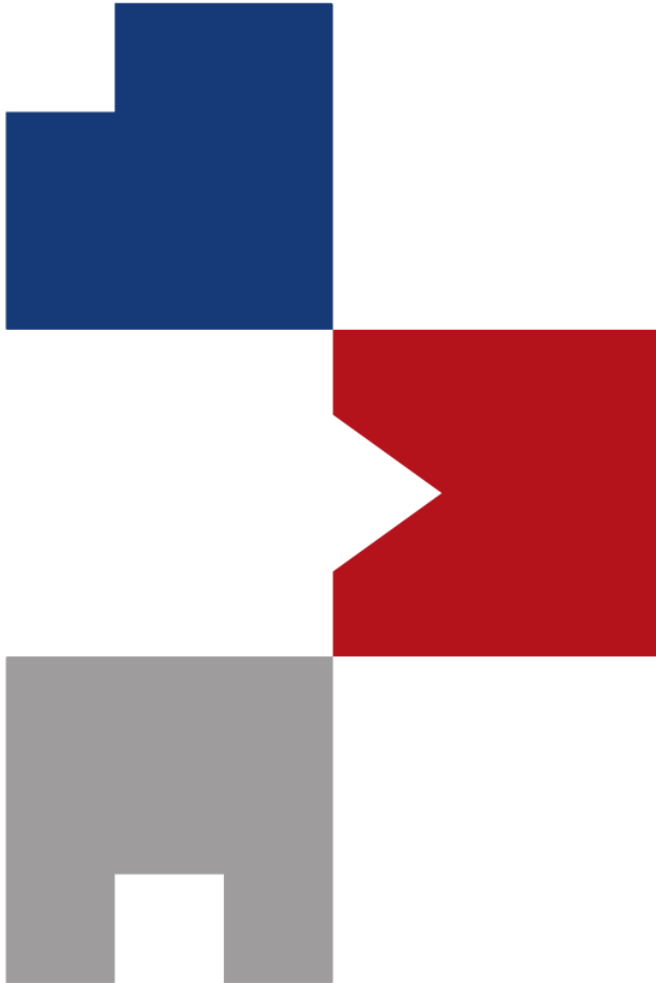


Image Processing



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(Digital) Image Processing

- Digital image processing is a process to analyze, modify, and synthesize digital images using a digital computer through an algorithm.
 - A subfield of digital signal processing

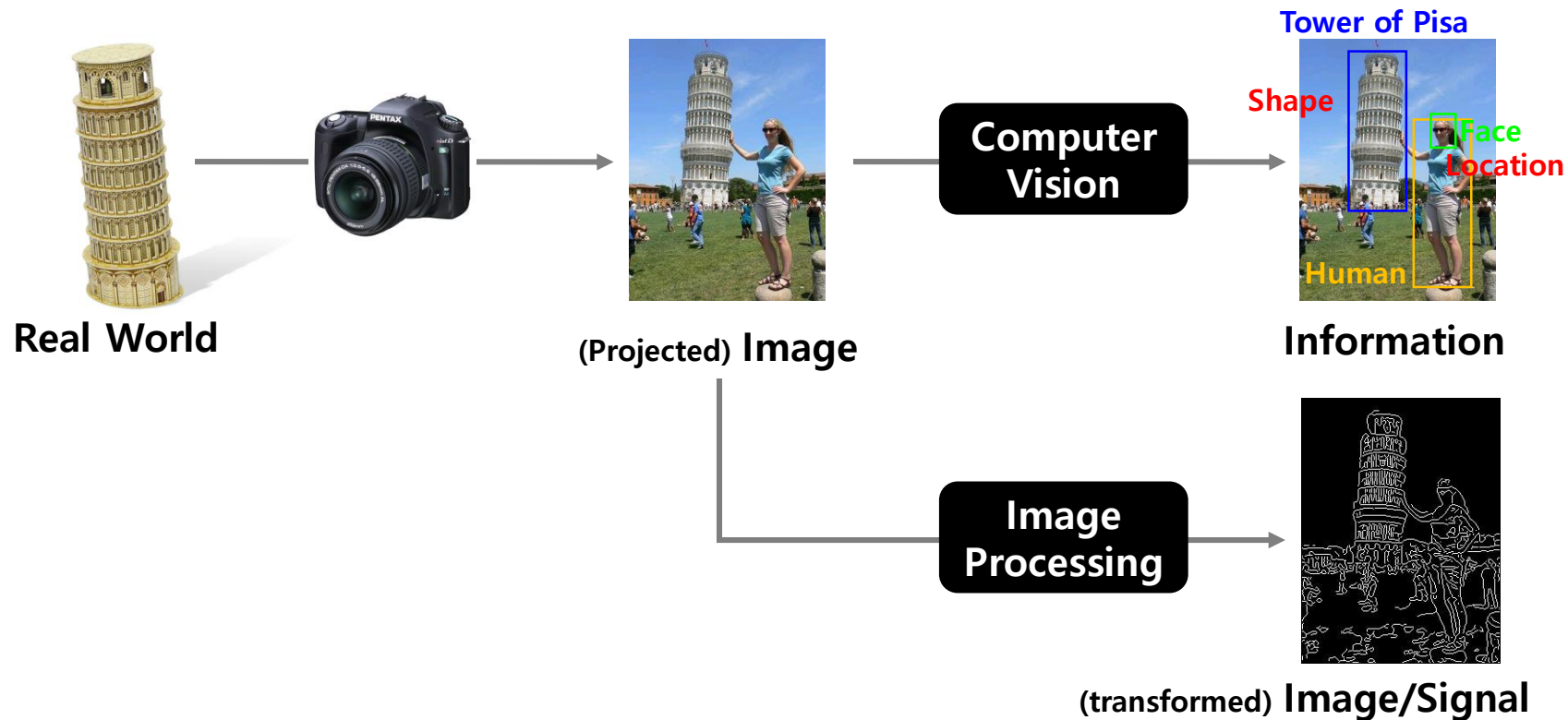


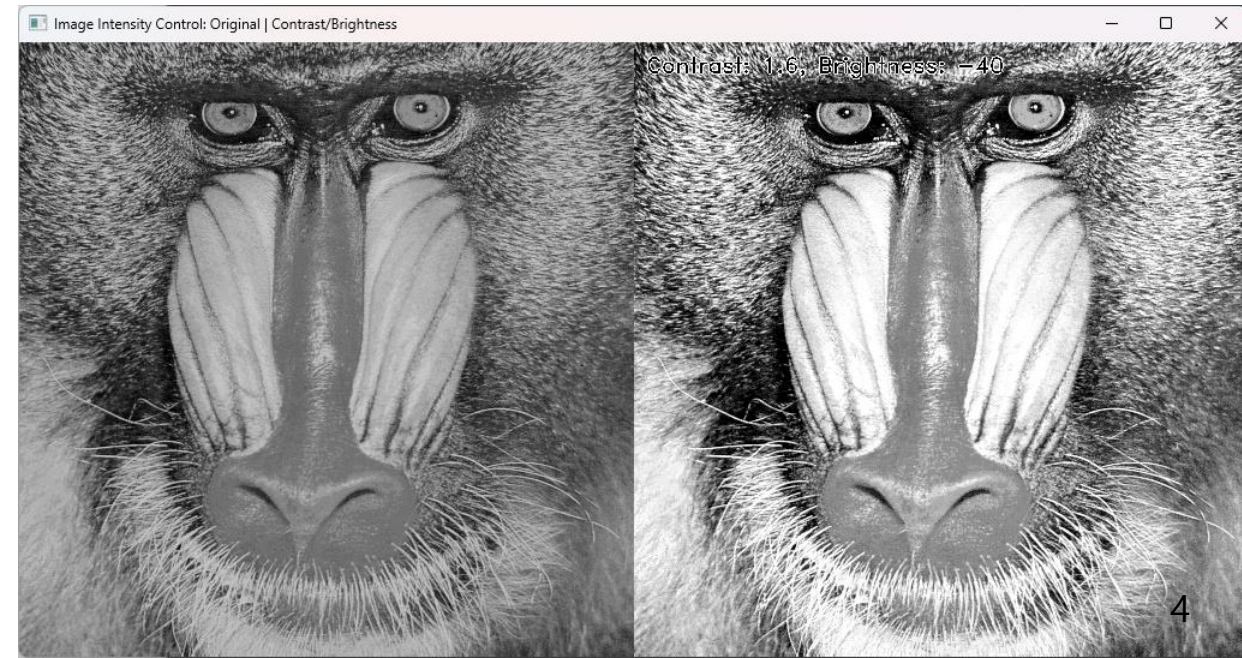
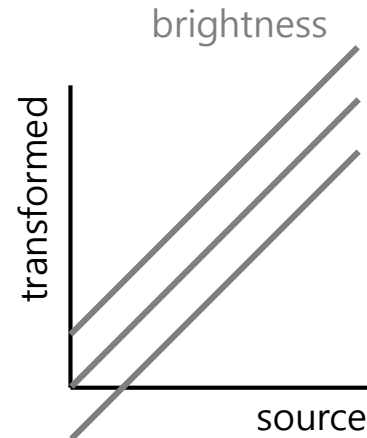
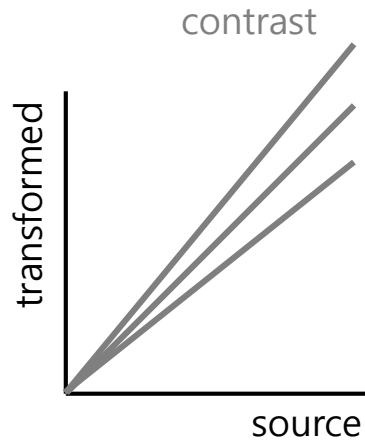
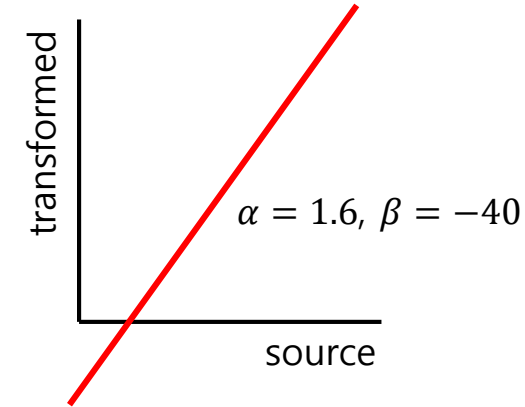
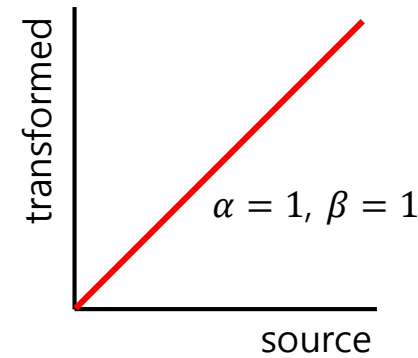
Table of Contents

- Digital Image Processing
- **Intensity Transformation**
 - Contrast Stretching
 - Histogram Equalization
- **Thresholding**
- **Image Filtering**
 - Smoothing
 - Edge Detection
 - Sharpening
- **Morphological Operations**
 - Erosion and Dilation
 - Opening and Closing

Review) Image Editing: Intensity Transformation

- Example) Intensity Transformation with contrast and brightness
 - Contrast* is the property that makes an object (or its representation in an image or display) distinguishable.
 - Brightness* is the strength of overall luminance.

- A simple formulation: $I' = \alpha I + \beta$
 - α : contrast (slope)
 - β : brightness (Y intercept)



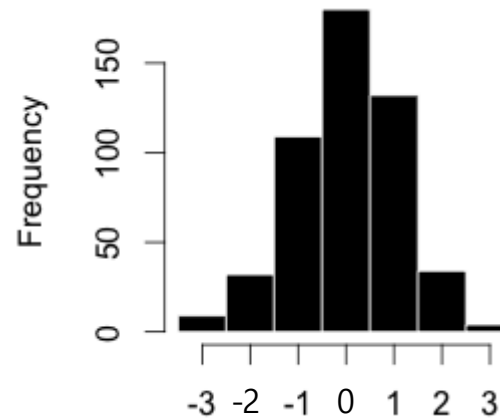
Histogram

- A [histogram](#) is an approximate graphical representation of the distribution of numerical data.
 - ~ Probability distribution
 - Note) The bin width (and data range) is important. → The number of bins
- Example) 500 items (1.27, 0.50, 0.12, 3.29, -1.18, ...)

Frequency table

Bin/Interval	Count/Frequency
-3.5 to -2.51	9
-2.5 to -1.51	32
-1.5 to -0.51	109
-0.5 to 0.49	180
0.5 to 1.49	132
1.5 to 2.49	34
2.5 to 3.49	4

Histogram



Histogram

- Example) Image histogram

```
def get_histogram(gray_img): # Alternative) cv.calcHist()  
    # Assume a gray input image  
    # Fix the bin range [0, 256) and bin size 256  
    hist = np.zeros((256), dtype=np.uint32)  
    for val in range(0, 256):  
        hist[val] = sum(sum(gray_img == val)) # Count the occurrence in 2D  
    return hist
```

```
def conv_hist2img(hist):  
    img = np.full((256, 256), 255, dtype=np.uint8)  
    max_freq = max(hist)  
    for val in range(len(hist)):  
        normalized_freq = int(hist[val] / max_freq * 255)  
        img[0:normalized_freq, val] = 0 # Mark as black  
    return img[::-1,:]
```

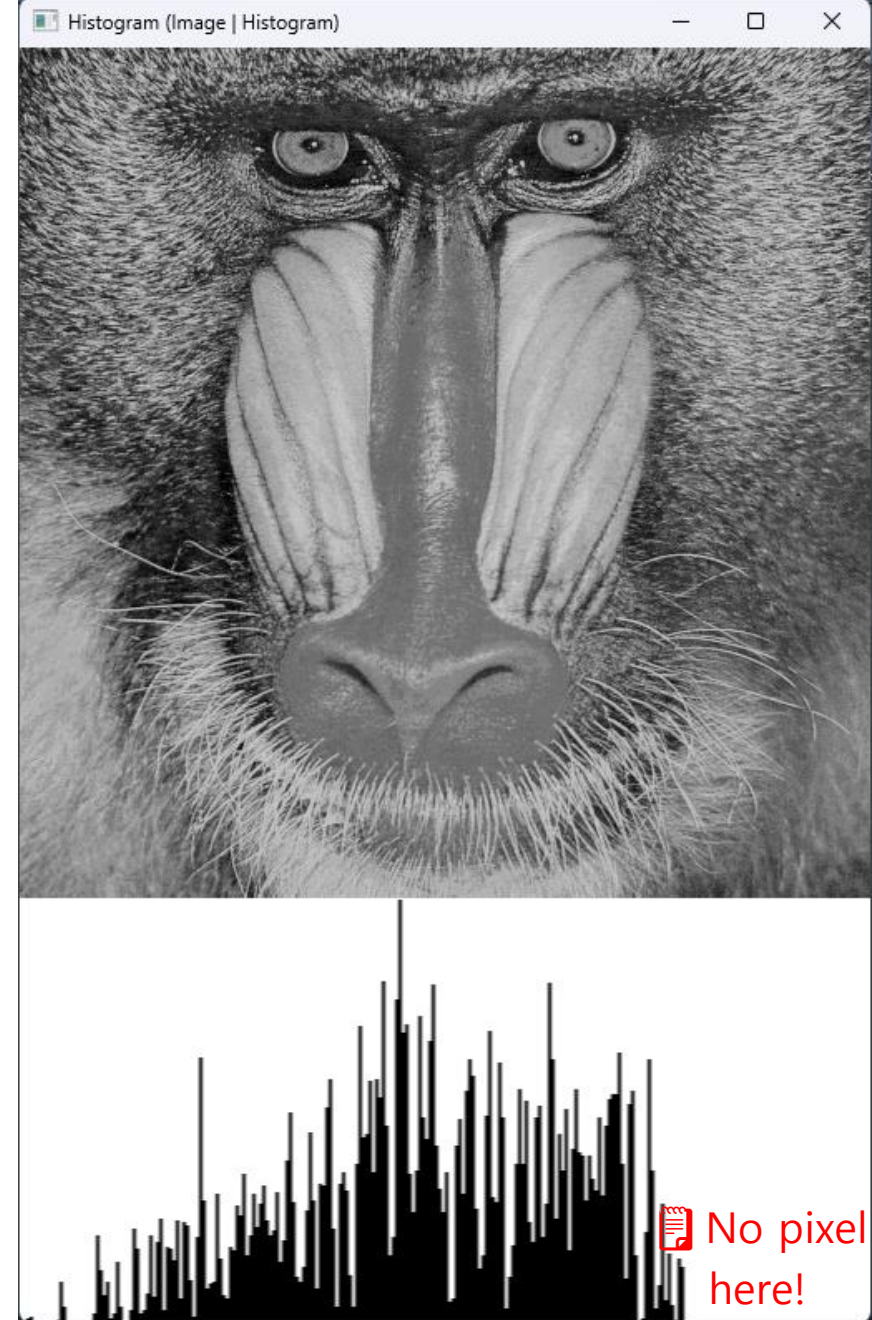
```
if __name__ == '__main__':  
    # Read the given image as gray scale  
    img = cv.imread('data/baboon.tif', cv.IMREAD_GRAYSCALE)
```

```
    # Get its histogram  
    hist = get_histogram(img)
```

```
    # Show the image and its histogram
```

