

# Computational Approaches for Life Scientists



Faculty of Biology  
Technion  
Spring 2013

## **Digital Image Processing(2)**

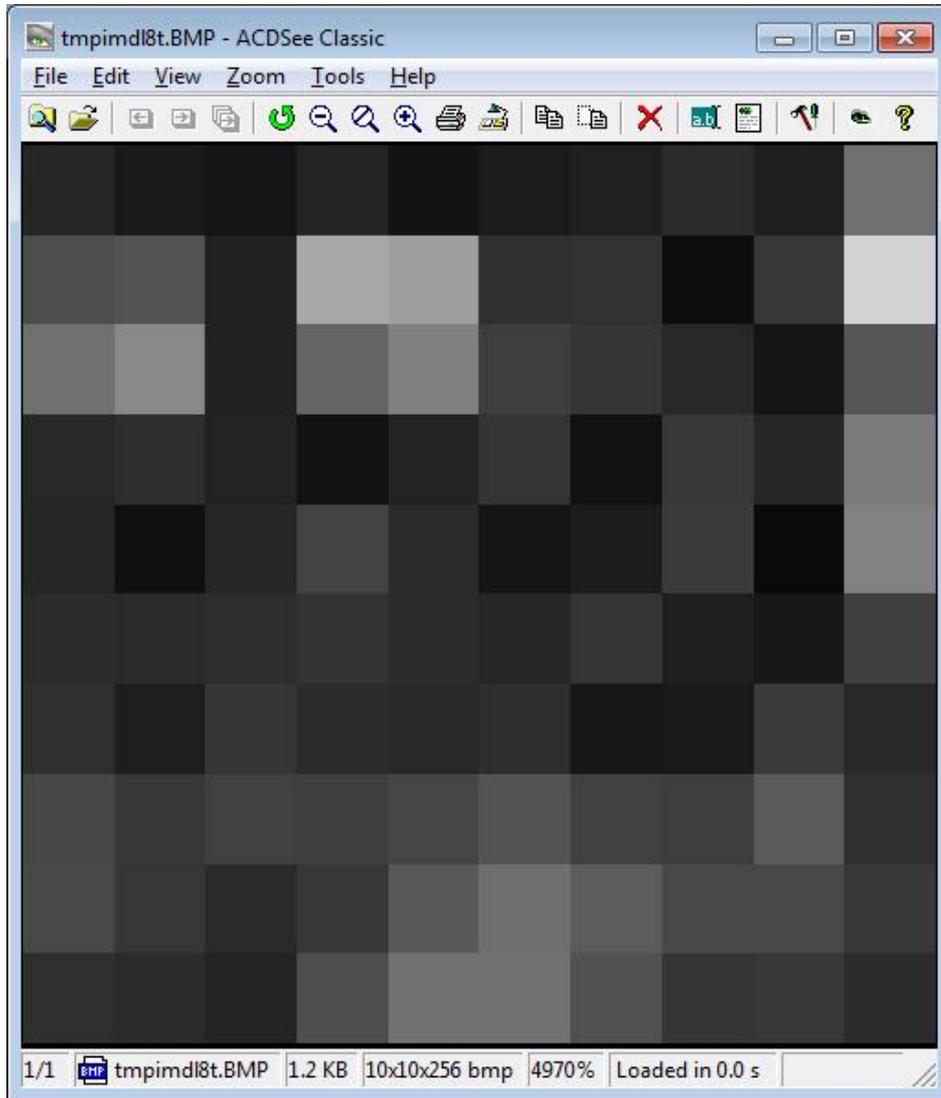
Based on lectures prepared by Benny Chor and Asaf Zaritsky,  
Modified by Amir Rubinstein

# Outline

## Introduction to Digital Images

- **representation**
- **synthetic** images
- simple **operators** on images
  
- **Segmentation by thresholding**
  - Otsu segmentation
  
- Next time (today):
- **Edge Detection**
  - using erosion and dilation
  
- **Noise Reduction (Denoising)**
  - local means and local medians

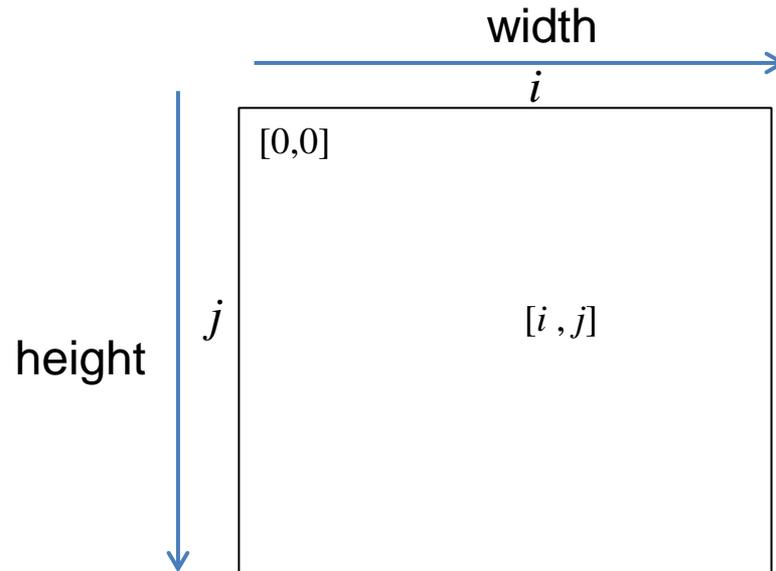
# Reminder – image representation



38, 26, 21, 36, 19, 28, 33, 44, 31, 112,  
77, 83, 34, 168, 159, 48, 50, 14, 55, 211,  
112, 137, 34, 101, 129, 62, 54, 40, 21, 86,  
41, 46, 35, 19, 35, 52, 18, 57, 39, 123,  
38, 16, 38, 67, 45, 21, 29, 59, 10, 130,  
45, 43, 46, 51, 44, 39, 53, 31, 24, 64,  
47, 30, 54, 45, 40, 46, 23, 26, 58, 40,  
71, 57, 66, 63, 70, 84, 65, 62, 91, 49,  
72, 55, 43, 57, 90, 111, 92, 73, 74, 56,  
47, 45, 36, 78, 114, 113, 81, 54, 57, 44

