Digital Image Processing

Introduction

Erchan Aptoula

Spring 2016-2017

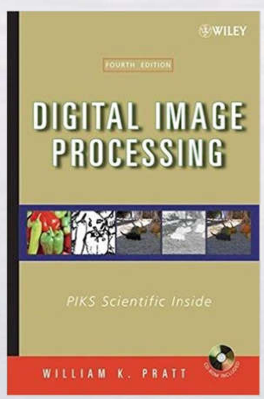
Introduction

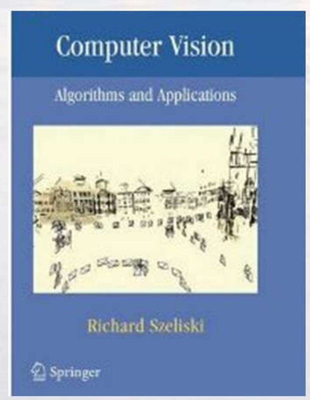
Contact

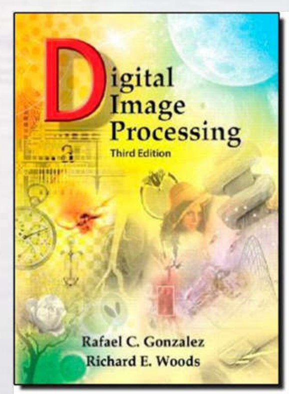
- Office #253; only at office hours.
- Faster responses through email: eaptoula@gtu.edu.tr
- All course related communication will run through moodle.

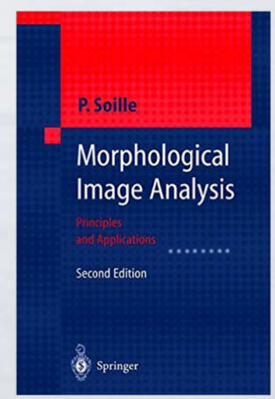
Popular textbooks

- R. Gonzalez & R. Woods, Digital image processing, 3r ed. 2008.
- W. K. Pratt, Introduction to digital image processing, 4th ed. 2007
- R. Szeliski, Computer vision: algorithms and applications, 2010
- P. Soille, Morphological image analysis, 2004









- Grading

	Undergraduates	Graduates
Homework	30%	30%
Midterm	30%	25%
Final Exam	30%	25%
Presentation	10%	20%

- Attendance is mandatory.
- Plagiarism will be **punished**.
- Late arrivals are not allowed.

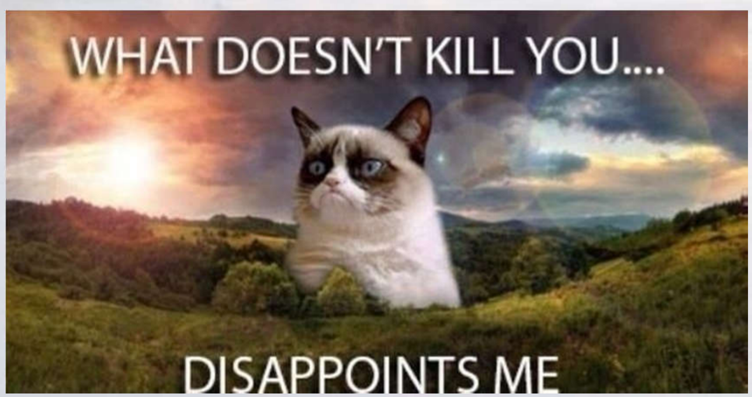
AA	BA	BB	CB	CC	DC	DD	FF
100-90	89-80	79-70	69-60	59-50	49-45	44-40	39-0

Course objectives **are**…

- To provide an introduction to the principles of digital image processing
- To provide an insight into digital image analysis
- To teach the use and properties of basic digital image processing/analysis tools
- To prepare you for the computer vision course

Course objectives **are NOT**…

- To teach you photoshop/coreldraw/autocad
- To teach you digital painting/drawing



Requirements

- Linear algebra
  - Matrices, matrix operations
  - Systems of linear equations
  - Eigenvalues, eigenvectors
- Statistics and probability
  - Probability density function
  - Mean, variance, co-variance
  - Gaussian distribution
- Programming skills (<u>Java</u> | C/C++/OpenCV | Matlab)

Digital image processing is about processing digital images;
i.e. an image stored in a digital medium.

And why process digital images?

- Acquisition: color balance correction
- Display or printing: color mapping, gamma-correction, half-toning
- Storage/transmission: compression
- Enhancement/restoration: noise reduction
- Information extraction: content description

etc.

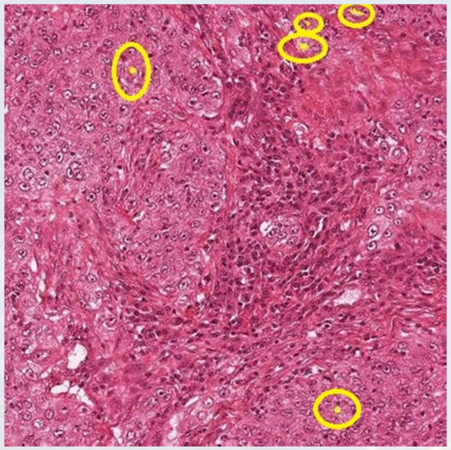
Image stitching

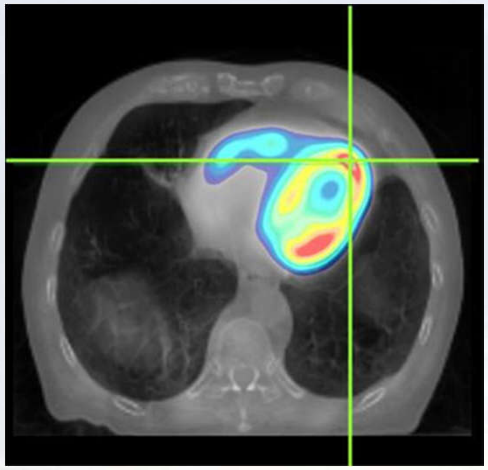
Image restoration

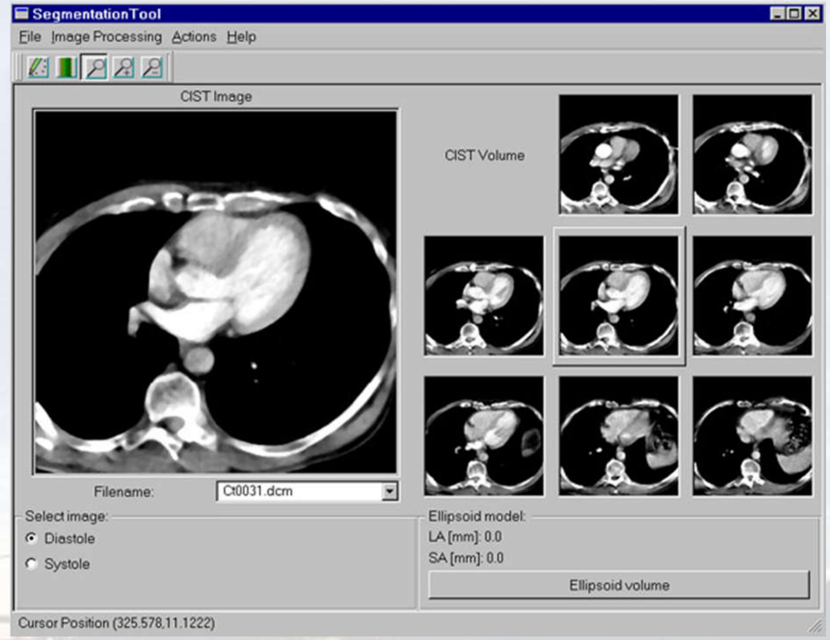
Automated visual industrial inspection

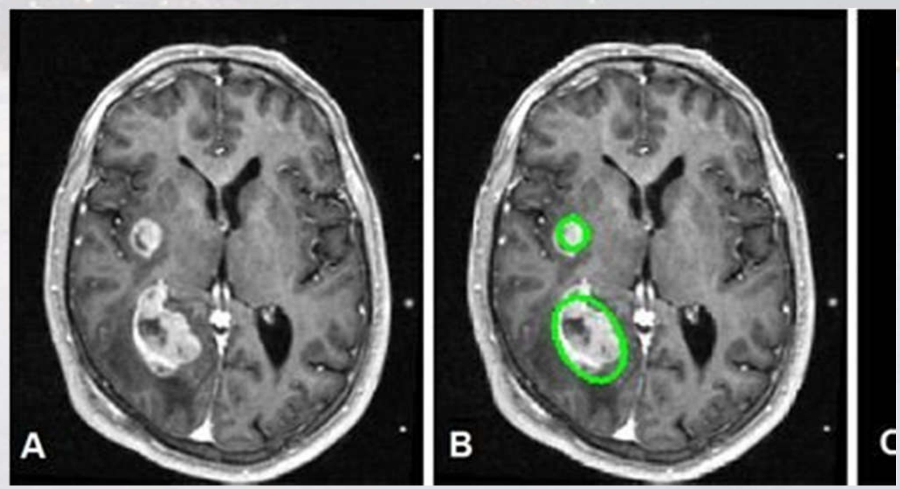
Introduction – image processing examples

(Bio)Medical image processing





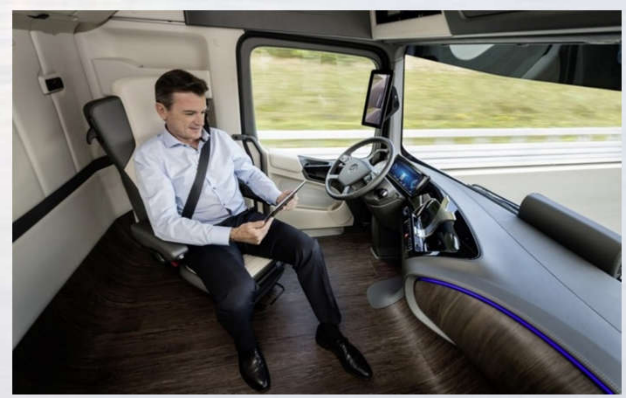




Introduction – image processing examples

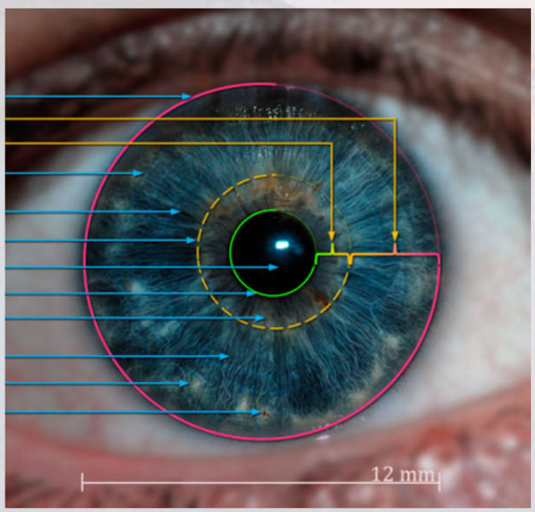
Autonomous vehicles





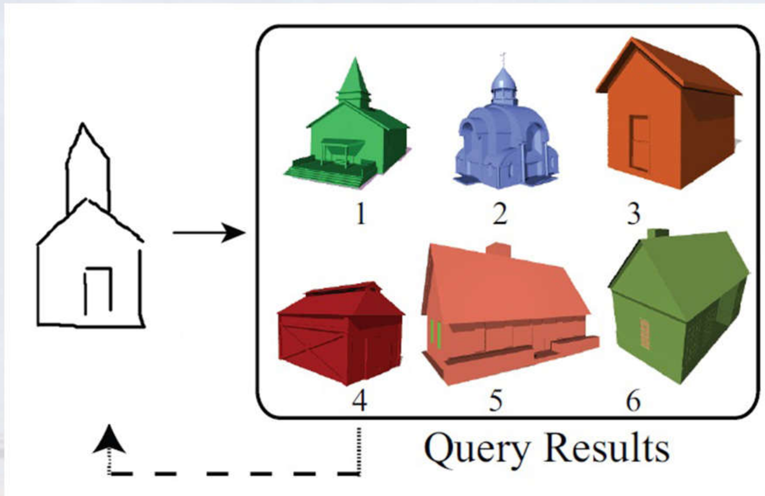
Introduction – image processing examples

