

# Visual Computing

## 2024/2025

Class 9

### Digital Image Processing

# Overview

- Digital Images
- The Processing Pipeline
- Pixel Operations
- Histogram-based Operations
- Filters

# Digital Image Processing

**Digital Image Processing**, as a scientific area, started when it became possible to use a computer to process images as collections of **pixels** with associated **numerical values**

A traditional goal is to **improve** an image to make it more amenable to processing:

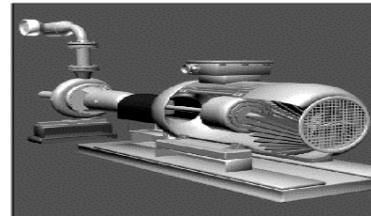
- By a **human observer**
- By some **automatic analysis** process

# Digital Images

Wide range of applications



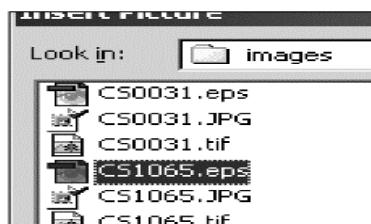
(a)



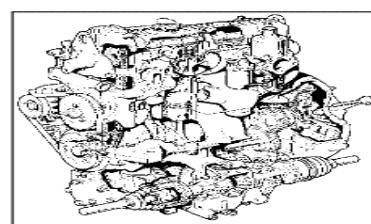
(b)



(c)



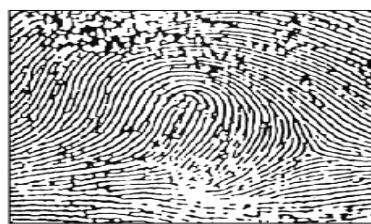
(d)



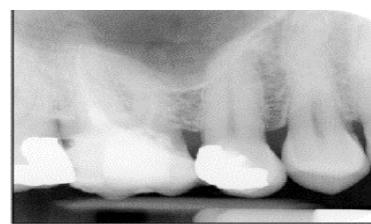
(e)



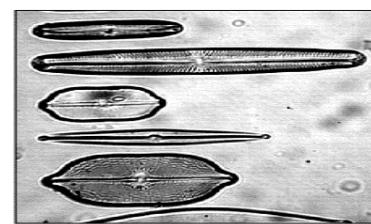
(f)



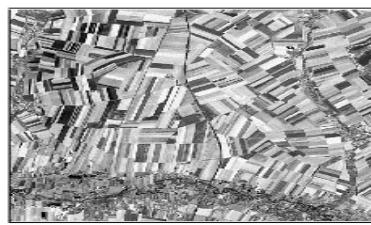
(g)



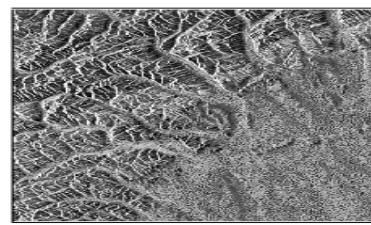
(h)



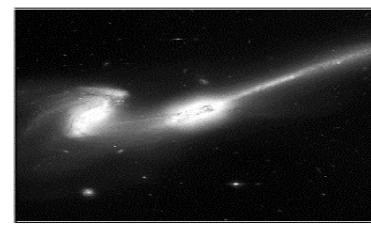
(i)



(j)



(k)



(l)

# Digital Image Acquisition

- Continuous light distribution is **spatially sampled**
- Still image created by **time sampling** that discrete distribution
- Resulting values are **quantized** to a finite set of numerical values

# Digital Image Acquisition

 $F(x, y)$ 

148	123	52	107	123	162	172	123	64	89	...
147	130	92	95	98	130	171	155	169	163	...
141	118	121	148	117	107	144	137	136	134	...
82	106	93	172	149	131	138	114	113	129	...
57	101	72	54	109	111	104	135	106	125	...
138	135	114	82	121	110	34	76	101	111	...
138	102	128	159	168	147	116	129	124	117	...
113	89	89	109	106	126	114	150	164	145	...
120	121	123	87	85	70	119	64	79	127	...
145	141	143	134	111	124	117	113	64	112	...
:	:	:	:	:	:	:	:	:	:	...
:	:	:	:	:	:	:	:	:	:	...

 $I(u, v)$

# Greyscale Images

Each pixel stores the brightness / intensity

No color (one channel)



Leonid Afremov

# Image Channels

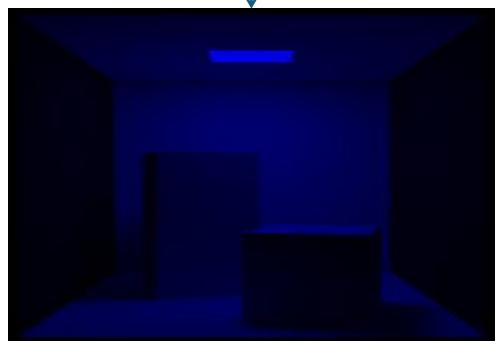
Original RGB image  
3 samples per pixel



Red channel  
1 sample per pixel



Green channel  
1 sample per pixel



Blue channel  
1 sample per pixel

# Convert from Color to Greyscale



Leonid Afremov

# Convert from Colour to Greyscale

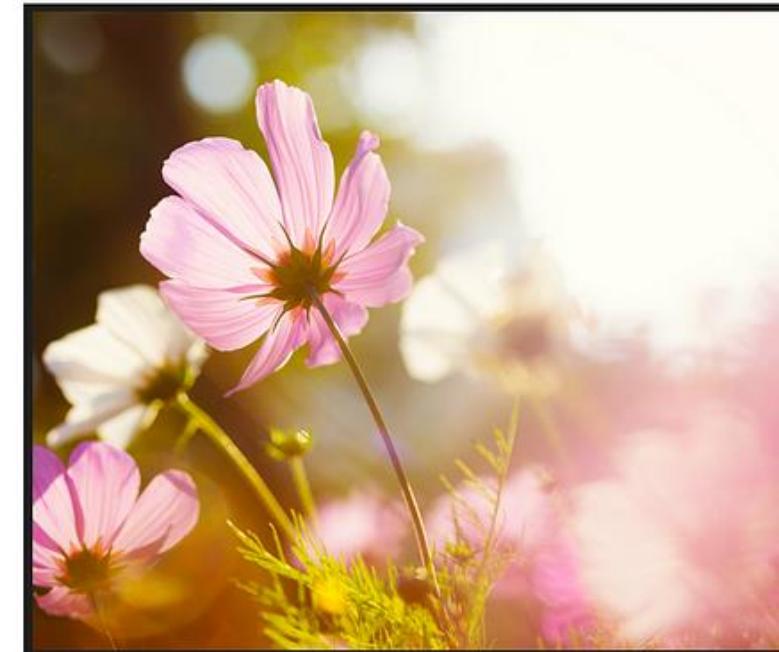
Average method

- $\text{Grey} = (\text{Red} + \text{Green} + \text{Blue}) / 3$

**But**, remember that the human eye perceives colour intensities differently

Weighted method

- $\text{Grey} = 0.299 * \text{Red} + 0.587 * \text{Green} + 0.114 * \text{Blue}$
- Can you guess how sensitive our eyes are to each color component?



# Pixel Values

## Grayscale (Intensity Images):

<i>Chan.</i>	<i>Bits/Pix.</i>	<i>Range</i>	<i>Use</i>
1	1	0...1	Binary image: document, illustration, fax
1	8	0...255	Universal: photo, scan, print
1	12	0...4095	High quality: photo, scan, print
1	14	0...16383	Professional: photo, scan, print
1	16	0...65535	Highest quality: medicine, astronomy

## Color Images:

<i>Chan.</i>	<i>Bits/Pix.</i>	<i>Range</i>	<i>Use</i>
3	24	$[0...255]^3$	RGB, universal: photo, scan, print
3	36	$[0...4095]^3$	RGB, high quality: photo, scan, print
3	42	$[0...16383]^3$	RGB, professional: photo, scan, print
4	32	$[0...255]^4$	CMYK, digital prepress

## Special Images:

<i>Chan.</i>	<i>Bits/Pix.</i>	<i>Range</i>	<i>Use</i>
1	16	$-32768...32767$	Whole numbers pos./neg., increased range
1	32	$\pm 3.4 \cdot 10^{38}$	Floating point: medicine, astronomy
1	64	$\pm 1.8 \cdot 10^{308}$	Floating point: internal processing

# Useful Concepts



# Contrast

- **Contrast** refers to the amount of noticeable difference among regions of an image
- **High-contrast** images have a larger variation in luminosity than low-contrast images
- Hence, in **low-contrast** images, regions are more hardly distinguishable



Low Contrast Image



High Contrast Image

# Image Exposure

- **Overexposed**

- Details of the image are lost since the **sensor receives much more light** than what it can handle

- **Underexposed**

- Details are lost since the **sensor is not able to detect** the amount of projected light

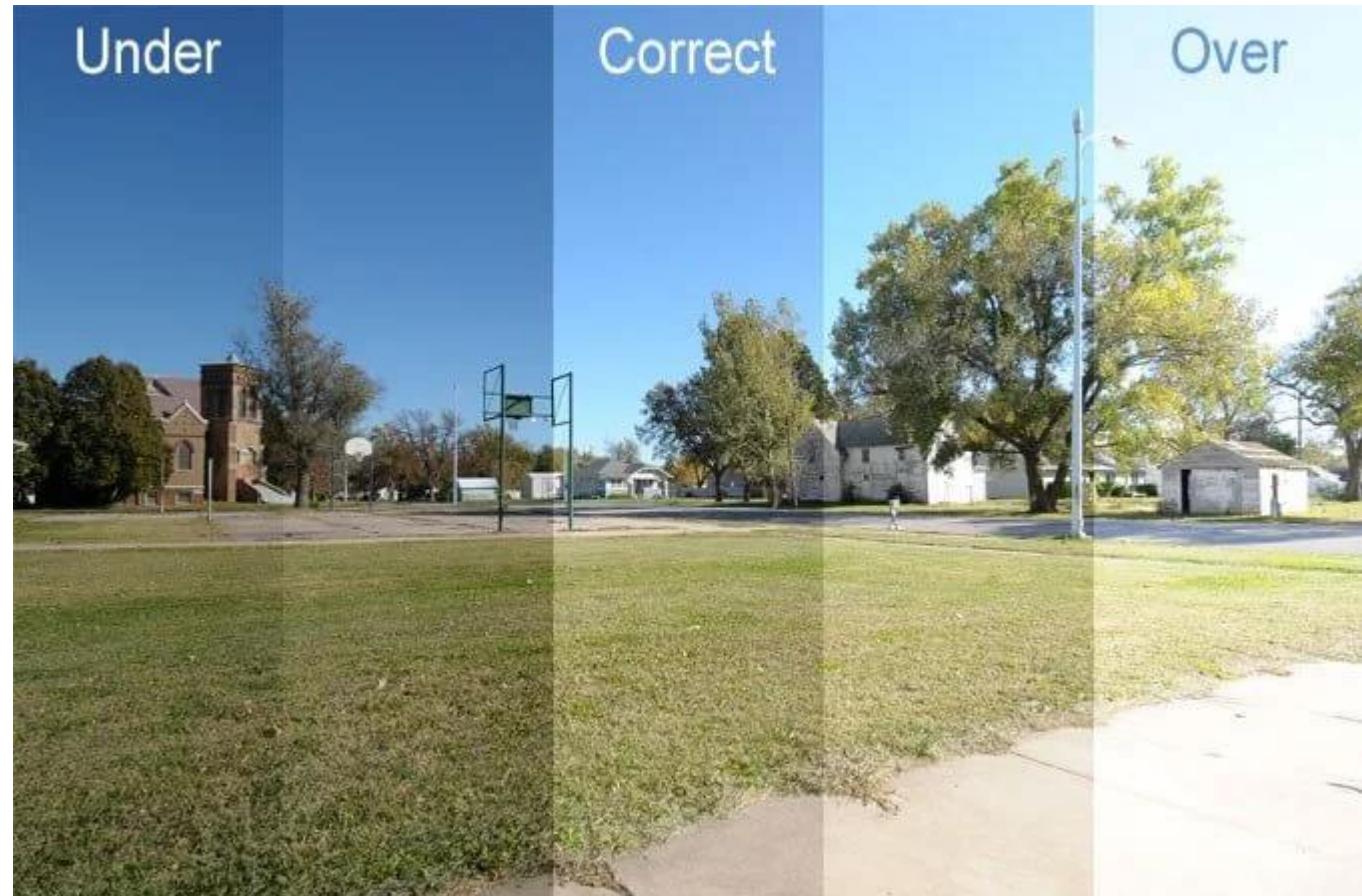


Image  
Potato Processing



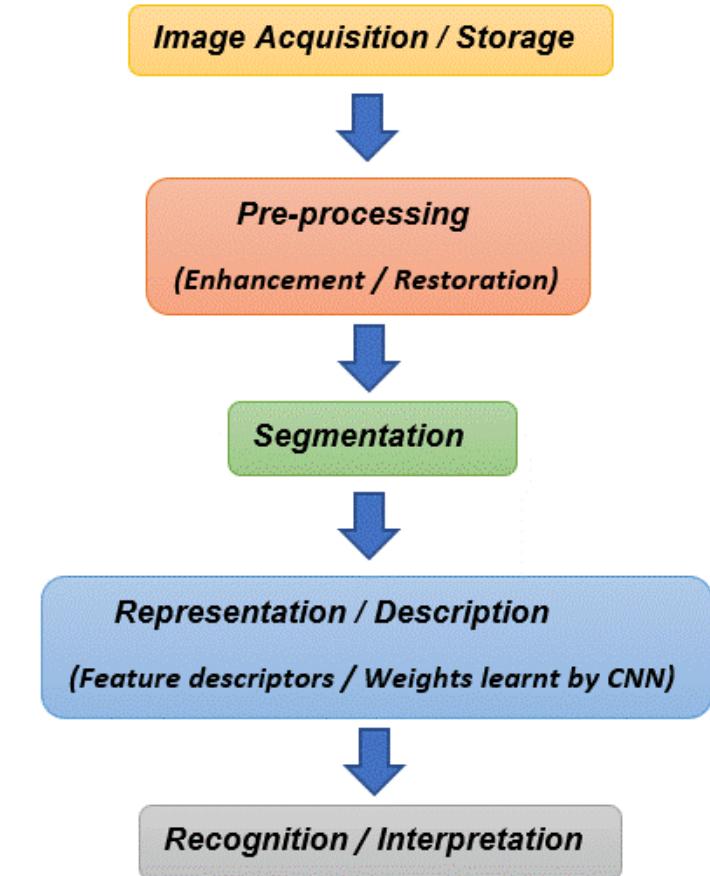
# Image Processing Pipeline

## Acquisition, storage, loading

- acquire image,
- store it on disk
- load it for showing or processing

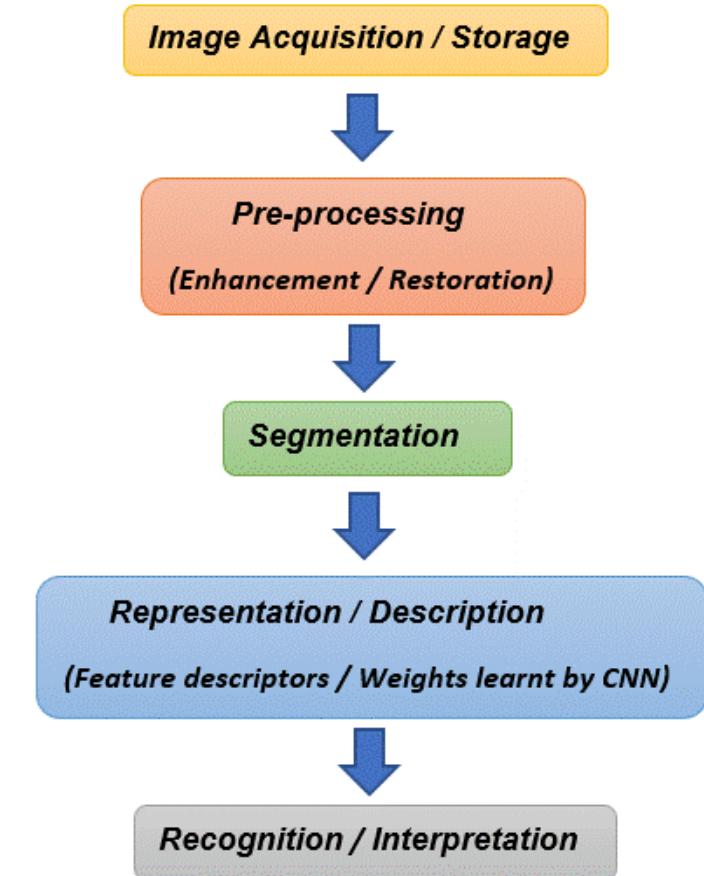
## Pre-processing

- Transform, convert to a different format
- Enhance quality (e.g., sharpening)
- Remove noise