# Reminder - images in Python

- The Python Imaging Library – PIL
  - Read / write images
  - Display image
  - Basic image processing
- download: <http://www.lfd.uci.edu/~gohlke/pythonlibs/#pil>
  - take the version that fits your machine and python version



# Reminder – handling images in Python

```
from PIL import Image

# load image
im = Image.open("./guess.jpg")

# turn a color image to B&W for simplicity
im = im.convert('L')

# get image data
#loads image into matrix
#changes to matrix WILL affect image
im_mat = im.load()
print(im_mat[0,0])
im_mat[0,0] = 255

print(im.size, im.format, im.mode)
```

```
# display
im.show()

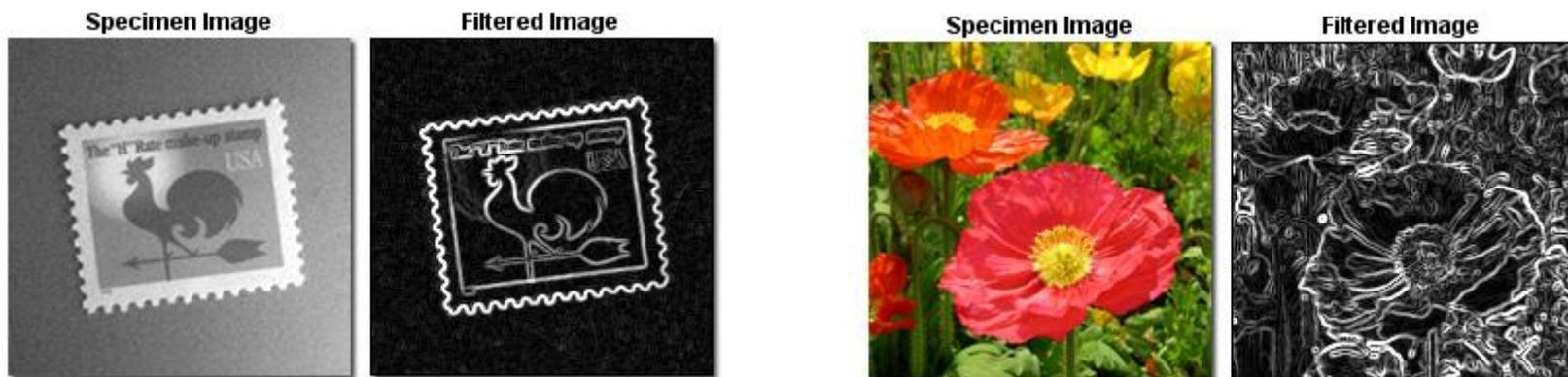
# crop
w, h = im.size
region = im.crop((200,410,210,420))
region.show()

# rotate
rot = im.rotate(45)
rot.show()

#save
im.save("./tmp.bmp", "bmp")
```

# Motivation – Edge Detection

- **Edge** - sharp change in intensity between close pixels
- Usually captures much of the meaningful information in the image

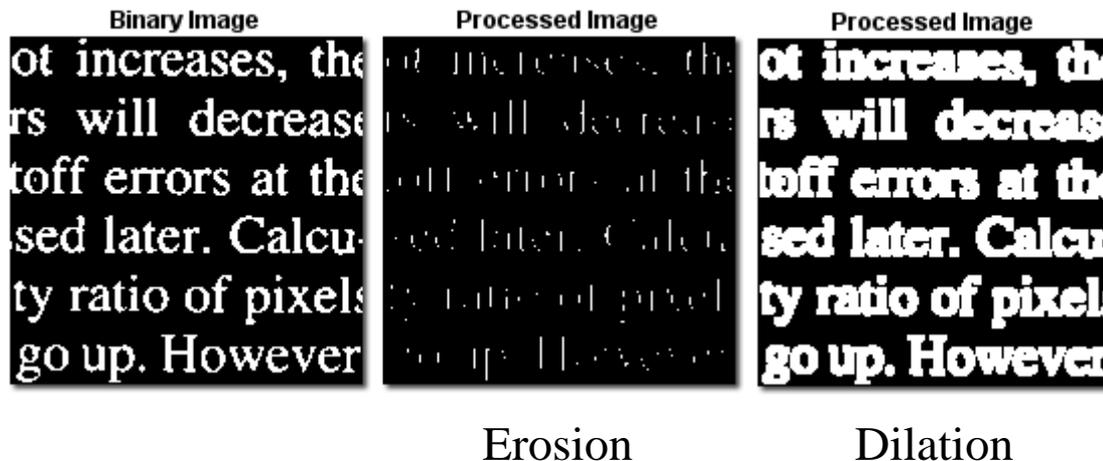


images extracted using Sobel filter from:

<http://micro.magnet.fsu.edu/primer/java/digitalimaging/russ/sobelfilter/index.html>

# Erosion and Dilation

- **Erosion** - the removal of pixels from the periphery of a (white) feature.
- **Dilation** - the adding of pixels to that periphery.



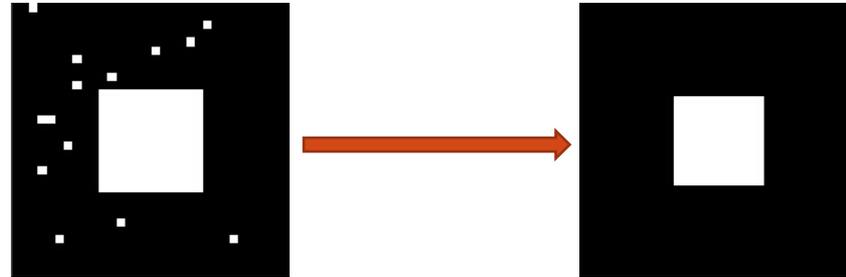
- If we assume **bright** foreground and **dark** background:
  - Erosion shrinks foreground areas, and holes grow.
  - Dilation enlarges foreground areas, and holes shrink.