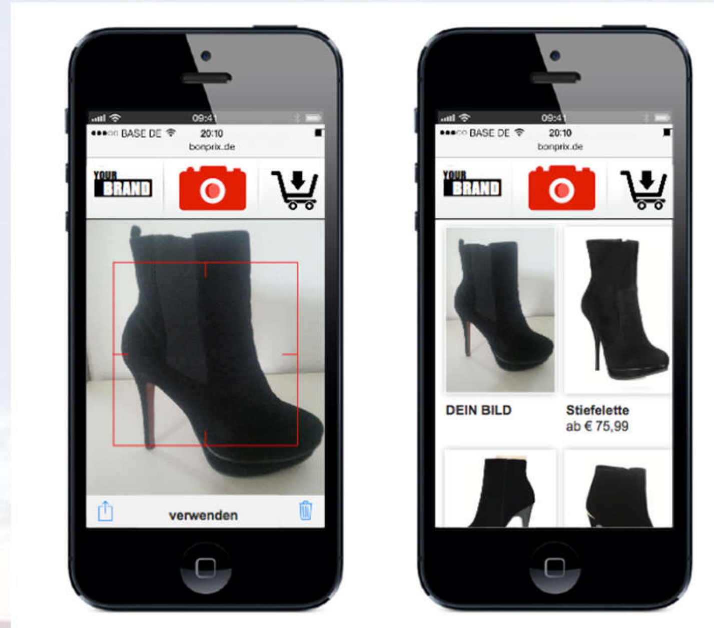
Biometrics and forensics

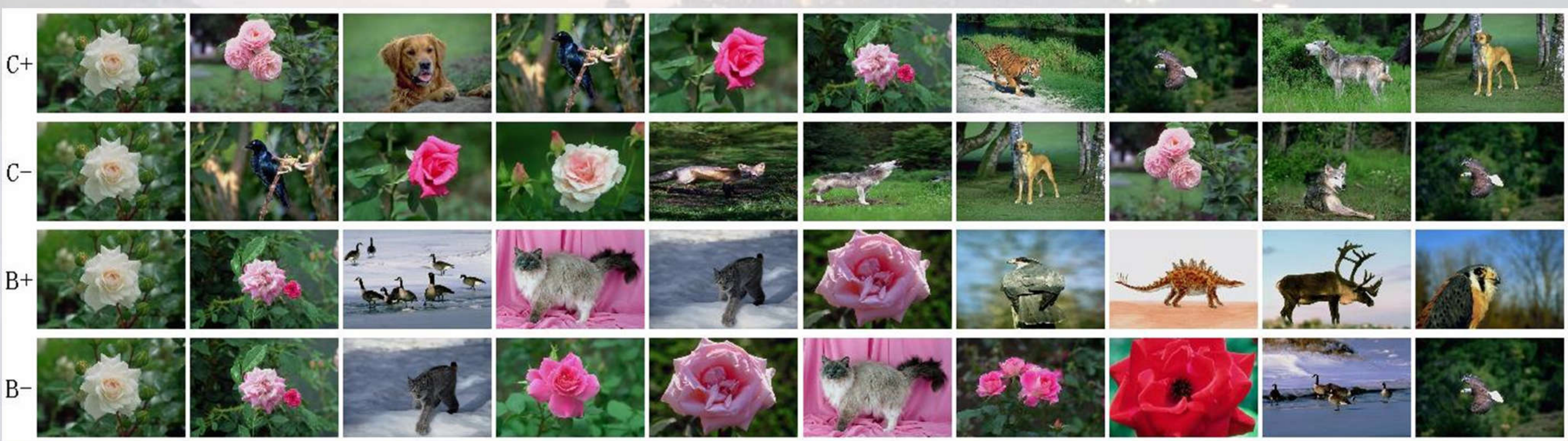


Introduction – image processing examples

Content based image retrieval

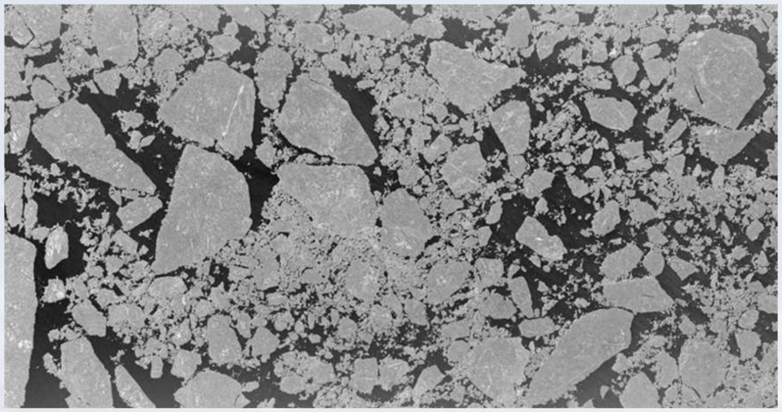


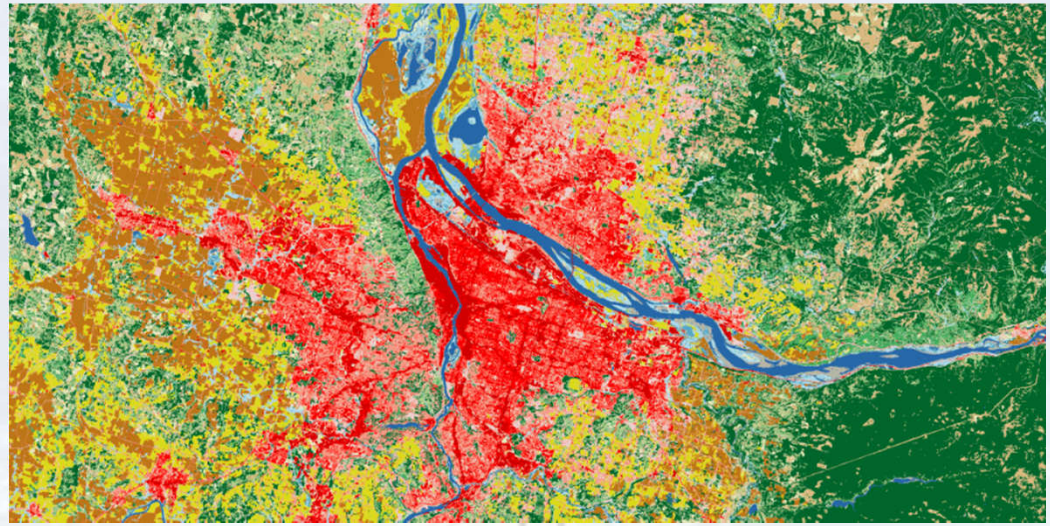




Introduction – image processing examples

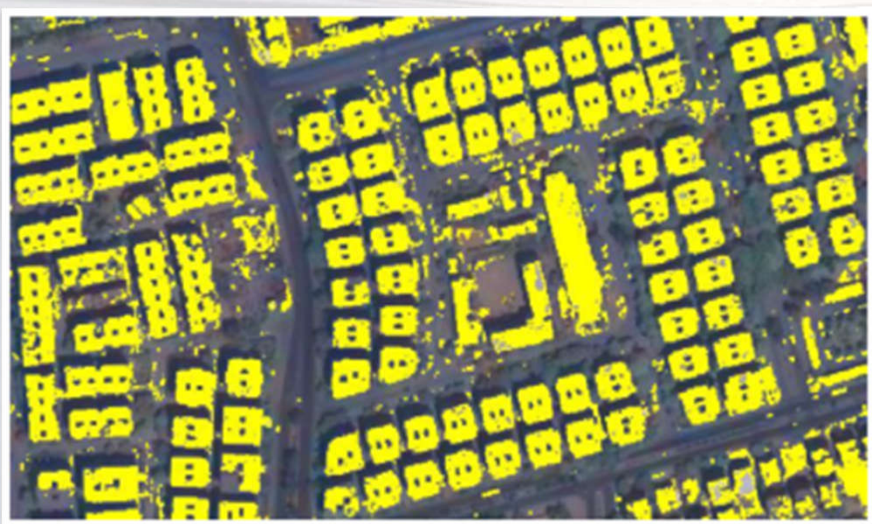
Remote sensing

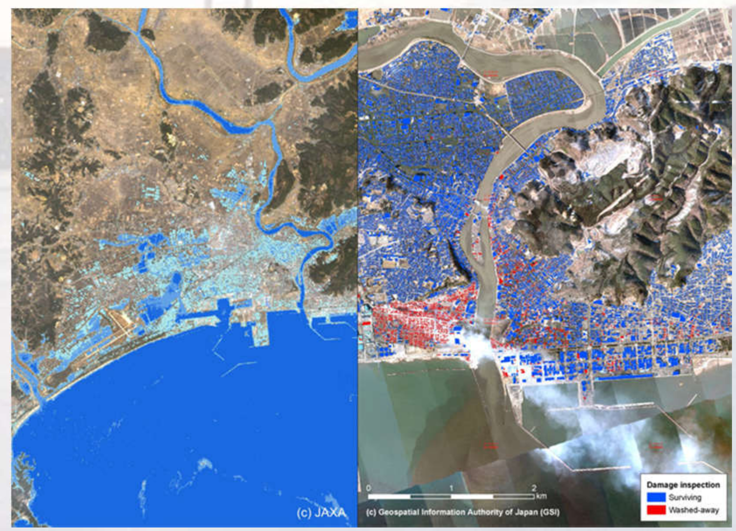




Environmental monitoring

Landcover classification

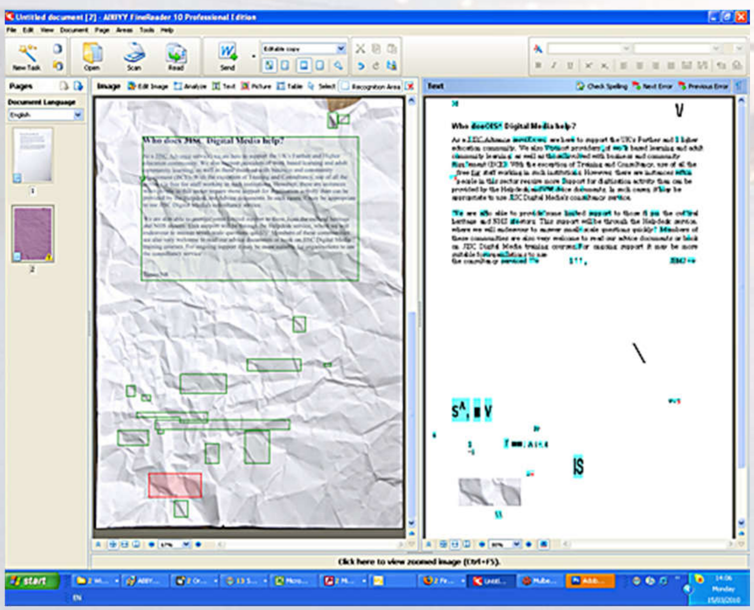




Building detection

Disaster management

Optical character recognition



Visual arts

Most of the aforementioned applications involve multi-level processing.

- Low-level (~**image processing**): both input and output are **often** images
- Mid-level (~**image analysis**): aims to extract useful information from images; constructs feature vectors, computes partitions, etc.
- High-level (~**computer vision**): aims to enable machines to "see"; to recognize and perceive concepts/objects, to interpret visual data semantically.

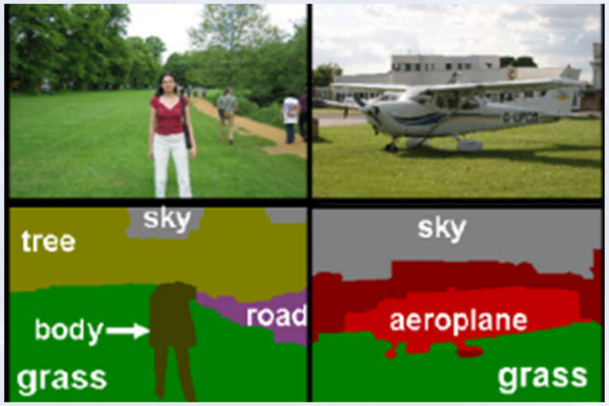
Low-level processing: edge detection

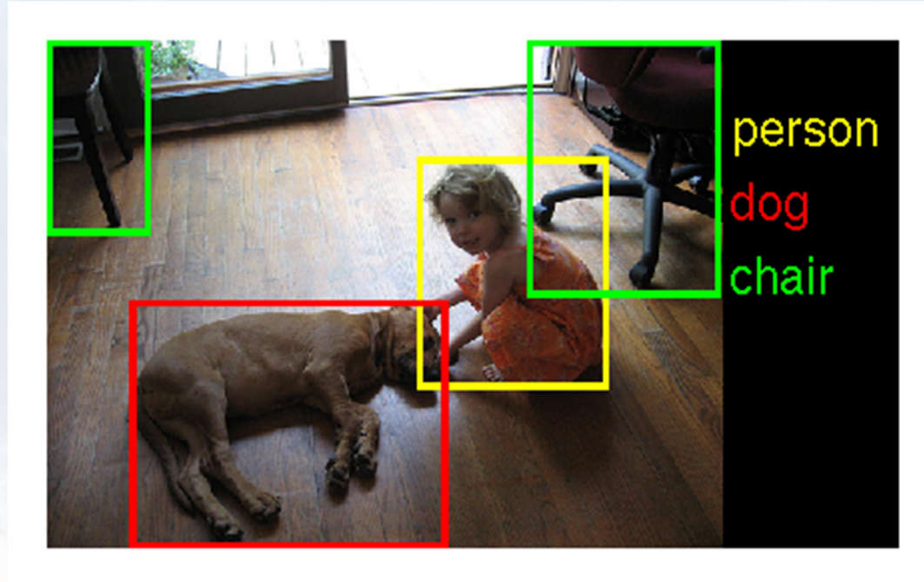
Mid-level processing: segmentation

$$[0.1. 0.5, 0.07, 0.55, 0.72]^T$$

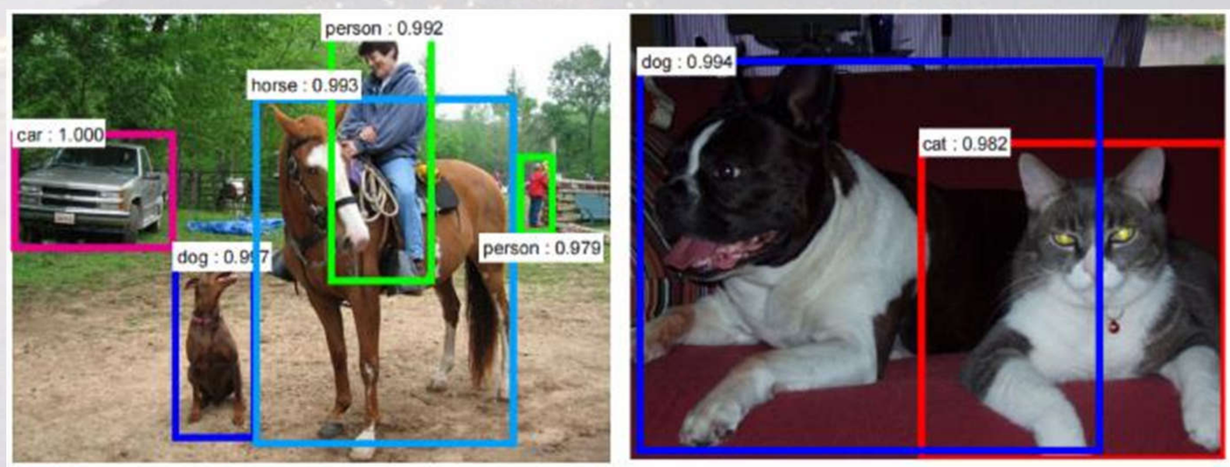
Mid-level processing: feature extraction

