

# Edge Detection using Image Processing

AS AN APPLICATION OF LINEAR ALGEBRA



original

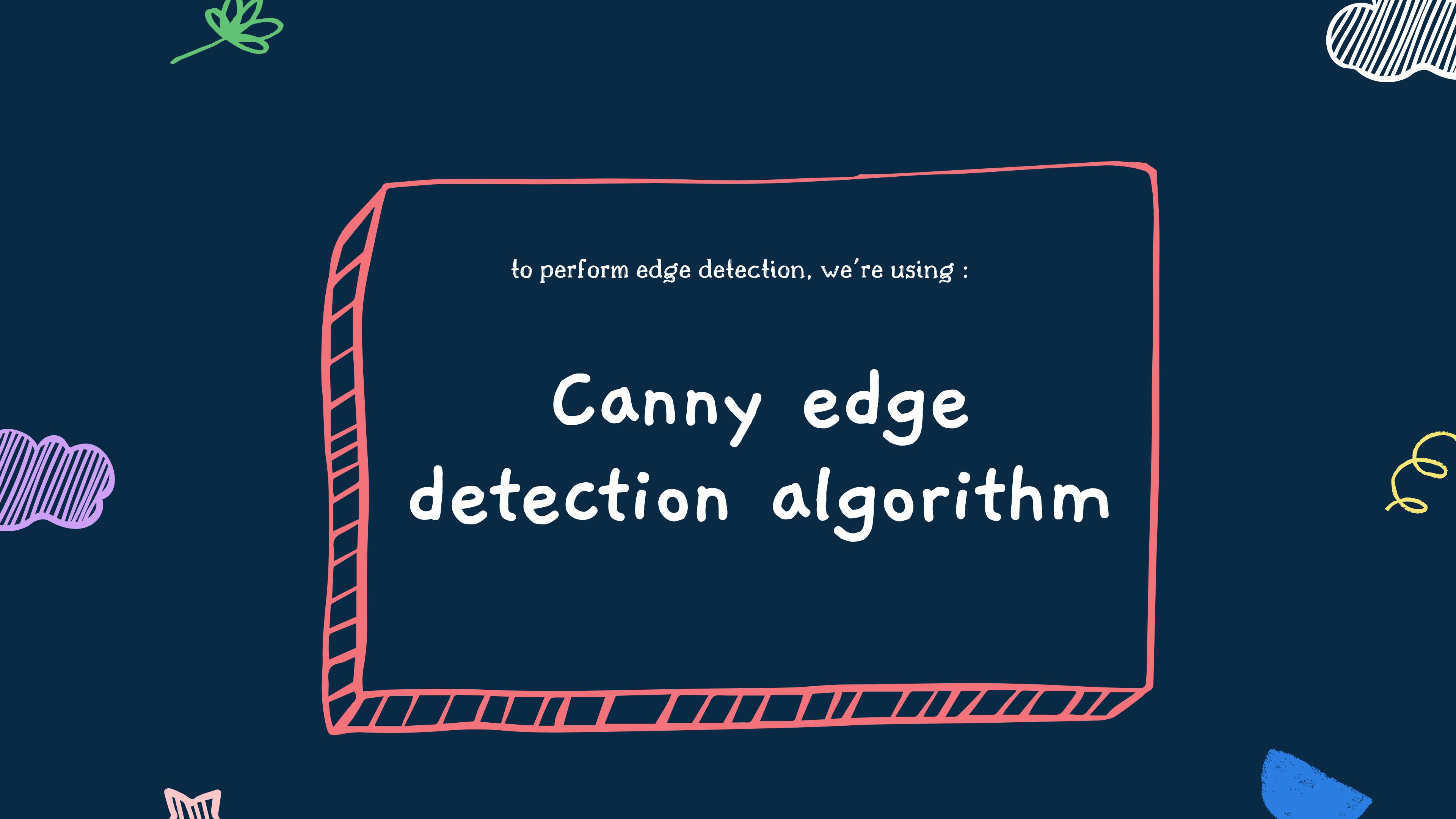


pixelated version

## What is edge detection?

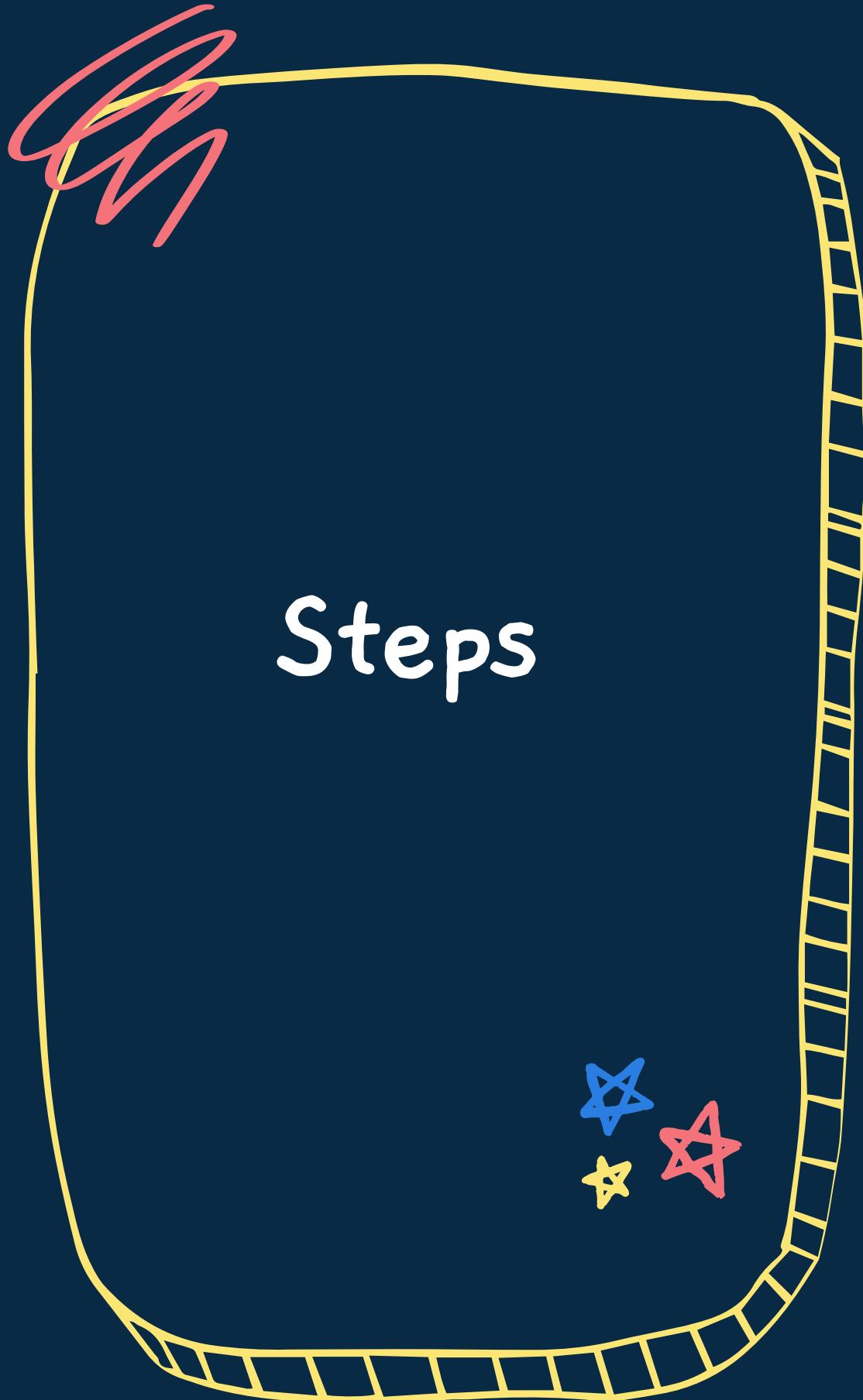
in digital images, which are just pictures made up of tiny dots called pixels, edges are places where the pixel values change a lot.

edge detection helps identify the boundaries or borders between different objects or regions in an image by looking for areas where the colours change a lot.



to perform edge detection, we're using :