# Image Processing Pipeline

- **Segmentation**
  - Extract regions/object of interest from the image
- **Information Extraction / Description**
  - Compute properties / descriptors of the image
- **Recognition / Interpretation:**
  - Image classification
  - Object recognition



# Image Acquisition

- **Synthesis** – images created by a computer
  - 2D painting / 3D rendering / procedural texturing
- **Capture** – images from the “real world”
  - Sampling of an analog signal
  - Digital camera
  - Frames from video
  - Data from sensors (optical, thermal, radiation, ...)
  - ...

# Preprocessing

- Fit image to a given **tone**, **size**, **shape**, etc.
- Match image to a desired feature or to other images
- Make a set of **dissimilar** images appear **similar**
  - E.g., to be composited later
- Make similar parts of an image appear dissimilar
  - E.g., **contrast enhancement**



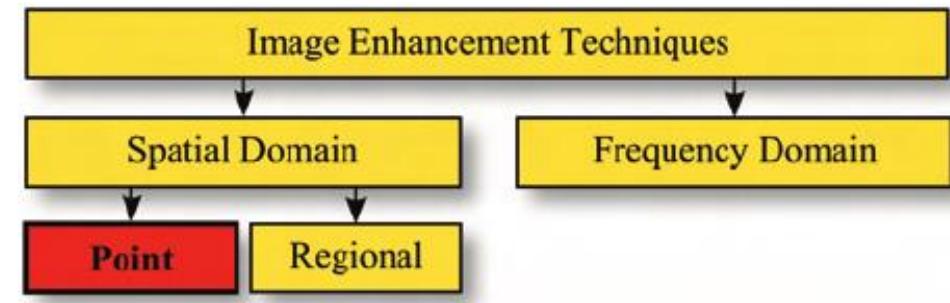
Original



Adjusted grayscale curve

# Preprocessing

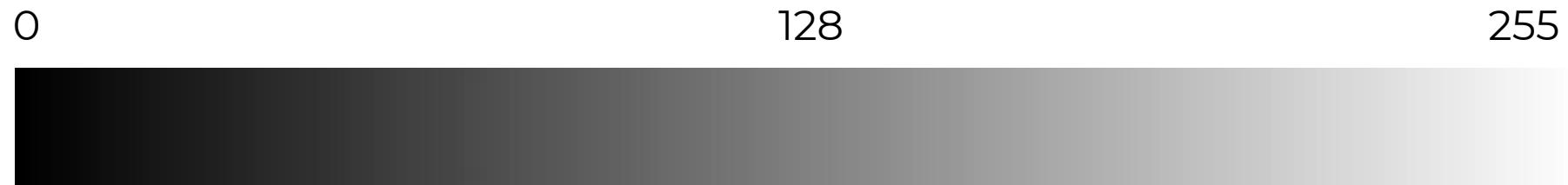
- We will consider methods for pixel processing in the **space-domain** (they operate on pixel intensity, colour, or position)
- There are other methods that operate on an image after it has been transformed to other domains (e.g., **frequency-domain**)
- **We will keep to the space-domain** (at least today... :D)



# Pixel Operations

In **point** (pixel) processing, a **single input** is processed to obtain a **single output** sample

Pixel intensity is modified through some operation, e.g., adding, subtracting, or multiplying



# Rescaling (Contrast and Brightness)

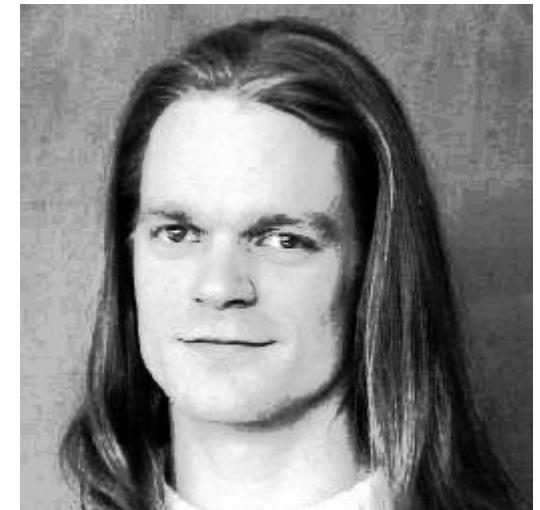
**Rescaling** is the operation by which we alter the contrast and/or brightness of an image



**Alpha** is the **gain**: controls overall **contrast**

- $> 1$ , image gets brighter and **more contrasted**
  - E.g., original: 5, 10, diff = 5; converted 5\*2, 10\*2, diff = 10 (diff got bigger)
- $< 1$ , image gets darker and **less contrasted**
  - E.g., original: 5, 10, diff = 5; converted: 5\*.5, 10\*.5, diff = ~3 (diff got smaller)

$$S_{\text{output}} = \alpha \cdot S_{\text{input}} + \beta.$$



# Rescaling (Contrast and Brightness)

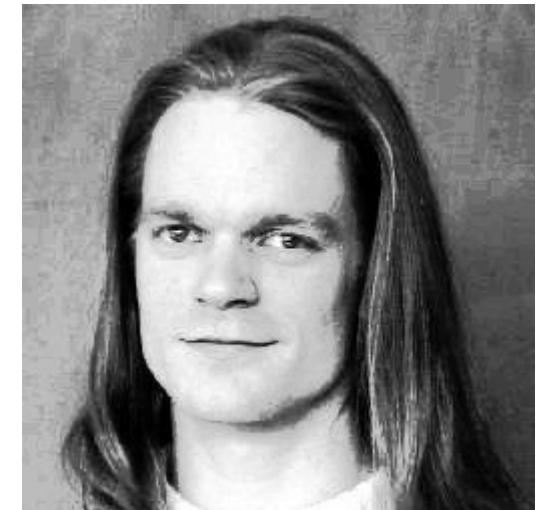
**Rescaling** is the operation by which we alter the contrast and/or brightness of an image



**Beta** is the **bias**: controls overall **brightness**

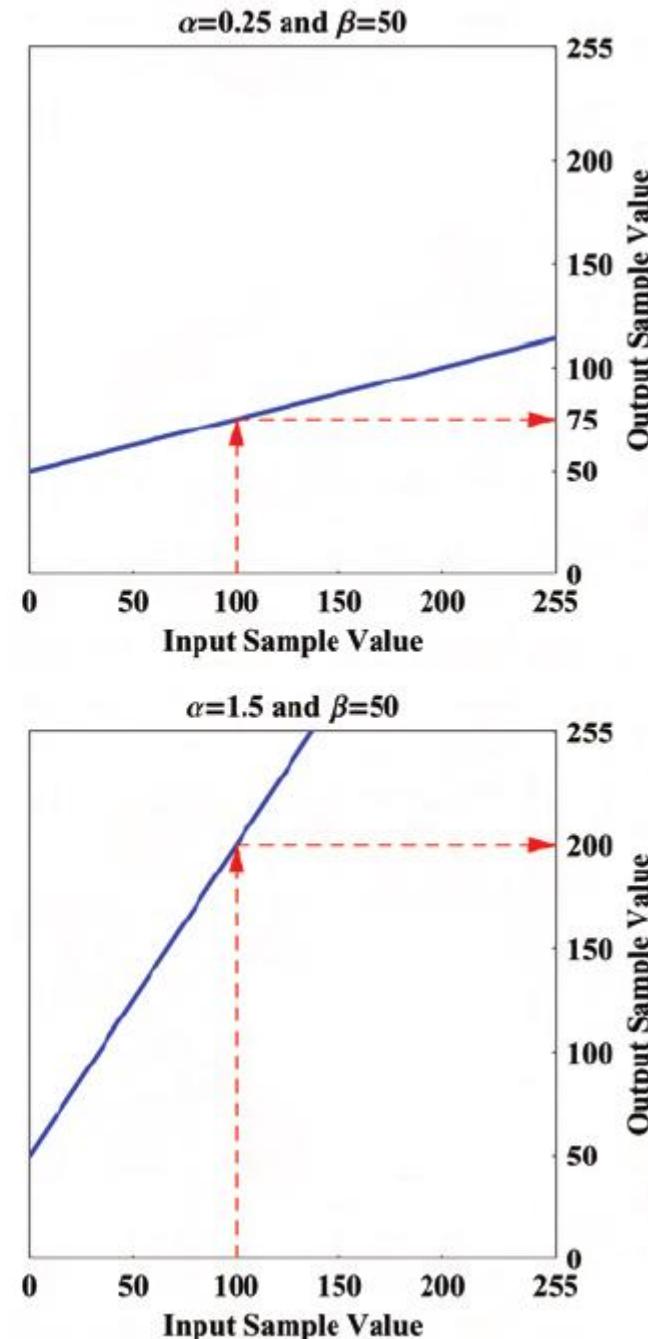
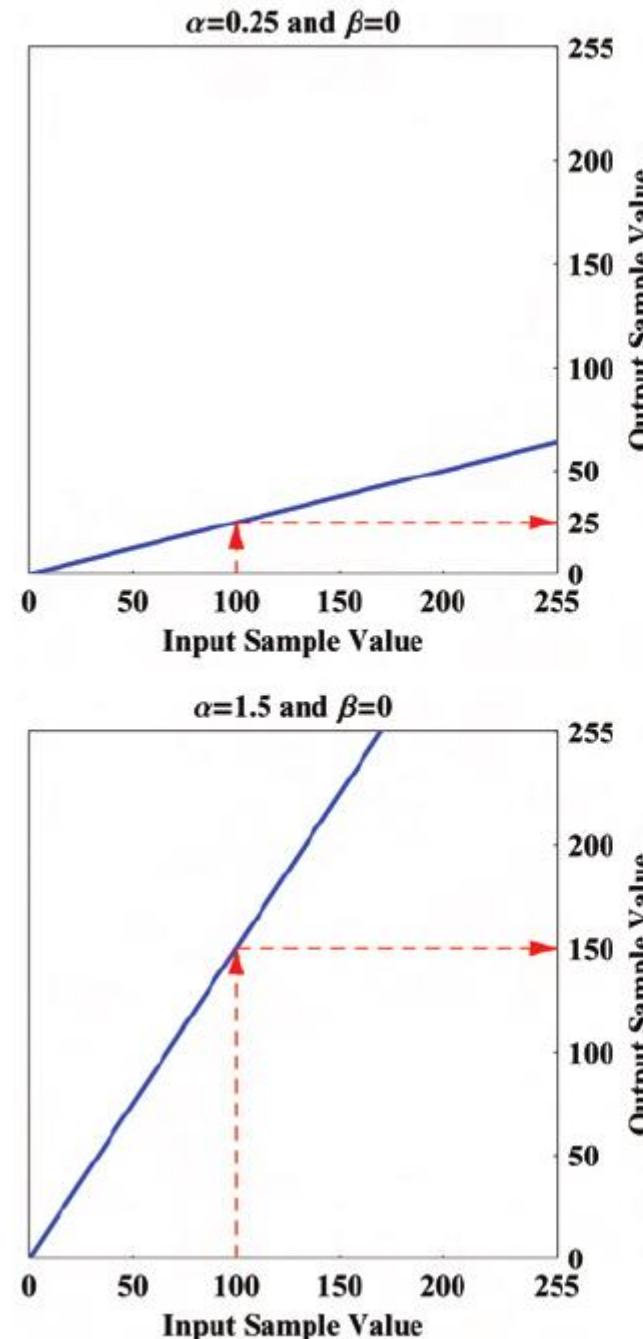
- $> 0$ , image gets **brighter**
  - E.g.,  $10 + 10 = 20$
- $< 0$ , image gets **darker**
  - E.g.,  $10 - 5 = 5$

$$S_{\text{output}} = \alpha \cdot S_{\text{input}} + \beta.$$



# Rescaling

- **Examples** of different values for alpha and beta and how they transform the inputs
- Note how **alpha > 1.0** extends the range of values (**more contrast**)
- Note how **beta** keeps contrast, but **changes mean intensity**



