Digital Image Basics

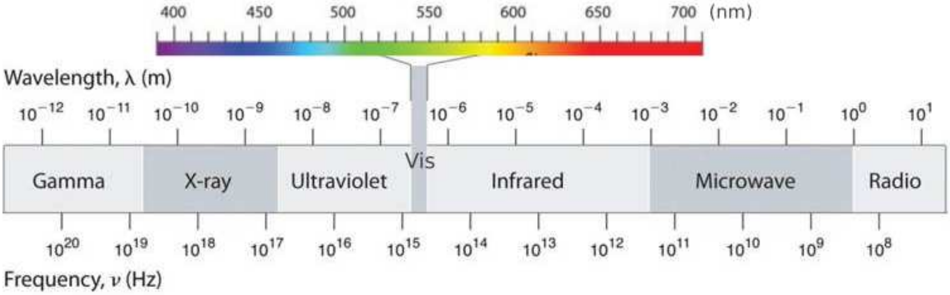
Lecture 02

Computer Vision for Geosciences

2021-03-05

Universidad Nacional Autónoma de México

Images can be constructed using the entire electromagnetic spectra



... a few examples in geosciences ...

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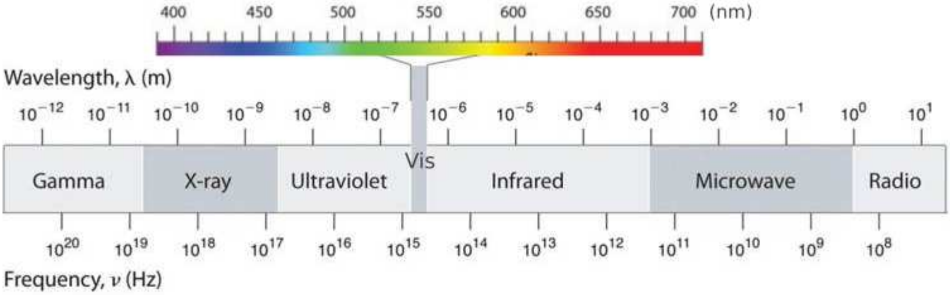

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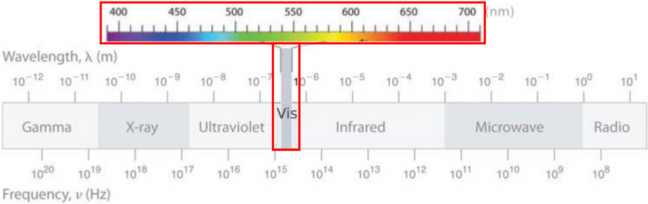
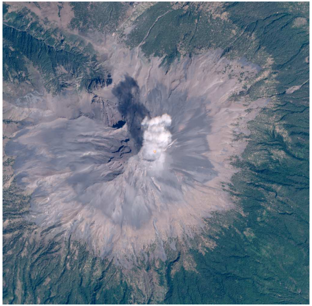


camera

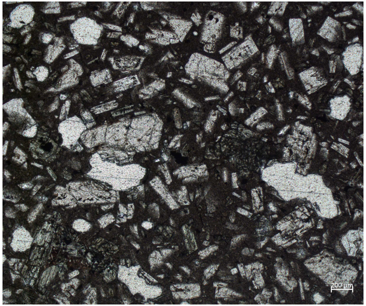
Popocatépetl 2020-04-16

satellite

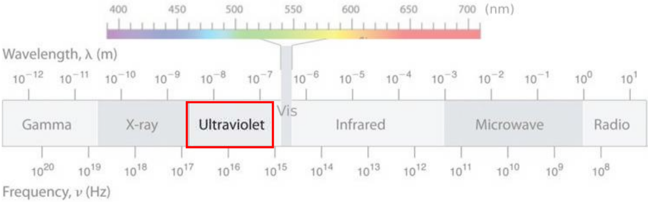


Popocatépetl 2021-02-25 (Sentinel-2, MOUNTS)

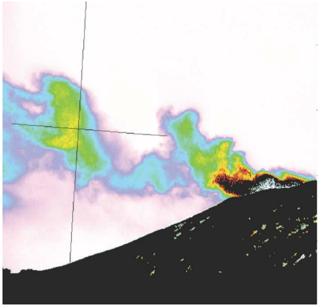
microscope



Popocatépetl 2019-01-22 (andesite, ©T.Boulesteix)

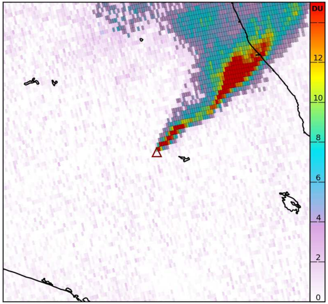


camera

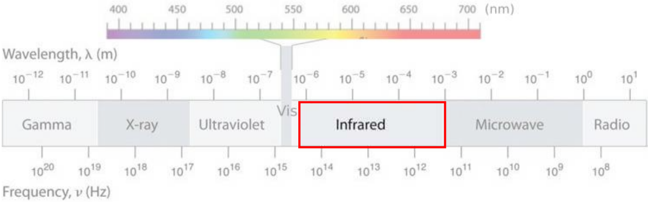


Popocatépetl 2013-01-29 (UV camera, Campion et al. 2018)

satellite



Popocatépetl 2019-02-17 (Sentinel-5P, MOUNTS)