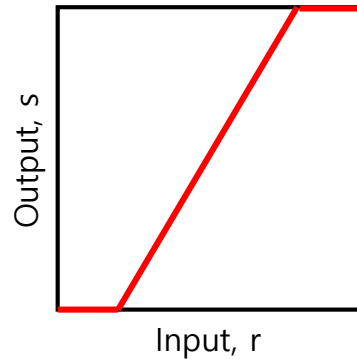
```
    img_hist = conv_hist2img(hist)
```

```
    img_hist = cv.resize(img_hist, (len(img[0]), len(img_hist))) # Note) Be careful at (width, height)
```

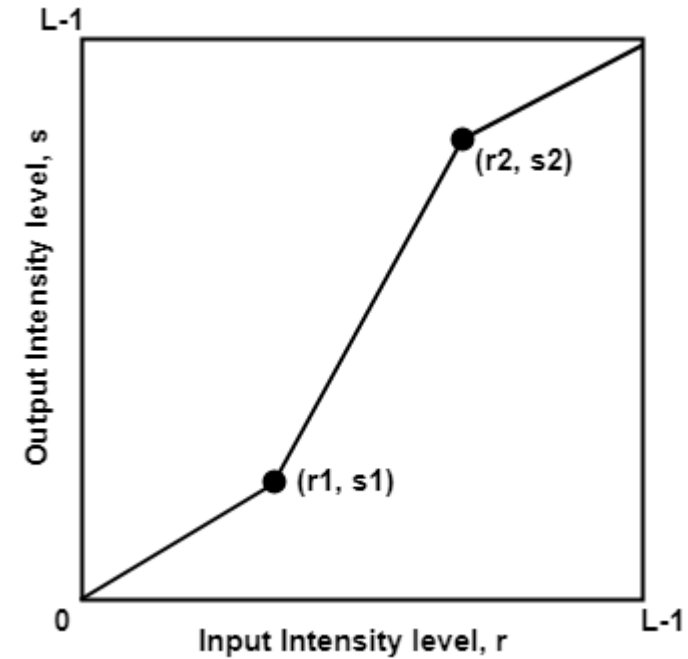
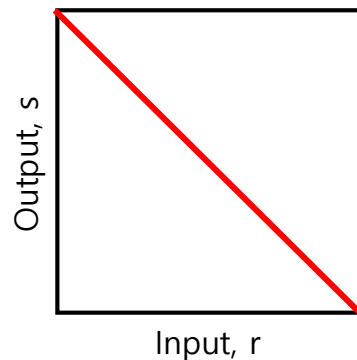


Intensity Transformation: Contrast Stretching

- [Contrast stretching](#) is a process to change the range of pixel intensity values.
- Note) Linear stretching API in OpenCV Intensity Transformation module,
 - `cv.intensity_transform.contrastStretching(input, output, r1, s1, r2, s2) → None`
 - $(r1, s1)$ and $(r2, s2)$: Two control points
 - e.g. Min-max stretching: $s1=0$ and $s2=255$



- e.g. Negative imaging: $(0, 255), (255, 0)$



Intensity Transformation: Contrast Stretching

- Example) Contrast stretching with min-max stretching

```
# Read the given image as gray scale
img = cv.imread('data/baboon.tif', cv.IMREAD_GRAYSCALE)
```

```
# Initialize control parameters
value_range = [20, 200] # [lower limit, upper limit]
```

```
while True:
```

```
    # Apply contrast and brightness
```

```
    # Alternative) cv.intensity_transform.contrastStretching() (with s1=0 and s2=255)
```

```
    img_tran = 255 / (value_range[1] - value_range[0]) * (img.astype(np.int32) - value_range[0])
```

```
    img_tran = img_tran.astype(np.uint8) # Apply saturation
```

```
    # Get image histograms
```

```
    hist = conv_hist2img(get_histogram(img))
```

```
    hist_tran = conv_hist2img(get_histogram(img_tran))
```

```
    # Mark the intensity range, 'value_range'
```

```
    if value_range[0] >= 0 and value_range[0] <= 255:
```

```
        mark = hist[:, value_range[0]] == 255
```

```
        hist[mark, value_range[0]] = 200
```

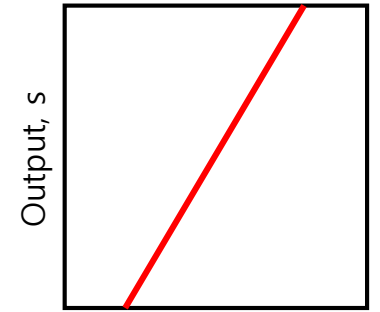
```
    if value_range[1] >= 0 and value_range[1] <= 255:
```

```
        mark = hist[:, value_range[1]] == 255
```

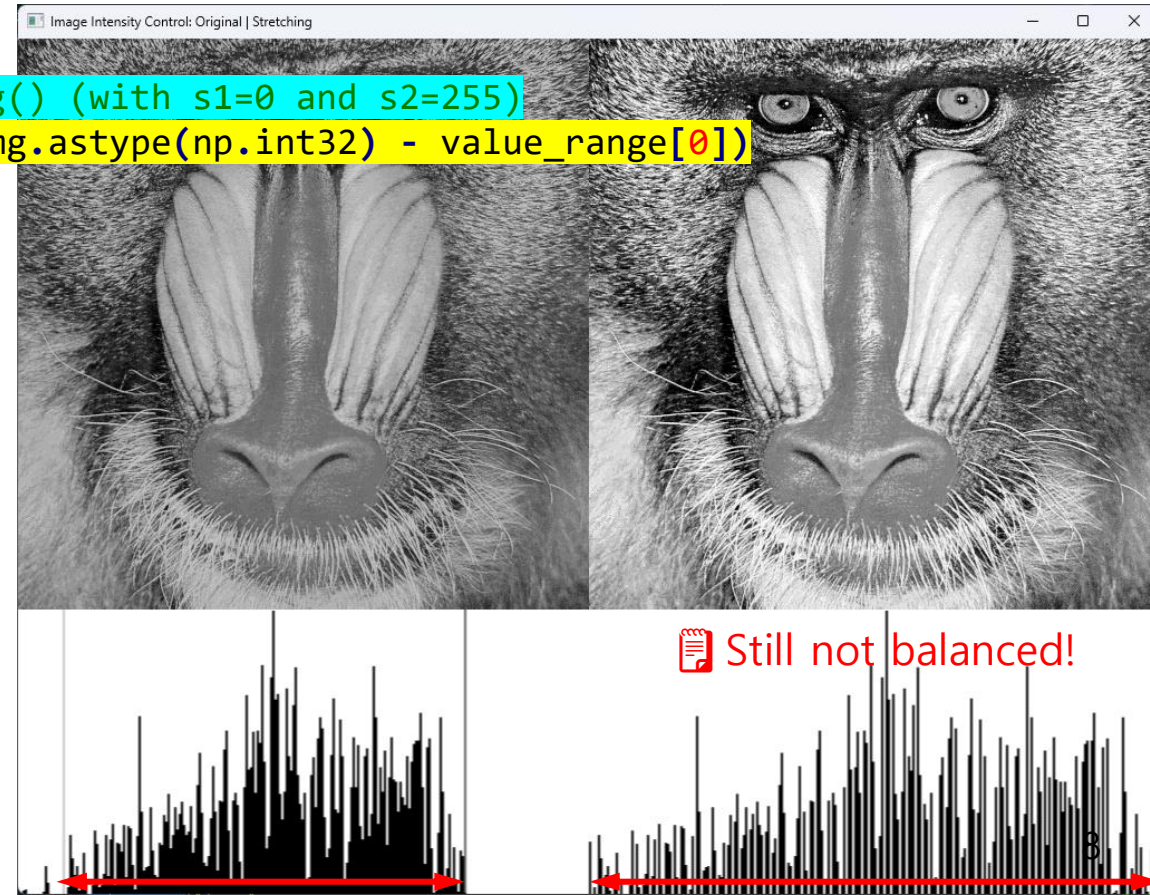
```
        hist[mark, value_range[1]] = 100
```

```
    ...
```

(value_range[1], 255)

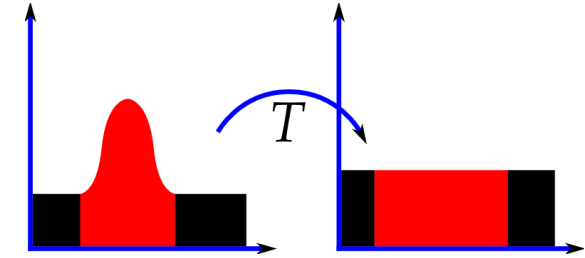
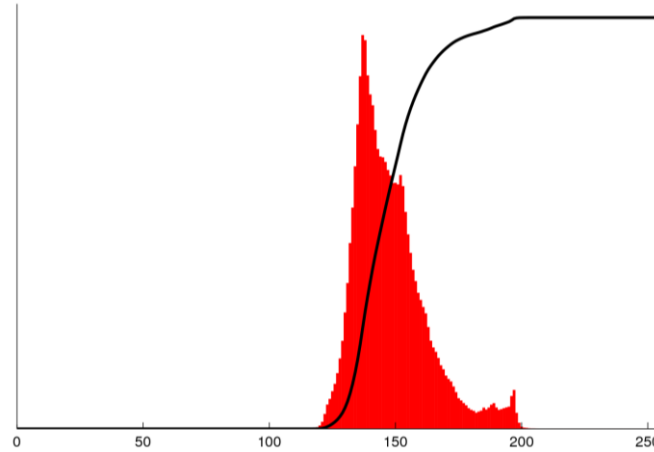


(value_range[0], 0)



Intensity Transformation: Histogram Equalization

- [Histogram equalization](#) is a contrast adjustment method to make intensity values distributed uniformly.
- Note) Histogram equalization API in OpenCV
 - `cv.equalizeHist(src[, dst]) → dst`
- Example) **Histogram** and **cumulative histogram (cdf)**



Mission) Make the **cdf** linear.

Key idea) Use the **cdf** as the transformation function.

Intensity Transformation: Histogram Equalization

- Example) Histogram equalization

```
import matplotlib.pyplot as plt
import cv2 as cv

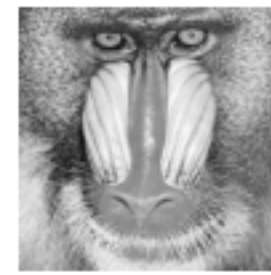
# Read the given image as gray scale
img = cv.imread('data/baboon.tif', cv.IMREAD_GRAYSCALE)

# Apply histogram equalization
img_tran = cv.equalizeHist(img)

# Derive the histogram
bin_width = 4 # Note) The value should be the power of 2.
bin_num = int(256 / bin_width)
hist = cv.calcHist([img], [0], None, [bin_num], [0, 255])
hist_tran = cv.calcHist([img_tran], [0], None, [bin_num], [0, 255])

# Show all images and their histograms
plt.subplot(2, 2, 1)
plt.imshow(img, cmap='gray')
plt.axis('off')
plt.subplot(2, 2, 2)
plt.plot(range(0, 256, bin_width), hist / 1000)
plt.xlabel('Intensity [0, 255]')
plt.ylabel('Frequency (1k)')
plt.subplot(2, 2, 3)
plt.imshow(img_tran, cmap='gray')
plt.axis('off')
```

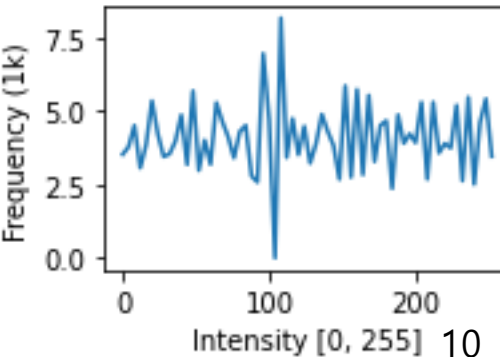
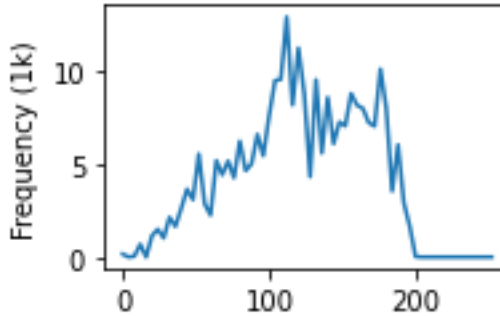
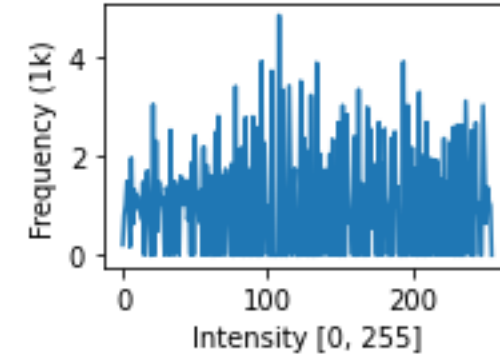
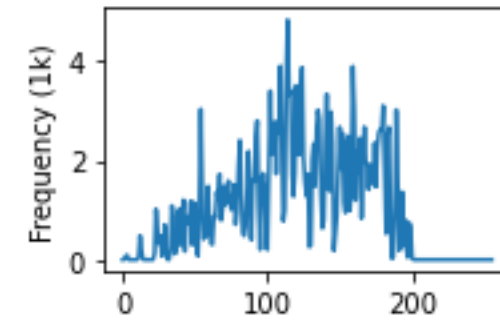
📄 Larger **bin_width** reveals uniform distribution.



bin_width = 1



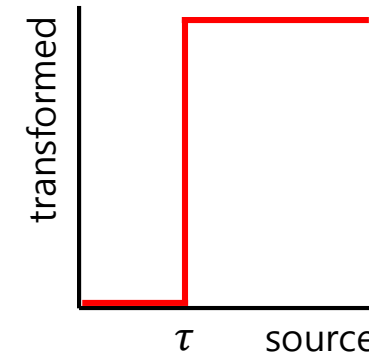
bin_width = 4



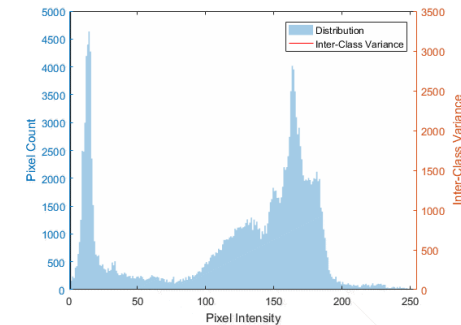
Thresholding

- **Thresholding**: The simplest method of segmenting images (with the given threshold value)

– e.g. $I'(x, y) = \begin{cases} 1 & \text{if } I(x, y) > \tau \\ 0 & \text{otherwise} \end{cases}$ will generate a [binary image](#) I' .