# Canny edge detection algorithm



GAUSSIAN SMOOTHING / NOISE DETECTION



GRADIENT CALCULATION



NON - MAXIMUM SUPPRESSION



DOUBLE THRESHOLDING



EDGE TRACKING BY HYSTERESIS

# I. Gaussian Smoothing / Noise Reduction

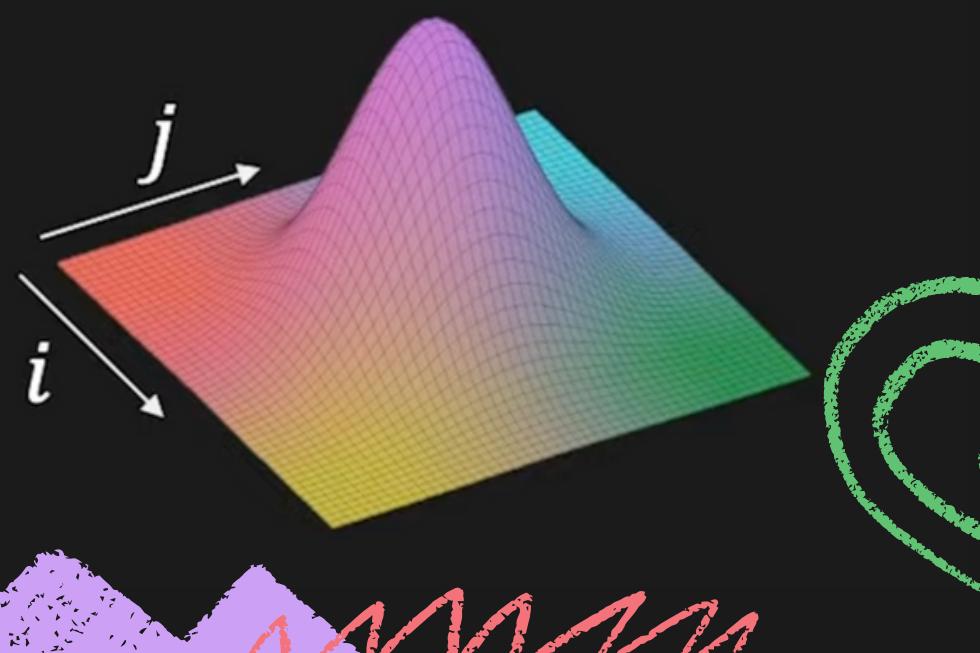
Mathematically, applying a Gaussian blur to an image is the same as convolving the image with a Gaussian function

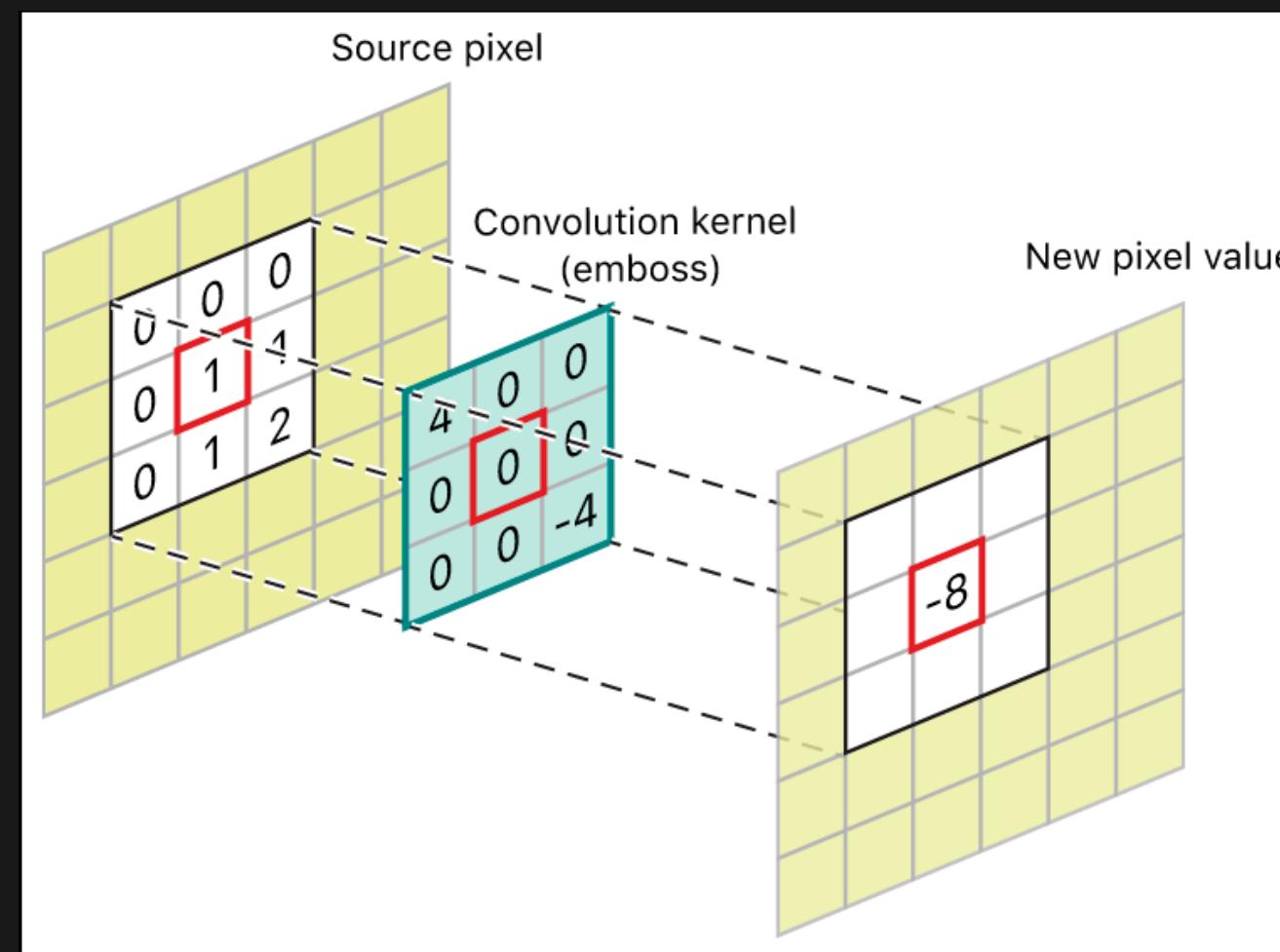
what is the gaussian function?

$$n_{\sigma}[i, j] = \frac{1}{2\pi\sigma^2} e^{-\frac{1}{2}\left(\frac{i^2+j^2}{\sigma^2}\right)}$$

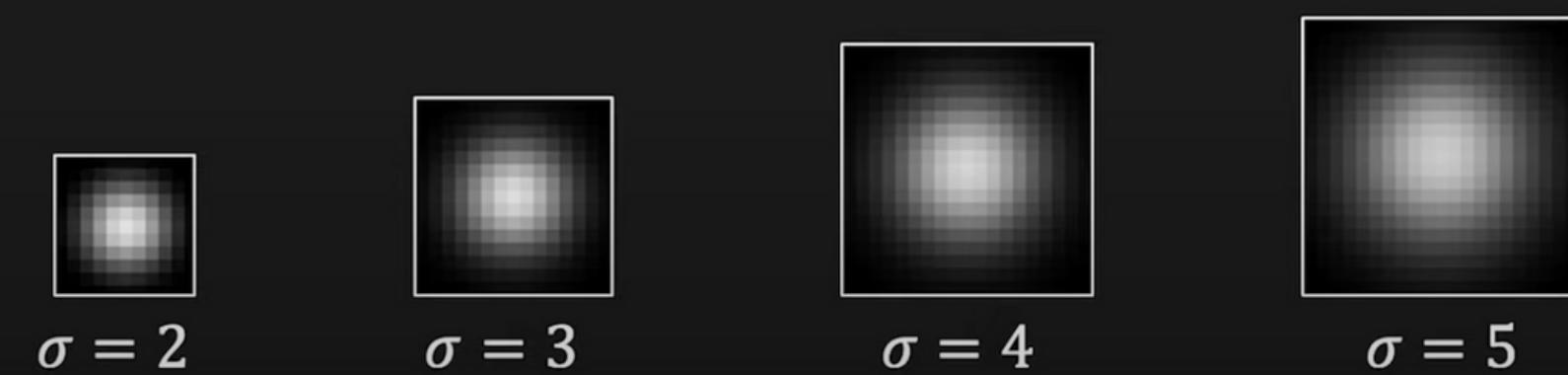
$$H_{ij} = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(i-(k+1))^2 + (j-(k+1))^2}{2\sigma^2}\right); 1 \leq i, j \leq (2k+1)$$

- $n_{\sigma}[i, j]$  is the value of the Gaussian function at a particular point  $[i, j]$  in the image with standard deviation  $\sigma$
- $\sigma$  (sigma) is a parameter called the standard deviation of the Gaussian function, which determines the width or spread of the curve. A larger  $\sigma$  value results in a wider curve and more smoothing





- The entries or values in the Gaussian kernel are calculated based on the Gaussian function formula.
- The Gaussian kernel is usually centered at the middle of the matrix or array, and the standard deviation ( $\sigma$ ) of the Gaussian function determines the size or spread of the kernel.
- The larger the  $\sigma$  value, the wider the kernel.



