



# Computer Vision

Arithmetic and Logic  
Operations  
Histograms

Fátima Leal



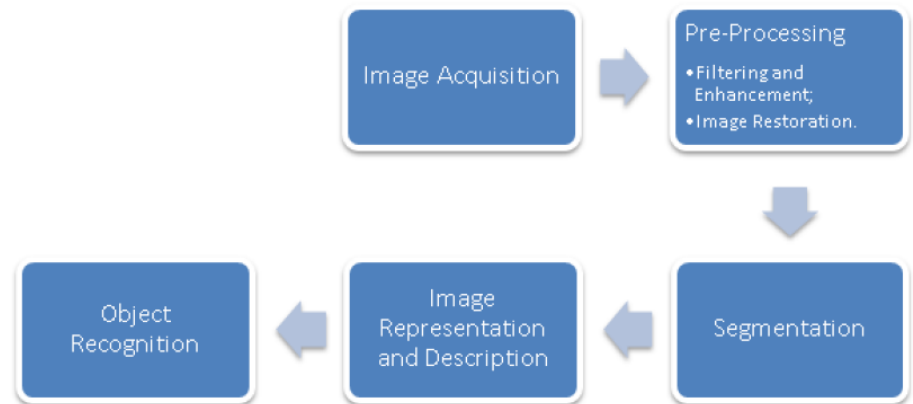
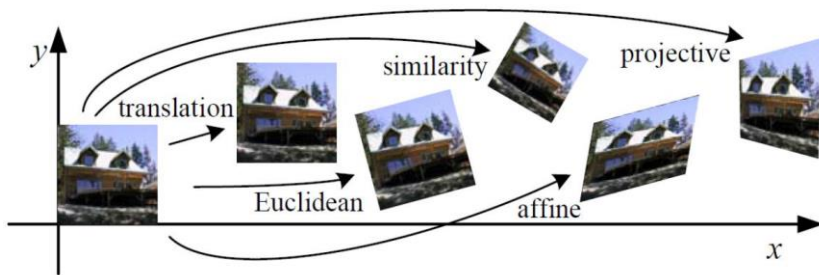
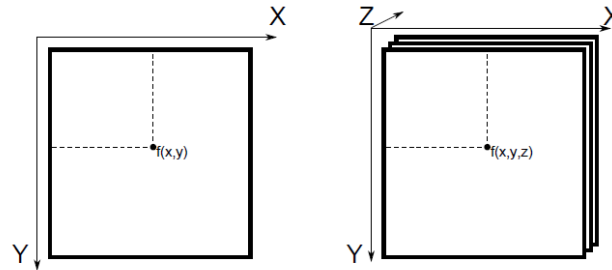
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# What we have learnt

- Fundamentals image concepts
- Machine vision systems
- Geometric operations



# Content

- Arithmetic operations
- Logic operations
- Histograms

# Arithmetic Operations

- We all know basic **arithmetic operations** like **addition** and **subtraction**.
- The idea is to apply a simple function:

$$y = f(x)$$

To each image values:

$$y = x \pm C$$

$$y = xC$$

Where  $C$  is a constant.

# Arithmetic Operations

- Note that, with **arithmetic operations** we need to keep in mind the limits of our colour space and data type
- **RGB images** have pixels that fall within the **range [0, 255]**
- What happens if we are examining a pixel with **intensity 250** and we try to **add 10** to it?
- Under **normal arithmetic** rules, we would end up with a **value of 260**.
- However, since **RGB images** are represented as **8-bit unsigned integers**, 260 is **not a valid** value.

# Arithmetic Operations

- So, what should happen? There isn't no correct way to handle image additions and subtractions that fall outside the range of [0, 255].
- It simply depends on how you are manipulating your pixels and your goals.
- The most common procedures are:
  - **Normalization:** store the result temporarily in a bigger type variable and recalculate the result using equation:

$$g = \frac{L_{max}}{f_{max} - f_{min}} (f - f_{min})$$

- **Truncation:** cut off everything that goes outside the range of used type.

# Arithmetic Operations

- Take note that there is a difference between OpenCV and NumPy addition
  - OpenCV ensures pixel values never fall outside the range [0, 255]
  - NumPy will perform a modular arithmetic and wrap around
- e.g.:  $200 + 100 =$ 
  - **OpenCV** – max: 255 and min 0
  - **Numpy** - 44

