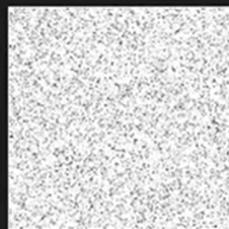


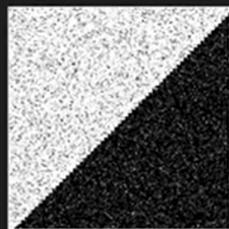
# Harris Corner Detector

## Corners

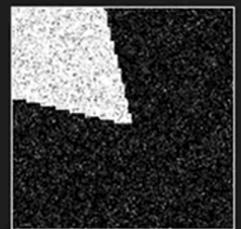
**Corner:** Point where Two Edges Meet. i.e., Rapid Changes of Image Intensity in **Two Directions** within a Small Region



"Flat" Region



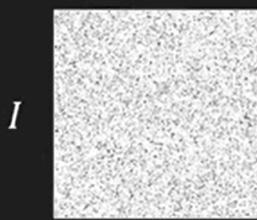
"Edge" Region



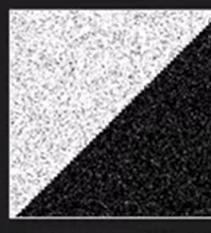
"Corner" Region

## Image Gradients

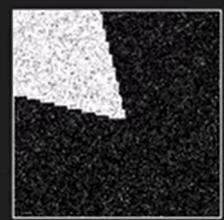
Flat Region



Edge Region

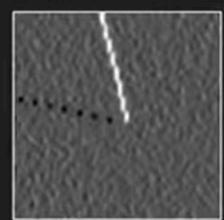
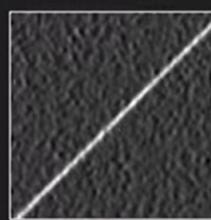
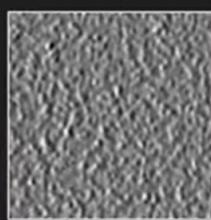


Corner Region



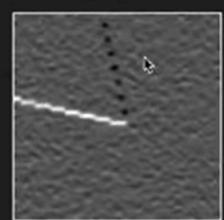
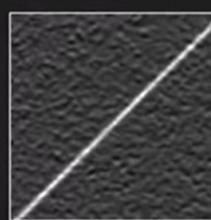
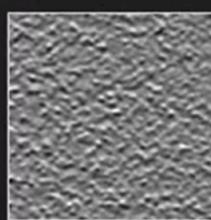
$I$

