LECTURE 03 IMAGE HISTOGRAM AND SPATIAL FILTERING

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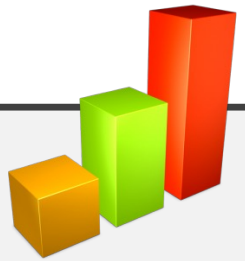
OBJECTIVES

- To understand how to describe an image using histogram and histogram equalization techniques
- To understand filtering techniques, e.g., image smoothing or sharpening

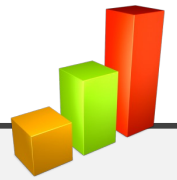
CONTENT

- Histogram
- Spatial Filtering

HISTOGRAM



HISTOGRAM PROCESSING

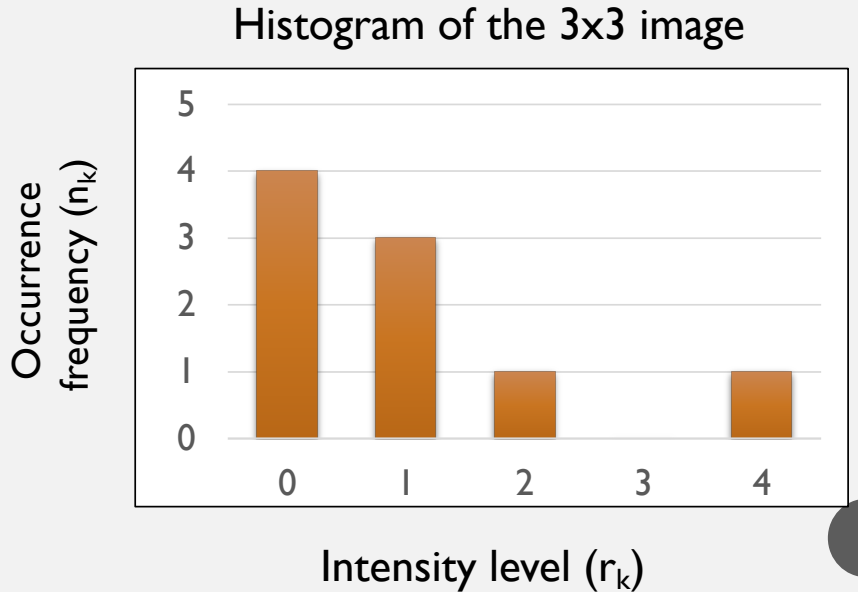


- A histogram is a graphical representation of a data distribution that uses bars to display the frequency or count of data points falling within specific intervals, known as "bins".
- It provides a visual way to understand the distribution of data and identify patterns, trends, and outliers.
- Histogram manipulation used for image enhancement, compression and segmentation.
- Provide useful statistics.

L = 5

0	0	1
0	1	0
1	2	4

A 3x3 image



HISTOGRAM PROCESSING

- The histogram of a digital image with gray levels in the range $[0, L-1]$ is a discrete function:

$$h(r_k) = n_k$$

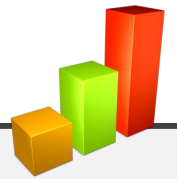
where r_k is the kth gray level and n_k is the number of pixels in the image having gray level r_k.

- A normalized histogram:

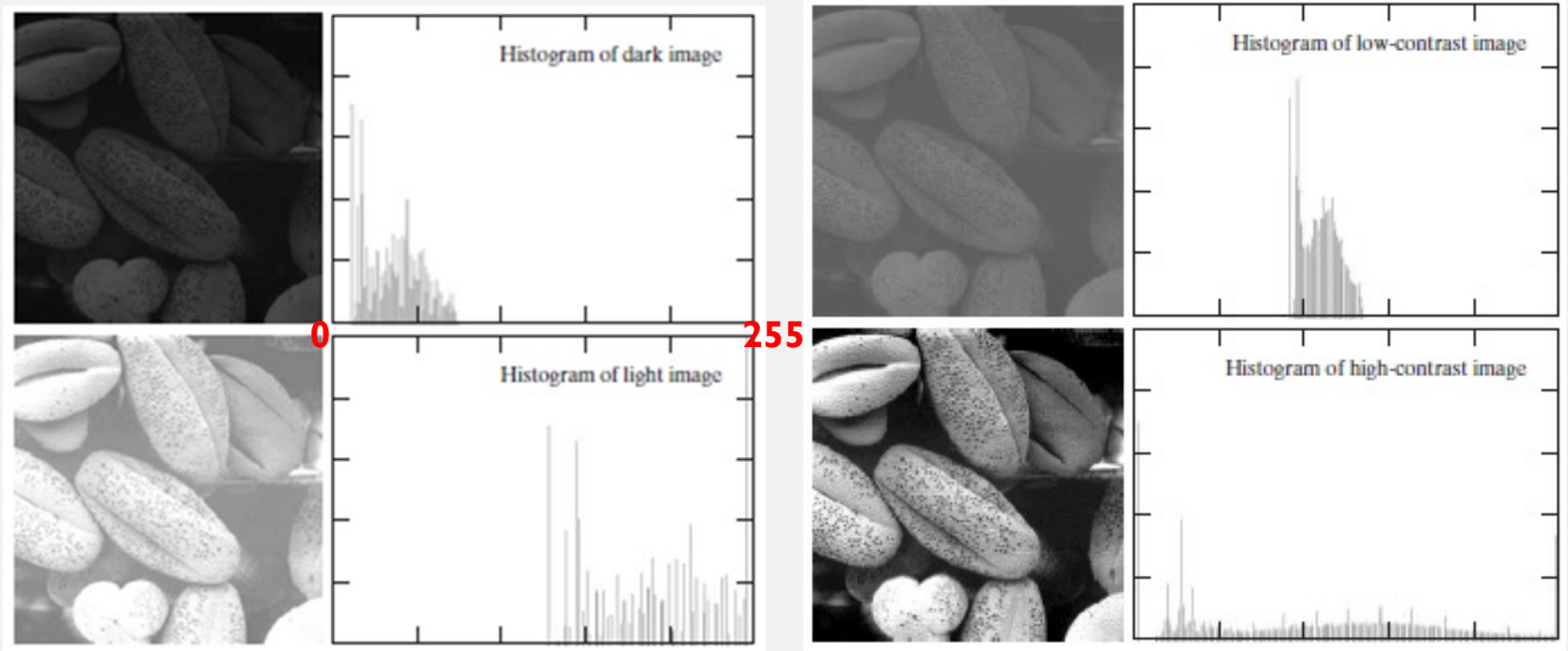
$$p(r_k) = n_k/n$$

- where *n* is the total number of pixels.
- $p(r_k)$ is an estimate of the probability of occurrence of gray level r_k; sum of all $p(r_k)$ = 1.

HISTOGRAM PROCESSING

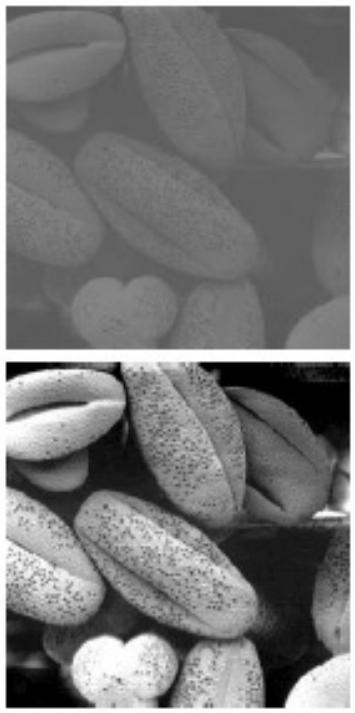


- Intensity levels in the range [0, *255*] (8-bit image)



- Minimum, maximum, and average intensity values.

HISTOGRAM EQUALIZATION



- Brighten some dark values and darken some light values?
- Histogram equalization: to find an intensity mapping function *T* resulting histogram is flat.

$$s = T(r)$$

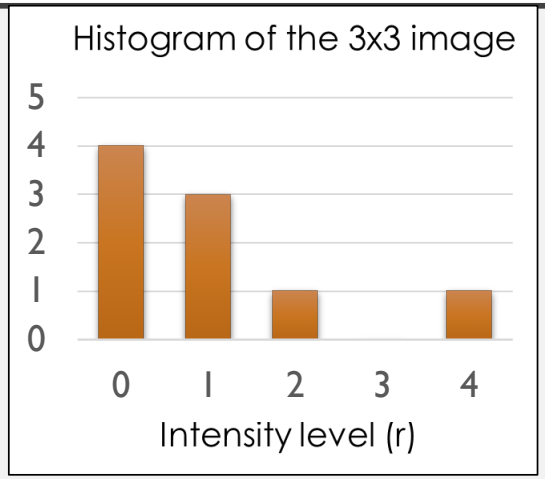
- **Trick**: find probability density function (PDF) to compute cumulative distribution function (CDF)

HISTOGRAM EQUALIZATION

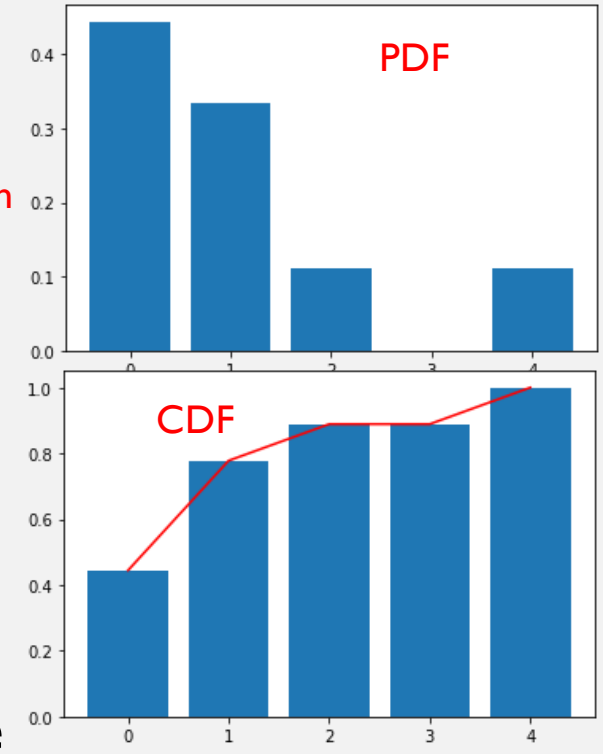
0	0	1
0	1	0
1	2	4

3x3 image

Histogram



Normalization



Cumulative distribution function:

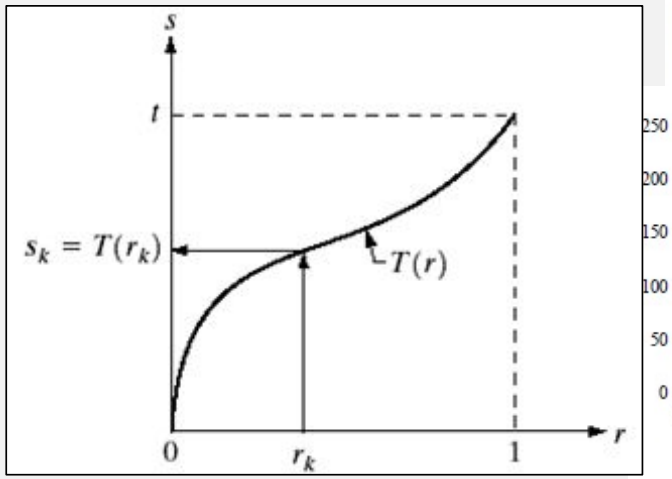
$$c(r_k) = \frac{1}{n}\sum_{j=0}^{k} h(r_j) = c(r_{k-1}) + p(r_k)$$

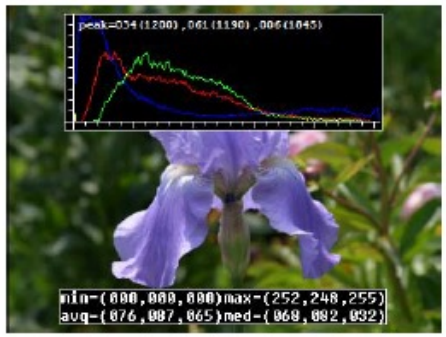
where h is histogram value at gray level r_k, n is the total number of pixels.