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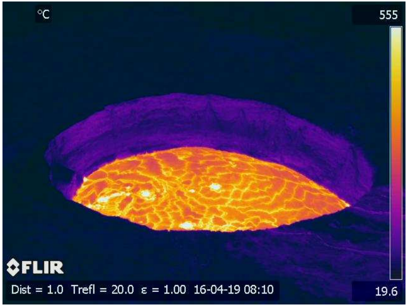
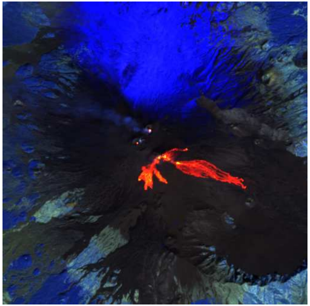
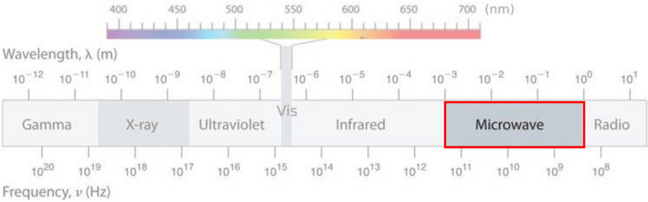


Nyiragongo 2016-04-16 (FLIR image, Valade et al. 2018)

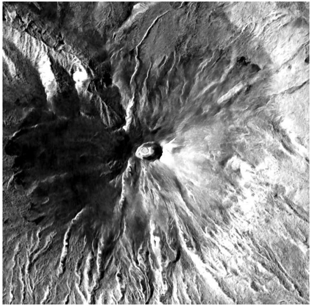
satellite



Etna 2021-02-23 (Sentinel-2 image, MOUNTS)

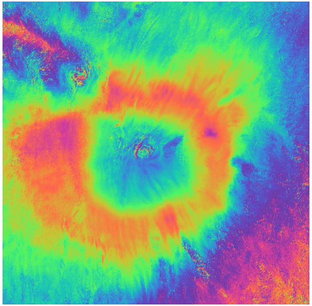


satellite (SAR)



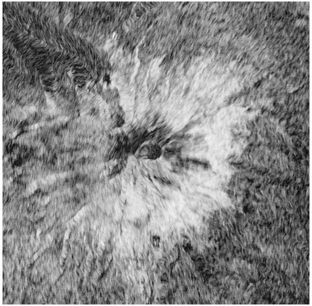
Popocatépetl 2021-02-28 (Sentinel-1, MOUNTS)

satellite (InSAR)

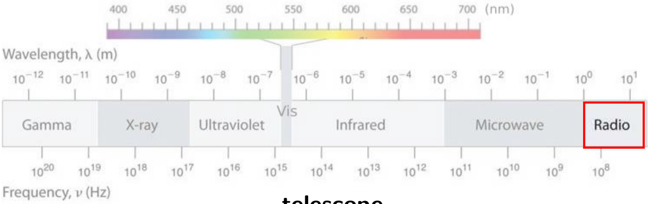


Popocatépetl InSAR interferogram (MOUNTS)

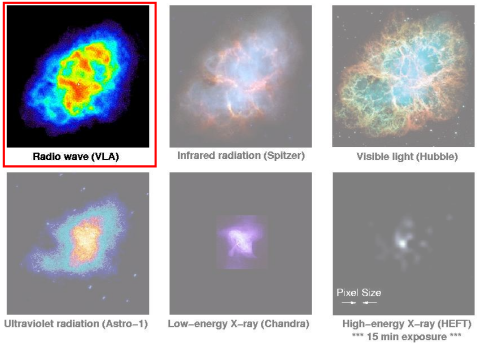
satellite (InSAR)



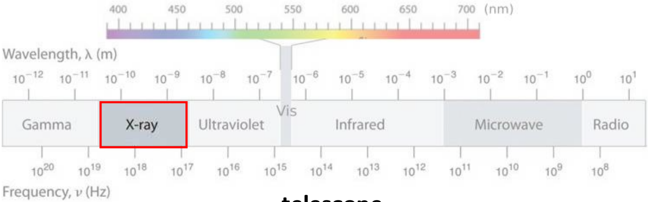
Popocatépetl InSAR coherence (MOUNTS)



telescope



Crab Nebula - remanent of an exploded star (supernova)



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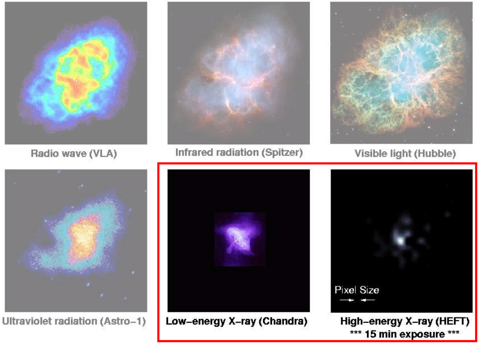