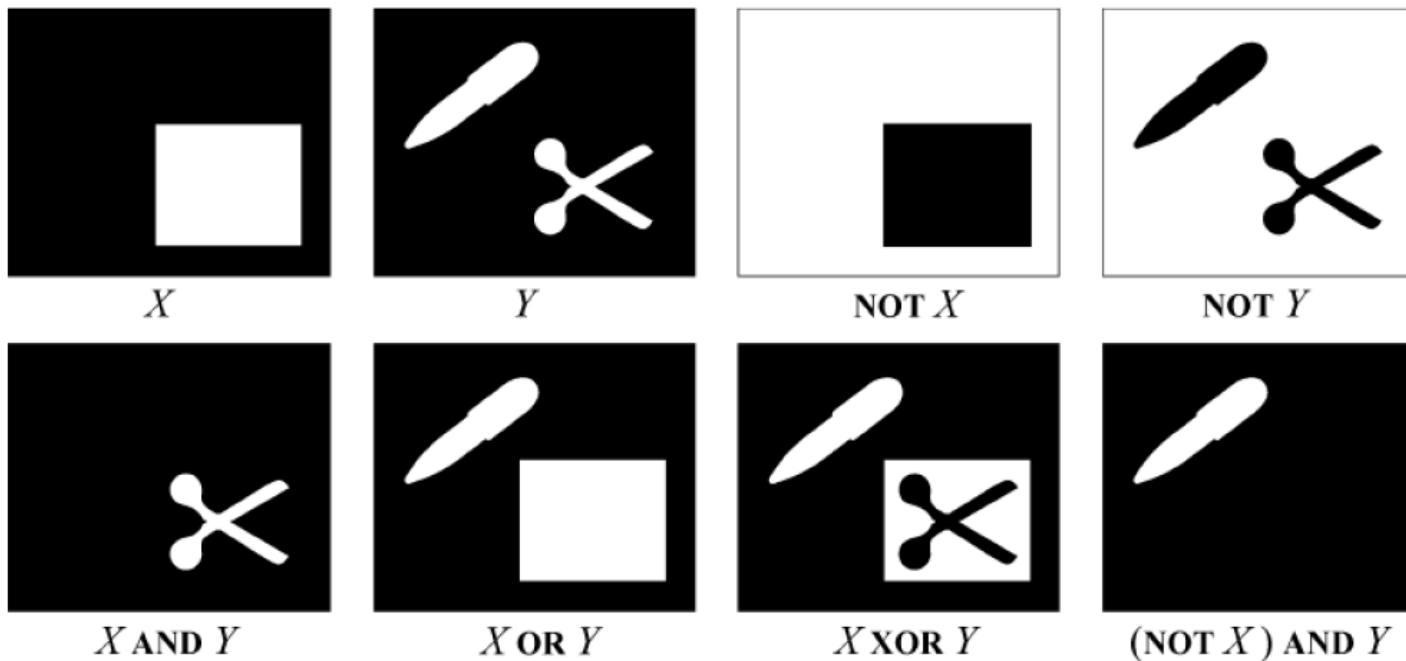
# Arithmetic Operations





# Logic Operations

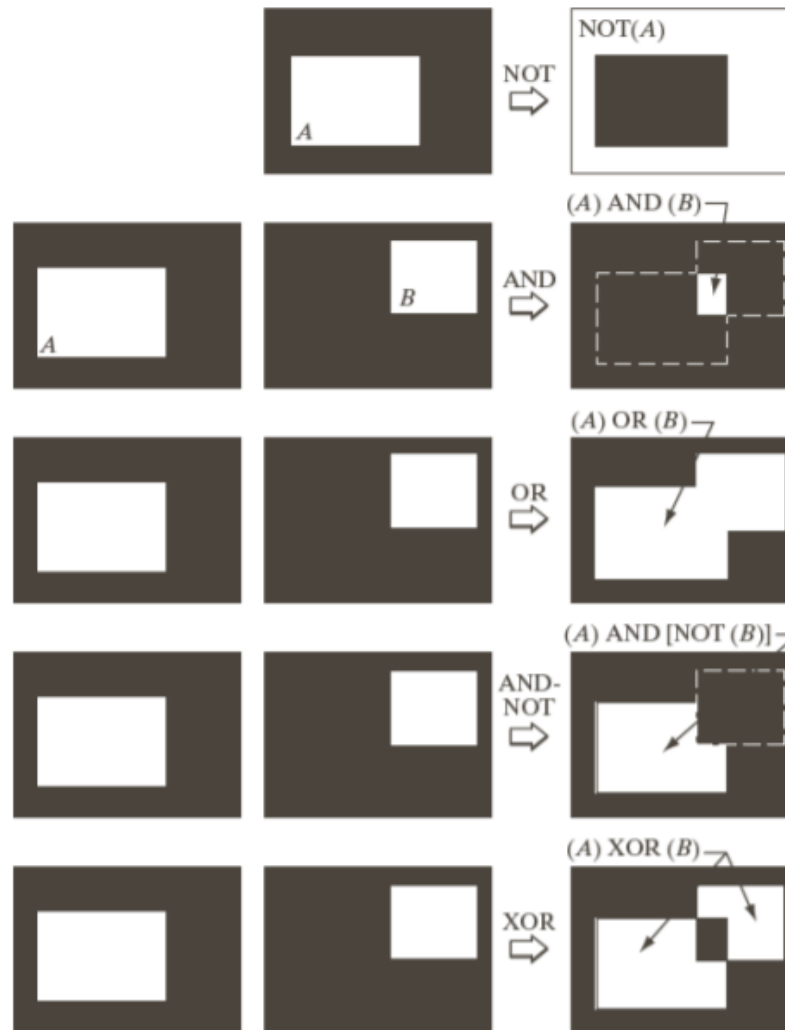
- Logic operations operate in a binary manner and are represented as grayscale images
- A given pixel is turned “off” if it has a value of zero, and it is turned “on” if the pixel has a value greater than zero



# Logic Operations

- **AND:** A bitwise AND is true if and only if both pixels are greater than zero
- **OR:** A bitwise OR is true if either of the two pixels are greater than zero
- **XOR:** A bitwise XOR is true if and only if either of the two pixels are greater than zero, but not both
- **NOT:** A bitwise NOT inverts the “on” and “off” pixels in an image.