Introduction





High-level processing: event recognition and object categorization



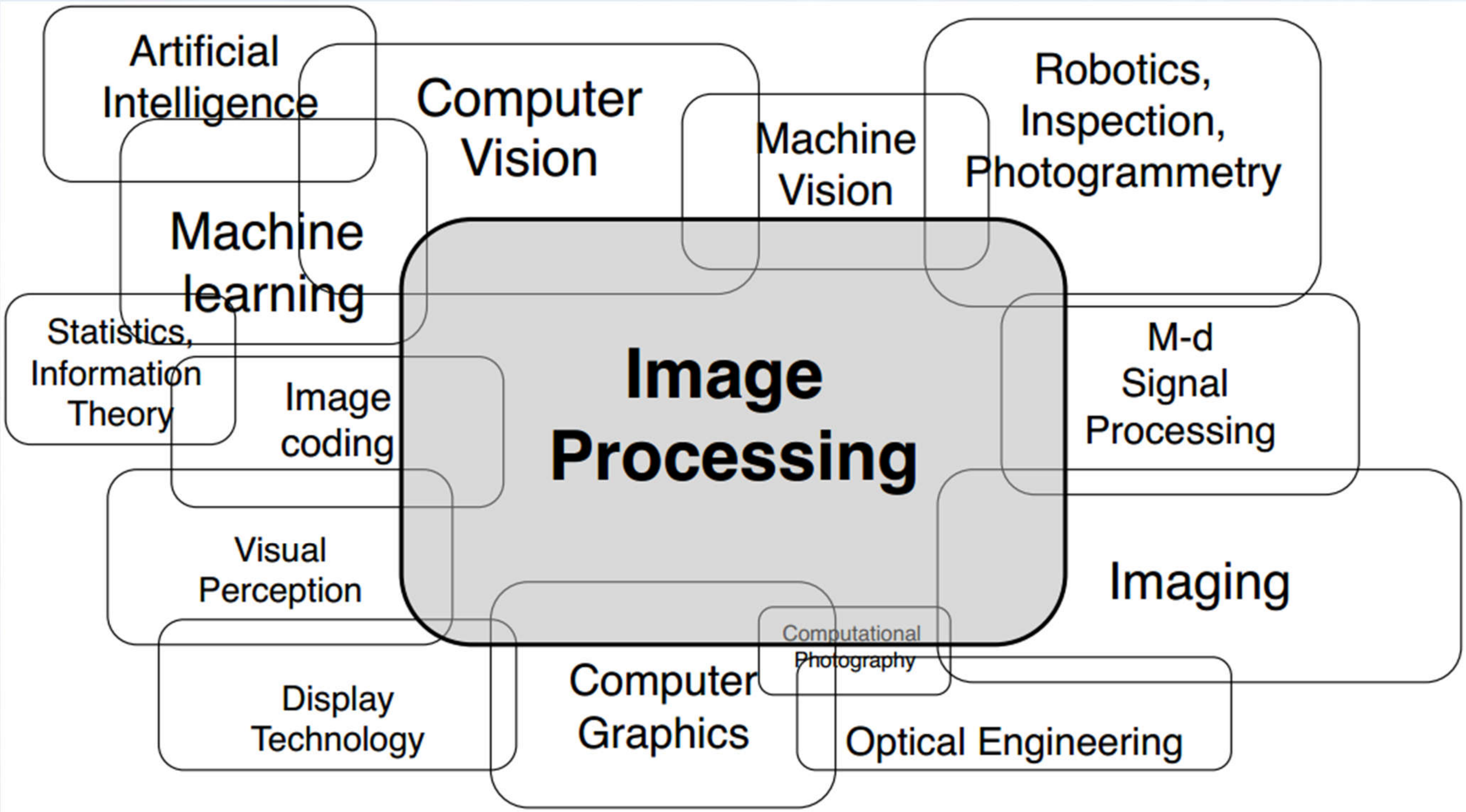


Image from Bernd Girod, Stanford

1. Introduction to digital image processing/analysis
2. Point processing
3. Binary image analysis
4. Spatial domain linear filtering
5. Frequency domain linear filtering
6. Non-linear filtering: mathematical morphology
7. Color image processing
8. Midterm
9. Content description
10. Case study 1
11. Segmentation
12. Case study 2
13. Student presentations
14. Case study 3

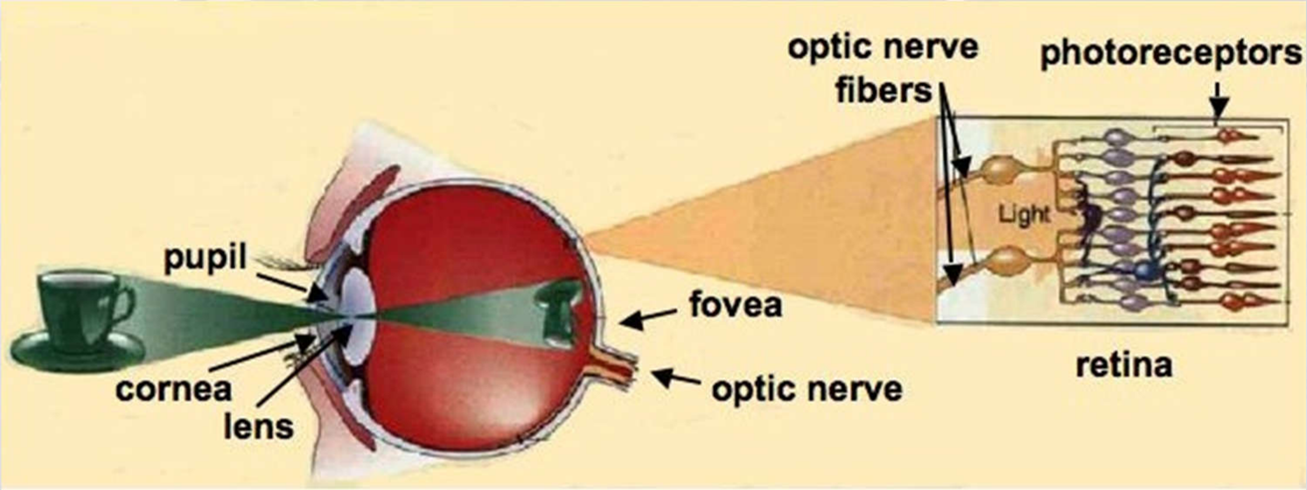
A mixture of image analysis and image processing

For the latest developments in this field:

- IEEE Transactions on Image Processing
- IEEE Transactions on Pattern Analysis and Machine Intelligence
- International Journal of Computer Vision
- Pattern Recognition
- Image and Vision Computing
- Computer Vision and Image Understanding
- International Conference on Computer Vision (ICCV)
- European Conference on Computer Vision (ECCV)
- Computer Vision and Pattern Recognition Conference (CVPR)
- International Conference on Image Processing (ICIP)

etc.

- When the eye is properly focused, light from an object outside the eye is imaged on the **retina**
- There are discrete light receptors on the retina.
- They transform light into electric signals, that are subsequently sent to the visual cortex for processing.
- There are two classes of receptors: **Cones** and **Rods**



Cones

- ~6 - 7 million cells, in the central portion of retina (fovea)
- Highly sensitive to color, we can see fine details with them
- Cone vision is called photopic or bright-light vision
- Women have more than men (we'll talk about them in a few weeks)

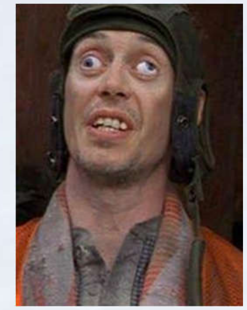
Rods

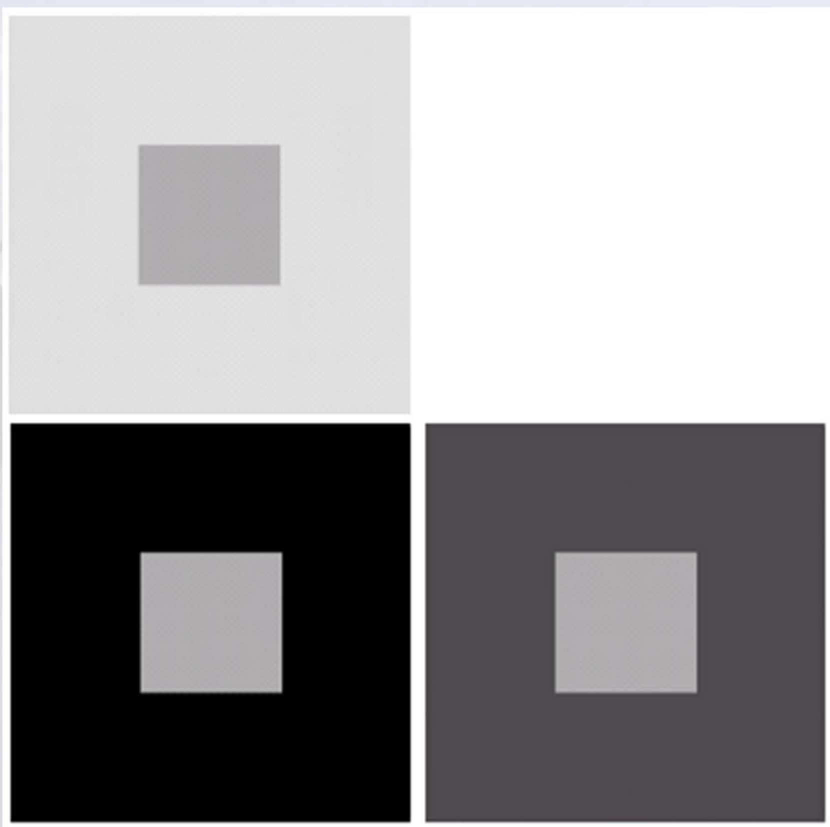
- ~75-150 million cells
- Less detail is discernible by them, they provide an overall picture of the FoV
- Sensitive to low-level illumination, rod vision is called scotopic or dim-light vision
- Men have more than women

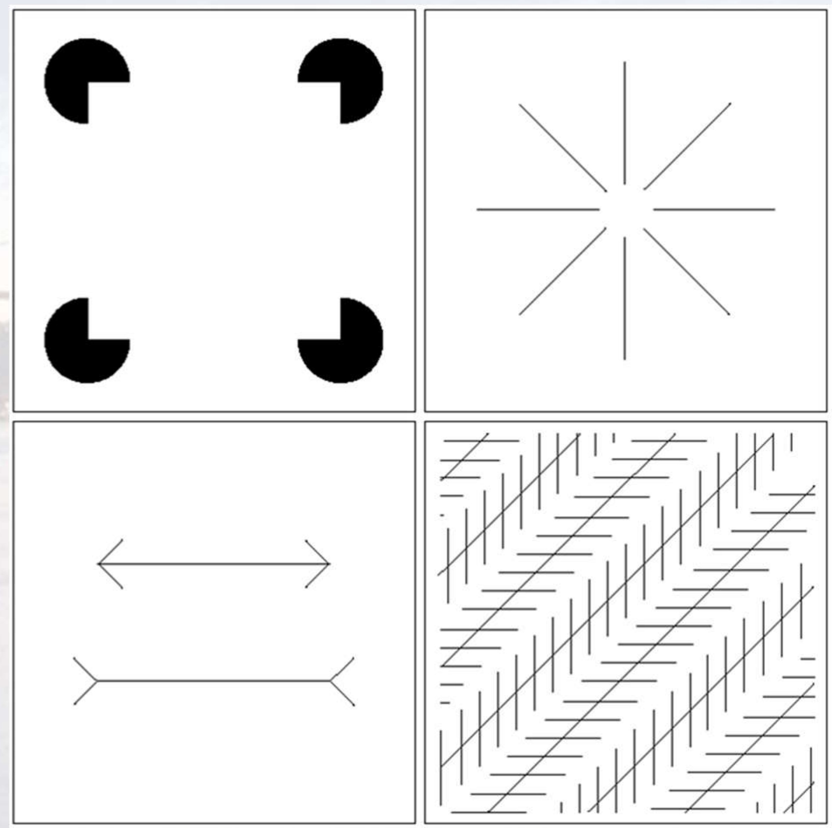
Introduction – Quick recall on the Human Vision System

