CAP 4453
Robot Vision

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Administrative details

- Homework due Friday 11:59pm via webcourses
- Point 5 – refers to filter center in second row
- Any other question?

Robot Vision

6. Edge detection II

Credits

- Some slides comes directly from:
  - Yogesh S Rawat (UCF)
  - Noah Snavely (Cornell)
  - Ioannis (Yannis) Gkioulekas (CMU)
  - Mubarak Shah (UCF)
  - S. Seitz
  - James Tompkin
  - Ulas Bagci
  - L. Lazebnik

Short Review from last class

Edge detectors

- Gradient operators
  - Prewit
  - Sobel
- Marr-Hildreth (Laplacian of Gaussian)
- Canny (Gradient of Gaussian)

Gradient operators edge detector algorithm

1. Compute derivatives
   - In x and y directions
   - Use Sobel or Prewitt filters
2. Find gradient magnitude
3. Threshold gradient magnitude

Sobel

1	0	-1
2	0	-2
1	0	-1

1	2	1
0	0	0
-1	-2	-1

Prewitt

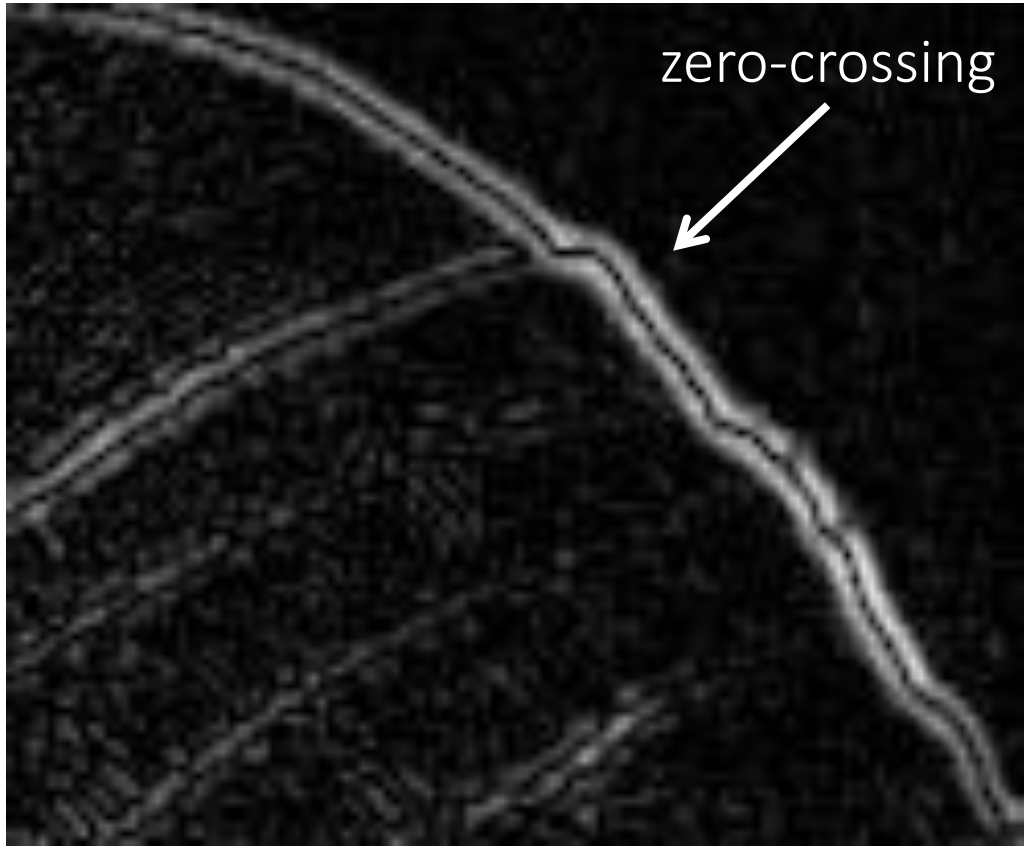
1	0	-1
1	0	-1
1	0	-1

1	1	1
0	0	0
-1	-1	-1

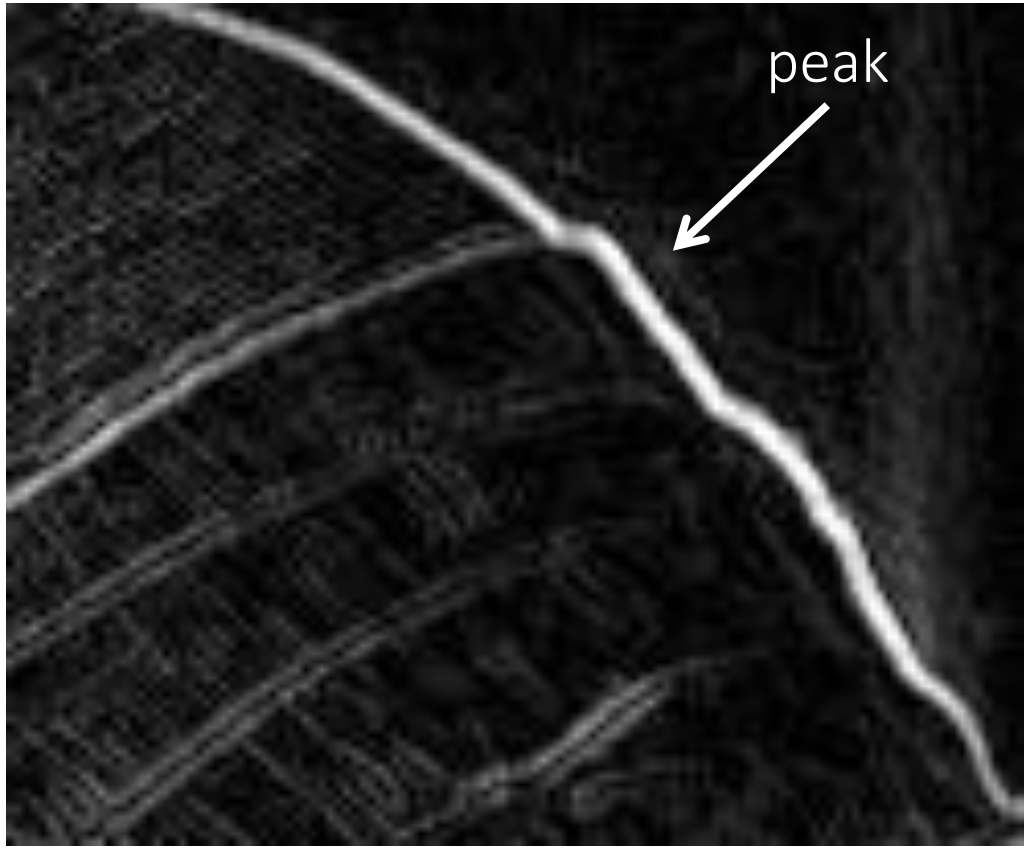
Marr-Hildreth edge detector algorithm

1. Smooth image by Gaussian filtering
2. Apply Laplacian to smoothed image
   - Used in mechanics, electromagnetics, wave theory, quantum mechanics
3. **Find Zero crossings**
   - Scan along each row, record an edge point at the location of zero-crossing.
   - Repeat above step along each column