- Application: Specifying a region-of-interest (ROI)
- Issue) How to select the threshold value?
 - User-defined vs. automatic (e.g. [Otsu's method](#))
 - Global thresholding vs. local thresholding (a.k.a. adaptive thresholding)
 - Global thresholding with a fixed threshold
 - Local thresholding with a locally adjustable threshold w.r.t. the local image region

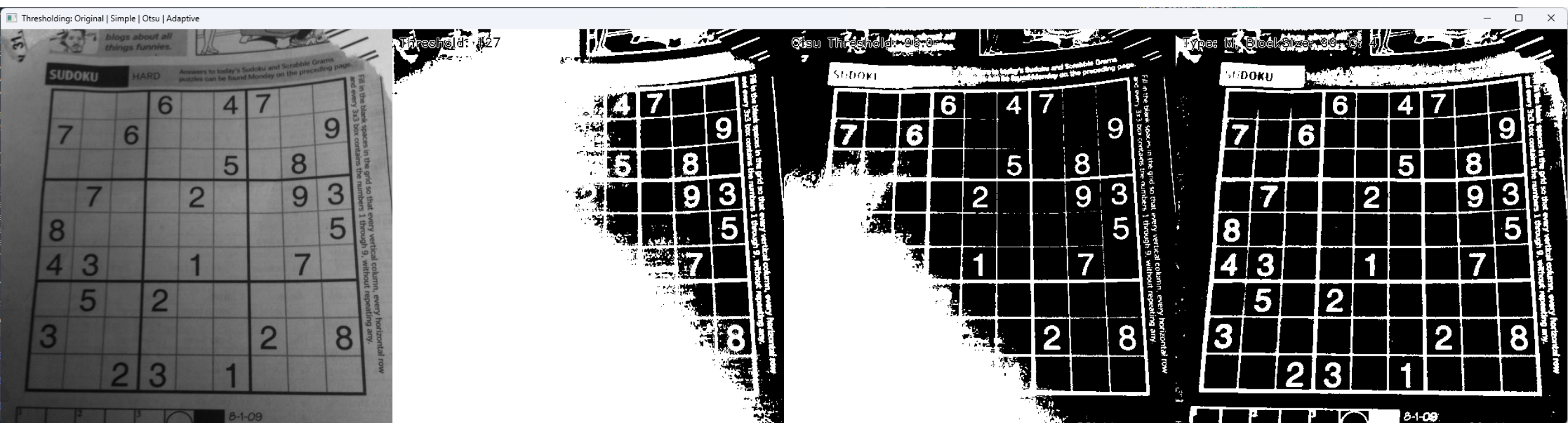


[Otsu's method](#)

minimizing intra-class variance
~ maximizing **inter-class variance**

Thresholding

- Example) Thresholding: **Original** | **User threshold** | **Otsu's method** | **Adaptive**



Thresholding

- Example) Thresholding

```
# Read the given image as gray scale
img = cv.imread('data/sudoku.png', cv.IMREAD_GRAYSCALE)
img_threshold_type = cv.THRESH_BINARY_INV # Type: Detect pixels close to 'black' (inverse)
```

```
# Initialize control parameters
threshold = 127
adaptive_type = cv.ADAPTIVE_THRESH_MEAN_C
adaptive_blocksize = 99
adaptive_C = 4
```

```
while True:
```

```
    # Apply thresholding to the image
    _, binary_user = cv.threshold(img, threshold, 255, img_threshold_type)
    threshold_otsu, binary_otsu = cv.threshold(img, threshold, 255, img_threshold_type | cv.THRESH_OTSU)
    binary_adaptive = cv.adaptiveThreshold(img, 255, adaptive_type, img_threshold_type, adaptive_blocksize, adaptive
```

```
    # Show the image and its thresholded result
```

```
    ...
```

```
    merge = np.vstack((np.hstack((img, binary_user)),
                        np.hstack((binary_otsu, binary_adaptive))))
    cv.imshow('Thresholding: Original | Simple | Otsu | Adaptive', merge)
```

```
    # Process the key event
```

```
    key = cv.waitKey()
```

```
    if key == 27: # ESC
```

```
        break
```

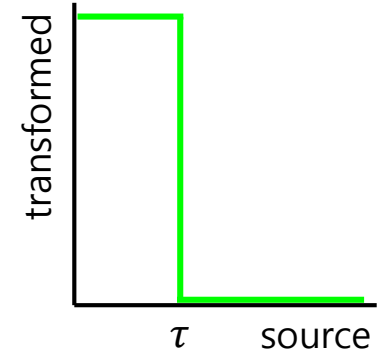


Table of Contents

- **Digital Image Processing**
- **Intensity Transformation**
 - Contrast Stretching
 - Histogram Equalization
- **Thresholding**
- **Image Filtering**
 - Smoothing
 - Edge Detection
 - Sharpening
- **Morphological Operations**
 - Erosion and Dilation
 - Opening and Closing

Image Filtering

- **Image filtering** is a process to modify or enhance image properties and/or to extract information such as edges, corners, and blobs.
 - Its process usually performed using **2D convolution** with a specific **kernel** (a.k.a. mask, operator)
 - Design factors
 - Kernel coefficients
 - Kernel size
 - Boundary handling (e.g. mirror, zero padding, ...)
 - Note) Some 2D convolutions can be replaced by two 1D convolutions (so-called a separable filter).
 - Their time complexity is reduced from $O(MNmn)$ to $O(MN(m + n))$.

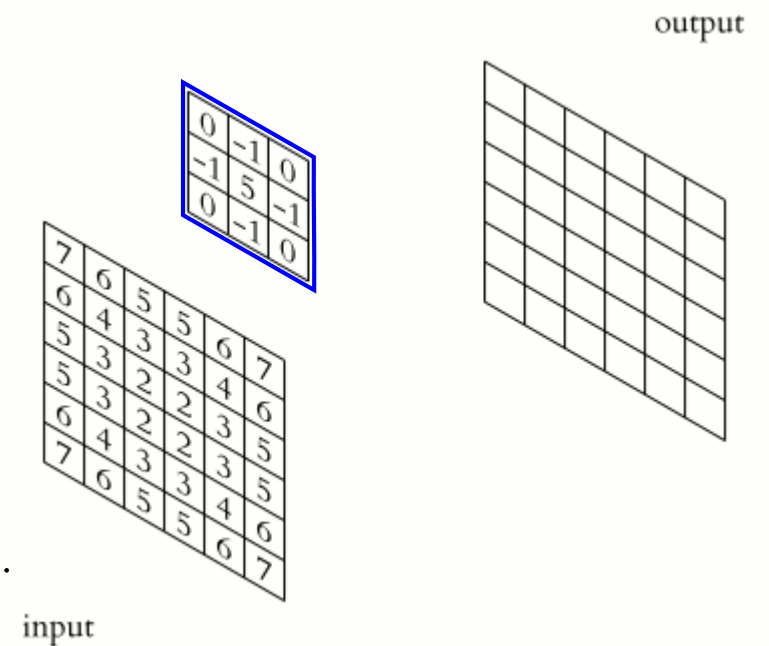


Image Filtering: **Smoothing** → For Noise/Detail Reduction

- **Box blur** (a.k.a. averaging smoothing)

- Each pixel has the (equally weighted) average value of its neighbor pixels.
 - Note) Due to the [central limit theorem](#), repeated box blur will result the same effect of Gaussian blur.
- e.g. 3-by-3 box kernel (~~radius: 1~~, kernel size: 3)
 - $G = \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} = \frac{1}{9} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} [1 \quad 1 \quad 1]$
- Note) The sum of all coefficients is **one**.

- **Gaussian blur** (a.k.a. Gaussian smoothing)

- Each pixel has the Gaussian-weighted average value of its neighbor pixels.
- e.g. 3-by-3 Gaussian kernel (kernel size: 3, sigma: 0.85)
 - $G = \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} = \frac{1}{16} \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} [1 \quad 2 \quad 1]$
- Note) Gaussian kernel and blur in OpenCV API
 - `cv.getGaussianKernel(ksize, sigma[, ktype]) → kernel1D`
 - `cv.GaussianBlur(src, ksize, sigmaX[, dst[, sigmaY[, borderType]]]) → dst`

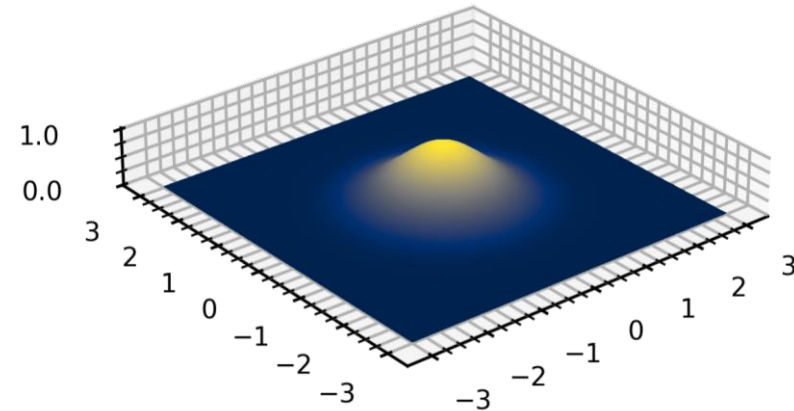


Image Filtering: Smoothing

- Example) Image filtering

```
# Define kernels
```

```
kernel_table = [
```

```
    {'name': 'Box 3x3',          'kernel': np.ones((3, 3)) / 9},      # Alternative: cv.boxFilter(), cv.blur()
```

```
    {'name': 'Gaussian 3x3',     'kernel': np.array([[1, 2, 1],      # Alternative: cv.GaussianBlur()
```

```
                    [2, 4, 2],
```

```
                    [1, 2, 1])) / 16},
```

```
    {'name': 'Box 5x5',          'kernel': np.ones((5, 5)) / 25},
```

```
    {'name': 'Gaussian 5x5',     'kernel': np.array([[1,  4,  6,  4,  1],
                    [4, 16, 24, 16, 4],
                    [6, 24, 36, 24, 6],
                    [4, 16, 24, 16, 4],
                    [1,  4,  6,  4,  1]]) / 256},
```

```
    ...
```

```
]
```

Image Filtering: Smoothing

- Example) Image filtering

```
img_list = ['data/lena.tif', ...]
```

```
# Initialize control parameters
```

```
kernel_select = 0
```

```
img_select = 0
```

```
while True:
```

```
    # Read the given image as gray scale
```

```
    img = cv.imread(img_list[img_select], cv.IMREAD_GRAYSCALE)
```

```
    # Apply convolution to the image with the given 'kernel'
```

```
    name, kernel = kernel_table[kernel_select].values() # Make (short) alias
```

```
    result = cv.filter2D(img, -1, kernel) # Note) dtype: np.uint8 (range: [0, 255])
```

```
    # Show the image and its filtered result
```

```
    merge = np.hstack((img, result))
```

```
    cv.imshow('Image Filtering: Original | Filtered', merge)
```

```
    # Process the key event
```

```
    key = cv.waitKey()
```

```
    if key == 27: # ESC
```

```
        break
```

```
    elif key == ord('+') or key == ord('='):
```

```
        kernel_select = (kernel_select + 1) % len(kernel_table)
```

```
    elif key == ord('-') or key == ord('_'):
```

```
        kernel_select = (kernel_select - 1) % len(kernel_table)
```

```
    elif key == ord('\t'):
```

```
        img_select = (img_select + 1) % len(img_list)
```


Image Filtering: **Smoothing**

- Example) Image filtering: **Original** | **Box Blur (5x5)** | **Gaussian Blur (5x5)**

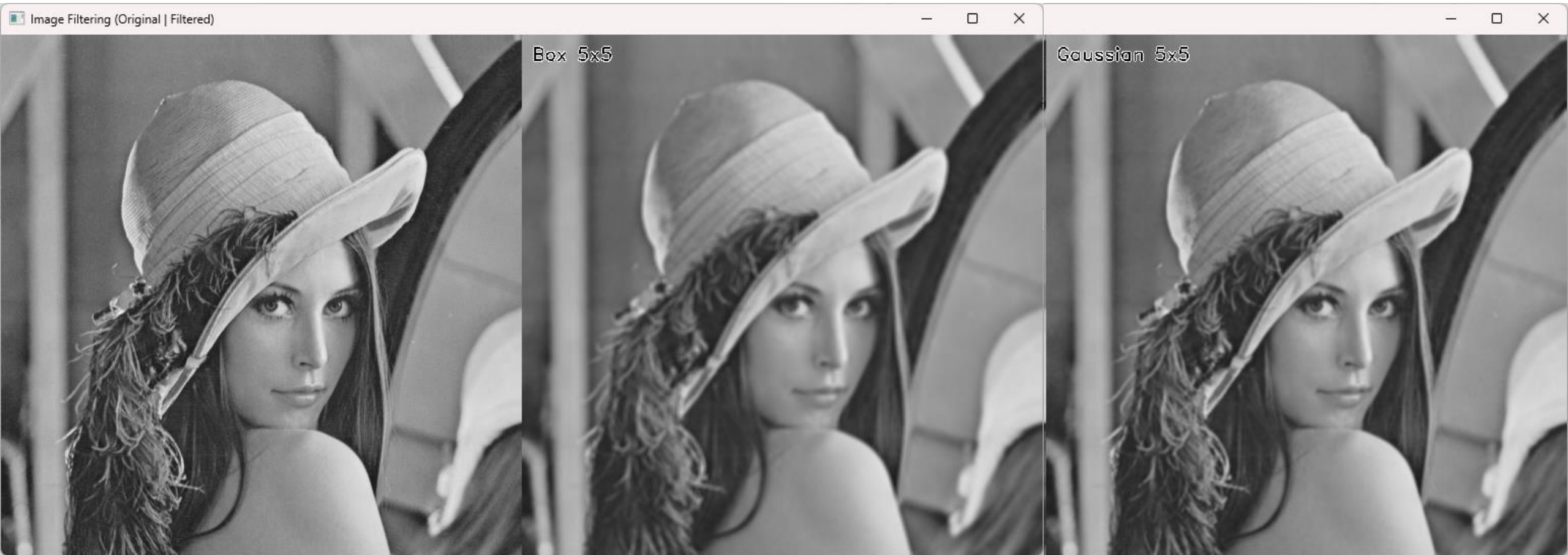


Image Filtering: **Smoothing**

- **Median filter**: A non-linear noise reduction filter using median instead of average
 - Process) Similar to 2D convolution process,
 - ~~Each pixel has the average value of its neighbor pixels in the kernel.~~
 - Each pixel has the median value of its neighbor pixels in the kernel
 - Advantages
 - Effective to remove impulse noise (e.g. [salt-and-pepper noise](#))
 - The median is less sensitive to outliers than average.
 - e.g. 1, 3, 5, **70**, 9 – Average: 17.6 / Median: 5
 - Image blurring, but preserving edges more than averaging
 - Disadvantage
 - Slower than averaging ← the median operation
 - Of course, the median operation is not separable.
 - Note) Median filter in OpenCV API
 - `cv.medianBlur(src, ksize[, dst]) → dst`



Image Filtering: Smoothing

- Example) Median filter

```
img_list = [..., 'data/black_circle.png', ...]
```

```
# Initialize control parameters
```

```
kernel_size = 5
```

```
img_select = -1
```

```
while True:
```

```
    # Read the given image
```

```
    img = cv.imread(img_list[img_select])
```

```
    # Apply the median filter
```

```
    result = cv.medianBlur(img, kernel_size)
```

```
    # Show all images
```

```
    merge = np.hstack((img, result))
```

```
    cv.imshow('Medial Filter: Original | Result', merge)
```

```
    # Process the key event
```

```
    key = cv.waitKey()
```

```
    if key == 27: # ESC
```

```
        break
```

```
    elif key == ord('+') or key == ord('='):
```

```
        kernel_size = kernel_size + 2
```

```
    elif key == ord('-') or key == ord('_'):
```

```
        kernel_size = max(kernel_size - 2, 3)
```

```
    elif key == ord('\t'):
```

```
        img_select = (img_select + 1) % len(img_list)
```



Image Filtering: Image Gradient and Robert Cross Kernels

- Image gradient kernels: X- and Y-directional changes (1st derivative) in an image
 - X-directional change: $I(x + 1, y) - I(x, y)$
 - $D_X = \begin{bmatrix} -1 & 1 \end{bmatrix}$
 - Y-directional change: $I(x, y + 1) - I(x, y)$
 - $D_Y = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$
 - Note) The sum of all coefficients is **zero**.
- Robert cross kernels: Diagonal directional changes in an image
 - The 1st diagonal directional changes: $I(x + 1, y + 1) - I(x, y)$
 - $D_D = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}$
 - The 2nd diagonal directional changes: $I(x + 1, y) - I(x, y + 1)$
 - $D_U = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$
 - Note) The sum of all coefficients is **zero**.