# Rescaling (Contrast and Brightness)

- alpha= 1.3, beta = 40

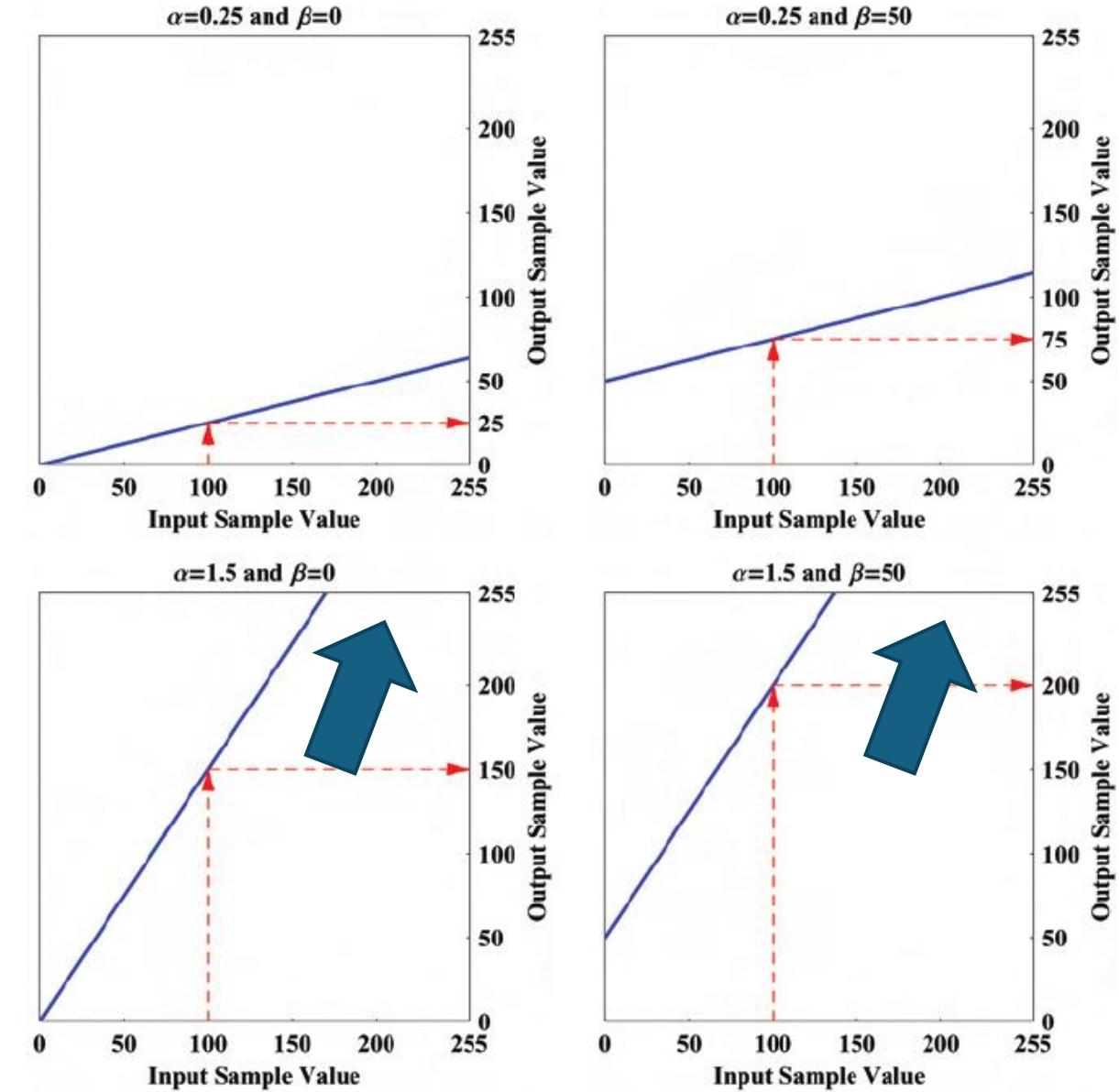
Notice clipping



# Clamping

- Applied after processing the image to **ensure that its pixel values are kept within what is admissible**, e.g., [0..255] for 8 bits, or [0.0... 1.0] for float representations.

$$clamp(x, min, max) = \begin{cases} \min & \text{if } \lfloor x \rfloor \leq \min, \\ \max & \text{if } \lfloor x \rfloor \geq \max, \\ \lfloor x \rfloor & \text{otherwise.} \end{cases}$$



# Contrast Stretching

Contrast stretching aims to **maximize the contrast of an image**

Given an image with intensities in the range  $[a, b]$ , then:

$$\begin{aligned}\alpha &= \frac{255}{b-a}, \\ \beta &= -\alpha \cdot a\end{aligned}$$

# Application Example

- Consider a **thermal camera** making readings of a Labrador on a summer evening
- The outcome ranges from **71.5 to 99.3** degrees Fahrenheit
- We want to visualize it in an image.  
We:
  - Round values to nearest integer
  - Show them as a greyscale image
- **Nicely done? How would you do it?**



# Application Example

Rescale so that:

- 71.5 corresponds to **black**
- 99.3 corresponds to **white**

So, contrast stretching:

$$\alpha = \frac{255}{b-a},$$
$$\beta = -\alpha \cdot a$$

$$\begin{aligned}\alpha &= \frac{255}{99.3 - 71.5} \\ &= 9.17, \\ \beta &= -\alpha \cdot a \\ &= -9.17 \cdot 71.5 \\ &= -655.85.\end{aligned}$$



# Perceptually Uniform Pipeline

- An image travels a long way from acquisition to visualization:
  - **Acquire image with camera**
  - Store into digital form
  - Decode the stored data
  - **Display on one (or more) output devices**
- Ideally, we want that the image seen on the display **is perceptually equivalent** to what was captured by the camera,

**but...**

# Gamma Value

Cameras and displays introduce nonlinear distortions in the images they produce

For a display, this can be described as a **power-law relationship** between the **level of light that is displayed and the amount of light intended for display**:

$$\hat{S}_{\text{displayed}} = (\hat{S}_{\text{intended}})^\gamma$$

**Gamma**, in the formula, determines the **amount of distortion** introduced by the output device (1.0 = no distortion)

Computer monitors and TVs have gamma values in the range of [1.2 to 2.5]

# Gamma Correction

- Gamma correction aims to **keep a perceptually uniform sample value** throughout an entire imaging pipeline by compensating for this distortion
- The **intended sample is gamma corrected** for the display:

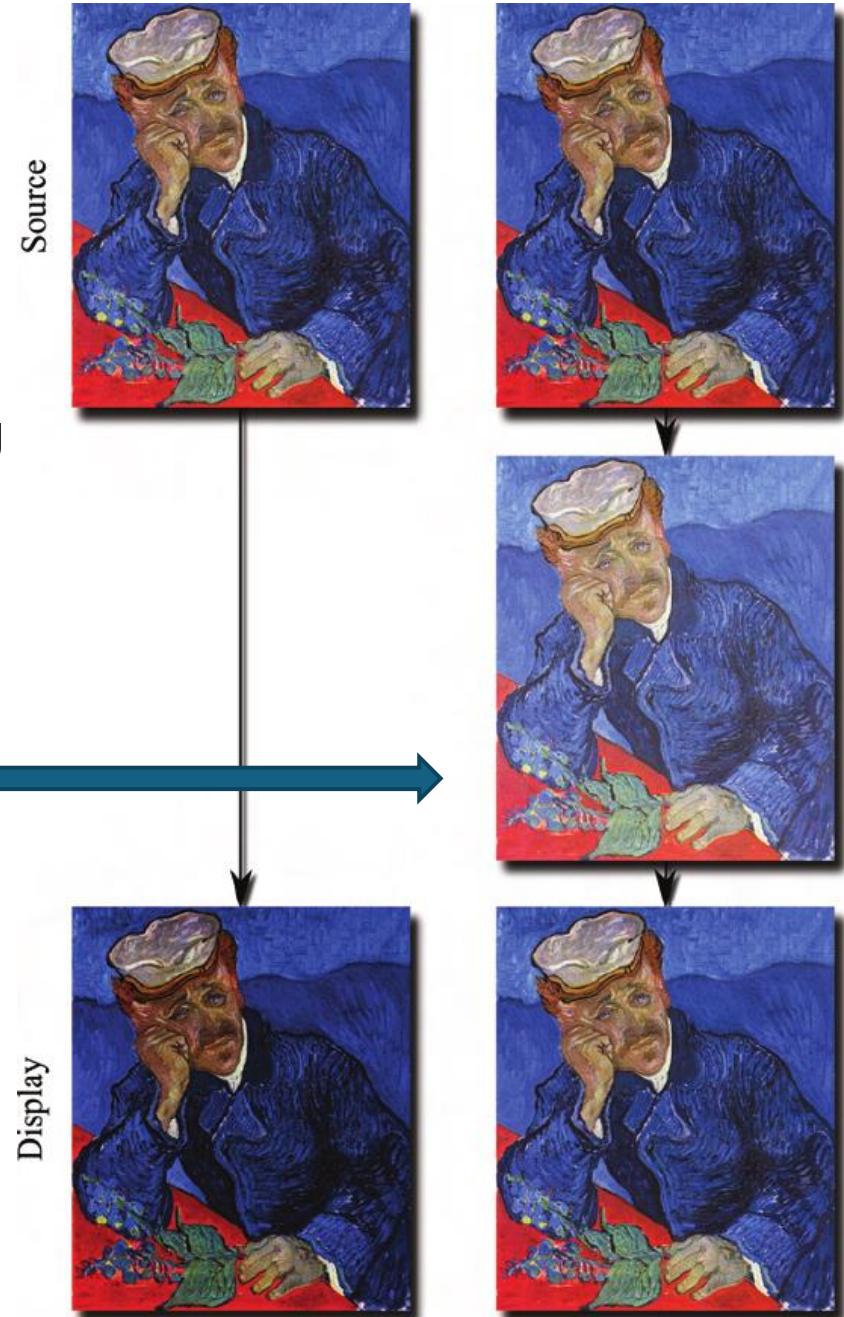
$$\hat{S}_{\text{corrected}} = (\hat{S}_{\text{intended}})^{1/\gamma}$$

When it is shown, then:

$$\hat{S}_{\text{displayed}} = (\hat{S}_{\text{corrected}})^\gamma,$$

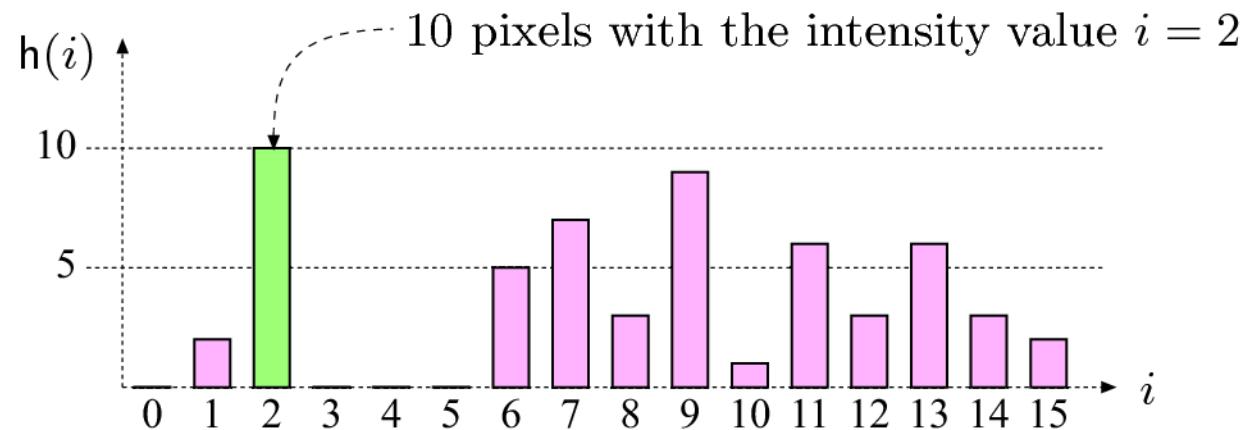
$$\hat{S}_{\text{displayed}} = \left( (\hat{S}_{\text{intended}})^{1/\gamma} \right)^\gamma$$

$$\hat{S}_{\text{displayed}} = \hat{S}_{\text{intended}}.$$



# Image Histogram

A histogram shows the number of times each pixel value occurs, in the image



$h(i)$	0	2	10	0	0	0	5	7	3	9	1	6	3	6	3	2
$i$	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

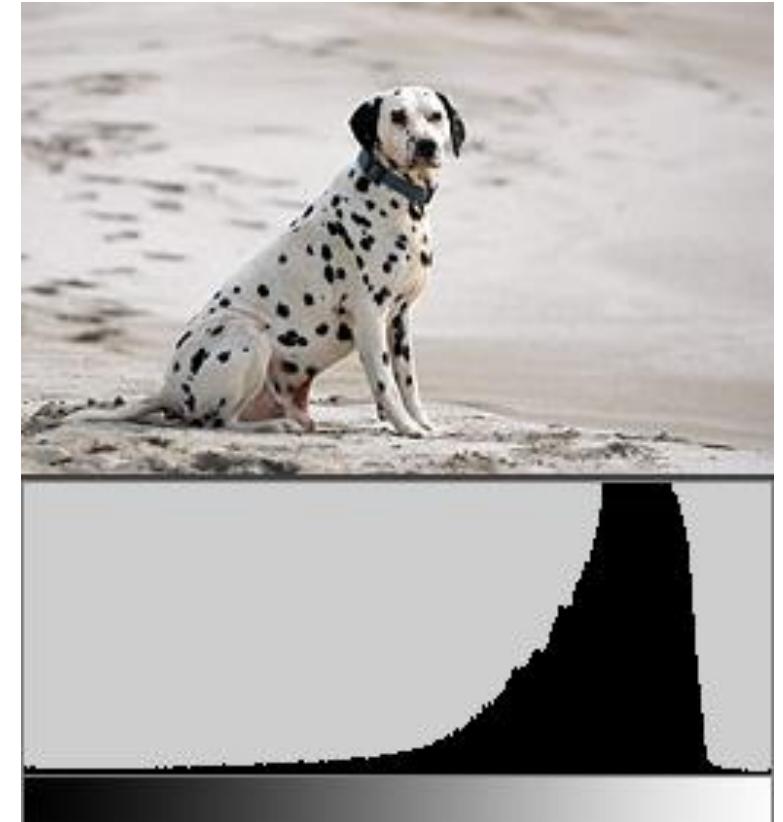
# Image Histogram

Provides a **general idea of the image gray levels** and allows choosing an adequate processing operation

Ideally an image histogram should occupy the entire grayscale

Histogram-based processing has **two stages**:

- Computing and analyzing the **histogram**
- **Image enhancement** based on histogram features