Wonders of the human eye

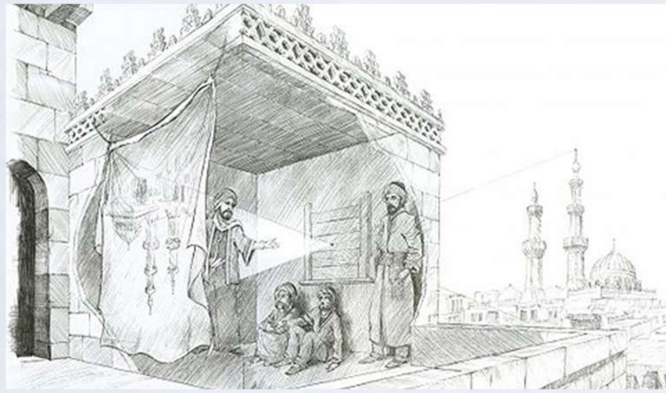
- Very high adaptation capability to brightness variations
- Perceived brightness depends on context
- Very little is known about higher human vision





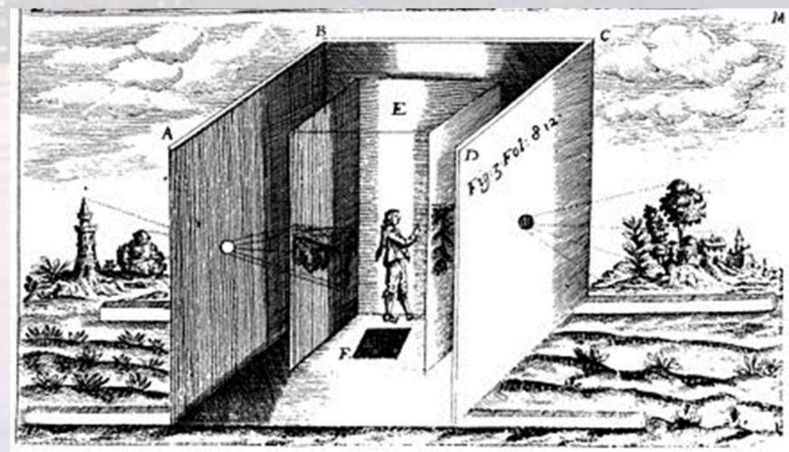


Introduction – A short history of image acquisition

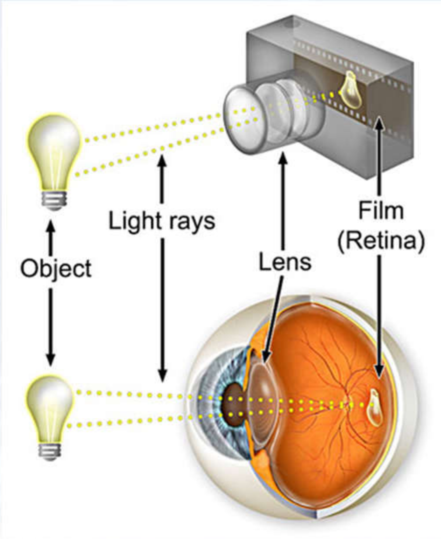


İbn-i Heysem, 10th century, author of the “Book of Optics”, inventor of the scientific method

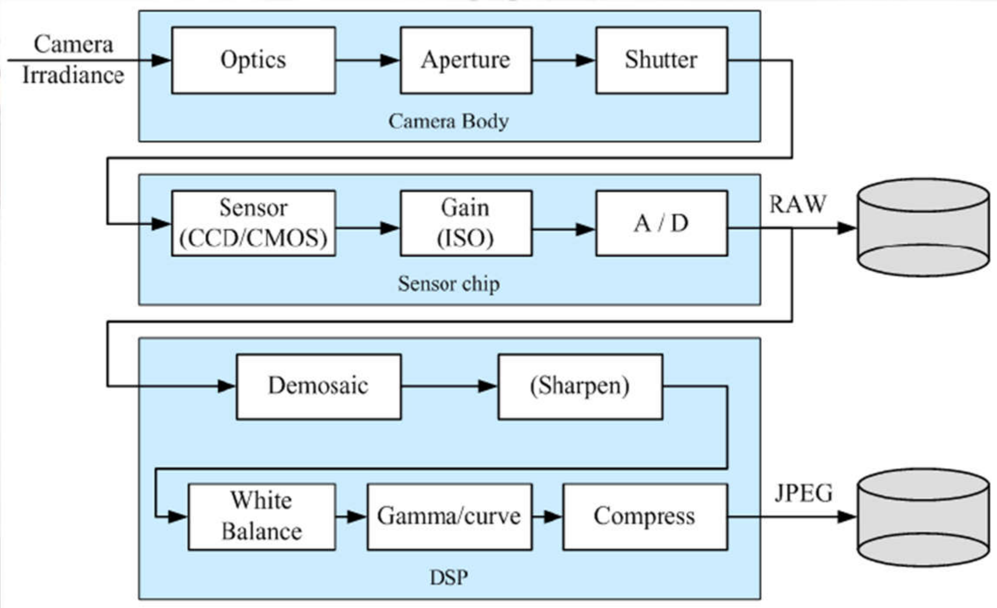
The “camera obscura”, 16th century.



Nicephore Niepse; first photograph, 19th century.



From analog to digital, invention of the Charged Coupled Device (CCD) in 1969 by Boyle & Smith; Physics Nobel Prize, 2009.

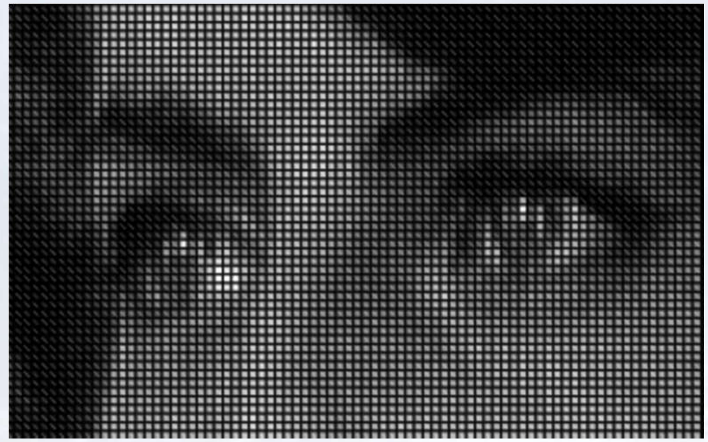


- **A** 2D **image** or a visual scene, can be modeled through a function $f(x, y)$ where f represents the "brightness intensity or color" at location (x, y).
- f is a continuous function in both amplitude and space.

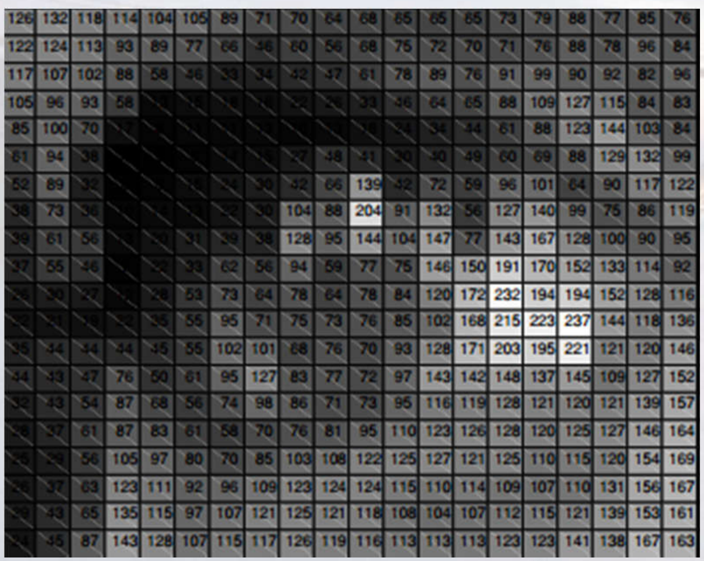
A digital image refers to a discretized version of $f(x, y)$, represented as $f[x, y]$ in the form of a 2D array. Every element of this array is referred to as a **pixel**, and the digitized brightness value is called a **gray level**.

$f[x, y] = \begin{bmatrix} f[0,0] & \cdots & f[W,0] \\ \vdots & \ddots & \vdots \\ f[0,H] & \ldots & f[W,H] \end{bmatrix}$, $0 \leq f[x, y] \leq G$-1, and G is a power of 2.

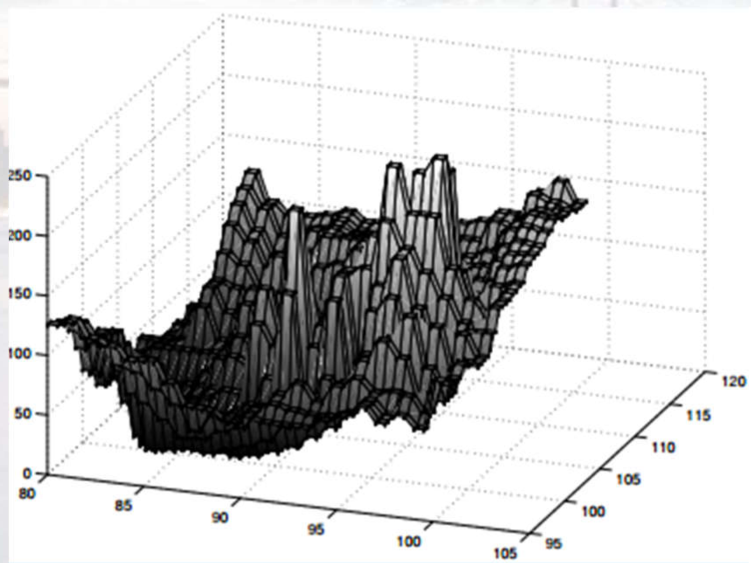
Introduction – Image acquisition

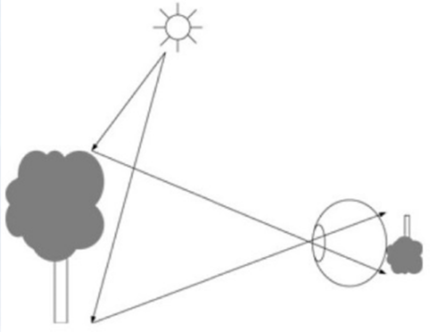


Discrete grid



Gray values/levels





But how is the **gray level** calculated?

In short (assuming zero noise):

1 – An object is illuminated with light

2 – The light is partly absorbed and partly reflected

3 – The reflected photon of energy E_{λ_a} at wavelength λ_a reaches a sensor with a sensitivity curve $s(\lambda)$

4 – The product $E_{\lambda_a} \times s(\lambda_a)$ is computed and accumulated.

5 – The total energy collected by the sensor (during the exposure) is used in order to calculate the gray level/intensity corresponding to that sensor.

The intensities of pixels are significant only **relatively** to each other, and are **meaningless** in absolute terms. Pixel values of different images, can be compared only if either the acquisition conditions were identical, or if the images have been normalized to remove the effect of different physical processes; in which case we say the sensors have been **calibrated**.

Example

You possess a single sensor and its sampled sensitivity. You also have (in some units) the energy amounts E_{λ_i} corresponding to wavelength λ_i. The shutter of the camera is open long enough for 5 photons to reach the sensor. The wavelengths of the photons are: $\lambda_0, \lambda_3, \lambda_3, \lambda_0, \lambda_2$. Calculate the value recorded by the sensor. Assume zero noise.

Wavelength	Sensor	Energy
λ_0	0.0	1.00
λ_1	0.1	0.95
λ_2	0.2	0.85
λ_3	0.3	0.76
λ_4	0.1	0.66
λ_5	0.0	0.59

$$f(0,0) = 2E_{\lambda_0} \times 0.0 + E_{\lambda_2} \times 0.2 + 3E_{\lambda_3} \times 0.3$$
$$= 0.85 \times 0.2 + 2.28 \times 0.3 = 0.17 + 6.84 = 7.01$$

Terminology

Radiance: total amount of energy flowing from a light source, measure in Watts (W).

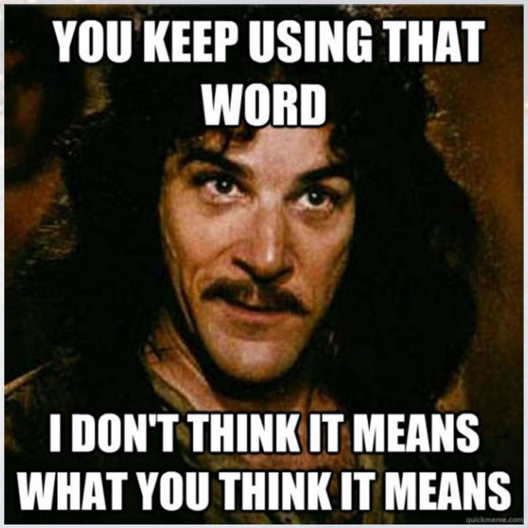
Luminance: the amount of energy an observer perceives from a light source; measures in lumens (lm). For instance, a radiator, radiates a lot in infrared wavelengths, but we, as observers perceive very little of it.