Images from:

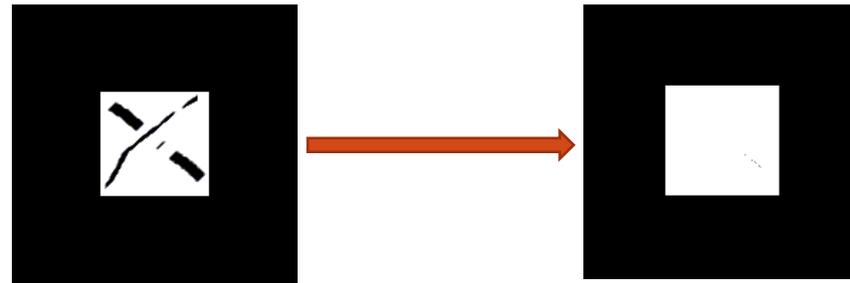
<http://micro.magnet.fsu.edu/primer/java/digitalimaging/russ/erosiondilation/index.html>

# Erosion and Dilation - examples

Erosion



Dilation

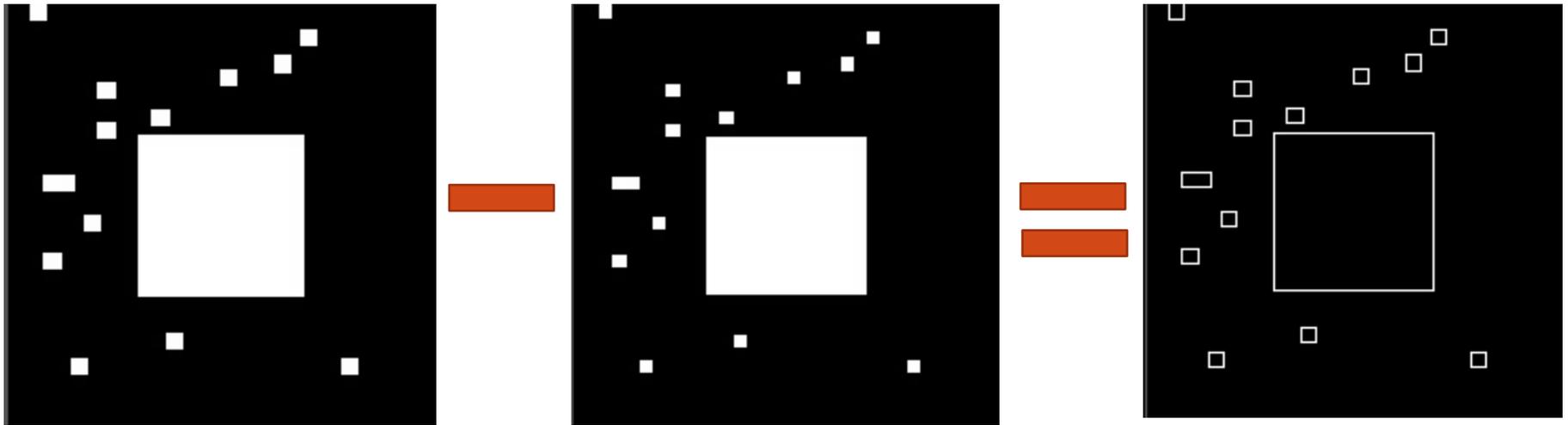


# Dilation for Edge Detection

```
im1 = Image.open('square.bmp')
```

```
im2 = dilation(im, 1, 1)
```

```
edges = diff(im2, im)
```



- Next: - diff  
- erosion/dilation using morphological operators

# Diff - Code

```
# create diff between two images
```

```
def diff(im1, im2):
```

```
    assert im1.size == im2.size
```

```
    out = Image.new('L', im1.size, 'white')
```

```
    out_pix = out.load()
```

```
    mat1 = im1.load()
```

```
    mat2 = im2.load()
```

```
    width, height = im1.size
```

```
    for y in range(height):
```

```
        for x in range(width):
```

```
            out_pix[x, y] = mat1[x, y] - mat2[x, y]
```

```
    return out
```

# Neighborhood

- **Neighborhood/Environment** of the pixel  $[x,y]$ :  
the set of all pixels whose coordinates are **close** to  $[x,y]$ .
- A neighborhood commonly considered is the  $(2k + 1)$ -by- $(2k + 1)$  **square matrix** of coordinates centered at  $[x,y]$
- $k$  is a small integer - typically 1 or 2.

$$N_{3 \times 3}(x, y) = \begin{bmatrix} x - 1, y + 1 & x, y + 1 & x + 1, y + 1 \\ x - 1, y & x, y & x + 1, y \\ x - 1, y - 1 & x, y - 1 & x + 1, y - 1 \end{bmatrix}$$

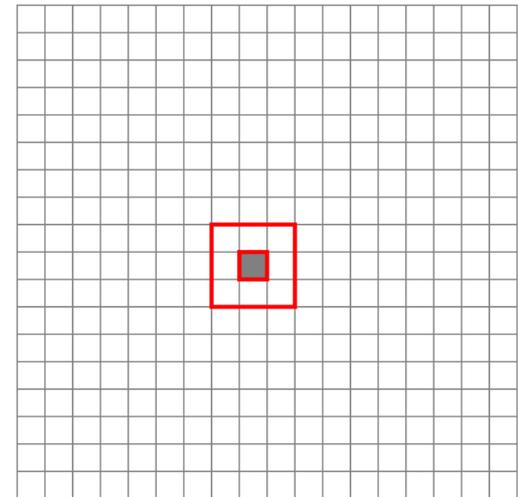
- We may, however, prefer a **non-square** neighborhood in some cases.
  - rectangular
  - circular / elliptical
  - non-symmetric...
- We may also want to assign **different weights** to different neighbors

# Neighbors - Code

Create a pixel's environment:

```
def neighbours(mat, width, height, x, y, nx=1, ny=1):  
    nlst = []  
    for yy in range(max(y-ny, 0), min(y+ny+1, height)):  
        for xx in range(max(x-nx, 0), min(x+nx+1, width)):  
            nlst.append(mat[xx, yy])  
    return nlst
```

- What's the neighborhood in the image boundaries?