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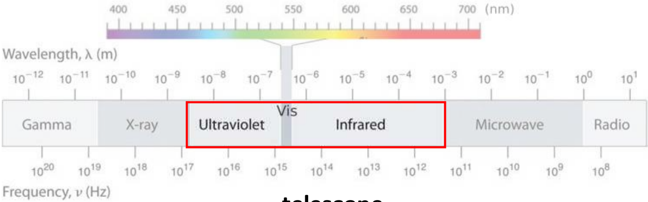

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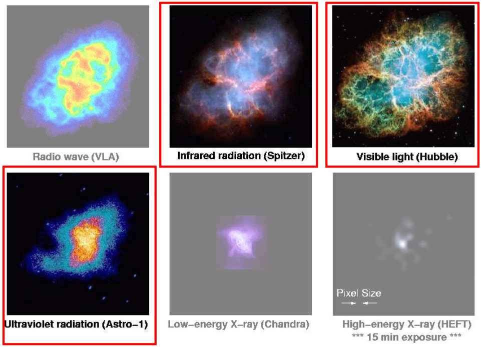

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Comparison between human eye and pinhole camera

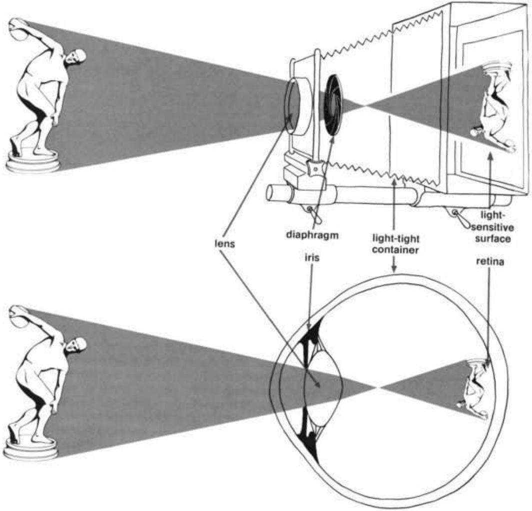
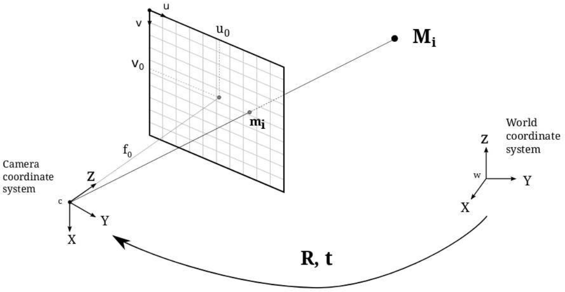


Image $=$ 3D world projection on 2D
$\Rightarrow$ projection using the **pinhole camera** model:



(from PyTorch Geometry)

Perspective transformation:

$$s\ m' = K[R|t]M' \tag{1}$$

$$s \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & u_0 \\ 0 & f_y & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \tag{2}$$

where:

- M' $=$ 3D point in space with coordinates $[X, Y, Z]^T$ expressed in Euclidean coordinates
- m' $=$ projection of the 3D point M' onto the image plane with coordinates $[u, v]^T$ expressed in pixel units
- K $=$ camera calibration matrix (a.k.a instrinsics parameters matrix)
  - fx, fy $=$ focal lengths expressed in pixel units
  - u_0, v_0 $=$ coordinates of the optical center (aka principal point), origin in the image plane
- $[R|t]$ $=$ joint rotation-translation matrix (a.k.a. extrinsics parameters matrix), describing the camera pose, and translating from world coordinates to camera coordinates

Image = 3D world projection on 2D

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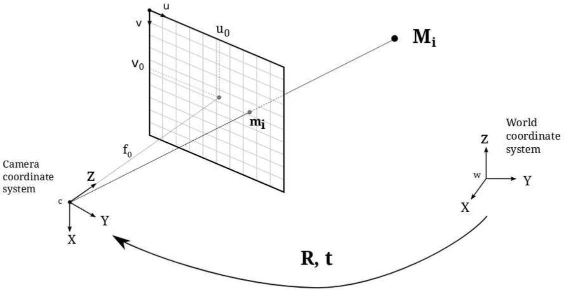

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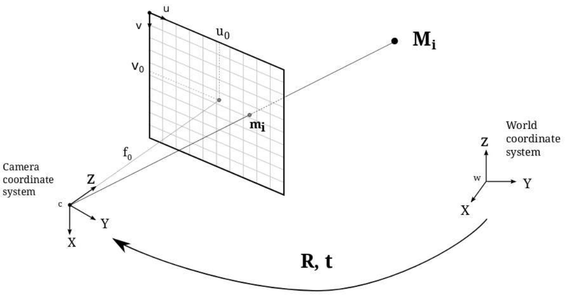

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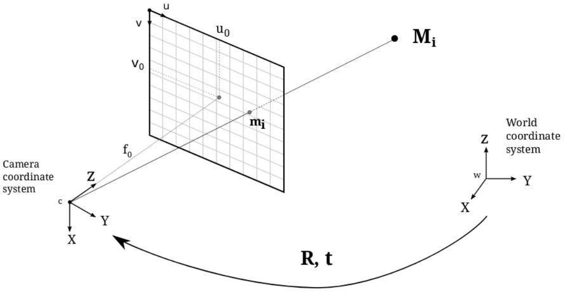