Brightness: a subjective descriptor of light perception; impossible to measure.

Wavelength λ (nm), frequency ν (Hz), speed of light c:

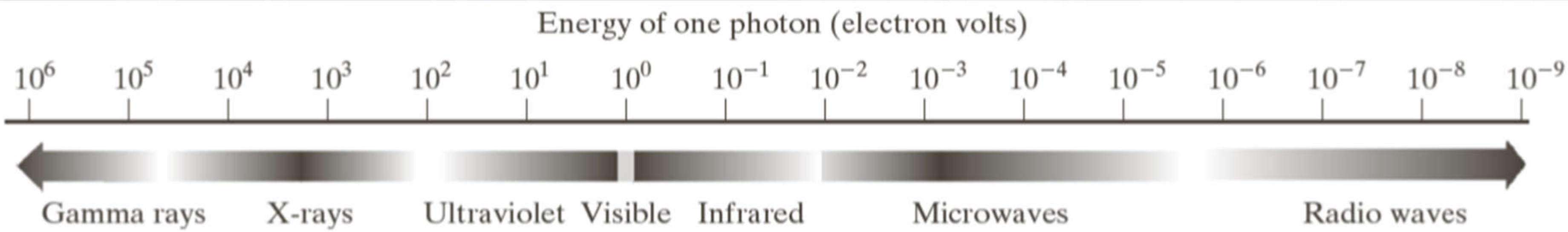
$$\boldsymbol{\lambda = \frac{c}{\nu}}$$

And energy $\boldsymbol{E = \nu h}$, with h the Planck constant.



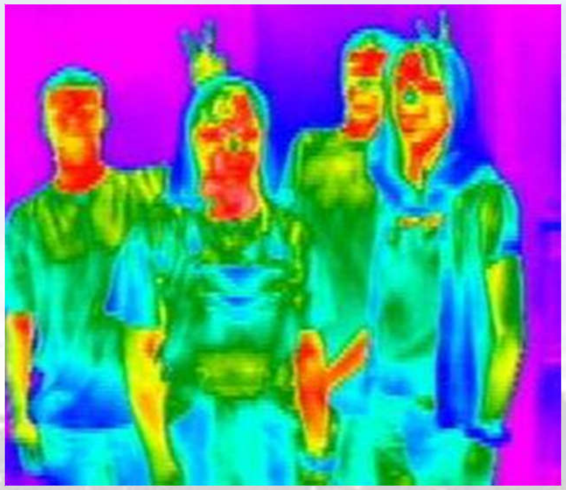
Human eyes have a sensitivity curve too, we can sense only the wavelengths between approximately 390 and 700nm; i.e. the **visible spectrum**.

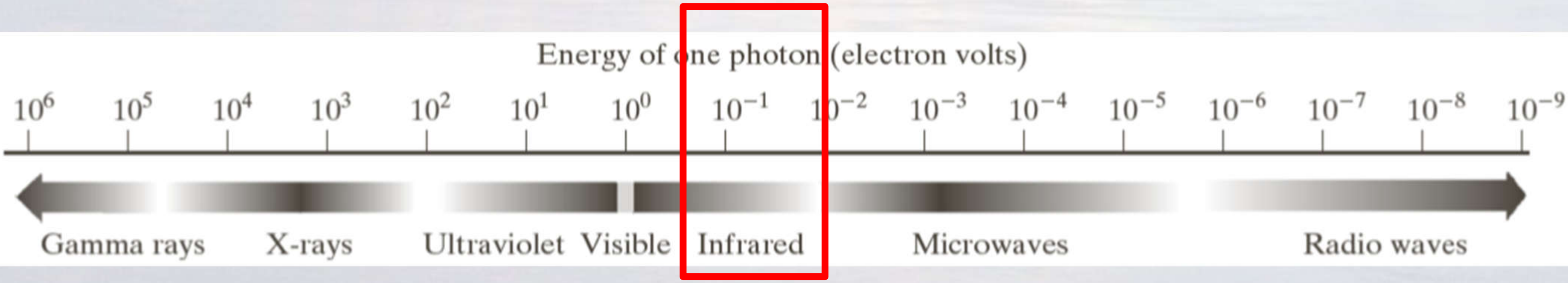
For the rest, we have cameras ☺



- **Gamma-ray imaging**: nuclear medicine and astronomical observations
- **X-rays**: medical diagnostics, industry, and astronomy, etc.
- **Ultraviolet**: lithography, industrial inspection, microscopy, lasers, biological imaging, and astronomical observations
- **Visible and infrared bands**: light microscopy, astronomy, remote sensing, industry, and law enforcement
- **Microwave band**: radar
- **Radio band**: medicine (such as MRI) and astronomy

Infrared, i.e. thermal imaging; **often noisy**!





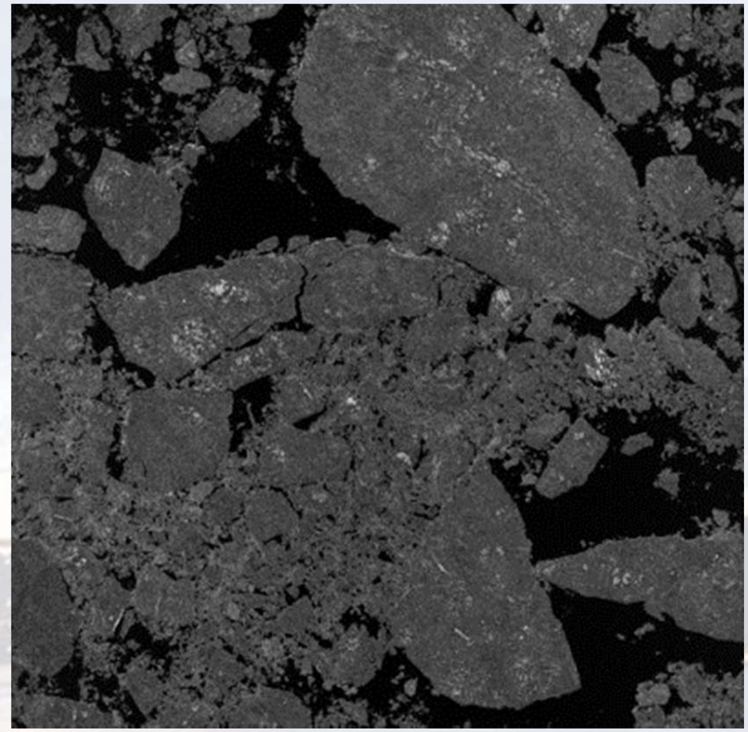
Introduction – Digital image acquisition

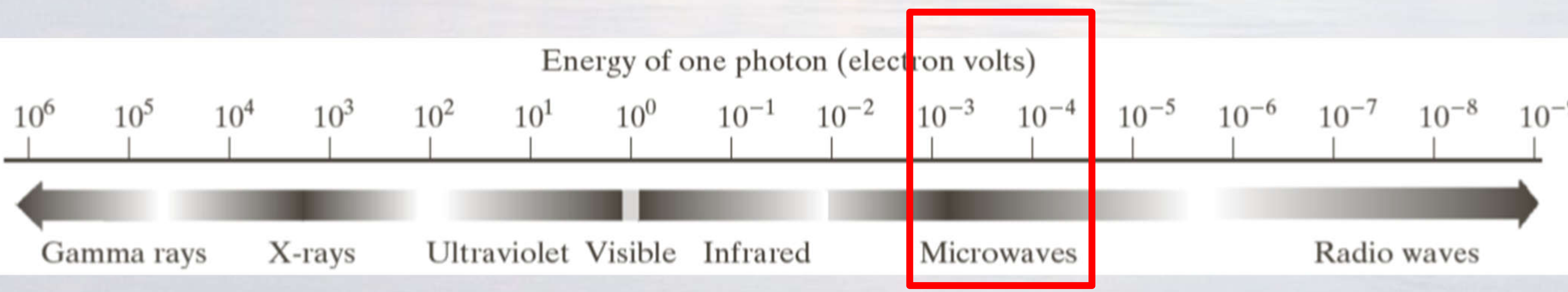
Radar imaging; synthetic aperture radar (SAR) – Göktürk 3, 2019.

Acquired using the Doppler principle.

~**Unaffected** by clouds or weather conditions.

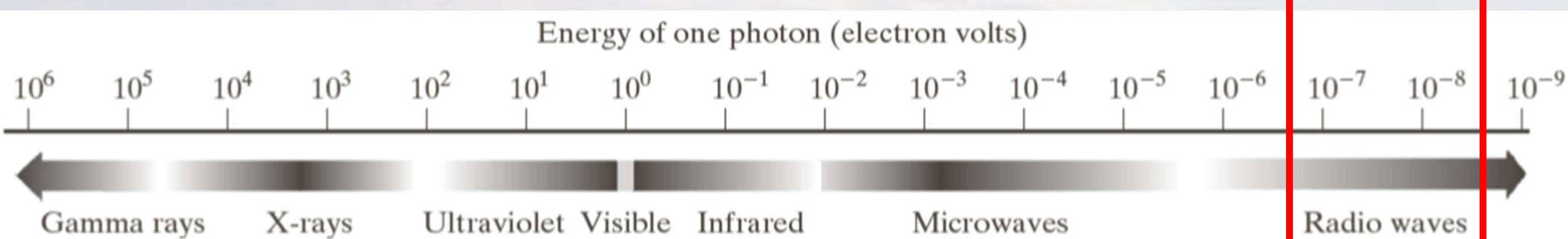
Can be acquired **day or night**.



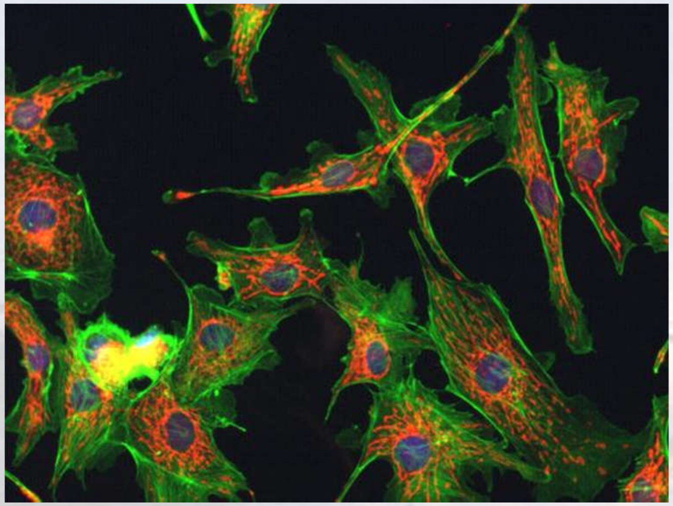


Magnetic resonance imaging (MRI);

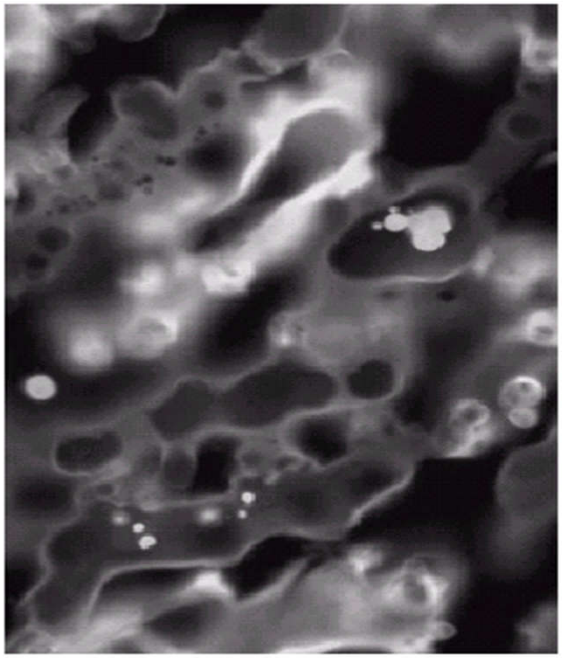
knee spine head



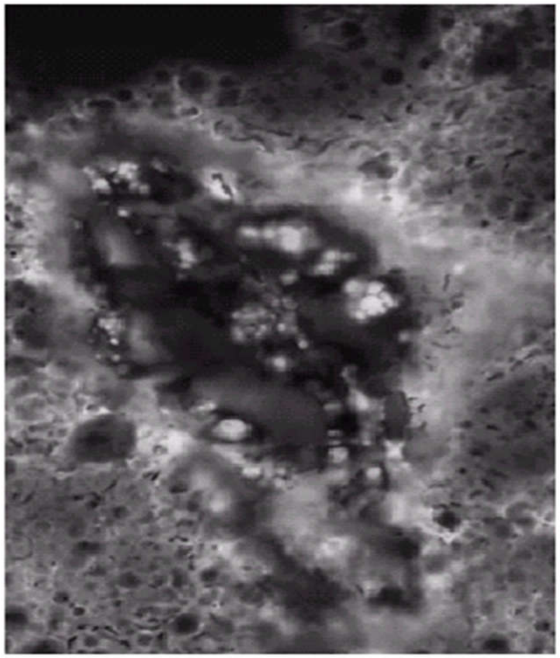
Fluorescense microscopy imaging;