Image Filtering: Image Gradient and Robert Cross Kernels

- Example) Image filtering (with 'data/lena.tif')

```
# Define kernels
kernel_table = [
    {'name': 'Gradient X',      'kernel': np.array([[ -1,  1]])},
    {'name': 'Robert DownRight', 'kernel': np.array([[ -1,  0],
                                                       [ 0,  1]])},
    {'name': 'Gradient Y',      'kernel': np.array([[ -1], [ 1]])},
    {'name': 'Robert UpRight',  'kernel': np.array([[ 0,  1],
                                                       [-1,  0]])},
    ...
]

img_list = ['data/lena.tif', ...]

# Initialize control parameters
kernel_select = 0
img_select = 0

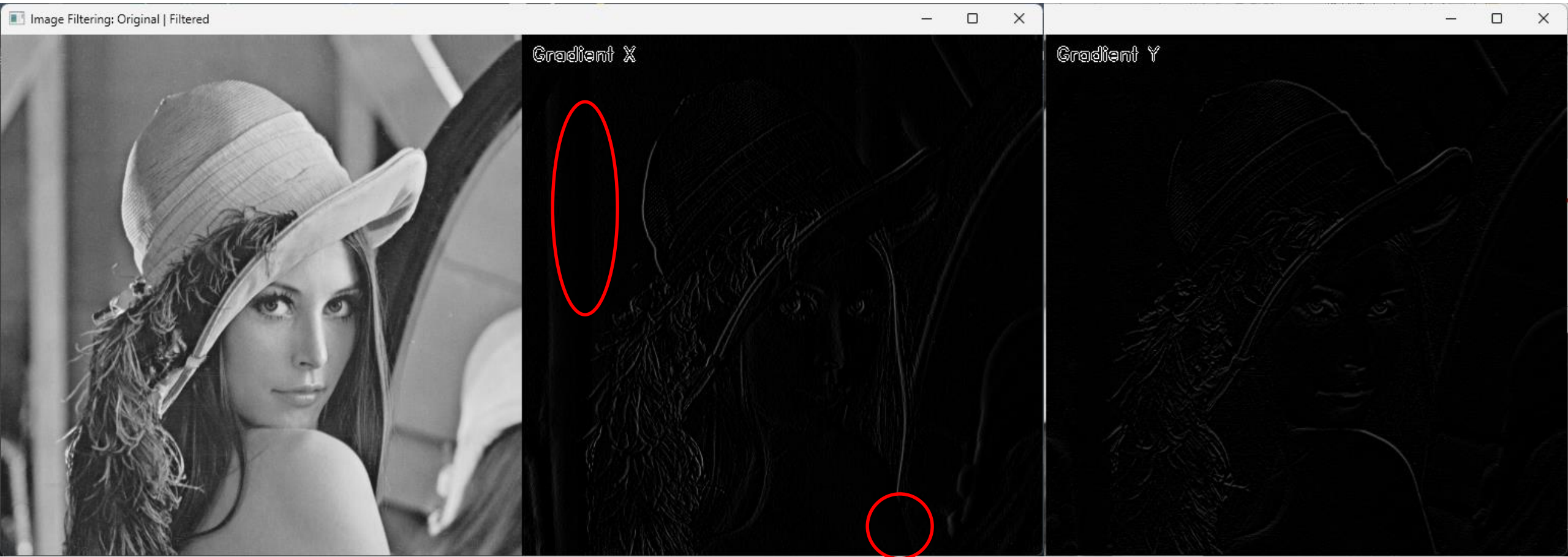
while True:
    # Read the given image as gray scale
    img = cv.imread(img_list[img_select], cv.IMREAD_GRAYSCALE)

    # Apply convolution to the image with the given 'kernel'
    name, kernel = kernel_table[kernel_select].values() # Make (short) alias
    result = cv.filter2D(img, -1, kernel)               # Note) dtype: np.uint8 (range: [0, 255])

    # Show the image and its filtered result
```


Image Filtering: Image Gradient and Robert Cross Kernels

- Example) Gradients (with 'data/lena.tif')



📄 Where is gradient?

Image Filtering: Image Gradient and Robert Cross Kernels

- Example) Gradients (with 'data/lena.tif')

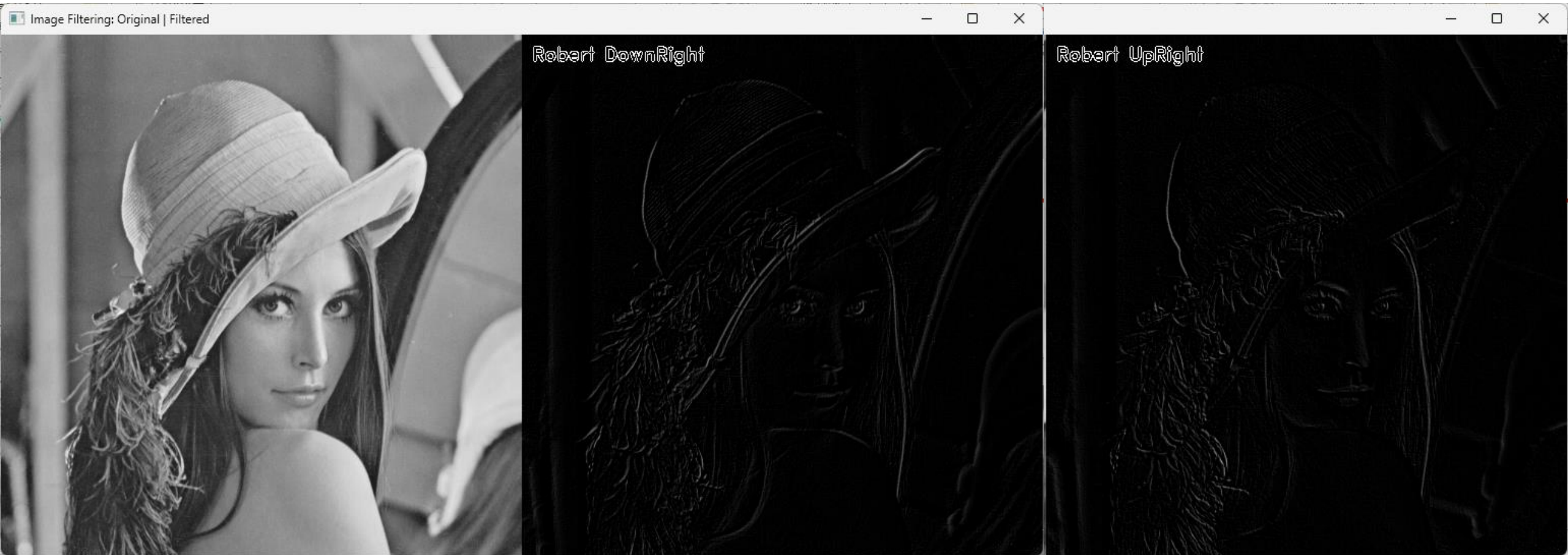


Image Filtering: Image Gradient and Robert Cross Kernels

- Example) Gradients (with 'data/black_circle.png')

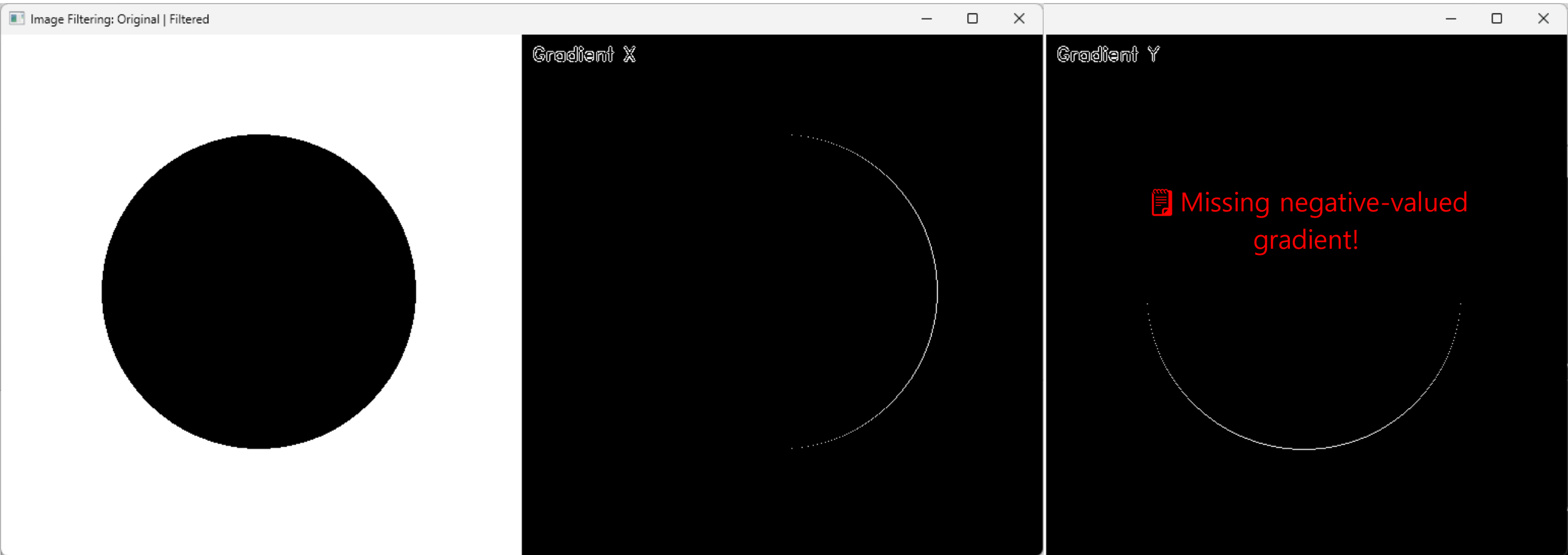


Image Filtering: Image Gradient and Robert Cross Kernels

- Example) Gradients (with 'data/black_circle.png')

```
# Define kernels
kernel_table = [
    {'name': 'Gradient X',      'kernel': np.array([[ -1,  1]])},
    {'name': 'Robert DownRight', 'kernel': np.array([[ -1,  0],
                                                       [  0,  1]])},
    ...
]
```

```
img_list = ['data/lena.tif', ...]
```

```
# Initialize control parameters
```

```
kernel_select = 0
```

```
img_select = 0
```

```
while True:
```

```
    # Read the given image as gray scale
```

```
    img = cv.imread(img_list[img_select], cv.IMREAD_GRAYSCALE)
```

```
    # Apply convolution to the image with the given 'kernel'
```

```
    name, kernel = kernel_table[kernel_select].values() # Make (short) alias
```

```
    result = cv.filter2D(img, cv.CV_64F, kernel) # Note) dtype: np.float64
```

```
    result = cv.convertScaleAbs(result) # Convert 'np.float64' to 'np.uint8' with saturation
```

```
    # Show the image and its filtered result
```

```
    merge = np.hstack((img, result))
```

```
    cv.imshow('Image Filtering: Original | Filtered', merge)
```

📖 Be careful when your kernel coefficients derive values out of [0, 255].

Image Filtering: Image Gradient and Robert Cross Kernels

- Example) Gradients (with 'data/black_circle.png')

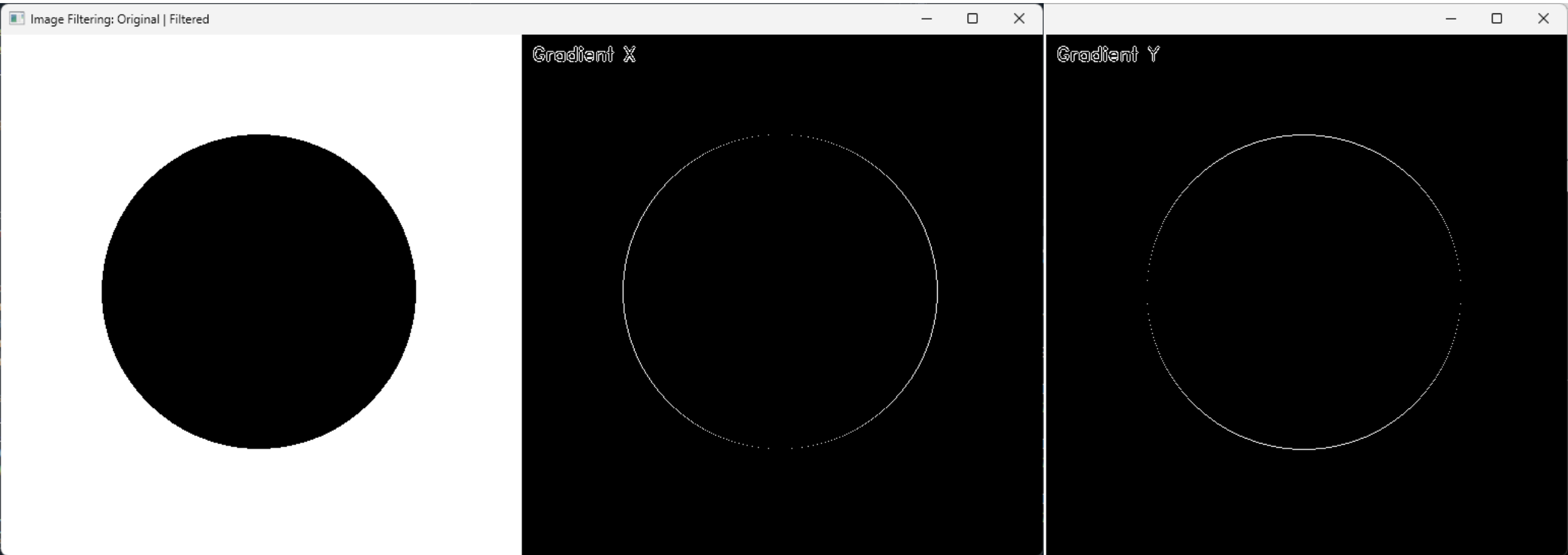


Image Filtering: Image Gradient and Robert Cross Kernels

- Example) Gradients (with 'data/lena.png')

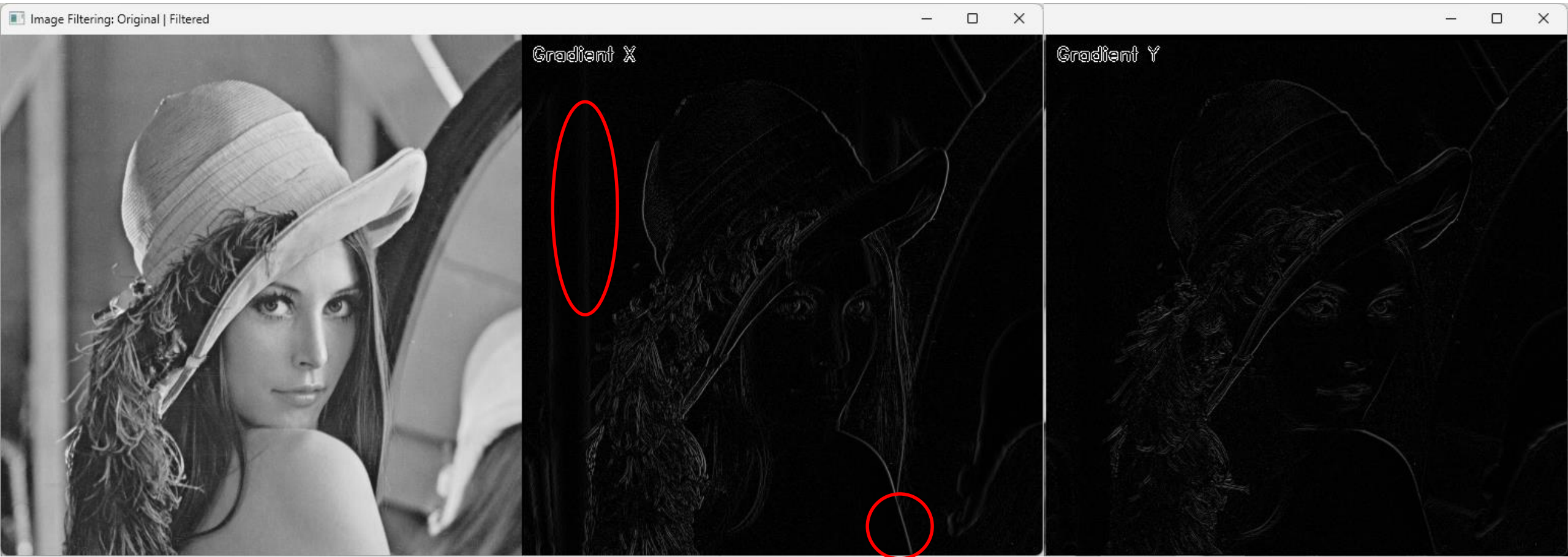


Image Filtering: Prewitt, Sobel, and Scharr Edge Kernels

- Prewitt kernels: X- and Y-directional edges in an image

- X-directional edges

- $G_X = \begin{bmatrix} -1 & 0 & 1 \\ -1 & \mathbf{0} & 1 \\ -1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 \\ \mathbf{1} \\ 1 \end{bmatrix} \begin{bmatrix} -1 & \mathbf{0} & 1 \end{bmatrix}$

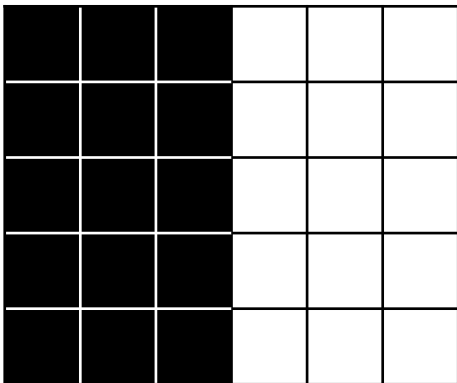
- Y-directional edges

- $G_Y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & \mathbf{0} & 0 \\ 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} -1 \\ \mathbf{0} \\ 1 \end{bmatrix} \begin{bmatrix} 1 & \mathbf{1} & 1 \end{bmatrix}$

- Note) The sum of all coefficients is **zero**.