# Morphological Operators - Code

Framework:

```
def morphological(im, operator, nx = 1, ny = 1):  
    w, h = im.size  
    out_im = Image.new('L', (width, height), 'white')  
    in_pix = im.load()  
    out_pix = out_im.load()  
  
    for y in range(h):  
        for x in range(w):  
            nlst = neighbours(in_pix, w, h, x, y, nx, ny)  
            out_pix[x, y] = operator(nlst)  
  
    return out_im
```

# Erosion and Dilation - Code

```
def erosion(im, nx = 1, ny = 1):  
    return morphological(im, min, nx, ny)
```

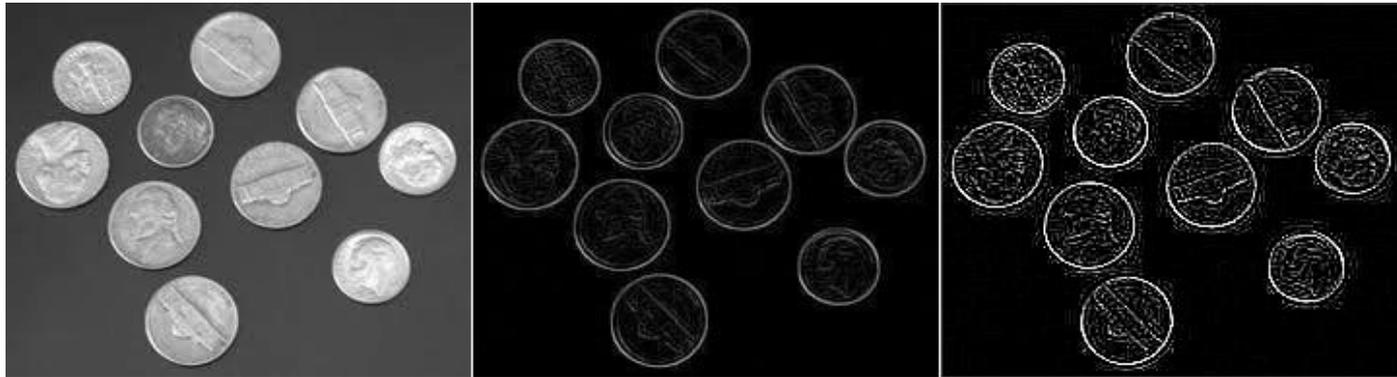
```
def dilation(im, nx = 1, ny = 1):  
    return morphological(im, max, nx, ny)
```

# Runs

original

Diff

PIL's filter



coins.jpg

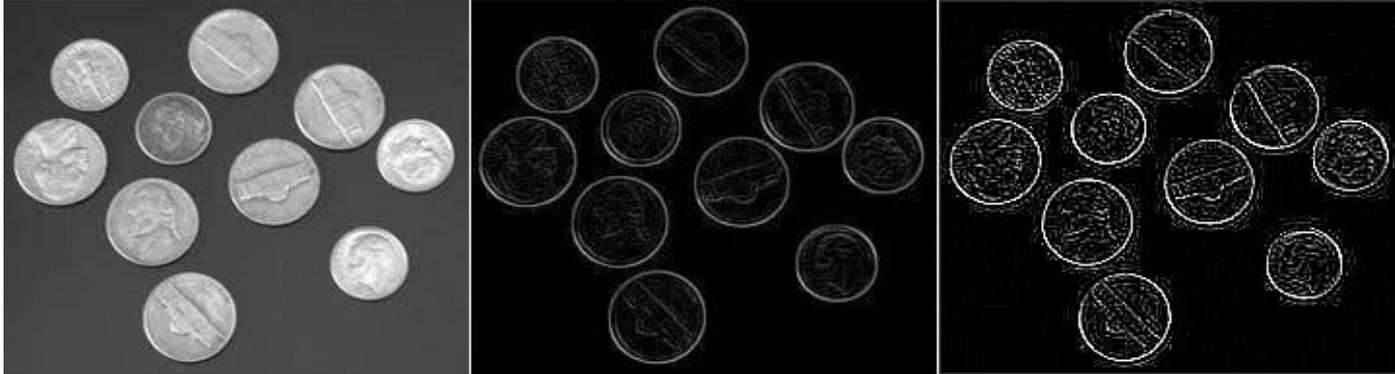
```
from PIL import ImageFilter
```

```
im = Image.open("./coins.jpg")
```

```
new = im.filter(ImageFilter.FIND_EDGES)
```

```
new.show()
```

# Join images for easy display



```
def join(*images):  
    w,h = images[0].size  
    n = len(images) #number of images  
    new = Image.new('L',(w*n+n,h), 'white')  
  
    for i in range(len(images)):  
        new.paste(images[i], (w*i+i,0))  
  
    return new
```

```
from PIL import ImageFilter  
  
im = Image.open("./coins.jpg")  
im = im.convert('L')  
out_im = diff(dilation(im,1,1),im)  
out_im2 = im.filter(ImageFilter.FIND_EDGES)  
join(im,out_im, out_im2).show()
```