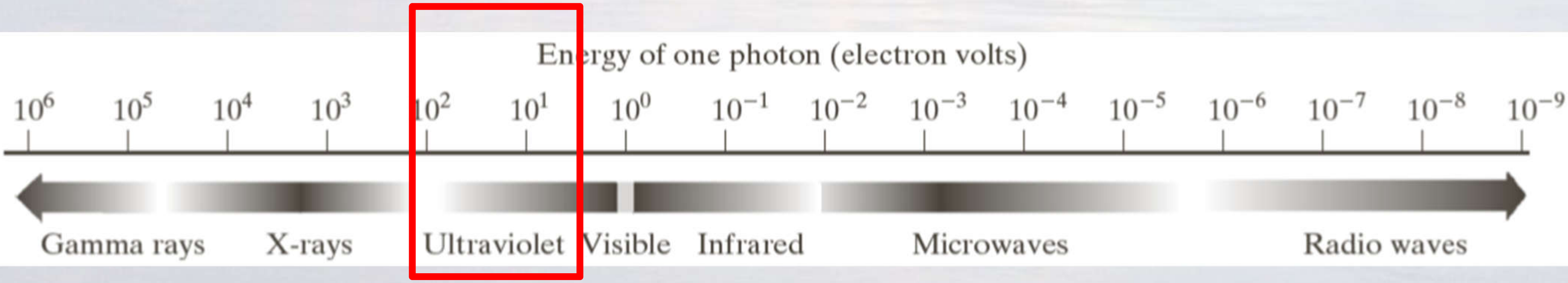
cells



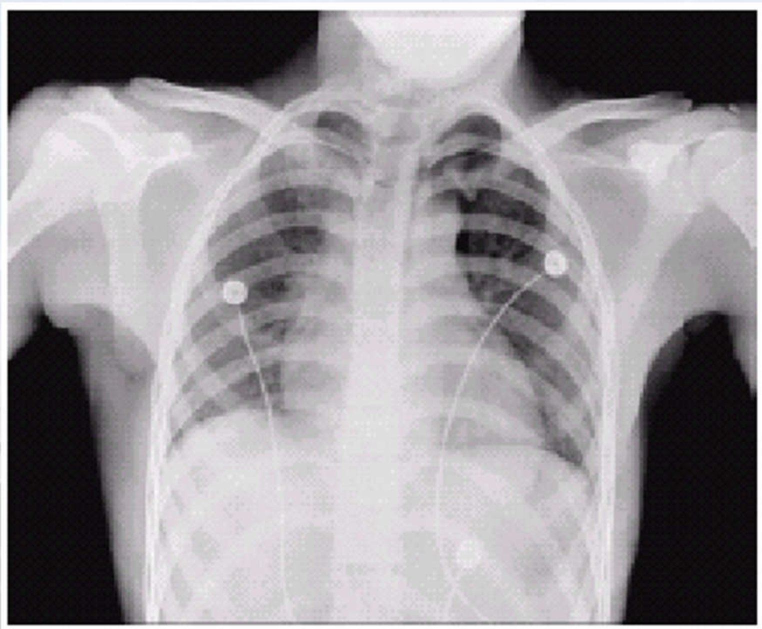
healthy corn

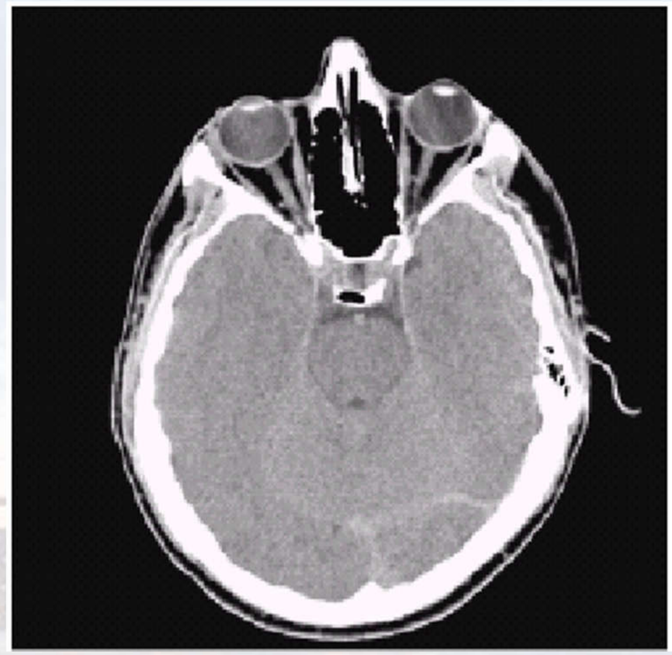


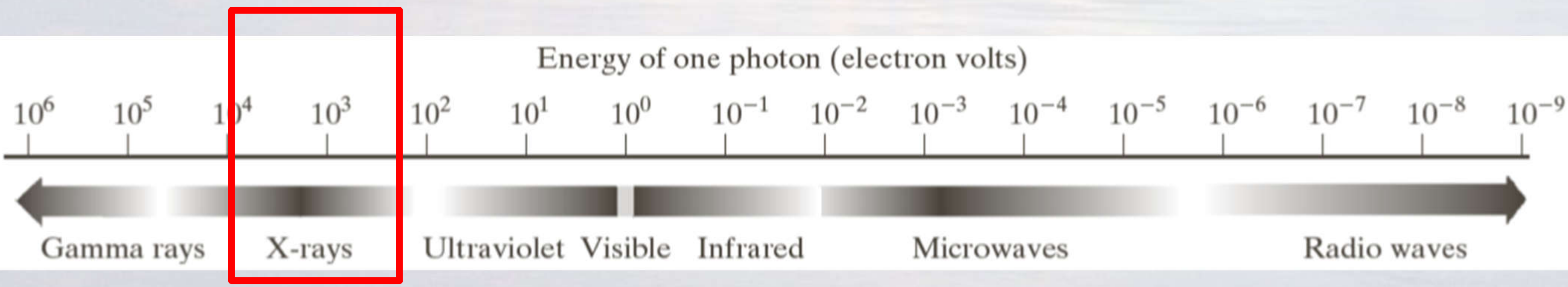
smut corn



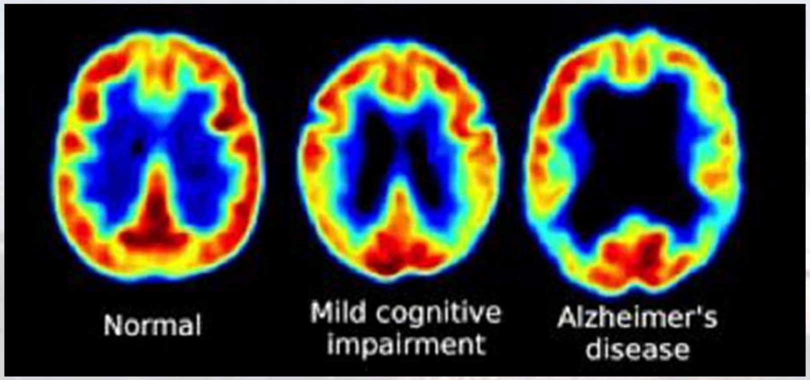
X-ray imaging;

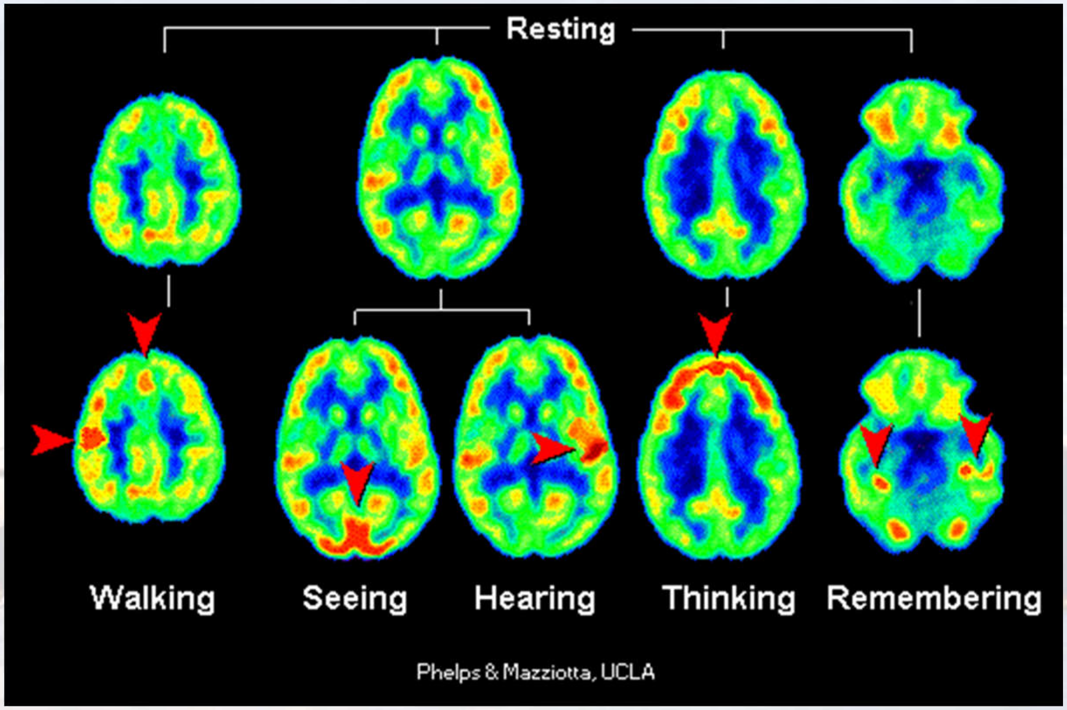


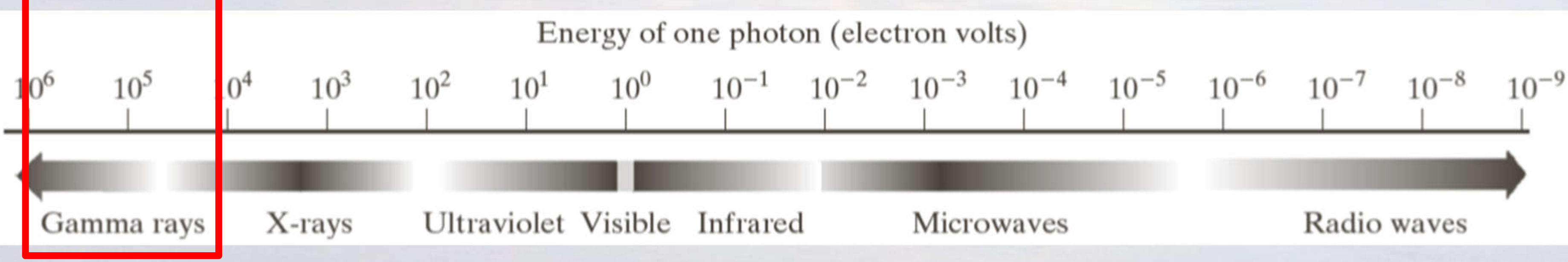




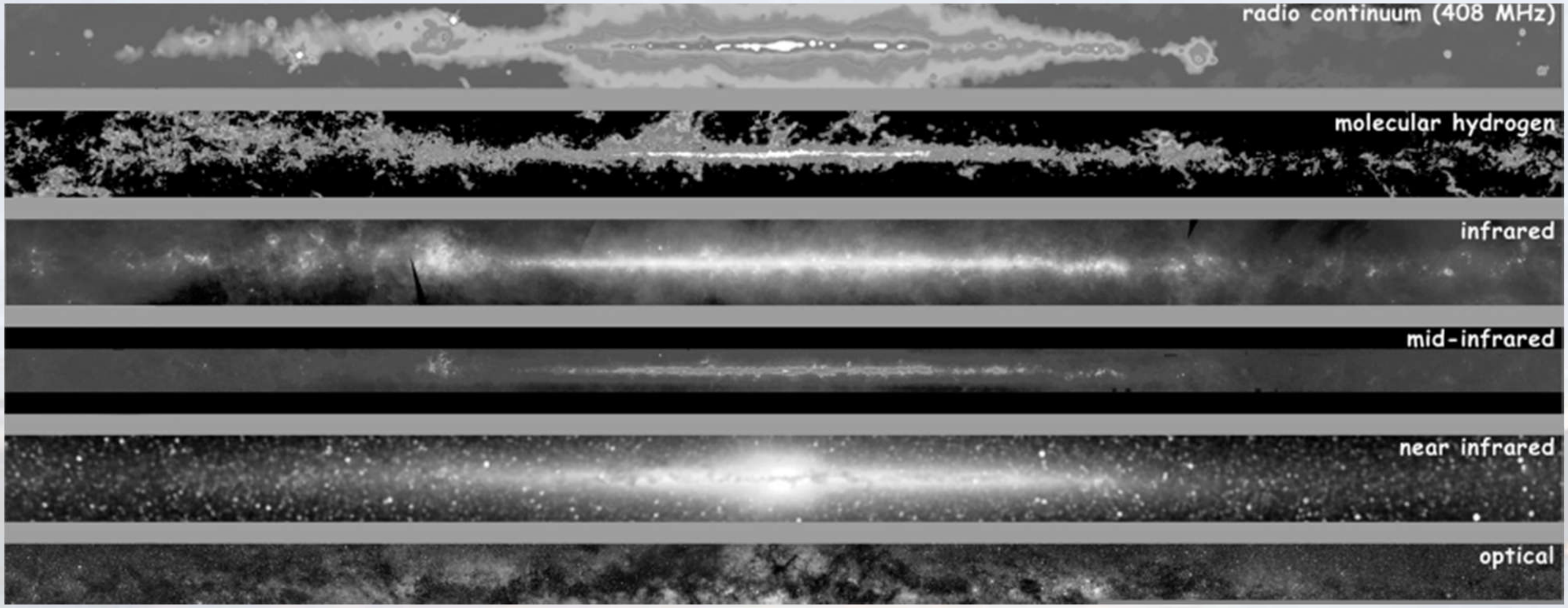
Positron Emission Tomography (PET);