$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 4 \\ 0 & 1 & 2 \end{bmatrix} \times \begin{bmatrix} 4 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -4 \end{bmatrix}$$

pixels                          gaussian kernel

$$= \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -8 \end{bmatrix} \rightarrow \boxed{-8}$$

adding up the result

- Repeat this process for every pixel in the image, applying the Gaussian kernel and updating the intensity values accordingly.
- The resulting image will be a smoothed or blurred version of the original image, with the degree of smoothing controlled by the standard deviation ( $\sigma$ ) of the Gaussian function.

The result :



original



after applying gaussian blur

## 2.Gradient calculation

- Mathematically, the gradient of a two-variable function (here the image intensity function) at each image point is a 2D vector with the components given by the derivatives in the horizontal and vertical directions
- The most common way to approximate the image gradient is to convolve an image with a kernel, such as the Sobel operator or Prewitt operator.

What is a gradient function?

$$gradf(x, y) = \nabla f(x, y) = \frac{\partial f}{\partial x} + \frac{\partial f}{\partial y}$$

where,

- $\nabla f$ ,  $f$  is a vector-valued function.

$$\frac{\partial f}{\partial x} \approx (f(i+1, j) - f(i-1, j))/2$$

$$\frac{\partial f}{\partial y} \approx (f(i, j+1) - f(i, j-1))/2$$

our matrix =  $\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ 1 & -1 & -1 \end{bmatrix}$  after  $\frac{\partial f}{\partial x} \rightarrow \begin{bmatrix} 2-0/2 & 1-1/2 & 1-2/2 \\ 0-1/2 & 0-0/2 & 0-0/2 \\ -1-1/2 & -1+1/2 & -1+0/2 \end{bmatrix}$

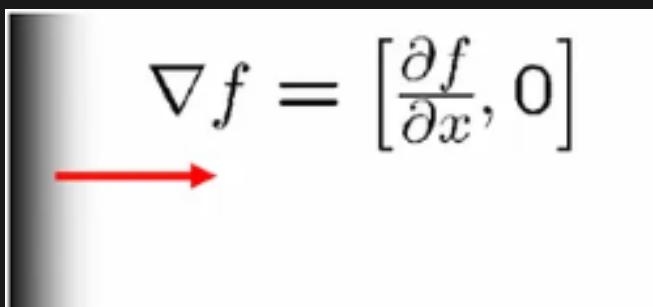
The Gradient matrix represents the strength of the edges at each pixel location, with higher values indicating stronger edges.

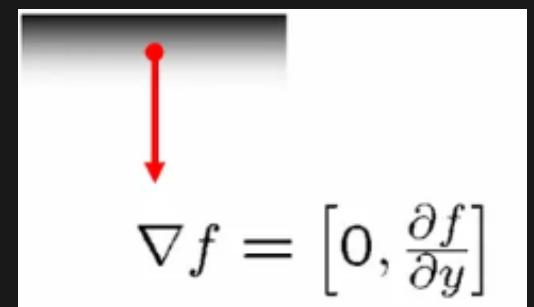
$\| \|^2_{xy}$ ,  
 $\frac{\partial f}{\partial y} = \begin{bmatrix} -y_2 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1/2 & -1/2 \end{bmatrix}$

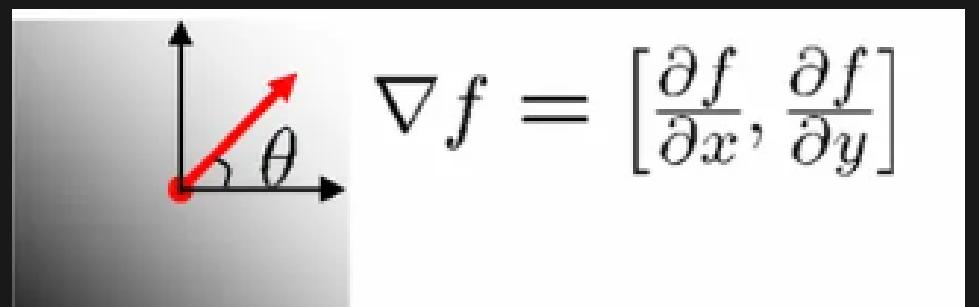
$$\begin{bmatrix} y_2 & 0 & -y_2 \\ -y_2 & 0 & y_2 \\ -1 & 0 & 1 \end{bmatrix}$$

## 2.Gradient calculation

The gradient points in the x, y and both the direction respectively w.r.t intensity change:

$$\nabla f = \left[ \frac{\partial f}{\partial x}, 0 \right]$$


$$\nabla f = \left[ 0, \frac{\partial f}{\partial y} \right]$$


$$\nabla f = \left[ \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right]$$


The gradient direction(orientation of edge normal) is given by:

$$\theta = \tan^{-1} \left( \frac{\partial f}{\partial y} / \frac{\partial f}{\partial x} \right)$$

NOTE:

Gradient points in the direction of most rapid increase in intensity (theta)

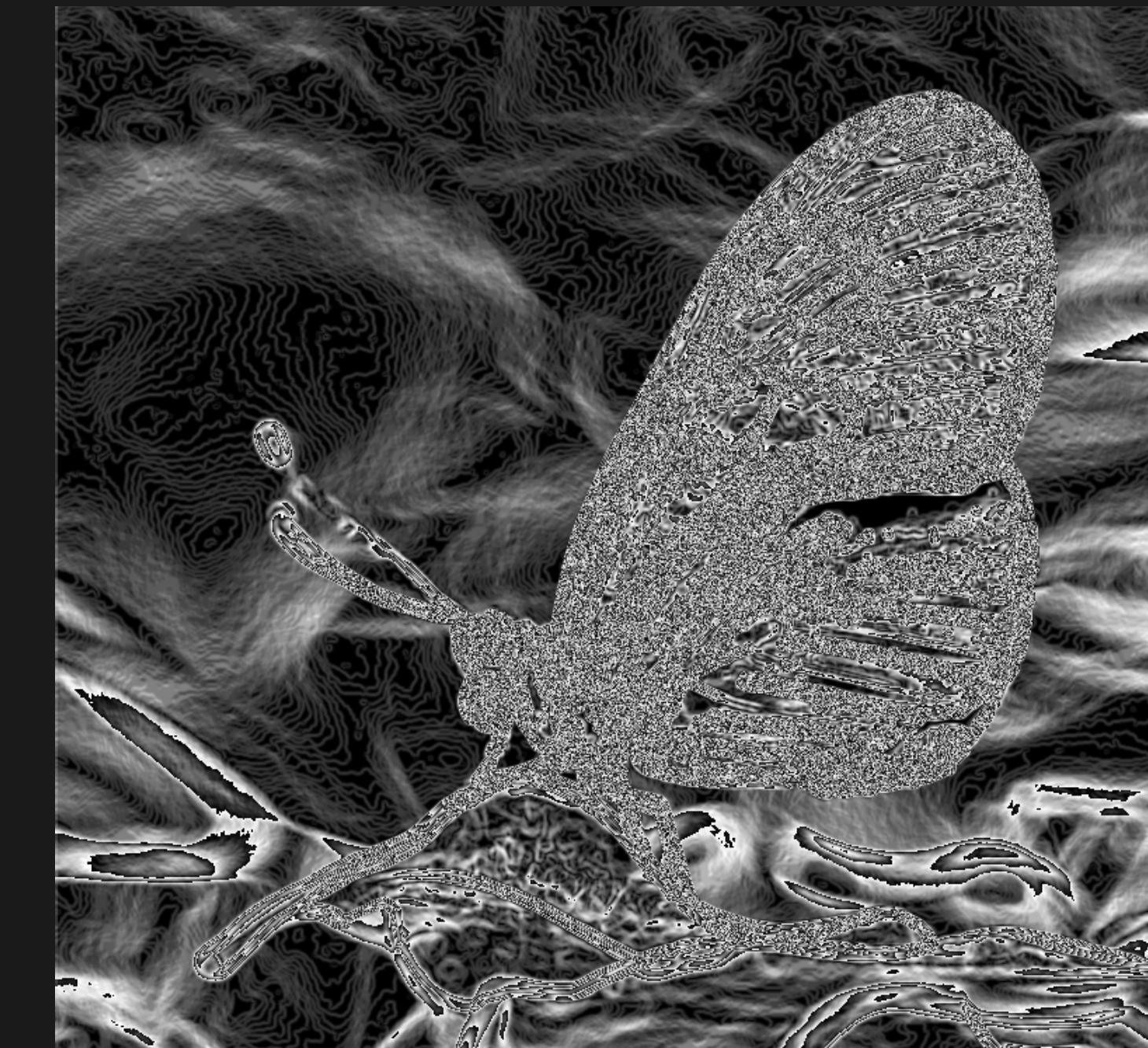
The edge strength is given by the gradient magnitude:

$$||\nabla f|| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

## 2.Gradient calculation



original



after gradient calculation

### 3. Non-maximum suppression

refines the edges detected by gradient calculation

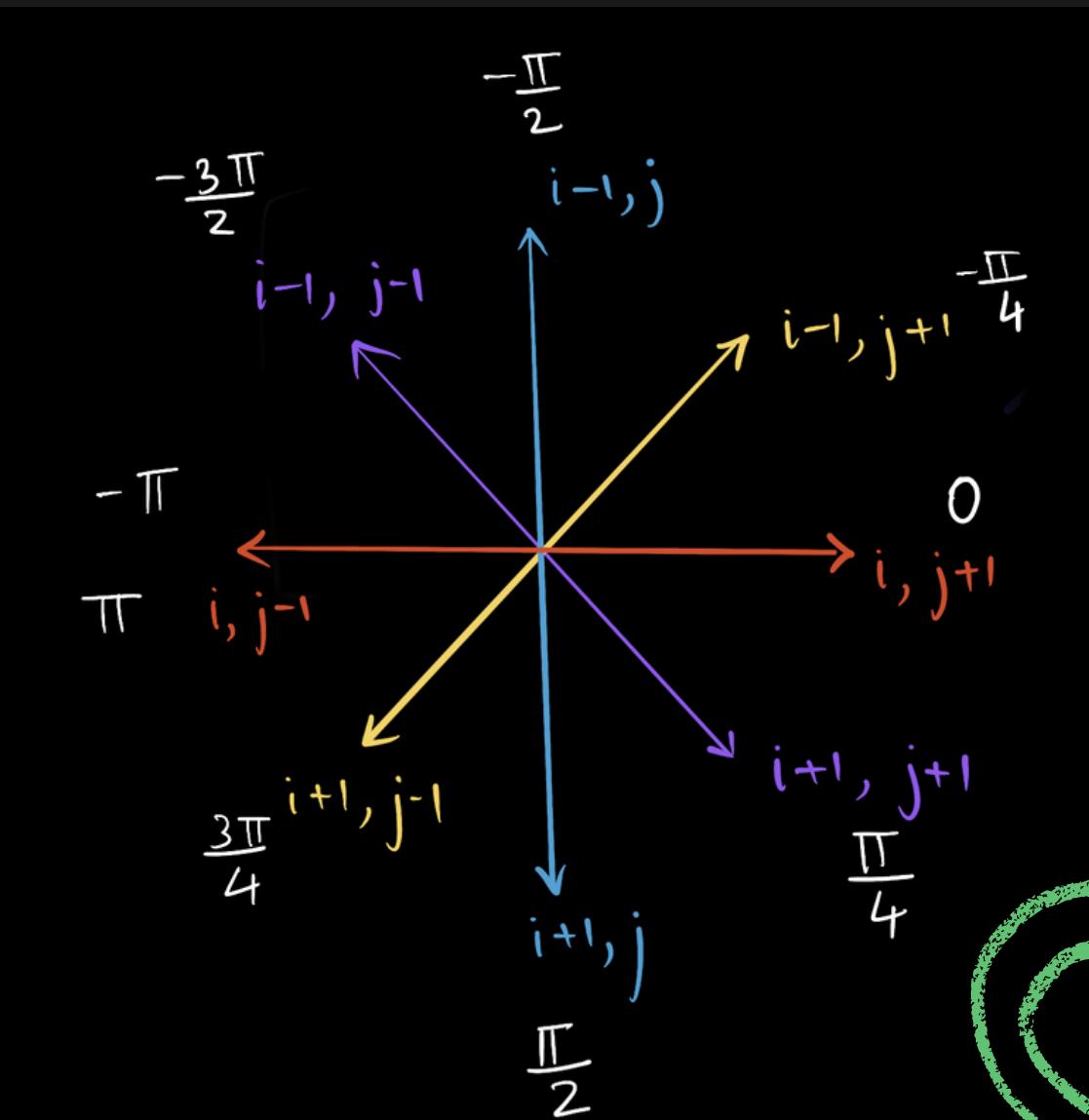
we get theta from gradient calculation, which should be quantised to the nearest multiple of 45 degrees

63.43	63.43	90.00
71.57	0.00	180.00
-116.57	-135.00	-135.00

quantised  $\theta =$

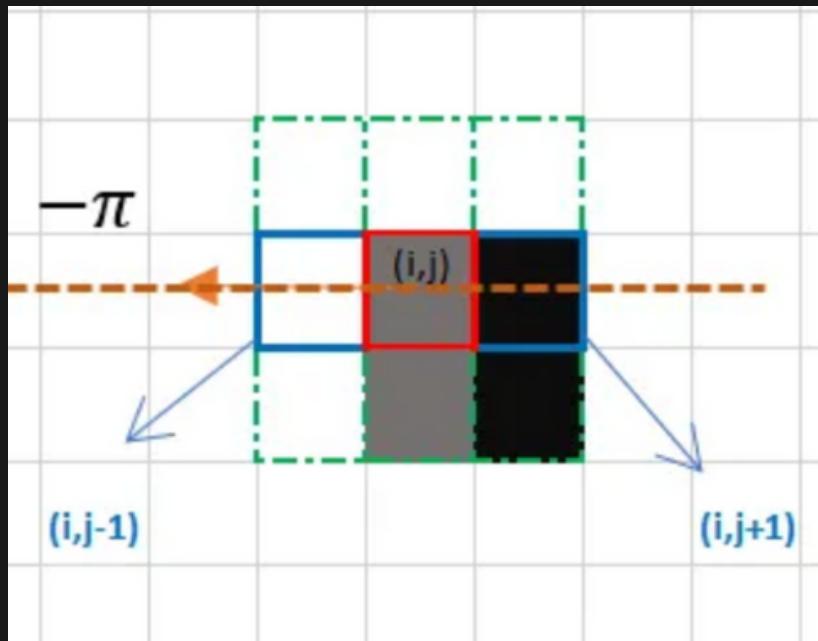
45	45	90
90	0	180
-135	-135	-135

- 3 matrices are considered here:
- the pixel matrix after gradient calculation
  - the angle matrix
  - the output matrix after suppression



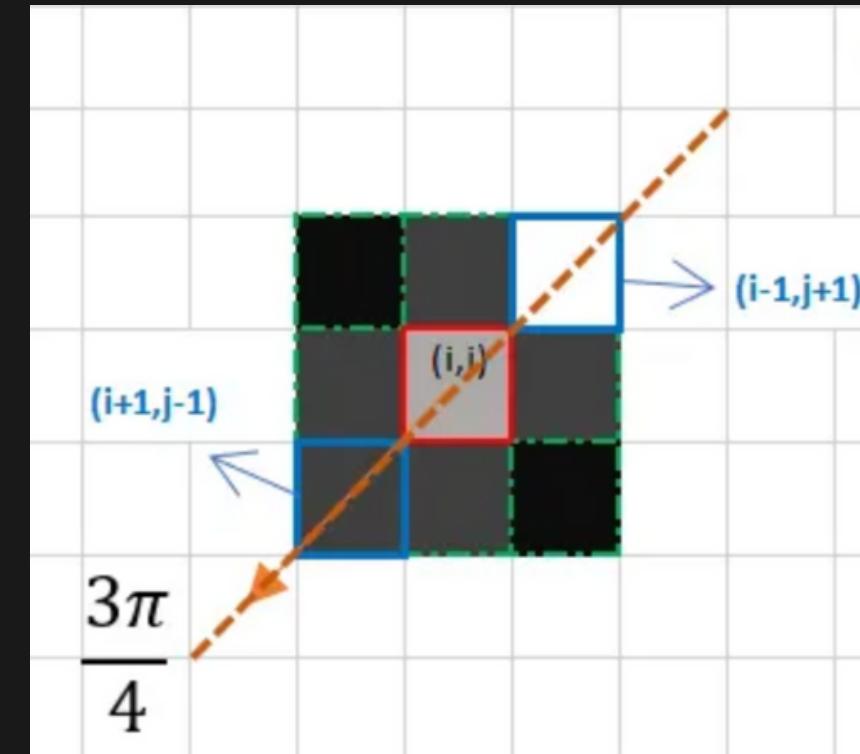
### 3. Non-maximum suppression

(directions are considered for each pixel using the quantised theta matrix)



pixel at  $(i,j-1)$  has more intensity(255) , hence in the output matrix value of  $(i,j)$  is suppressed. it is made 0 in output matrix.