Laplacian of Gaussian vs Derivative of Gaussian



Laplacian of Gaussian filtering

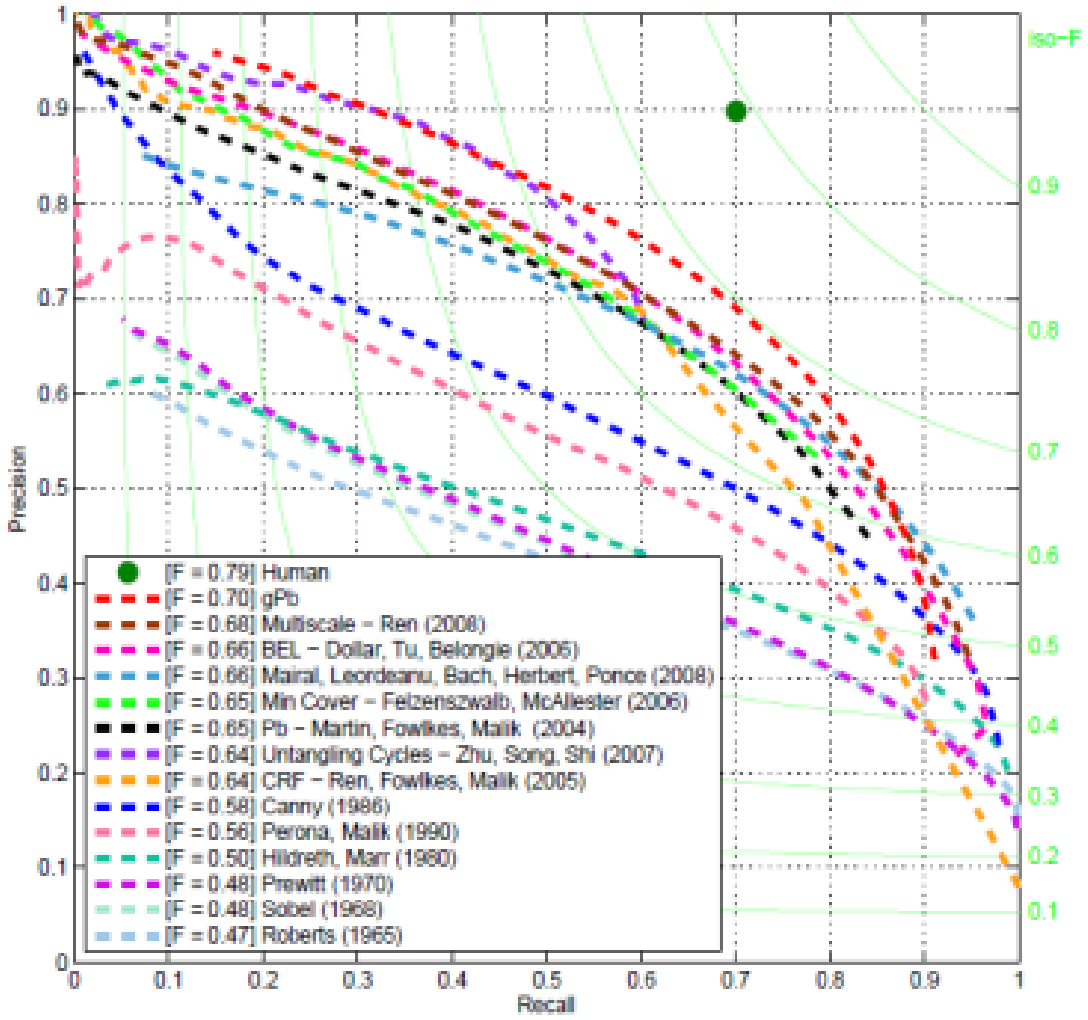


Derivative of Gaussian filtering

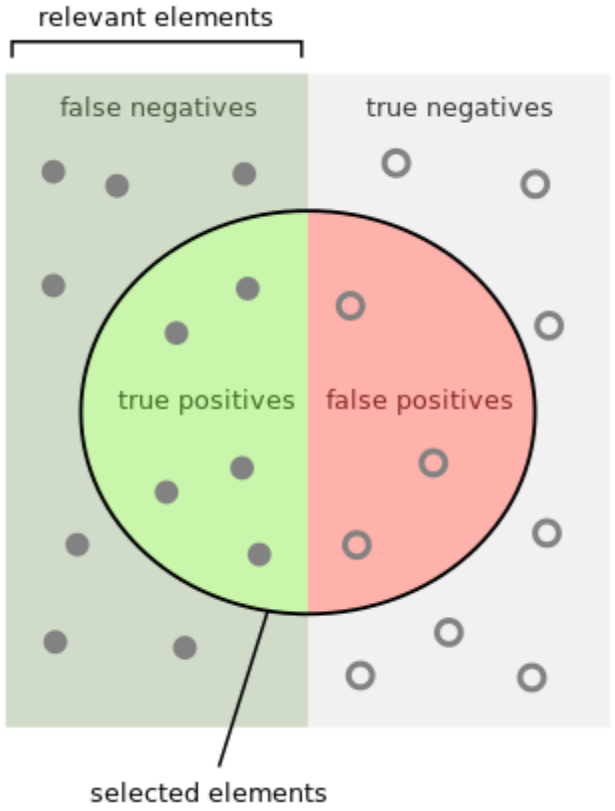
Zero crossings are more accurate at localizing edges.

45 years of boundary detection

[Pre deep learning]



Precision Recall



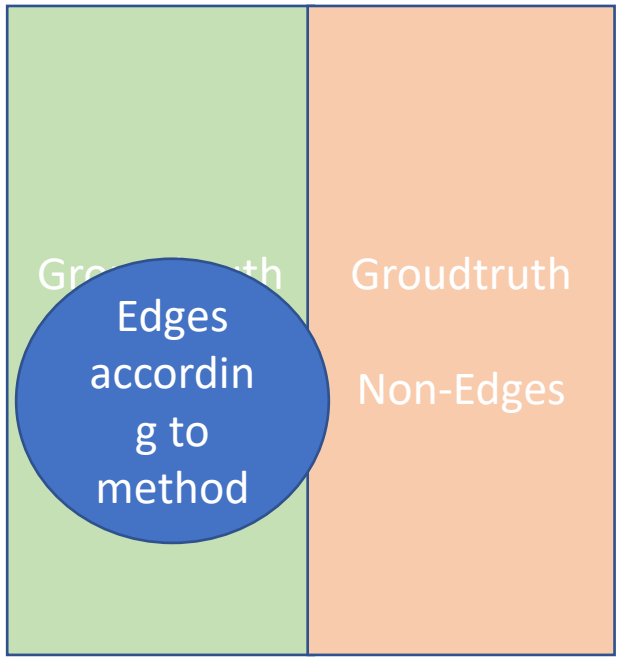
How many selected items are relevant?

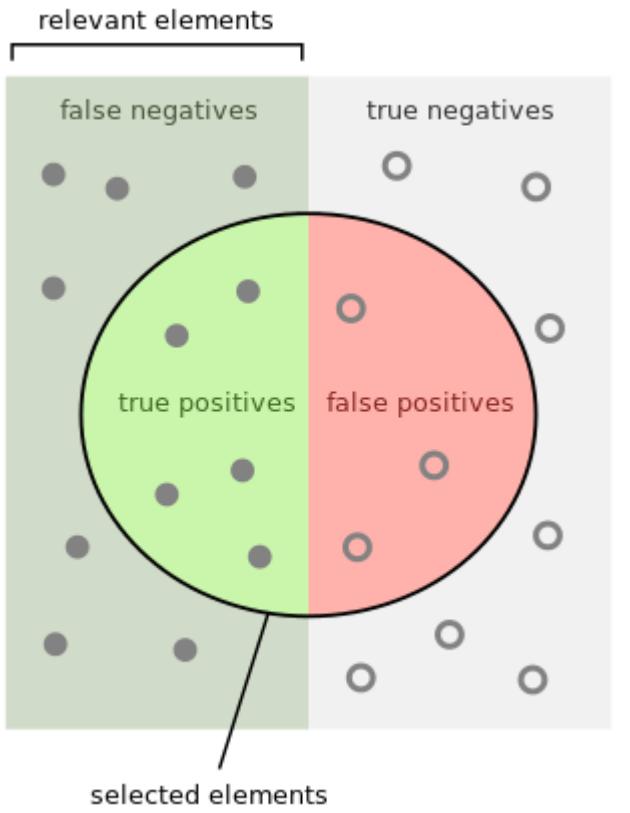
$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are selected?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

Precision Recall





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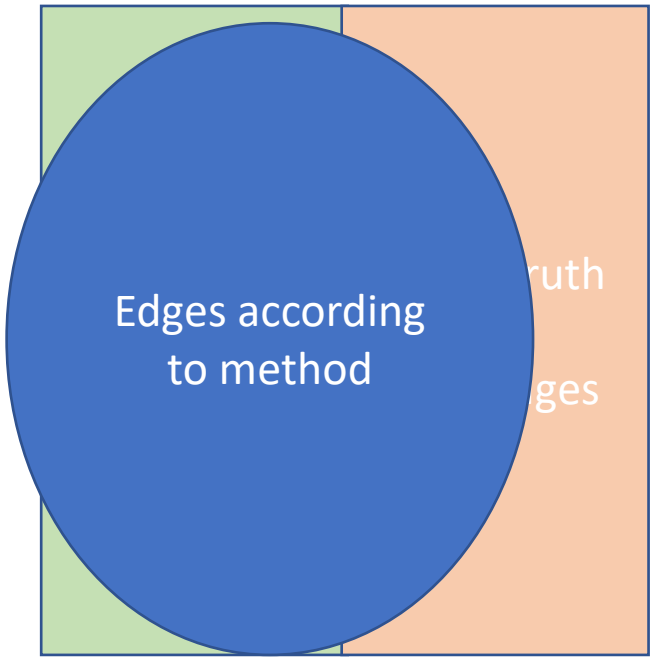
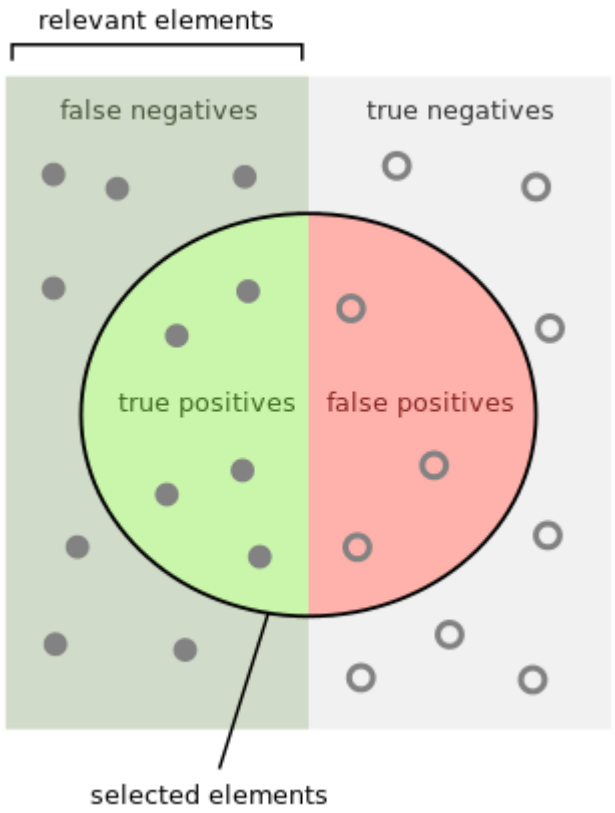
Precision Recall





How many selected items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are selected?

