Univerza v Ljubljani
Fakulteta za elektrotehniko

Computer Vision 06 – Image processing and analysis 1a

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Quick recap of the previous lectures

- Geometric aspects of image formation
  - WHERE does the image appear on the sensor/film/screen
- Photometric aspects of image formation
  - HOW bright is the image that appears on the sensor
- Color (last week)
  - Human perception of color
  - Sensing of color in digital cameras
  - Reproducing color & color matching functions
    - Because neither people nor cameras capture full spectrum!
    - That's the reason why we need color matching
  - Color spaces
    - There are other color spaces besides RGB

Outline

- Algorithms for image processing and analysis
  - I assume you have been waiting for this!
- Terminology & overview
  - Image processing
  - Image enhancement
  - Image restoration
  - Geometric transformations
  - Image analysis
- Point operations
- Histogramming
- local operations, filtering

Image processing

Image processing operation

h(x,y), k(x,y), w(x,y), g(x,y)
h(i,j), k(i,j), w(i,j), g(i,j)

Input Image
$f_I(x,y)$, $f_I(i,j)$
I(i,j), …

Output Image
$f_O(x,y)$, $f_O(i,j)$
J(i,j),…

Various notations are in use ….

- The purpose of image processing is:
  - to produce new image that is in *some aspect* better than the original image
  - And thus *more appropriate* for further processing.
  - Sometimes people call this “Image preprocessing”
    - Because the input is the image, and the output is image as well
    - Therefore it comes before the *core algorithms* of computer vision

Image processing

- Typical goals:
  - to reduce noise, improve S/N ratio
    - Blurring, filtering
  - to improve brightness/contrast, to compensate variations in brightness in contrast
  - to save space/bandwidth, i.e. image compression, before transmitting the image to the processing unit
    - Lossy (JPEG)
    - Lossless (GIF, PNG)
  - to normalize the image, geometrically or photometrically
    - Remember Task 2 from your Lab Assignment 2
    - What happened to the chessboard?

Image (pre) processing

Input Image → Preprocessing operation → Output Image

- Two basic approaches:
  - Image *enhancement*: enhancement model
  - Image *restoration*: degradation -> restoration model
- In CV, IP is one of the first steps within processing pipeline.
  - Therefore, we often call it preprocessing.
- In machine vision/industrial applications
  - We try to avoid enhancement/degradation!
  - The images should be captured at best quality possible!

Image enhancement

- We have input image that needs *improvement*
  - Therefore, we suitably process the input image to obtain *improved* output image.
  - We perform enhancement most often when the images are meant to be observed by eyes (not for further processing)
- Examples
  - Pixel value manipulation, linear, nonlinear to improve visibility of details, contrast, color, ...
  - image filtering, in spatial or frequency domain, linear or non-linear to improve S/N ratio, morphological filtering, ...

Image enhancement – example

- Manipulating the brightness and contrast
  - Task: to make low contrast details visible

Before | After

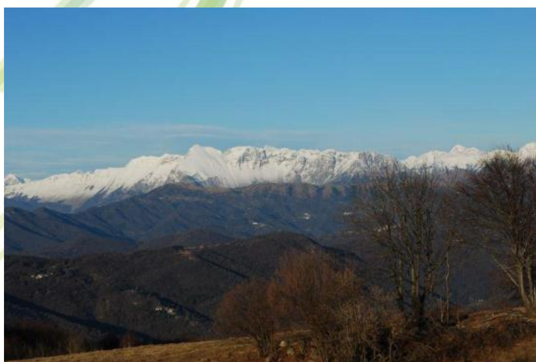
  - Why do we do it mainly for human observation?
    - Good CV algorithms don't care about absolute pixel values
    - Contrast of 5 pixels is as good as contrast of 50 pixels

Image restoration

- We have *degraded* image
  - We possibly know (or can estimate) the actual process of degradation
- We want to infer the *original image before degradation*, based on
  - our image and degradation model
- Image restoration approaches:
  - Unsharp masking to improve contrast
  - (Blind) deconvolution
  - Wiener filtering
- Sometimes restoration is treated as a special case of enhancement.

Geometric transformations

Image filtering, etc., work on pixel values (image range)



f(x,y)

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

$$f(x,y) \rightarrow \boxed{H} \rightarrow g(x,y)$$

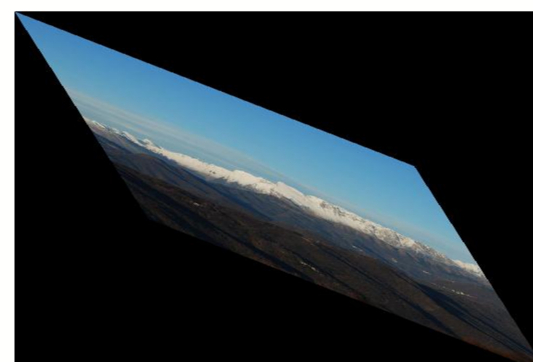
g(x,y)

Geometric image transformations work on pixel positions (image domain)

f(x,y)

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

$$f(x,y) \rightarrow \boxed{T} \rightarrow g(u,v)$$



g(u,v)

Image analysis

Input Image
f(x,y), f(i,j), I(i,j) → Image analysis → Description of an image

- Task of image analysis
  - to extract *meaningful information* from images
- Approaches:
  - Segmentation: divide image into meaningful regions
  - Object detection, localization
  - Feature detection & extraction
  - edge, corner detection
  - Shape, texture, appearance analysis
- Goal:
  - Qualitative and/or quantitative description of image

Wrap-up on IP and IA

- Various categorizations of image processing & image analysis exist
  - Sometimes image enhancement and restoration are put into the same category.
  - There is not clear distinction between IP and IA
- In computer vision, IP is used as one of the first steps – if it is used at all
- IA in computer vision one of the most important components, and sometimes sufficient for solving a problem at hand.

Questions?

Simple preprocessing operations

Image preprocessing

- Point operations
  - Pixel -> pixel
  - e.g. arithmetic and logic operations, +, -, *, /, AND, OR,...
- Local operations
  - Local area -> pixel
  - e. g. linear / nonlinear filtering to suppress noise
- Global operations
  - Whole image -> result
  - Result depends on the whole image
  - e.g. Image histogram

Point operations

- Value of the output pixel $I_{out}(i,j)$ depends solely on the value of the input pixel $I_{in}(i,j)$