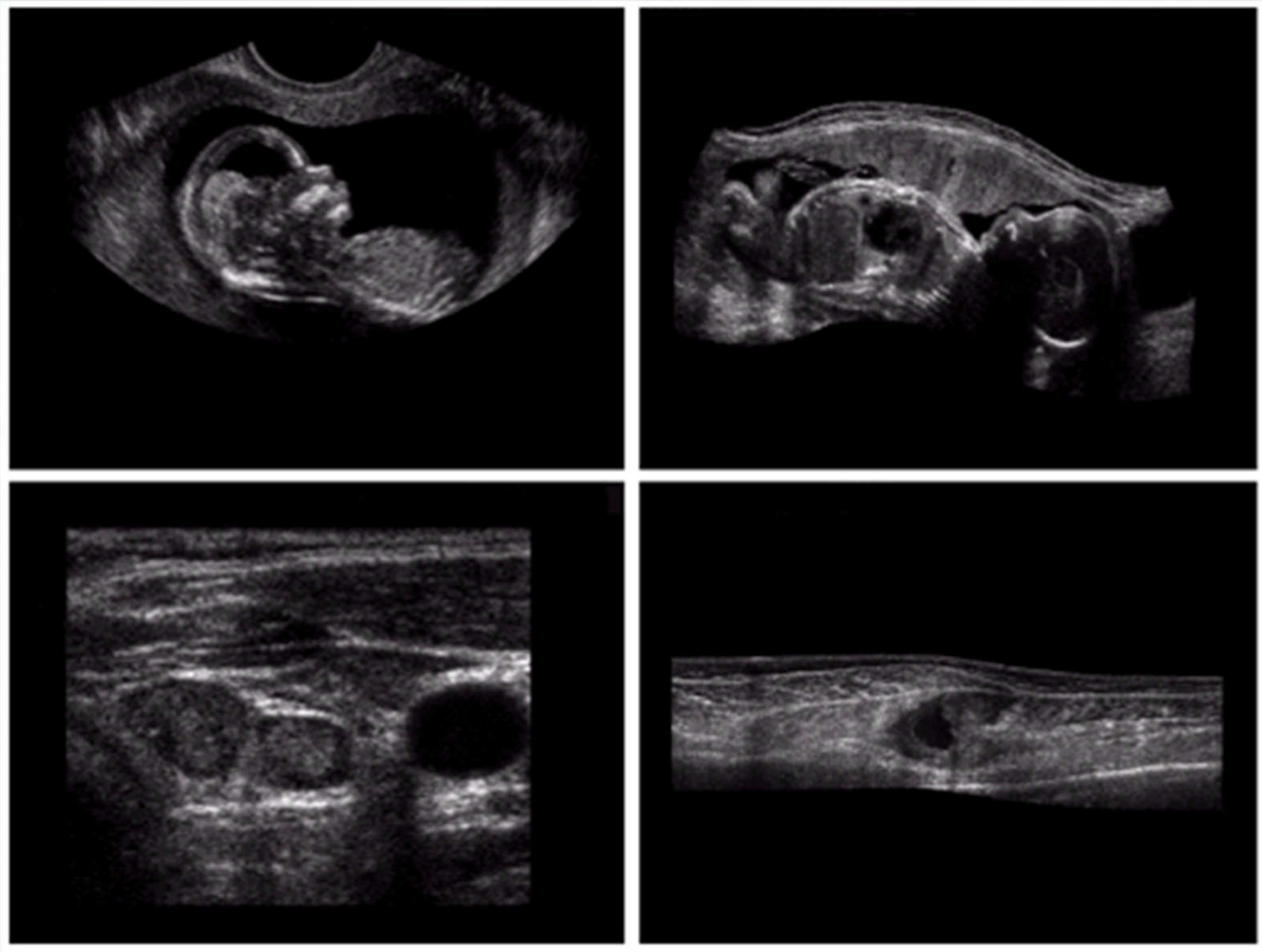




The wavelengths provide much more…



We are not limited with electromagnetic waves; sound waves can also be used to produce **ultrasound** images.



Digital image acquisition is basically about transforming the view of a continuous object $f(x,y)$ into a discrete one $f[x,y]$, so that we can store it on a digital medium, and process it.

It involves two stages: **sampling** and **quantization**, that correspond respectively to the discretization of **space** and **amplitude** of the original continuous function.

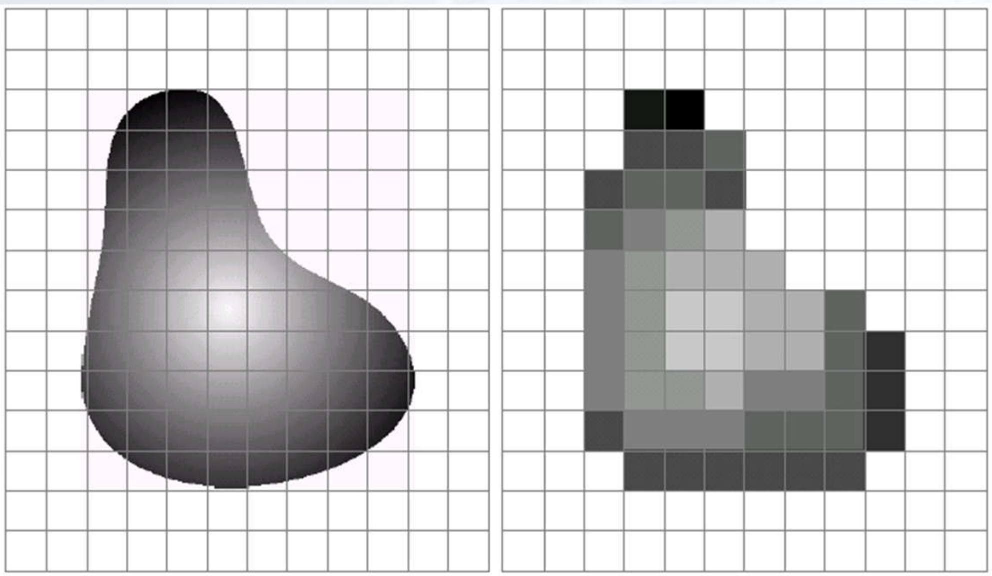


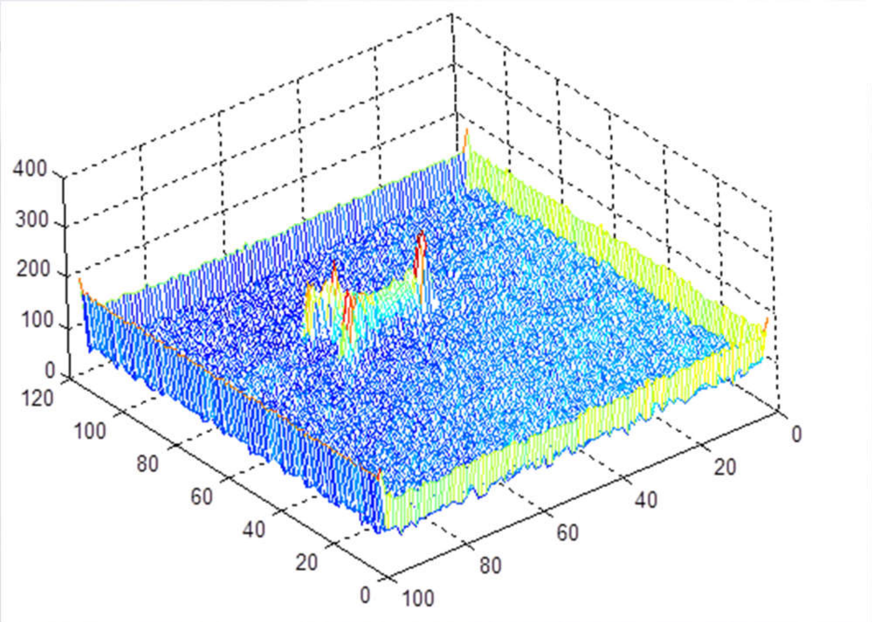
FIGURE 2.17 (a) Continuos image projected onto a sensor array. (b) Result of image sampling and quantization.

In signal processing, **sampling** is the conversion of a continuous function in space (or time) into a discrete one.

Problem 1: how to determine the sampling frequency? If too high, the data becomes too large, if too low, we lose information ☹

Problem 2: how to determine the value of each sample?

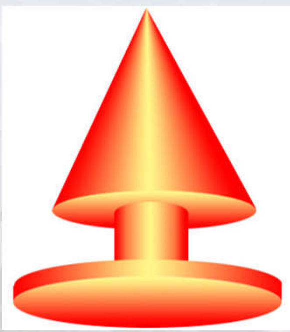
For problem 2; we use the "rain gauge" principle, and measure the amount of "photon rain" that falls into every sample.



Introduction – Digital image acquisition

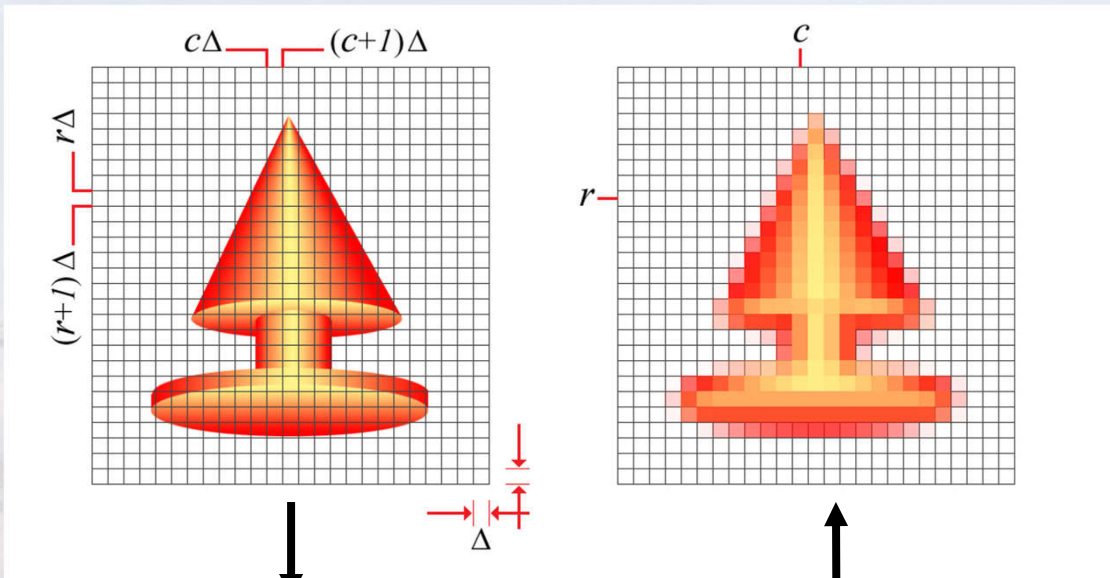
Amount of “photon rain”, i.e. the integral of photons in every grid square

Take the average within each square.