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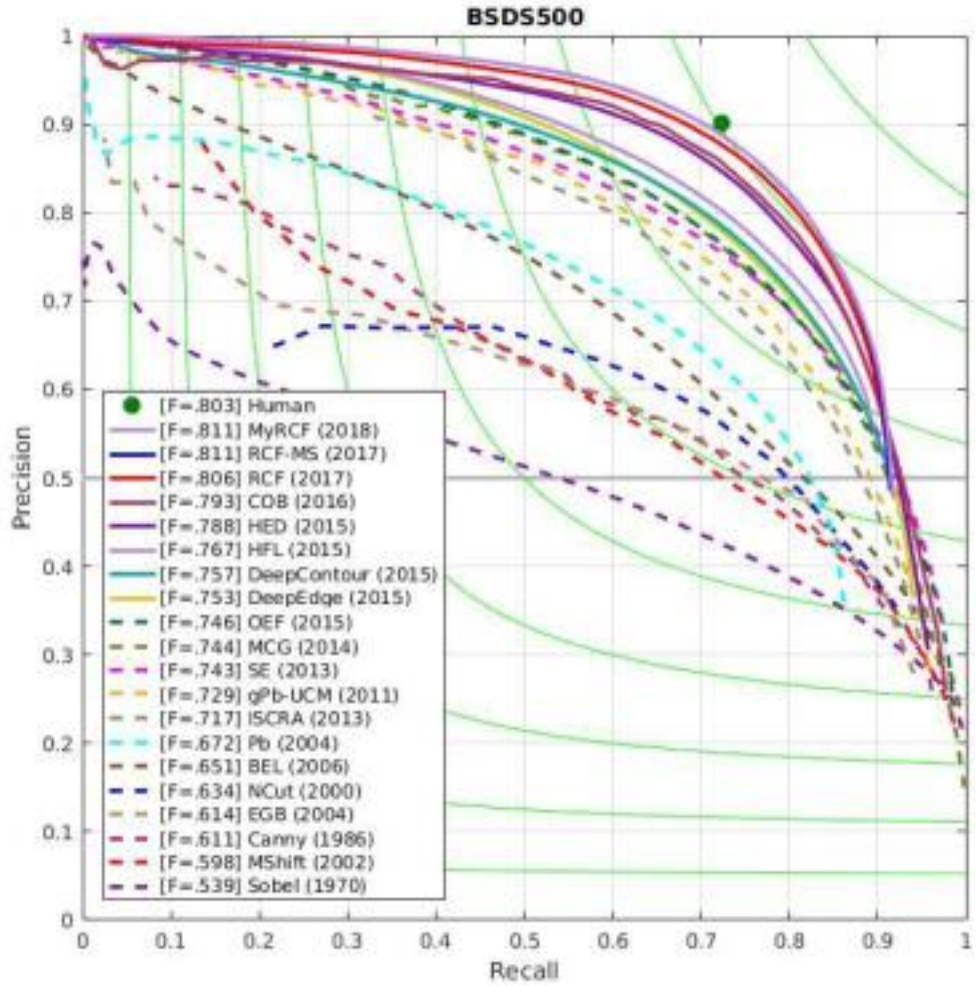
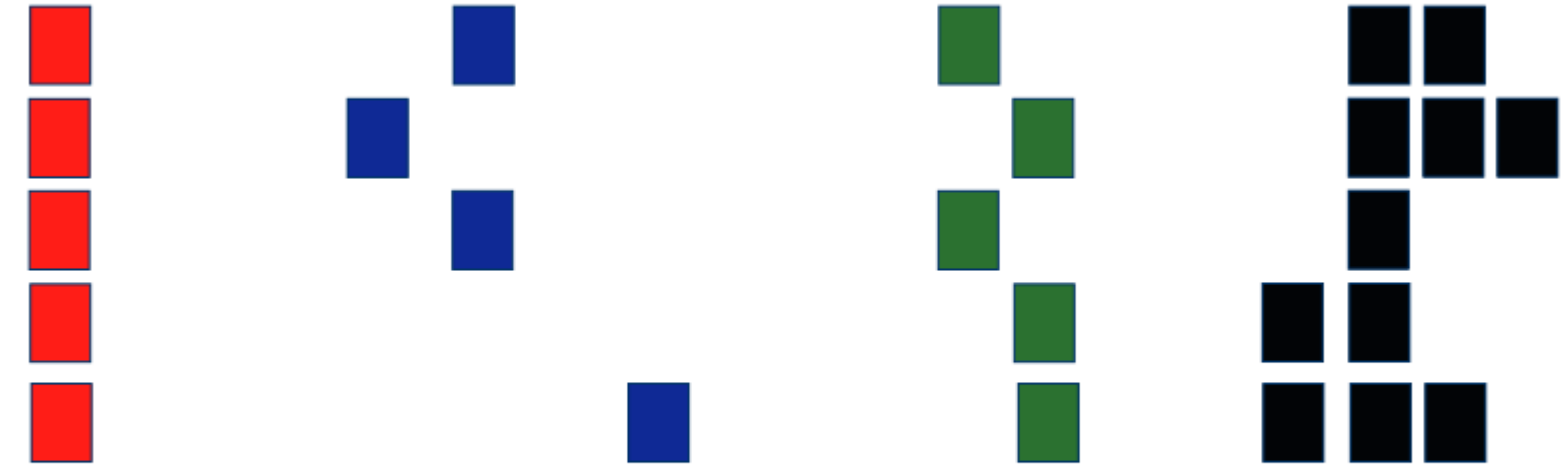
Edge Detection with Deep Learning



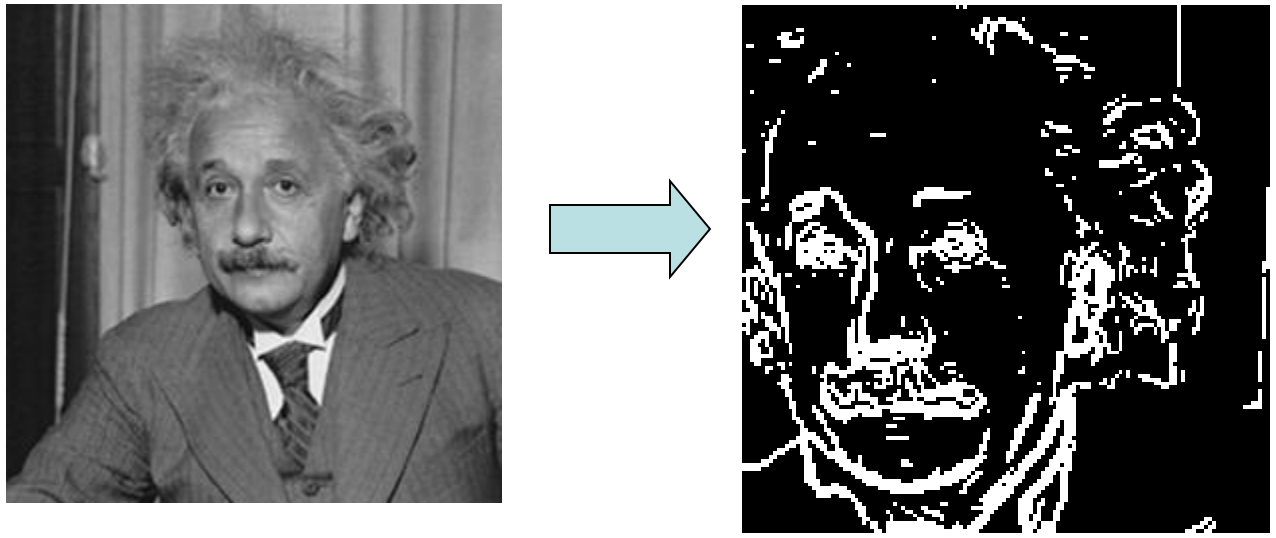
Canny edge detector

Design Criteria for Edge Detection

- Good detection: find all real edges, ignoring noise or other artifacts
- Good localization
  - as close as possible to the true edges
  - one point only for each true edge point