  $I_{out}(i,j) = T(I_{in}(i,j))$

  $I_{out}(i,j)$ – output image

  $I_{in}(i,j)$ – input image

  T – Pixel transformation

- Example

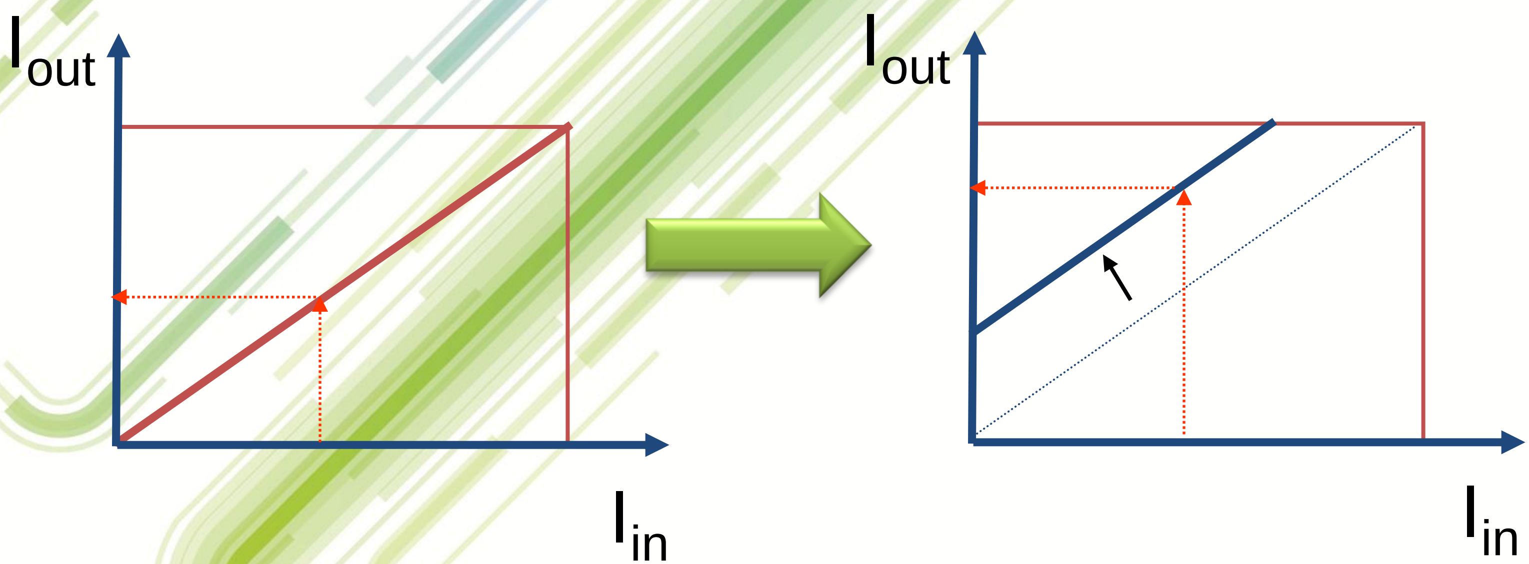
  $I_{out}(i,j) = a*I_{in}(i,j)+b$

  a – contrast adjustment, b – intensity adjustment

  – In theory, *a* and *b* could be different for each pixel, $a(i,j)$, $b(i,j)$

Brightness

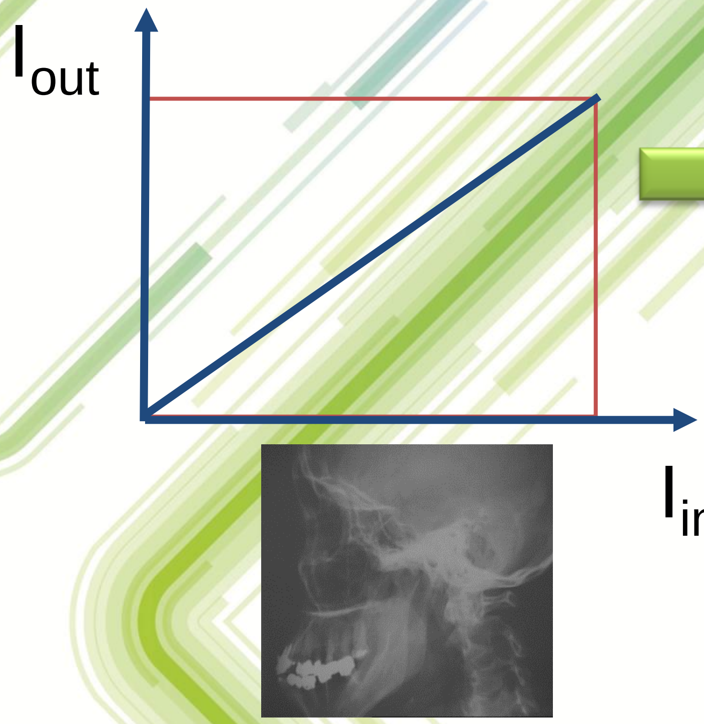
- Brightness change: $I_{out}(i,j)=I_{in}(i,j)+k$

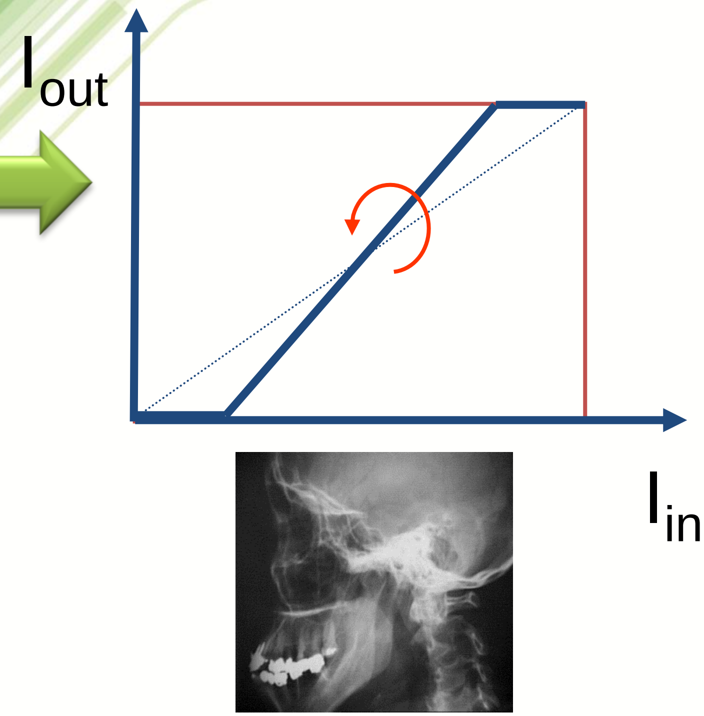


- $I_{out}(i,j)$ – output brightness (grayness) levels
- $I_{in}(i,j)$ – input brightness (grayness) levels

Contrast

- (linear) contrast change: $I_{out}(i,j)=k*I_{in}(i,j)$



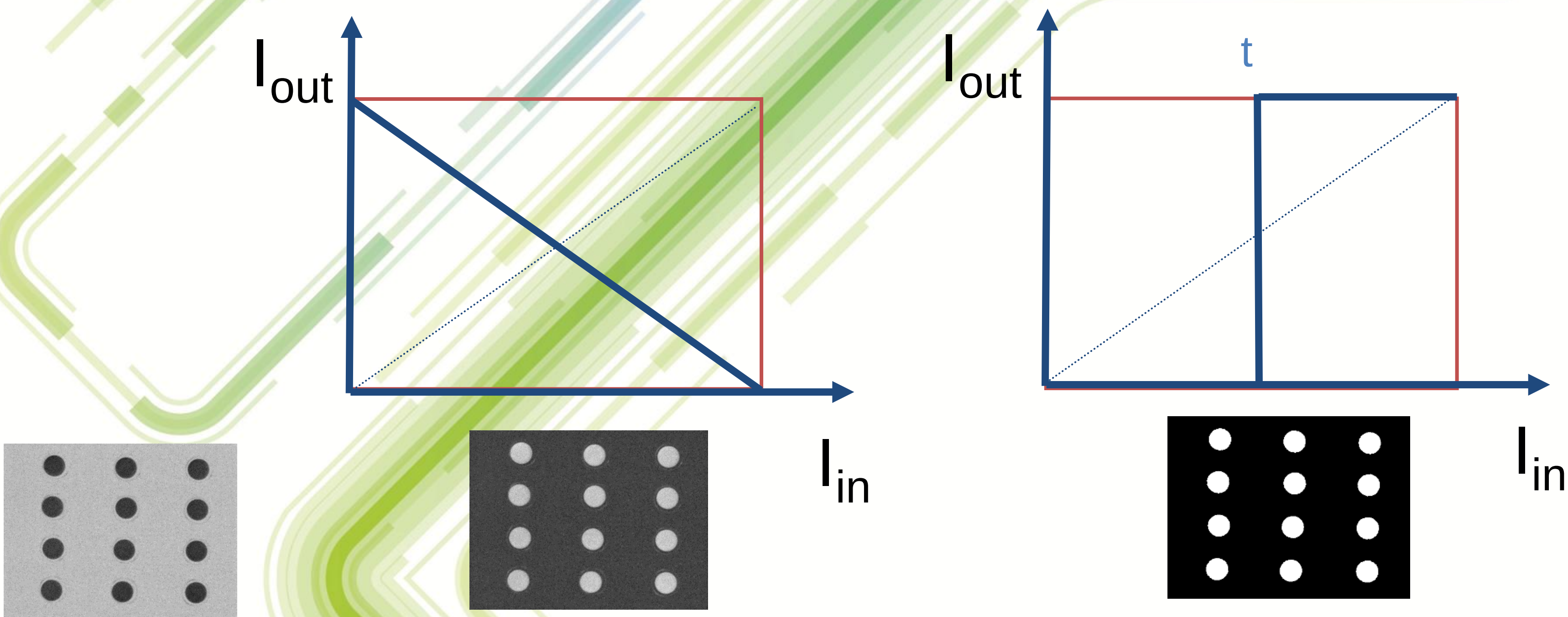


Remember: as with brightness, no information gain!