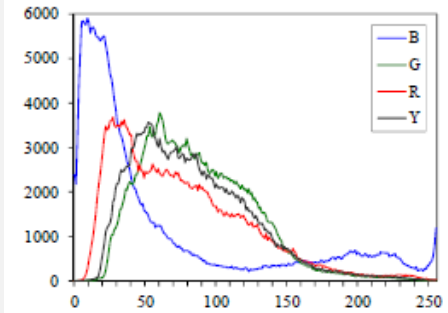
HISTOGRAM EQUALIZATION

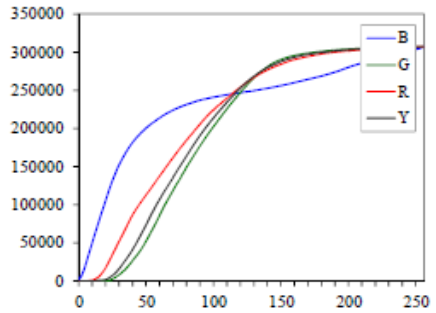
Considering normalized r to the interval [0, 1]:

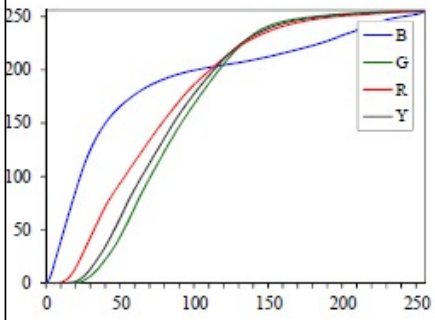
$$s = T(r)$$

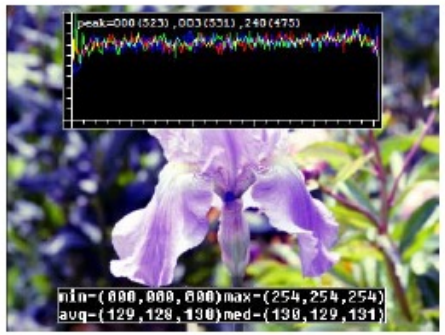


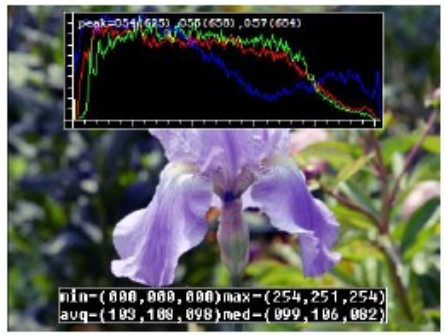












(d) (e) (f)

Figure 3.7 Histogram analysis and equalization: (a) original image (b) color channel and intensity (luminance) histograms; (c) cumulative distribution functions; (d) equalization (transfer) functions; (e) full histogram equalization; (f) partial histogram equalization.

HISTOGRAM EQUALIZATION

Enhance its contrast by stretching out its histogram - Histogram Equalization

1. Our image L different gray levels: $0,1,2, \ldots L-1$
2. Gray level i occurs n_i times in the image.
3. We change gray level i to

$$\left(\frac{n_0 + n_1 + \cdots + n_i}{N}\right)(\mathrm{L}-1)$$

N is the total number of image pixel

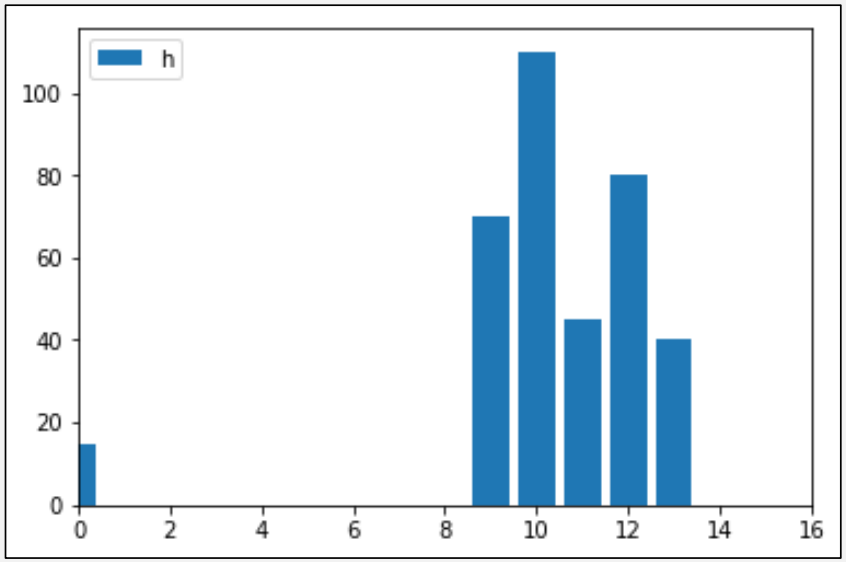
4. Rounded to the nearest integer.

HISTOGRAM EQUALIZATION

```
bar(x, height, *, align='center', **kwargs)
bar(x, height, width, *, align='center', **kwargs)
bar(x, height, width, bottom, *, align='center', **kwargs)
```

- Histogram Equalization

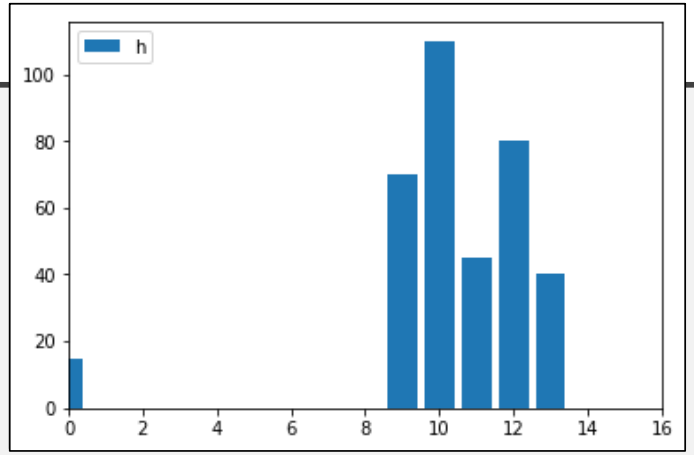
```
gray_level = np.arange(0,16,1)
n_i = np.array([15, 0, 0, 0, 0, 0,  0,   0,  0,  70, 110, 45, 80, 40, 0,  0])
plt.bar(gray_level,n_i)
```

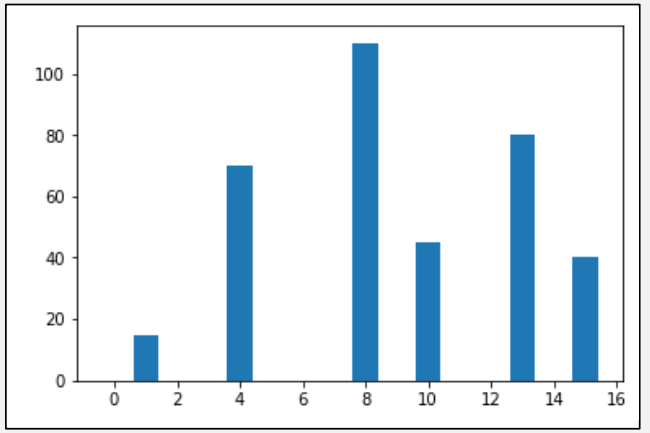


HISTOGRAM EQUALIZATION

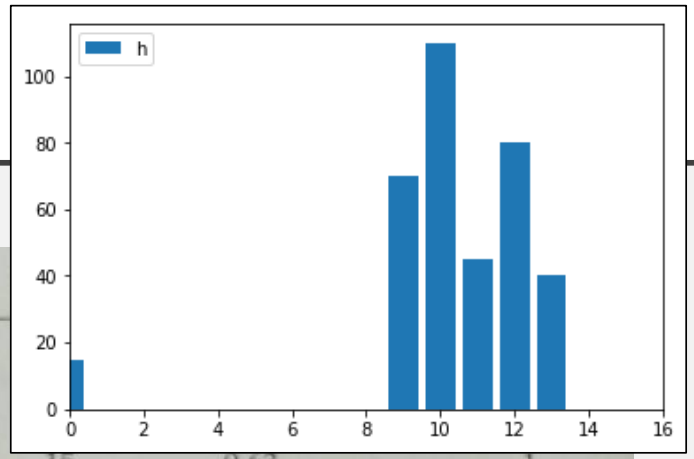
- Histogram Equalizat $\left(\frac{L-1}{n}\right) = 15/360 = 1/24$

Gray level i	n_i	Σn_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
14	0	360	15	15
15	0	360	15	15

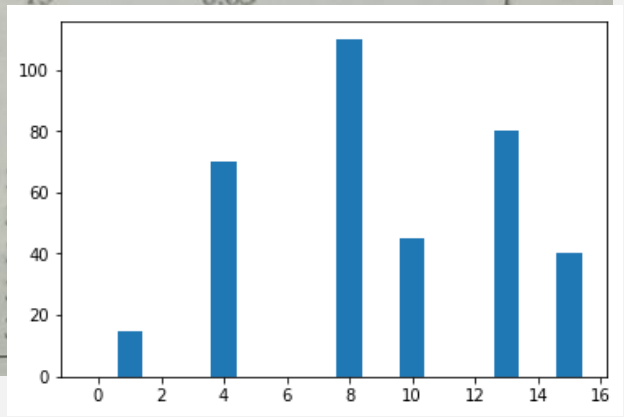




Gray level i	n_i
0	15
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	70
10	110
11	45
12	80
13	40
14	0
15	0



15 0.63 1
15 0.63 1
15 0.63 1
15 0.63 1



HISTOGRAM EQUALIZATION

- Histogram Equalization
- EX#1: the number of pixels at each of the gray levels 0-15 (gray value only)

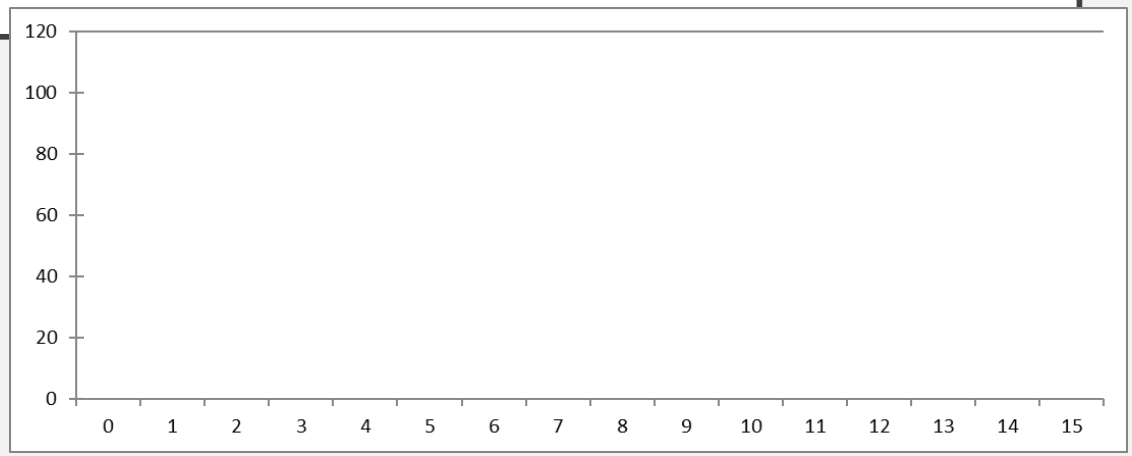
0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	40	80	45	110	70	0	0	0	0	0	0	0	0	15

- Perform a histogram equalization and draw the resulting histogram.

