# Feature detection
# Lecture 3.1 - Line features

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# Edges and lines

An edge is a place of rapid change of image intensity, colour or texture, representing:

- Boundaries of objects
- Shadow boundaries
- Creases
- …

Edge points (*edgels*) can be grouped into:

- Curves/contours
- Straight line segments
- Piecewise linear contours
- …

# Edge operators (edge enhancement filters)

*Edge pixels are found at extrema of the first derivative of the image intensity function.*

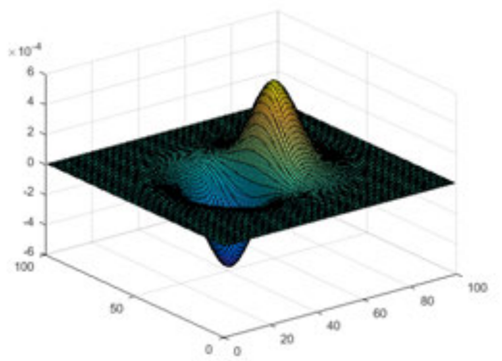
**Image gradient** (noisy):

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

Gradient magnitude:

$$||\nabla f|| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

**Derivative of Gaussian** (smoother result):




$$\frac{\partial}{\partial u} h_\sigma(u,v)$$

$$h_\sigma(u,v) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{u^2+v^2}{2\sigma^2}\right)}$$

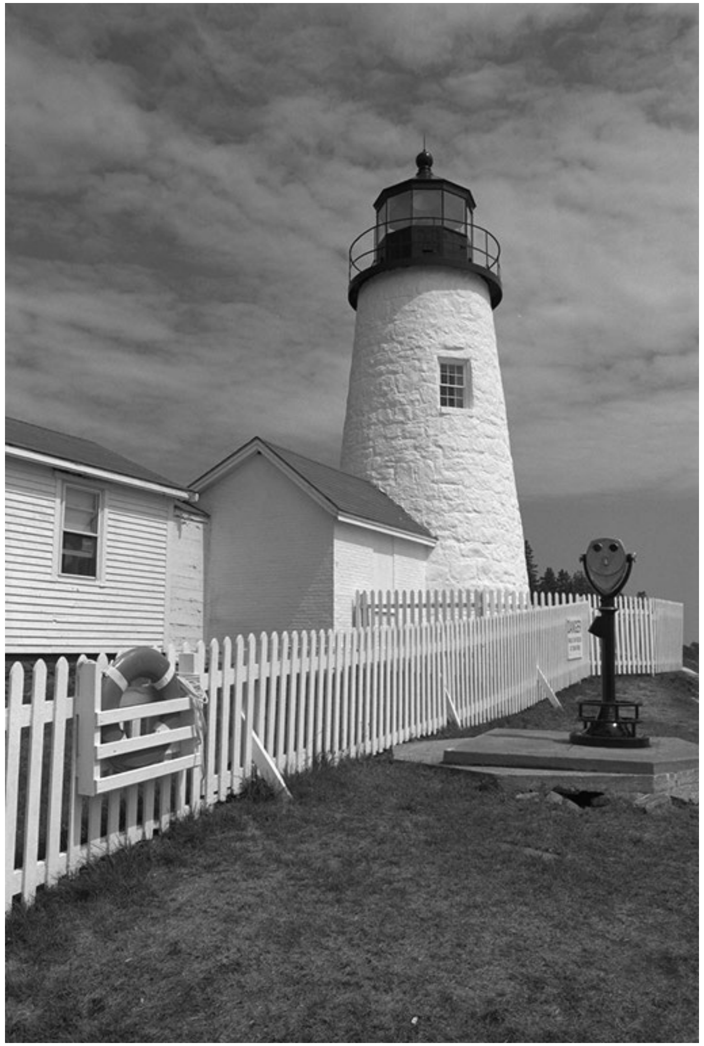
Prewitt operator:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \qquad G_y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