# Gathering insight from histograms

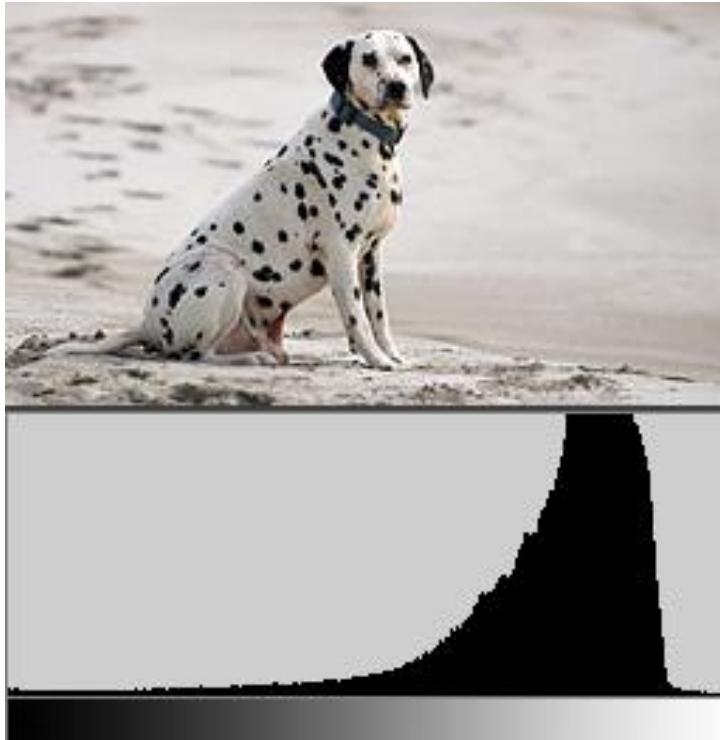
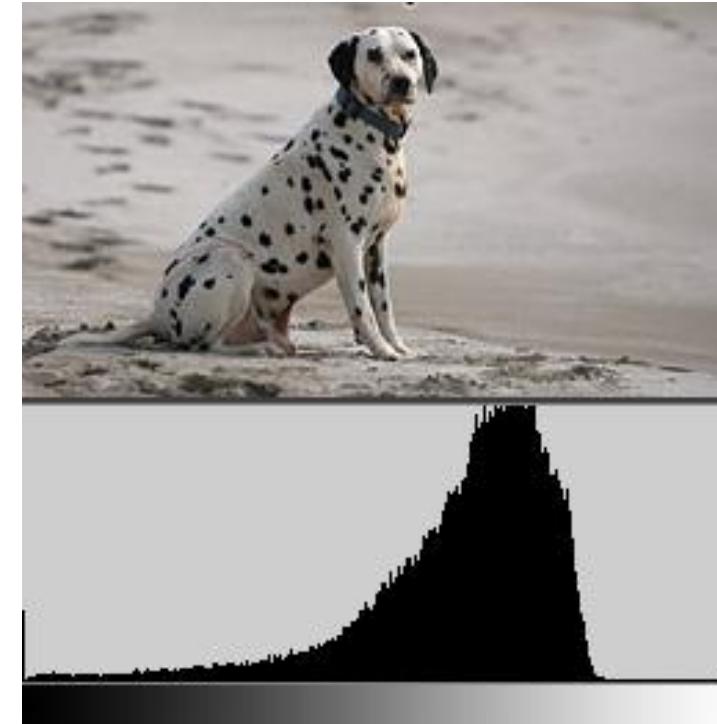
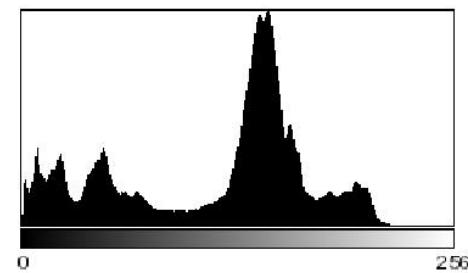


Image and histogram

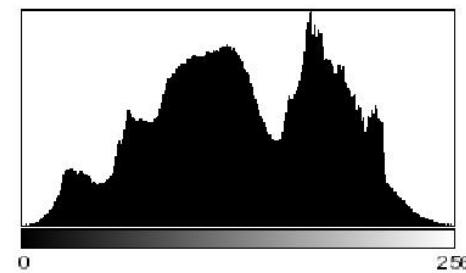


Underexposed image:  
slightly darker

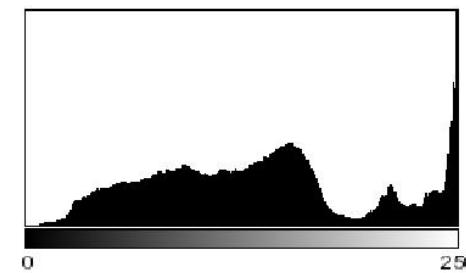
# Gathering insight from histograms



(a)



(b)



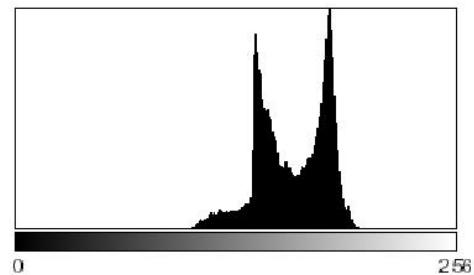
(c)

(a) – Underexposed image: loss of detail in the darker areas

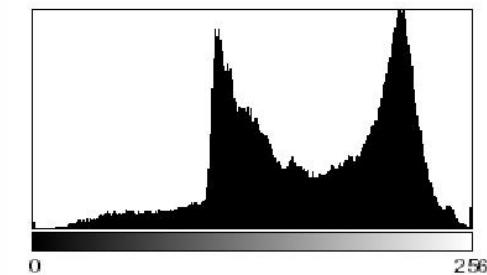
(c) – Overexposed image: loss of detail in the brighter areas

# Gathering insight from histograms

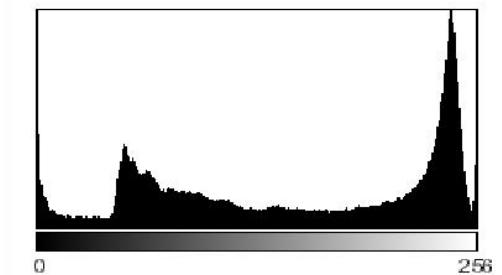
- Contrast



(a)



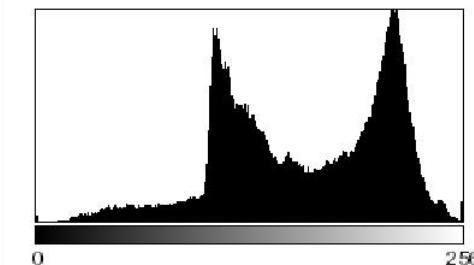
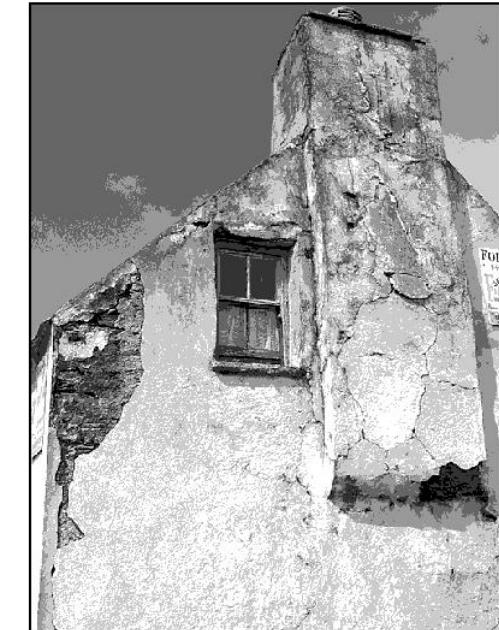
(b)



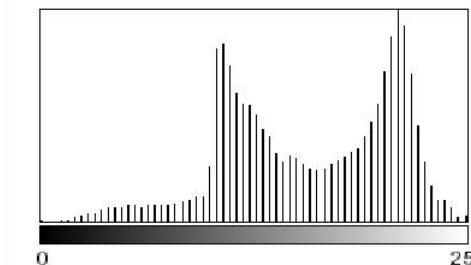
(c)

# Gathering insight from histograms

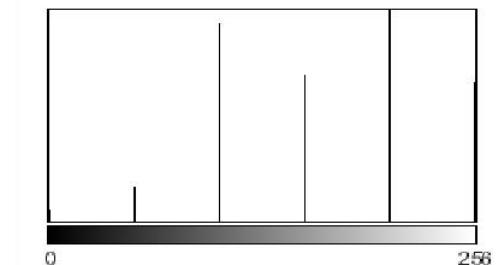
- Number of intensity levels



(a)



(b)



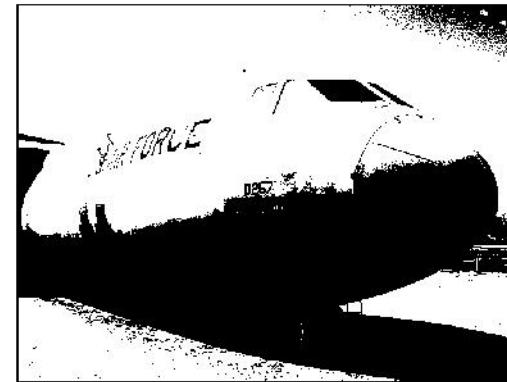
(c)

# Thresholding

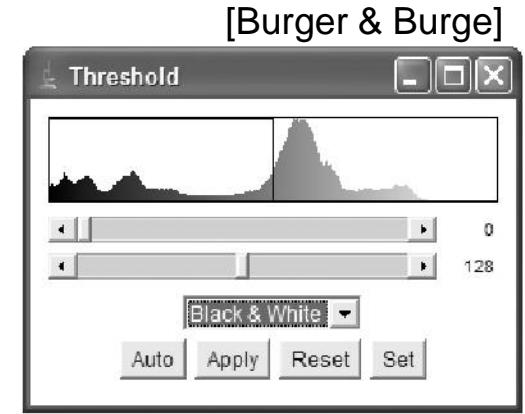
- Thresholding allows selecting an interval of the histogram and change it



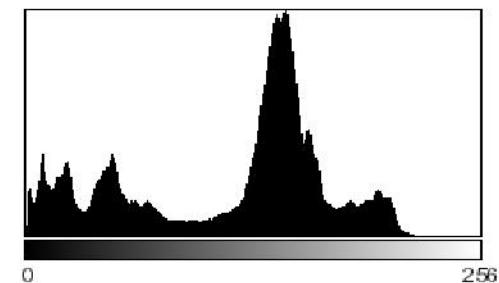
(a)



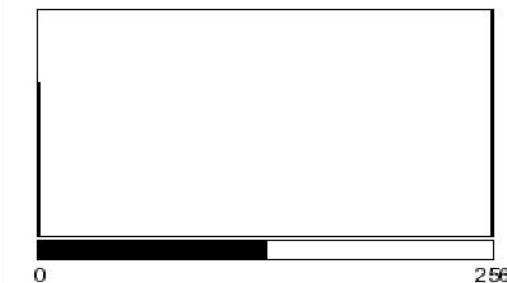
(b)



(e)



(c)



(d)

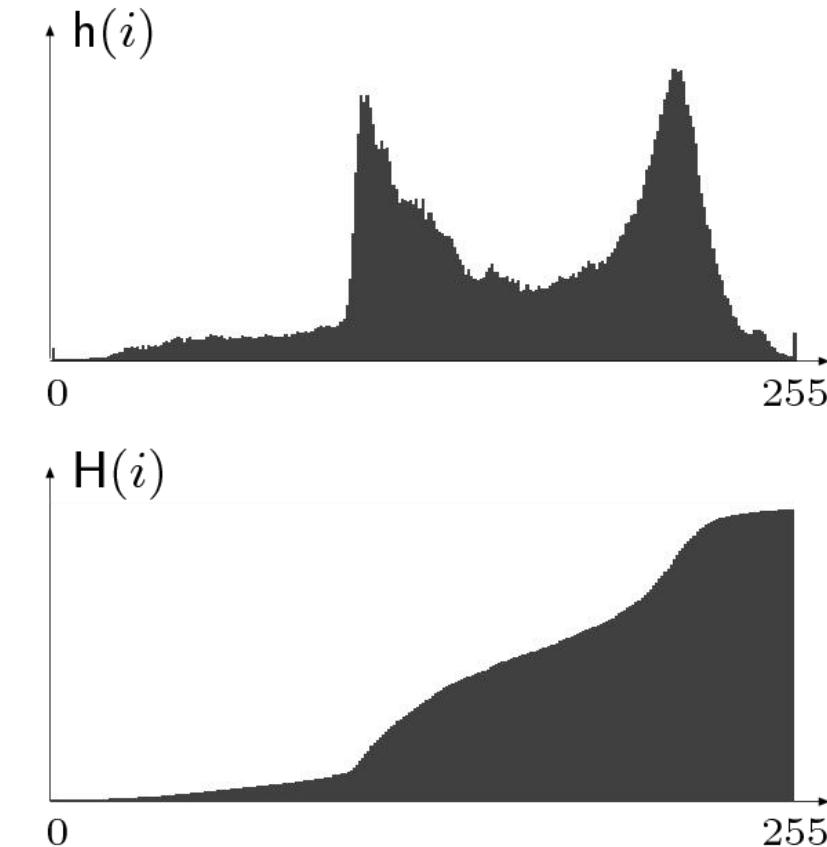
# Thresholding



# Cumulative histogram

Answers the question:  
**How many pixels have a value equal or below i?**

When normalized it approximates a probability distribution function



# Histogram Equalization

Used to optimize image contrast

Can be seen as a more advanced  
contrast-stretching

Works by flattening the histogram  
of an image



# Histogram Equalization

The image is analyzed and a function  $T(z)$  is computed in order to obtain an image with a **~ equiprobable histogram**

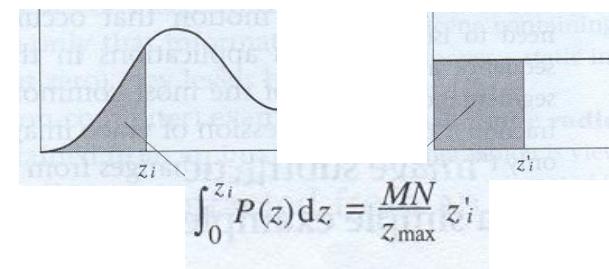
It is assumed that:

- $z$  is continuous
- the image has a continuous probability density function  $P(z)$
- the resulting image has an **equiprobable distribution**  $Q(z)$

$$\int_0^{z_1} P(z) dz = \int_0^{z'_1} Q(z) dz = \frac{MN}{z_{\max}}$$

$$z'_i = T(z_i) = \frac{z_{\max}}{MN} \int_0^{z_1} P(z) dz$$

$$z'_i = \frac{z_{\max}}{MN} \sum_0^{z_1} H(z) dz$$



$M \times N - n^{\circ}$  de pixels da imagem

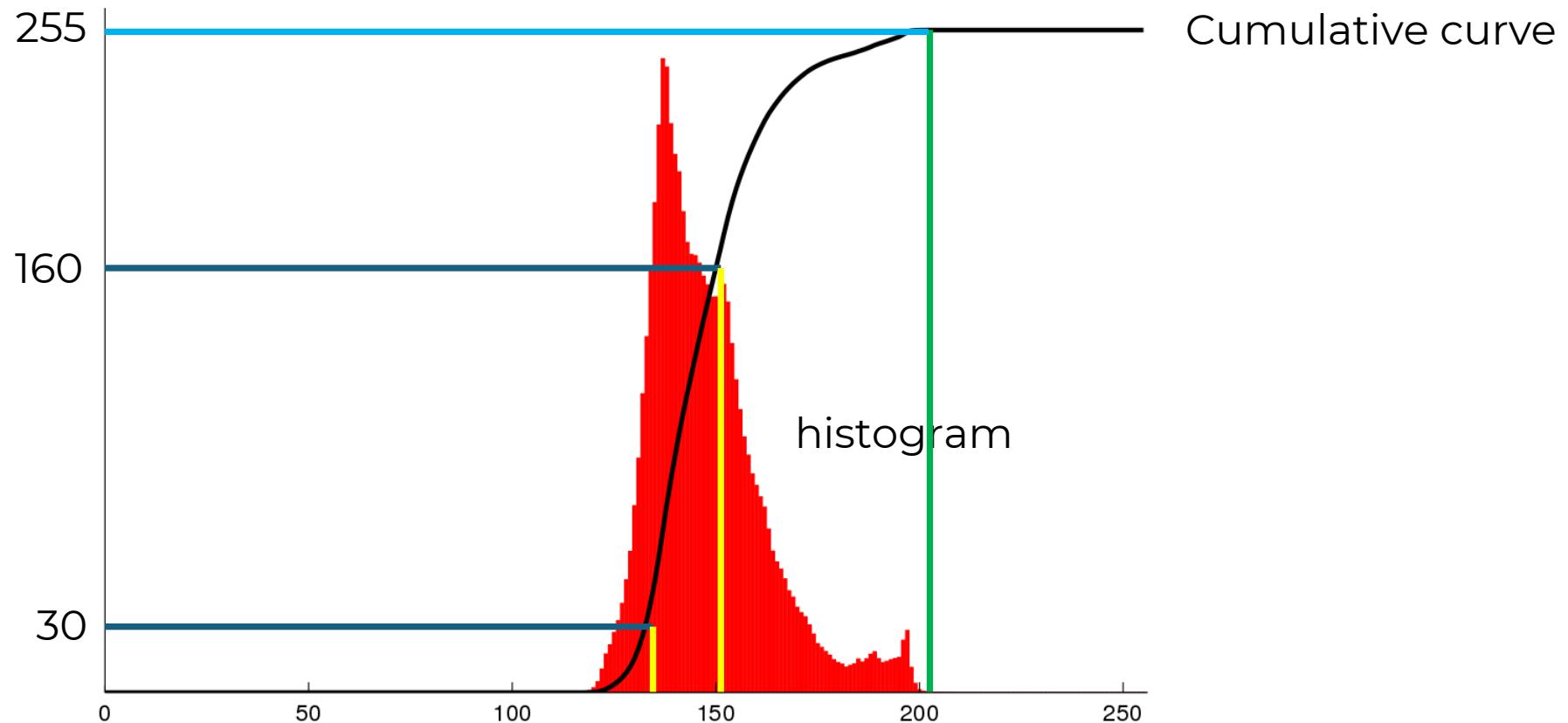
é a aproximação discreta e  
H é o histograma discreto



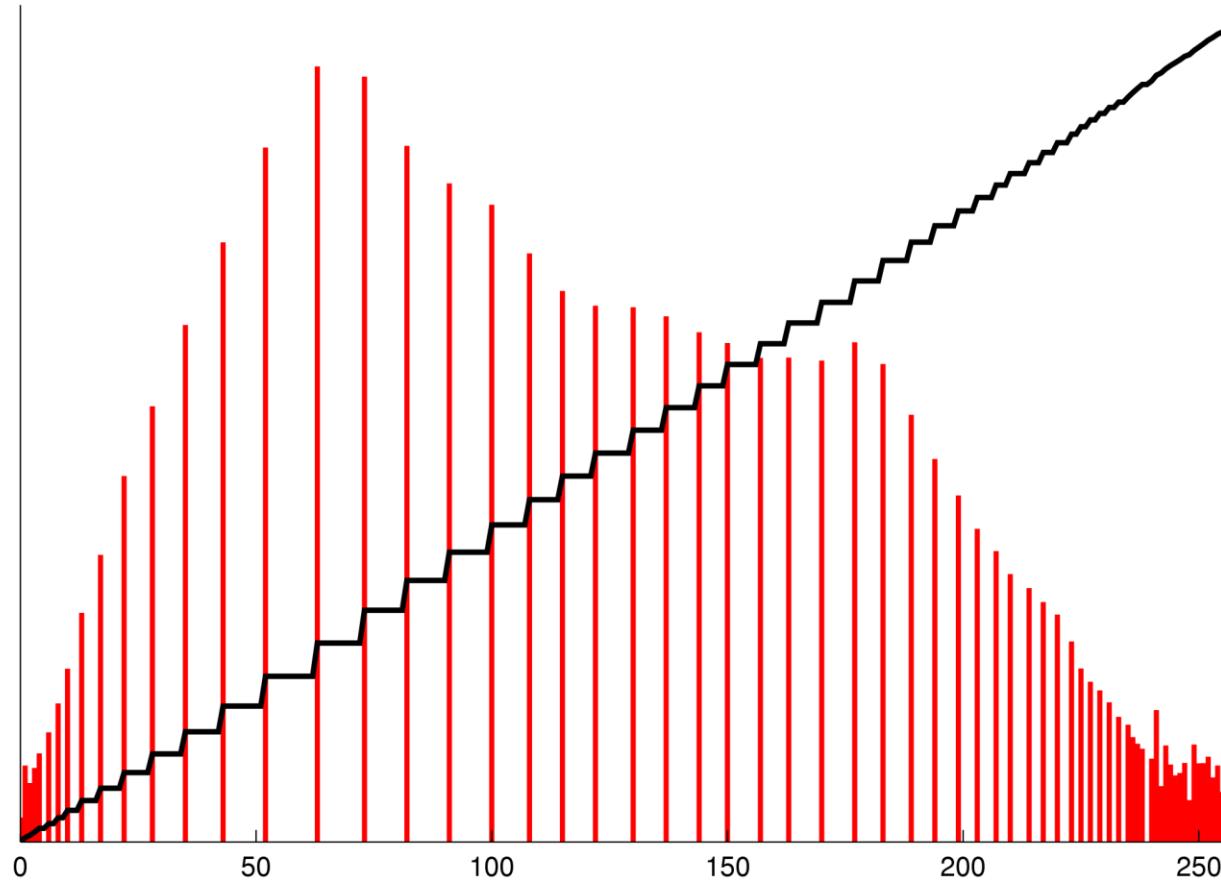
Oh my god, they killed Kenny!

You b\$"##rds!!

# Histogram Equalization



# Histogram Equalization

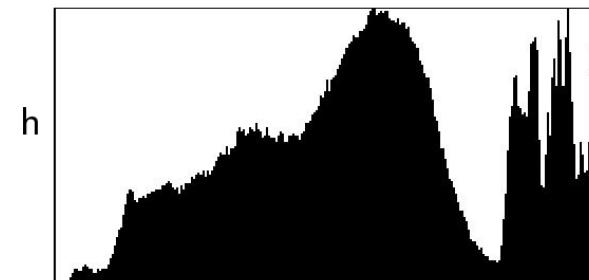


# Linear Histogram Equalization

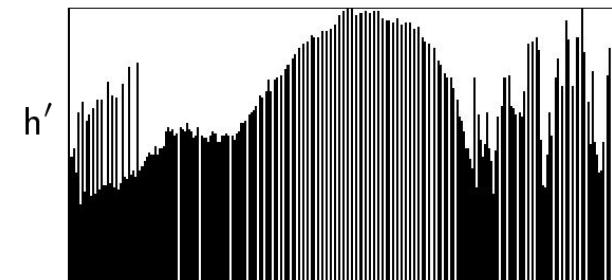


(a)

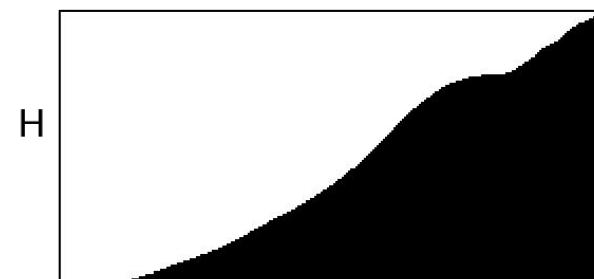
(b)



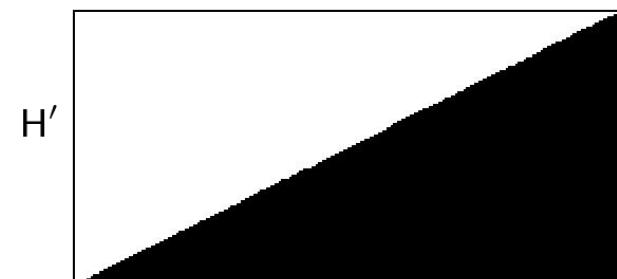
(c)



(d)



(e)

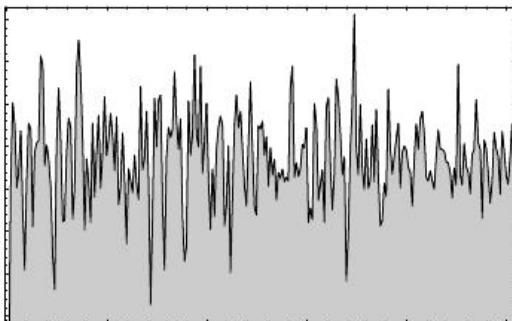
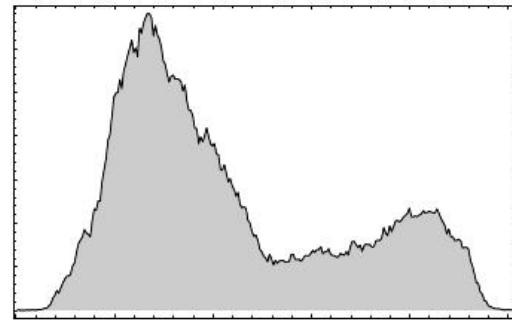


(f)

Cumulative histogram

[Burger & Burge]

# Histogram Equalization

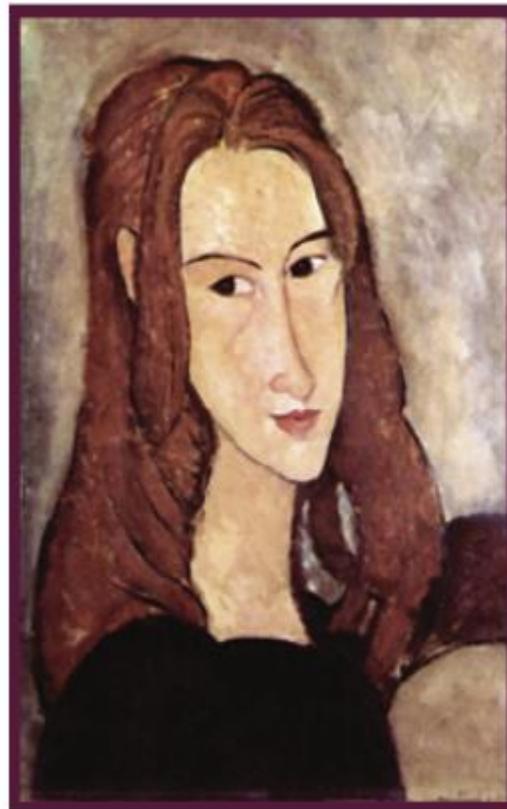




# Arithmetic Operations

# Arithmetic Operations

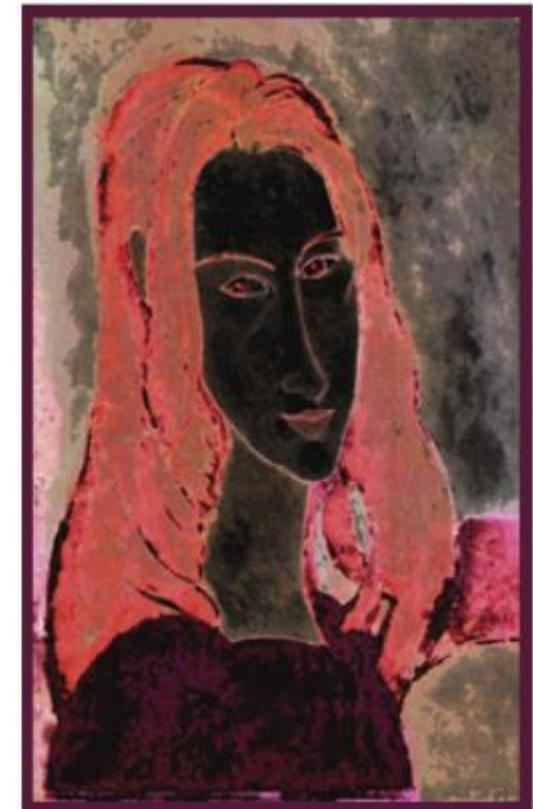
- Images can be added, subtracted, multiplied
- Watch out for saturation or negative values



(a)  $I_a$ .



(b)  $I_b$ .



(c)  $I_a - I_b$ .

# Alpha Blending

- Two sources are added after being scaled by an alpha value

$$s_{\text{dst}} = \alpha \cdot s_1 + (1 - \alpha) \cdot s_2$$

- Allows the concept of **transparency** to be implemented
- Works for the whole image
- **Alpha compositing** can also be implemented **at the pixel level**
  - RGBA



# Alpha Blending



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# Logical Image Operations

e.g., for  
masking



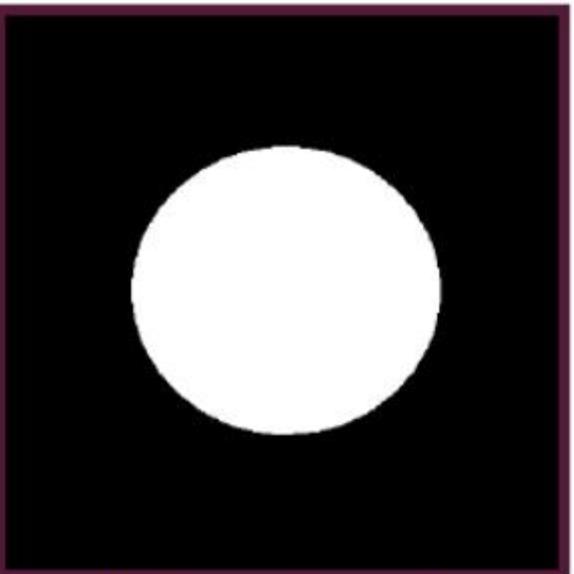
(a) Binary Source 1.



(c) Conjunction.



(e) Disjunction.



(b) Binary Source 2.



(d) Exclusive or.



(f) Negation.