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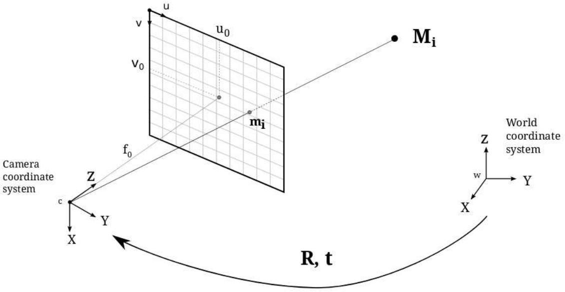

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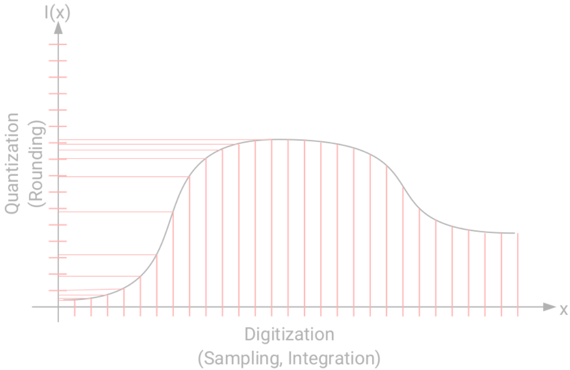
- at each point we record incident light
- digitalization of an analog signal involves two operations
  - **spatial sampling** (= discretization of space domain)
  - **intensity quantization** (= discretization of incoming light signal)



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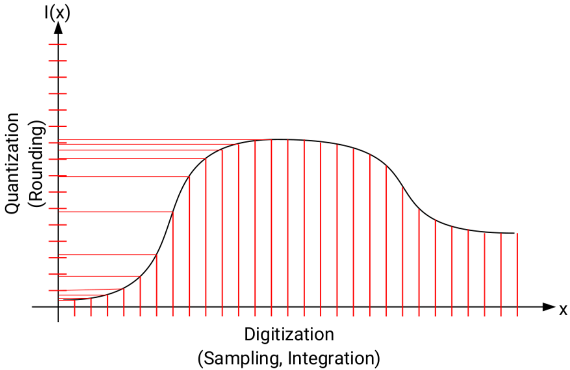


spatial sampling (= discretization of space domain)

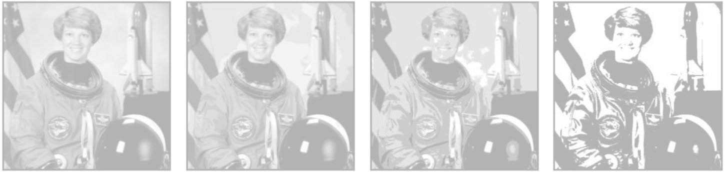
⇒ smallest element resulting from the discretization of the space is called a pixel (=picture element)

(512, 512) (128, 128) (64, 64) (32, 32)

intensity quantization (= discretization of light intensity signal)

⇒ typically, 256 levels (8 bits/pixel = 2^8 values) suffices to represent the intensity

8-bit resolution $2^8 = 256$ gray levels | 3-bit resolution $2^3 = 8$ gray levels | 2-bit resolution $2^2 = 4$ gray levels | 1-bit resolution $2^1 = 2$ gray levels



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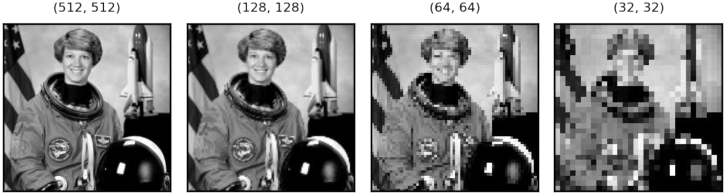

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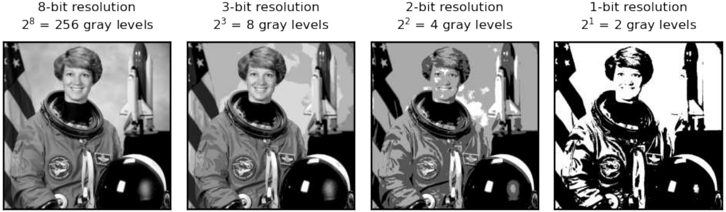
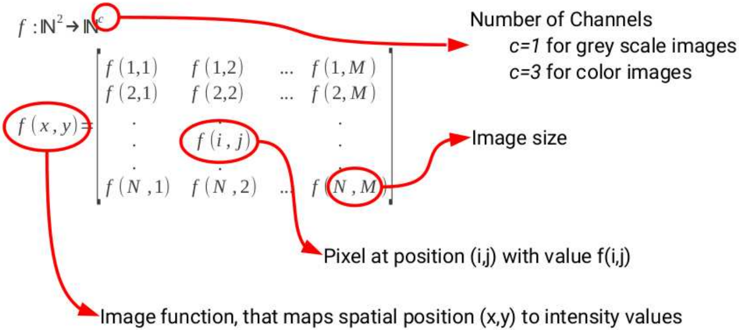