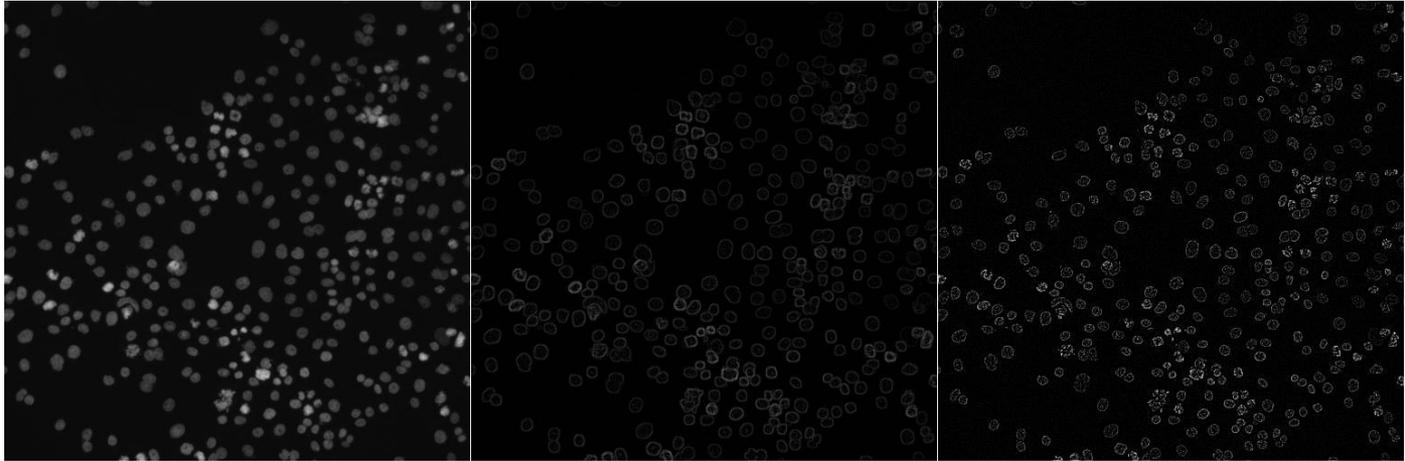
# Runs (2)

original

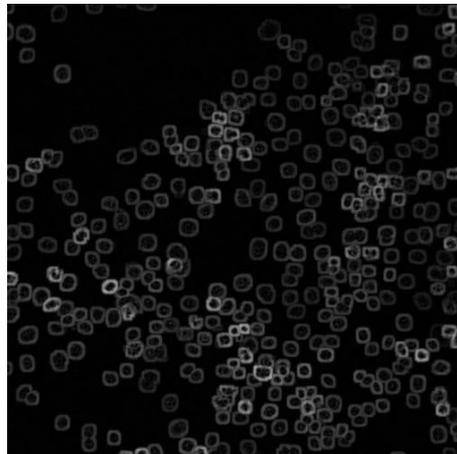
Diff (3X3)

PIL's filter

T29 human  
cancer



Diff (7X7)



# Noise and Denoising

# Noise and Denoising

The **observed value** at pixel  $x, y$ ,  $S(x, y)$ , equals the sum of the true value  $I(x, y)$  plus **noise**  $N(x, y)$ .

$$S(x, y) = I(x, y) + N(x, y) .$$

The goal of **denoising** algorithms is, given the observed image  $S(x, y)$  ( $0 \leq x < k$ ,  $0 \leq y < \ell$ ) to produce a new image,  $\hat{I}(x, y)$ , which should be close to the original image  $I(x, y)$  ( $0 \leq x < k$ ,  $0 \leq y < \ell$ ).

Obviously such goal is **not well defined**, and thus cannot be solved, if there are no constraints on the image and on the noise.

**Image model:** We assume the **image** is **piecewise smooth**: Most of the image's area consists of large, smooth regions where light intensity varies continuously – if  $x_1, y_1$  and  $x_2, y_2$  are neighbors, then  $I(x_1, y_1)$  and  $I(x_2, y_2)$  attain close enough values.

# Gaussian Noise Model

Gaussian noise model: The noise at pixel  $x, y$ ,  $N(x, y)$ , is a random variable. It is usually assumed that  $N(x, y)$  is “white noise”, distributed independently of the noise at other pixels.

```
def add_gauss(im, sigma=20):
```

```
    """ Generates Gaussian noise with mean 0 and SD sigma.
```

```
        Adds indep. noise to pixel, keeping values in 0..255"""
```

```
    out_im = im.copy()
```

```
    in_pix = im.load()
```

```
    out_pix = out_im.load()
```

```
    w,h = im.size
```

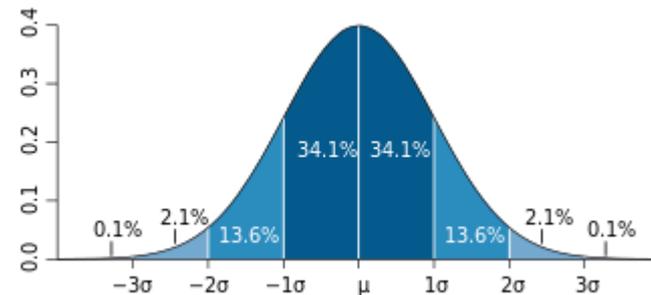
```
    for y in range(h):
```

```
        for x in range(w):
```

```
            noise = round(random.gauss(0,sigma))
```

```
            out_pix[x, y] = min(max(in_pix[x, y] + noise, 0), 255)
```

```
    return out_im
```