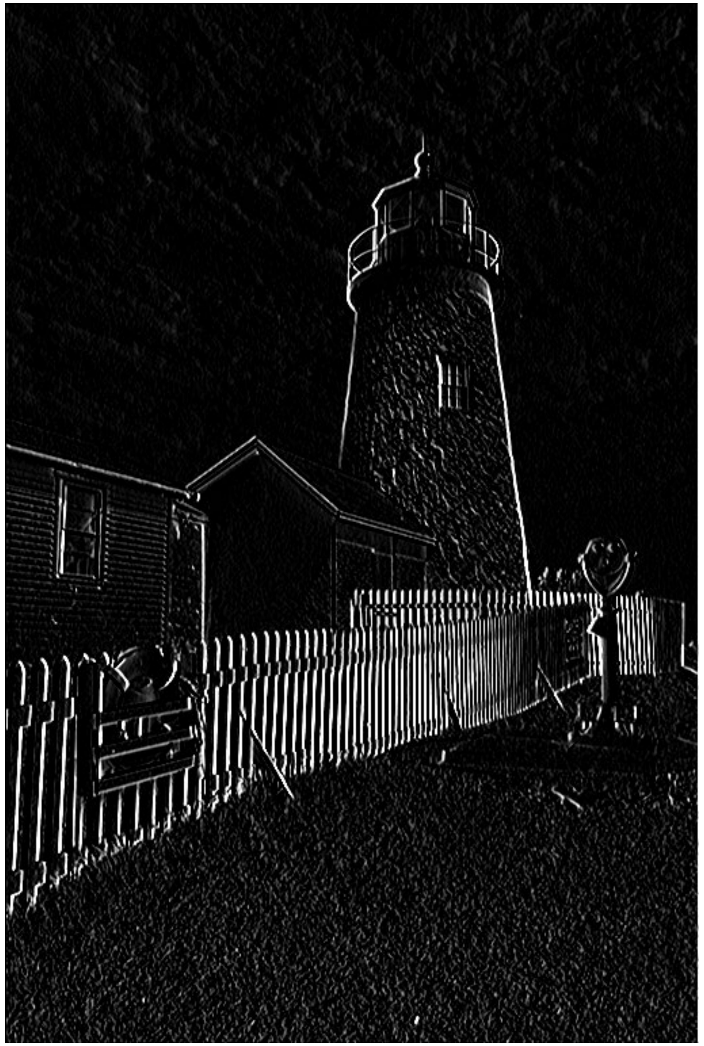
Sobel operator:

$$S_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad S_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