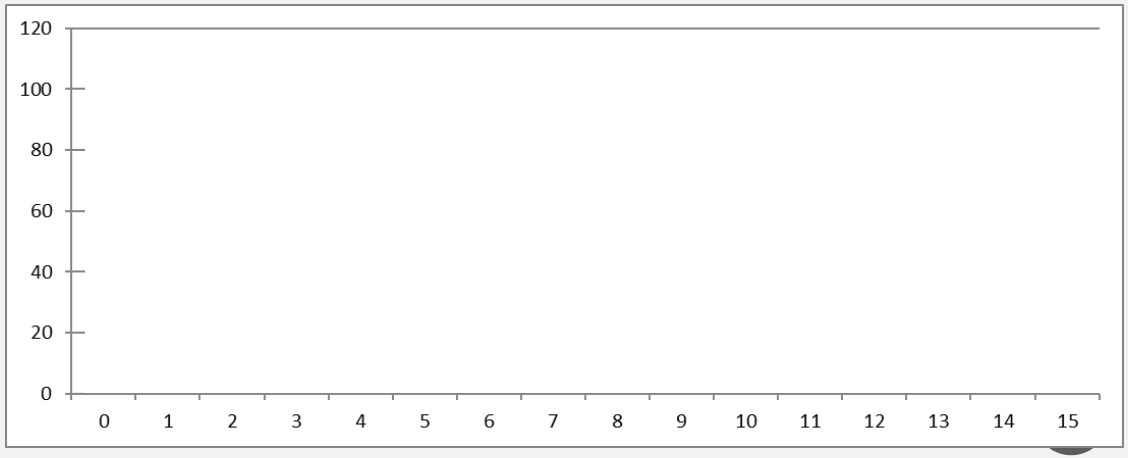
HISTOGRAM EQUALIZATION

gray level	n_i	sum(n_i)	(1/360*15)*sum(n_i)	round value
0				
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				
11				
12				
13				
14				
15				

Original Histogram



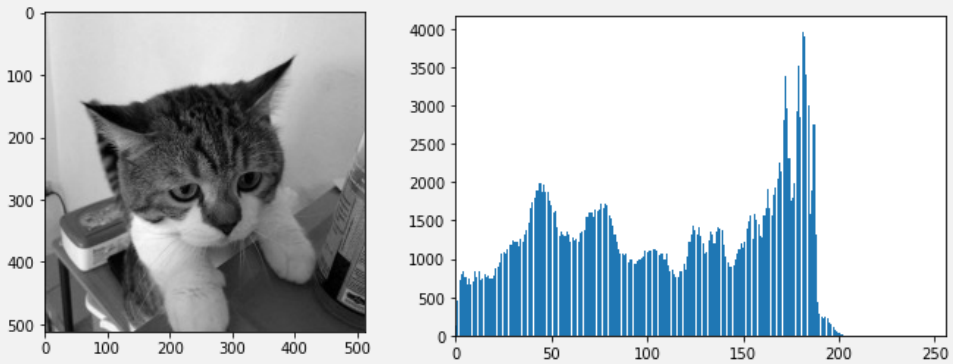
After Histogram Equalisation



PYTHON: HISTOGRAM CALCULATION

1. cv2.calcHist()

```
import cv2
img = cv2.imread("kitty.jpg")
img_gray = cv2.cvtColor(img,cv2.COLOR_BGR2GRAY)
hist = cv2.calcHist([img_gray], [0], None, [256], [0, 256])
plt.imshow(img_gray,cmap='gray');plt.show()
plt.bar(range(0,256),hist[:,0])
plt.xlim([0, 256])
plt.show()
```



◆ calcHist() [1/3]

```
void cv::calcHist ( const Mat *     images,
                    int             nimages,
                    const int *     channels,
                    InputArray      mask,
                    OutputArray     hist,
                    int             dims,
                    const int *     histSize,
                    const float **  ranges,
                    bool            uniform = true ,
                    bool            accumulate = false
                  )
```

Python:

hist = cv.calcHist(images, channels, mask, histSize, ranges[, hist[, accumulate]])

```
#include <opencv2/imgproc.hpp>
```

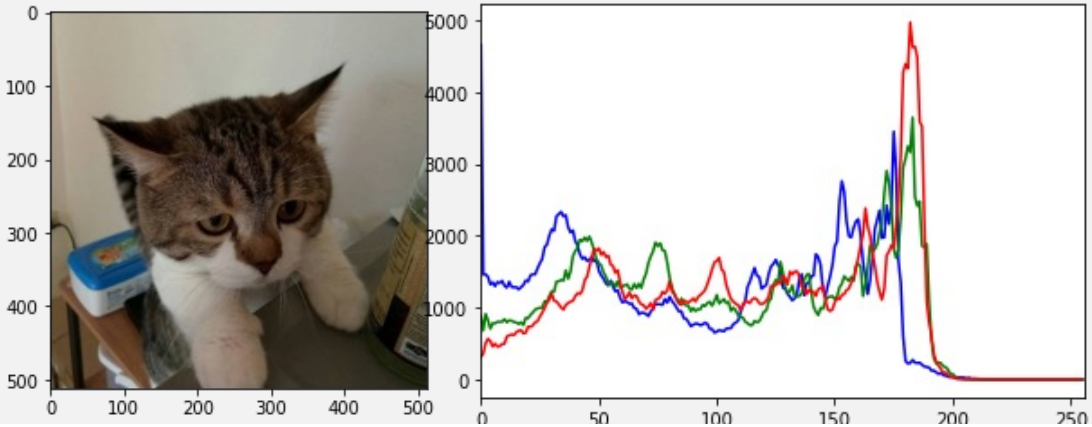
Calculates a histogram of a set of arrays.

https://docs.opencv.org/4.5.1/d6/dc7/group__imgproc__hist.html#ga4b2b5fd75503ff9e6844cc4dcdaed35d

PYTHON: HISTOGRAM CALCULATION

1. cv2.calcHist()

```
plt.imshow(img[:,:,::-1]);plt.show()

chans = cv2.split(img)
colors = ("b", "g", "r")
for (chan, color) in zip(chans, colors):
    # create a histogram for the current channel and plot it
    hist = cv2.calcHist([chan], [0], None, [256], [0, 256])
    plt.plot(hist, color=color)
    plt.xlim([0, 256])
    plt.show()
```



◆ calcHist() [1/3]

```
void cv::calcHist ( const Mat *     images,
                    int             nimages,
                    const int *     channels,
                    InputArray      mask,
                    OutputArray     hist,
                    int             dims,
                    const int *     histSize,
                    const float **  ranges,
                    bool            uniform = true ,
                    bool            accumulate = false
                  )
```

Python:

```
hist = cv.calcHist( images, channels, mask, histSize, ranges[, hist[, accumulate]] )
```

```
#include <opencv2/imgproc.hpp>
```

Calculates a histogram of a set of arrays.

https://docs.opencv.org/4.5.1/d6/dc7/group__imgproc__hist.html#ga4b2b5fd75503ff9e6844cc4dcdaed35d

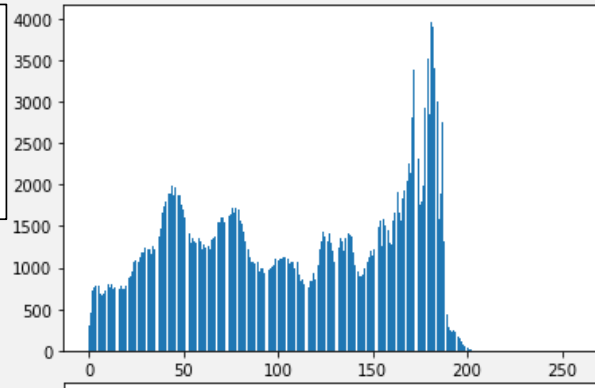
PYTHON: HISTOGRAM CALCULATION

2. np.histogram()

```
img = cv2.imread("kitty.jpg",0)
hist,bins = np.histogram(img.flatten(),256,[0,256])
plt.bar(range(0,256),hist)
plt.show()
```

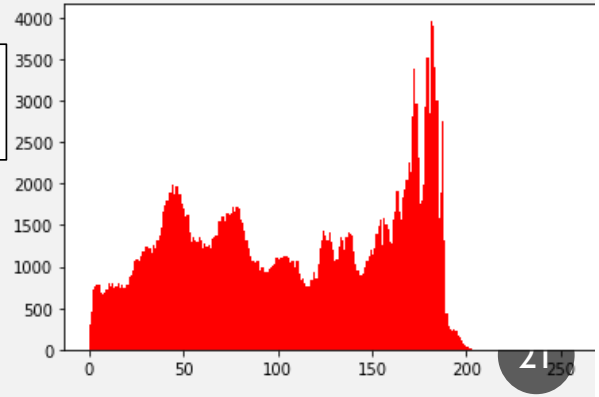
Examples

```
>>> a = np.array([[1,2], [3,4]])
>>> a.flatten()
array([1, 2, 3, 4])
```



3. plt.hist()

```
plt.hist(img.flatten(),256,[0,256], color = 'r')
plt.show()
```

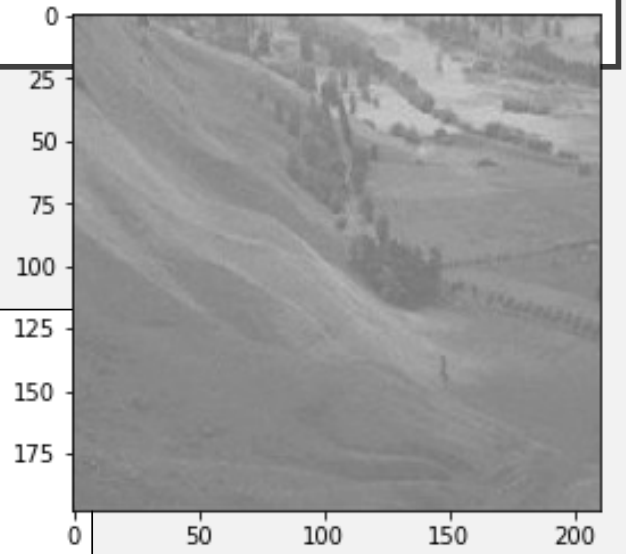


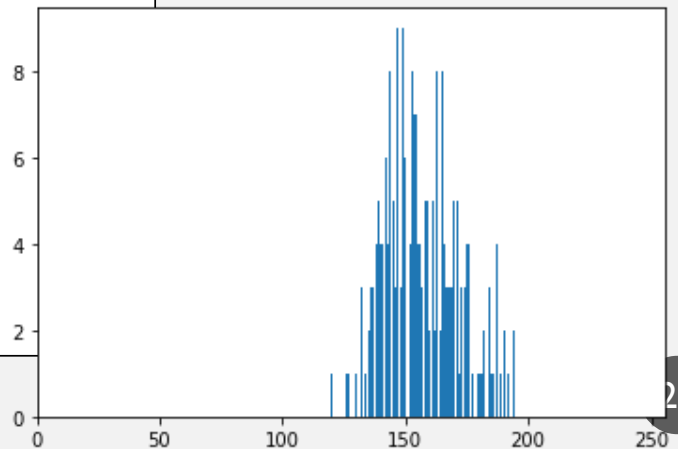
- What do you think about the histogram?

HISTOGRAM EQUALIZATION

- Histogram Equalization

```
import cv2
img = cv2.imread("area.jpg")
img_gray = cv2.cvtColor(img,cv2.COLOR_BGR2GRAY)
hist = cv2.calcHist(img_gray, [0], None, [256], [0, 256])
plt.imshow(img_gray,cmap='gray',vmin=0,vmax=255);plt.show()
plt.bar(range(0,256),hist[:,0])
plt.xlim([0, 256])
plt.show()
```





What do you think about the histogram?

HISTOGRAM EQUALIZATION

◆ equalizeHist()

```
void cv::equalizeHist ( InputArray  src,
                        OutputArray dst
                      )
```

Python:

```
dst = cv.equalizeHist( src[, dst] )
```

```
#include <opencv2/imgproc.hpp>
```

Equalizes the histogram of a grayscale image.

The function equalizes the histogram of the input image using the following algorithm:

- Calculate the histogram H for src .
- Normalize the histogram so that the sum of histogram bins is 255.
- Compute the integral of the histogram:

$$H'_i = \sum_{0 \le j < i} H(j)$$

- Transform the image using H' as a look-up table: $\texttt{dst}(x,y) = H'(\texttt{src}(x,y))$

The algorithm normalizes the brightness and increases the contrast of the image.

Parameters

src Source 8-bit single channel image.

dst Destination image of the same size and type as src .

Examples:

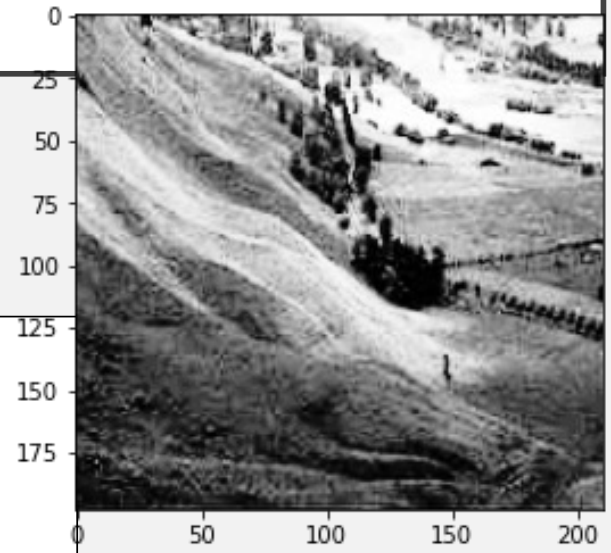
samples/cpp/facedetect.cpp.