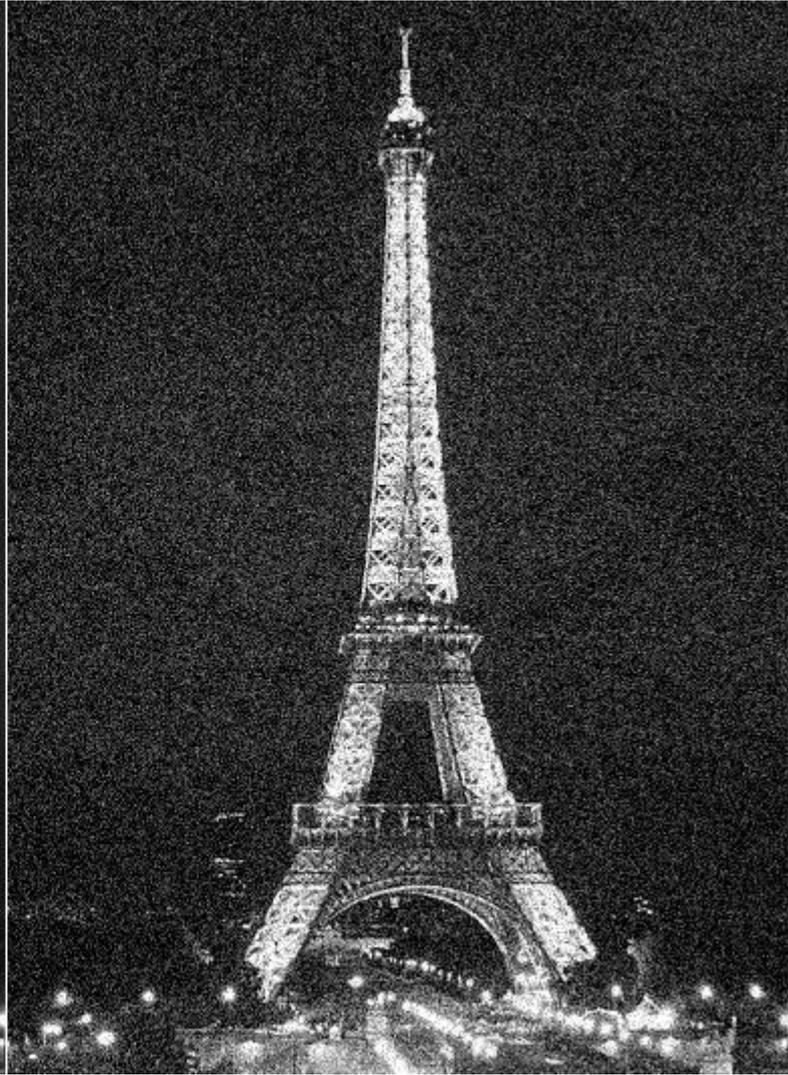


The function `random.gauss(mu, sigma)` returns a floating point number of Gaussian distribution with expected value  $\mu$  and standard deviation  $\sigma$

# Gaussian Noise example



original



`add_gauss(im, 30)`

# Salt and Pepper Noise Model

A different type of noise is the so called **salt and pepper** noise – extreme grey levels (white and black), or **bursts**, appearing at random and independently in a small number of pixels.

```
def add_SP(im, p=0.01):
```

```
    out_im = im.copy()
```

```
    in_pix = im.load()
```

```
    out_pix = out_im.load()
```

```
    w,h = im.size
```

```
    for y in range(h):
```

```
        for x in range(w):
```

```
            rand = random.random()
```

```
            if rand < p:
```

```
                if rand < p/2:
```

```
                    out_pix[x, y] = 0
```

```
                else:
```

```
                    out_pix[x, y] = 255
```

} 50:50 chance for black or white

```
    return out_im
```

# Salt and Pepper Noise example



original

`add_gauss(im, 30)`

`add_SP(im, 0.05)`

# Denoising algorithms

- We will discuss two approaches to denoising:
  1. Local **Means**
  2. Local **Medians**
- Of course, these are only the **tip of the iceberg**.

# Local Means

- Replace pixel at [x,y] by the **average** (mean) of its **neighborhood**.

```
def mean(lst):  
    return sum(lst)//len(lst)  
  
def denoise_mean(im, nx = 1, ny = 1):  
    return morphological(im, mean, nx, ny)
```

9, 0, 0, 5	→	2, 1, 0, 1
0, 0, 0, 0		1, 1, 1, 1
0, 0, 5, 0		0, 0, 0, 0
0, 0, 0, 0		0, 0, 0, 1

- if image is piecewise smooth → small change → **preserves** original signal
- average SD reduces to  $\sigma/(2k+1)$  → noise is **reduced**

→ good for Gaussian noise

# Weighted Local Means

Uniform averaging based on the whole neighborhood, as discussed before, can be expressed as the **matrix dot product**

$$\begin{pmatrix} S[x-1, y+1] & S[x, y+1] & S[x+1, y+1] \\ S[x-1, y] & S[x, y] & S[x+1, y] \\ S[x-1, y-1] & S[x, y-1] & S[x+1, y-1] \end{pmatrix} \begin{pmatrix} 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \end{pmatrix}$$