# Logic Operations



# Logic Operations: AND



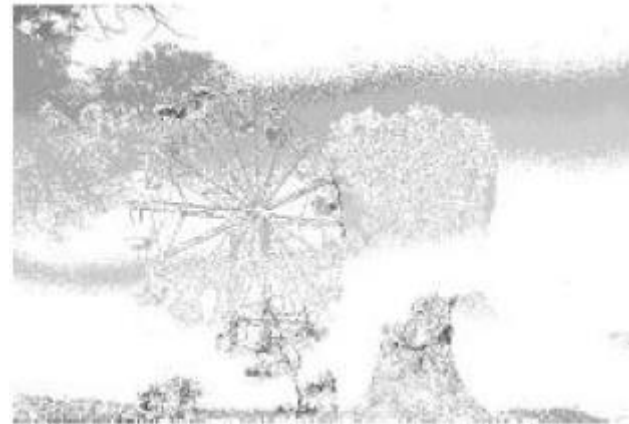
A bitwise AND is true if and only if both pixels are greater than zero



# Logic Operations: OR



A bitwise OR is true if either of the two pixels are greater than zero



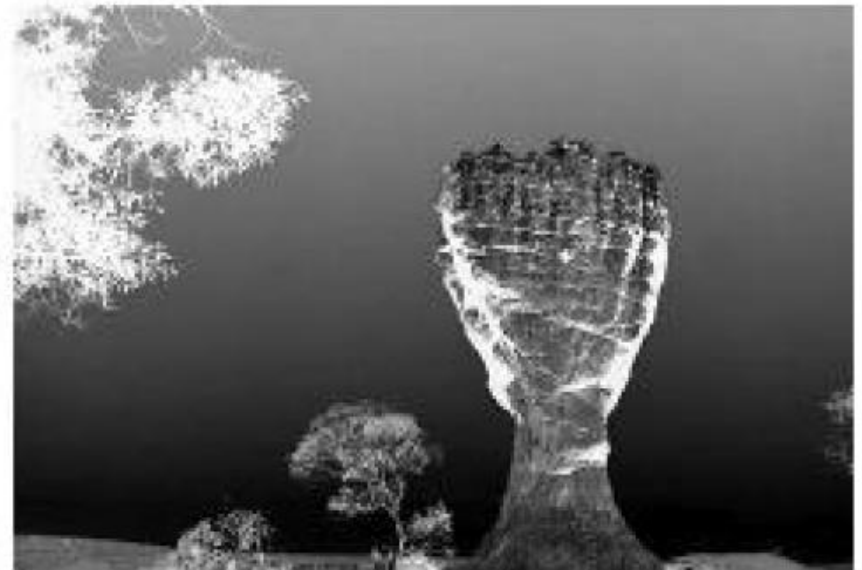
# Logic Operations: XOR



A bitwise XOR is true if and only if either of the two pixels are greater than zero, but not both



# Logic Operations: NOT



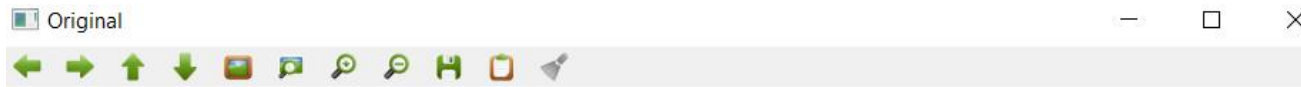
A bitwise NOT inverts the “on” and “off” pixels in an image.

# Masking

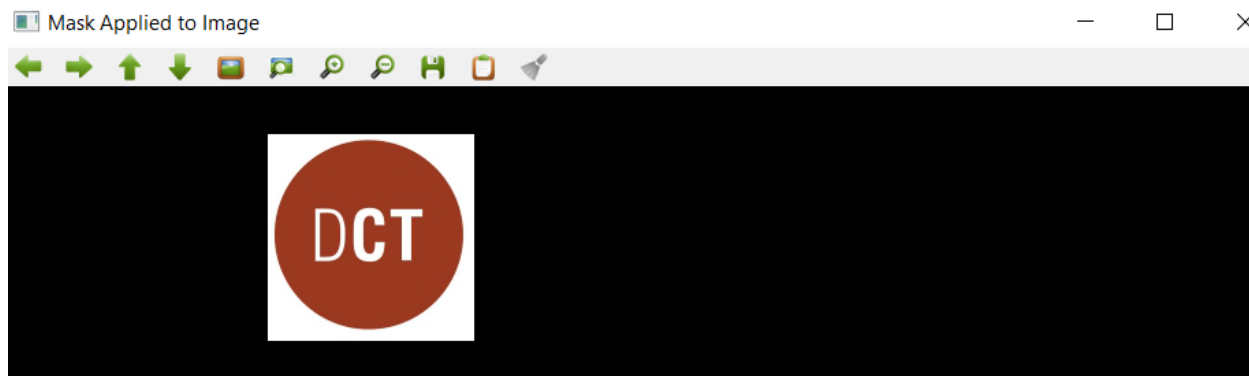
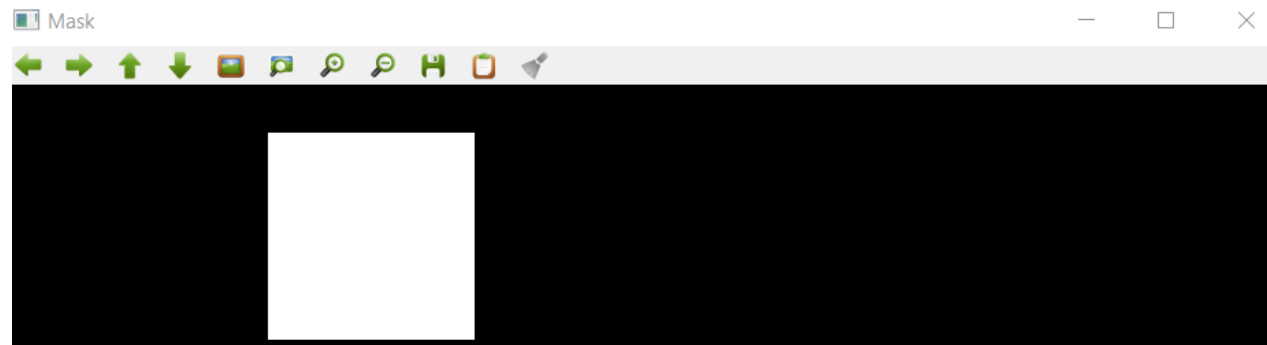
- **Masking** is an extremely powerful and useful technique in computer vision and image processing
- It allows to **focus only on the portions** of the image that **interests** to us
- Imagine we were building a computer vision system to recognize faces. The only parts of the image we want are those which contain faces
- The remaining content is discarded.