Inversion and thresholding

Inversion: $I_{out}(i,j)=255-I_{in}(i,j)$
(8 bits per pixel)

Thresholding: $I_{out}(i,j) = (I_{in}(i,j)>t)$
(t=threshold)

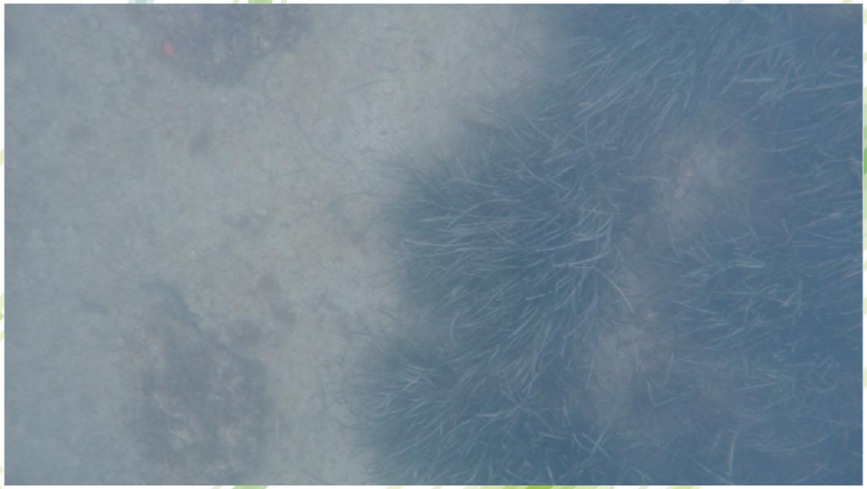


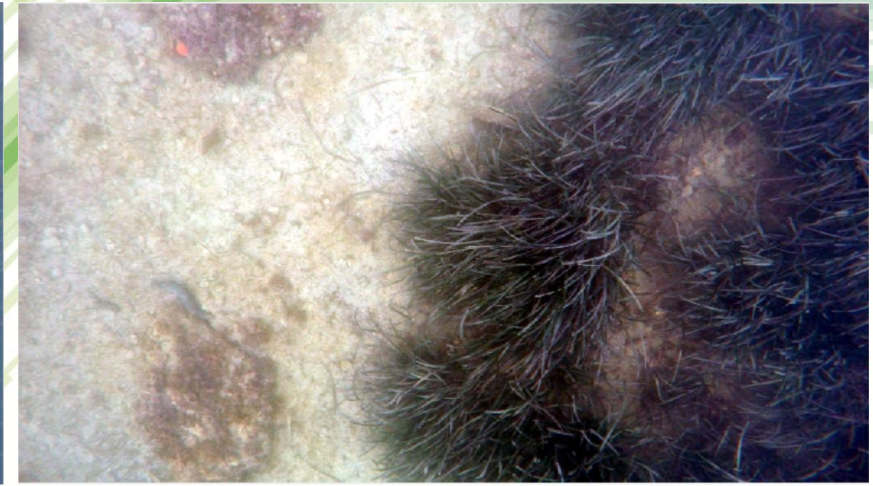
General linear transformation

$$I_{out} = (I_{in} - c)\frac{b-a}{d-c} + a$$

- I_{out} – output brightness (grayness) level
- I_{in} – input brightness (grayness) level
- d – max input value
- c – min input value
- b – max output value
- a - min output value

Point operations example





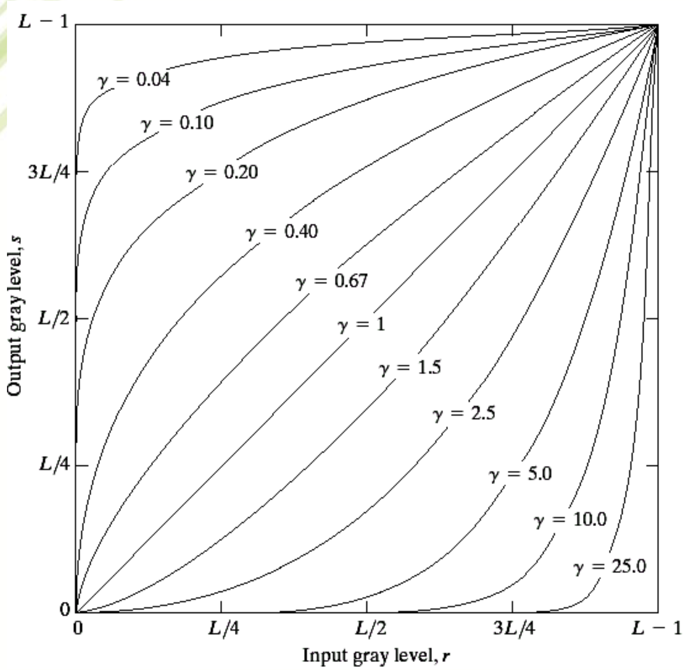
$$I_{out} = (I_{in} - c)\frac{b-a}{d-c} + a$$

- Matlab function: imadjust()
  - Note: imadjust works for grayscale and color images.
  - But you can apply imadjust on each RGB channel individually

Gamma correction

- Originates from nonlinearity of CRT displays.
  - the relationship between screen luminance and the applied electric signal is exponential.
  - The lightness/brightness sensitivity of human eye is not linear as well.

Gama compression



Gama expansion

$$I_{out}(i,j) = c \cdot I_{in}^{\gamma}(i,j)$$

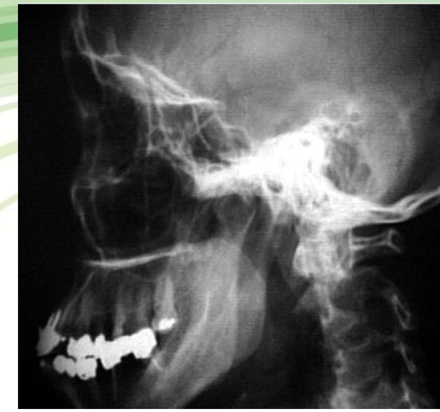
Gamma correction

$$I_{out}(i, j) = c \cdot I_{in}^{\gamma}(i, j)$$

- Transforms a narrow dark/bright band
  - to a wider band (thus whitens) or
  - the opposite (darkens) the image.
- Parameter is γ
  - The constant c is chosen such that functions start and end in bottom left/upper right corners.
  - Conventional value for gamma is 2.2 (for CRTs), or 1/2.2 (for camera devices)
  - Sometimes, gamma correction is used (abused)
    - to nonlinearly adjust brightness levels
    - even when there is no CRT or known source of nonlinearity

Gamma adjustment example

$\gamma = 1{,}5$



$\gamma = 0{,}5$

Matlab function:

```
imadjust( Image,  stretchlim(Image), [0;1], Gamma);
```

LUT for point operations

- LUT = look-up table

Input Image → **Point operation with Look-Up-Table (LUT)** → Output Image

Possible, when pixel values are quantized (e.g. with 8 bit grayscale image, we need a LUT with 256 entries)

Significant speedup for operations.

0	255
1	254
2	253
	252
	….
255	0

LUT entries are calculated in advance
This example shows Inversion operation (negative)

Image arithmetics

- Image addition:
  - mostly to improve S/N ratio
  - Example: Σ Sequence of dark images of a stationary object

- Image subtraction:
  - Change detection (object detection & tracking)
  - Background subtraction (non-uniform lighting)
  - to evaluate how much and where two images differ.