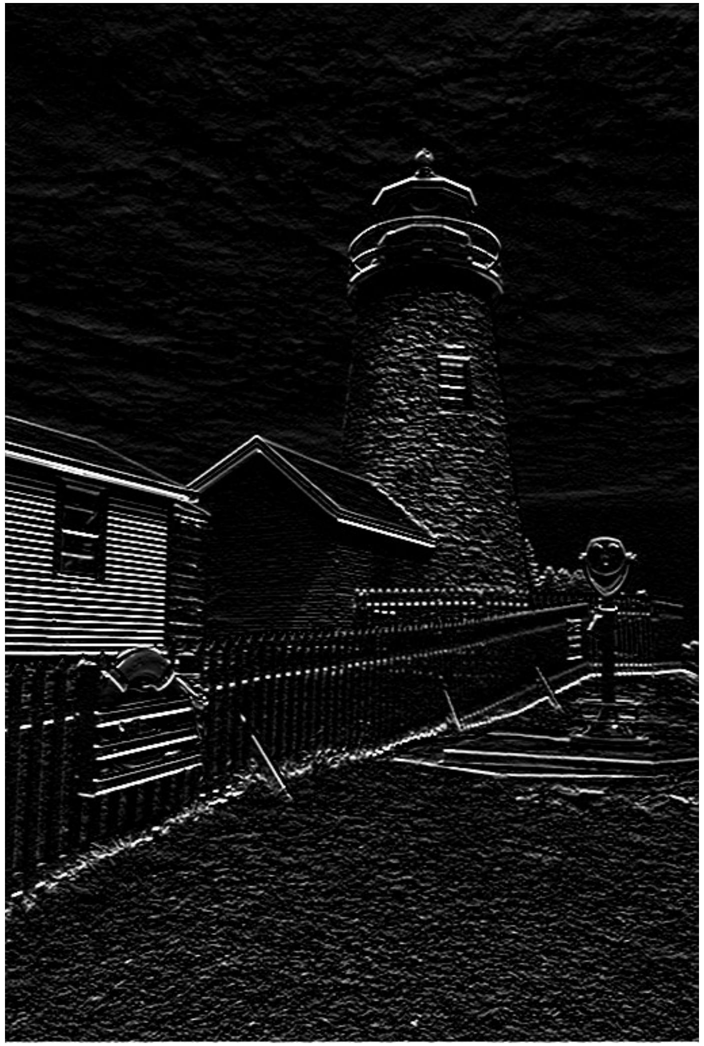
# Image derivatives - Sobel



Gray level image

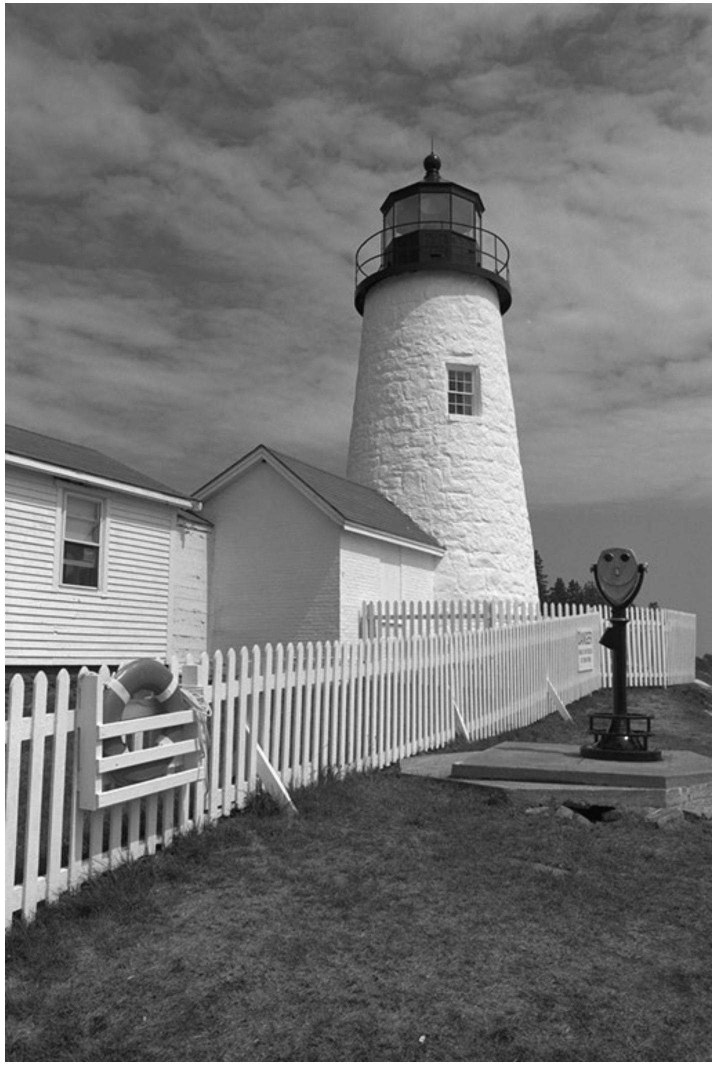


x-component

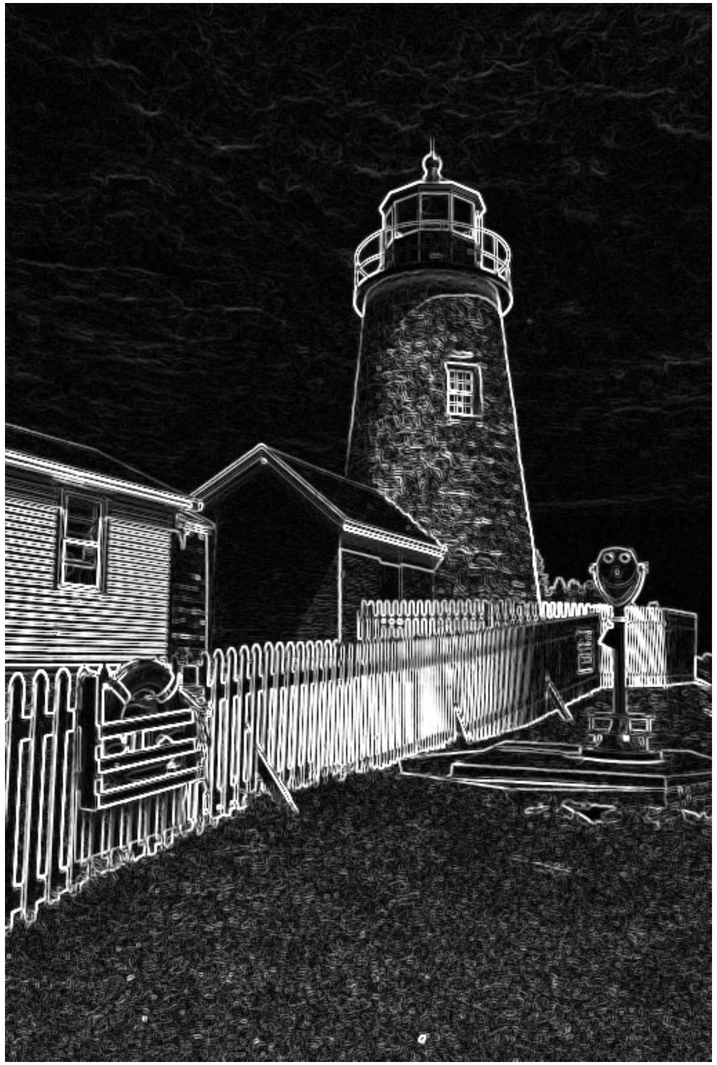


y-component

