ASS 2

Part A

Canny Edge Detection

1. In an image, an edge is a curve that follows a path of rapid change in image intensity.
Edges are always associated with the boundary of object in a scene.
The most powerful edge-detection method that a edge provides is the Canny method

The Canny method differs from the other edge detection methods in that it use 2 different thresholds (to detect the strong & weak edges)
And the weak edges are involved in the output only if they are connected to the strong edges.

The Canny Edge detection algorithm is composed of 5 steps

1. Noise Reduction
2. Gradient Calculation
3. Non-maximum suppression
4. Double theshold
5. Edge Tracking.

Here, I am trying to apply the Canny Edge detection on ~~the~~ one of the buildings of GSU i,e Urbanlife3.jpg.

Which will be considered to be having an image size of 3024 x 4032

According to the problem statement considered we need to select/consider a patch size of 5x5 dimensioned from image Urbanlife~~centre~~

To get rid of the noise on the image, which is performed by applying Gaussian blur to smooth. For considering a kernel of $(2k+1) \times (2k+1)$ size can be calculated as

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

We smooth the obtained patch by using the Gaussian filter.
The image is smoothened, the derivates used are I_x, I_y w.r.t x, y.
Consider the 5x5 patches (30, 35)

that constitute in the following format

165	165	165	165	165
165	165	165	165	165
163	163	163	163	163
163	163	163	163	163
163	163	163	163	163

$\Rightarrow g(x,y) = \frac{1}{2\pi\sigma^2} e^{\left(\frac{-(x^2+y^2)}{2\sigma^2}\right)}$

$\Rightarrow x = 163, y = 165$

$\pi = 3.14 \quad \sigma = 2$

$\Rightarrow 6.28\, e^{\left(\frac{-((163)^2+(165)^2)}{2\times 4}\right)}$

$6.28 \cdot e^{(-82)}$

$\Rightarrow 2.44 \times 6.28$

$\Rightarrow 1.53$

While, we continue to perform the gradient of the gaussian function & find its derivatives.

$$\boxed{\nabla g \cdot I}$$

i.e $g \rightarrow$ gaussian function

$I \rightarrow$ Image

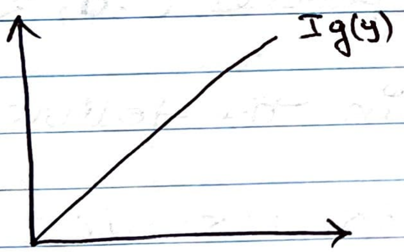
Using the above derivative equation we can find the magnitude & orientation at each pixel.

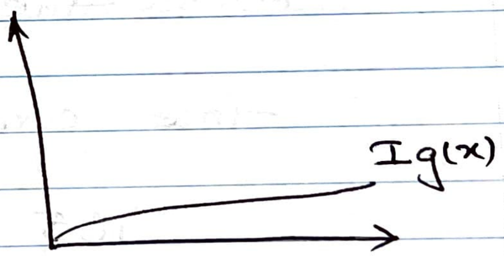
$$|\nabla g \cdot I|$$

While Calculating the orientation w.r.t a Specific Image.

$$\boxed{\bar{N} = \frac{\nabla g \cdot I}{|\nabla g \cdot I|}}$$

These can be represented in the following graphical format.





Edge Pixel :- If the gradient at (σ) the pixel is tend to be high then we can say it as an edge pixel.

Non-Edge Pixel :- If the gradient (σ) at the pixel is tend to be low then we can say it as a non-edge pixel.

→ High threshold is used to identify the strong pixels [intensity higher than the high threshold]

→ Low threshold is used to identify the non-relevant pixels [i,e the intensity is lower than the low threshold.

We consider the pixels closest to the gradient direction to estimate the non maximum suppressi

Computing the gradient orientation let us consider the angle to be 'θ'

$$\theta = \text{arc}\,\tan^2\left(\frac{y_w}{x_w}\right)$$

$$\theta = \text{arc}\,\tan^2\left(\frac{165}{163}\right)$$

$$\theta = (\tan^2)^{-1}(0.99)$$

$$\theta = 0.44$$

All the other pixels have an intensity which are weak & help us to identify the non-relevant pixels.

Where, we are generated with the detected pixel values.

$$\begin{bmatrix} 0.6 & 0 & 0 & 0 & 0 \\ 0 & 0.4 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0.6 \\ 0 & 0 & 1 & 1 & 0 \\ 0.4 & 0 & 0 & 0 & 0.8 \end{bmatrix}$$

2.