$\Rightarrow$ digital image function $f(x, y)$



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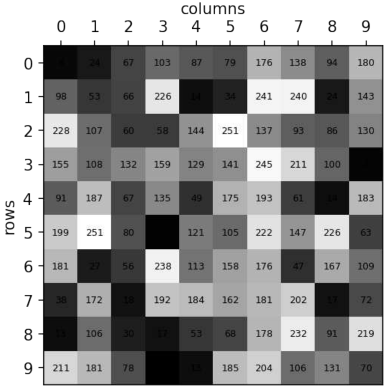
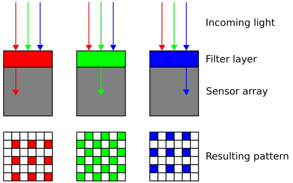


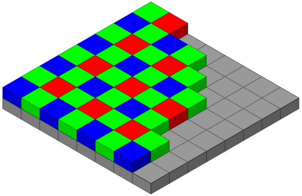
Typical ranges:

- uint8 = [0-255]
  (8 bits = 1 byte = 2^8 = 256 values per pixel)
- float32 = [0-1]
  (32 bits = 4 bytes = 4.3e9 values per pixel)

How do we record colors?

$\Rightarrow$ **Bayer Filter**: color filter array for arranging RGB color filters on a square grid of photosensors





(source wikipedia)

How do we record colors?

⇒ **Bayer Filter**: color filter array for arranging RGB color filters on a square grid of photosensors

1. Original scene
2. Output of a 120×80-pixel sensor with a Bayer filter
3. Output color-coded with Bayer filter colors
4. Reconstructed image after interpolating missing color information (a.k.a. demosaicing)
5. Full RGB version at 120×80-pixels for comparison

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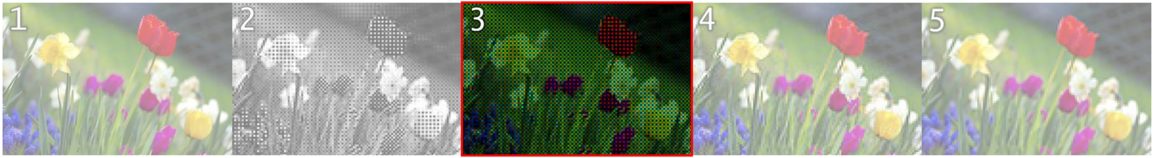

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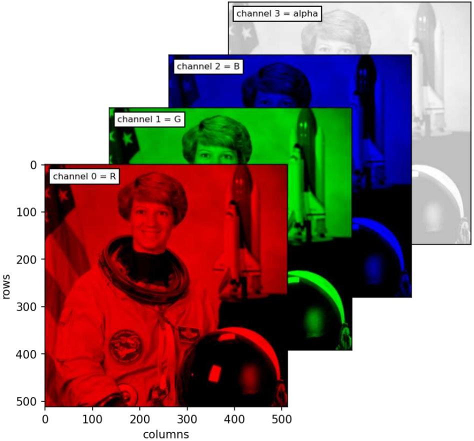
$\Rightarrow$ color image = 3D tensor in colorspace

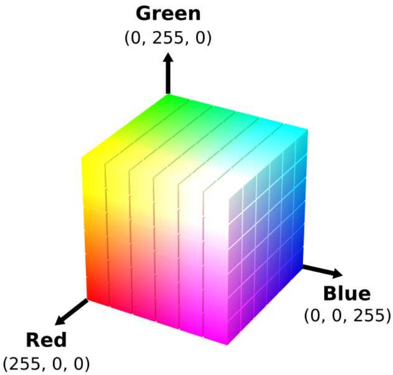
- **RGB** = Red + Green + Blue bands (.JPEG)
- **RGBA** = Red + Green + Blue + Alpha bands (.PNG, .GIF, .BMP, TIFF, .JPEG 2000)

$\longrightarrow$

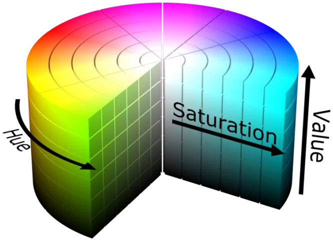


Other ways to represent the color information?

RGB colorspace



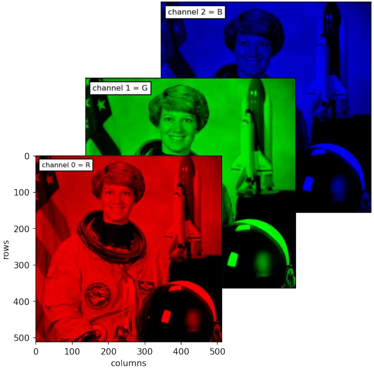
HSV colorspace



- Hue (H) = [0-360] $\Rightarrow$ shift color
- Saturation (S) = [0-1] $\Rightarrow$ shift intensity
- Value (V) = [0-1] $\Rightarrow$ shift brightness

3D tensor with different information

RGB colorspace



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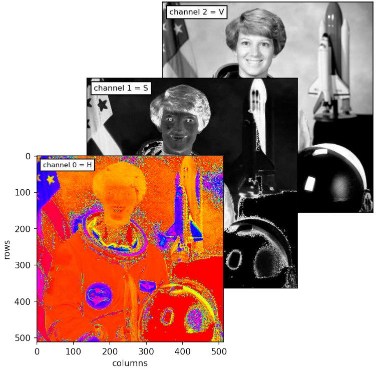