$$I_x = \frac{\partial I}{\partial x}$$



$$I_y = \frac{\partial I}{\partial y}$$

Bree K. Nayar

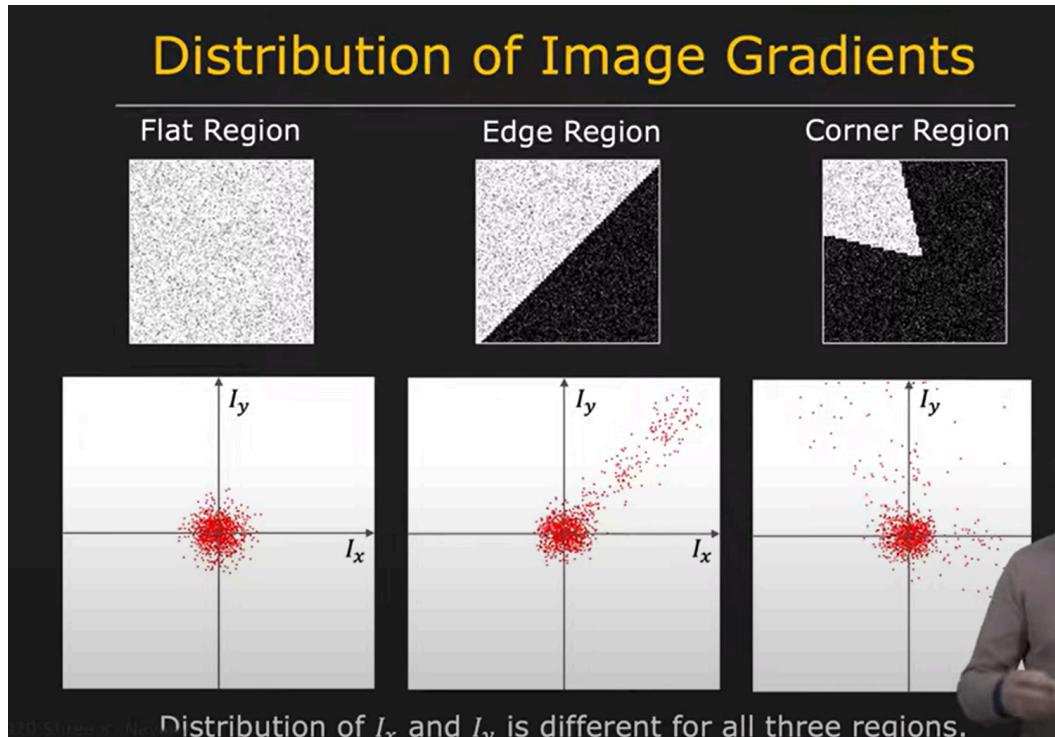


How come edge map can contain negative values?

If gradient of edge matches the gradient of the filter, then you will get some form of resonance and get a large positive number.

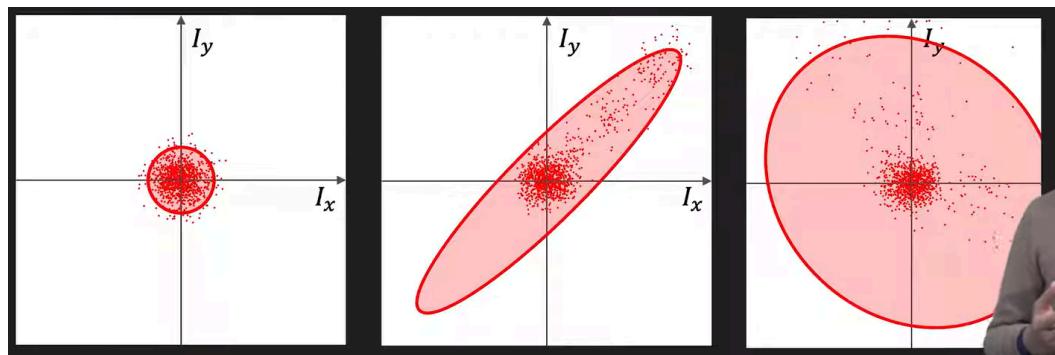
If the gradient of the edge is opposite to the gradient of the filter (for eg: the gradient of the edge is bright to dark and your filter is dark to bright), you will see on the edge map (in that direction,  $G_x$ ,  $G_y$  or whatever), you will see large negative number at the position of that edge.

Images are normalized such that white means strong positive value, black means strong negative value and gray means near 0.

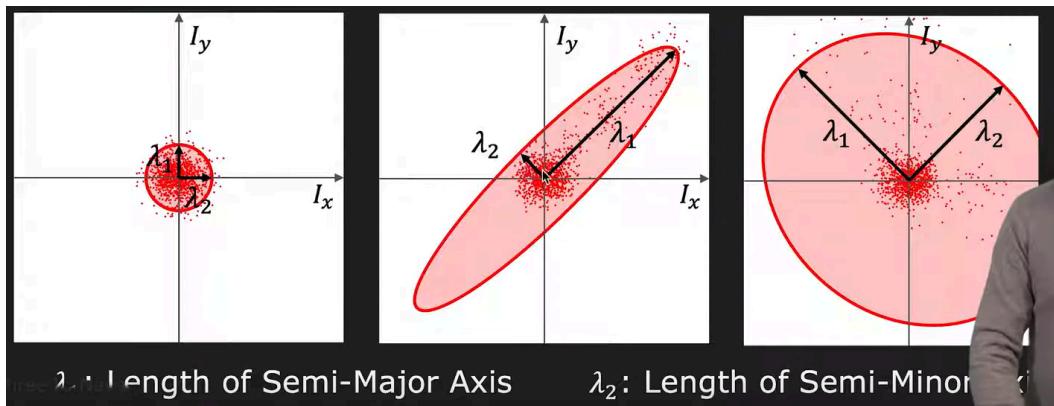


So the goal is to somehow quantify this structure and describe the structure of the distribution with a small number of parameters to classify the region.