Image addition

- Example
  - We have *N* images of a stationary scene
  - Images are affected by noise
  - Noise is uncorrelated, zero mean Gaussian noise
- Calculate new image I as a mean of all images:

$$I = \frac{I_1 + I_2 + ... + I_N}{N}$$

- The noise variance decreases by the factor N:
  - And the noise standard deviation by the factor of: $\sqrt{N}$

$$\sigma_I = \sigma / \sqrt{N}$$

Image arithmetics - examples

- Image summation

- Image subtraction:

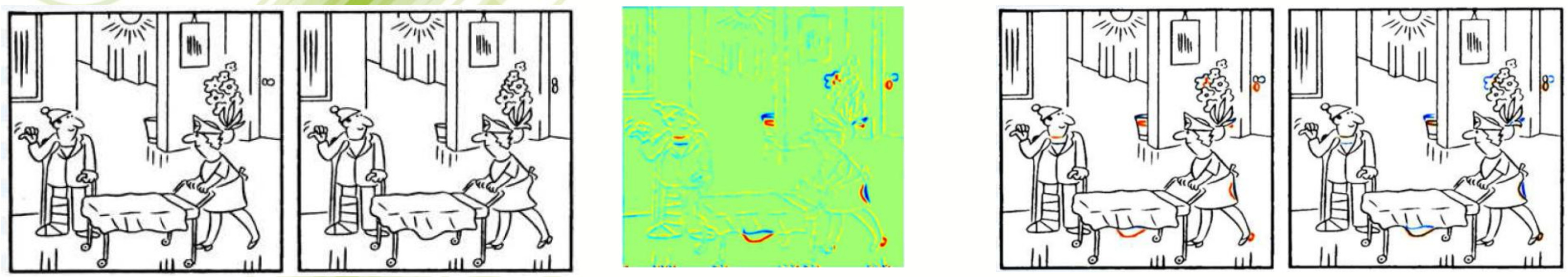


Image arithmetics in Matlab

- One can manipulate images as matrices
  - E.g. C=A+B - Preferred way for labs, requires no toolboxes
- But there are specialized functions as well:

• imabsdiff	Absolute difference of two images
• imadd	Add two images or add constant to image
• imapplymatrix	Linear combination of color channels
• imcomplement	Complement image
• imdivide	Divide one image with another or divide image by constant
• imlincomb	Linear combination of images
• immultiply	Multiply two images or multiply image by constant
• imsubtract	Subtract one image from another or subtract constant from image

Questions?

Histogramming

Histogramming

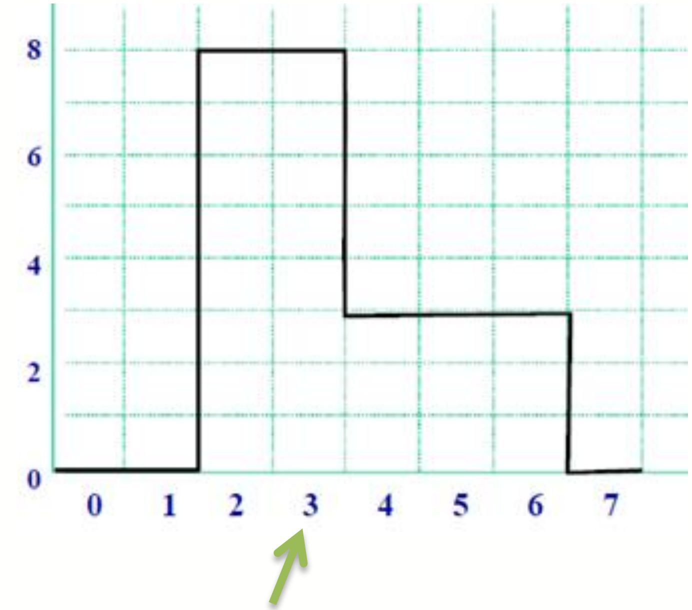
- We treat the pixel value as a realization of random variable, defined by its
  - range [0..255], $I=i_1,i_2, \ldots\ i_k \ldots\ i_N$
  - and probability distribution $P(I)=P(i=i_k)=(p_1,p_2, \ldots\ p_k \ldots\ p_N)$, $\sum_{k=1}^{N} p_k = 1$
- We scan the image
  - and count the number of occurrences of each pixel value, for all pixel values
- Finally
  - We plot a number of occurrences of each pixel value as a function of pixel value. This is *histogram* $H(i_k)$, $k=1,2 \ldots N$
  - If normalized, $\sum_{k=1}^{N} H_k = 1$ the histogram is *approximation* (derived empirically) of a probability distribution

Histogram example

- Let us assume a small grayvalue image with pixel values within [0..7]
- We compute a grayvalue histogram, and this is what we get.

Drawing conclusions:

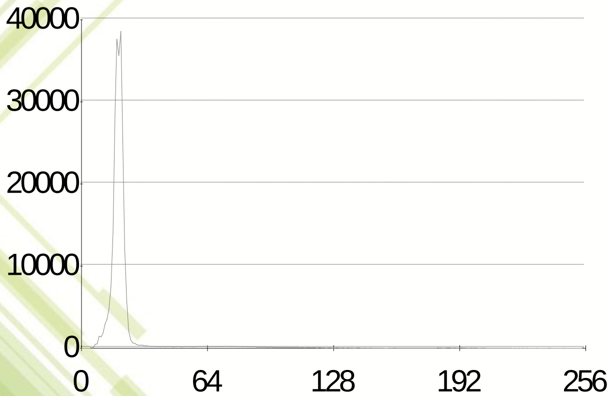
- There are no pixels with values 0,1, and 7.
- There are 8 pixels of value 2, or 3.
- There are 25 pixels in the image (5x5 perhaps)
- Histogram is not normalized.
- How to normalize?
- Compute mean, E(I) =
- Compute variance, $E[I - E(I)^2]$=

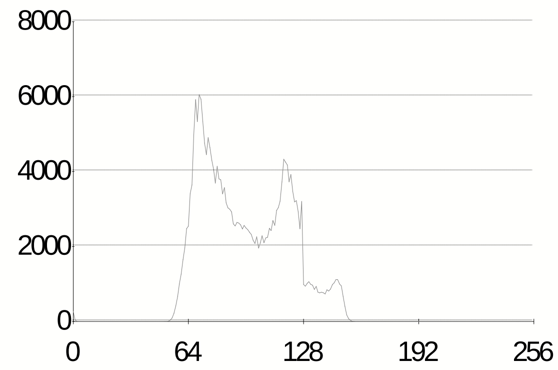


Histogram cell or “bin”

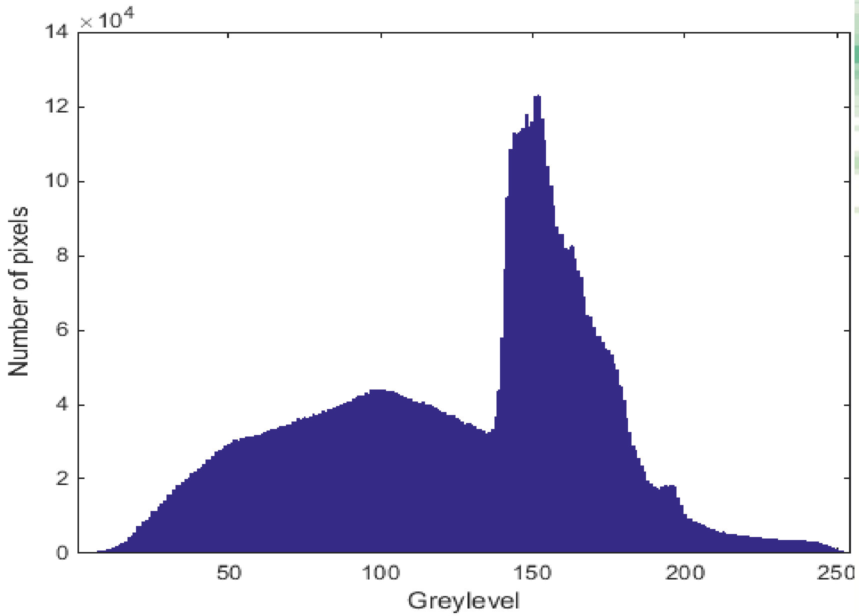
Histogramming

- There are many things that we can say about an image, based just on a grey-value histogram.
  - dynamic range, either well covered, or not,
  - image brightness, too dark, too bright, appropriate, perfect,
  - image contrast, low, high,
  - one, or more grey values is/are dominating the image.
- What can we say about images from these histograms?