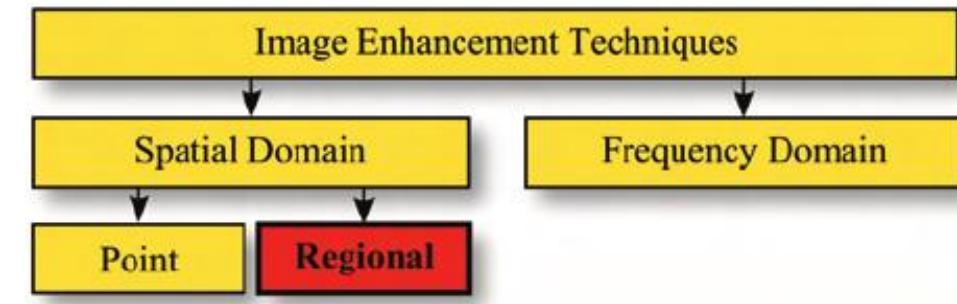
# Image Filters

Region-based processing  
Spatial-domain

# Regional Processing

In **point** (pixel) processing, a **single input** is processed to obtain a **single output** sample

In **regional** processing, the output sample **depends on multiple inputs** residing in a neighbourhood



# Image Filters

- First, we select the neighbourhood to process around the pixel using a matrix
- In image filtering this matrix is called a **kernel**
- Its values are related with how each neighbour will contribute to the output

-1	0	+1	
-1	-1	0	1
0	-1	0	1
+1	-1	0	1

Kernel

	X-1	X	X+1		
Y-1	32	45	55	48	89
Y	37	41	59	46	78
Y+1	38	54	55	49	57
	40	50	65	56	71
	49	53	63	59	61

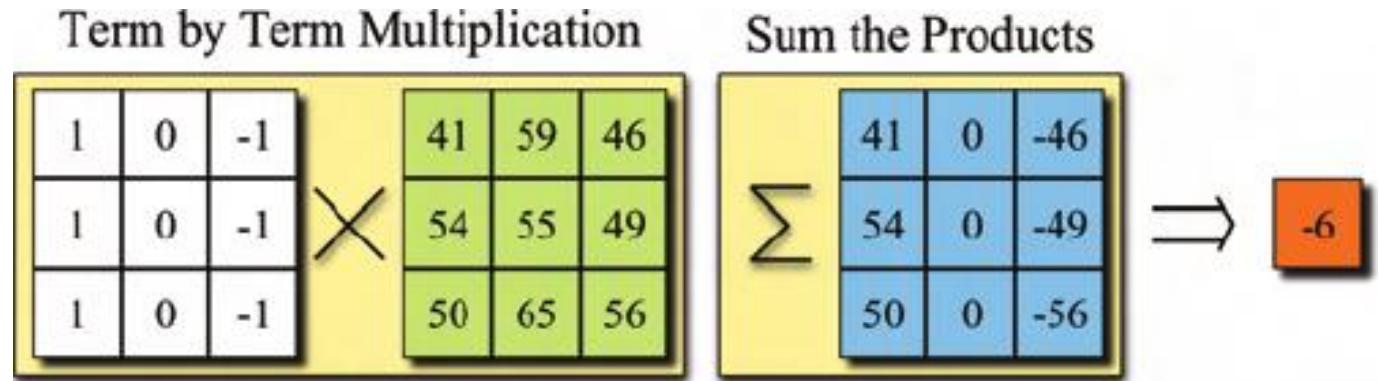
Digital Image

# Convolution

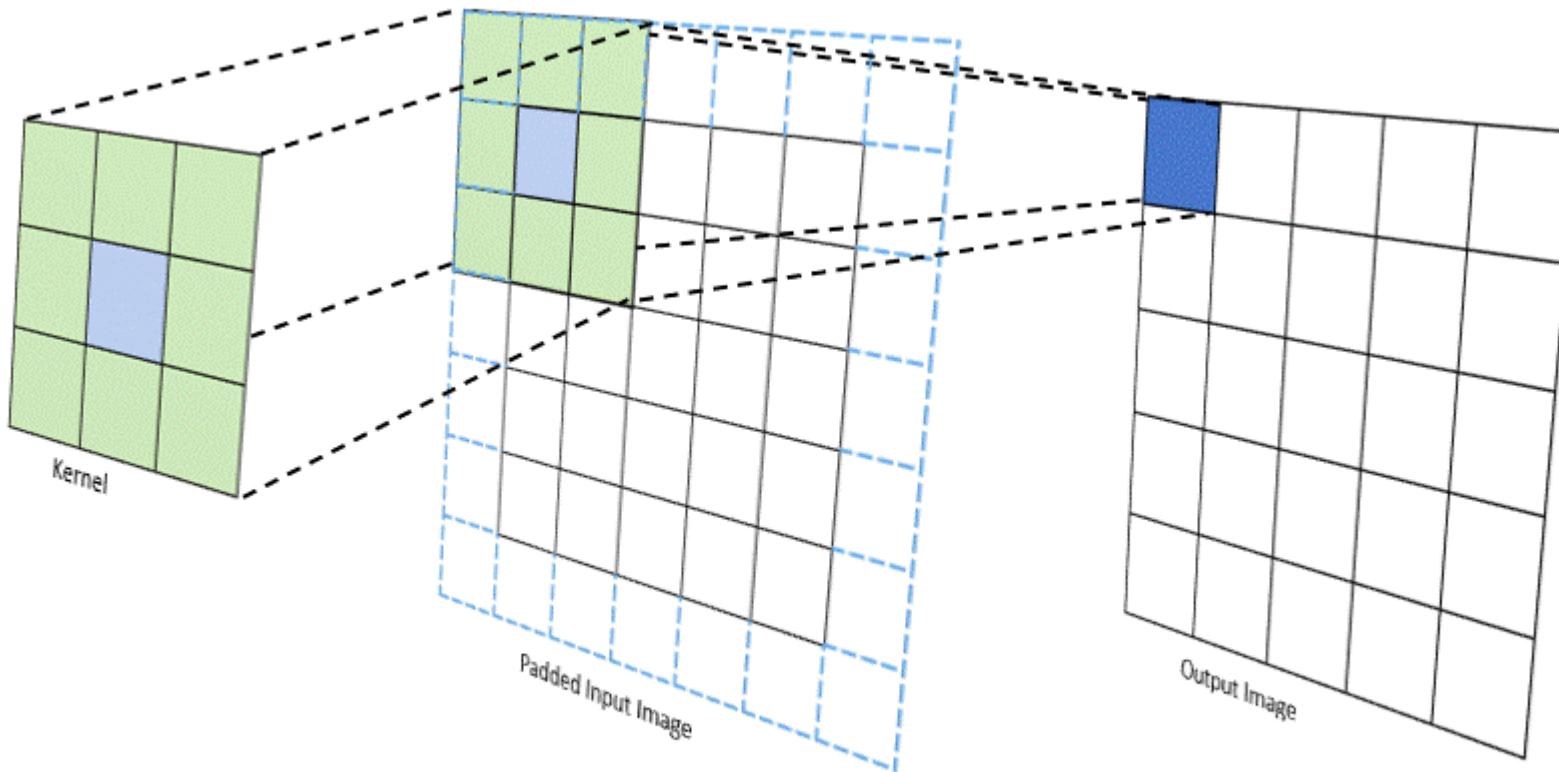
To apply the filter **the kernel is moved over the image stopping at each pixel** and performing the computation

Each **pixel value** at the origin is **transformed** into another pixel value at the destination **based on the kernel**

This operation of multiplying the kernel is called **convolution**



# Convolution



[https://miro.medium.com/v2/resize:fit:1400/1\\*juGbsuRpNjg15OCMwSmrmA.gif](https://miro.medium.com/v2/resize:fit:1400/1*juGbsuRpNjg15OCMwSmrmA.gif)

A close-up photograph of a chaotic tangle of numerous thin, colorful wires or threads. The colors are varied, including shades of red, yellow, green, blue, and white. The wires are intertwined in a complex, non-linear fashion, creating a dense and messy texture.

# Linear Filters

# Smoothing

Also called **neighborhood averaging**, can be used to reduce image noise

The **kernel** slides over the original image and the **intensity** of the resulting pixel in the final image is given by:

$$\sum_{i=0}^{N-1} W_i \cdot I_i$$

Other filters allow reducing noise **without blurring** (e.g., **median filter**)

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

**3 x 3 Averaging Filter**

All weights are 1/9

**Why 1/9?**

# Smoothing / Blurring

[Burger & Burge]

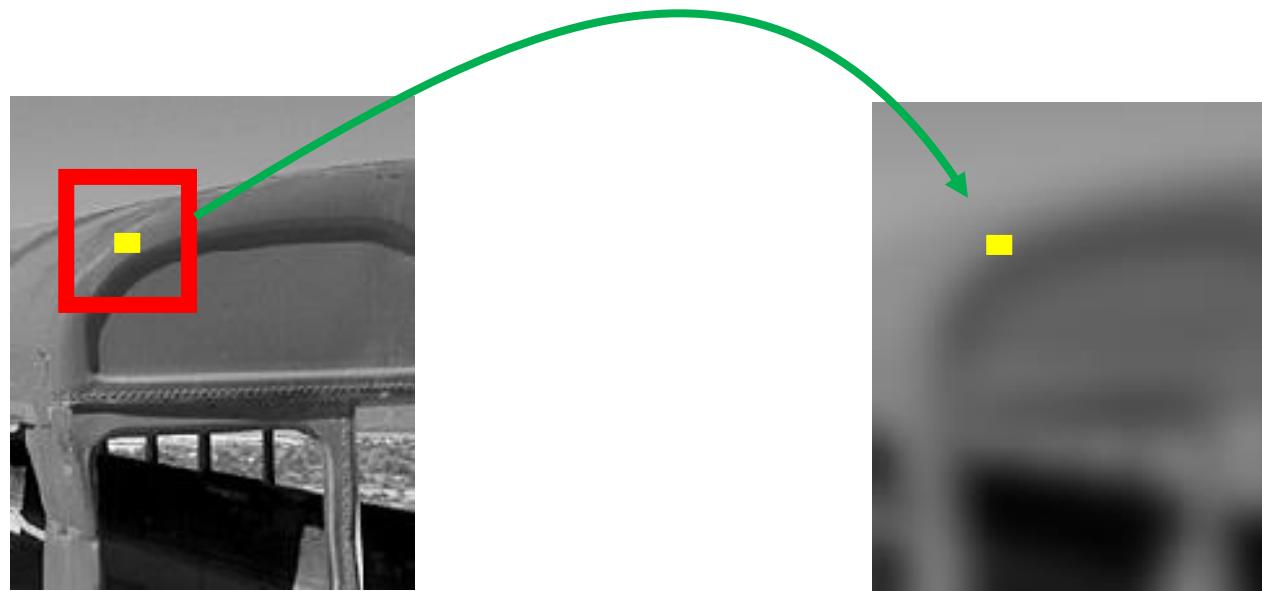


Averaging is an easy method for smoothing, but it also causes blurring

The bigger the kernel, bigger the smoothing (blurring)

# Smoothing / Blurring

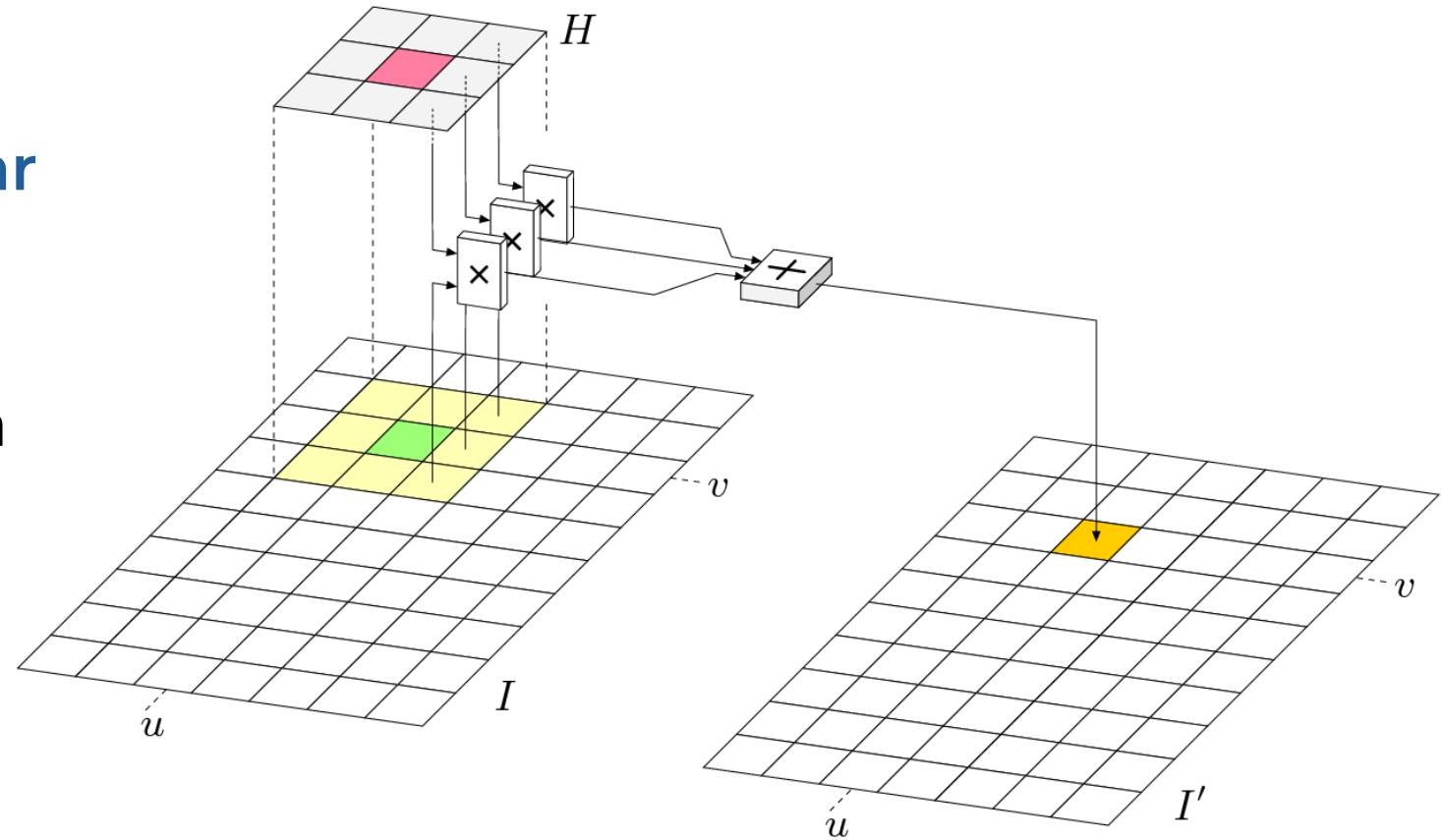
This is the basic principle of all filtering performed with kernel convolution. What changes is the weights



# Linear Filter

Averaging is a type of **linear filter**

Pixel value is obtained by a linear operation over its neighbourhood



# Smoothing kernels

A kernel where **all nonzero coefficients are identical** is called a **uniform filter**

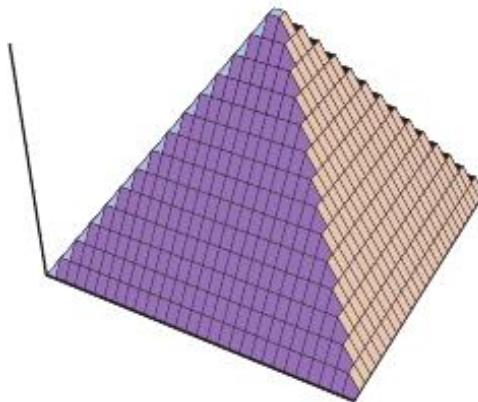
$$\frac{1}{25} \times \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

(a) Box filter.

$$\frac{1}{21} \times \begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \end{bmatrix}$$

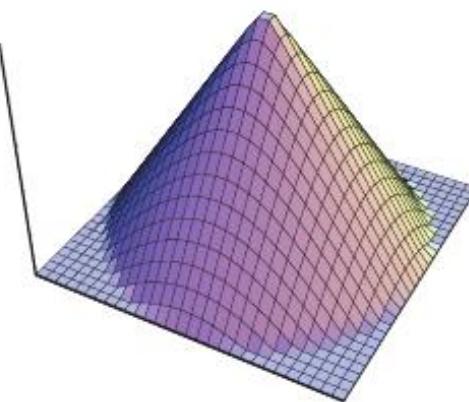
(b) Circular box filter.