Problems



- We get thick edges
- Redundant, especially if we going to be searching in places where edges are found

Solution

- Identify the local maximums
- Called “non-maximal suppression”

Canny Edge detector algorithm

1. Smooth image with Gaussian filter
2. Compute derivative of filtered image
3. Find magnitude and orientation of gradient
4. Apply “Non-maximum Suppression”
5. Apply “Hysteresis Threshold”

Canny Edge detector algorithm

1. **Smooth image with Gaussian filter**

$$S = I * g(x,y) = g(x,y) * I \qquad g(x,y) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

2. **Compute derivative of filtered ·**

$$\nabla S = \nabla(g * I) = (\nabla g) * I \qquad \nabla g = \begin{bmatrix} \frac{\partial g}{\partial x} \\ \frac{\partial g}{\partial y} \end{bmatrix} = \begin{bmatrix} g_x \\ g_y \end{bmatrix}$$

$$\nabla S = \begin{bmatrix} g_x \\ g_y \end{bmatrix} * I = \begin{bmatrix} g_x * I \\ g_y * I \end{bmatrix}$$

Canny Edge detector algorithm

1. **Smooth image with Gaussian filter**

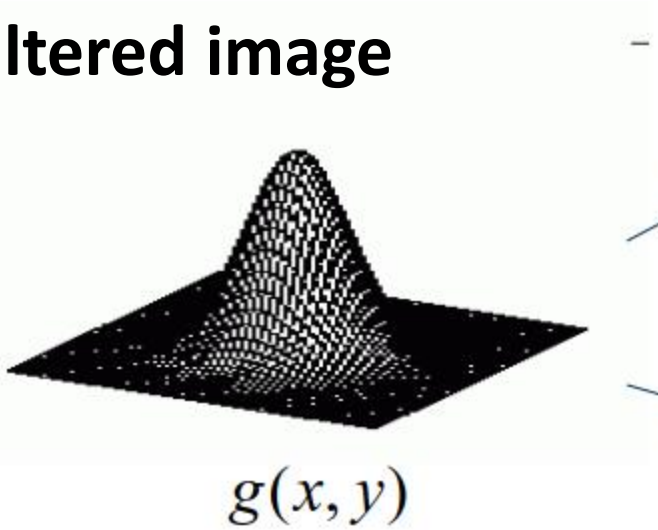
$$S = I * g(x,y) = g(x,y) * I$$

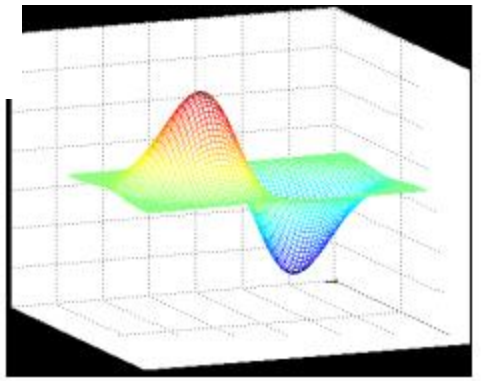
$$g(x,y) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

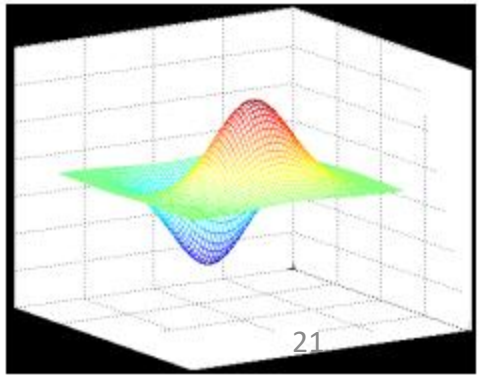
2. **Compute derivative of filtered image**

$$\nabla S = \begin{bmatrix} g_x \\ g_y \end{bmatrix} * I = \begin{bmatrix} g_x * I \\ g_y * I \end{bmatrix}$$

$$\nabla g = \begin{bmatrix} \frac{\partial g}{\partial x} \\ \frac{\partial g}{\partial y} \end{bmatrix} = \begin{bmatrix} g_x \\ g_y \end{bmatrix}$$

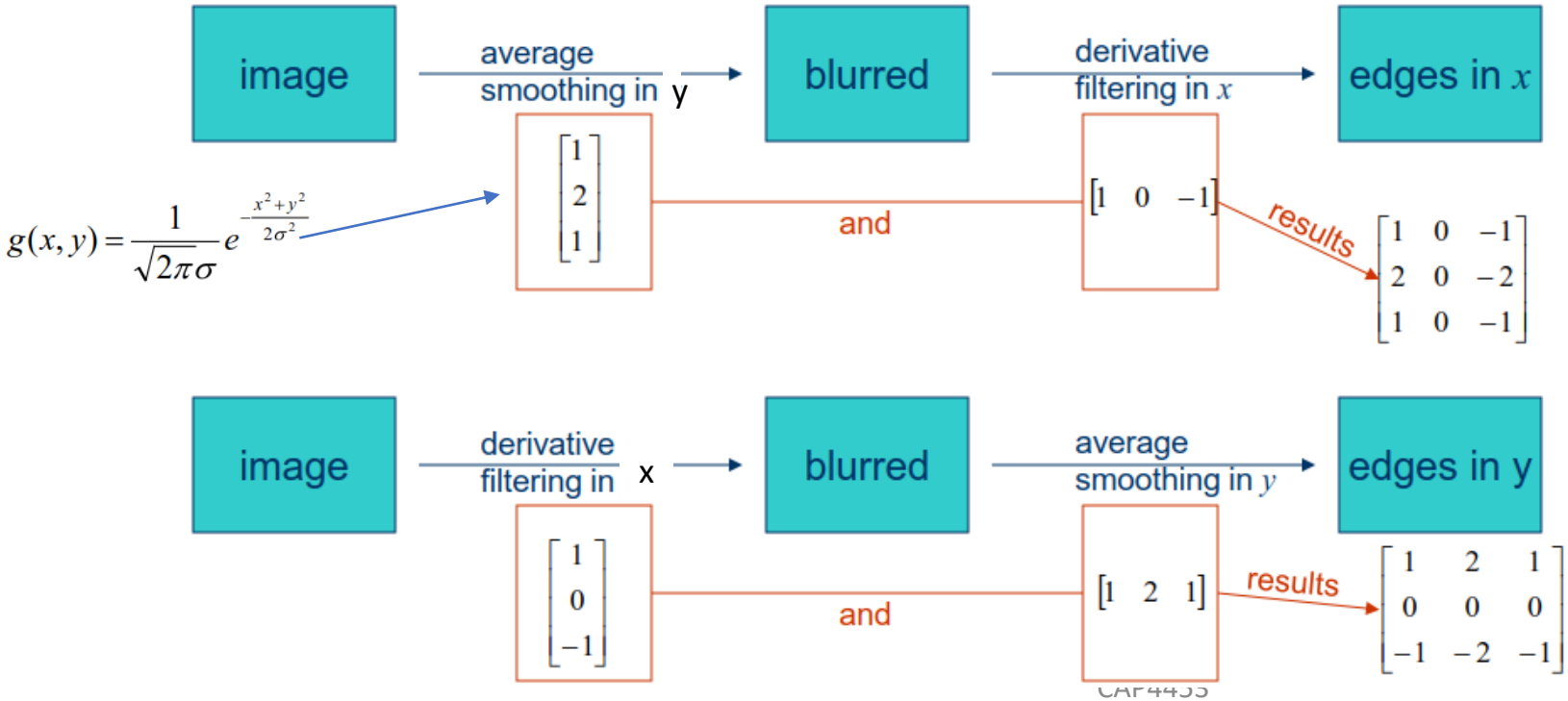






Canny Edge detector algorithm

1. **Smooth image with Gaussian filter**
2. **Compute derivative of filtered image**



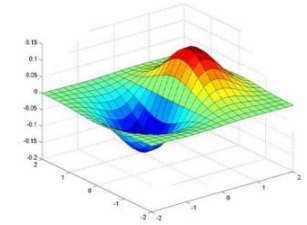
Canny Edge detector algorithm

1. Smooth image with Gaussian filter
2. Compute derivative of filtered image
3. **Find magnitude and orientation of gradient**
4. Apply “Non-maximum Suppression”
5. Apply “Hysteresis Threshold”

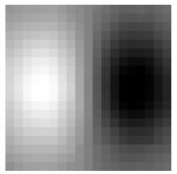
Canny Edge detector algorithm

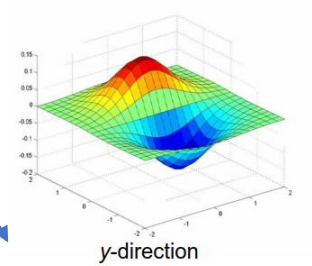
3. Find magnitude and orientation of gradient

original image (Lena)