# Masking



using the  
`cv2.bitwise_and`  
function



# Splitting and Merging Channels

- A colour image consists of **multiple channels**: RGB
- We can **access** those components **via NumPy** arrays
- Is it possible to **split an image** into its respective components?

YES!

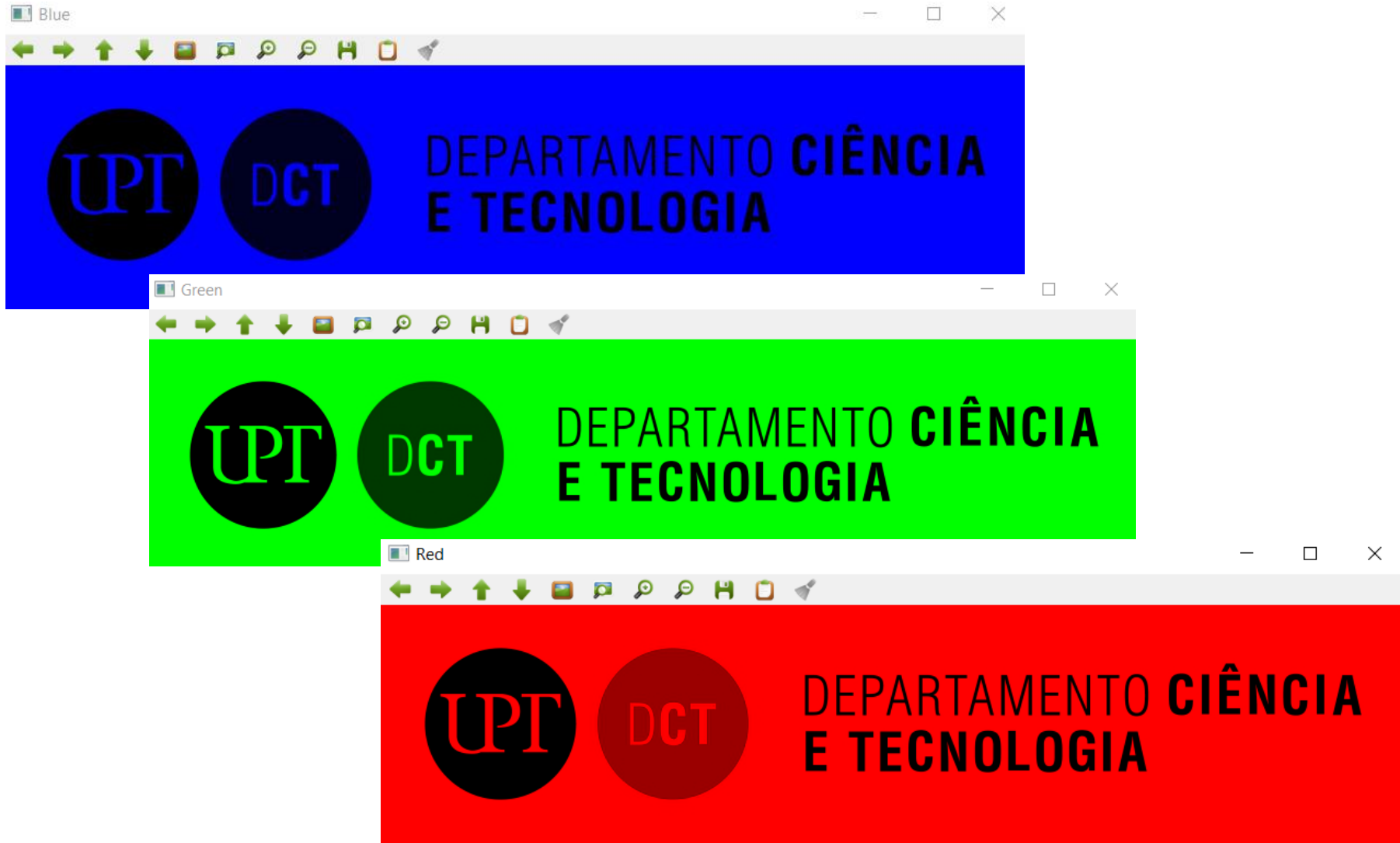


# Splitting

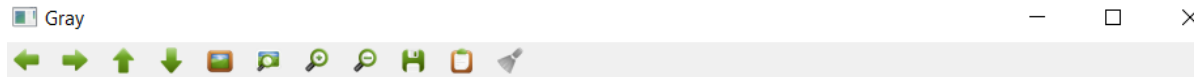
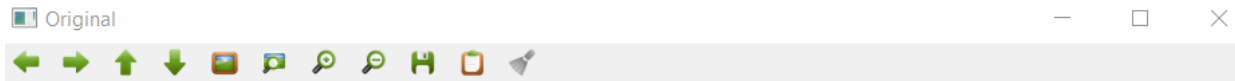