Harris Corner Detection

Harris Corner Detector is a corner detection operator, that is commonly used in CV algorithms to extract corners and infer features of an image.
Compared to the previous one, i,e Moravec's Corner detection, the Harris corner detector takes the differential of the corner score into account
Here we are going to consider a small window of size 5x5 as mentioned in the q's that determines to be our image patch from the picture.
→ The main idea that undertakes is to identity the unique pixel values / window by a small amount of change that occurs w.r.t to the pixel values.
→ Let us define the change function $E(u,v)$ as the sum of all the sum squared distances (SSD), where u,v are the x,y co-ordinates of every pixel in our 3x3 window & I is the intensity values of $E(u,v)$ as defined by some threshold.

$$\boxed{E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u, y+v) - I(x,y)\right]^2}$$

We have to maximize the function $E(u,v)$ for corner detection
i,e we need to maximize the second term.

∴ By the application of Taylor Expansion to the above equation & some mathematical steps we get

$$E(u,v) \approx [u \ v] \left(\sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \right) \begin{bmatrix} u \\ v \end{bmatrix}$$

i,e $$M = \sum w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

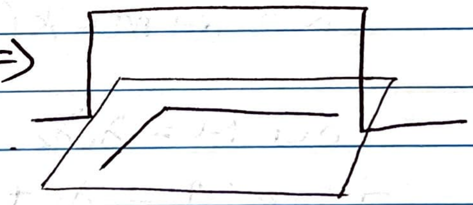
$$\Rightarrow E(u,v) \approx [u \ v] \, M \begin{bmatrix} u \\ v \end{bmatrix}$$

$w(x,y) \longrightarrow$ Window function

$I(x+u, y+v) \longrightarrow$ Shifted Intensity

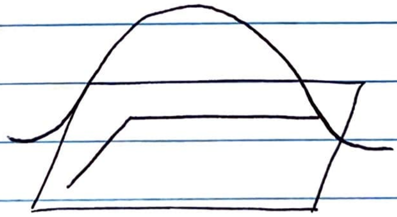
$I(x,y) \longrightarrow$ Intensity

window function $w(x,y)$ $\Rightarrow$



1 in window
0 outside.

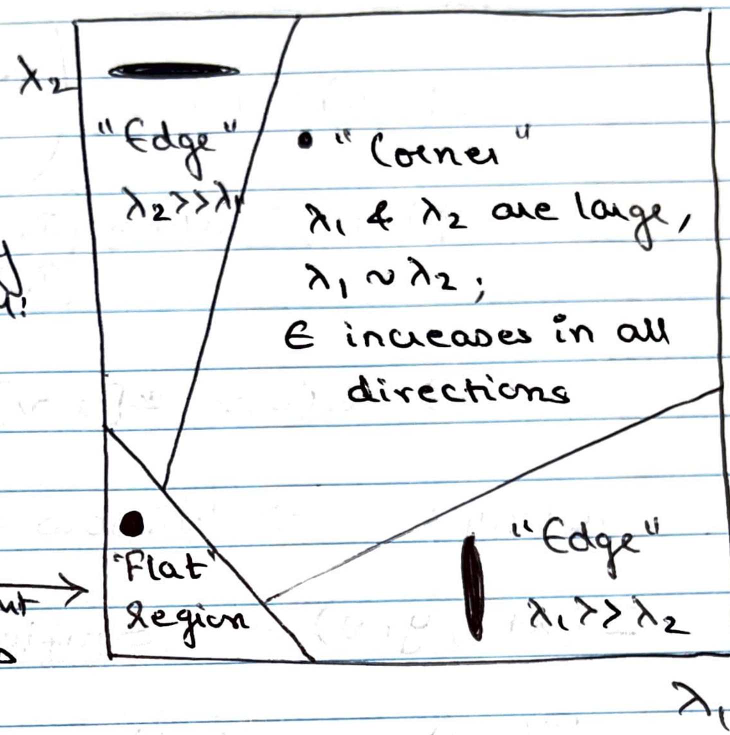
(a)



Gaussian

Classification via Eigen Values

Classification of image points using eigen values of M!



λ_1 & λ_2 are small,
E is almost constant
in all directions

Corner Response Measure

$$R = \det M - k(\text{trace } M)^2$$

$$\det M = \lambda_1 \lambda_2$$
$$\text{trace } M = \lambda_1 + \lambda_2$$