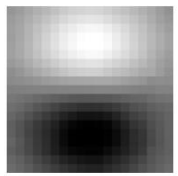


x-direction





y-direction



S_x

X-Derivative of Gaussian

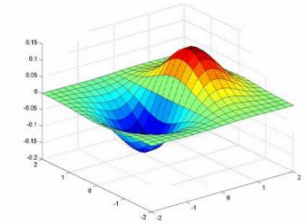
S_y

Y-Derivative of Gaussian

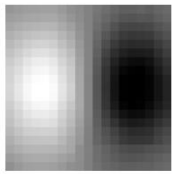
Canny Edge detector algorithm

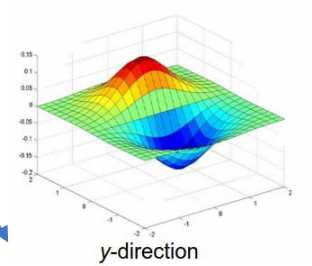
3. Find magnitude and orientation of gradient

original image (Lena)

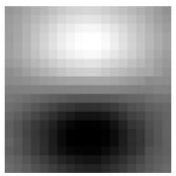


x-direction

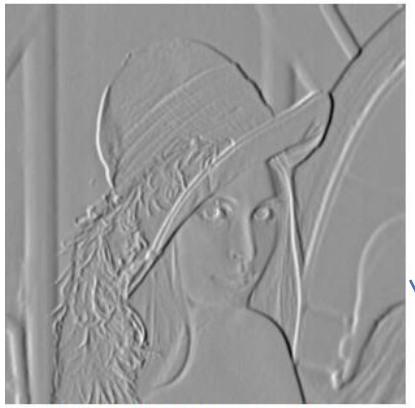




y-direction



S_x



X-Derivative of Gaussian

S_y

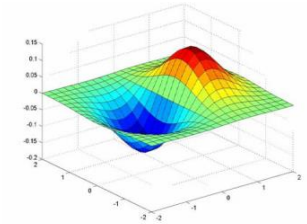
Y-Derivative of Gaussian

$$\text{magnitude} = \sqrt{(S_x^2 + S_y^2)}$$

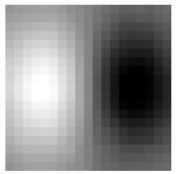
Canny Edge detector algorithm

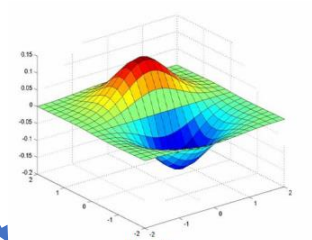
3. Find magnitude and orientation of gradient

original image (Lena)

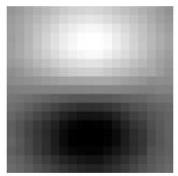


x-direction

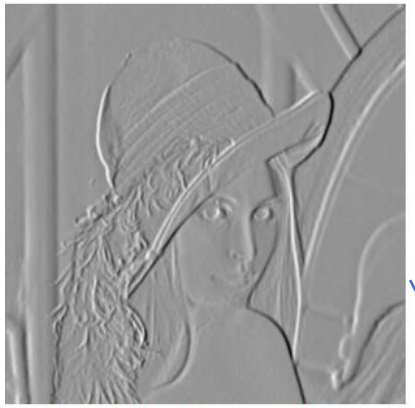




y-direction



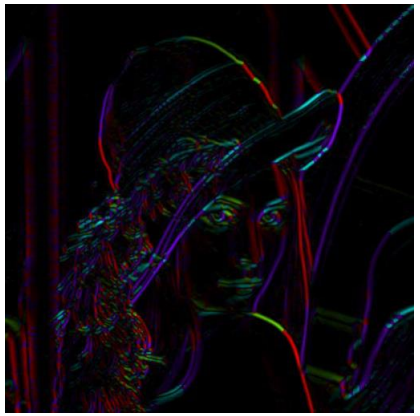
S_x



X-Derivative of Gaussian

S_y

Y-Derivative of Gaussian



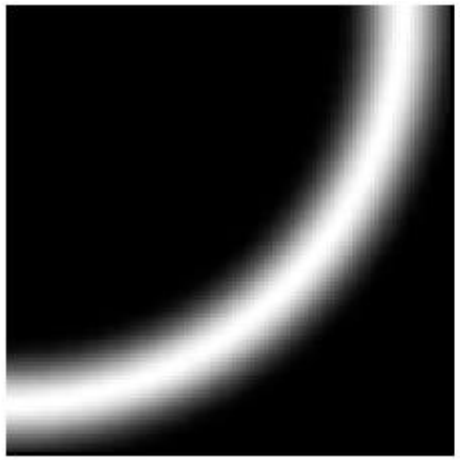
$Theta = \text{atan2}(S_y, S_x)$

Canny Edge detector algorithm

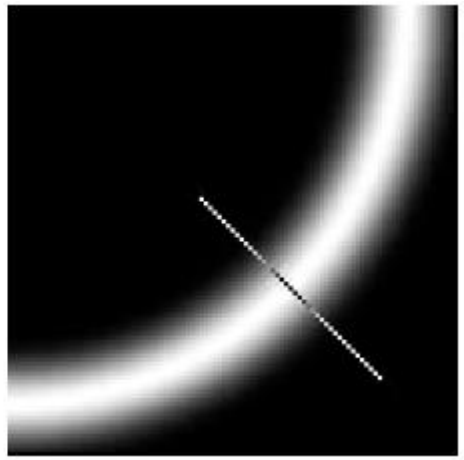
1. Smooth image with Gaussian filter
2. Compute derivative of filtered image
3. Find magnitude and orientation of gradient
4. **Apply "Non-maximum Suppression"**
5. Apply "Hysteresis Threshold"

Canny Edge detector algorithm

4. **Apply "Non-maximum Suppression"**



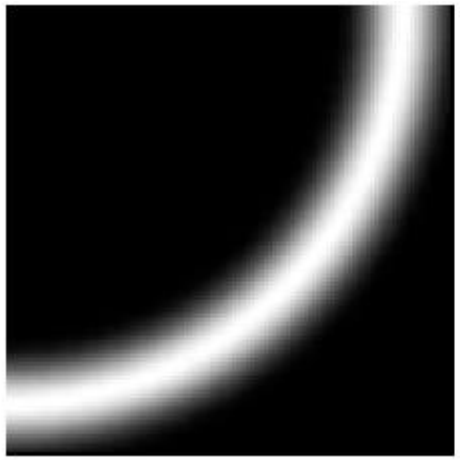
Goal: keep pixels along the curve where magnitude is largest



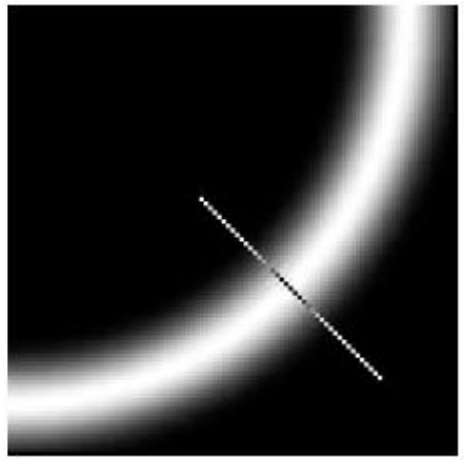
How to: looking for a maximum along a slice normal to the curve

Canny Edge detector algorithm

4. **Apply "Non-maximum Suppression"**



Goal: keep pixels along the curve where magnitude is largest



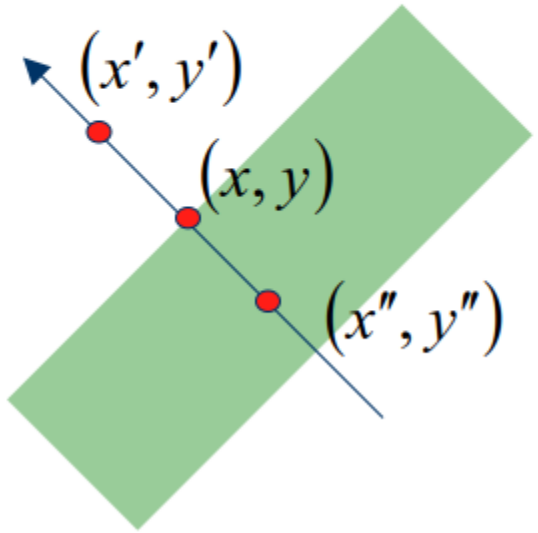
How to: looking for a maximum along a slice <u>normal to the curve</u>

That is the direction of the gradient !