# Merging





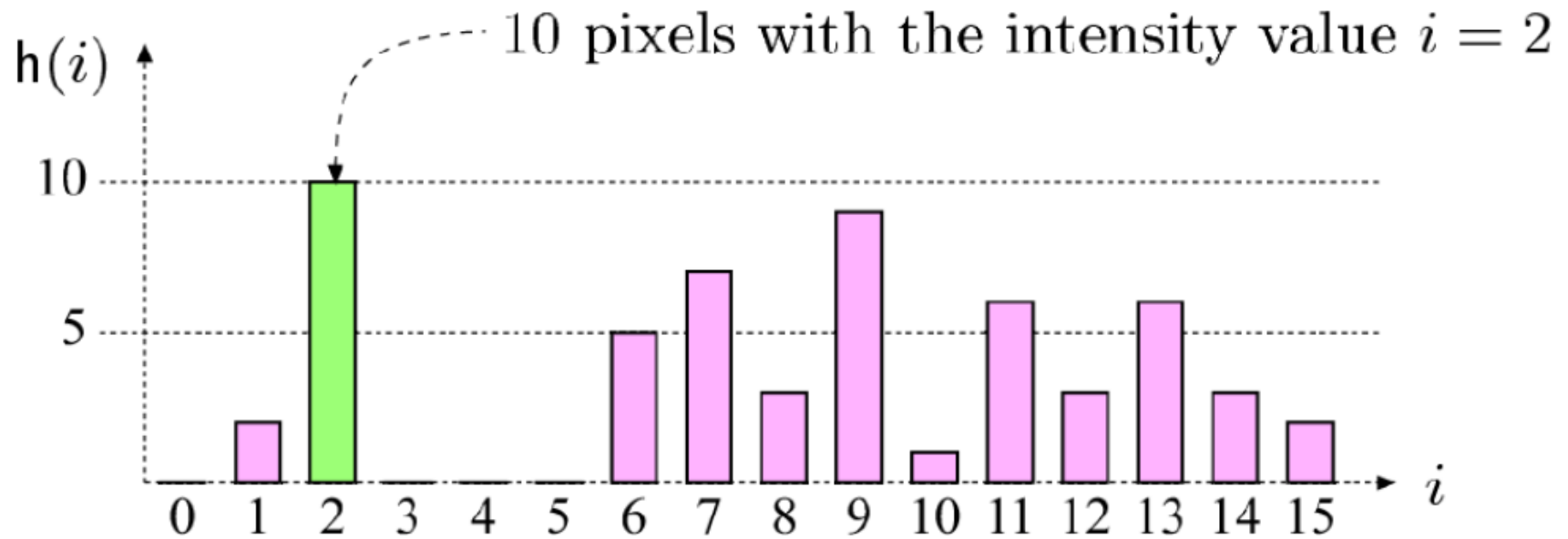
# Colour spaces



# Histograms

- **Histograms** have become a popular tool for **image statistics**
- It helps to determine certain problems in an image
- A histogram represents the **distribution of pixel intensities**
- In histograms, the X-axis serves as our “bins”
- If we construct a histogram with 256 bins, then we are effectively counting the number of times each pixel value occurs

# Histograms



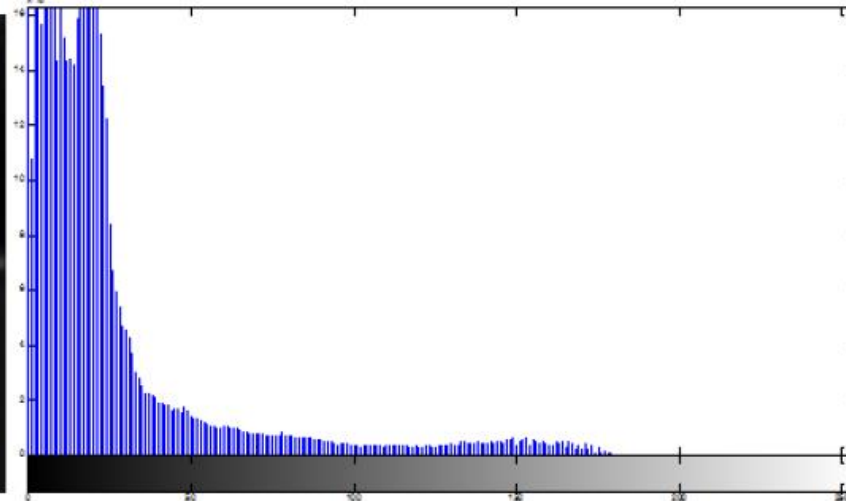
$h(i)$	0	2	10	0	0	0	5	7	3	9	1	6	3	6	3	2
$i$	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15



