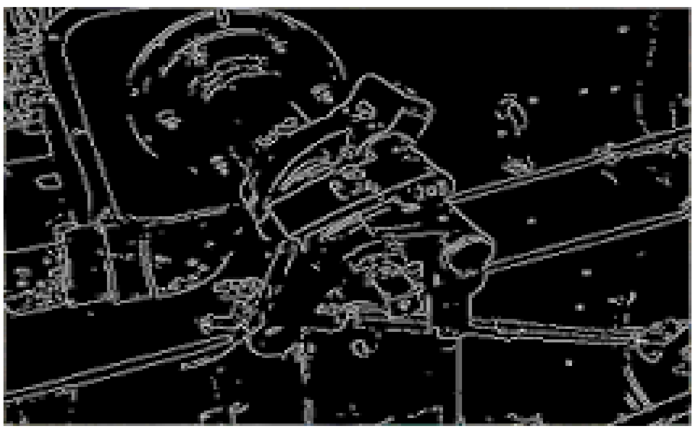
Aim: To study Edge detection with Canny.

Objective : Perform Canny Edge detector using Noise reduction using Gaussian filter, Gradient calculation along the horizontal and vertical axis, Non-Maximum suppression of false edges, Double thresholding for segregating strong and weak edges, Edge tracking by hysteresis.

Theory :
The Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images. It was developed by John F. Canny in 1986. Canny also produced a computational theory of edge detection explaining why the technique works.



What are the three stages of the Canny edge detector
To fulfill these objectives, the edge detection process included the following stages.

- Stage One - Image Smoothing.
- Stage Two - Differentiation.
- Stage Three - Non-maximum Suppression.

The basic steps involved in this algorithm are:

- Noise reduction using Gaussian filter.
- Gradient calculation along the horizontal and vertical axis.
- Non-Maximum suppression of false edges.
- Double thresholding for segregating strong and weak edges.
- Edge tracking by hysteresis.

Now let us understand these concepts in detail:
1. Noise reduction using Gaussian filter
This step is of utmost importance in the Canny edge detection. It uses a Gaussian filter for the removal of noise from the image, it is because this noise can be assumed as edges due to sudden intensity change by the edge detector. The sum of the elements in the Gaussian kernel is 1, so the

kernel should be normalized before applying convolution to the image. In this Experiment, we will use a kernel of size 5 X 5 and sigma = 1.4, which will blur the image and remove the noise from it. The equation for Gaussian filter kernel is

$$G_\sigma = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

2. Gradient calculation
When the image is smoothed, the derivatives Ix and Iy are calculated w.r.t x and y axis. It can be implemented by using the Sobel-Feldman kernels convolution with image as given:

$$K_x = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}, K_y = \begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix}.$$

after applying these kernel we can use the gradient magnitudes and the angle to further process this step. The magnitude and angle can be calculated as

$$|G| = \sqrt{I_x^2 + I_y^2},$$
$$\theta(x, y) = arctan\left(\frac{I_y}{I_x}\right)$$

3. Non-Maximum Suppression
This step aims at reducing the duplicate merging pixels along the edges to make them uneven. For each pixel find two neighbors in the positive and negative gradient directions, supposing that each neighbor occupies the angle of pi /4, and 0 is the direction straight to the right. If the magnitude of the current pixel is greater than the magnitude of the neighbors, nothing changes, otherwise, the magnitude of the current pixel is set to zero.

4. Double Thresholding
The gradient magnitudes are compared with two specified threshold values, the first one is lower than the second. The gradients that are smaller than the low threshold value are suppressed, the gradients higher than the high threshold value are marked as strong ones and the corresponding pixels are included in the final edge map. All the rest gradients are marked as weak ones and pixels corresponding to these gradients are considered in the next step.

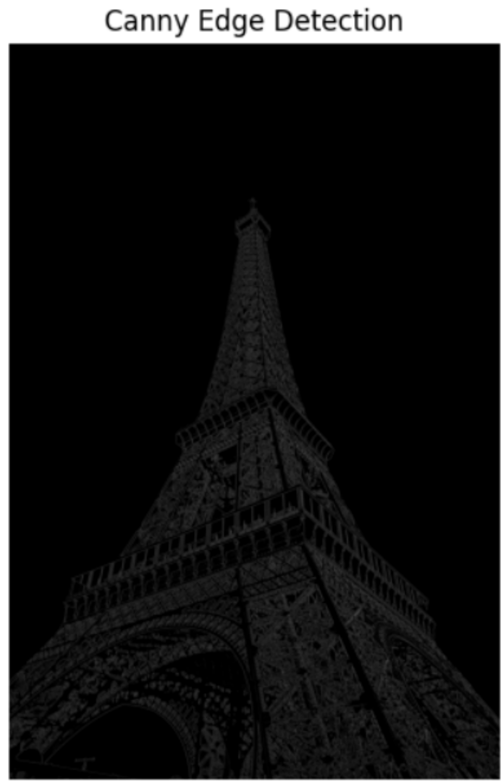
5. Edge Tracking using Hysteresis
Since a weak edge pixel caused by true edges will be connected to a strong edge pixel, pixel W with weak gradient is marked as edge and included in the final edge map if and only if it is involved in the same connected component as some pixel S with strong gradient. In other words, there should be a chain of neighbor weak pixels connecting W and S (the neighbors are 8 pixels around the considered one). We will make up and implement an algorithm that finds all the connected components of the gradient map considering each pixel only once. After that, you can decide which pixels will be included in the final edge map.