Canny Edge detector algorithm

4. **Apply "Non-maximum Suppression"**

- Suppress the pixels in $|\nabla S|$ which are not local maximum



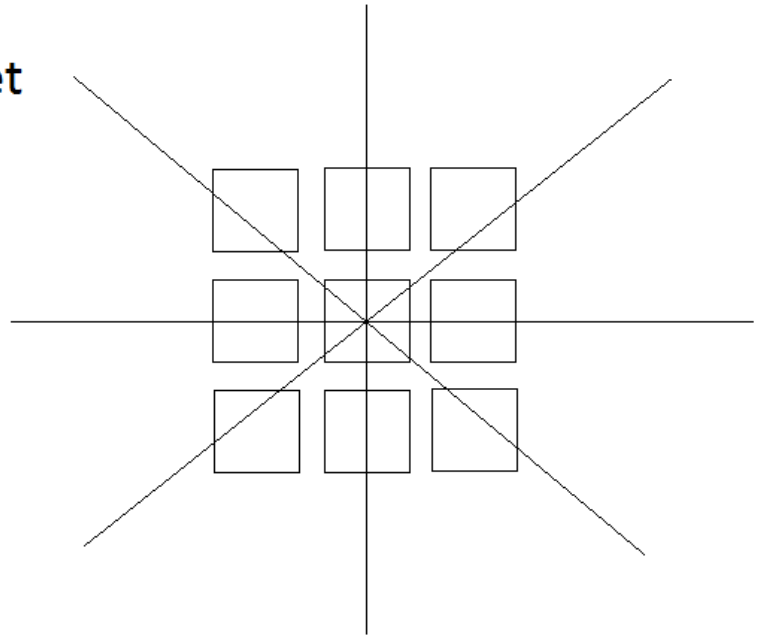
$$M(x,y) = \begin{cases} |\nabla S|(x,y) & \text{if } |\nabla S|(x,y) > |\Delta S|(x',y') \\ & \& \, |\Delta S|(x,y) > |\Delta S|(x'',y'') \\ 0 & \text{otherwise} \end{cases}$$

x' and **x**" are the neighbors of **x** along normal direction to an edge

Canny Edge detector algorithm

4. **Apply "Non-maximum Suppression"**

Consider a 3x3 set of pixels.

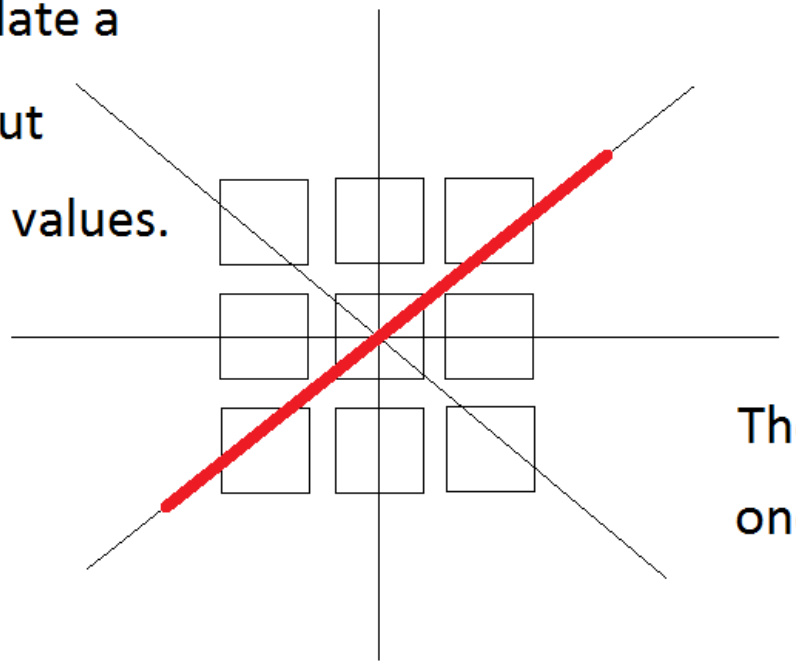


We need to examine triples along the directions shown to see if the center pixel is a peak (in magnitude) compared to its two neighbors.

Canny Edge detector algorithm

4. **Apply "Non-maximum Suppression"**

So, we need to isolate a triple, and ask about the three adjacent values.

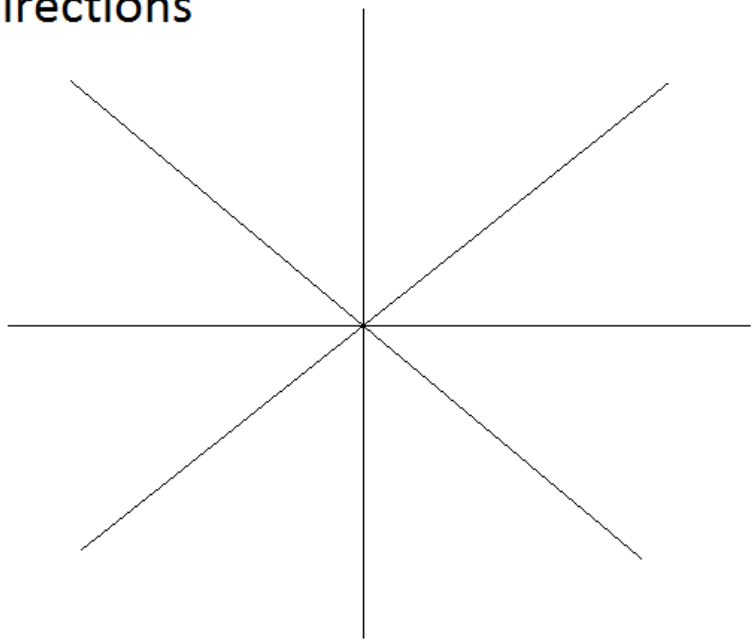


There are 4 such directions, one triple per direction.

Canny Edge detector algorithm

4. **Apply "Non-maximum Suppression"**

So, consider the 4 directions



For each direction, we will ask whether the center mag value exceeds the mag value of neighbor on one side, and neighbor on other side; if yes, mark as peak.

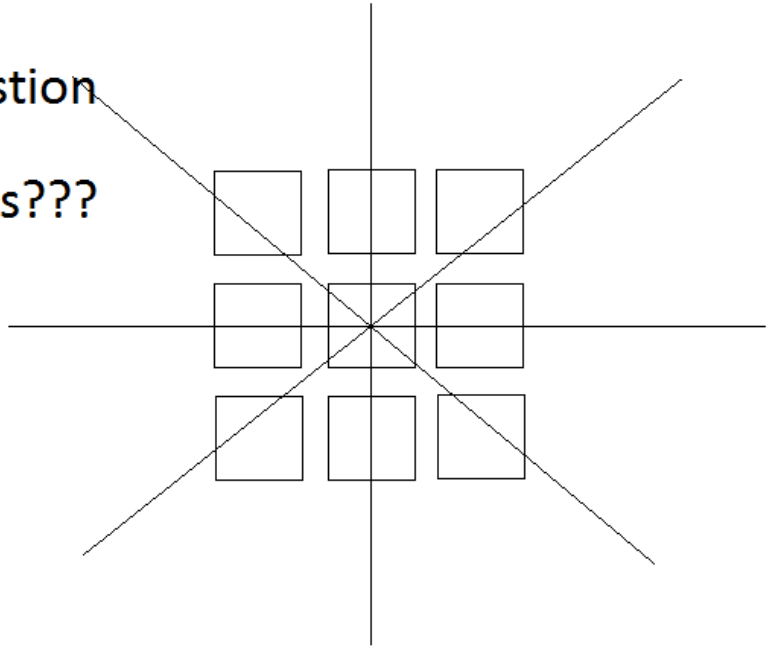
Canny Edge detector algorithm

4. **Apply “Non-maximum Suppression”**

For a center pixel, do we

ask the maxing question

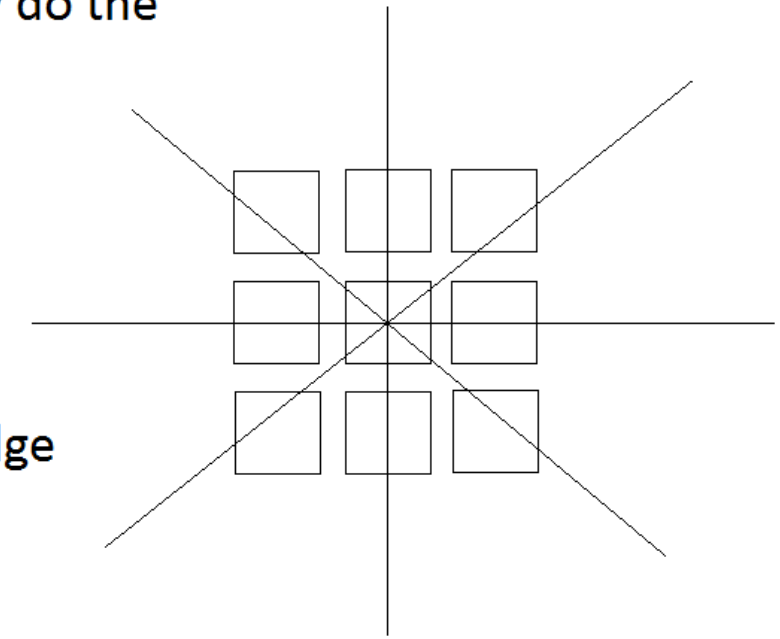
for all four directions???