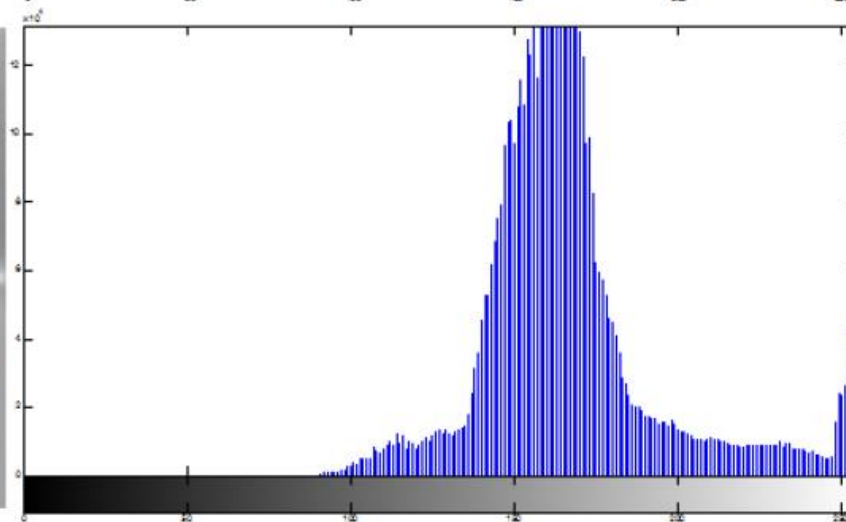
# Histograms

- A **histogram is not enough** to draw **qualitative conclusions** about the overall quality of the image (presence or absence of noise, etc.)
- Nevertheless, it **carries significant qualitative and quantitative** information about the corresponding image (e.g., minimum, average, and maximum grey level values, dominance of bright or dark pixels, etc.).
- By simply **examining the image histogram**, we have a general understanding regarding the **contrast, brightness, and intensity distribution**
- The **left side** of the histogram corresponds to **lower pixel values**. If the frequency at lower pixel values is very high, it indicates darkness
- The **right side** of the histogram corresponds to **higher pixel values**. If the frequency at higher pixel values is very high, it indicates saturation.