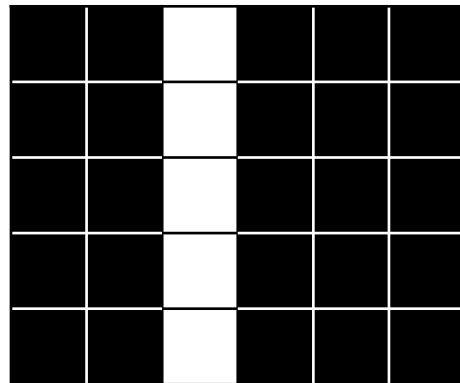
- Discussion) Why 3-by-3 kernel for edges? (A 1-by-2 gradient kernels also can extract edges.)

Input image



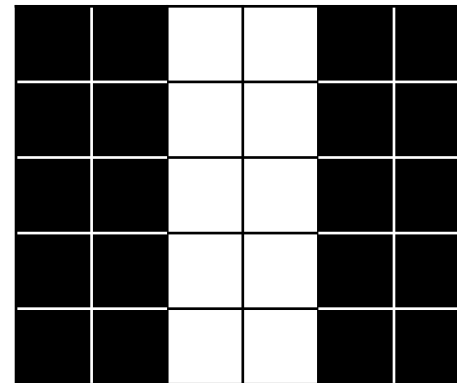
→

Gradient kernel



vs.

Prewitt kernel



📄 Central difference operator

$$\sim \frac{I(x+1, y) - I(x-1, y)}{2}$$

Image Filtering: Prewitt, Sobel, and Scharr Edge Kernels

- **Sobel kernels**: X- and Y-directional edges in an image with weighted smoothing

- X-directional edges

- $G_X = \begin{bmatrix} -1 & 0 & 1 \\ -2 & \mathbf{0} & 2 \\ -1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 \\ \mathbf{2} \\ 1 \end{bmatrix} \begin{bmatrix} -1 & \mathbf{0} & 1 \end{bmatrix}$

- Y-directional edges

- $G_Y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & \mathbf{0} & 0 \\ 1 & 2 & 1 \end{bmatrix} = \begin{bmatrix} -1 \\ \mathbf{0} \\ 1 \end{bmatrix} \begin{bmatrix} 1 & \mathbf{2} & 1 \end{bmatrix}$

- **Scharr kernels**: Sobel kernels with more optimized coefficients (in the view of rotational symmetry)

- X-directional edges

- $G_X = \begin{bmatrix} -3 & 0 & 3 \\ -10 & \mathbf{0} & 10 \\ -3 & 0 & 3 \end{bmatrix} = \begin{bmatrix} 3 \\ \mathbf{10} \\ 3 \end{bmatrix} \begin{bmatrix} -1 & \mathbf{0} & 1 \end{bmatrix}$

- Y-directional edges

- $G_Y = \begin{bmatrix} -3 & -10 & -3 \\ 0 & \mathbf{0} & 0 \\ 3 & 10 & 3 \end{bmatrix} = \begin{bmatrix} -1 \\ \mathbf{0} \\ 1 \end{bmatrix} \begin{bmatrix} 3 & \mathbf{10} & 3 \end{bmatrix}$

Note) 5-by-5 Scharr kernel (X-direction)

$$G_X = \begin{bmatrix} -1 & -2 & 0 & 2 & 1 \\ -4 & -8 & 0 & 8 & 4 \\ -6 & -12 & \mathbf{0} & 12 & 6 \\ -4 & -8 & 0 & 8 & 4 \\ -1 & -2 & 0 & 2 & 1 \end{bmatrix}$$

Image Filtering: Prewitt, Sobel, and Scharr Edge Kernels

- Example) X-directional edge detection: **Prewitt** | **Sobel** | **Scharr**

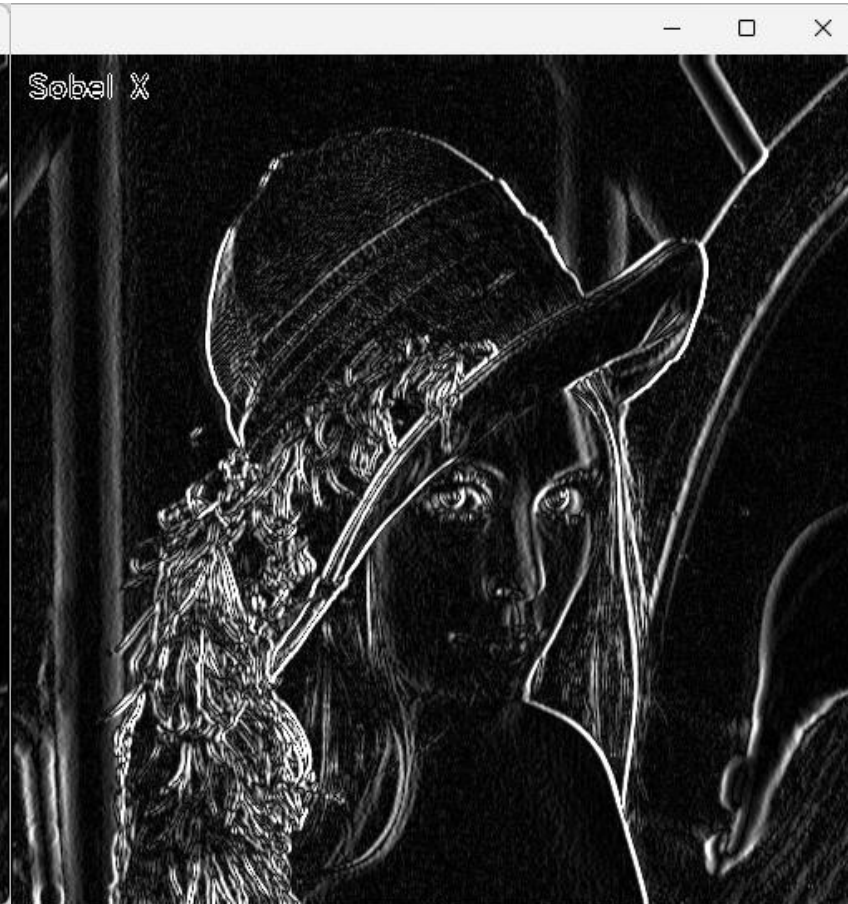
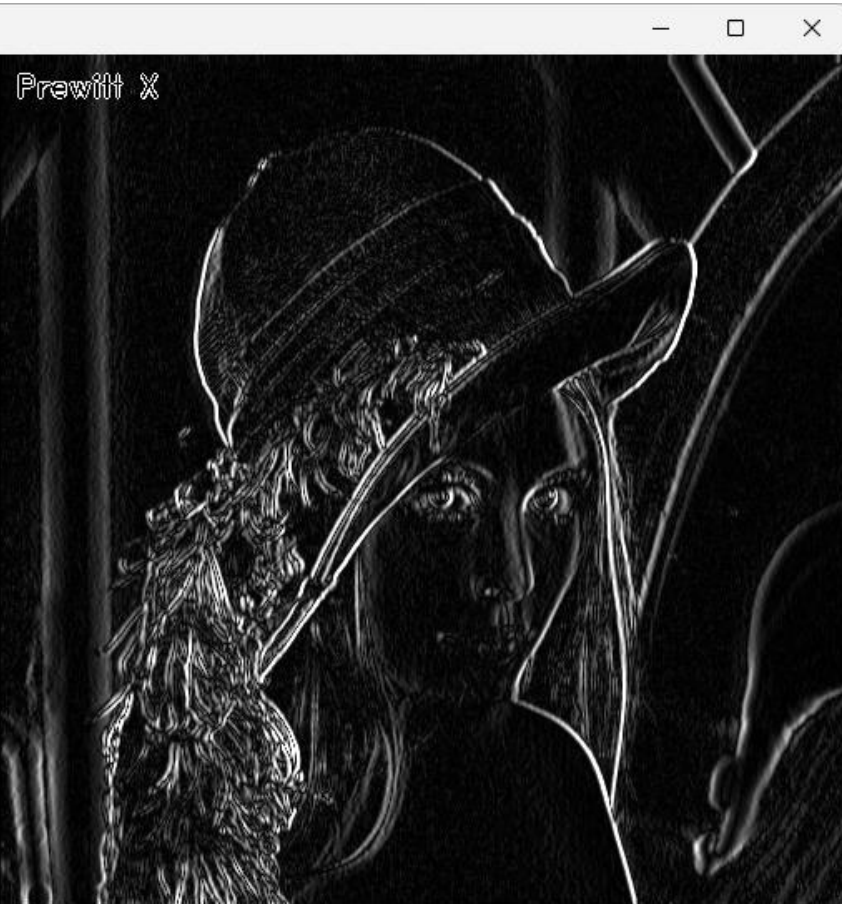
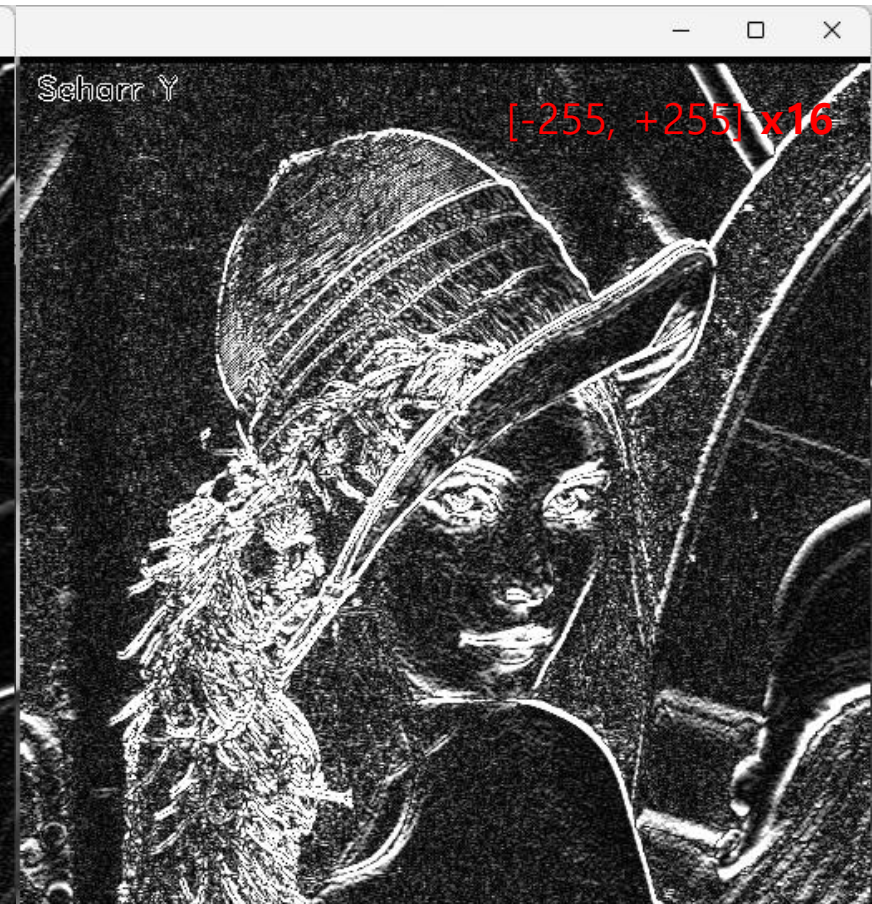
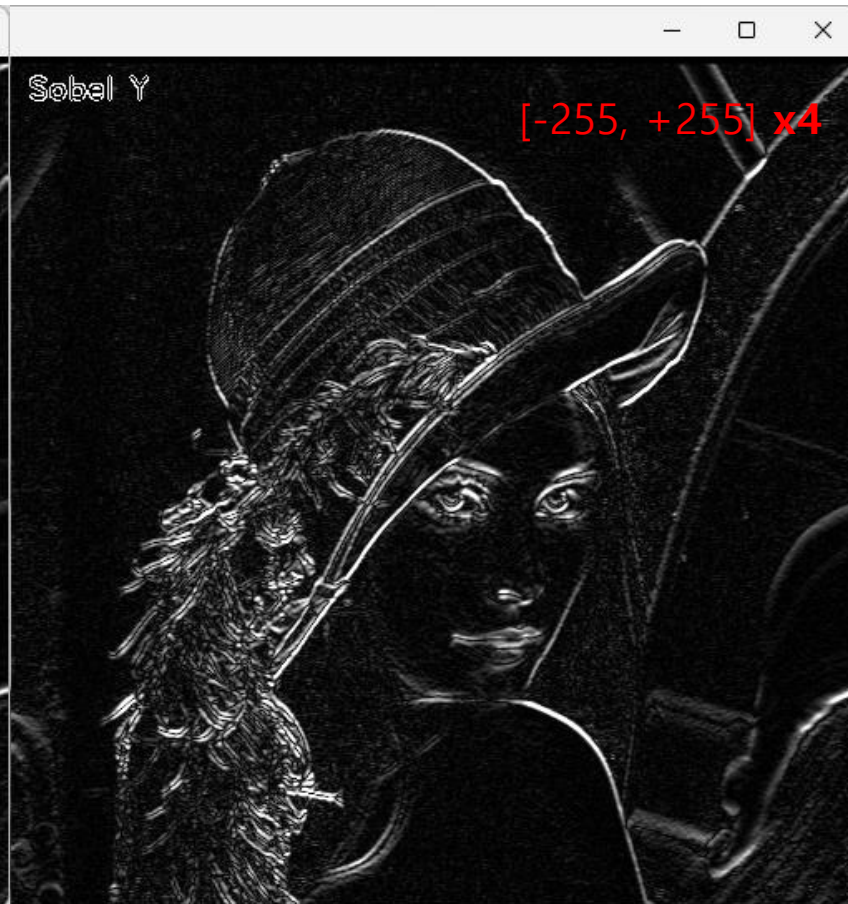
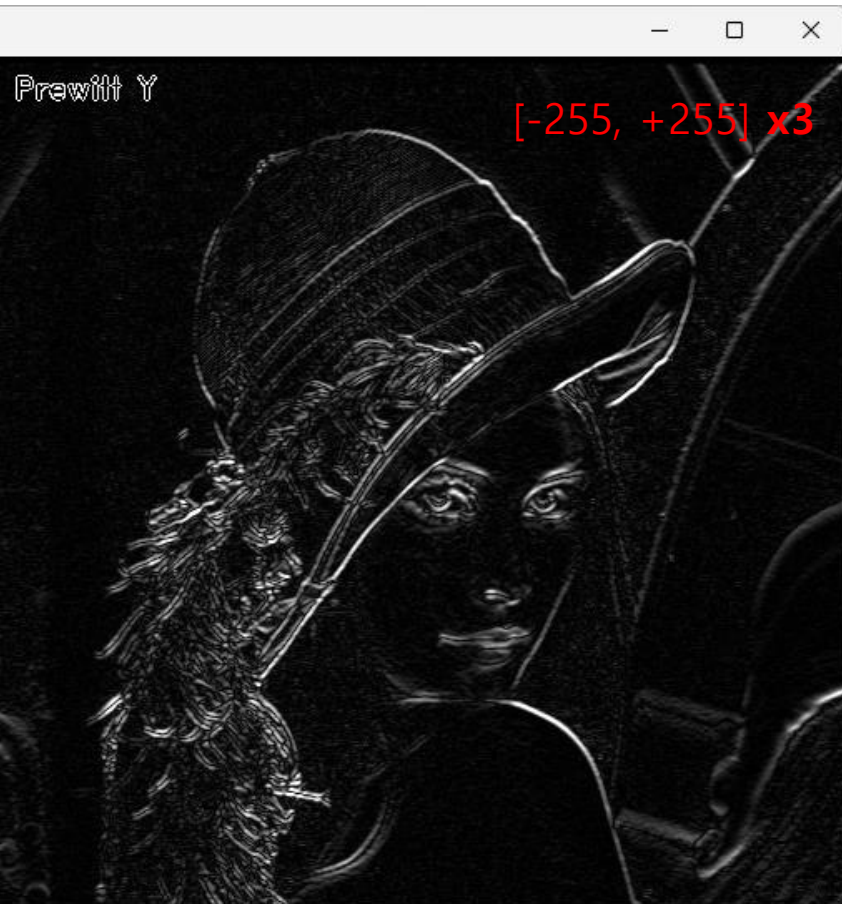