# Smoothing Kernels



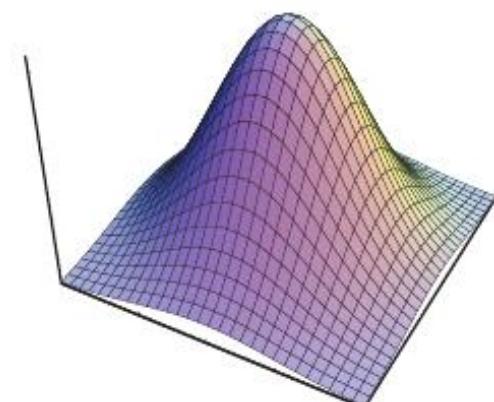
1	2	3	2	1
2	4	6	4	2
3	6	9	6	3
2	4	6	4	2
1	2	3	2	1

(a) Pyramid.



0	0	1	0	0
0	2	2	2	0
1	2	5	2	1
0	2	2	2	0
0	0	1	0	0

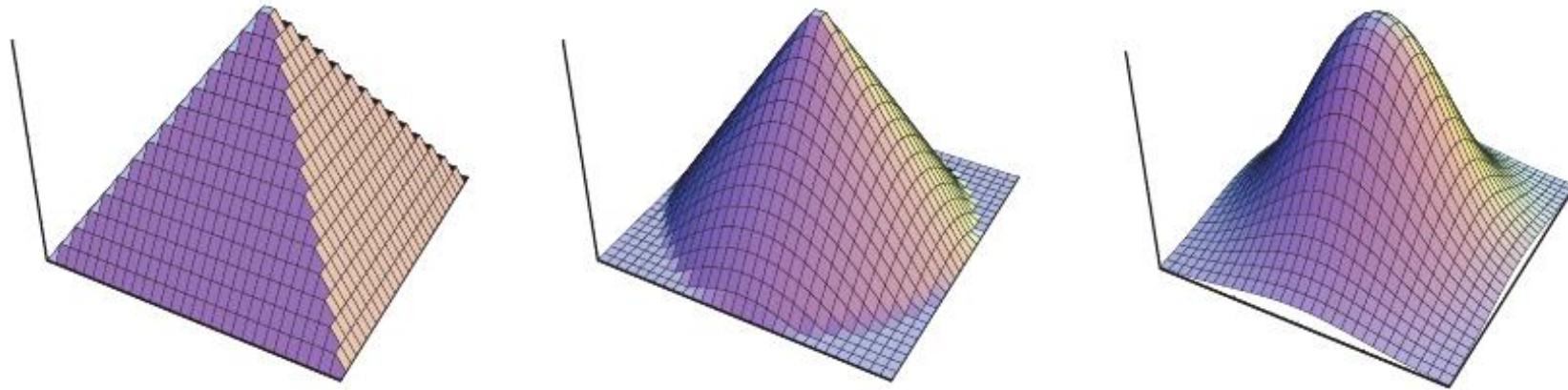
(b) Cone.



1	4	7	4	1
4	16	28	16	4
7	28	49	28	7
4	16	28	16	4
1	4	7	4	1

(c) Gaussian.

# Smoothing Kernels



The Gaussian kernel is the preferred given its smoothness

# Smoothing



source



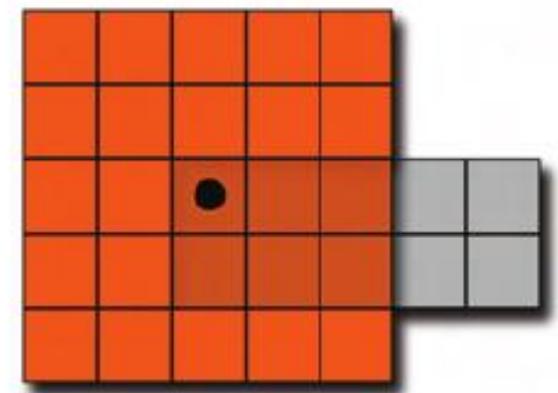
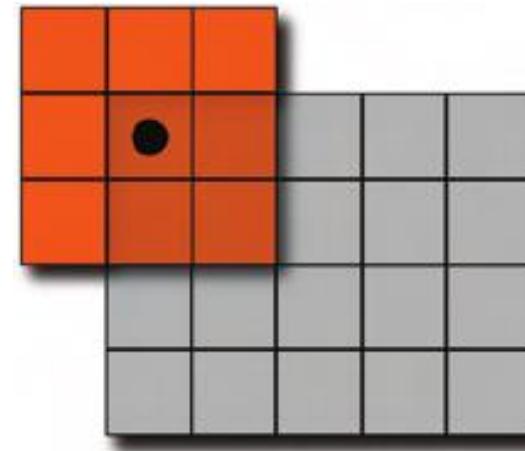
17 x 17 box



Gaussian

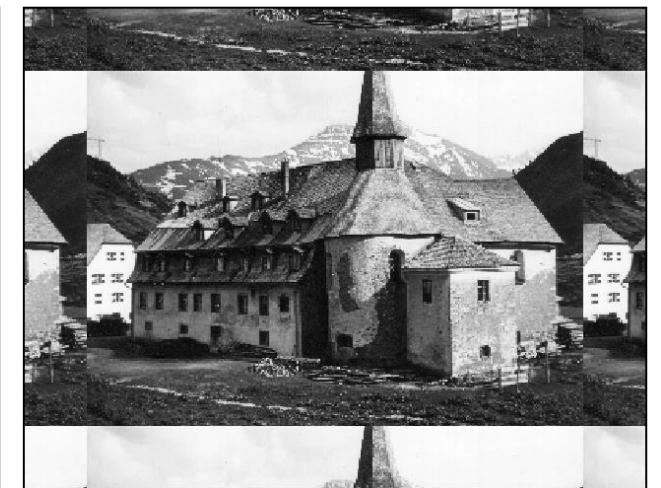
# The Boundary Problem

- When applying convolution to process an image, what happens...
  - When we process **border pixels?**
  - When the **kernel is bigger than the image?**



# How to handle image borders?

- Simple solutions can be:
  - Zero
  - Keep the same value
- Solutions that behave better include:
  - Padding
  - Mirroring
  - Circular tiling
  - Extend border values



# Sharpening

-1	-1	-1
-1	8	-1
-1	-1	-1

It is an **approximation** to the **high-pass filter** in the frequency-domain

Implemented in the space-domain

If all the pixels in the neighborhood have the **same intensity** value (gray level) the corresponding pixel in the result image has value **zero** (black)



# Sharpening Laplacian Filtering

0	-1	0
-1	4	-1
0	-1	0

-1	-1	-1
-1	8	-1
-1	-1	-1



# Sharpening



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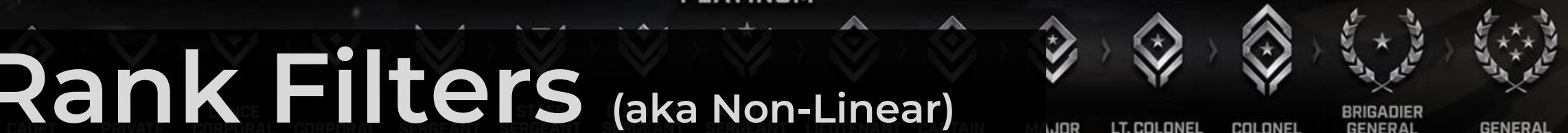
## SILVER



## GOLD



## PLATINUM



# Rank Filters (aka Non-Linear)

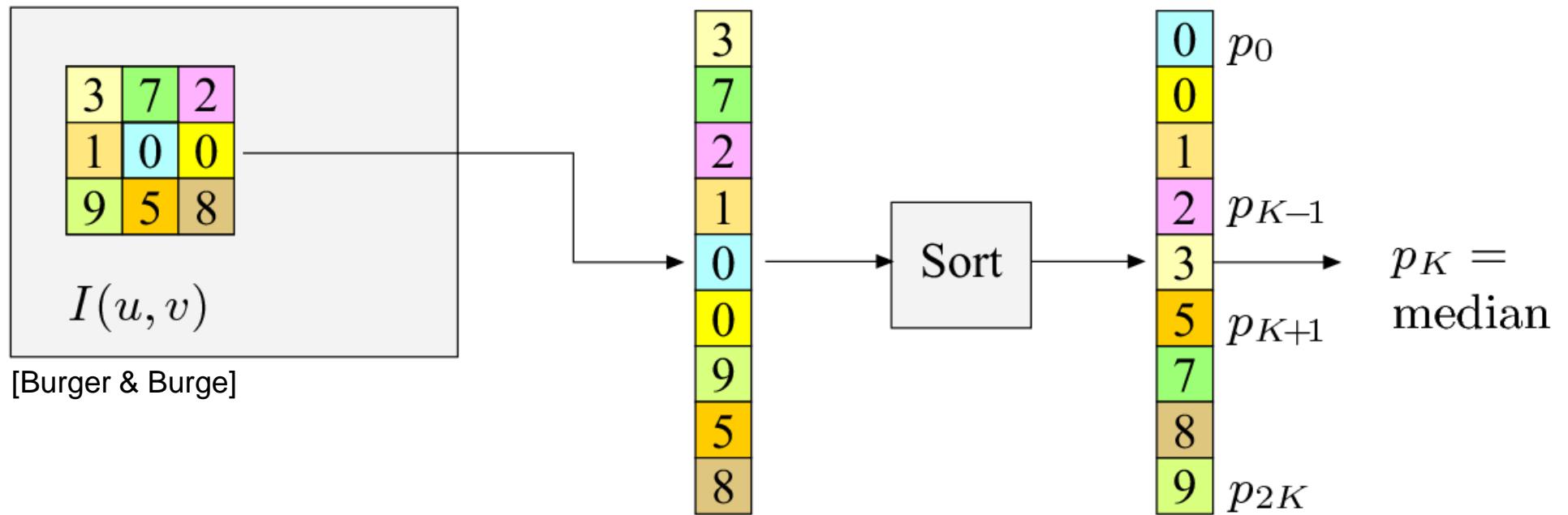
Based on a statistical analysis of the neighbourhood



## ONYX



# Median Filter



# Median vs Averaging

A median filter is better than the averaging filter at smoothing salt and pepper noise.

Why?



original



median



Gaussian

# Averaging Filter vs Median Filter

[Burger & Burge]