# Histograms

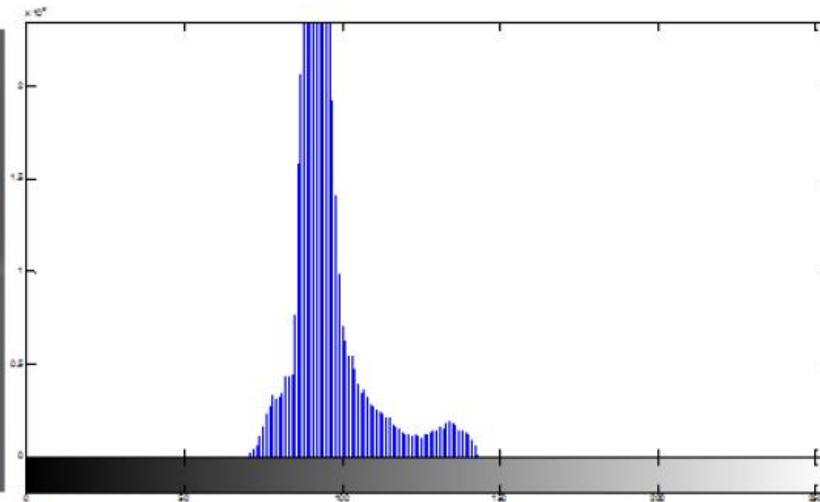


Dark image

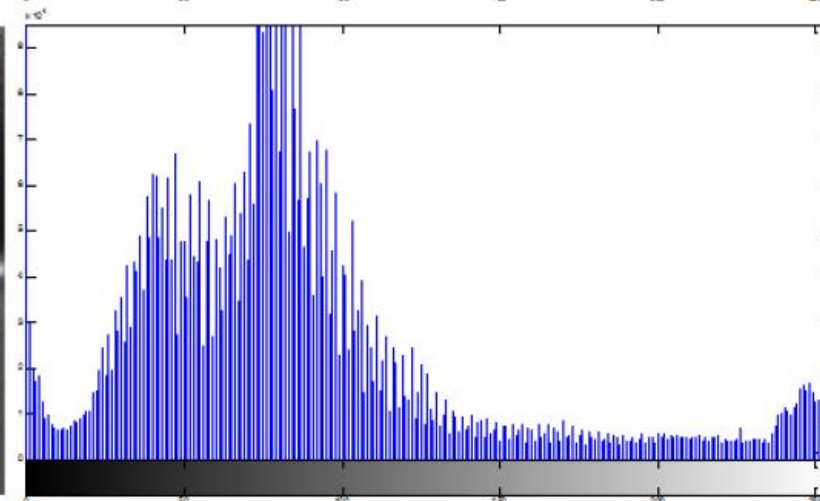


Bright image

# Histograms



Low contrast image



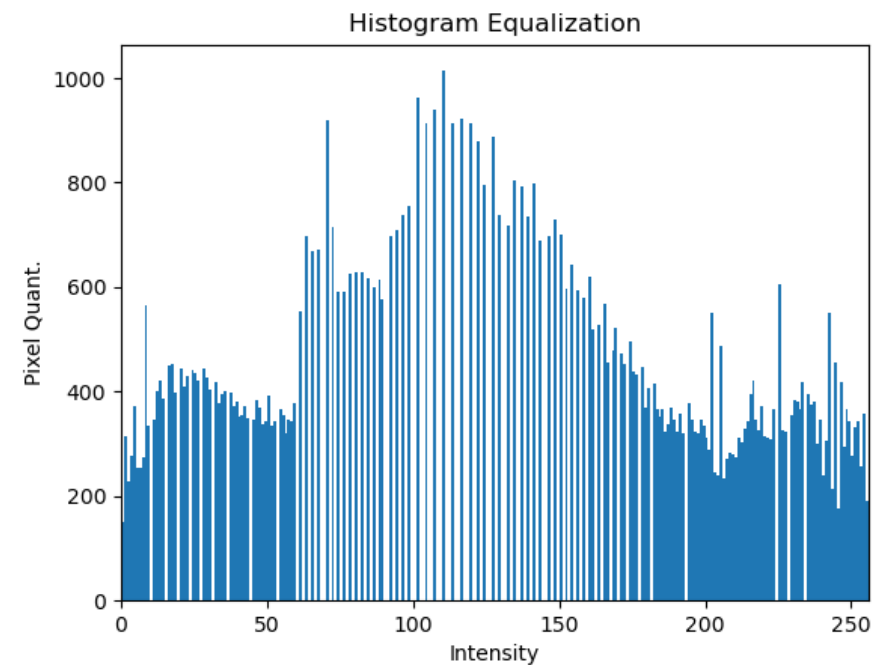
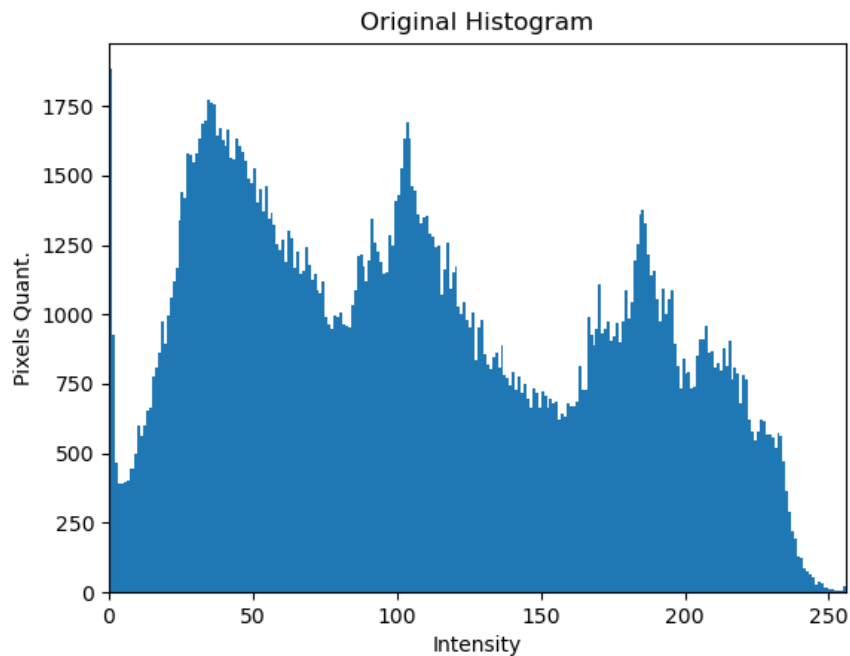
High contrast image

# Histograms Equalization

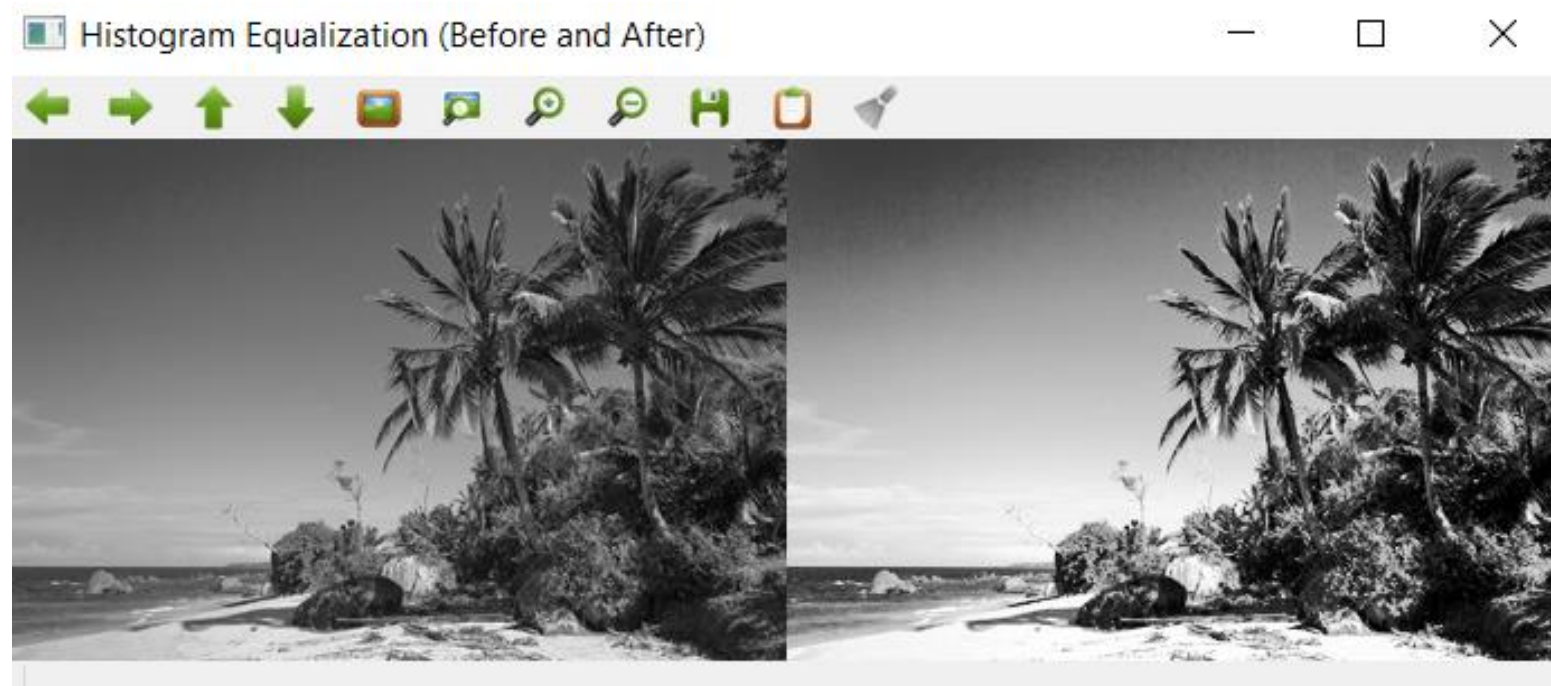
- The goal is to **improve the contrast** of an image by rescaling the histogram
- Consider a histogram with a large peak in the centre. Applying histogram equalization, the **pixel intensity will be distributed through the image**
- Histogram equalization is applied to **grayscale images**
- This method is useful when an image contains **foregrounds and backgrounds** that are both **dark or light**
- It tends to produce **unrealistic effects** in photographs; however, it is normally useful when **enhancing the contrast of medical or satellite** images.