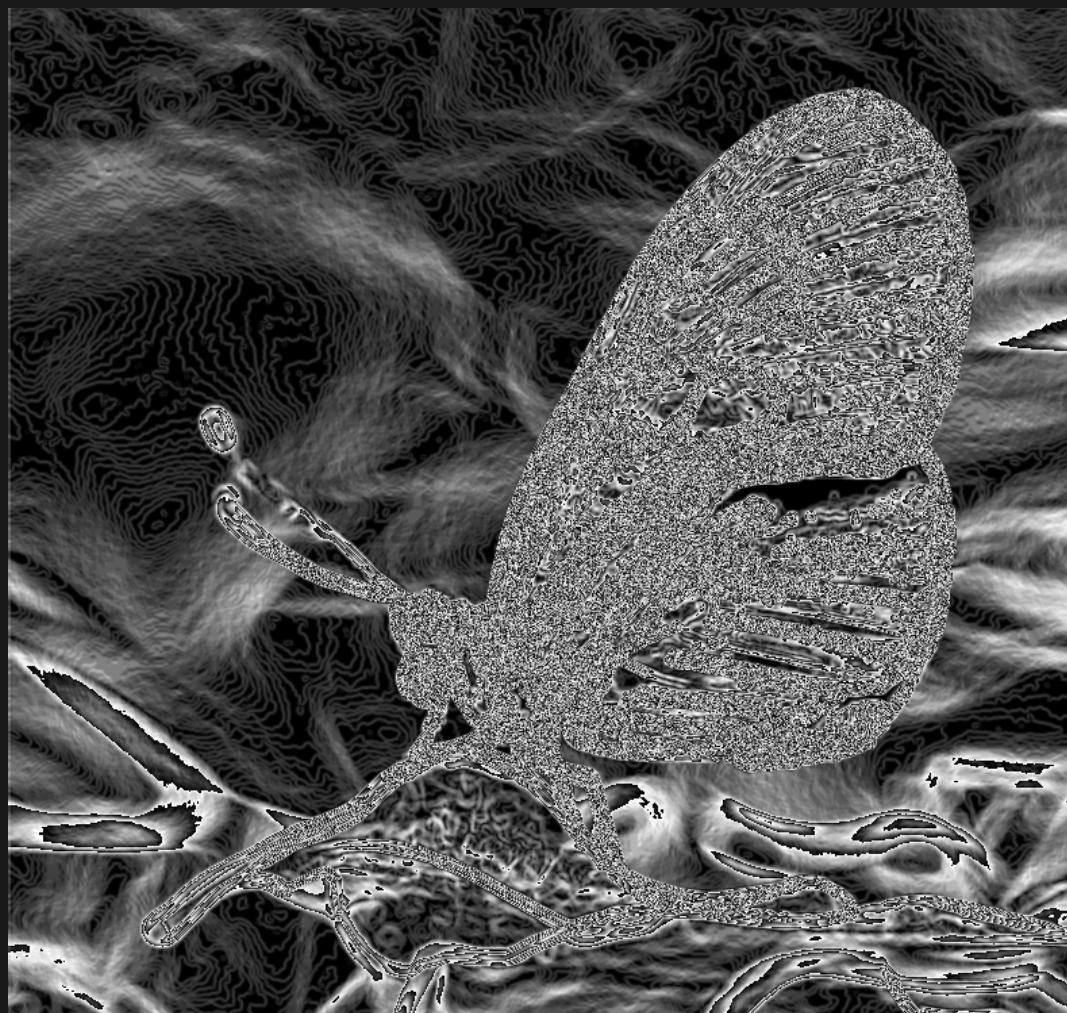
the most intense pixel in this direction is the pixel  $(i-1, j+1)$ .



# The result:



original



gradient calculation



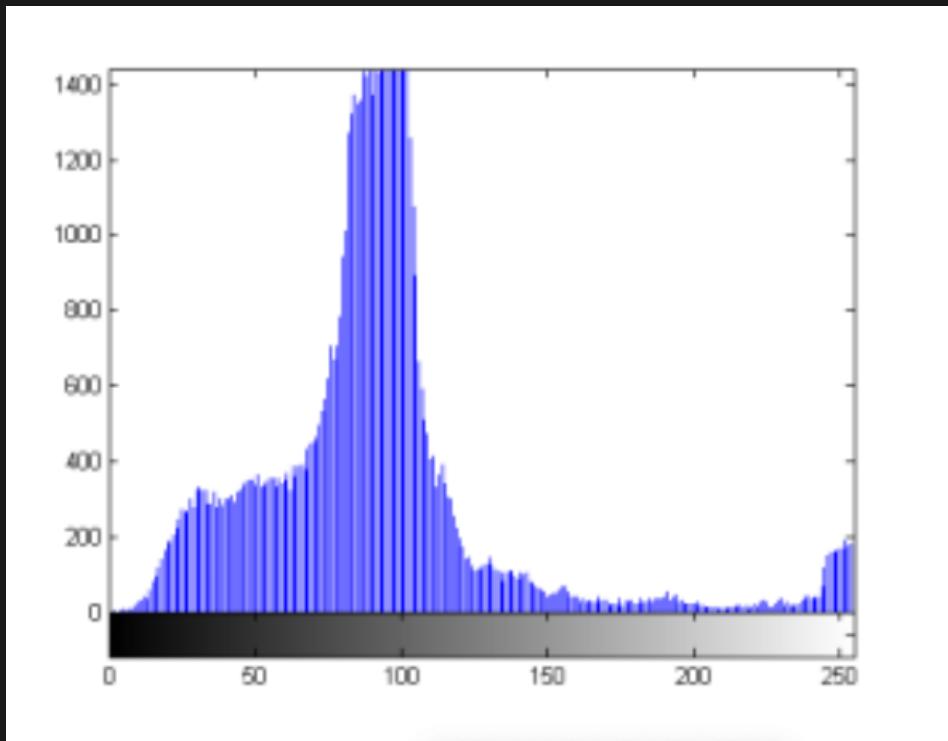
non maximum suppression



non-maximum suppression helps  
to enhance the accuracy and  
thinness of the detected edges  
in the final edge map

## 4. Double Thresholding

The double threshold step aims at identifying 3 kinds of pixels: strong, weak, and non-relevant



1. plot a histogram of the output matrix obtained from non maximum suppression
2. apply a gaussian filter
3. The threshold values are selected as a percentage of the maximum value in the smoothed histogram

how are pixels classified here?

$\text{pixel} > \text{high threshold}$

gives strong pixels

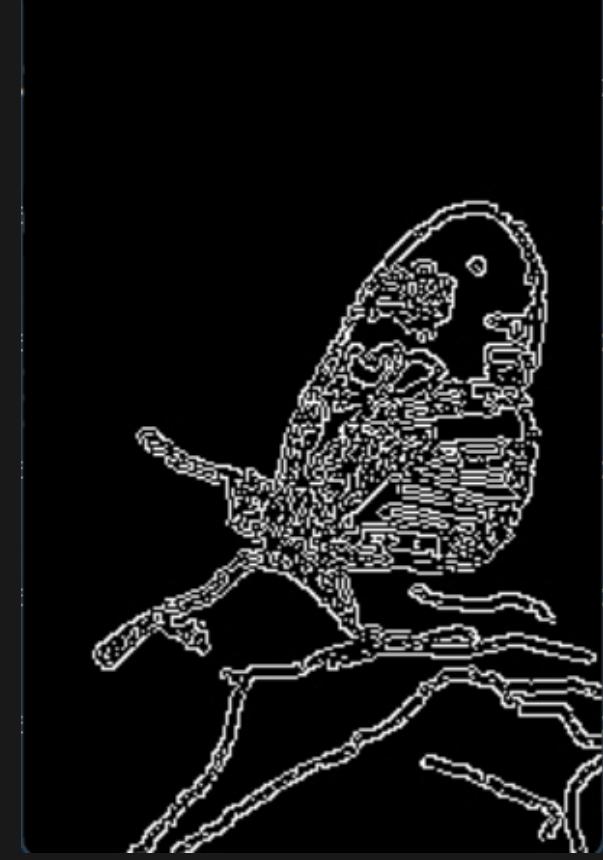
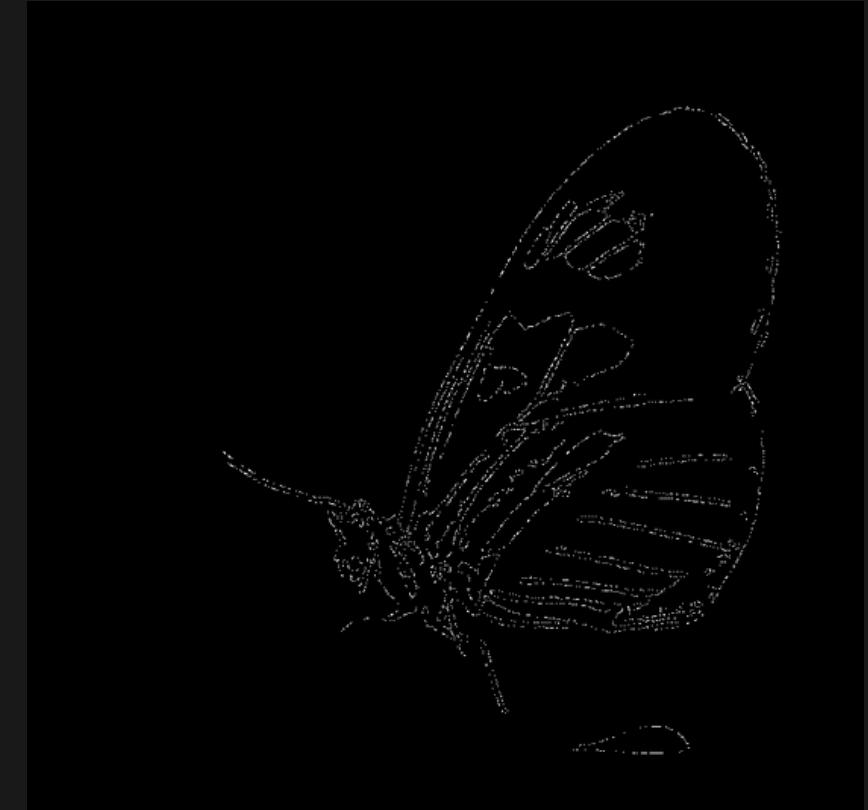
$\text{low threshold} < \text{pixel} < \text{high threshold}$