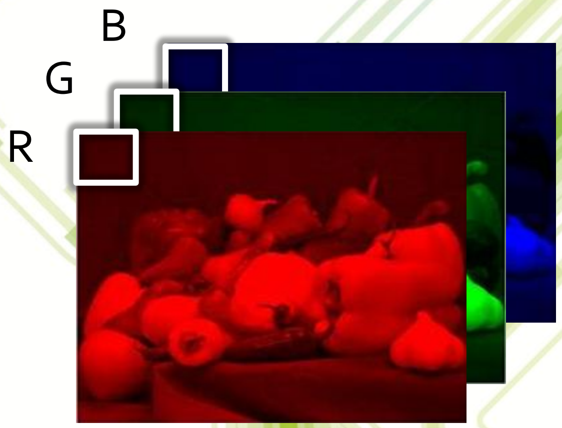
Histogram example



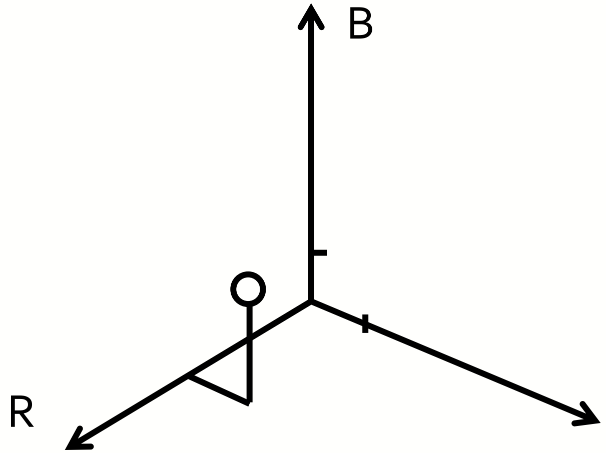
- Histogram of grayscale image, not normalized
- Gray values between 140 and 170 dominate (perhaps sky region?)
- Note: Histograms are best displayed as bar graphs
- Matlab function: *imhist()* or *hist()*

Color histogram

- Grayvalue histogram is 1D
- Color histogram is 3D

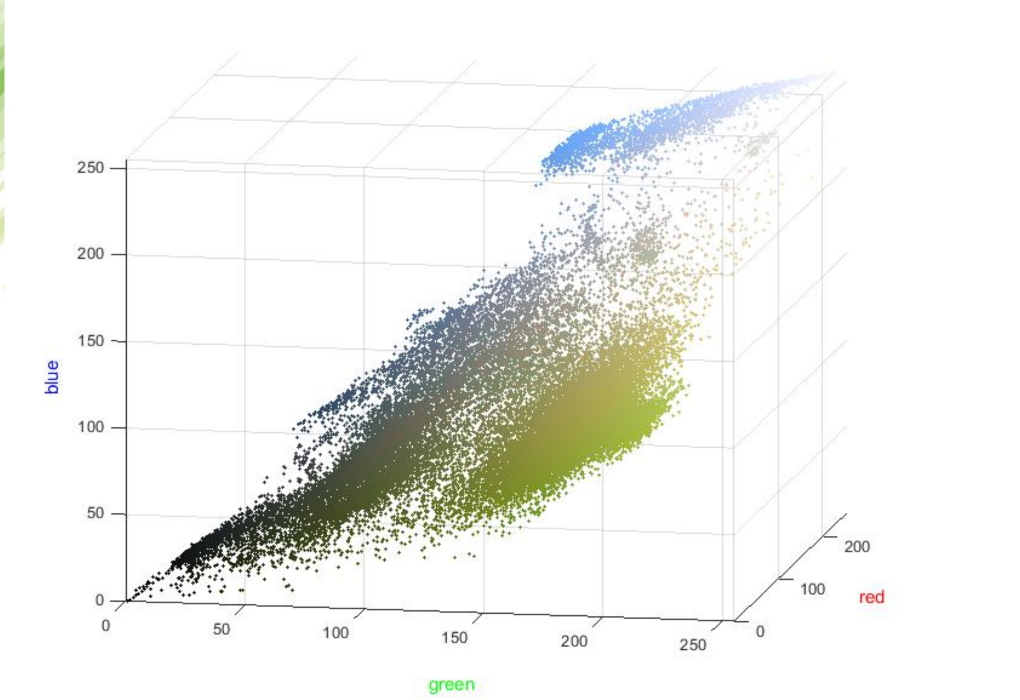


i=[20,10,10]



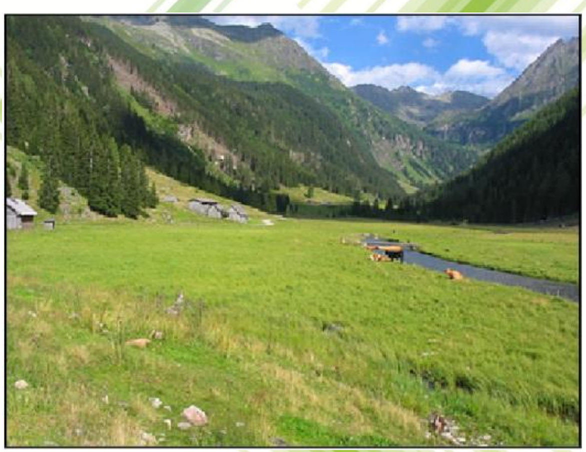
3D Color histogram

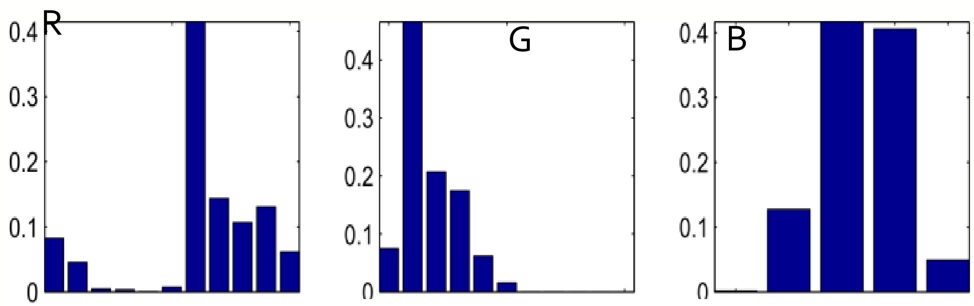
- Example of 3D color histogram



3x 1D color histograms

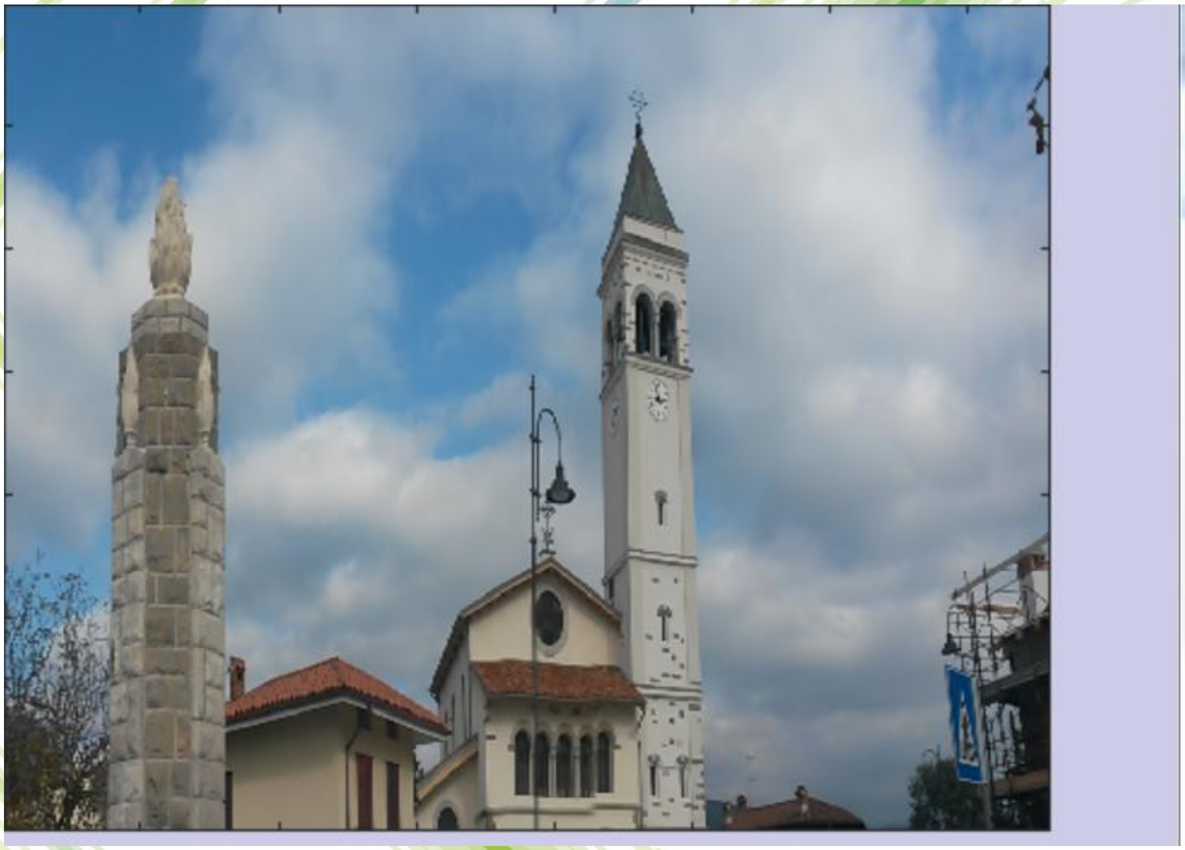
- Alternatively, we can represent color image with 3 x 1D color histograms
- 1 histogram per R,G,B channel
- This is NOT the same as 3D color histogram

