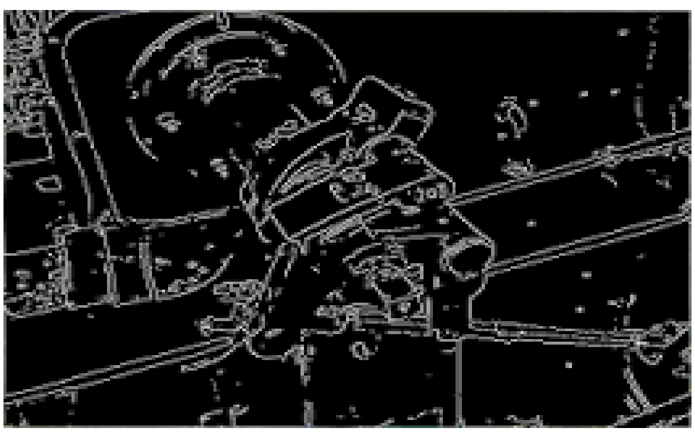
Aim: To study Edge detection with Canny

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

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

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

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

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

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. Below is the implementation.

```
import numpy as np
import os
```

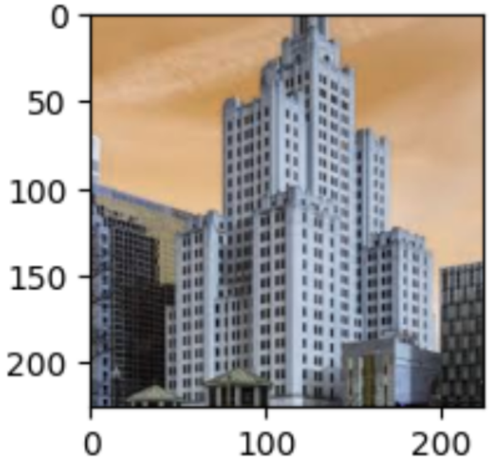
```python
import cv2
import matplotlib.pyplot as plt


# 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 neighbours 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):
```

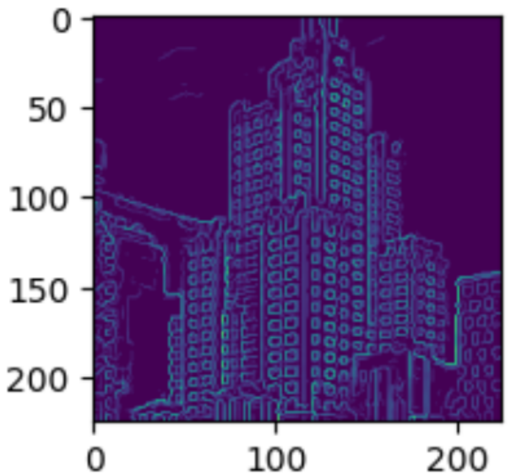
```python
            neighb_1_x, neighb_1_y = i_x-1, i_y
            neighb_2_x, neighb_2_y = i_x + 1, i_y

        # 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
```

```python
    # finally returning the magnitude of
    # gradients of edges
    return mag


frame = cv2.imread('food.jpeg')


# calling the designed function for
# finding edges
canny_img = Canny_detector(frame)


# Displaying the input and output image
plt.figure()
f, plots = plt.subplots(2, 1)
plots[0].imshow(frame)
plots[1].imshow(canny_img)
```

Input Image :



Output image :



Conclusion:

In conclusion, the study aimed to explore the intricacies of edge detection through the implementation of the Canny edge detection algorithm. By dissecting its multi-stage process and experimenting with parameter adjustments on real-world images, we gained valuable insights into its ability to accurately identify significant transitions in image intensity. The Canny algorithm's robustness in minimizing false positives and negatives makes it a pivotal tool in fields like robotics and medical imaging, albeit with an awareness of its applicability relative to other edge detection techniques in different contexts. This study underscores the significance of the Canny algorithm in advancing image processing and computer vision applications.