Canny Edge detector algorithm

4. **Apply "Non-maximum Suppression"**

No, we should only do the maxing test for the direction that is dictated by the direction of the edge

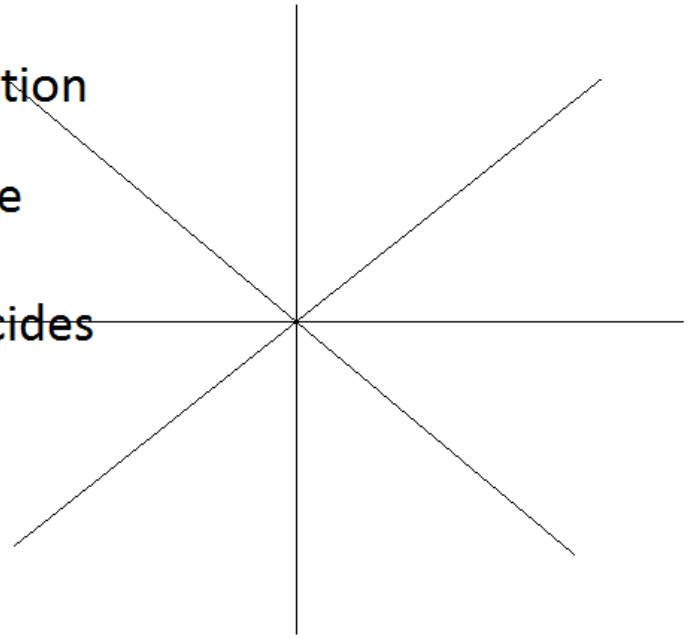


We always want to max-test in the direction perpendicular to the edge, i.e., across the edge. This means in the direction of the gradient vector.

Canny Edge detector algorithm

4. **Apply "Non-maximum Suppression"**

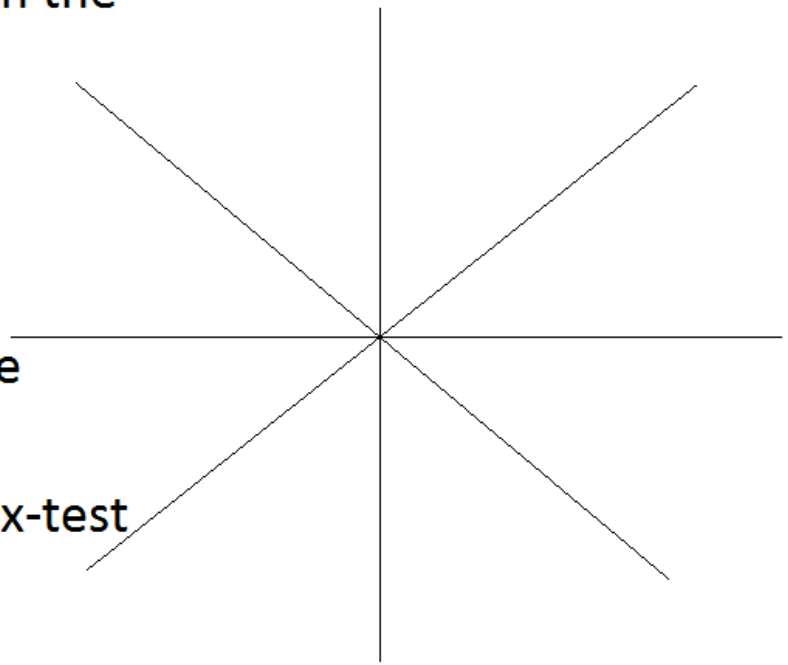
So, given these 4 possible directions, each direction will be called up, if the gradient vector coincides with the max-test direction.



Canny Edge detector algorithm

4. **Apply “Non-maximum Suppression”**

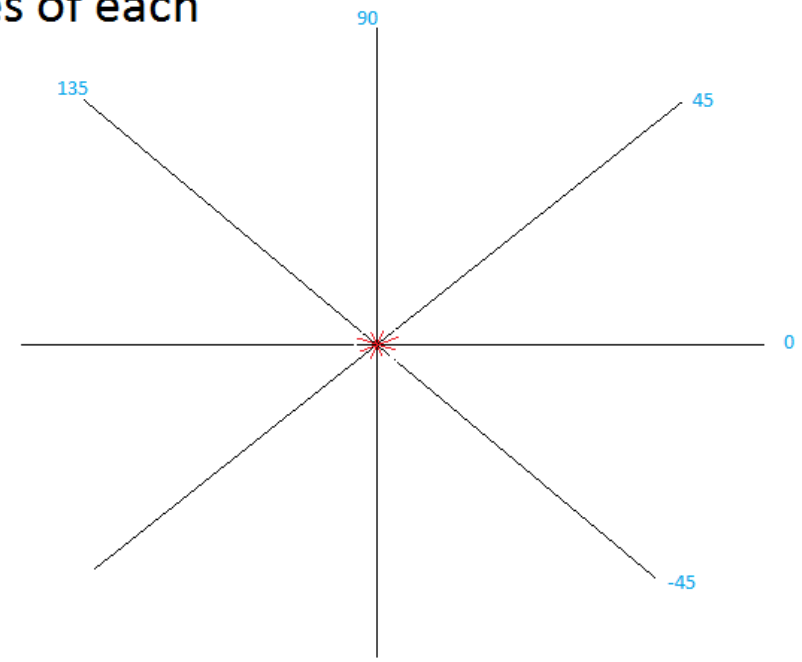
Hence, we ascertain the gradient vector's direction, and then depending on it, we proceed to the max-test



Canny Edge detector algorithm

4. **Apply "Non-maximum Suppression"**

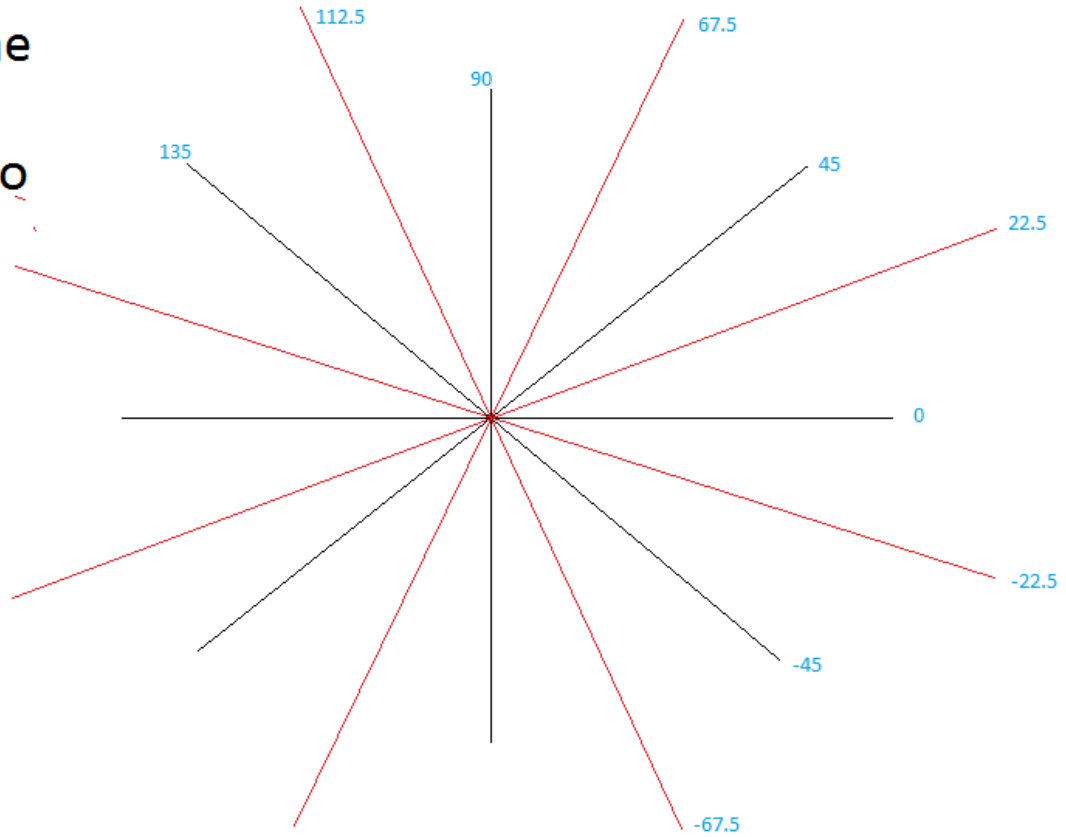
We know the angles of each direction.