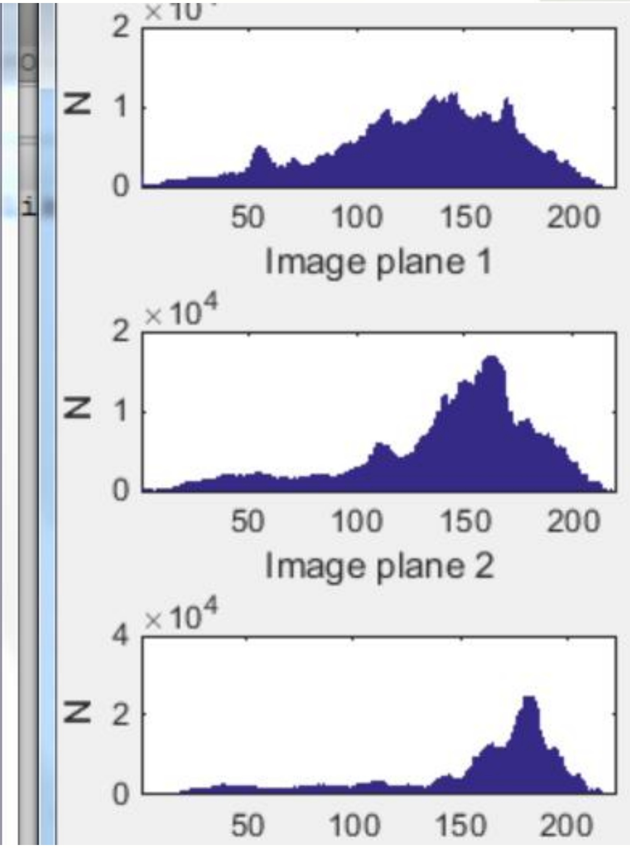




3x 1D color histograms example

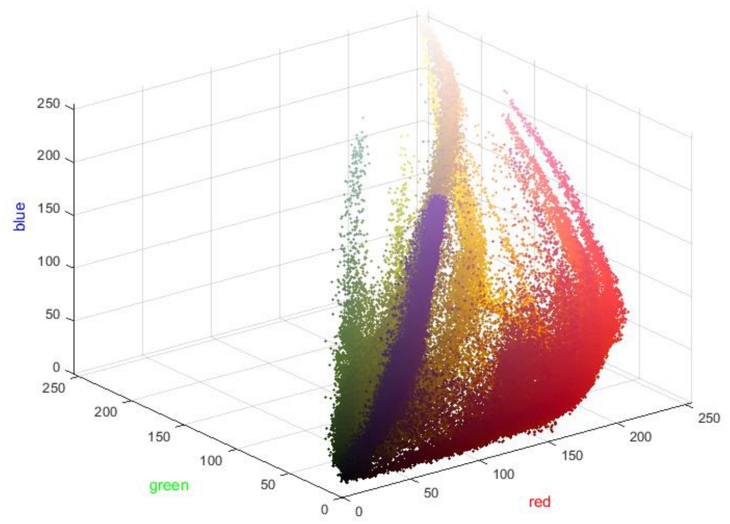
- 3 histograms (R,G,B) of a color RGB image





3D color histogram example

- 3D histogram of a color RGB image



3D color histogram and binning

- True color image, 8-bits per color channel.
- 3D color histogram: 256 x 256 x 256 array!
  - Pretty large array, about 16 M x (no. of bytes for one value)
  - An 1920 x 1080 color image: about 2 megapixels.
  - This means, 3D histograms are large *and sparse.*
  - Therefore, we usually apply ‚binning' of pixel values into bins.
  - For example, bins of 16 values wide result in 8 x 8 x 8 = 512 3D color histogram.
  - Binning is not specific to images, one can use it whenever the histogram would be too sparse!

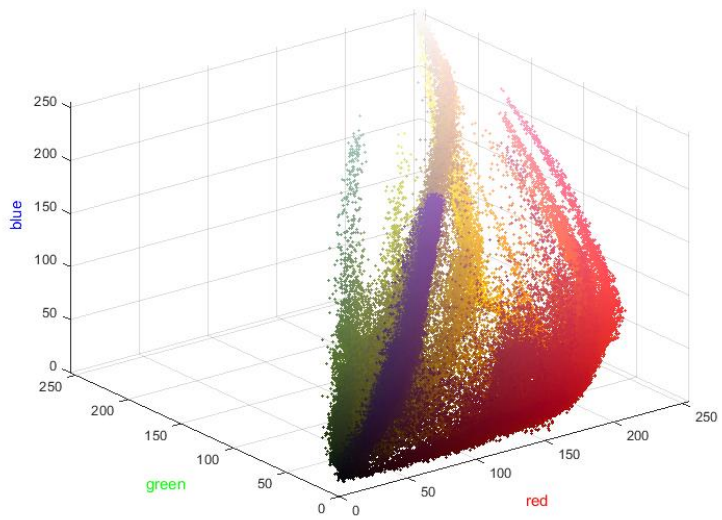
0..15 : bin 0
16..31 : bin 1
32..47: bin 2
46..63: bin 3
e.t.c.

Histogram uses

- Brightness / contrast correction
- Thresholding (*binarization)* to produce two valued (logical) image)
- Histogram equalization
  - for an arbitrary image with grey-value distribution
  - Make distribution of the new image uniform.
  - The idea: more frequently used values should get larger range.
- Histogram specification:
  - Starting with an arbitrary image, produce a new image with a specified histogram.

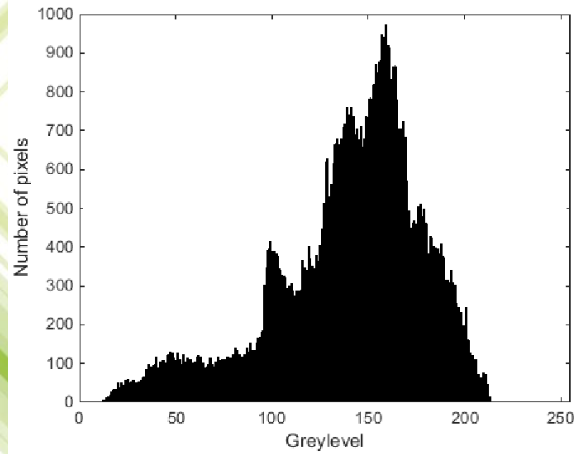
Histogram uses

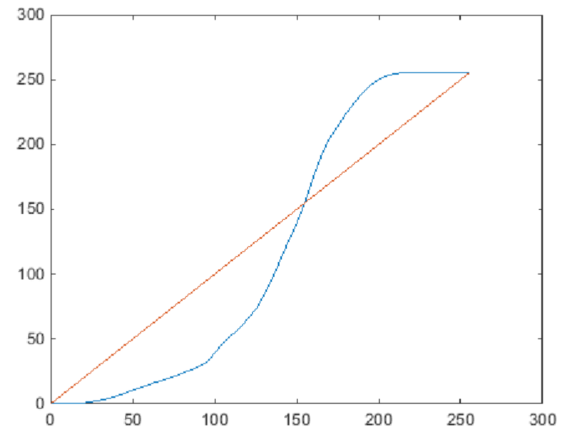
- Histogram can be used as image descriptor!
  - Either 3D histogram with proper binning
  - Or descriptor, formed by concatenating 3 x 1D histograms!
  - What does such descriptor describe?