- more saturation S

$\Rightarrow$ more intense colors

- more value V

$\Rightarrow$ brighter colors

- shift hue H

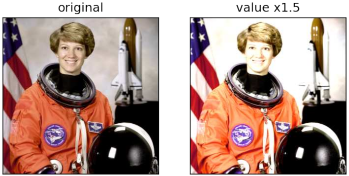
$\Rightarrow$ shift color

- more saturation S

⇒ more intense colors

- more value V

⇒ brighter colors



- shift hue H

⇒ shift color

- more saturation S

⇒ more intense colors

original

saturation x2

- more value V

⇒ brighter colors

original

value x1.5

- shift hue H

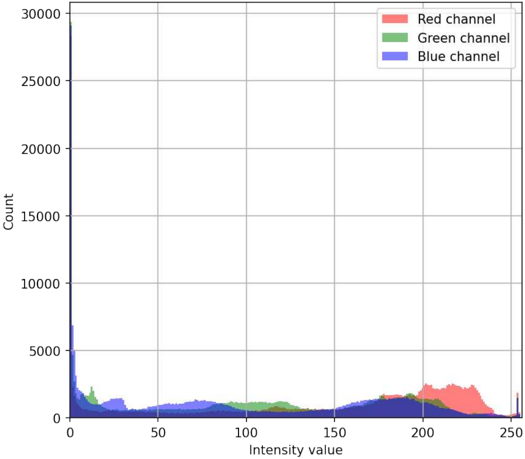
⇒ shift color

original

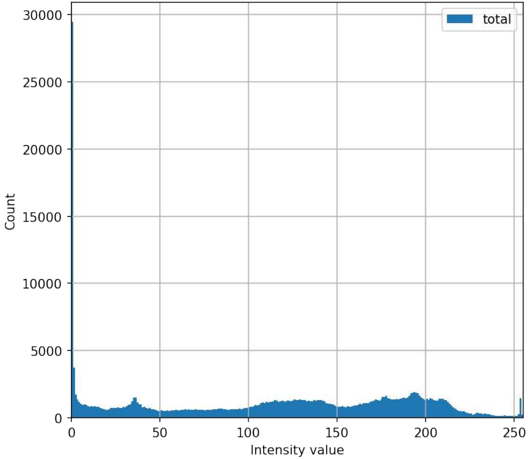
hue x5

Histogram of pixel values in each band:

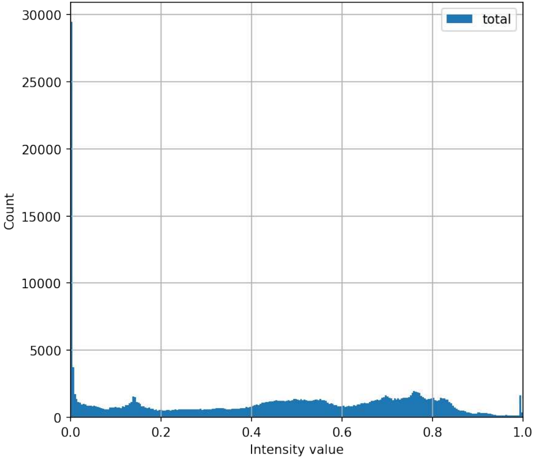
original (uint8)



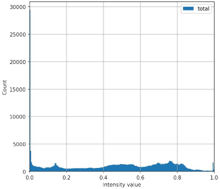
Histogram of pixel values after conversion from RGB (3-bands) to gray-scale (1-band):



Histogram of pixel values after conversion to float values (range [0-1])



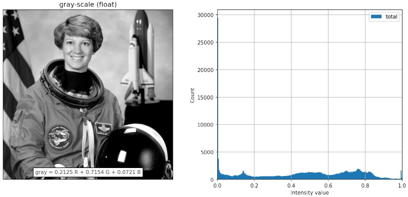
- original gray-scale



- histogram rescale to 10-90 percentiles
$\Rightarrow$ contrast stretching

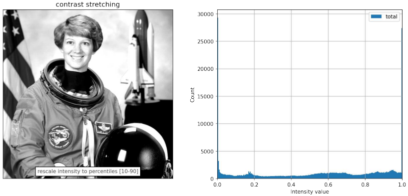
- histogram equalize
$\Rightarrow$ spread out the most frequent intensity values

- original gray-scale



- histogram rescale to 10-90 percentiles

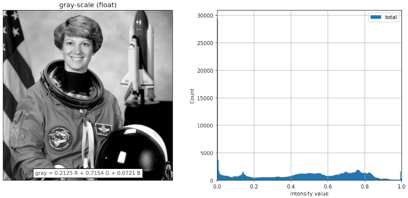
⇒ contrast stretching



- histogram equalize

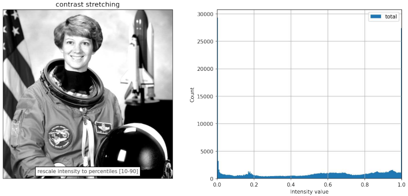
⇒ spread out the most frequent intensity values

- original gray-scale



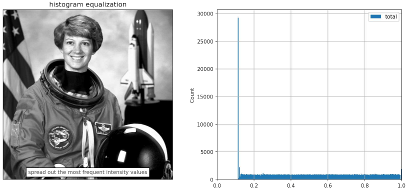
- histogram rescale to 10-90 percentiles