Code:
```
import numpy as np
import os
import cv2
import matplotlib.pyplot as plt

# defining the canny detector function
# here weak_th and strong_th are thresholds for
# double thresholding step
def Canny_detector(img, weak_th = None, strong_th = None):
  # conversion of image to grayscale
  img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
  # Noise reduction step
  img = cv2.GaussianBlur(img, (5, 5), 1.4)
  # Calculating the gradients
  gx = cv2.Sobel(np.float32(img), cv2.CV_64F, 1, 0, 3)
  gy = cv2.Sobel(np.float32(img), cv2.CV_64F, 0, 1, 3)
  # Conversion of Cartesian coordinates to polar
  mag, ang = cv2.cartToPolar(gx, gy, angleInDegrees = True)

  # setting the minimum and maximum thresholds
  # for double thresholding
  mag_max = np.max(mag)
  if not weak_th:weak_th = mag_max * 0.1
  if not strong_th:strong_th = mag_max * 0.5

  # getting the dimensions of the input image
  height, width = img.shape
```

```
# Looping through every pixel of the grayscale
# image
for i_x in range(width):
  for i_y in range(height):
    grad_ang = ang[i_y, i_x]
    grad_ang = abs(grad_ang-180) if abs(grad_ang)>180 else abs(grad_ang)

    # selecting the neighbors of the target pixel
    # according to the gradient direction
    # In the x axis direction
    if grad_ang<= 22.5:
      neighb_1_x, neighb_1_y = i_x-1, i_y
      neighb_2_x, neighb_2_y = i_x + 1, i_y
    # top right (diagonal-1) direction
    elif grad_ang>22.5 and grad_ang<=(22.5 + 45):
      neighb_1_x, neighb_1_y = i_x-1, i_y-1
      neighb_2_x, neighb_2_y = i_x + 1, i_y + 1

    # In y-axis direction
    elif grad_ang>(22.5 + 45) and grad_ang<=(22.5 + 90):
      neighb_1_x, neighb_1_y = i_x, i_y-1
      neighb_2_x, neighb_2_y = i_x, i_y + 1
    # top left (diagonal-2) direction
    elif grad_ang>(22.5 + 90) and grad_ang<=(22.5 + 135):
      neighb_1_x, neighb_1_y = i_x-1, i_y + 1
      neighb_2_x, neighb_2_y = i_x + 1, i_y-1

    # Now it restarts the cycle
    elif grad_ang>(22.5 + 135) and grad_ang<=(22.5 + 180):
      neighb_1_x, neighb_1_y = i_x-1, i_y
      neighb_2_x, neighb_2_y = i_x + 1, i_y
    # Non-maximum suppression step
    if width>neighb_1_x>= 0 and height>neighb_1_y>= 0:
      if mag[i_y, i_x]<mag[neighb_1_y, neighb_1_x]:
        mag[i_y, i_x]= 0
        continue
    if width>neighb_2_x>= 0 and height>neighb_2_y>= 0:
```

```
      if mag[i_y, i_x]<mag[neighb_2_y, neighb_2_x]:
        mag[i_y, i_x]= 0
  weak_ids = np.zeros_like(img)
  strong_ids = np.zeros_like(img)
  ids = np.zeros_like(img)
  # double thresholding step
  for i_x in range(width):
    for i_y in range(height):
      grad_mag = mag[i_y, i_x]
      if grad_mag<weak_th:
        mag[i_y, i_x]= 0
      elif strong_th>grad_mag>= weak_th:
        ids[i_y, i_x]= 1
      else:
        ids[i_y, i_x]= 2

  # finally returning the magnitude of
  # gradients of edges
  return mag
frame = cv2.imread('image.jpg')
# calling the designed function for
# finding edges
canny_img = Canny_detector(frame)

# Displaying the input and output image
plt.figure(figsize=(8, 10))  # Set the size of the figure (adjust width and height as desired)
f, plots = plt.subplots(2, 1, figsize=(8, 10))  # Set the size of subplots (adjust width and height)
# Display the input image
plots[0].imshow(cv2.cvtColor(frame, cv2.COLOR_BGR2RGB))
plots[0].set_title('Input Image')
plots[0].axis('off')  # Hide the axis ticks and labels
# Display the output image (Canny edge-detected) in grayscale
plots[1].imshow(canny_img, cmap='gray')
plots[1].set_title('Canny Edge Detection')
plots[1].axis('off')  #Hide the axis ticks and labels
plt.tight_layout()  #Adjust spacing between subplots for better visualization
plt.show()
```

Output:



Conclusion:

Canny edge detection remains a fundamental technique in computer vision due to its robustness, accuracy, and simplicity. It serves as a valuable building block for more advanced image processing and computer vision tasks, making it an indispensable tool for researchers and practitioners in the field. The implementation code for Canny edge detection provides a simple and clear representation of how the algorithm works. It takes an input image, applies the Canny edge detection function (Canny_detector), and displays both the input image and the Canny edge-detected output side by side. The implementation code allows users to visualize the edges detected in the input image and make adjustments to the threshold values (weak_th and strong_th) as needed. Canny edge detection is a versatile tool with various applications, such as object detection, image segmentation, feature extraction, and edge linking. It is known for its effectiveness in detecting edges accurately while reducing noise and preserving thin and weak edges.