gives weak pixels

$\text{pixel} < \text{low threshold}$

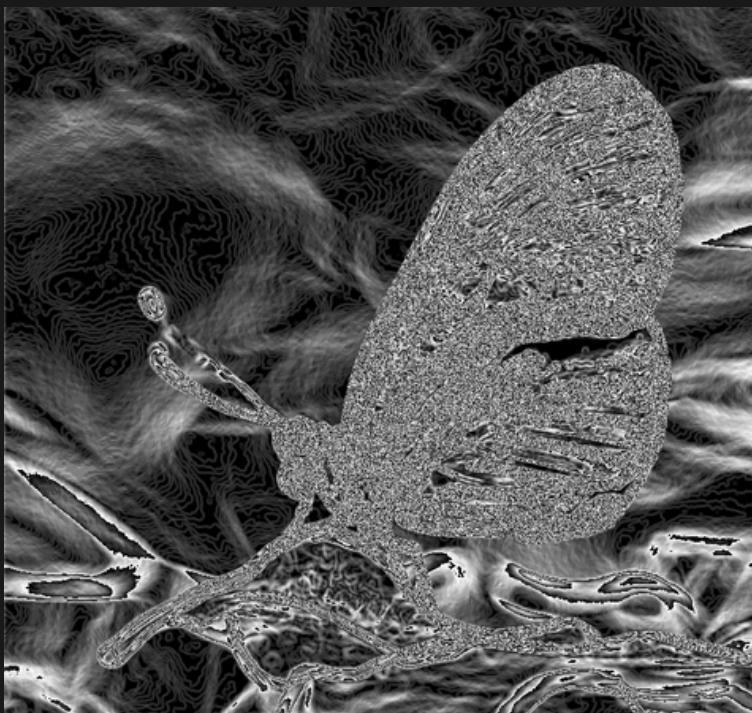
gives non relevant pixels

# The result:

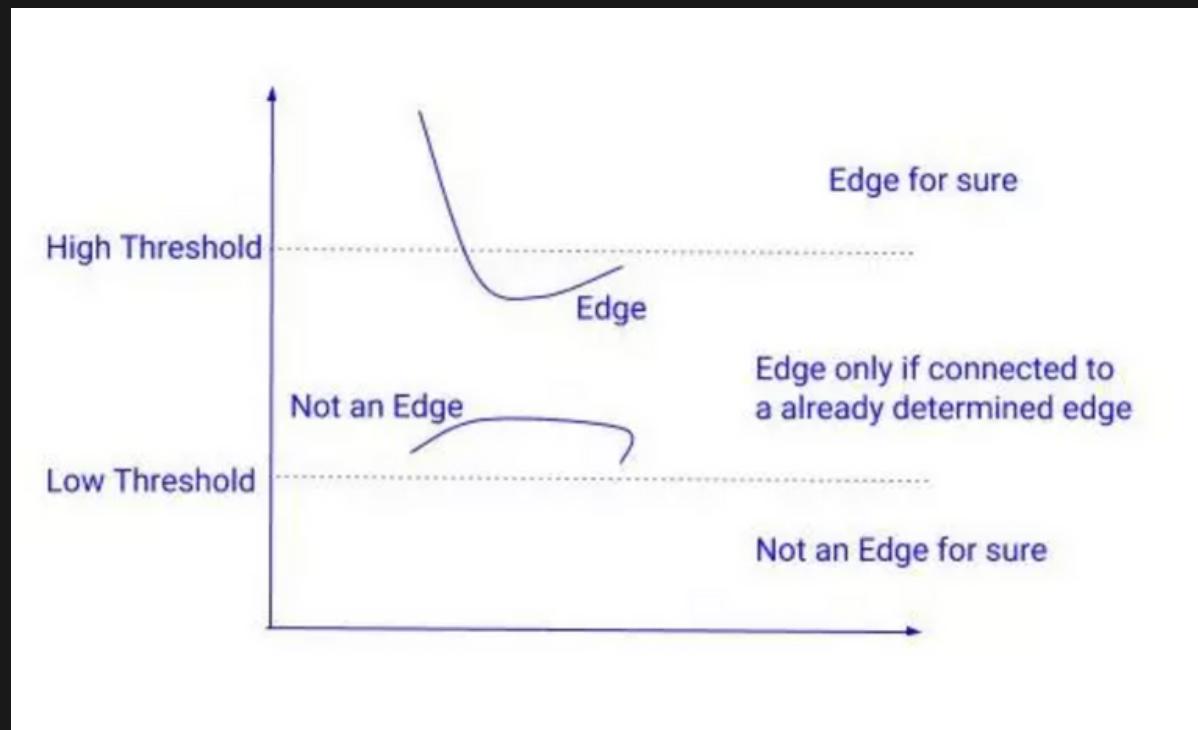


after double thresholding

carried out with the assumption  
that the range of intensity levels  
covered by objects of interest is  
different from the background

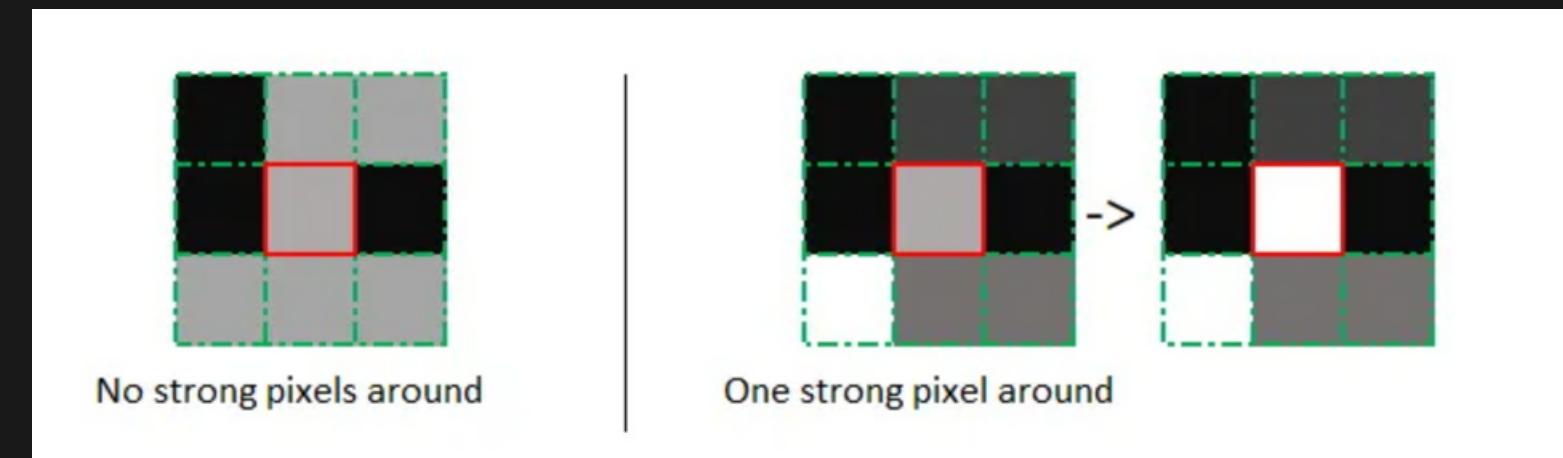


# 5. Edge tracking by hysteresis



Strong edges are interpreted as “certain edges”, Weak edges are included if and only if they are connected to strong edges.