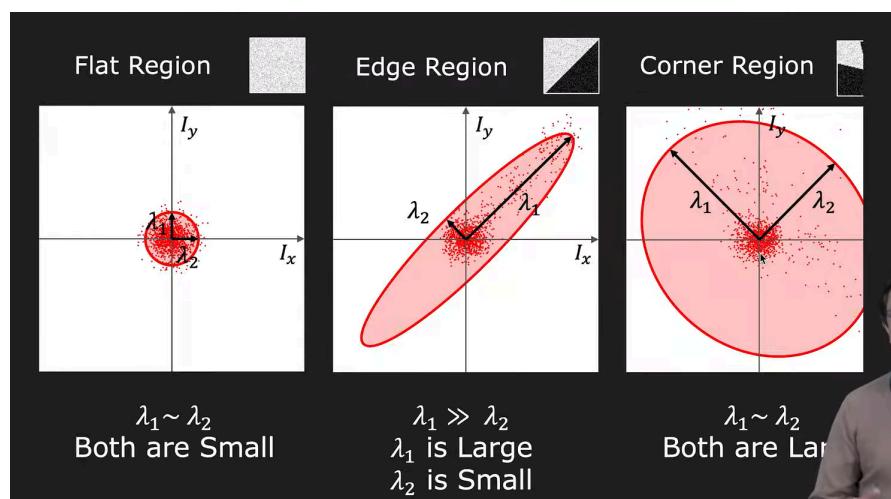
Do this by taking the distribution and fitting an ellipse around it.



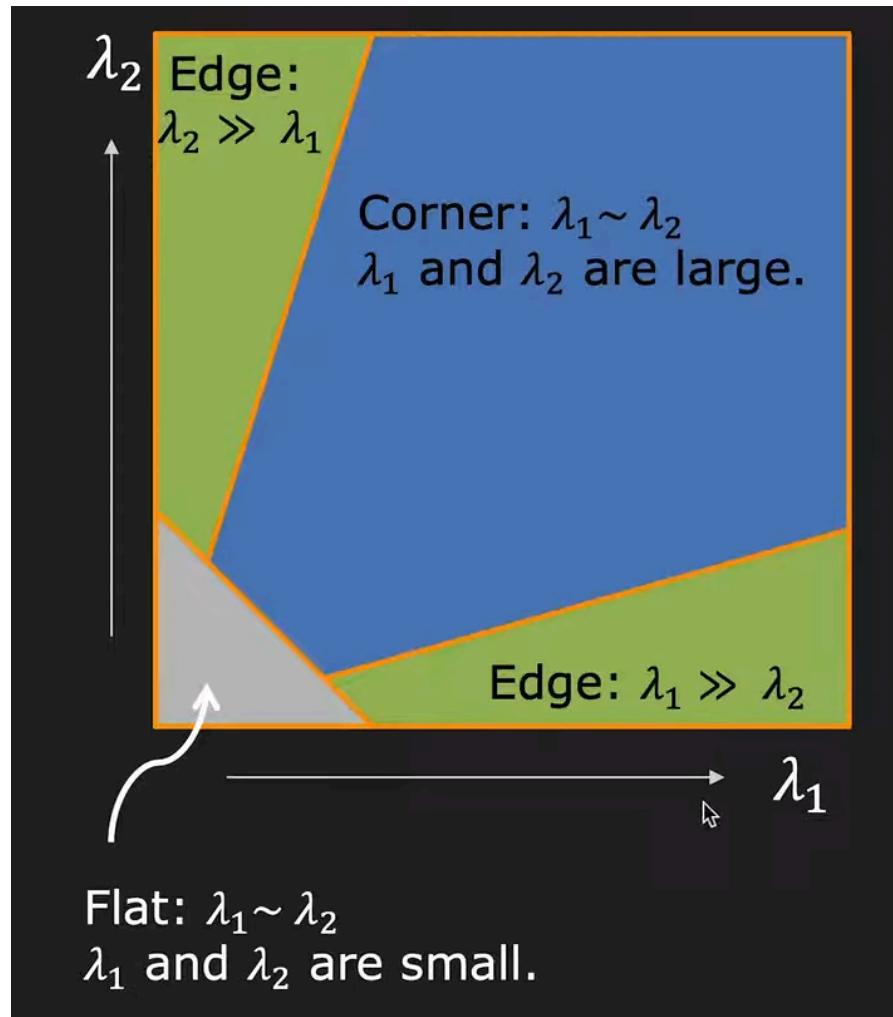
In doing so, you get a semi major (the longer) and a semi minor (the shorter) axis for the ellipse.