Histogram equalization

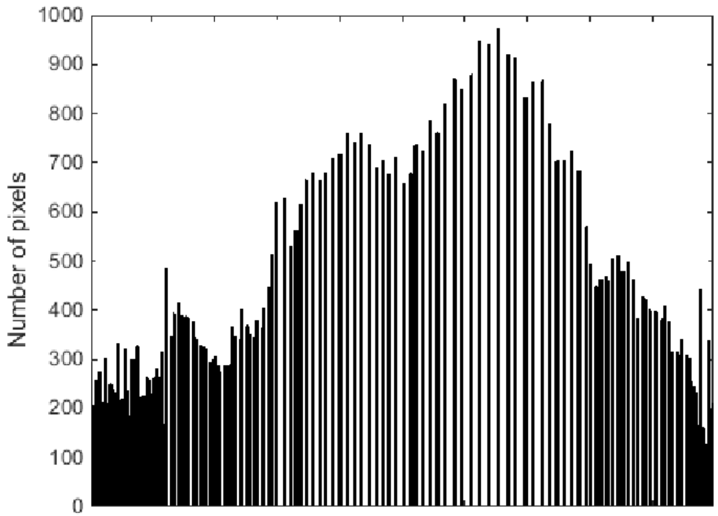
- Finding a transformation of image, that would yield equalized histogram (all bins the same)
  1. Compute histogram with 256 cells (bins) from I, I--> h.
  2. Compute cumulative histogram h_c
  3. Normalize cumulative histogram, h_nc = h_c / max(h_c)
  4. Multiply h_nc with maximum (output) value, e.g. 255, -> h_mnc
  5. Use h_mnc as LUT, R(i,j) = LUT(I(i,j))

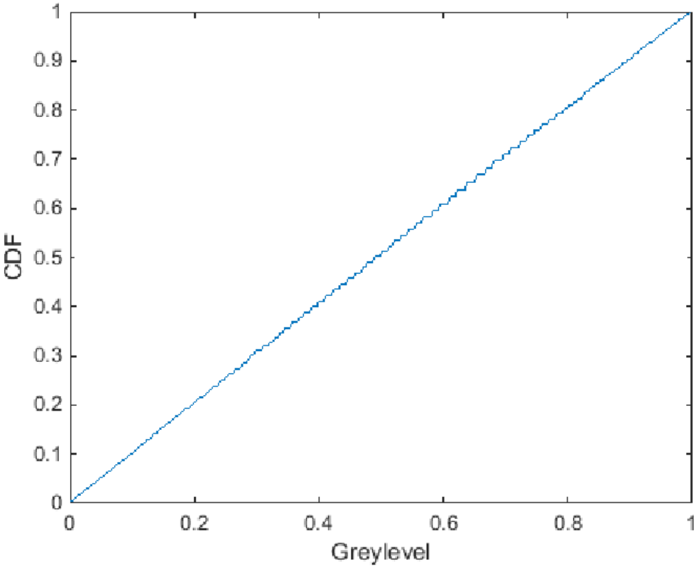




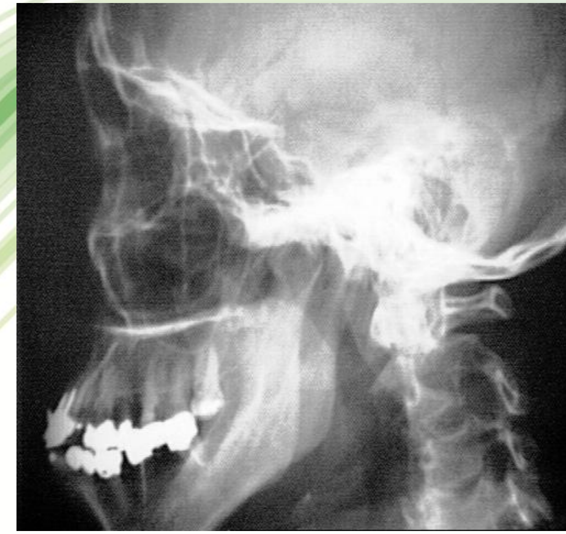
Histogram equalization

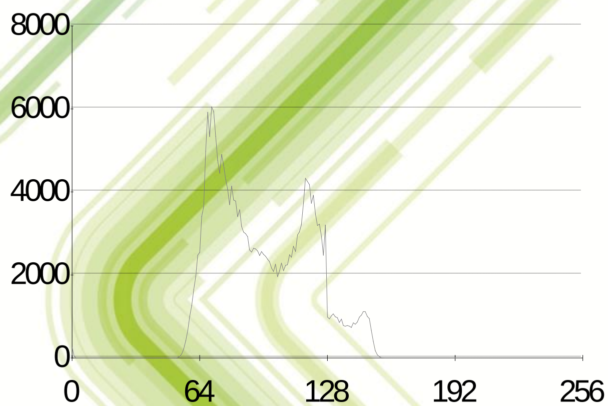
- Result:
  - Not exactly uniform histogram
  - But better than original
  - Cumulative histogram is almost ideal