the hysteresis consists of transforming weak pixels into strong ones, if at least one of the pixels around the one being processed is a strong one



## 5. Edge tracking by hysteresis

original



gap is not included

Strong  
edges  
only



Strong +  
connected  
weak edges

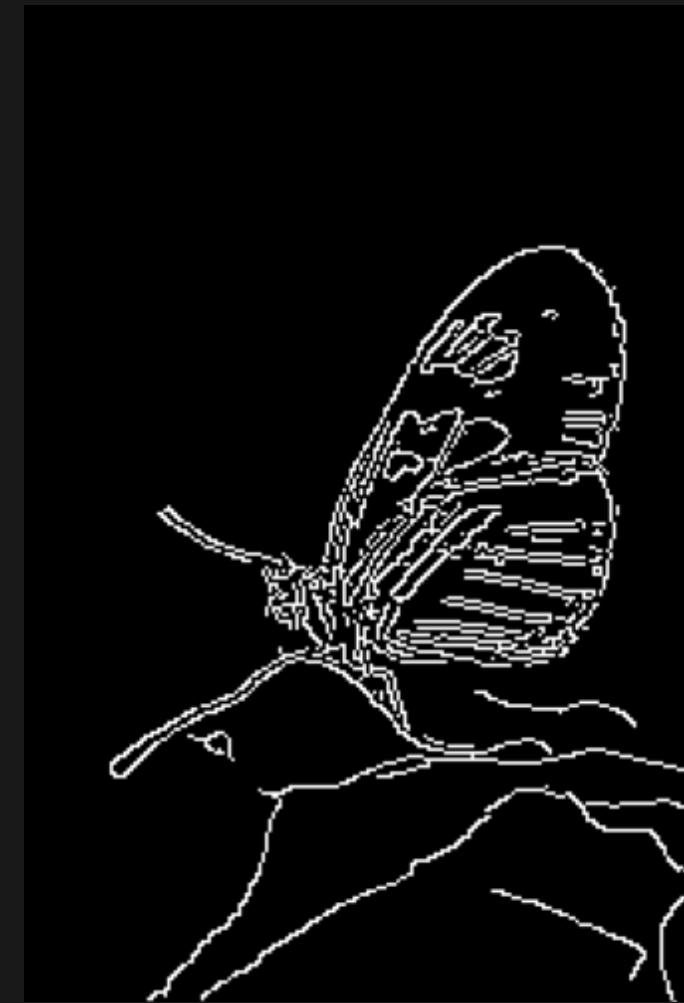


Weak  
edges

The result:



original



after edge hysteresis



# Code and its Implementation

## I. Gaussian kernel function:

```
def gaussian_kernel(self, size, sigma=1):
    size = int(size) // 2
    x, y = np.mgrid[-size:size+1, -size:size+1]
    normal = 1 / (2.0 * np.pi * sigma**2)
    g = np.exp(-((x**2 + y**2) / (2.0*sigma**2))) * normal
    return g
```

## 2. Sobel Filter function:

```
def sobel_filters(self, img):
    Kx = np.array([[-1, 0, 1], [-2, 0, 2], [-1, 0, 1]], np.float32)
    Ky = np.array([[1, 2, 1], [0, 0, 0], [-1, -2, -1]], np.float32)

    Ix = ndimage.filters.convolve(img, Kx)
    Iy = ndimage.filters.convolve(img, Ky)

    G = np.hypot(Ix, Iy)
    G = G / G.max() * 255
    theta = np.arctan2(Iy, Ix)
    return (G, theta)
```

### 3. Non-Maximum Suppression function:

```
def non_max_suppression(self, img, D):
    M, N = img.shape
    Z = np.zeros((M,N), dtype=np.int32)
    angle = D * 180. / np.pi
    angle[angle < 0] += 180

    for i in range(1,M-1):
        for j in range(1,N-1):
            try:
                q = 255
                r = 255

                #angle 0
                if (0 <= angle[i,j] < 22.5) or (157.5 <= angle[i,j] <= 180):
                    q = img[i, j+1]
                    r = img[i, j-1]
                #angle 45
                elif (22.5 <= angle[i,j] < 67.5):
                    q = img[i+1, j-1]
                    r = img[i-1, j+1]
                #angle 90
                elif (67.5 <= angle[i,j] < 112.5):
                    q = img[i+1, j]
                    r = img[i-1, j]
                #angle 135
                elif (112.5 <= angle[i,j] < 157.5):
                    q = img[i-1, j-1]
                    r = img[i+1, j+1]

                if (img[i,j] >= q) and (img[i,j] >= r):
                    Z[i,j] = img[i,j]
                else:
                    Z[i,j] = 0
            except IndexError as e:
                pass
    return Z
```

## 4. Threshold function:

```
def threshold(self, img):  
  
    highThreshold = img.max() * self.highThreshold;  
    lowThreshold = highThreshold * self.lowThreshold;  
  
    M, N = img.shape  
    res = np.zeros((M,N), dtype=np.int32)  
  
    weak = np.int32(self.weak_pixel)  
    strong = np.int32(self.strong_pixel)  
  
    strong_i, strong_j = np.where(img >= highThreshold)  
    zeros_i, zeros_j = np.where(img < lowThreshold)  
  
    weak_i, weak_j = np.where((img <= highThreshold) & (img >= lowThreshold))  
  
    res[strong_i, strong_j] = strong  
    res[weak_i, weak_j] = weak  
  
    return (res)
```

## 5. Hysteresis function:

```
def hysteresis(self, img):
    M, N = img.shape
    weak = self.weak_pixel
    strong = self.strong_pixel

    for i in range(1, M-1):
        for j in range(1, N-1):
            if (img[i,j] == weak):
                try:
                    if ((img[i+1, j-1] == strong) or (img[i+1, j] == strong) or (img[i+1, j+1] == strong)
                        or (img[i, j-1] == strong) or (img[i, j+1] == strong)
                        or (img[i-1, j-1] == strong) or (img[i-1, j] == strong) or (img[i-1, j+1] == strong)):
                        img[i, j] = strong
                    else:
                        img[i, j] = 0
                except IndexError as e:
                    pass

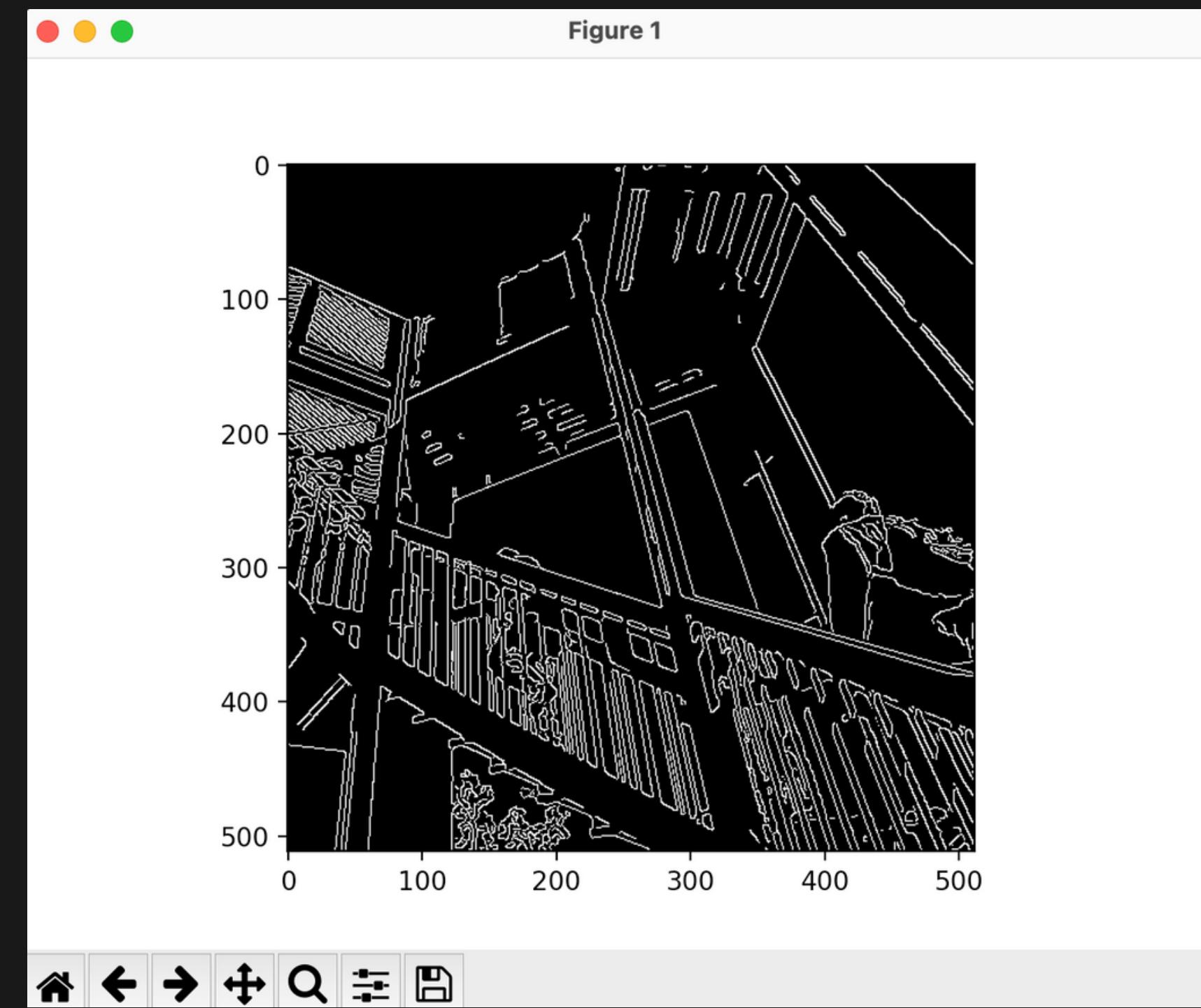
    return img
```