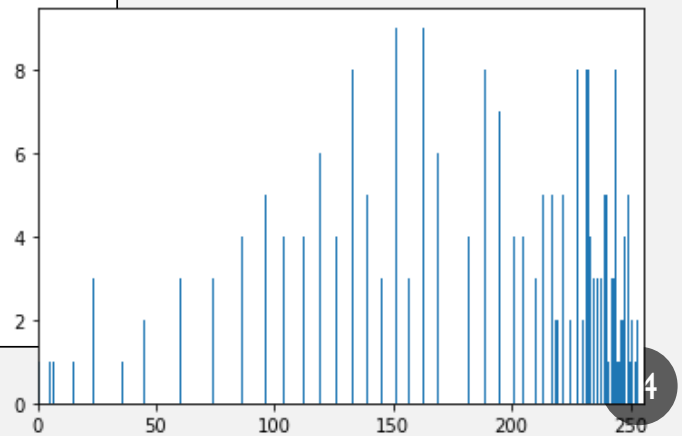
https://docs.opencv.org/4.5.0/d6/dc7/group__imgproc__hist.html#ga7e54091f0c937d49bf84152a16f76d6e

HISTOGRAM EQUALIZATION

- Histogram Equalization

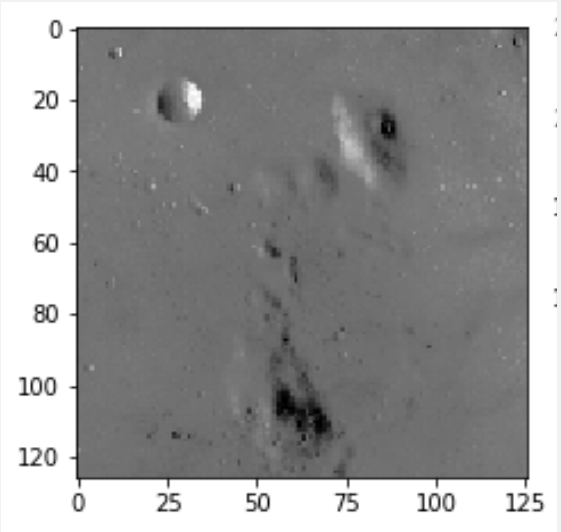
```
import cv2
img = cv2.imread("area.jpg")
img_gray = cv2.cvtColor(img,cv2.COLOR_BGR2GRAY)
hist = cv2.calcHist(img_gray, [0], None, [256], [0, 256])
plt.imshow(img_gray,cmap='gray',vmin=0,vmax=255);plt.show()
plt.bar(range(0,256),hist[:,0])
plt.xlim([0, 256])
plt.show()

equ = cv2.equalizeHist(img_gray)
plt.imshow(equ,cmap='gray')
plt.show()
```





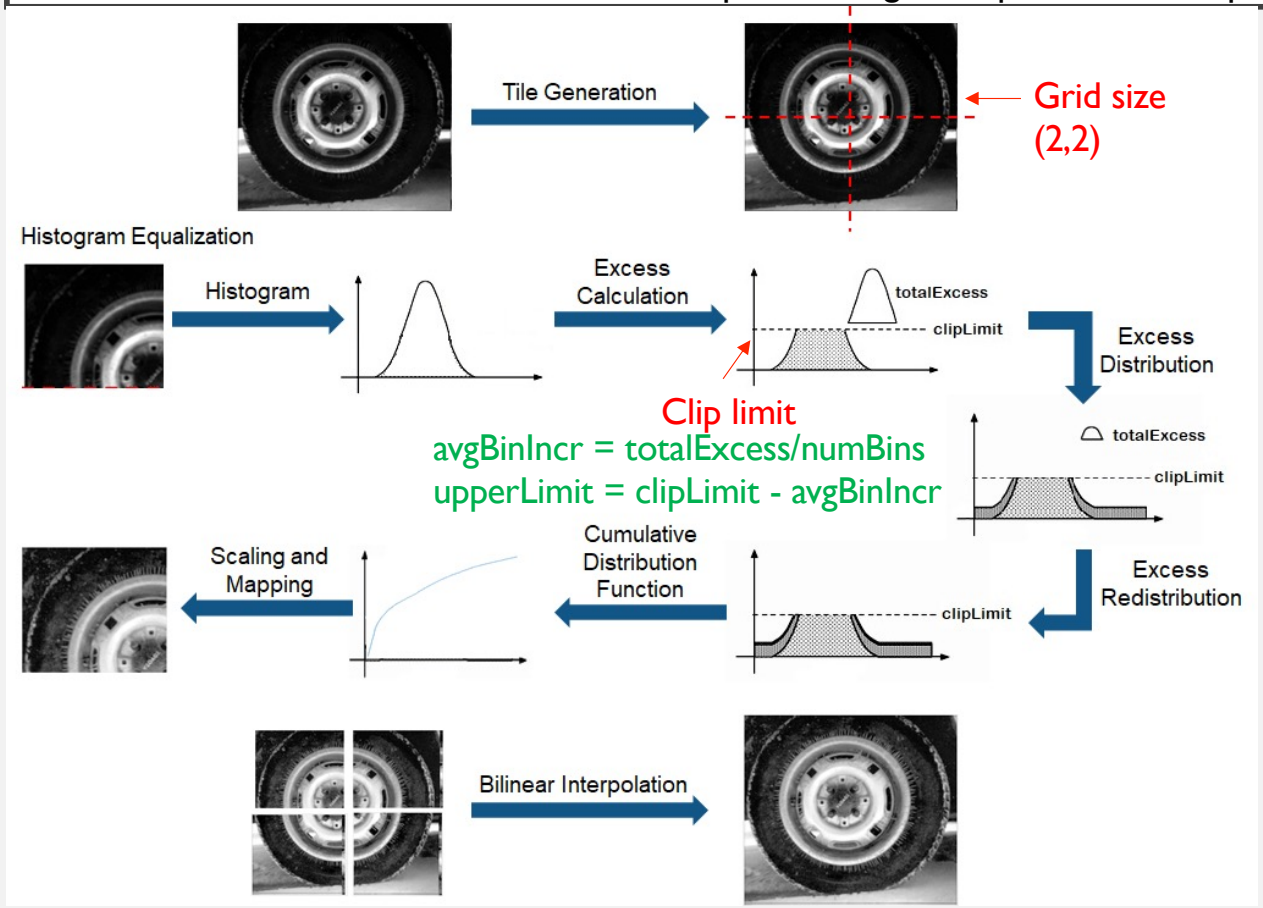
EXERCISE #1 HISTOGRAM EQU ON SPACE.PNG

- Histogram Equalization
- use **equalizeHist** with 'space.png'. Compare histogram of the original image and the image after histogram equalization. Plot the transformation function from equalization. (only used for 8-bit grayscale!)



CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION (CLAHE)

Karel Zuiderveld, "Contrast Limited Adaptive Histogram Equalization", Graphics Gems IV, p. 474-485, code: p. 479-484.



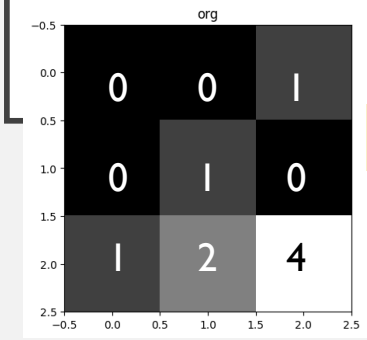
CLAHE:

1. Image is subdivided into non-overlapping grids.
2. A histogram is calculated for each grid.
3. Histogram value that
   - is greater than the clip limit, it is replaced with the clip limit.
   - is less than the upper limit, it is increased by the average bin increment
   - is between the clip limit and the upper limit, the histogram value is replaced with the clip limit
4. Scale and map new image using cumulative distribution function of the new histogram
5. To combine grids of image together using bilinear interpolation

- Two parameters
  - Clip limit
  - Grid size

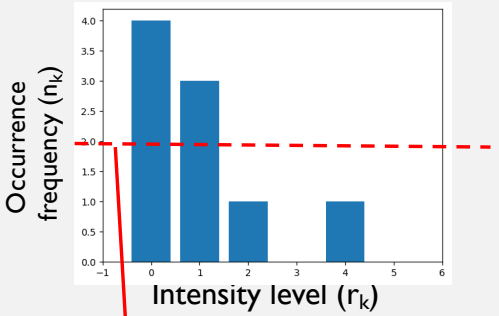
https://www.mathworks.com/help/visionhdl/ug/contrast-adaptive-histogram-equalization.html#d126e9601

CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION (CLAHE)

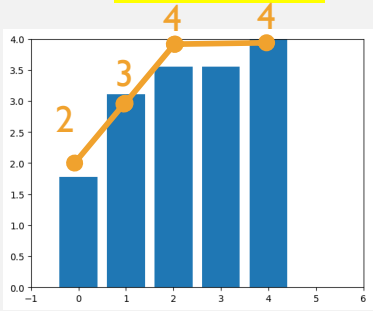


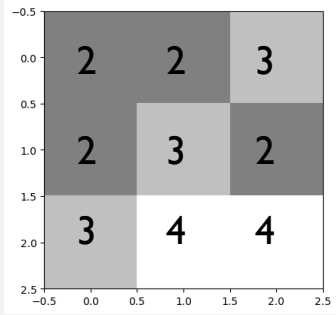
Original Image

Histogram of the 3x3 image



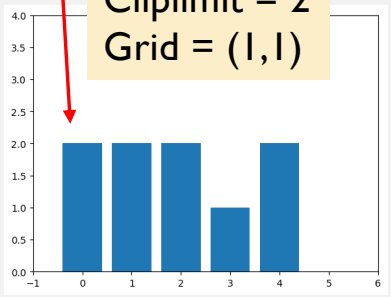
Transformation function



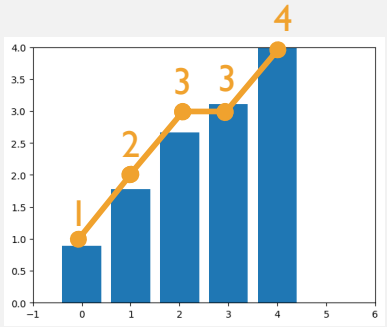


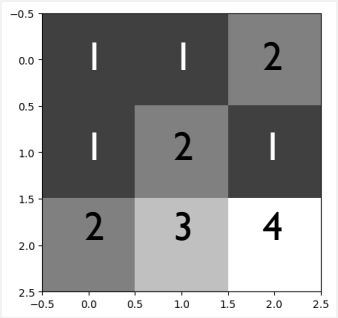
Histogram Equalization

Cliplimit = 2
Grid = (1,1)



CLAHE





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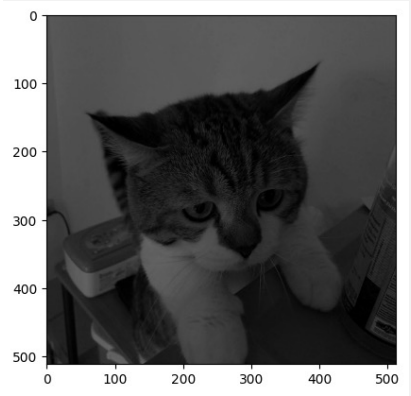
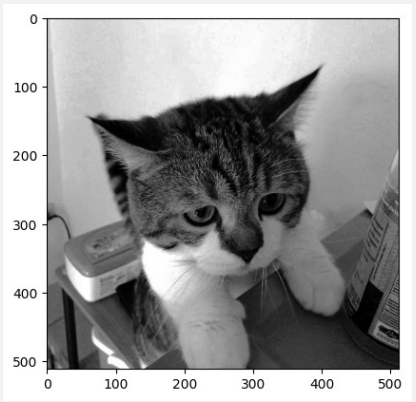
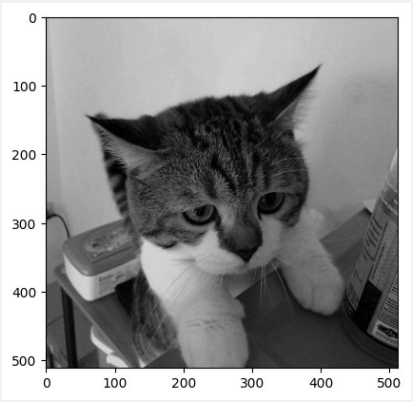