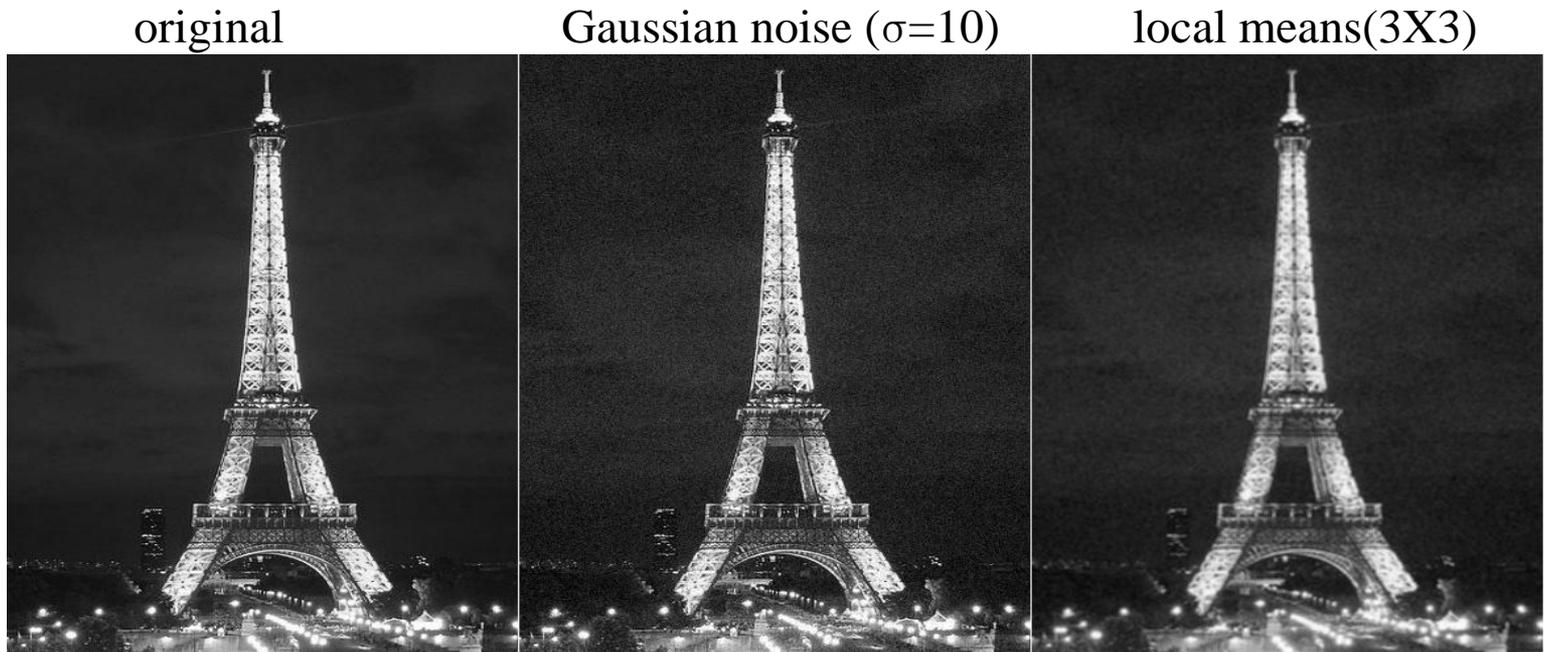
A common variant puts more weight close to the central pixel. For example, in our case of the 3-by-3 neighborhood, replacing the  $1/9$  matrix by

$$\begin{pmatrix} 1/12 & 1/12 & 1/12 \\ 1/12 & 1/3 & 1/12 \\ 1/12 & 1/12 & 1/12 \end{pmatrix}.$$

We point out that while this maintains more of the original signal, the noise reduction here is smaller.

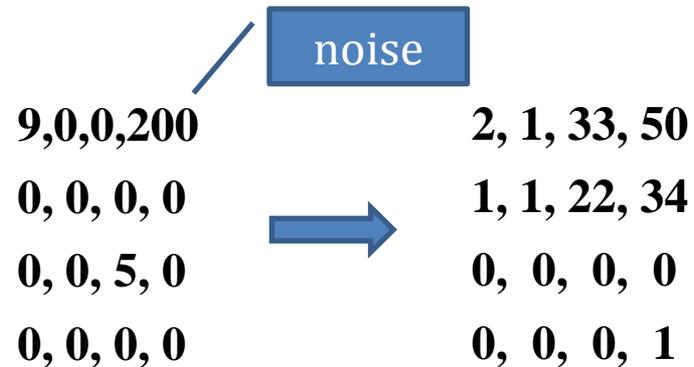
# Local Means - limitations

- Does **not** perform well on areas **not piecewise smooth** (edges !)



- sensitive to extreme outliers:

→ bad for Salt and pepper noise



# Local Medians

- Replace pixel at [x,y] by the **median** of its **neighborhood**.

```
def median(lst):  
    lst.sort()  
    return lst[len(lst)//2]  
  
def denoise_median(im, nx = 1, ny = 1):  
    return morphological(im, median, nx, ny)
```

9,0,0,200	→	0, 0, 0, 0
0, 0, 0, 0		0, 0, 0, 0
0, 0, 5, 0		0, 0, 0, 0
0, 0, 0, 0		0, 0, 0, 0

- advantages:
  - preserves edges
  - not sensitive to extreme outliers → good for S&P noise
- disadvantages:
  - eliminate small, fine features
  - slower than local means (median calculation takes more time than average)