Image Filtering: Prewitt, Sobel, and Scharr Edge Kernels

- Example) Y-directional edge detection: **Prewitt** | **Sobel** | **Scharr**

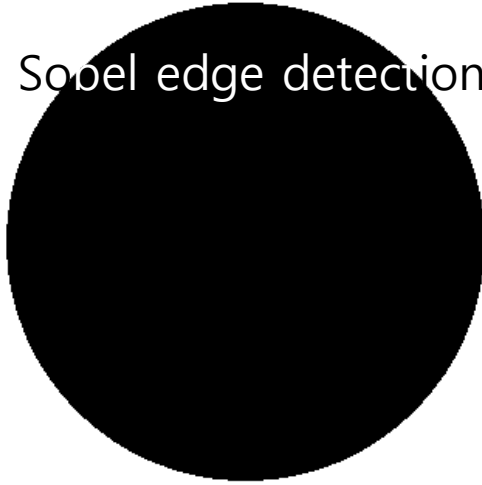


Why stronger edge response?
Bigger kernel coefficients

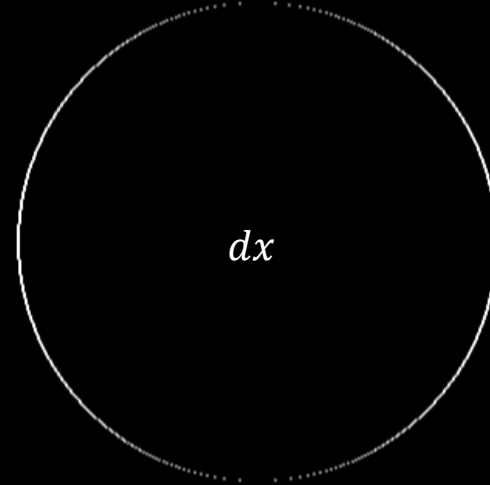
Original

Image Filtering: Prewitt, Sobel, and Scharr Edge Kernels

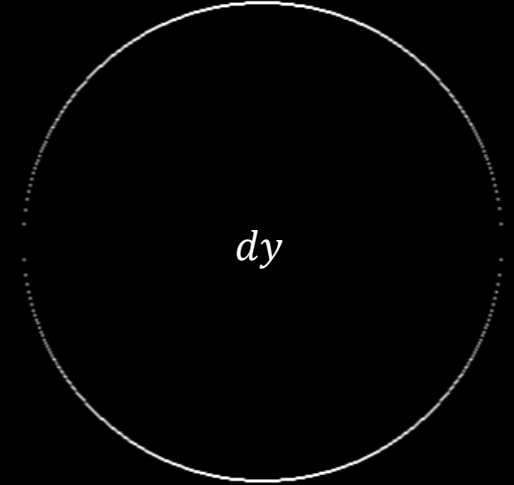
- Example) Sobel edge detection



SobelX

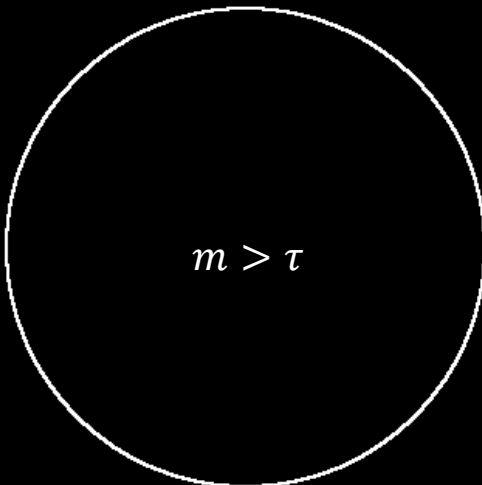


SobelY

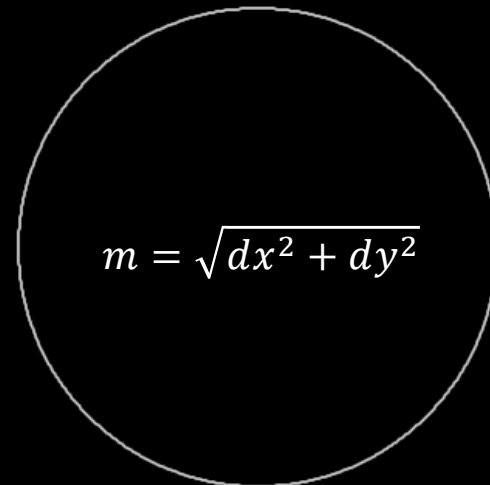


EdgeThreshold: 0.10

Edge image with the threshold (τ)



Magnitude



Orientation

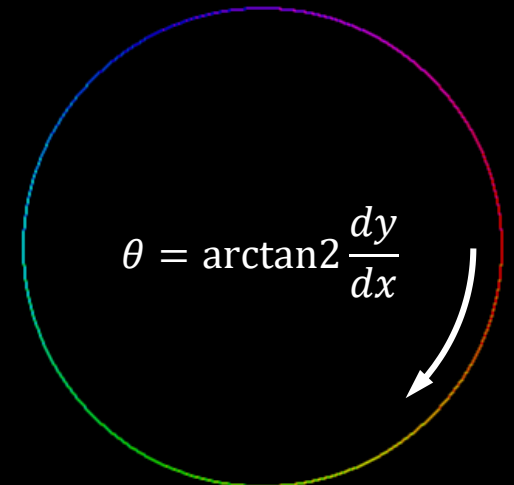


Image Filtering: Prewitt, Sobel, and Scharr Edge Kernels

- Example) Sobel edge detection

```
img_list = [..., 'data/black_circle.png', ...]
```

```
# Initialize control parameters
```

```
edge_threshold = 0.1
```

```
img_select = 3
```

```
while True:
```

```
    # Read the given image as gray scale
```

```
    img = cv.imread(img_list[img_select], cv.IMREAD_GRAYSCALE)
```

```
    # Extract edges using two-directional Sobel responses
```

```
    # and normalize their values within [0, 1] (Note: 1020 derived from 255 * (1+2+1))
```

```
    dx = cv.Sobel(img, cv.CV_64F, 1, 0) / 1020 # Sobel x-directional response
```

```
    dy = cv.Sobel(img, cv.CV_64F, 0, 1) / 1020 # Sobel y-directional response
```

```
    mag = np.sqrt(dx*dx + dy*dy) / np.sqrt(2) # Sobel magnitude
```

```
    ori = np.arctan2(dy, dx) # Sobel orientation
```

```
    edge = mag > edge_threshold # Alternative) cv.threshold(), cv.adaptiveThreshold()
```

```
    # Prepare the orientation image as the BGR color
```

```
    ori[ori < 0] = ori[ori < 0] + 2*np.pi # Convert [-np.pi, np.pi) to [0, 2*np.pi)
```

```
    ori_hsv = np.dstack((ori / (2*np.pi) * 180, # HSV color - Hue channel
```

```
                        np.full_like(ori, 255), # HSV color - Saturation channel
```

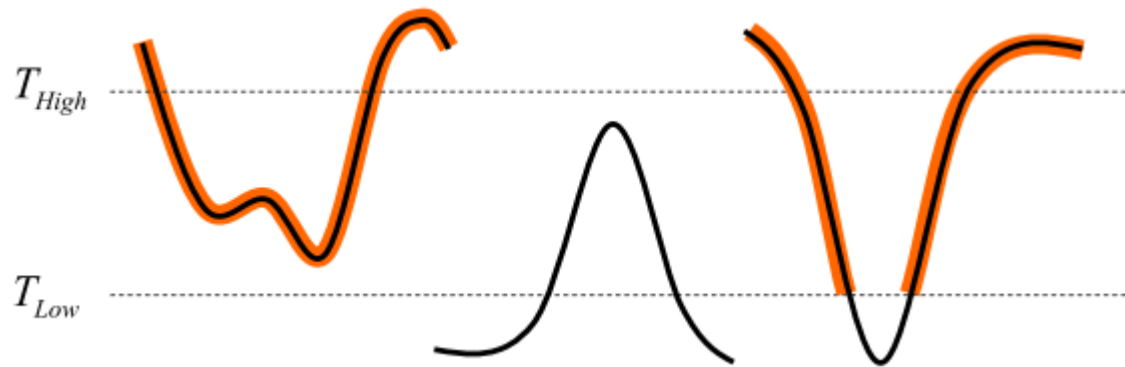
```
                        mag * 255)) # HSV color - Value channel
```

```
    ori_bgr = cv.cvtColor(ori_hsv.astype(np.uint8), cv.COLOR_HSV2BGR)
```

```
    # Prepare the original, Sobel X/Y, magnitude, and edge images as the BGR color
```

Image Filtering: Prewitt, Sobel, and Scharr Edge Kernels

- Canny edge detector: A popular multi-stage edge detector
 - Process
 1. Gaussian smoothing (for noise reduction)
 2. Sobel kernel (for edge detection)
 3. Sobel magnitude thresholding (for edge candidate selection)
 - Double thresholding (strong/weak edge candidates)
 4. Edge tracking by hysteresis (Note: Useful for abnormal toggling)



- Advantages: Accurate edges and suitable to various images
- Disadvantages: Heavy computation and difficult to adjust parameters

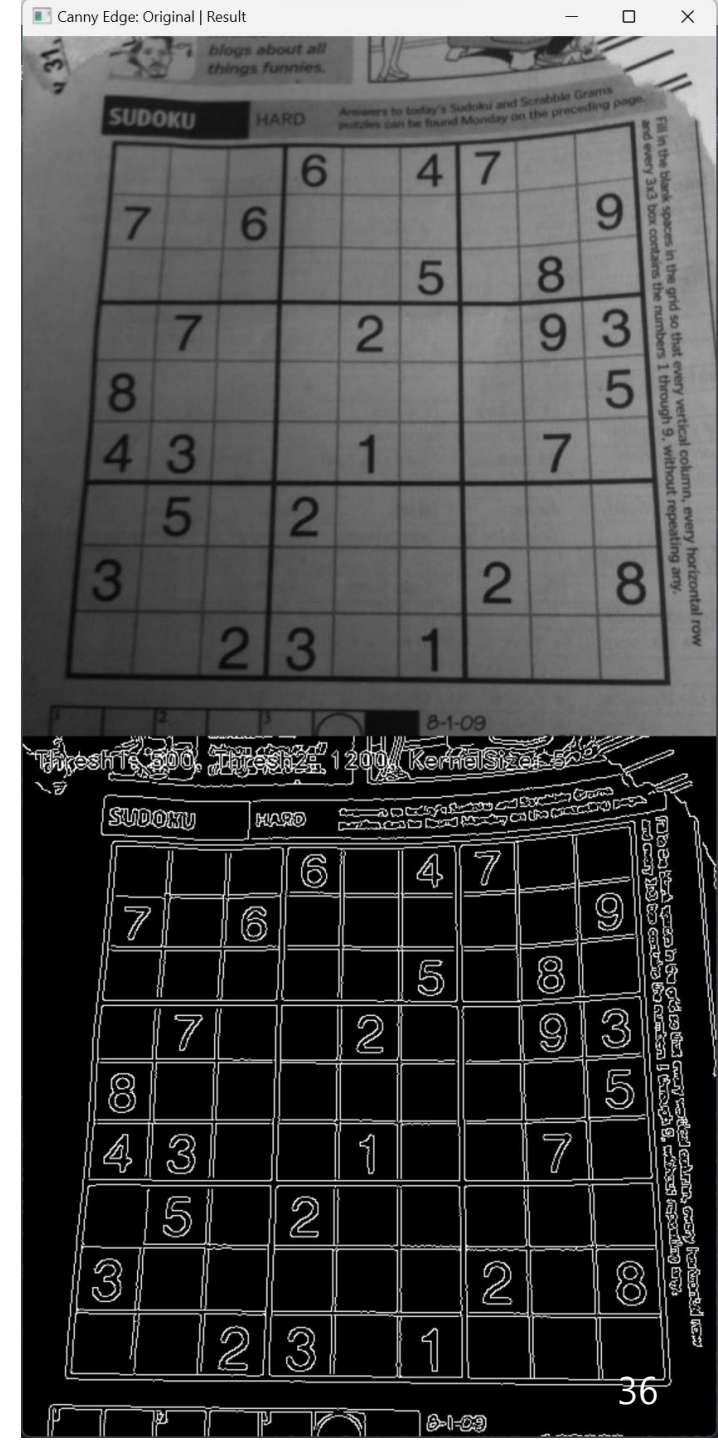


Image Filtering: Prewitt, Sobel, and Scharr Edge Kernels

- Example) Canny edge detection

```
import cv2 as cv
import numpy as np

img_list = [..., 'data/sudoku.png']

# Initialize control parameters
threshold1 = 500
threshold2 = 1200
aperture_size = 5
img_select = -1

while True:
    # Read the given image
    img = cv.imread(img_list[img_select], cv.IMREAD_GRAYSCALE)
    assert img is not None, 'Cannot read the given image, ' + img_list[img_select]

    # Get the Canny edge image
    edge = cv.Canny(img, threshold1, threshold2, apertureSize=aperture_size)

    # Show all images
    ...
    merge = np.hstack((img, edge))
    cv.imshow('Canny Edge: Original | Result', merge)

    # Process the key event
    key = cv.waitKey()
    if key == 27: # Esc
```