# Calling the functions:

```
def detect(self):
    imgs_final = []
    for i, img in enumerate(self.imgs):
        self.img_smoothed = convolve(img, self.gaussian_kernel(self.kernel_size, self.sigma))
        self.gradientMat, self.thetaMat = self.sobel_filters(self.img_smoothed)
        self.nonMaxImg = self.non_max_suppression(self.gradientMat, self.thetaMat)
        self.thresholdImg = self.threshold(self.nonMaxImg)
        img_final = self.hysteresis(self.thresholdImg)
        self.imgs_final.append(img_final)

    return self.imgs_final
```

# Output:

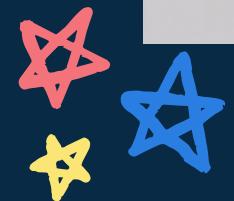
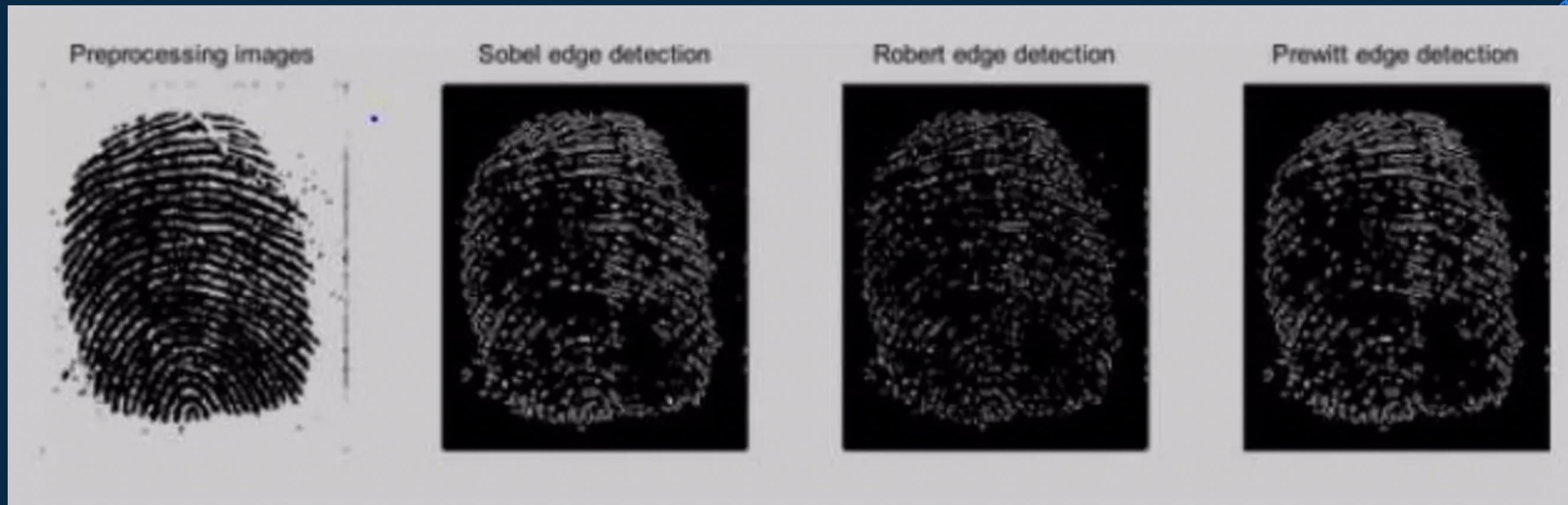


# Real Life Applications of Edge Detection

FINGER PRINT RECOGNITION  
SATELLITE IMAGING  
ROBOTICS VISION  
MEDICAL SCANS  
and many more...

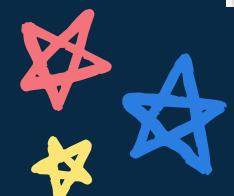
# I. Finger Print Recognition

- At present, finger print recognition has been used widely, such as in mobile phones.
- Edge detection techniques enhance the quality of image and cause the improvement in the image recognition.



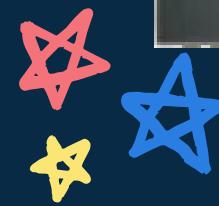
## 2. Satellite Imaging

- The edge map generated by bilateral filtering based edge contain more accurate and well localized edge map.
- It also suppresses noise and produces more realistic edge map.



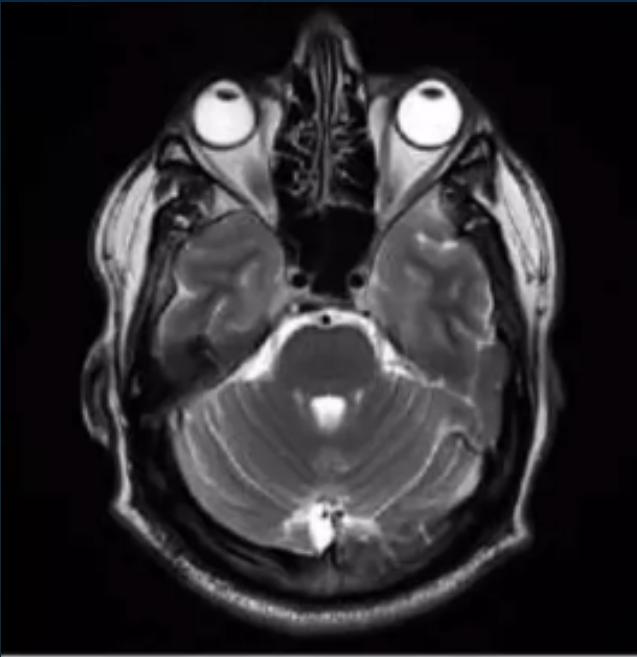
### 3. Robotics Vision

- The present and near future main application areas of edge detection are robotics vision, like in self-driving vehicles.

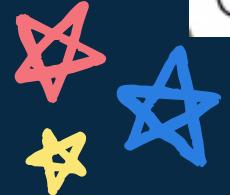


# 4. Medical Scans

- Another important area being developed involving edge detection is finding "pathological" objects in medical images such as tumors.
- Medical image edge detection is an important method in the recognition of the human organs and it is an important pre-processing step in 3D reconstruction such as the reconstruction of brain images,



Original MRI Scan



from Sobel operator



from Canny operator





## More Applications

...



PORTRAIT MODE AND DEPTH EFFECTS IN CAMERAS



IMAGE EDITING TO REMOVE BACKGROUND OBJECTS



AUTONOMOUS VEHICLES



QUALITY CONTROL TO DETECT DEFECTS AND FLAWS



SURVEILLANCE TO DETECT MOVING OBJECTS

## Advantages

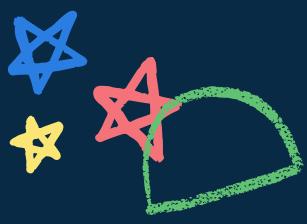
- Good Accuracy
- Low error rate
- Handles noise well
- Single edge detection
- Tunable parameters

## Disadvantages

- Computationally expensive
- Not suitable for all images
- Missing low-contrast edges
- Sensitivity to lighting changes



THANK YOU!



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