$\Rightarrow$ contrast stretching



- histogram equalize

$\Rightarrow$ spread out the most frequent intensity values



$$g(x,y) = T(f(x,y), x, y)$$

Value of original image at position (x,y)

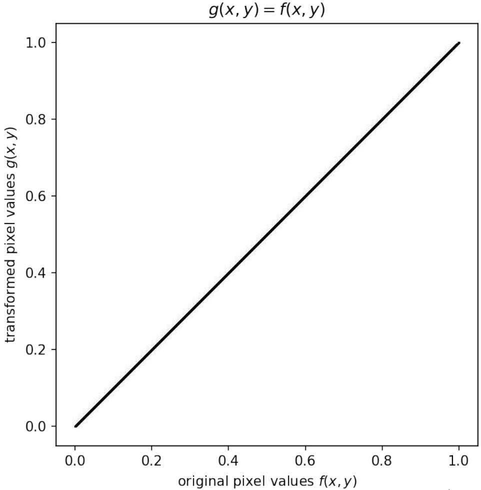
Operator function

Value of output image

Inhomogeneous PO: T is dependent on (x,y)
Homogeneous PO: T is NOT dependent on (x,y)

Homogeneous Point Operations (does not depend on pixel position)

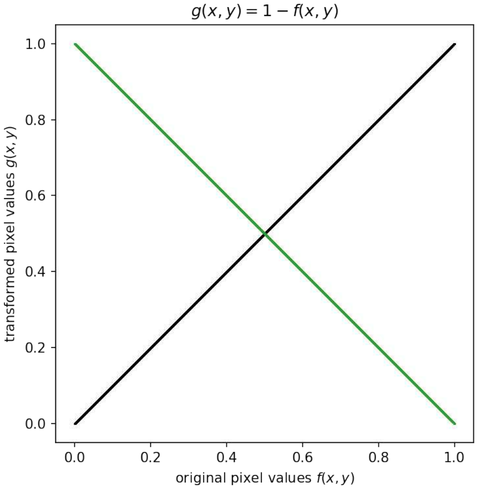
identity



Homogeneous Point Operations (does not depend on pixel position)

identity

inverse



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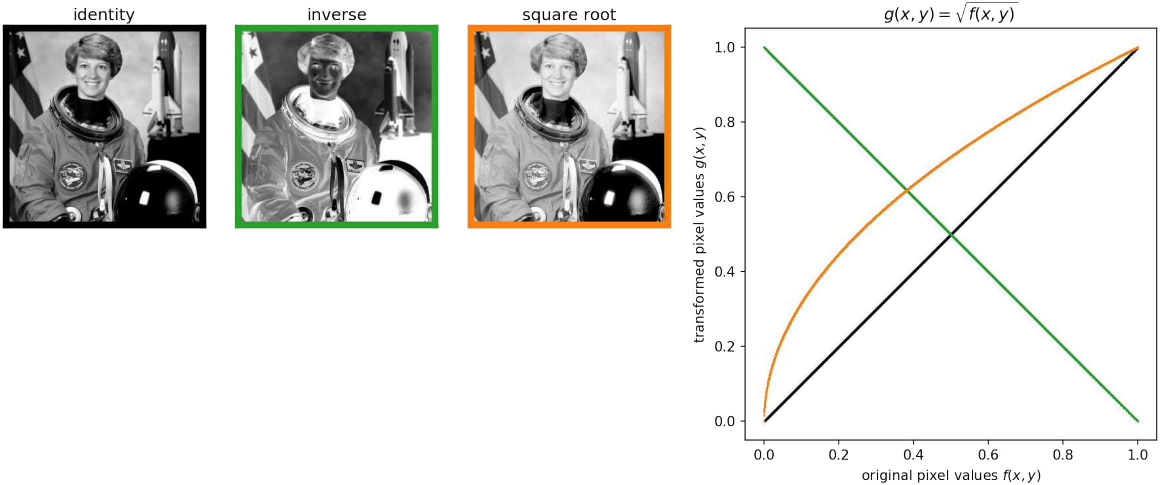


Homogeneous Point Operations (does not depend on pixel position)

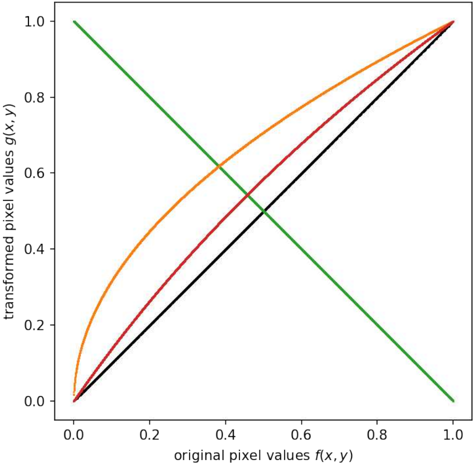
identity

inverse

square root

logarithm

$g(x, y) = a \cdot \log(f(x, y) + 1)$



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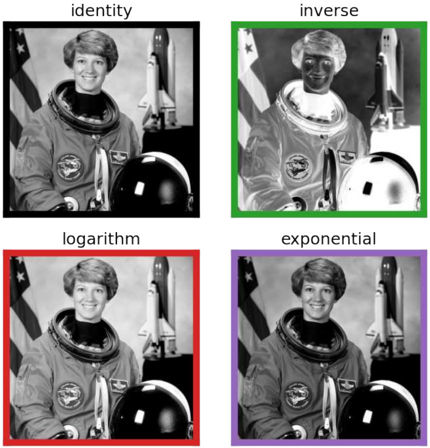