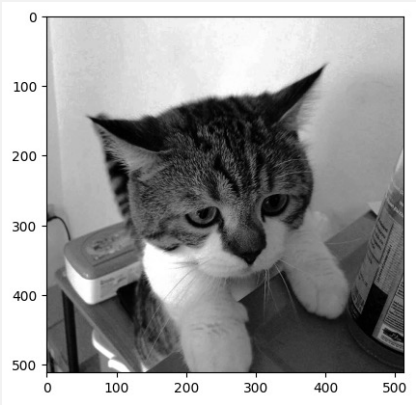
Original Image



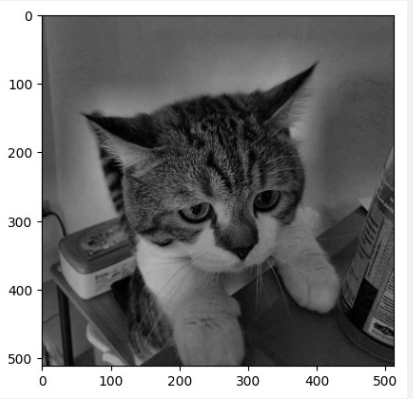
Histogram Equalization



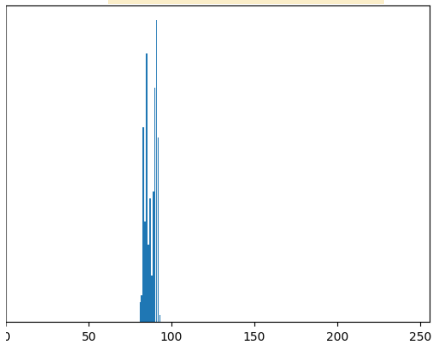
CLAHE with cliplimit = 2

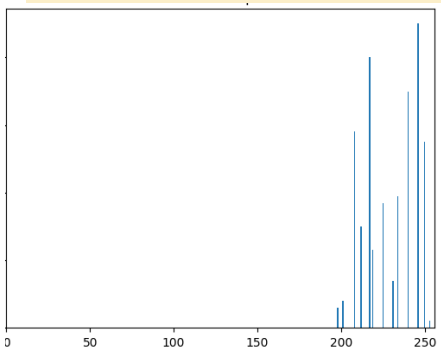


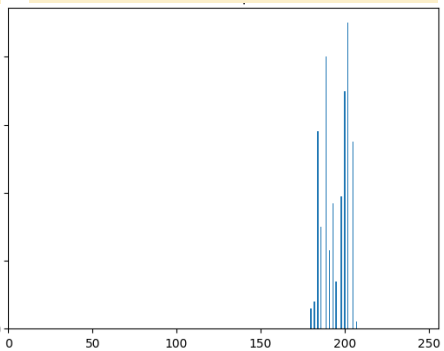
CLAHE with cliplimit = 10

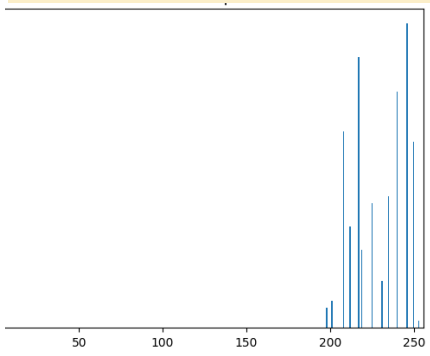


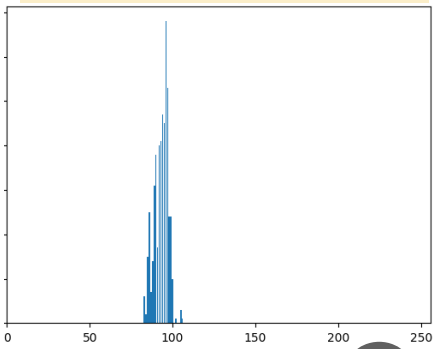
CLAHE with cliplimit = 2











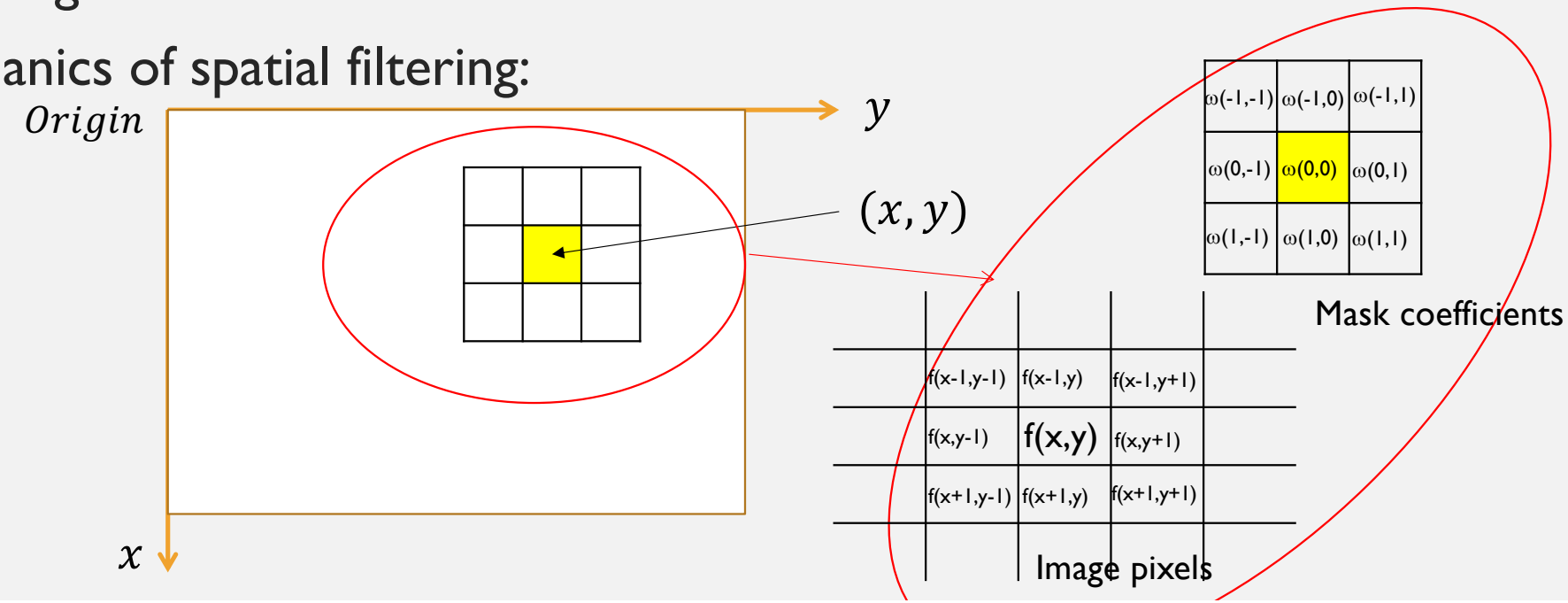
Grid = (1,1)

Grid = (8,8)

SPATIAL FILTERING

SPATIAL FILTERING

- Neighborhood operations: image pixels and sub-image (neighborhood size); sub-image -> **filter, mask, kernel, template or window**. Values in the sub-image -> **coefficients**.
- Mechanics of spatial filtering:



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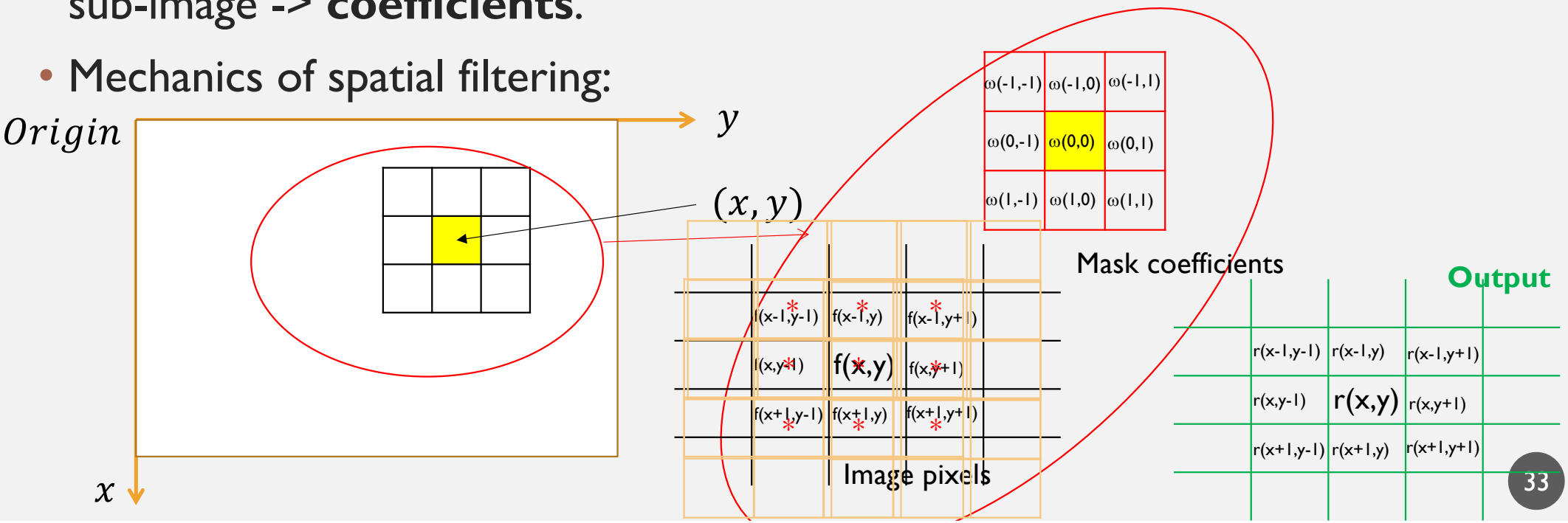
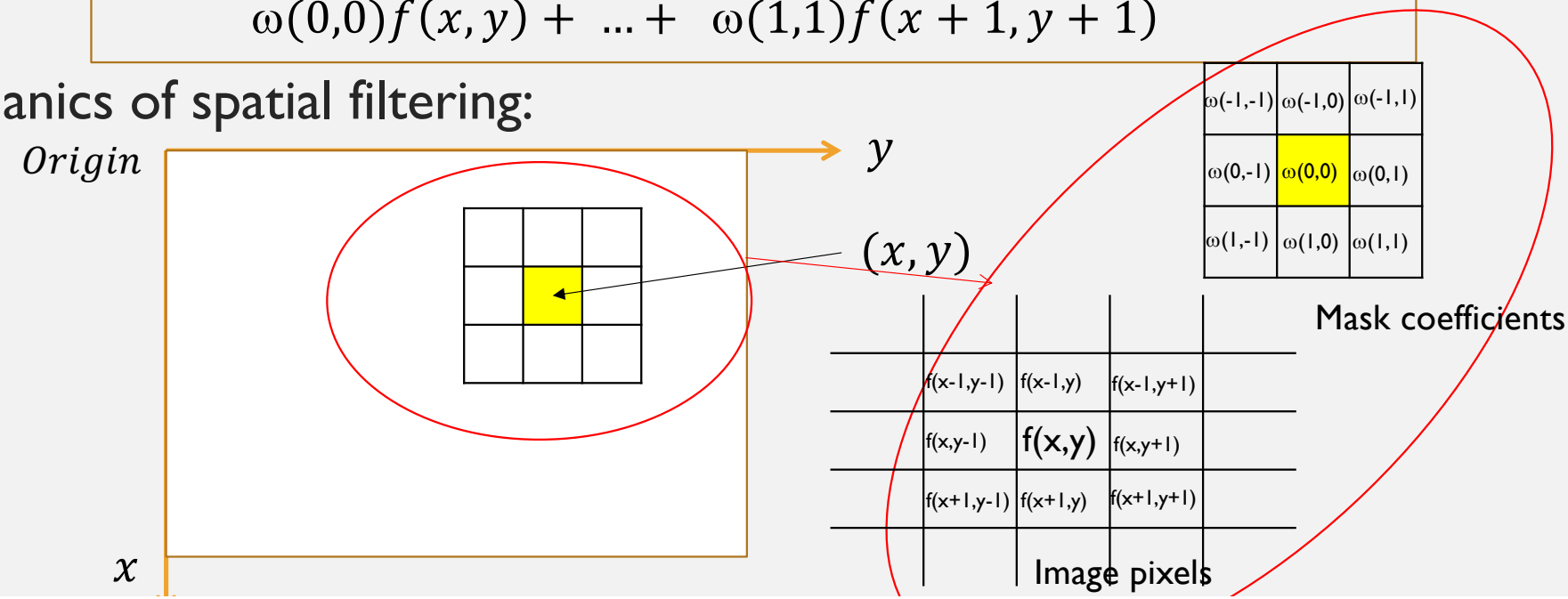


SPATIAL FILTERING

- Response of linear filtering - filter mask at a point (x,y) is

$$R = \omega(-1,-1)f(x-1,y-1) + \omega(-1,0)f(x-1,y) \ldots$$
$$\omega(0,0)f(x,y) + \ldots + \omega(1,1)f(x+1,y+1)$$

- Mechanics of spatial filtering:



SPATIAL FILTERING

- In general, linear filtering of an image f of size M x N with a filter mask of size m x n is given by the expression:

$$g(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} \omega(s,t) f(x+s, y+t)$$

- where a = (m-1)/2, b = (n-1)/2
- Linear filtering similar to a frequency domain concept called **convolution.** Spatial filtering referred to as **convolving a mask with an image.** Filter masks can be called **convolution masks (kernel).**

SPATIAL FILTERING

- Simplified notation:

$$R = \sum_{i=1}^{mn} \omega_i z_i$$

ω are mask coefficients

z : values of image gray levels corresponding those coefficients

mn: the total number of coefficients in the mask.