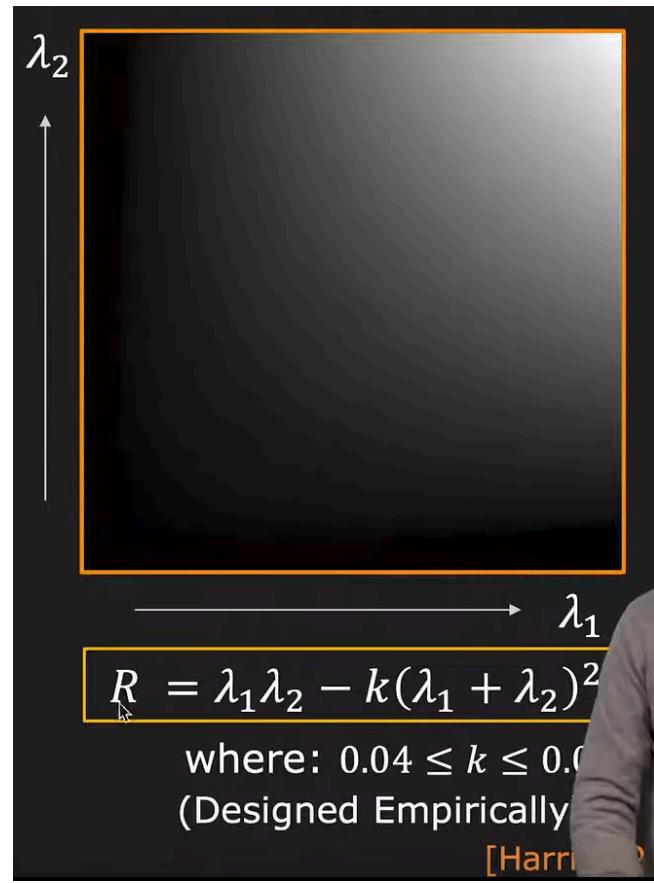
$\lambda_1$  is the length of the semi-major axis and  $\lambda_2$  is the length of the semi-minor axis.



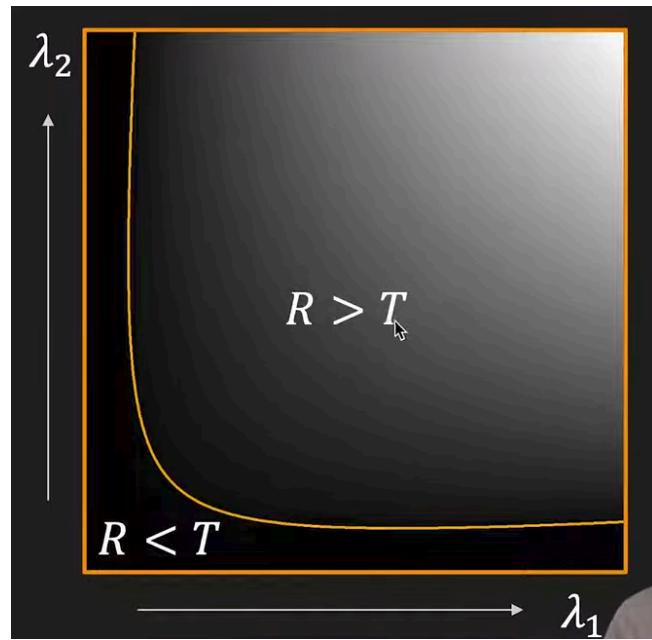
So in  $\lambda_1$ ,  $\lambda_2$  space, we classify accordingly:



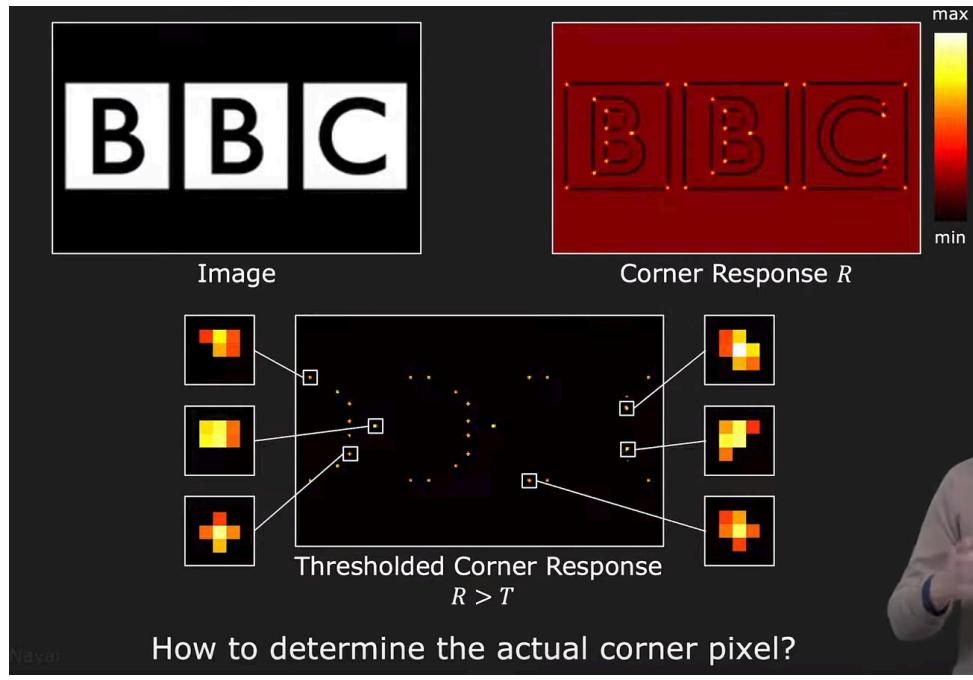
We want to do this simply, Harris came up with this expression where he maps the eigen values to a single real number. This is an empirically determined function ( $0.04 \leq k \leq 0.06$  is also empirical). This is the Harris Corner response function



R is being plotted in this image where the brightness of the point is proportional to R. So if you threshold this space wrt R:



Eg:



The thing is, after you threshold, you get clusters of pixels near the corner signaled as the corner. But we want to single out the pixel that is the corner (this would be the peak), so we apply NMS

## Non-Maximal Suppression

1. Slide a window of size  $k$  over the image.
2. At each position, if the pixel at the center is the maximum value within the window, label it as positive (retain it). Else label it as negative (suppress it).



Used for finding Local Extrema (Maxima/Minima)

# HARRIS CORNER DETECTOR

## Why Harris Corner Detector?

- **Rotation Invariance:** The Harris Corner Detector is invariant to image rotation, meaning the same corners can be detected even if the image is rotated.
- **Efficiency:** It's a computationally efficient way to detect corners, making it suitable for real-time applications.
- **Robust to Noise:** The algorithm can handle image noise reasonably well.

## Limitations:

- **Scale Invariance:** The Harris detector is not scale-invariant, meaning it may not perform well if the image is scaled (i.e., zoomed in or out).
- **Fixed Parameters:** The choice of parameters such as the threshold and  $k$  is crucial and may need to be manually tuned for different images.

The biggest limitation is that it's not scale invariant.

Specifically:

- **Changing Gradient Magnitudes:** Scaling an image affects the magnitude of the intensity gradients. If an image is scaled down, the pixel differences across a certain distance decrease, leading to smaller gradient values. Since the Harris detector's response is based on the squares and products of these gradients, the corner response will be lower for a scaled-down image, potentially causing genuine corners to fall below the detection threshold.
- **Fixed Window Size:** The local window used to compute the structure tensor has a fixed size in terms of pixels. When the image scale changes, this fixed window corresponds to a different physical area in the original scene. A corner feature that perfectly fits within the window at one scale might occupy a much larger or smaller area at a different scale. If the corner feature becomes larger than the window, only a part of it might be analyzed, potentially leading to it being misclassified as an edge or a flat region. If the feature becomes too small, its influence on the gradients within the window might be diminished.