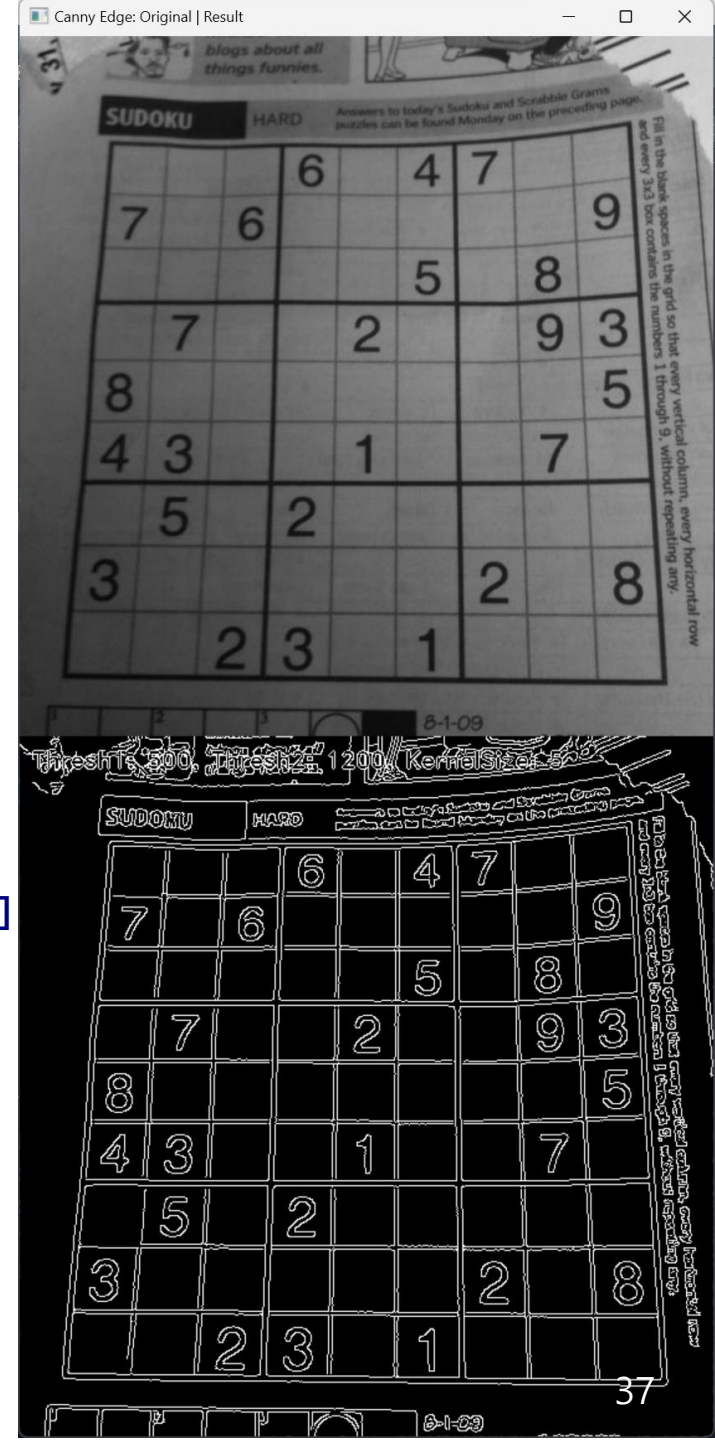


Image Filtering: Laplacian and Sharpening

- **Laplacian operator:** The sum of the 2nd-order derivatives (more mathematically divergence of gradient)
 - Note) 1D example: 1st-order derivative $D_X = [-1 \ 1] \rightarrow$ 2nd-order derivative $D_{XX} = [-1 \ 2 \ -1]$
 - 2D kernel: Not separable
 - $D_{XY} = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$
 - Effect: Finding edge boundaries
 - Note) The sum of all coefficients is **zero**.
- **Sharpening kernel:** Highlighting edge boundaries on an image
 - 2D kernel
 - $G = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$
 - Note) The sum of all coefficients is **one**.

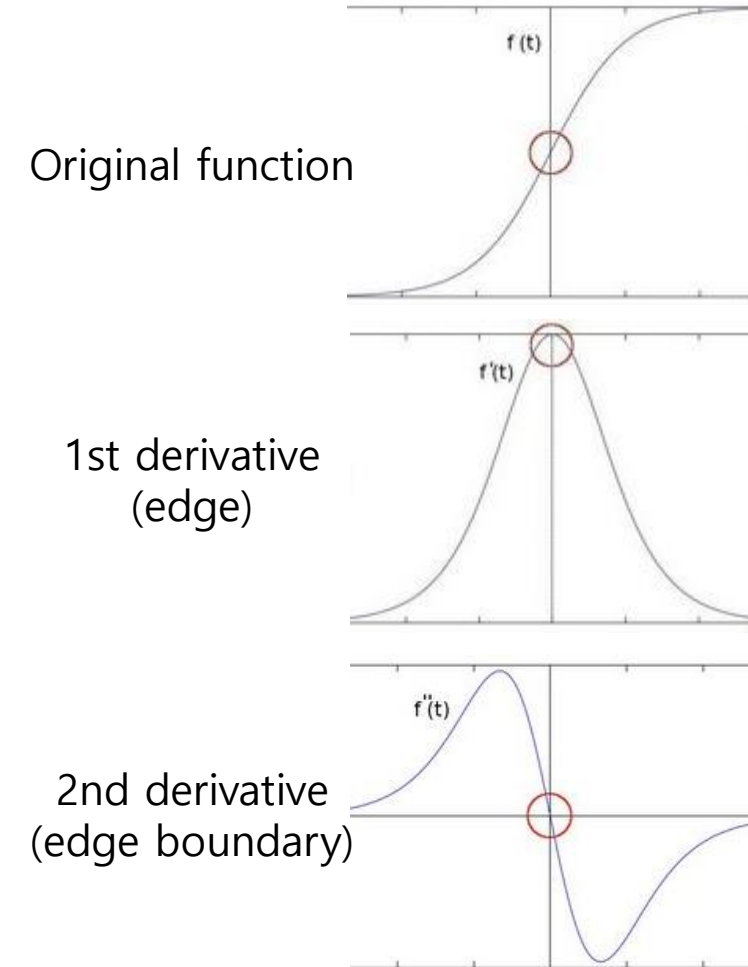


Image Filtering: Laplacian and Sharpening

- Example) Image sharpening: **Original** | **Laplacian** | **Sharpening**

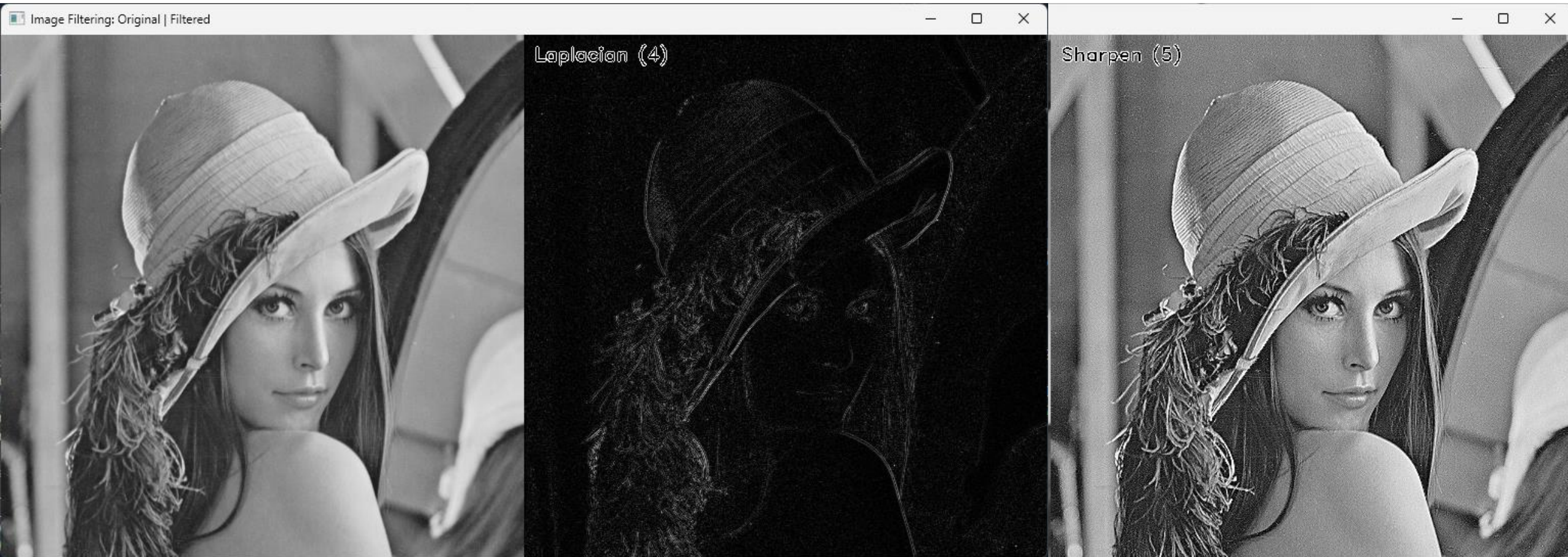
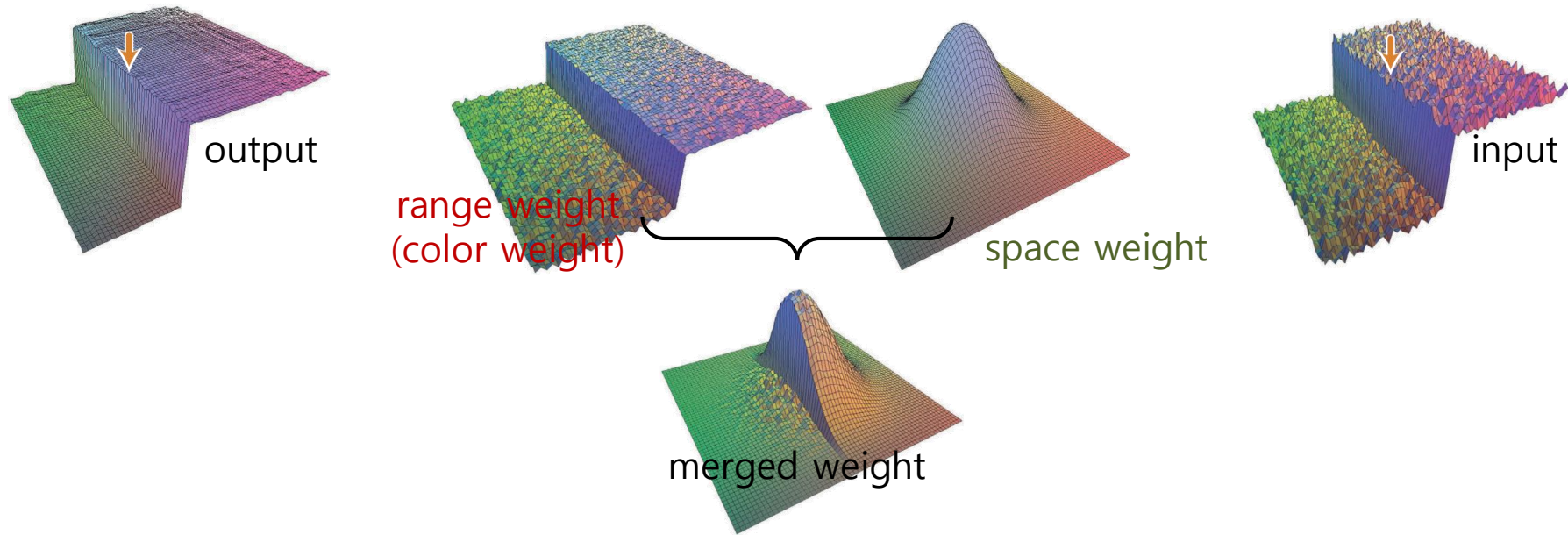


Image Filtering: Bilateral Filter

- Bilateral filter: A non-linear, edge-preserving, and smoothing filter for images
 - Process)

$$I^{BF}(\mathbf{x}) = \frac{1}{W_p} \sum_{\mathbf{x}_i \in \Omega} f_r(\|I(\mathbf{x}_i) - I(\mathbf{x})\|) g_s(\|\mathbf{x}_i - \mathbf{x}\|) I(\mathbf{x}_i)$$



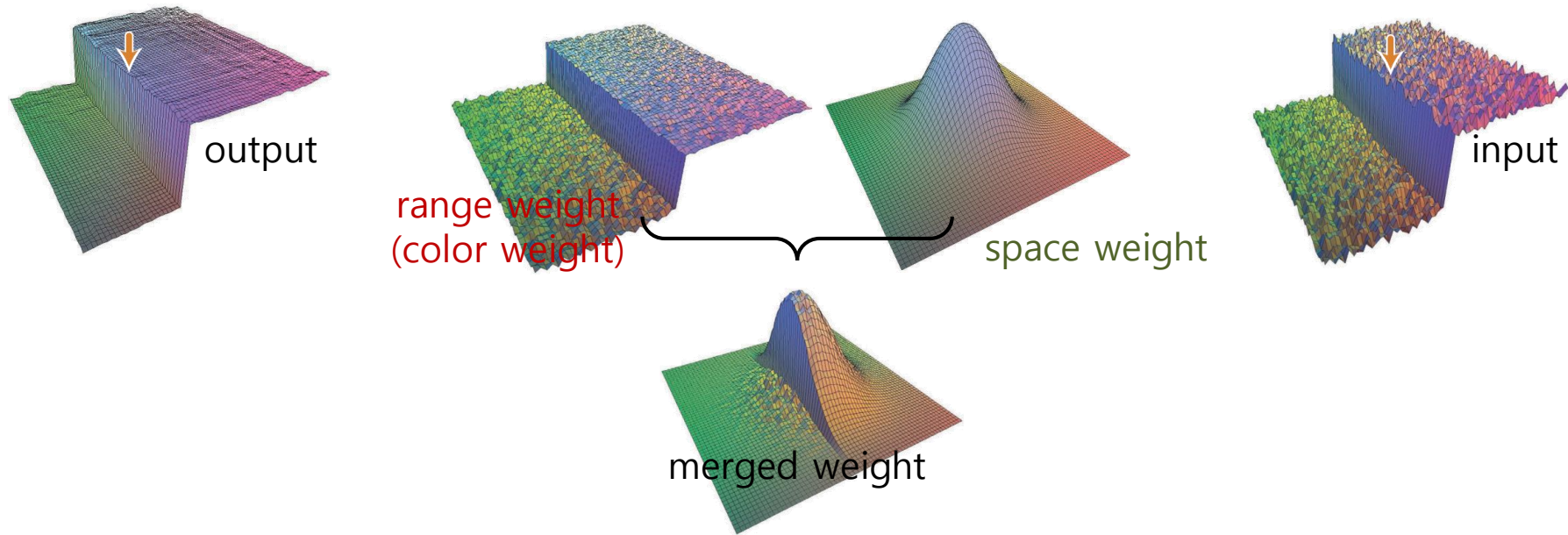
- Note) Bilateral filter in OpenCV API
 - `cv.bilateralFilter(src, d, sigmaColor, sigmaSpace[, dst[, borderType]]) → dst`
 - d: Diameter of kernel (kernel size) / If it is non-positive, it is computed from sigmaSpace.

Image Filtering: Bilateral Filter

- **Bilateral filter**: A non-linear, edge-preserving, and smoothing filter for images

– Process) When f_r and g_s are Gaussian,

$$I^{BF}(i, j) = \frac{\sum_{k, l} w(i, j, k, l) I(k, l)}{\sum_{k, l} w(i, j, k, l)} \quad \text{where} \quad w(i, j, k, l) = \exp \left(-\frac{\|I(i, j) - I(k, l)\|^2}{2\sigma_c^2} - \frac{(i - k)^2 + (j - l)^2}{2\sigma_s^2} \right)$$



– Note) Bilateral filter in OpenCV API

- `cv.bilateralFilter(src, d, sigmaColor, sigmaSpace[, dst[, borderType]]) → dst`
 - d: Diameter of kernel (kernel size) / If it is non-positive, it is computed from sigmaSpace.