# Histograms Equalization

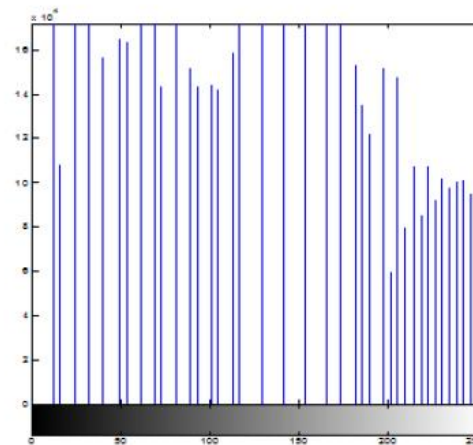
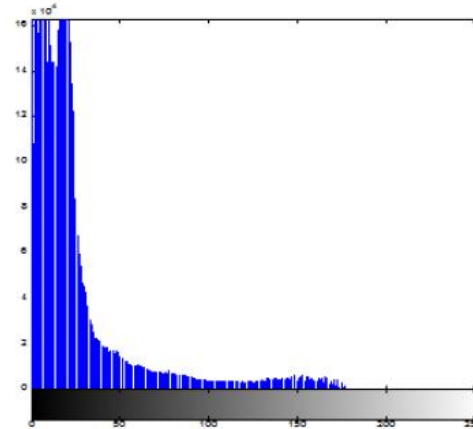
Figure 1



# Histograms Equalization



# Histograms Equalization



*Histogram Equalization*

MP\_GI

# Histograms Equalization

- The histogram equalization is very useful to recognize objects.
- It uses the following algorithm:
  - Compute the histogram
  - Normalize the histogram to ensure that all values are between 0 and 255
  - Cumulative distribution function
  - Transform the image
- The contrast enhancement is ensured

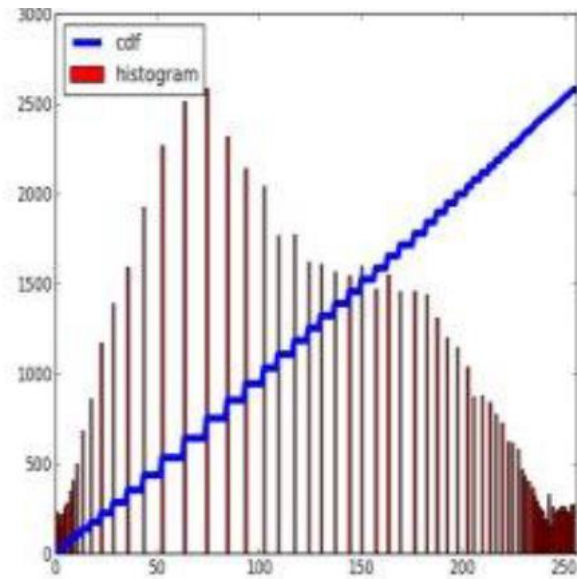
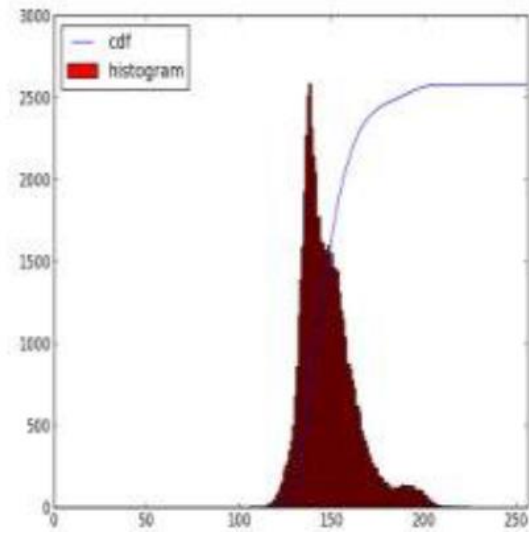


# Histograms Equalization

Grey level $i$	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
$n_i$	15	0	0	0	0	0	0	0	0	70	110	45	80	40	0	0

Grey level $i$	$n_i$	$\Sigma n_i$	$(1/24)\Sigma n_i$	Rounded value
0	15	15	0.63	1
1	0	15	0.63	1
2	0	15	0.63	1
3	0	15	0.63	1
4	0	15	0.63	1
5	0	15	0.63	1
6	0	15	0.63	1
7	0	15	0.63	1
8	0	15	0.63	1
9	70	85	3.65	4
10	110	195	8.13	8
11	45	240	10	10
12	80	320	13.33	13
13	40	360	15	15

Original grey level $i$	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Final grey level $j$	1	1	1	1	1	1	1	1	1	4	8	10	13	15	15	15

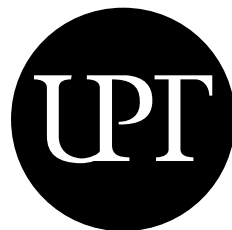


# Let's play with images!



# Examples

- Consider the matrix [250] and [10]. Add both matrixes using numpy and cv2. See the differences.
- Download images arithmetic1.jpg and arithmetic2.jpg from Moodle. Then, using the arithmetic operation add both images and see the result.
- Execute logic operations with both images: and, or, not. See the results
- Plot the histogram of arithmetic1.jpg and analyse the result



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Do conhecimento à prática.