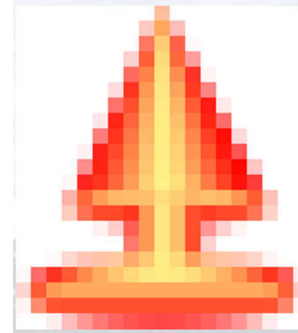


$$I_C(\rho,\chi)$$

continuous image



$$I_S(r,c)=\frac{1}{\Delta^2}\int_{r\Delta}^{(r+1)\Delta}\int_{c\Delta}^{(c+1)\Delta} I_C(\rho,\chi)\delta\rho\delta\chi$$

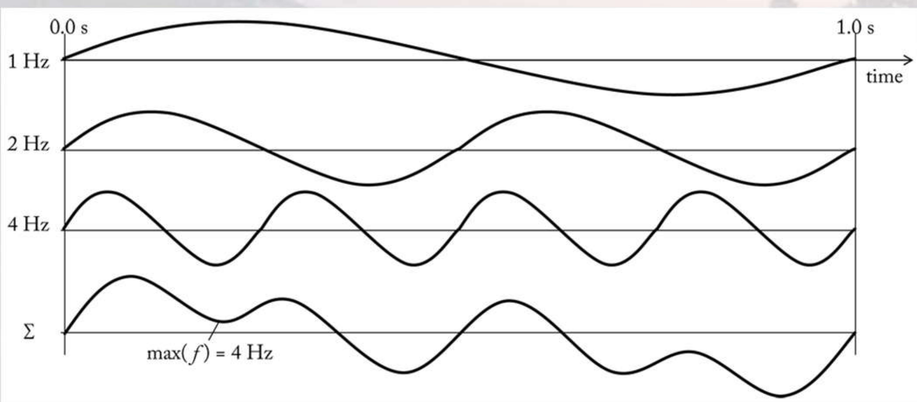


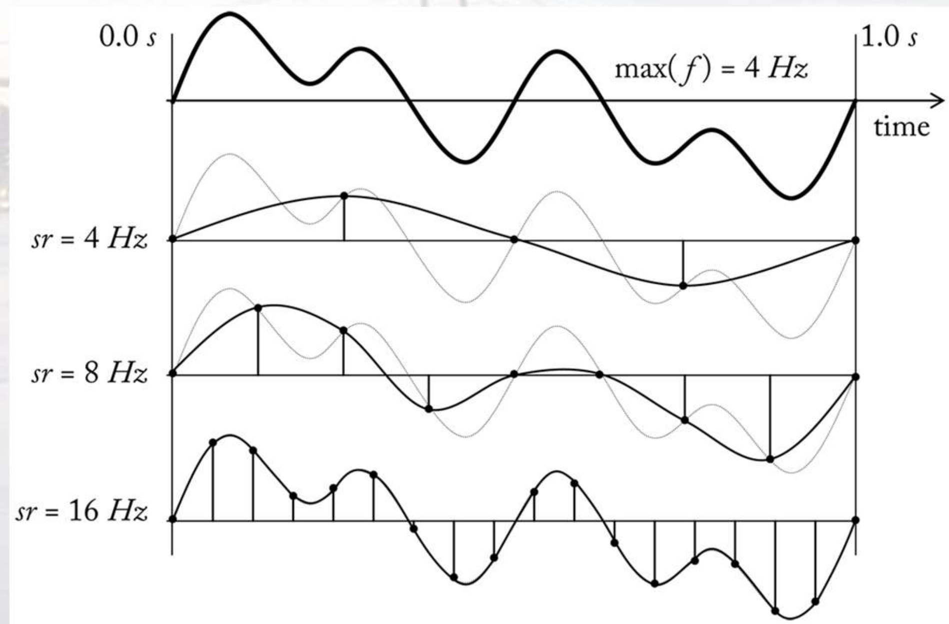
$$I_S(r,c)$$

sampled image

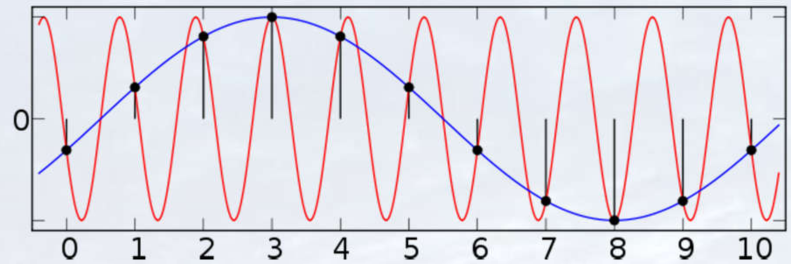
As to problem 1, the solution has been provided by the ***Nyquist-Shannon Sampling Theorem***, which provides a sufficient condition for a sampling frequency that permits a discrete sequence to capture all the information from a continuous function of finite bandwidth.

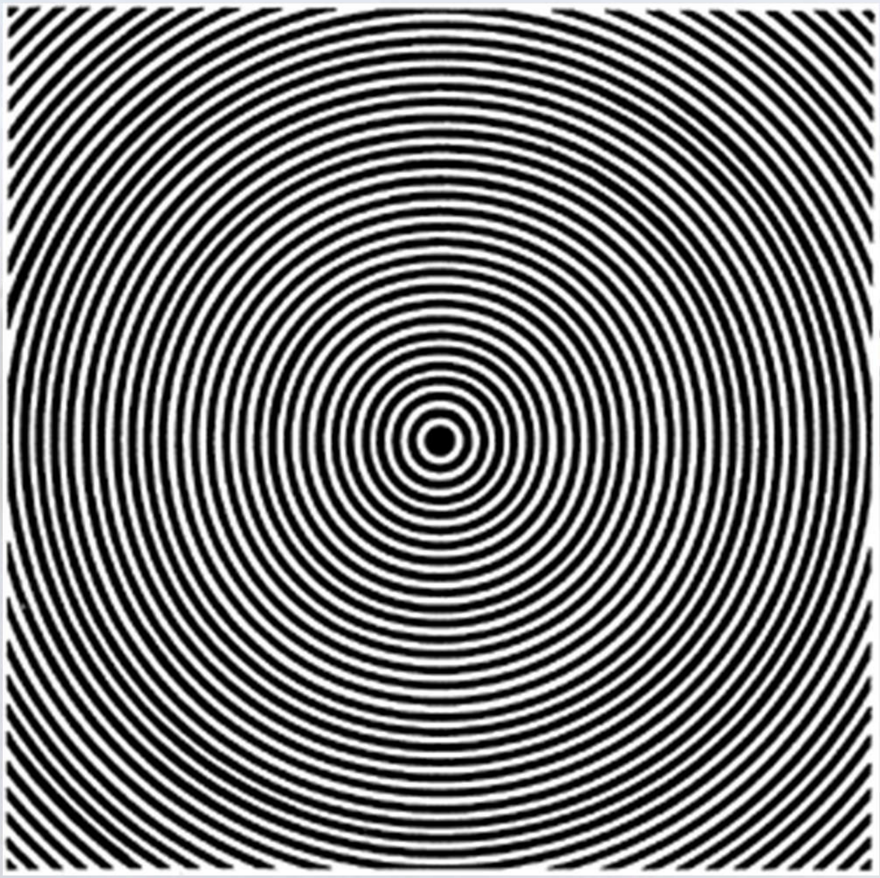
In short, the theorem states that if a continuous function has no higher frequency that B Hz, then it can be completely determined with a sampling frequency above 2B Hz.



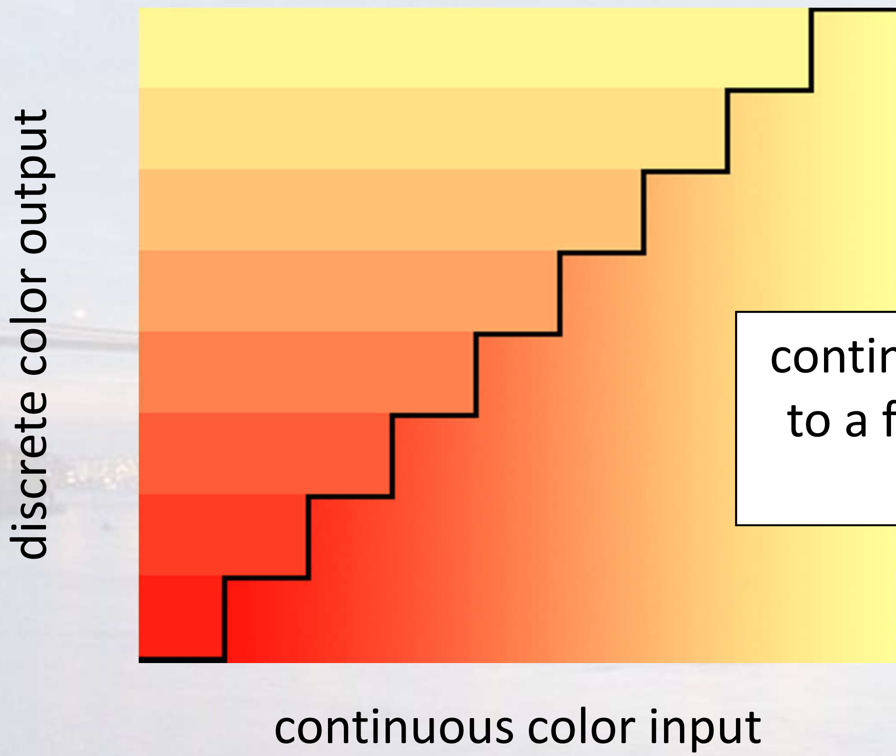


Failing to satisfy the Nyquist-Shannon Sampling Theorem, leads to *aliasing* or *Moiré patterns* in images.

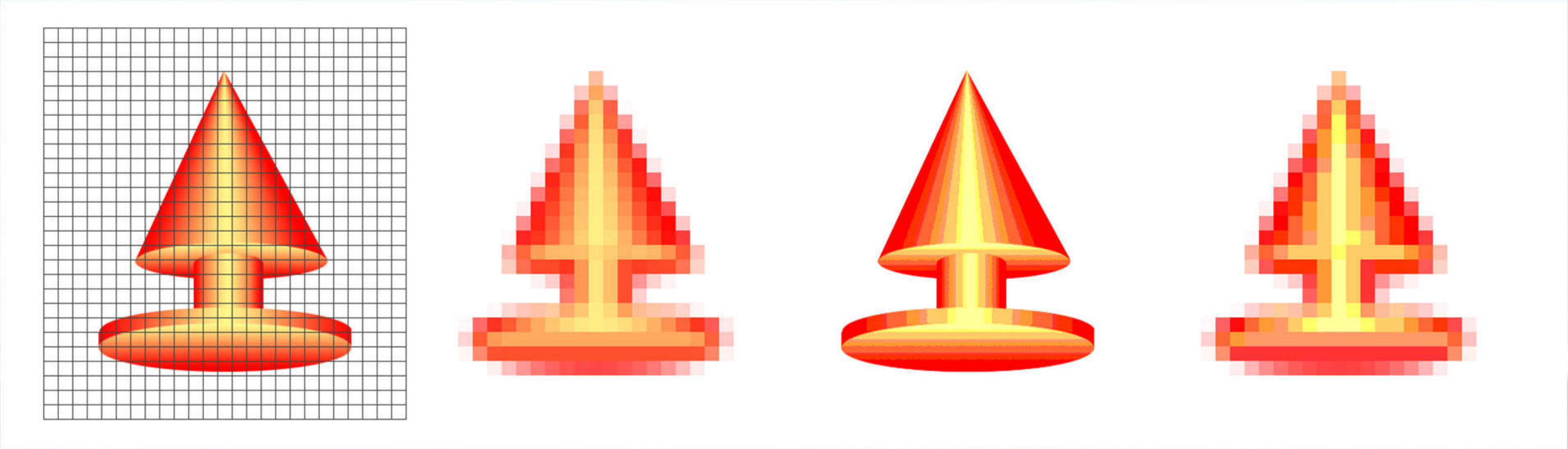




Quantization refers to the discretization of amplitude. There is an infinite number of possible pixel intensities, we can only store (and process) a finite amount!



continuous colors mapped to a finite, discrete set of colors.



real image | sampled | quantized | sampled & quantized

Spatial resolution is a measure of the smallest discernible detail in an image.
It is stated as line pairs per unit distance, e.g. 640x480, dots per inch (dpi), etc.

Intensity resolution is the smallest discernible change in intensity level.
It is stated in a bit number: k bits = 2^k colors.
So an 8-bit gray-level image can contain up to 2^8 =256 distinct levels.

256x256

128x128

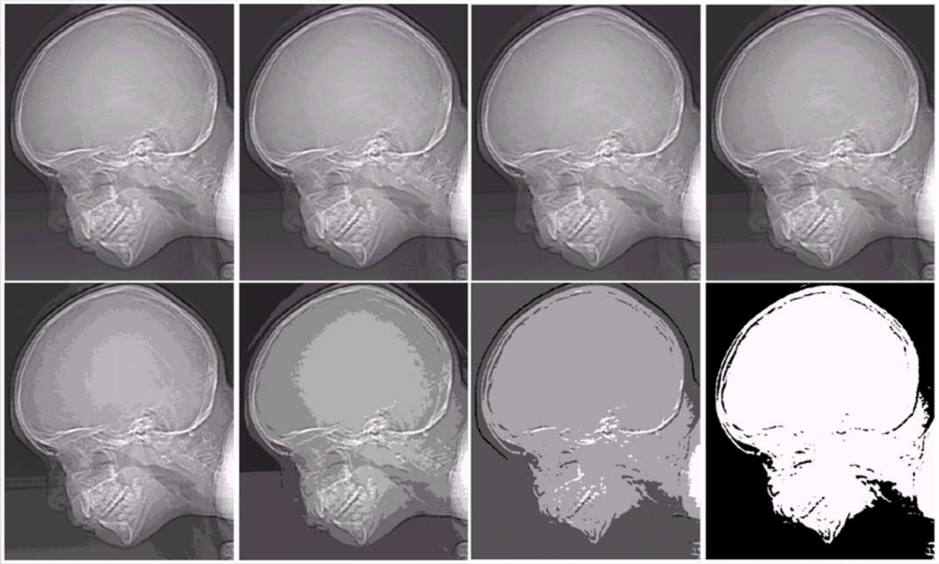
64x64

32x32

Images often have a size that is a power of 2; e.g. 512x512, 1024x1024, 2048x1024. This is because it simplifies calculations (e.g. Mip-mapping, Fourier Transform).

How many bits do we need to store an image? Well, if the image is of size $W \times H$, and it has an intensity resolution of n bits, that means every pixel can possess 2^n distinct values; thus we need $n \times W \times H$ bits for storing this image.

256 (8 bits), 128, 64, 32 gray levels



16 (4 bits), 8, 4, 2 gray levels

Image file formats (https://en.wikipedia.org/wiki/Image_file_formats)

Raster formats: JPEG, TIFF, BMP, PNG, PPM, etc

Vector formats: SVG, etc.

With various properties in terms of image quality, file size, and intended context of use.

Read chapters 1 and 2 (2.1, 2.2, 2.3, 2.4) from DIP.