Image Filtering: Bilateral Filter

- Example) Bilateral filter

```
img_list = ['data/lena.tif', ...]
```

```
# Initialize control parameters
```

```
kernel_size = 9
```

```
sigma_color = 150
```

```
sigma_space = 2.4
```

```
n_iterations = 1
```

```
img_select = 0
```

```
while True:
```

```
    # Read the given image
```

```
    img = cv.imread(img_list[img_select])
```

```
    assert img is not None, 'Cannot read the given image, ' + img_list[img_select]
```

```
    # Apply the bilateral filter iteratively
```

```
    result = img.copy()
```

```
    for itr in range(n_iterations):
```

```
        result = cv.bilateralFilter(result, kernel_size, sigma_color, sigma_space)
```

```
    # Show all images
```

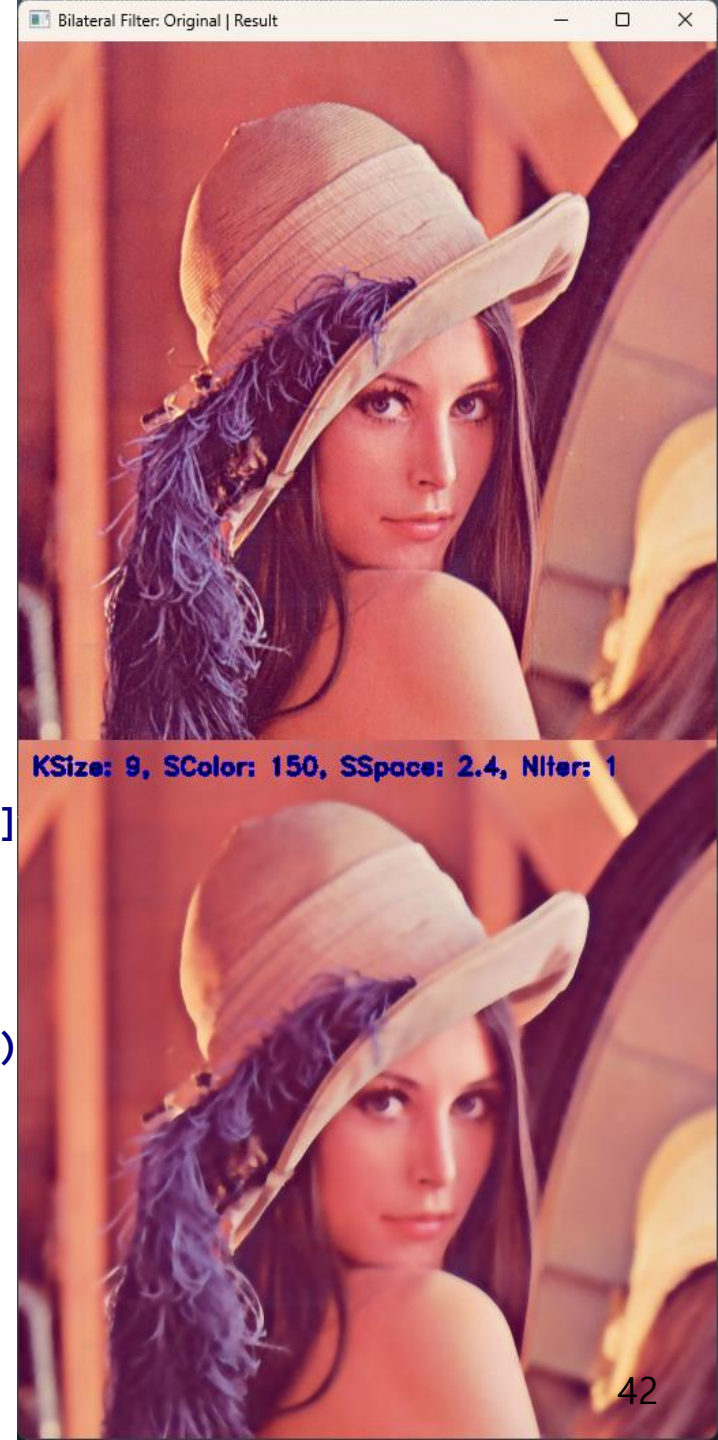
```
    merge = np.hstack((img, result))
```

```
    cv.imshow('Bilateral Filter: Original | Result', merge)
```

```
    # Process the key event
```

```
    key = cv.waitKey()
```

```
    if key == 27: # ESC
```



Morphological Operations

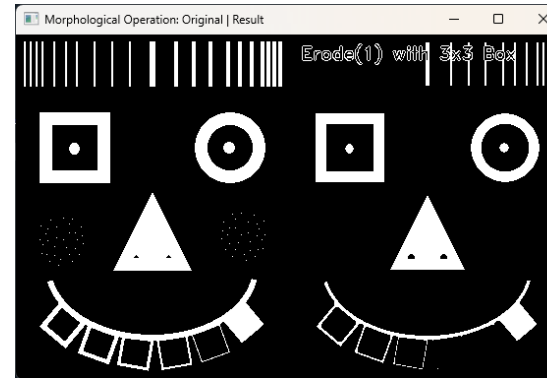
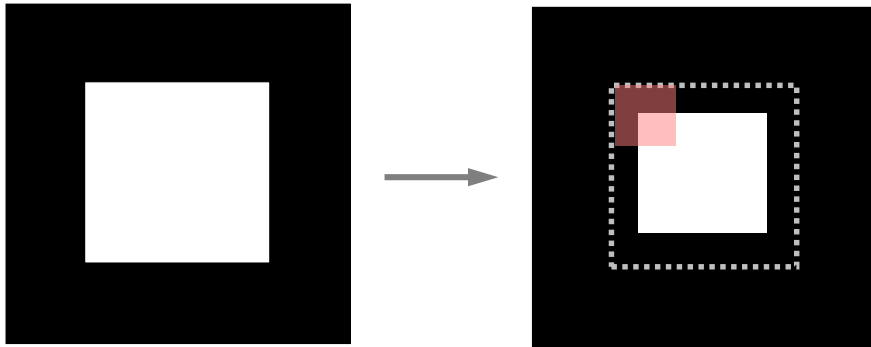
- **Morphological operations** are image processing techniques to manipulate the shape or structure of objects in an image, usually a [binary image](#) (e.g. 1: object, 0: otherwise).
 - It is based on [mathematical morphology](#) developed by Georges Matheron and Jean Serra in 1964.
 - It has two fundamental operations ([erosion](#) and [dilation](#)) and their combinations makes various operations.
 - Its operations works similar to *image filtering* with a [kernel](#) without coefficients (a.k.a. sliding window).
- [Erosion](#) (침식 in Korean): An operation for reducing the shape
 - $$I'(x, y) = \begin{cases} 1 & \text{if all pixels in the window is 1} \\ 0 & \text{otherwise} \end{cases} \quad \sim \text{logical conjunction (intersection)}$$
- [Dilation](#) (팽창 in Korean): An operation for expanding the shape
 - $$I'(x, y) = \begin{cases} 1 & \text{if any pixels in the window is 1} \\ 0 & \text{otherwise} \end{cases} \quad \sim \text{logical disjunction (union)}$$

Morphological Operations

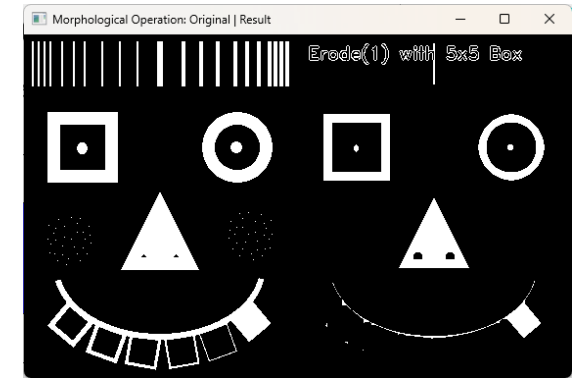
- **Erosion** (침식 in Korean): An operation for reducing the shape

$$I'(x, y) = \begin{cases} 1 & \text{if all pixels in the window is 1} \\ 0 & \text{otherwise} \end{cases}$$

~ logical conjunction (intersection)



3x3
Box

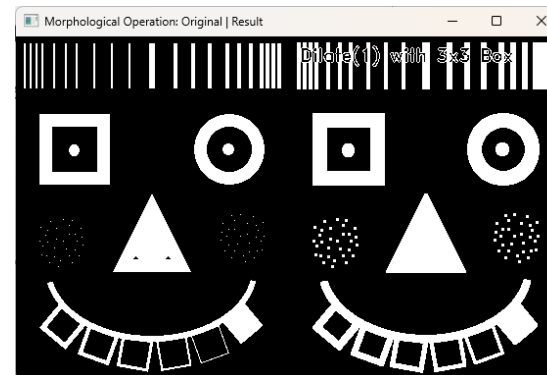
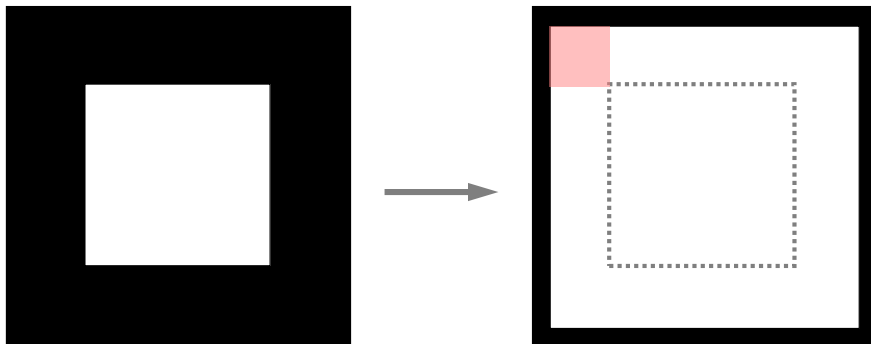


5x5
Box

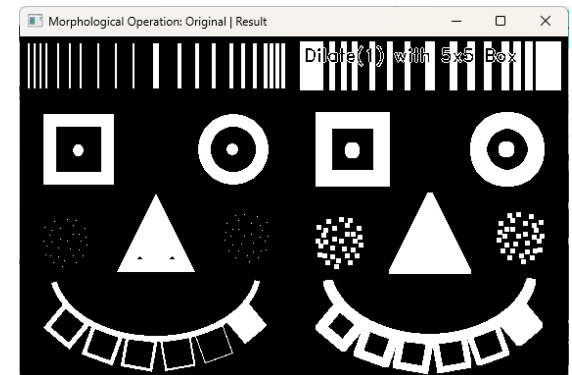
- **Dilation** (팽창 in Korean): An operation for expanding the shape

$$I'(x, y) = \begin{cases} 1 & \text{if any pixels in the window is 1} \\ 0 & \text{otherwise} \end{cases}$$

~ logical disjunction (union)



3x3
Box



5x5
Box

Morphological Operations

- [Erosion](#) (`cv.MORPH_ERODE`) : `erode(src)`
 - Applications: Thinning lines, removing small dots
- [Dilation](#) (`cv.MORPH_DILATE`) : `dilate(src)`
 - Applications: Thickening lines
- [Opening](#) (`cv.MORPH_OPEN`) : `dilate(erode(src))`
 - Applications: Growing holes (while keeping object size)
- [Closing](#) (`cv.MORPH_CLOSE`) : `erode(dilate(src))`
 - Applications: Shrinking or blocking holes
- Gradient (`cv.MORPH_GRADIENT`) : `dilate(src) - erode(src)`
- Tophat (`cv.MORPH_TOPHAT`) : `src - open(src)`
- Blackhat (`cv.MORPH_BLACKHAT`) : `close(src) - src`
- ...

Morphological Operations

- Example) Morphological operations

```
# Define morphological operations and kernels
```

```
morph_operations = [  
    {'name': 'Erode',      'operation': cv.MORPH_ERODE}, # Alternative) cv.erode()  
    {'name': 'Dilate',    'operation': cv.MORPH_DILATE}, # Alternative) cv.dilate()  
    ...]
```

```
kernel_tables = [  
    {'name': '3x3 Box',    'kernel': np.ones((3, 3), dtype=np.uint8)},  
    {'name': '5x5 Box',    'kernel': np.ones((5, 5), dtype=np.uint8)},  
    ...]
```

```
# Read the given image as gray scale
```

```
img = cv.imread('data/face.png', cv.IMREAD_GRAYSCALE)
```

```
# Initialize a control parameter
```

```
morph_select = 0
```

```
kernel_select = 0
```

```
n_iterations = 1
```

```
while True:
```

```
    # Apply morphological operation to the image with the given 'kernel'
```

```
    m_name, operation = morph_operations[morph_select].values() # Make alias
```

```
    k_name, kernel = kernel_tables[kernel_select].values()      # Make alias
```

```
    result = cv.morphologyEx(img, operation, kernel, iterations=n_iterations)
```

```
    # Show the image and its filtered result
```


Morphological Operations

- Application) Change detection (foreground extraction)

`while True:`

`...`

`# Get the difference between the current image and background`

`img_blur = cv.GaussianBlur(img, blur_ksize, blur_sigma)`

`img_diff = img_blur - img_back`

`# Apply thresholding`

`img_norm = np.linalg.norm(img_diff, axis=2)`

`img_bin = np.zeros_like(img_norm, dtype=np.uint8)`

`img_bin[img_norm > diff_threshold] = 255`

`# Apply morphological operations`

`img_mask = img_bin.copy()`

`img_mask = cv.erode(img_mask, box(3))`

`img_mask = cv.dilate(img_mask, box(5))`

`img_mask = cv.dilate(img_mask, box(3))`

`fg = img_mask == 255`

`img_mask = cv.erode(img_mask, box(3), iterations=2)`

`# Suppress small noise`

`# Connect broken parts`

`# Connect broken parts`

`# Keep the (thick) foreground mask`

`# Restore the thick mask thin`

`# Update the background`

`# Alternative) cv.createBackgroundSubtractorMOG2(), cv.bgsegm`

`bg = ~fg`

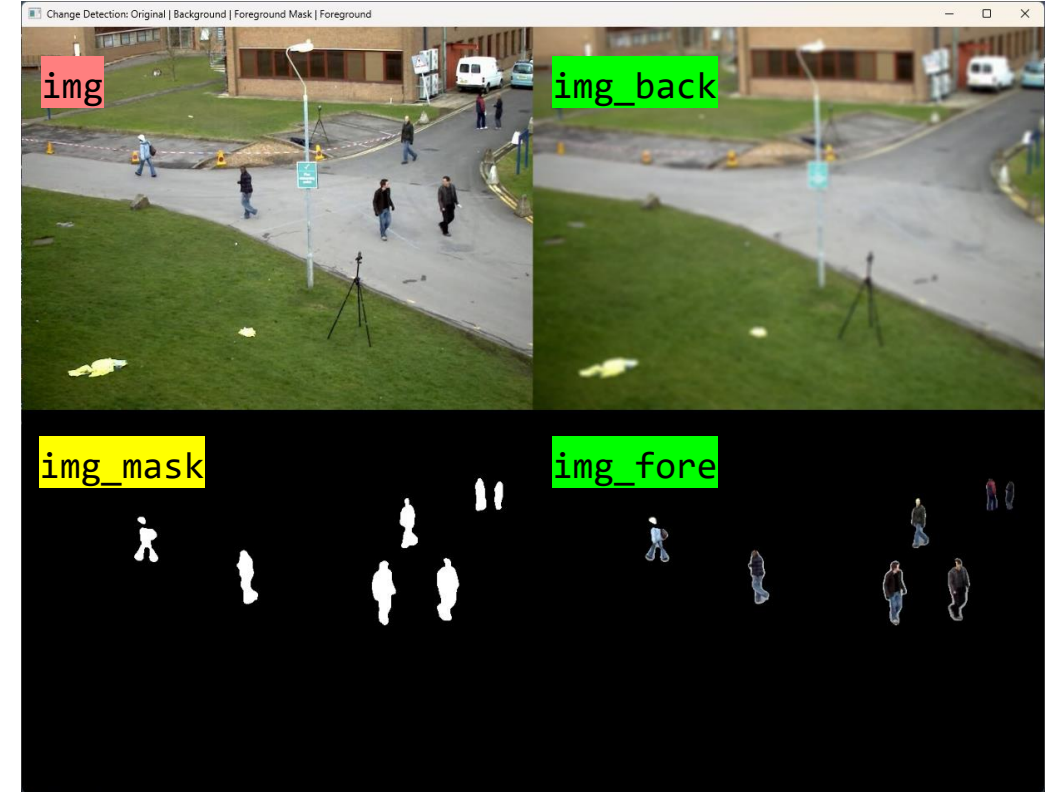
`img_back[bg] = (bg_update_rate * img_blur[bg] + (1 - bg_update_rate) * img_back[bg])` # With the higher weight

`img_back[fg] = (fg_update_rate * img_blur[fg] + (1 - fg_update_rate) * img_back[fg])` # With the lower weight

`# Get the foreground image`

`img_fore = np.zeros_like(img)`

`img_fore[img_mask == 255] = img[img_mask == 255]`



Summary

point-wise processing

- **Intensity Transformation**
 - Contrast stretching
 - Histogram equalization
 - How to eliminate user parameters?
- **Thresholding**
 - How to select the threshold?

region-wise processing

- **Image Filtering**
 - Smoothing filters
 - Advanced filters: Median Filter, bilateral filter
 - Edge detection (1st derivative): Prewitt, Sobel, Scharr
 - Popular edge detector: Canny edge detector
 - Laplacian operator (2nd derivative) → Sharpening
- **Morphological Operations**
 - Erosion, Dilation → Opening, Closing, ...
 - Application) Change detection (foreground extraction)