- **Image border**:
  - partial filter mask
  - use 'padding' the image by adding rows and columns of 0's
  - padding by replicating rows or columns.
  - [perfectly filtered] limit excursions of the centre of the filter mask to distance to less than (n-1)/2 pixels from the border.

SPATIAL FILTERING

- **Non-linear filters**:
  - Operate on neighborhoods
  - Filtering operations **conditionally** based on the value of neighborhood pixels under consideration. (not just use sum-of-products manner) e.g., median filters

SPATIAL FILTERING

- 1) Smoothing Linear Filters
- 2) Sharpening Spatial Filters

SMOOTHING SPATIAL FILTERS

- Used for blurring and for noise reduction.
- Blurring – preprocessing steps, such as removal of small details from an image prior to object extraction, and bridging of small gaps in lines or curves.
- **1) Smoothing linear filters**
- **2) Order statistical filters**

SMOOTHING SPATIAL FILTERS

- **1) Smoothing linear filters**
  - Averaging filters or lowpass filters.
  - Method: replacing the value of every pixel in an image by the average of the gray levels in the neighborhood defined by the filter mask.
  - Reduce 'sharp' transitions in gray levels.
  - Noise reduction - Noise typically has sharp transitions in gray levels.
  - Undesirable side effect – blur edges.

SMOOTHING SPATIAL FILTERS

- **1) Smoothing linear filters**

ω_1	ω_2	ω_3
ω_4	ω_5	ω_6
ω_7	ω_8	ω_9

$\frac{1}{9}$ x

1	1	1
1	1	1
1	1	1

$\frac{1}{16}$ x

1	2	1
2	4	2
1	2	1

Mask coefficients

	z_1	z_2	z_3	
	z_4	z_5	z_6	
	z_7	z_8	z_9	

Image pixels

$$R = \sum_{i=1}^{mn} \omega_i z_i \qquad R = \frac{1}{9} \sum_{i=1}^{9} z_i$$

which is the average of the gray levels of the pixels in the 3 x 3 neighborhood

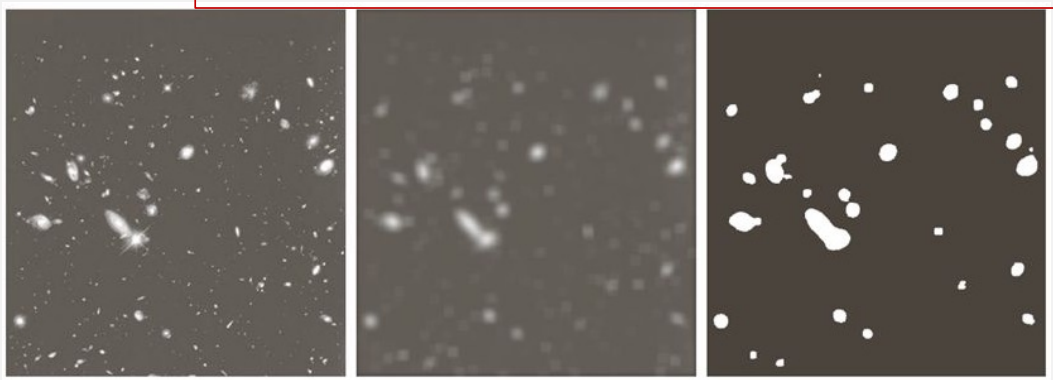
-A spatial averaging filter -> **box filter**

-the right mask (1/16) called **weighted average**

SMOOTHING SPATIAL FILTERS

- **1) Smoothing linear filters**
- General implementation M x N image with a weight averaging filter of size m x n is given by the expression:

$$g(x,y) = \frac{\sum_{s=-a}^{a}\sum_{t=-b}^{b}\omega(s,t)f(x+s,y+t)}{\sum_{s=-a}^{a}\sum_{t=-b}^{b}\omega(s,t)}$$



a b c

FIGURE 3.34 (a) Image of size 528 × 485 pixels from the Hubble Space Telescope. (b) Image filtered with a 15 × 15 averaging mask. (c) Result of thresholding (b). (Original image courtesy of NASA.)

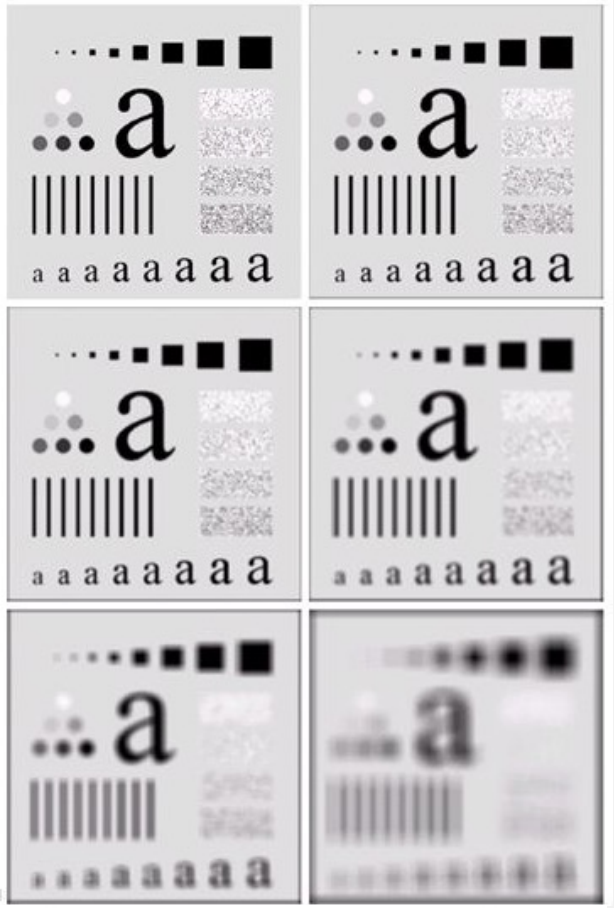


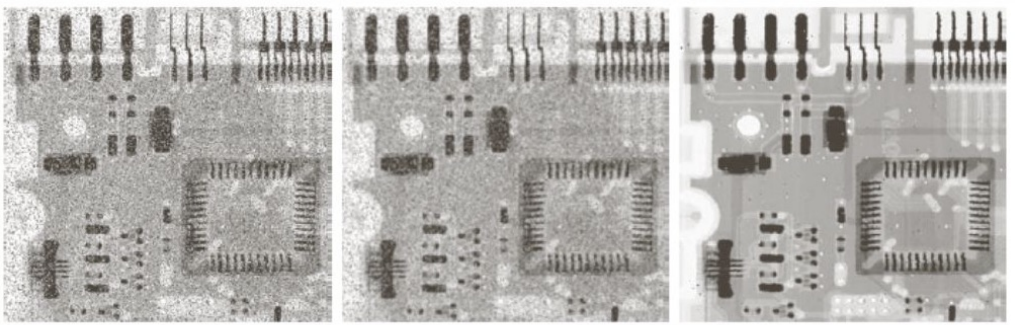
Fig. 3.35 (a) Original image, of size 500 x 500 pixels. (b) – (f) Result of smoothing with square averaging filter masks of size n = 3, 5, 9, 15, and 35 respectively.

SMOOTHING SPATIAL FILTERS

- **2) Order statistical filters**
  - non-linear filters – involved ranking process, e.g., median filter (replace the centre with the median of the gray levels in the neighborhood of that pixel.
  - Principal function is to force points with distinct gray levels to be more like their neighbors.
  - Effective in presence of impulse noise (salt and pepper noise).

SMOOTHING SPATIAL FILTERS

- **2) Order statistical filters**
  - X-ray image of a circuit board corrupted by impulse noise.
  - Averaging filters: less visible noise but blurring
  - Median filters: better suited for removal the impulse noise.



a b c

FIGURE 3.35 (a) X-ray image of circuit board corrupted by salt-and-pepper noise. (b) Noise reduction with a 3×3 averaging mask. (c) Noise reduction with a 3×3 median filter. (Original image courtesy of Mr. Joseph E. Pascente, Lixi, Inc.)

SPATIAL FILTERING

- 1) Smoothing Linear Filters
- 2) Sharpening Spatial Filters

SHARPENING SPATIAL FILTERS

- To highlight fine detail in an image or to enhance detail that has been blurred.
- Used in electronic printing and medical imaging, industrial inspection and autonomous guidance in military systems.
- Accomplished by spatial differentiation; the strength of the response of a derivative operator ≈ degree of discontinuity of the image.
- Enhance edge and other discontinuities (such as noise) and deemphasizes areas with slowly varying gray-level values.

SHARPENING SPATIAL FILTERS

- Derivatives of a digital function are defined in terms of differences.
- **Digital values**: finite and the shortest distance over which that change can occur is between adjacent pixels.
- Definition of the first-order derivative of a 1-D f(x) is

$$\frac{\partial f}{\partial x} = f(x+1) - f(x)$$

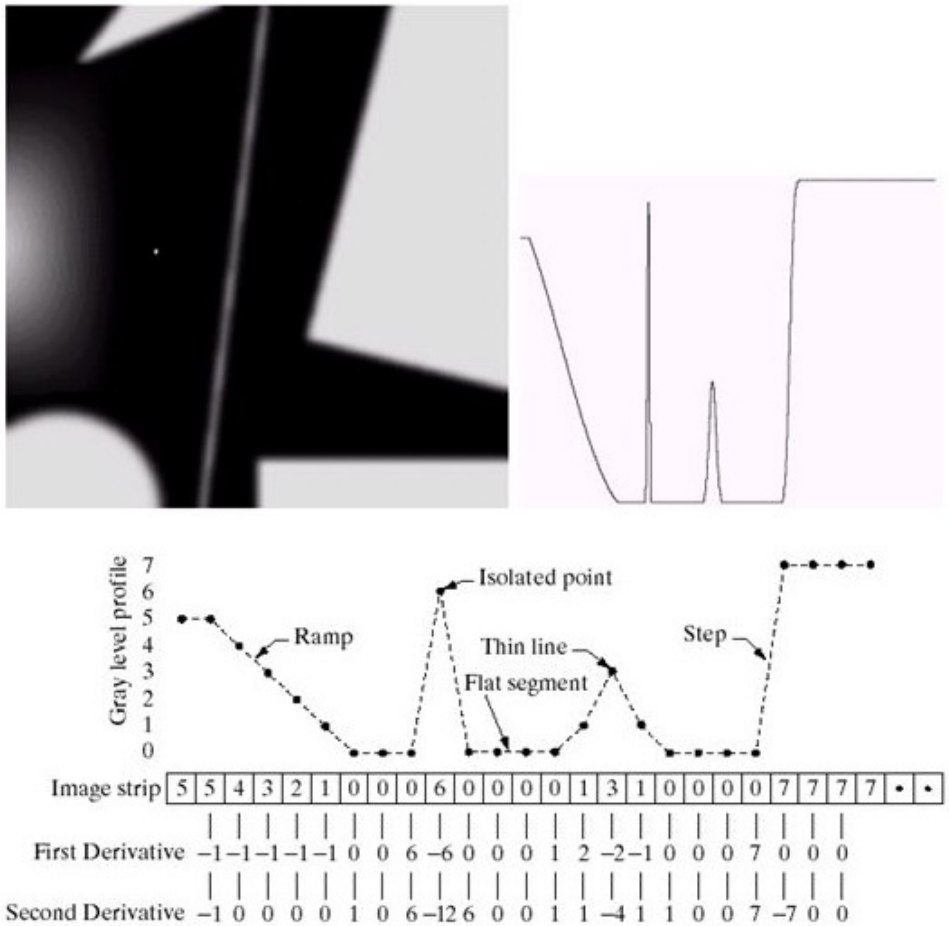
- Second-order derivative as the difference:

$$\frac{\partial^2 f}{\partial^2 x} = f(x+1) + f(x-1) - 2f(x)$$

SHARPENING SPATIAL FILTERS

a b
c

FIGURE 3.38
(a) A simple image. (b) 1-D horizontal gray-level profile along the center of the image and including the isolated noise point.
(c) Simplified profile (the points are joined by dashed lines to simplify interpretation).