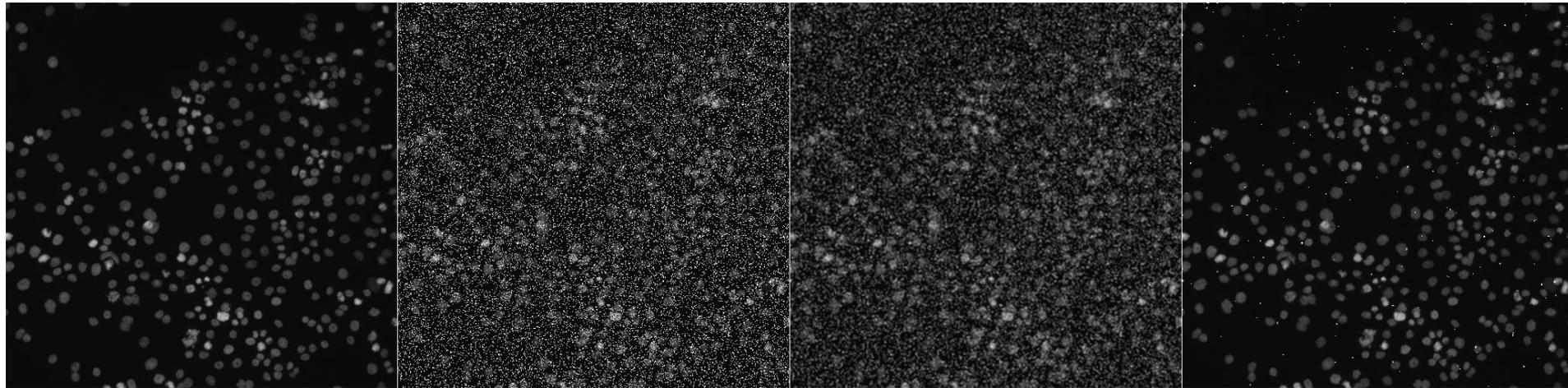
# Local Medians examples

original

20% S&P

local means

local medians



# A glance to Non-Local approaches

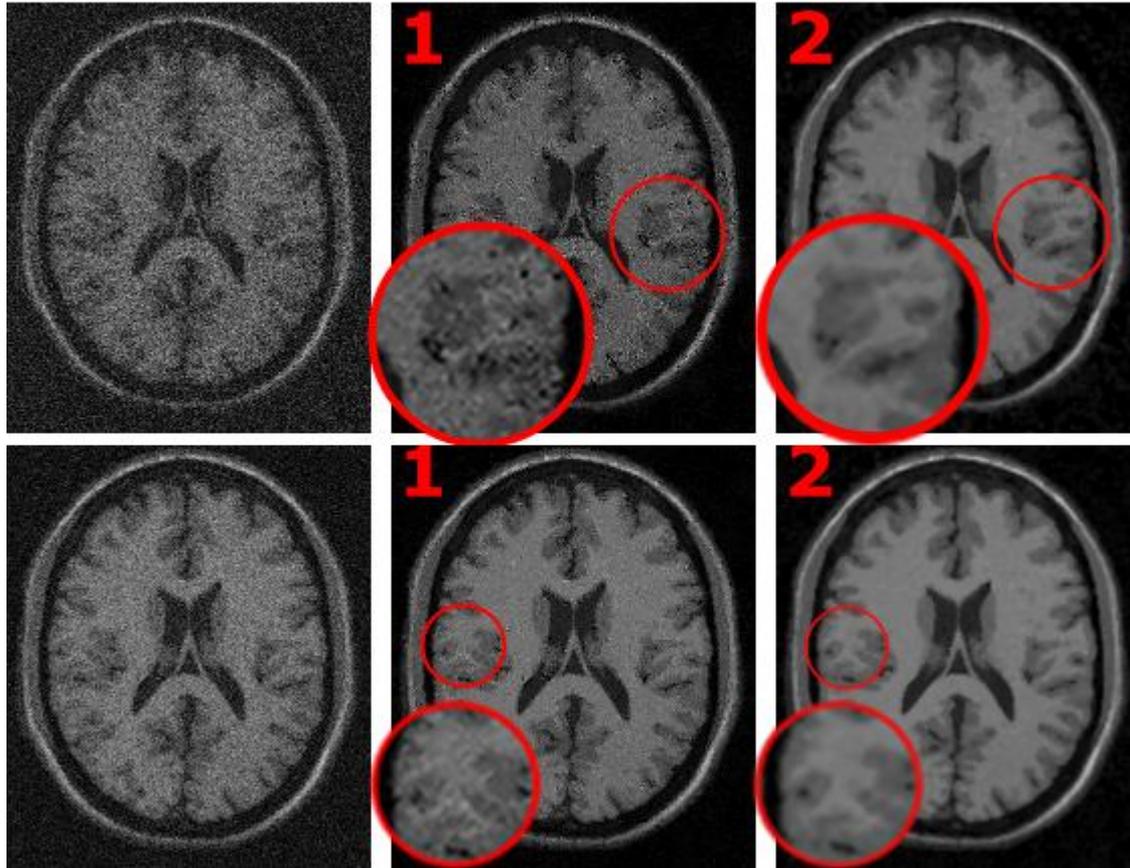
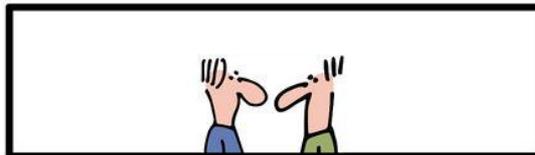
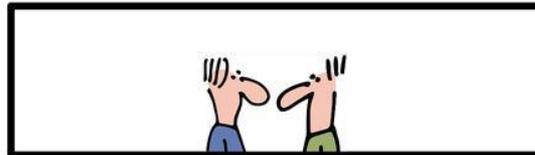
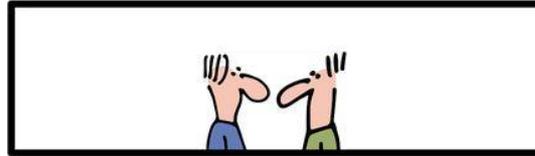


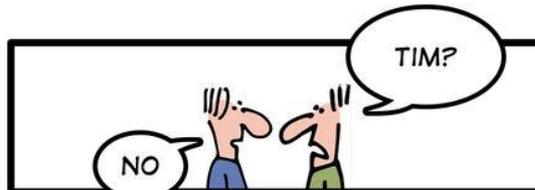
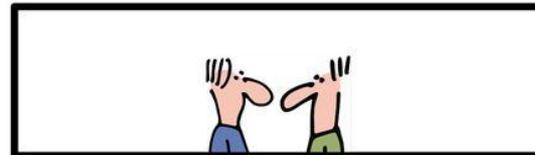
image from:

[http://www.nitrc.org/project/list\\_screenshots.php?group\\_id=518&screenshot\\_id=400](http://www.nitrc.org/project/list_screenshots.php?group_id=518&screenshot_id=400)

*SIMPLY EXPLAINED:  
FACIAL RECOGNITION*



geek & poke



*THANK GOD WE HAVE FACEBOOK*

# Exercises

1. Here's an image with a spot of size 4X4 somewhere.  
Which method would you use to denoise it, with what neighborhood size (the parameter  $k$ )?

Check your answer by experiments:

- First download the image (eifel.jpg).
- Create a 4X4 white spot on a dark part of it, as shown:
- try denoising with local means/medians, and with several neighborhood sizes



2. Iterated denosing:  
Instead of using larger  $k$ 's, try using  $k=1$  several times to clean the spot from Q1.

Draw your conclusions.