy of Dr. David R. Pickens, Department of Radiology & Radiological Sciences, Vanderbilt University Medical Center.)



16	8
4	2

Sampling & Quantization

Example 3: what happens when we vary both N and k?

Isopreference curves (in the Nk-plane)

low level detail medium level detail high level detail

a b c

FIGURE 2.25 (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.)

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Isopreference [Huang 1965] curves are plotted in the Nk-plane, where each point represents an image having values of N and k equal to the coordinates of that point.

Points lying on an isopreference curve correspond to images of equal subjective quality.

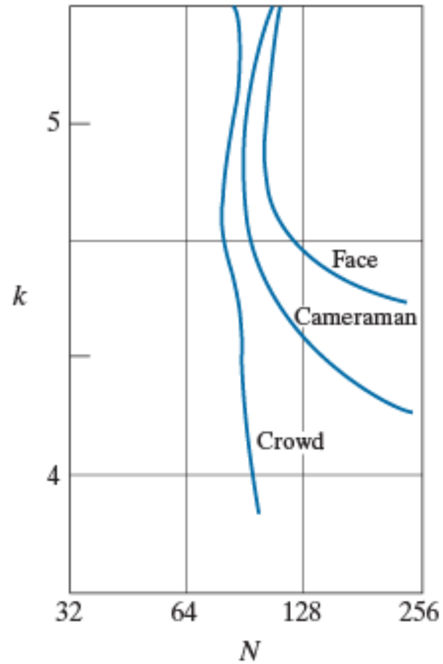

FIGURE 2.26 Representative isopreference curves for the three types of images in Fig. 2.25.

Observations:

1. Isopreference curves tend to shift right and upward (i.e. better image quality)
2. In images with a large amount of details, only a few gray levels are needed
3. In the other two image categories, the perceived quality remained the same in some intervals in which N was increased but k actually decreased! (more contrast in the image is perhaps preferred by some people!)

Sampling & Quantization

- Conclusions:
  - Quality of images increases as N & k increase
  - For some images, for fixed N, quality improves by decreasing k (perceived contrast is increased)
  - For images with large amounts of detail, few gray levels may be enough

Nonuniform Sampling
Nonuniform Quantization

- So far we assumed uniform sampling and uniform quantization
- An adaptive sampling scheme can improve the appearance of an image, where the sampling would consider the characteristics of the image.
  - i.e. fine sampling in the neighborhood of sharp gray-level transitions (e.g. boundaries)
  - Coarse sampling in relatively smooth regions
- Considerations: boundary detection, detail content

Nonuniform Sampling & Quantization

- Nonuniform quantization
  - few gray levels in the neighborhood of boundaries
  - more in regions of smooth gray-level variations (reducing thus false contours)

- Nonuniform sampling and nonuniform quantization are outside the scope of this course.