- **Ramps**: first-order is nonzero all along, second-order only at the onset and end of the ramp.
- **Isolated noise**: second-order much more aggressive in enhancing sharp changes.
- **Thin line**: fine details (second-order stronger)

- First-order – thicker edges,
- Second-order – stronger response to fine detail & produce double response at step changes.

SHARPENING SPATIAL FILTERS

- **1) Second-derivatives (Laplacian)**
- Isotropic filters – independent of the direction of the discontinuities in the image + rotation invariant.
- Laplacian of f(x,y):

$$\nabla^2 f = \frac{\partial^2 f}{\partial^2 x} + \frac{\partial^2 f}{\partial^2 y}$$

$$\frac{\partial^2 f}{\partial^2 x} = f(x+1, y) + f(x-1, y) - 2f(x, y)$$

$$\frac{\partial^2 f}{\partial^2 y} = f(x, y+1) + f(x, y-1) - 2f(x, y)$$

$$\nabla^2 f = [f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1)] - 4f(x, y)$$

SHARPENING SPATIAL FILTERS

- **1) Second-derivatives (Laplacian) (cont')**

0	1	0
1	-4	1
0	1	0

1	1	1
1	-8	1
1	1	1

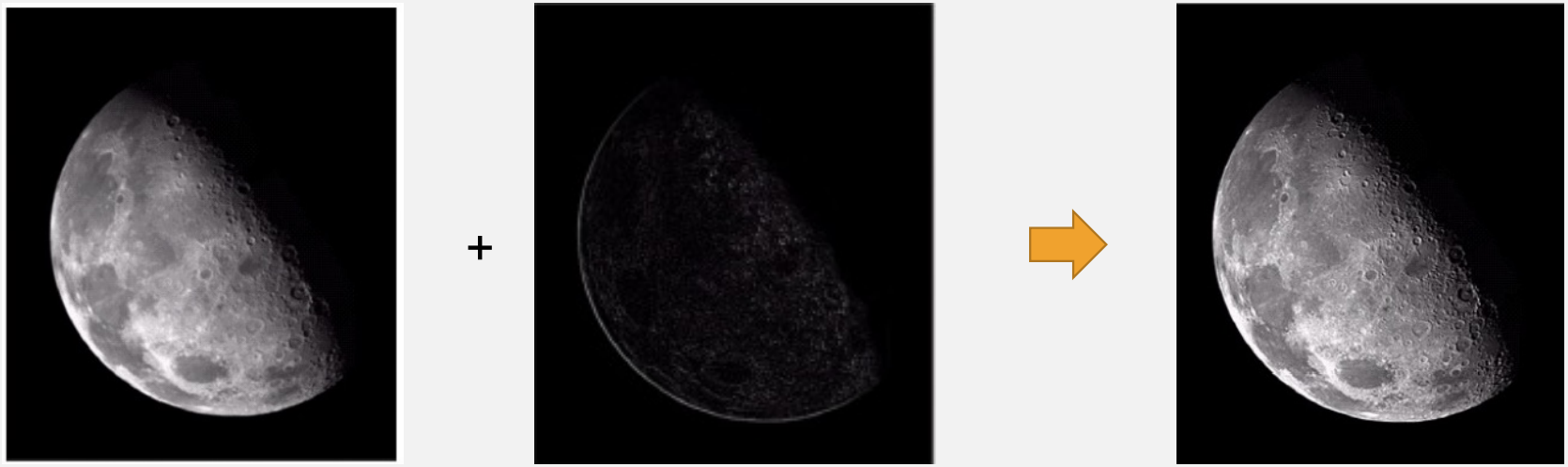
0	-1	0
-1	4	-1
0	-1	0

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

- Highlights gray-level discontinuities in an image and deemphasizes regions (slowly varying gray levels).
- Combining original and Laplacian images – sharpening effect and with background features

SHARPENING SPATIAL FILTERS

- **1) Second-derivatives (Laplacian) (cont')**



Original image + Laplacian image → Combined image

- Combining original image and the Laplacian image:
  - the detail in this image is clearer and sharper than in the original image.
  - increasing the contrast at the locations of gray-level discontinuities.

SHARPENING SPATIAL FILTERS

- The basic way in which we use the Laplacian for image enhancement is as follows:

$$g(x,y) = \begin{cases} f(x,y) - \nabla^2 f(x,y) & \text{if the center coefficient of the Laplacian mask is negative} \\ f(x,y) + \nabla^2 f(x,y) & \text{if the center coefficient of the Laplacian mask is positive} \end{cases}$$

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

for example,

$$\begin{aligned} g(x,y) &= f(x,y) - [f(x+1,y) + f(x-1,y) \\ &\quad + f(x,y+1) + f(x,y-1) - 4f(x,y)] \\ &= 5f(x,y) - [f(x+1,y) + f(x-1,y) \\ &\quad + f(x,y+1) + f(x,y-1)] \end{aligned}$$

SHARPENING SPATIAL FILTERS

- **2) First-derivatives**
- The gradient where the gradient of function f(x,y) is defined as 2D column vector:

$$\nabla \boldsymbol{f} = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

- The magnitude:

$$\nabla f = mag(\nabla \boldsymbol{f}) = \left[G_x^2 + G_y^2\right]^{1/2}$$

$$= \left[\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2\right]^{1/2}$$

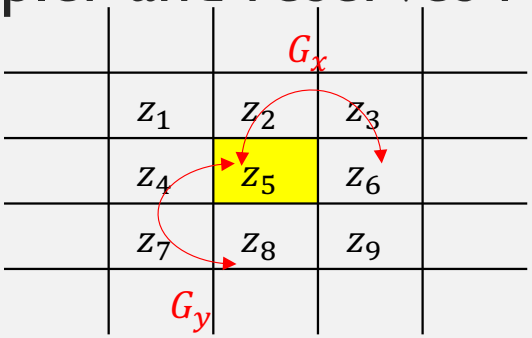
$$\nabla f \approx |G_x| + |G_y|$$

SHARPENING SPATIAL FILTERS

- **2) First-derivatives**
- To reduce computational burden, use absolute values instead:

$$\nabla f \approx |G_x| + |G_y|$$

- Simpler and reserves relative changes in gray levels.



$$G_x = (z_6 - z_5)$$

$$G_y = (z_8 - z_5)$$

Early development, Roberts [1965]:

$$G_x = (z_9 - z_5)$$

$$G_y = (z_8 - z_6)$$

$$\nabla f \approx |z_9 - z_5| + |z_8 - z_6|$$

Robert cross-gradient operators:

SHARPENING SPATIAL FILTERS

- Robert cross-gradient operators:

$$\nabla f \approx |z_9 - z_5| + |z_8 - z_6|$$

0	-1
1	0

-1	0
0	1

$G_x = (z_9 - z_5)$ $G_y = (z_8 - z_6)$

- Even size – awkward to implement
- Sobel operators:

$$\nabla f \approx \left|(z_7+2z_8+z_9) - (z_1+2z_2+z_3)\right| + \left|(z_3+2z_6+z_9) - (z_1+2z_4+z_7)\right|$$

z_1	z_2	z_3	
z_4	z_5	z_6	
z_7	z_8	z_9	

Gx

-1	-2	-1
0	0	0
1	2	1

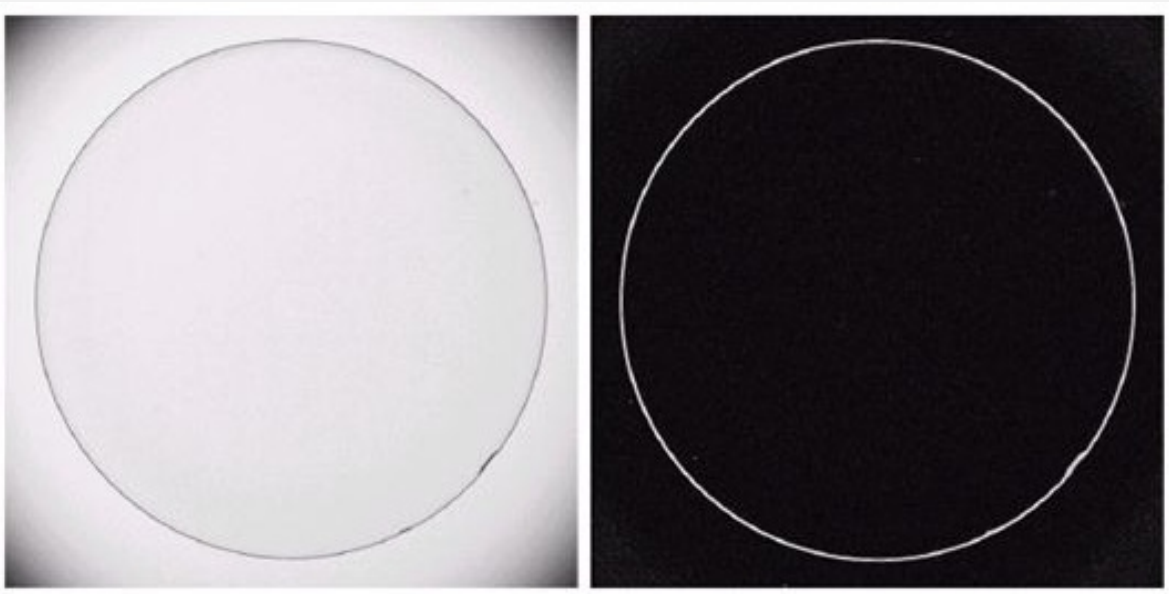
-1	0	1
-2	0	2
-1	0	1

Gy

Gx detects horizontal edges; Gy for vertical edges. Sometimes, Gx and Gy concepts are swap. (OpenCV library)

SHARPENING SPATIAL FILTERS

- **Applications**:
- Aid human in the detection of defects: preprocessing step.

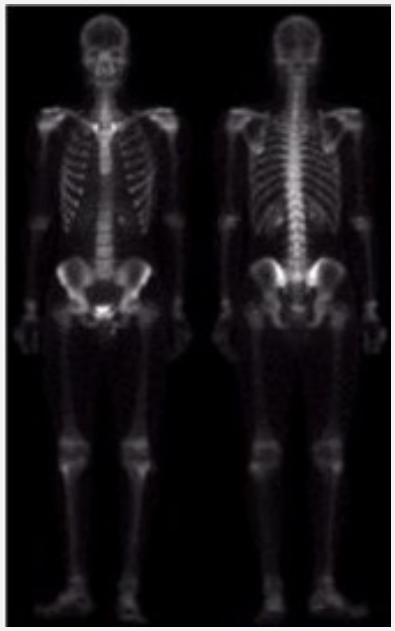


a b

FIGURE 3.45 Optical image of contact lens (note defects on the boundary at 4 and 5 o'clock). (b) Sobel gradient. (Original image courtesy of Mr. Pete Sites, Perceptics Corporation.)

COMBINING SPATIAL ENHANCEMENT METHODS

- Whole body bone scan for detecting bone infection or tumors.