by the way, this is Lena

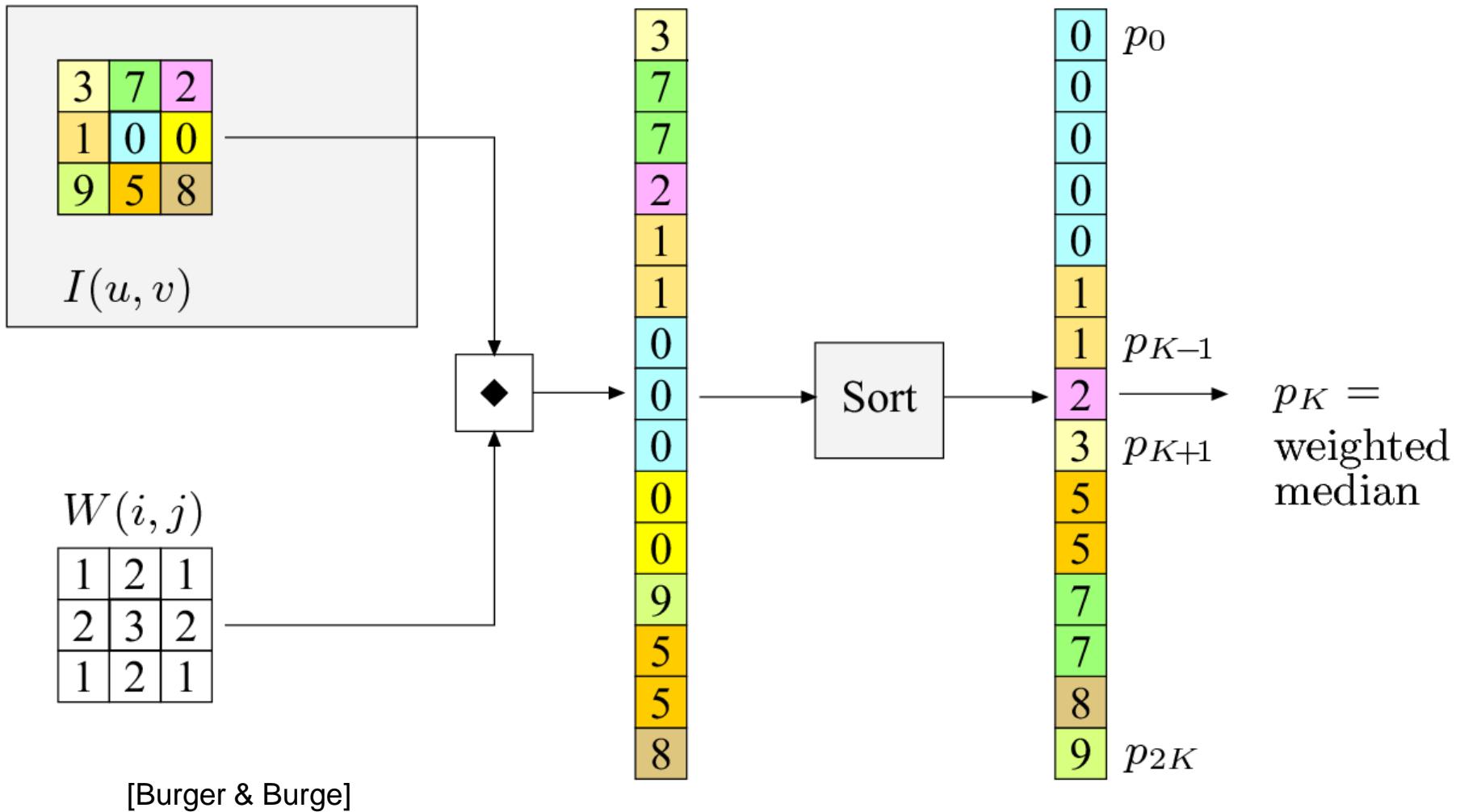


original

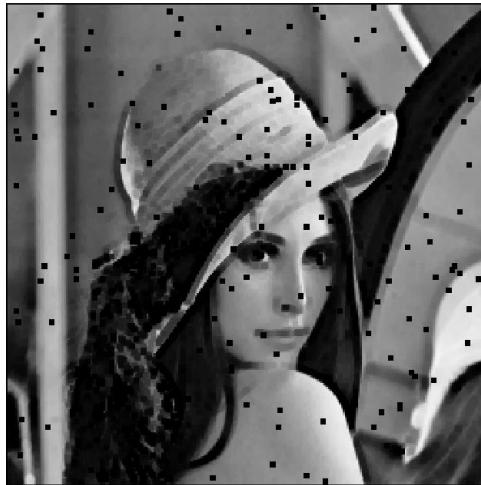
averaging

median

# Weighted Median Filter



# Minimum Filter vs Maximum Filter



original

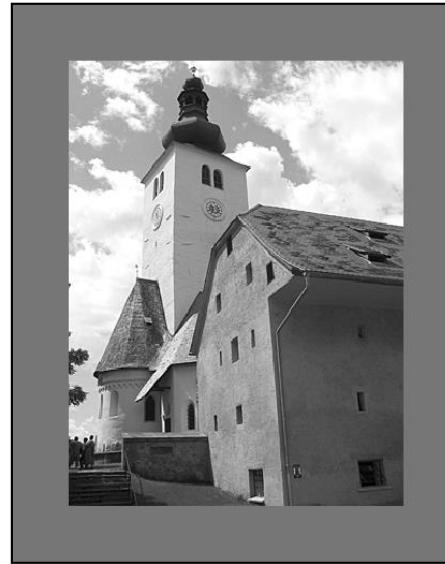
minimum

maximum

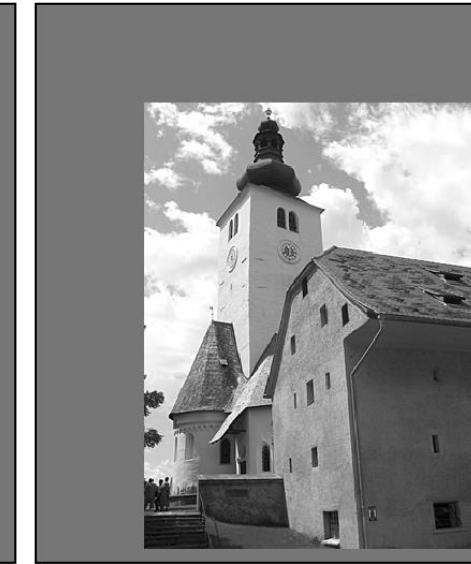
# Geometric Transformations

- Another possibility is to **operate on pixel position** and not on intensity or color values:
  - Correction of geometric distortion due to acquisition effects
  - Distortion of an image into another (image warping, morphing)
  - Texture mapping

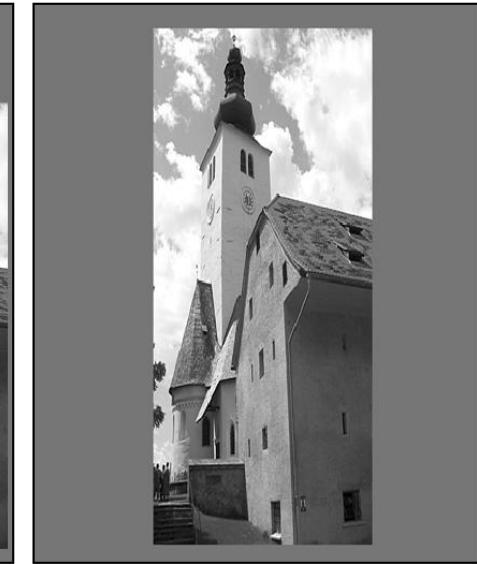
# Global geometric transformations



(a)



(b)



(c)



(d)



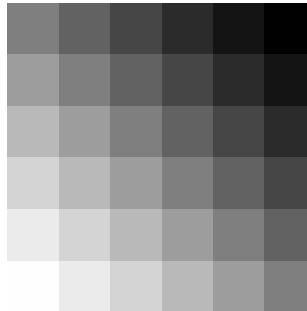
(e)



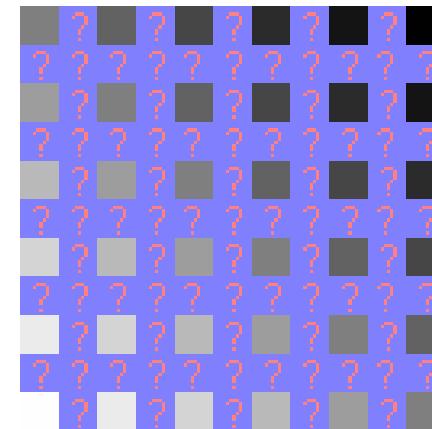
(f)

# Interpolation

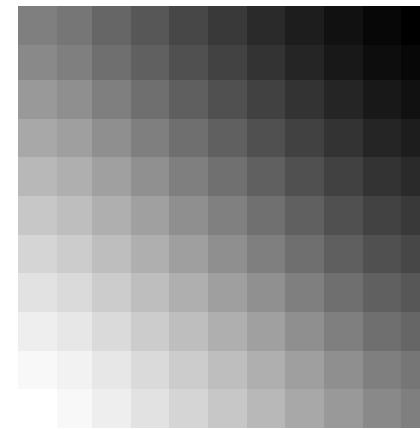
- When we **resize** an image, how do we fill the gaps?
- **Interpolation** works by using known data to estimate values of unknown points
- Interpolation **does not** add detail



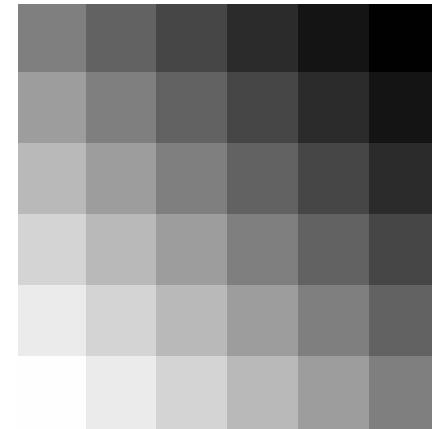
original



Before  
interpolation

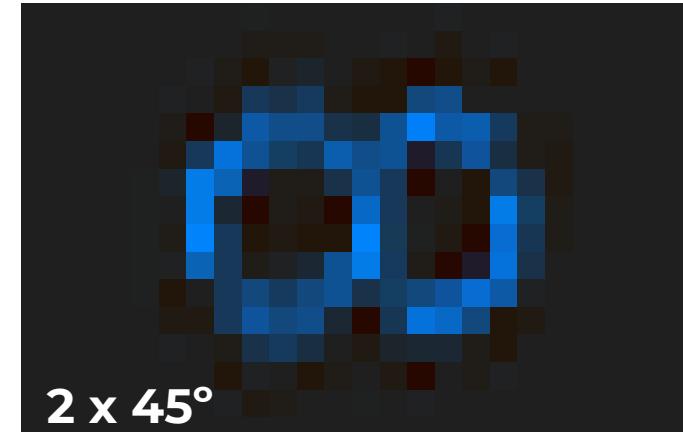
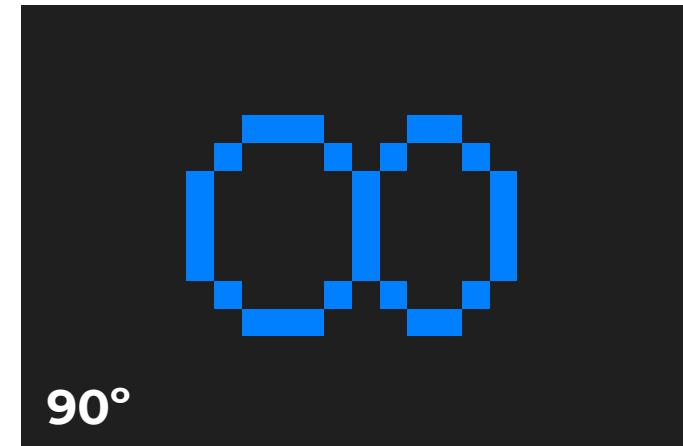
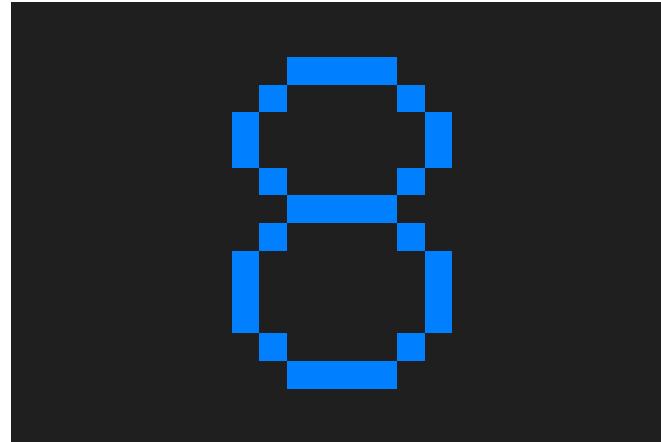


After  
interpolation



No  
interpolation

# Interpolation



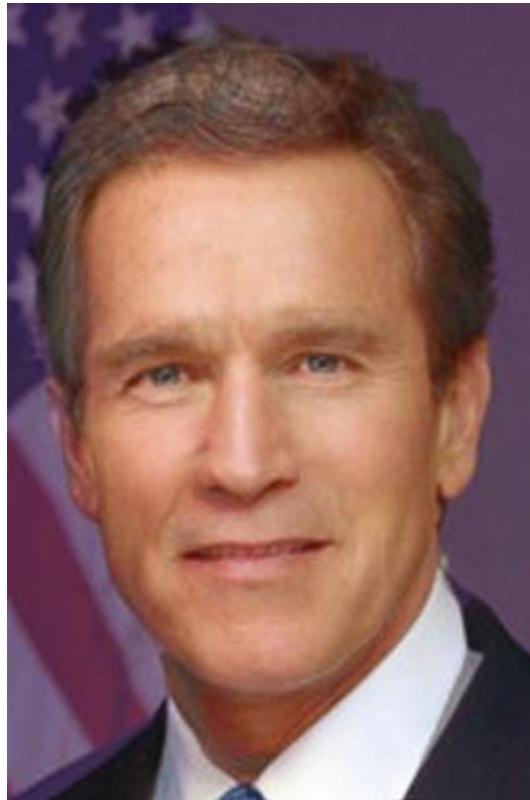
- Interpolation also happens when other transformations are applied to the image
  - **Rotations**, for instance, can have a **strong impact on image quality** due to interpolation
  - **Cumulative rotations** can be **catastrophic**
- 
- Avoid rotating images beyond what is necessary
  - Perform the **rotation in a single operation**

# Interpolation

Multiple methods for interpolation are available and provide increasing degrees of quality:

- Nearest neighbour
- Bilinear
- Bicubic
- Spline
- ...

# Who is this guy?

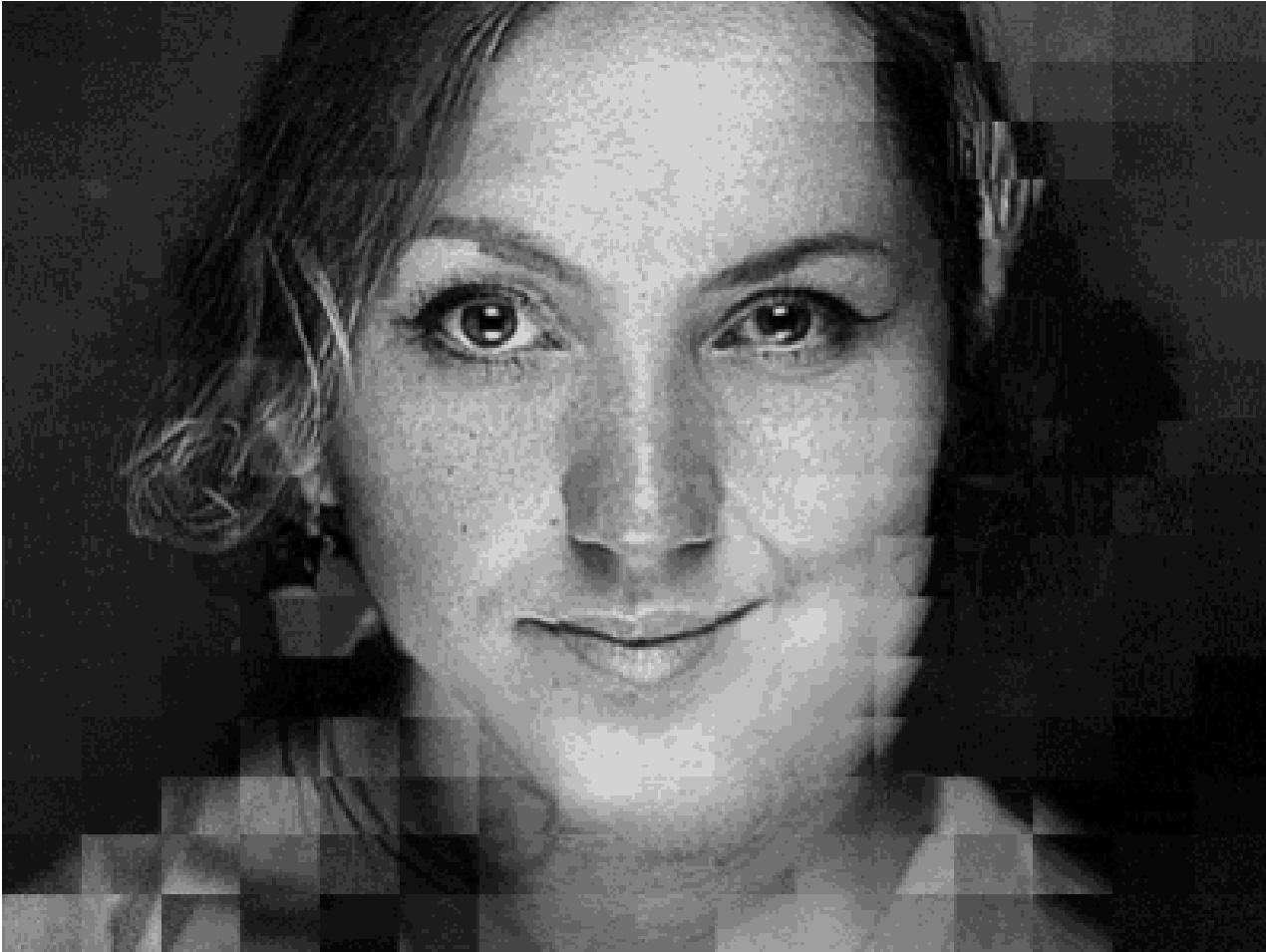


# Morphing



<https://educalingo.com/>

# Morphing



# Bibliography

- Kenny A. Hunt, “The Art of Image Processing with Java”, chapters 3, 5 and 6, AK Peters, 2010  
<https://learning.oreilly.com/library/view/the-art-of/9781439865590/>
- Alasdair McAndrew, “A Computational Introduction to Digital Image Processing”, 2<sup>nd</sup> ed., chapters 4, 5 and 6, CRC Press, 2016  
<https://learning.oreilly.com/library/view/a-computational-introduction/9781482247336/>