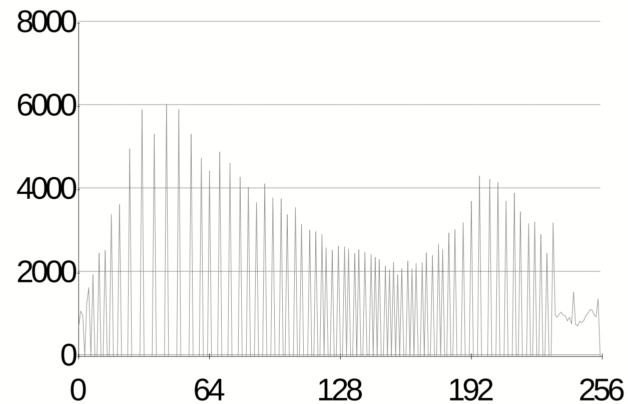




Histogram equalization - example





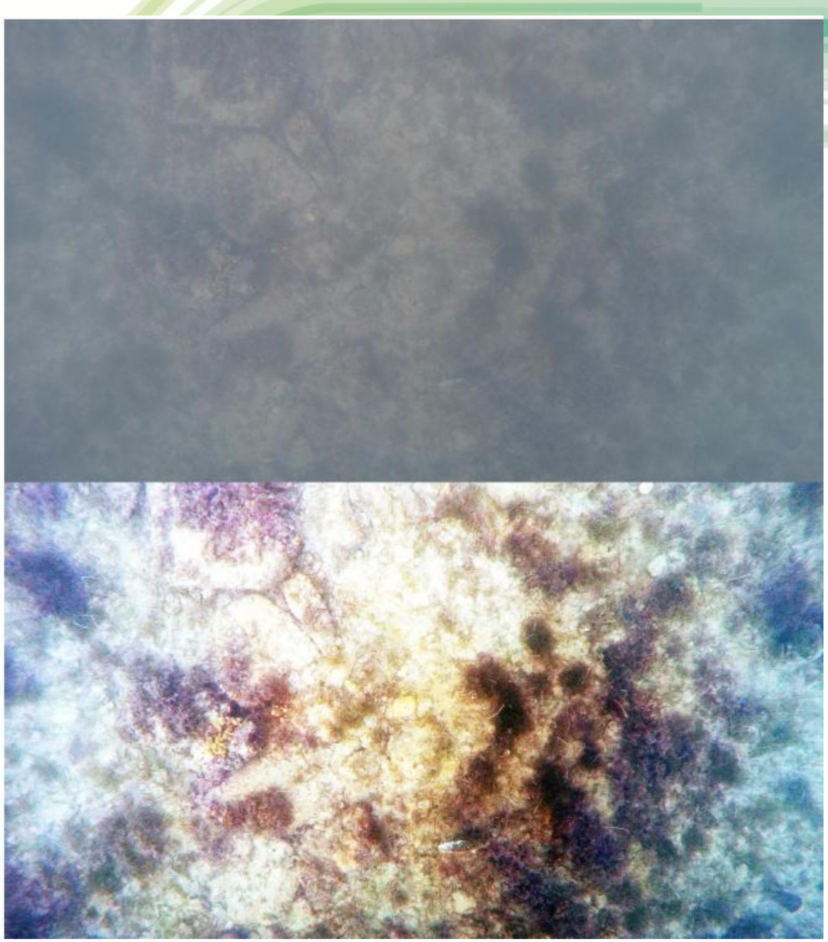


Matlab function: *histeq()*

Histogram equalization - example

- Underwater image

Matlab function: *histeq()* applied to each of the R,G,B channels separately

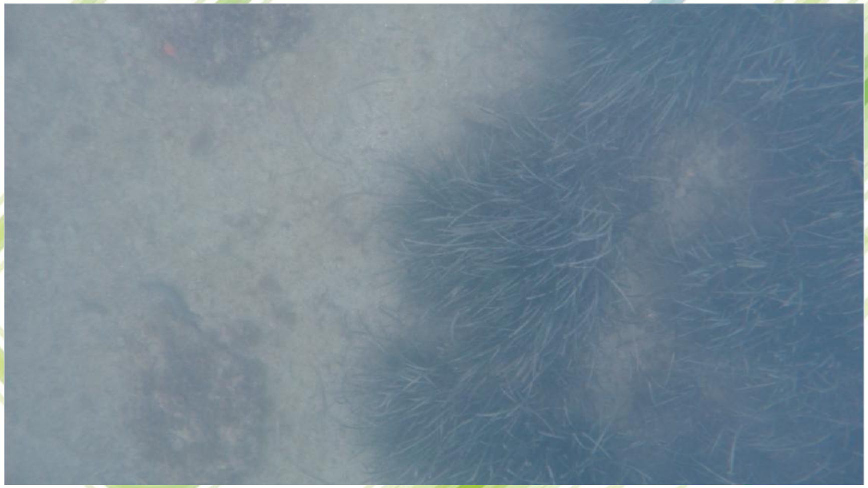


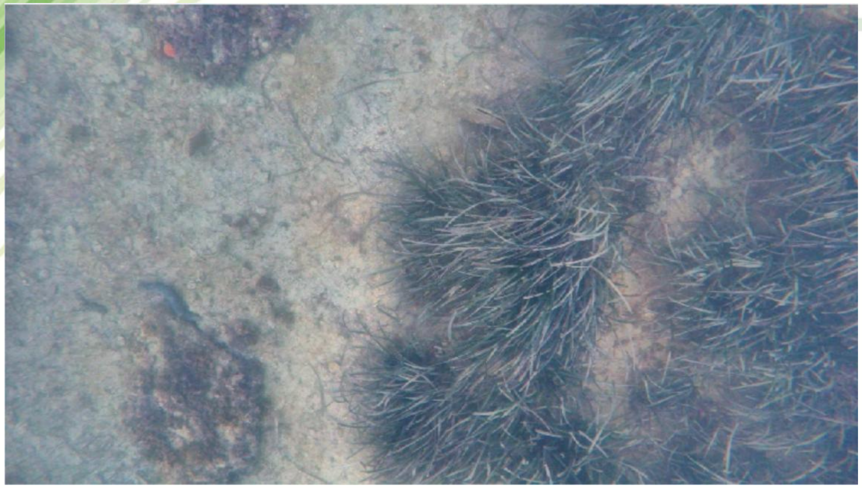
Adaptive histogram equalization

- Procedure
  - Divide the image into (possibly overlapping) regions (subimages).
  - Run histogram equalization on each individual region.
  - Combine the results into the final histogram equalized image.

- Note:
  - for RGB image you can equalize each color channel individualy. There are other options. One option would be to convert RGB to HSV, equalize V only, then convert back to RGB.

Adaptive histogram equalization - example





Matlab function: *adapthisteq()*

Histogram specification

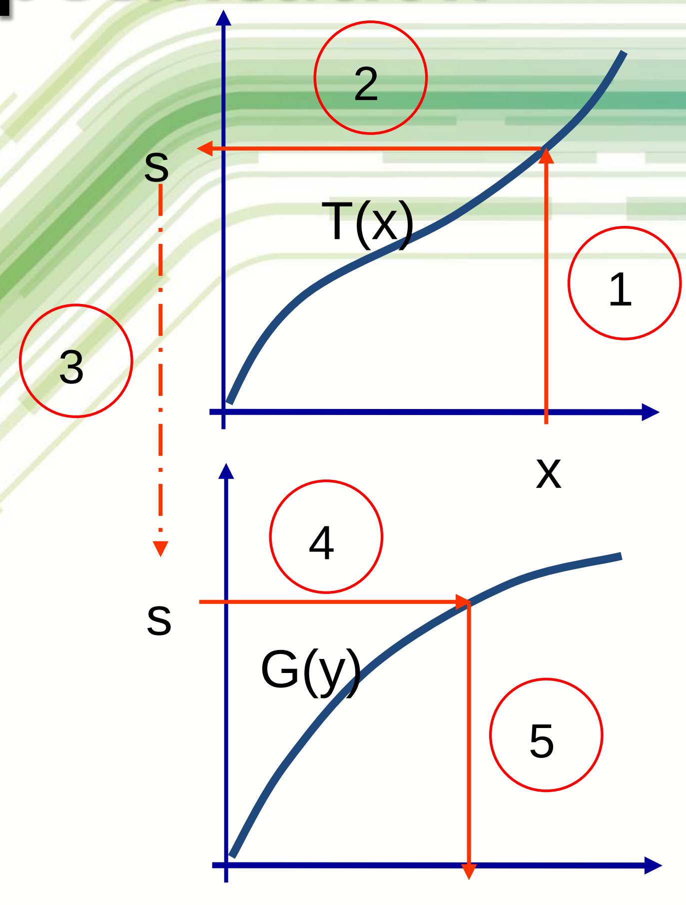
$$X \mapsto Y$$

$$\mathrm{p_x(x),\ p_y(y)}$$

$$\mathrm{s = T(x)} = \int_0^x p_x(x)dx$$

$$G(y) = \int_0^y p_y(y)dy = s$$

$$y = G^{-1}(s) = G^{-1}(\mathrm{T(x)})$$

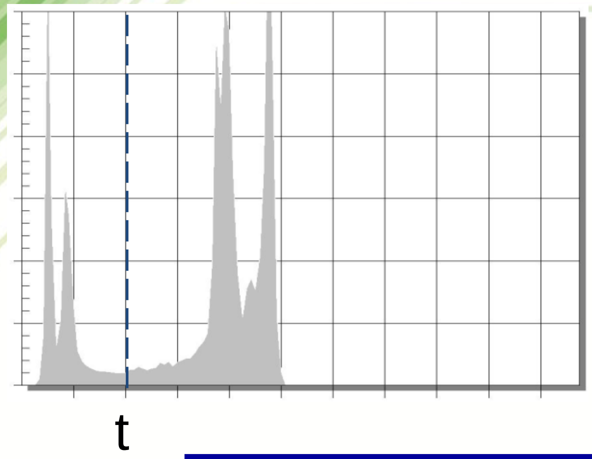


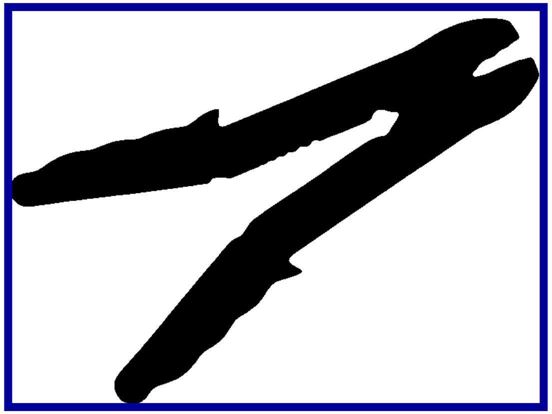
Can be efficiently implemented using LUTS

Function in Matlab *imhistmatch()*

Thresholding

We can use image histogram to select reasonable threshold!

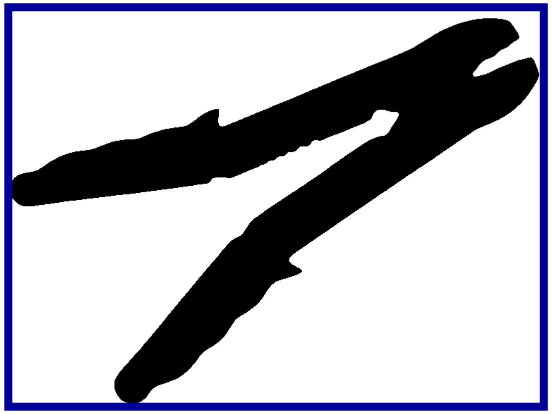




Where to we put t?
– Between two largest peaks
– In the widest valley
– Etc.

Why thresholding?

- Thresholding separates objects from background.
  - A binary image can then be used for further processing.
    - object counting' (connected components analysis)
    - ‚contour tracing / following'
    - topology
    - area, dimensions, orientation, ...
    - Shape analysis
  - Matlab function *regionprops()*



Questions?