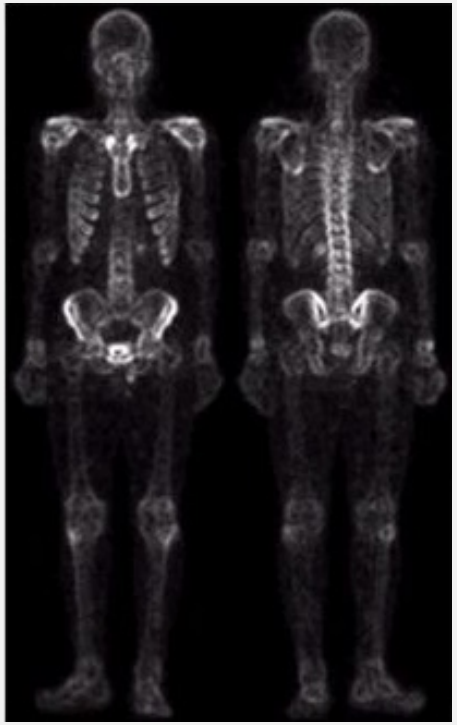
(a)
Original image

(b)
Laplacian of (a)

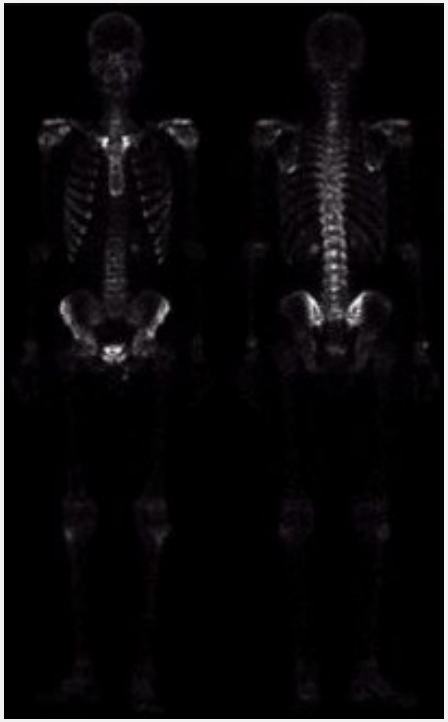
(c)
Sharpening
by (a) + (b)

(d)
Sobel of (a)

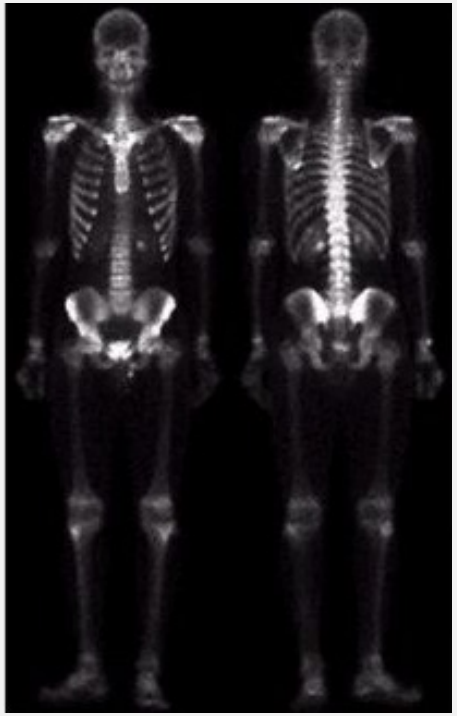
COMBINING SPATIAL ENHANCEMENT METHODS



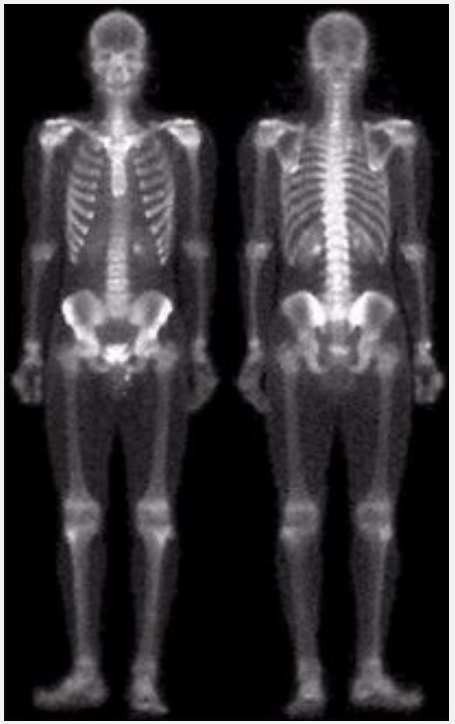
(e)
(d) Smoothed by an average filter



(f)
Mask from product of (c) and (e)



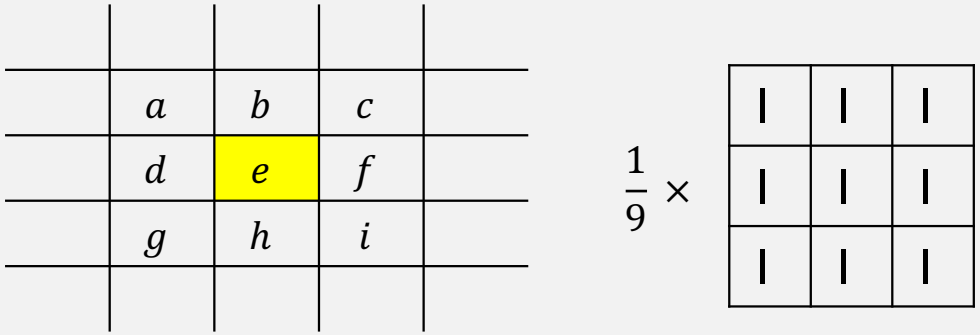
(g)
sum of (a) and (f)



(h)
Power-law transformation on (g)

PYTHON: SPATIAL FILTERING

- e is gray value of the current pixel in the original image.



- The average is the gray value of the corresponding pixel in the new image

$$\frac{1}{9}(a+b+c+d+e+g+h+i)$$

SPATIAL FILTERING

- 1) create a filter (kernel)

```
kernel = np.ones((3,3),np.float32)/9
```

- 2) apply on the image
- Using **filter2D** (2-D digital filter)

```
dst = cv2.filter2D(img,-1,kernel)
```

SPATIAL FILTERING

- **filter2D**

Python:

cv.filter2D(src, ddepth, kernel[, dst[, anchor[, delta[, borderType]]]]) -> dst

`#include <opencv2/imgproc.hpp>`

Convolves an image with the kernel.

The function applies an arbitrary linear filter to an image. In-place operation is supported. When the aperture is partially outside the image, the function interpolates outlier pixel values according to the specified border mode.

The function does actually compute correlation, not the convolution:

$$\texttt{dst}(x,y) = \sum_{\substack{0 \le x' < \texttt{kernel.cols} \\ 0 \le y' < \texttt{kernel.rows}}} \texttt{kernel}(x',y') * \texttt{src}(x+x'-\texttt{anchor.x}, y+y'-\texttt{anchor.y})$$

That is, the kernel is not mirrored around the anchor point. If you need a real convolution, flip the kernel using **flip** and set the new anchor to `(kernel.cols - anchor.x - 1, kernel.rows - anchor.y - 1)`.

The function uses the DFT-based algorithm in case of sufficiently large kernels (~`11 x 11` or larger) and the direct algorithm for small kernels.

Parameters

src	input image.
dst	output image of the same size and the same number of channels as src.
ddepth	desired depth of the destination image, see **combinations**
kernel	convolution kernel (or rather a correlation kernel), a single-channel floating point matrix; if you want to apply different kernels to different channels, split the image into separate color planes using split and process them individually.
anchor	anchor of the kernel that indicates the relative position of a filtered point within the kernel; the anchor should lie within the kernel; default value (-1,-1) means that the anchor is at the kernel center.
delta	optional value added to the filtered pixels before storing them in dst.
borderType	pixel extrapolation method, see **BorderTypes**. **BORDER_WRAP** is not supported.

Enumerator	
BORDER_CONSTANT Python: cv.BORDER_CONSTANT	`iiiiii|abcdefgh|iiiiiii` with some specified `i`
BORDER_REPLICATE Python: cv.BORDER_REPLICATE	`aaaaaa|abcdefgh|hhhhhhh`
BORDER_REFLECT Python: cv.BORDER_REFLECT	`fedcba|abcdefgh|hgfedcb`
BORDER_WRAP Python: cv.BORDER_WRAP	`cdefgh|abcdefgh|abcdefg`
BORDER_REFLECT_101 Python: cv.BORDER_REFLECT_101	`gfedcb|abcdefgh|gfedcba`
BORDER_TRANSPARENT Python: cv.BORDER_TRANSPARENT	`uvwxyz|abcdefgh|ijklmno`
BORDER_REFLECT101 Python: cv.BORDER_REFLECT101	same as BORDER_REFLECT_101
BORDER_DEFAULT Python: cv.BORDER_DEFAULT	same as BORDER_REFLECT_101
BORDER_ISOLATED Python: cv.BORDER_ISOLATED	do not look outside of ROI

SPATIAL FILTERING

```
small_im = np.random.random((5,5))*100
small_im = small_im.astype(np.uint8)

small_im
array([[71, 28, 50, 47, 59],
       [60, 68,  8, 75,  3],
       [50, 23, 87, 41, 77],
       [67, 32, 56, 50,  2],
       [57, 45,  4, 89, 69]], dtype=uint8)

kernel = np.ones((3,3),np.float32)/9
array([[ 0.11111111,  0.11111111,  0.11111111],
       [ 0.11111111,  0.11111111,  0.11111111],
       [ 0.11111111,  0.11111111,  0.11111111]], dtype=float32)

dst_im = cv2.filter2D(small_im,-1,kernel)
array([[58, 47, 47, 36, 51],
       [47, 49, 47, 50, 52],
       [47, 50, 49, 44, 46],
       [42, 47, 47, 53, 56],
       [45, 46, 46, 42, 50]], dtype=uint8)
```

- magic(n) returns an n-by-n matrix constructed from the integers 1 through n^2 with equal row and column sums

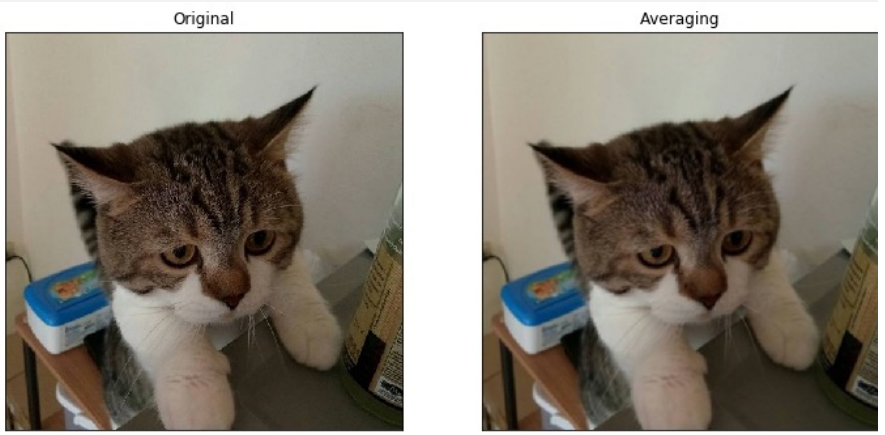
AVERAGING AN IMAGE

```
img = cv2.imread("camaraman.tif")

kernel = np.ones((3,3),np.float32)/9
dst = cv2.filter2D(img,-1,kernel)



plt.subplot(121),plt.imshow(img),plt.title('Original')
plt.xticks([]), plt.yticks([])
plt.subplot(122),plt.imshow(dst),plt.title('Averaging')
plt.xticks([]), plt.yticks([])
plt.show()
```



-What do you see?
-what if you change filter size?

SOBEL FILTER

```
img = cv2.imread("sudoku.jpg",0)
sobelx = cv2.Sobel(img,cv2.CV_8U,1,0,ksize=3)
sobely = cv2.Sobel(img,cv2.CV_8U,0,1,ksize=3)
```

EXERCISE #2 SPATIAL FILTERING

- Create a sharpening filter and apply on ‘cameraman.tif’ image.
- Hint: see 3 x 3 Laplacian filter

EXERCISE #3 CAN YOU ENHANCE THIS IMAGE?

- moon.png

REFERENCES

- Rafael C. Gonzalez and Richard E. Woods, Digital Image Processing, Addison- Wesley
  - Chapter 3, Section 3.3-3.8