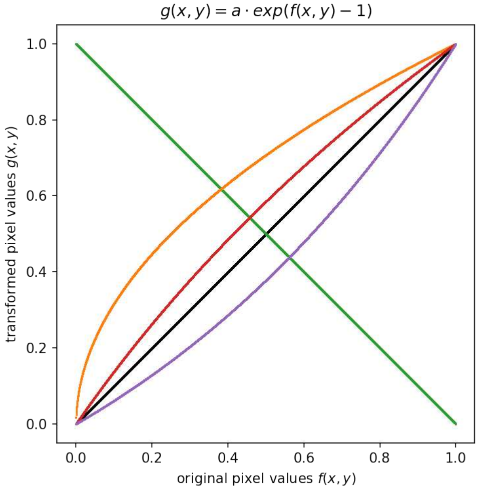

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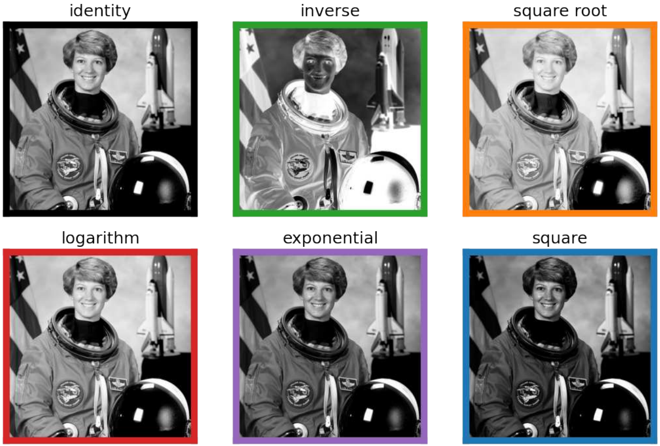
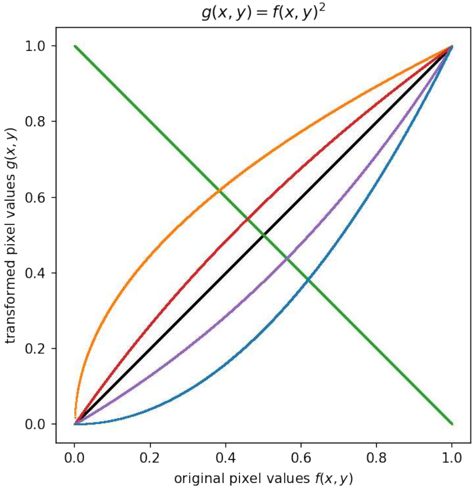




Inhomogeneous Point Operations (depends on pixel position)

EX: background detection / change detection

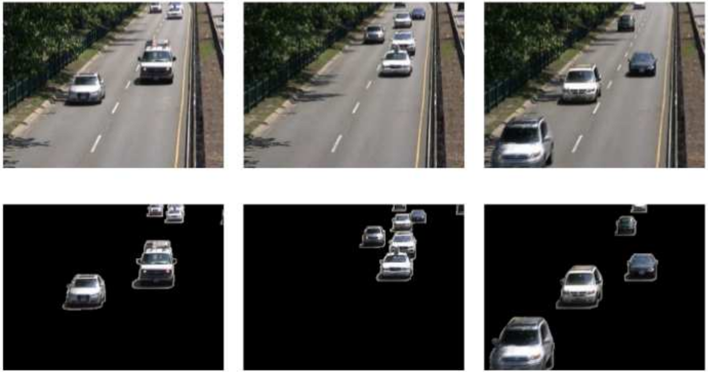
f_1 $\qquad$ f_i $\qquad$ f_N

$$a(x,y)=\frac{1}{N}\sum_{i=0}^{N} f_i(x,y)$$

$a(x,y)$

$$\begin{aligned} g_i(x,y) &= T(f(x,y),x,y) \\ &= f_i(x,y)-a(x,y) \end{aligned}$$

Inhomogeneous Point Operations (depends on pixel position)
EX: background detection / change detection



Computer Vision processing levels:

- Low-level vision
  - image manipulation
    (resizing, color adjustments, ...)
  - feature extraction
    (edges, gradients, ...)
- Mid-level vision
  - panorama stitching
  - Structure from Motion (SfM) $\Rightarrow$ 2D to 3D
  - Optical Flow $\Rightarrow$ velocities
- High-level vision
  - classification: what is in the image?
  - tagging: what are ALL the things in the image?
  - detection: where are they?
  - semantic segmentation $\Rightarrow$ segment image and give names

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In Binder:

$\Rightarrow$ Open CV4GS_02_imagebasics/CV4GS_02_numpy-tutorial.ipynb

$\Rightarrow$ Open CV4GS_02_imagebasics/CV4GS_02_exercices.ipynb

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