Canny Edge detector algorithm

4. **Apply “Non-maximum Suppression”**

We break up the angle space into 4 cones of directions

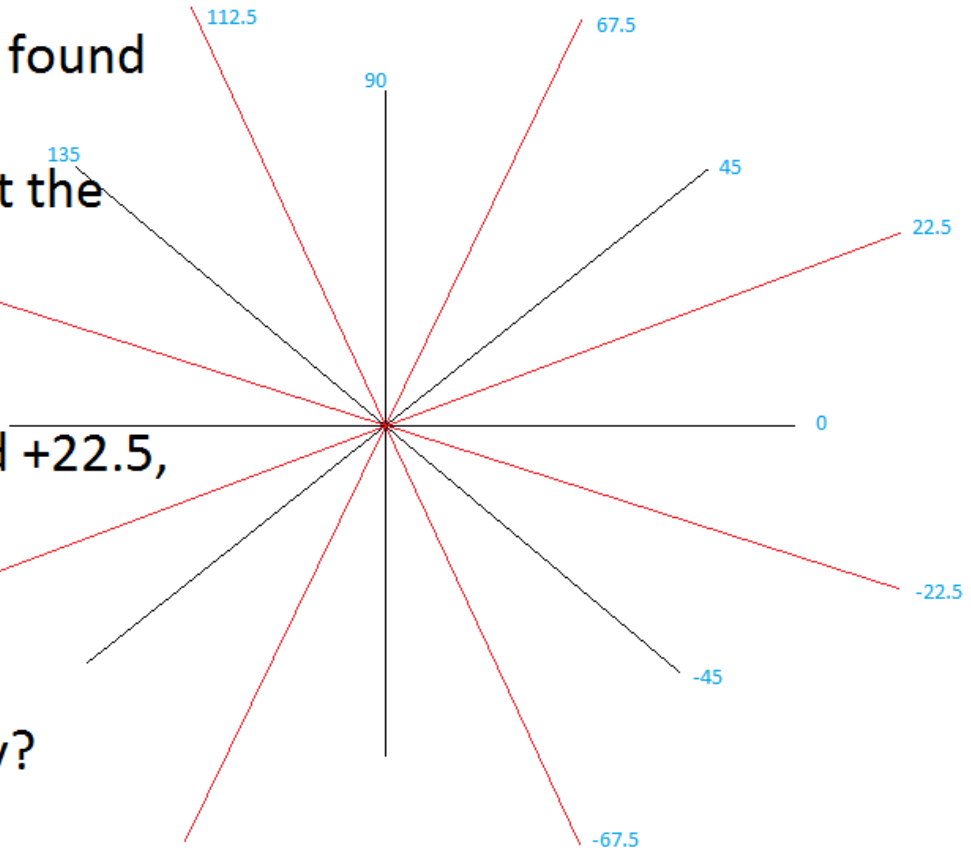


Canny Edge detector algorithm

4. **Apply "Non-maximum Suppression"**

For example, if it is found that the gradient at the center pixel is between -22.5 and +22.5,

Which max-test should we employ?



Canny Edge detector algorithm

4. **Apply "Non-maximum Suppression"**

So, put = sign in

And, remove Vertical

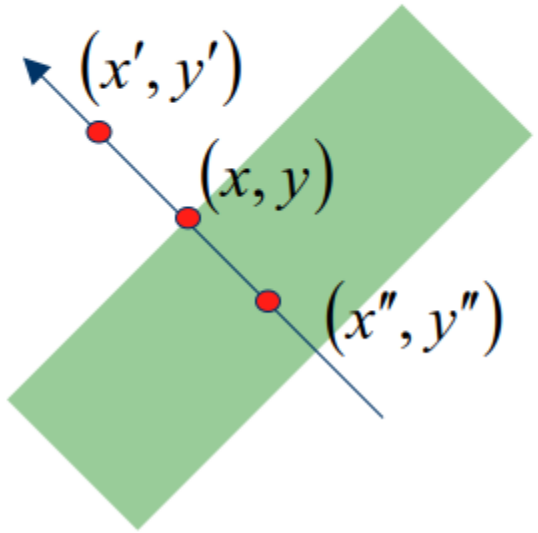
cone test, use "otherwise"

```
For each pixel (i.e., double-for loop)
    Get pixel's gradient direction , Dir
    If - 22.5 < Dir <=22.5
        Employ Horizontal Max-Test
    else if +22.5 < Dir <=+67.5
        Employ Test involving SW and NE pixels
    else if -67.5 < Dir <=-22.5
        Employ Test involving SE and NW pixels
    else Employ Vertical test
```

Canny Edge detector algorithm

4. **Apply "Non-maximum Suppression"**

- Suppress the pixels in $|\nabla S|$ which are not local maximum



$$M(x,y) = \begin{cases} |\nabla S|(x,y) & \text{if } |\nabla S|(x,y) > |\Delta S|(x',y') \\ & \& \, |\Delta S|(x,y) > |\Delta S|(x'',y'') \\ 0 & \text{otherwise} \end{cases}$$

x' and **x**" are the neighbors of **x** along normal direction to an edge

Canny Edge detector algorithm

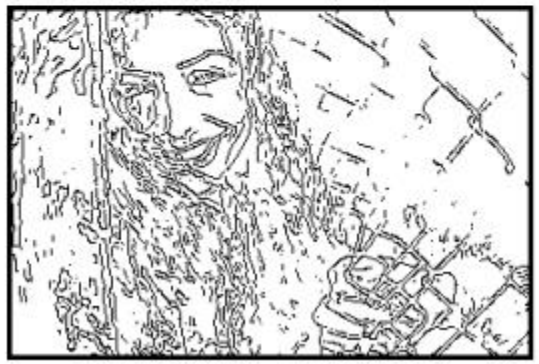
4. **Apply "Non-maximum Suppression"**

$$|\Delta S| = \sqrt{S_x^2 + S_y^2}$$

M

For visualization

$M \geq Threshold = 25$



Comparison

Gradient Thresholding

With non-maximal suppression

Canny Edge detector algorithm

1. Smooth image with Gaussian filter
2. Compute derivative of filtered image
3. Find magnitude and orientation of gradient
4. Apply “Non-maximum Suppression”
5. **Apply “Hysteresis Threshold”**

Hysteresis Thresholding

- Edges tend to be continuous
- Still threshold the gradient
- Use a lower threshold if a neighboring point is an edge
- The “Canny Edge Detector” uses all of these heuristics

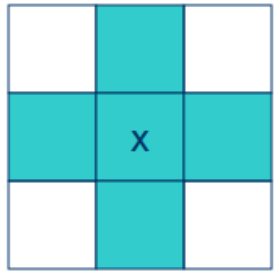
Canny Edge detector algorithm

5. Apply "Hysteresis Threshold"

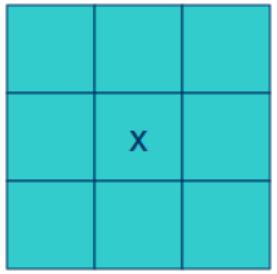
- If the gradient at a pixel is
  - above "**High**", declare it as an '**edge pixel**'
  - below "**Low**", declare it as a "**non-edge-pixel**"
  - **between** "low" and "high"
    - Consider its neighbors iteratively then declare it an "edge pixel" if it is **connected** to an 'edge pixel' **directly** or via pixels **between** "low" and "high".

Canny Edge detector algorithm

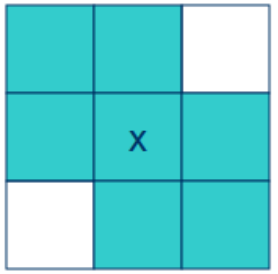
- Connectedness



4 connected



8 connected



6 connected

5. Apply "Hysteresis Threshold"

- If the gradient at a pixel is
  - above "**High**", declare it as an '**edge pixel**'
  - below "**Low**", declare it as a "**non-edge-pixel**"
  - **between** "low" and "high"
    - Consider its neighbors iteratively then declare it an "edge pixel" if it is **connected** to an 'edge pixel' **directly** or via pixels **between** "low" and "high".

Canny Edge detector algorithm

5. Apply "Hysteresis Threshold"

- Scan the image from left to right, top-bottom.
  - The gradient magnitude at a pixel is above a high threshold declare that as an edge point
  - Then recursively consider the *neighbors* of this pixel.
    - If the gradient magnitude is above the low threshold declare that as an edge pixel.

Canny Edge detector algorithm

5. Apply "Hysteresis Threshold"

M

regular

$M \geq 25$

Hysteresis

$High = 35$

$Low = 15$

Canny Edge detector algorithm

Before non-max suppression

After non-max suppression

Canny Edge detector algorithm

Final Canny Edge

Threshold at low/high levels to get weak/strong edge pixels

- Do connected components, starting from strong edge pixels

Canny Edge detector algorithm

Final Canny Edge

Effect of σ (Gaussian kernel spread/size)

original Canny with $\sigma = 1$ Canny with $\sigma = 2$

The choice of σ depends on desired behavior

- large σ detects large scale edges
- small σ detects fine features

Source: S. Seitz

Questions?