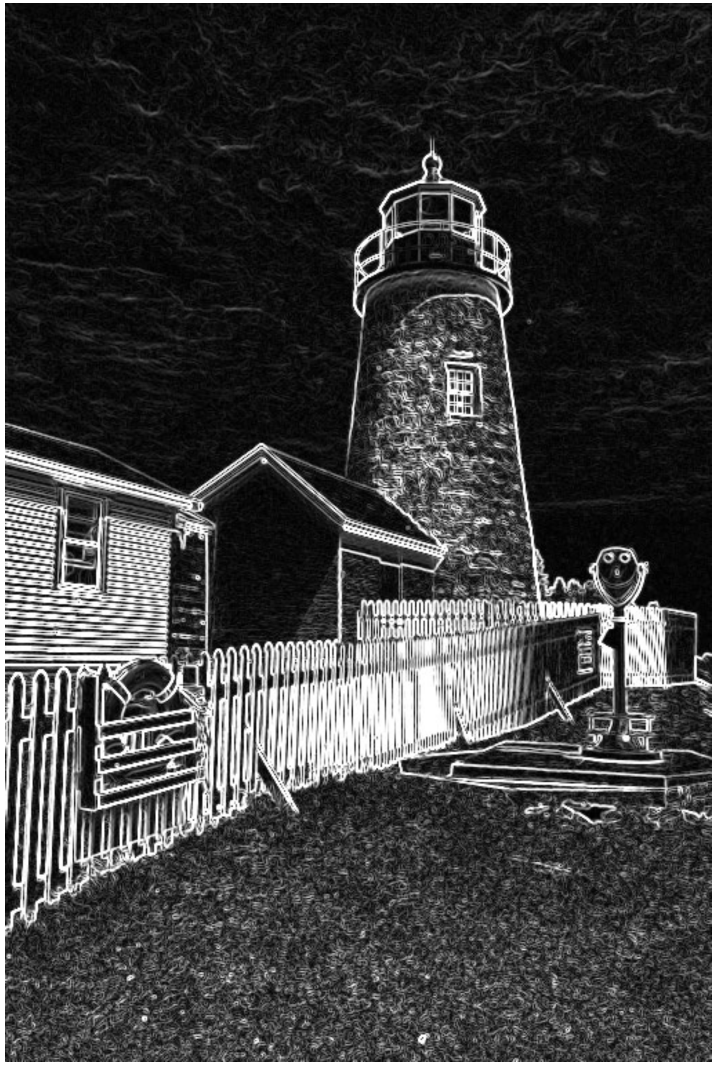
# Gradient magnitude



Gray level image



Gradient magnitude - Prewitt

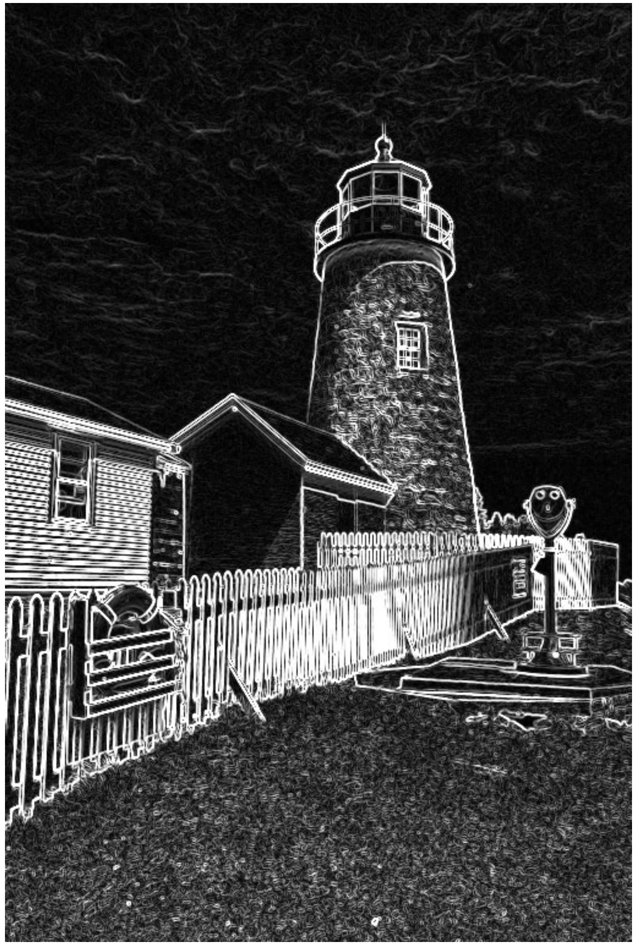


Gradient magnitude - Sobel

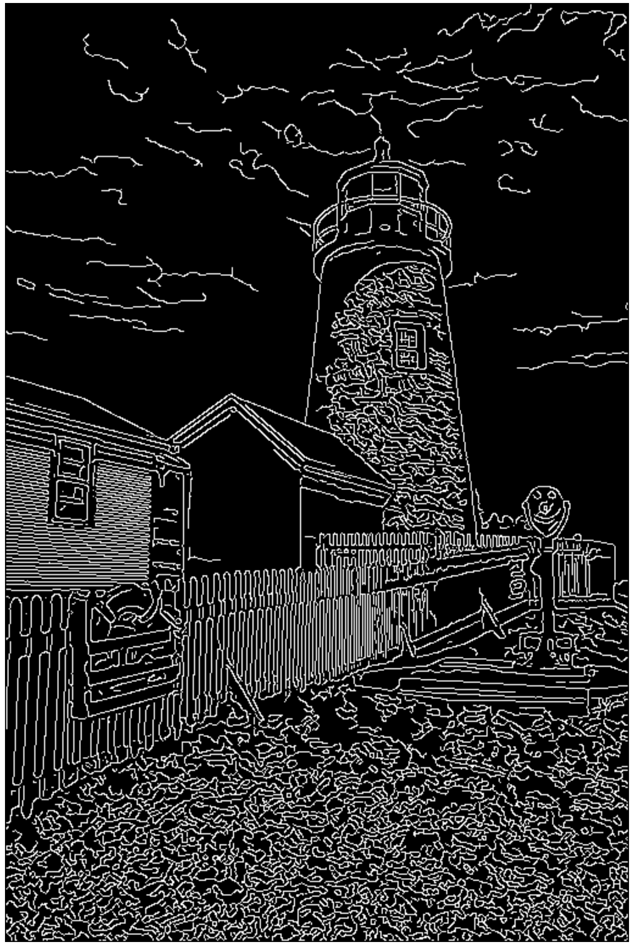
# Thinning and thresholding

- Detection of local maxima (i.e. suppression of non-maxima)
- Thresholding

Binary image with isolated edges (single pixels at discrete locations along edge contours)



Edge enhanced image (Sobel)

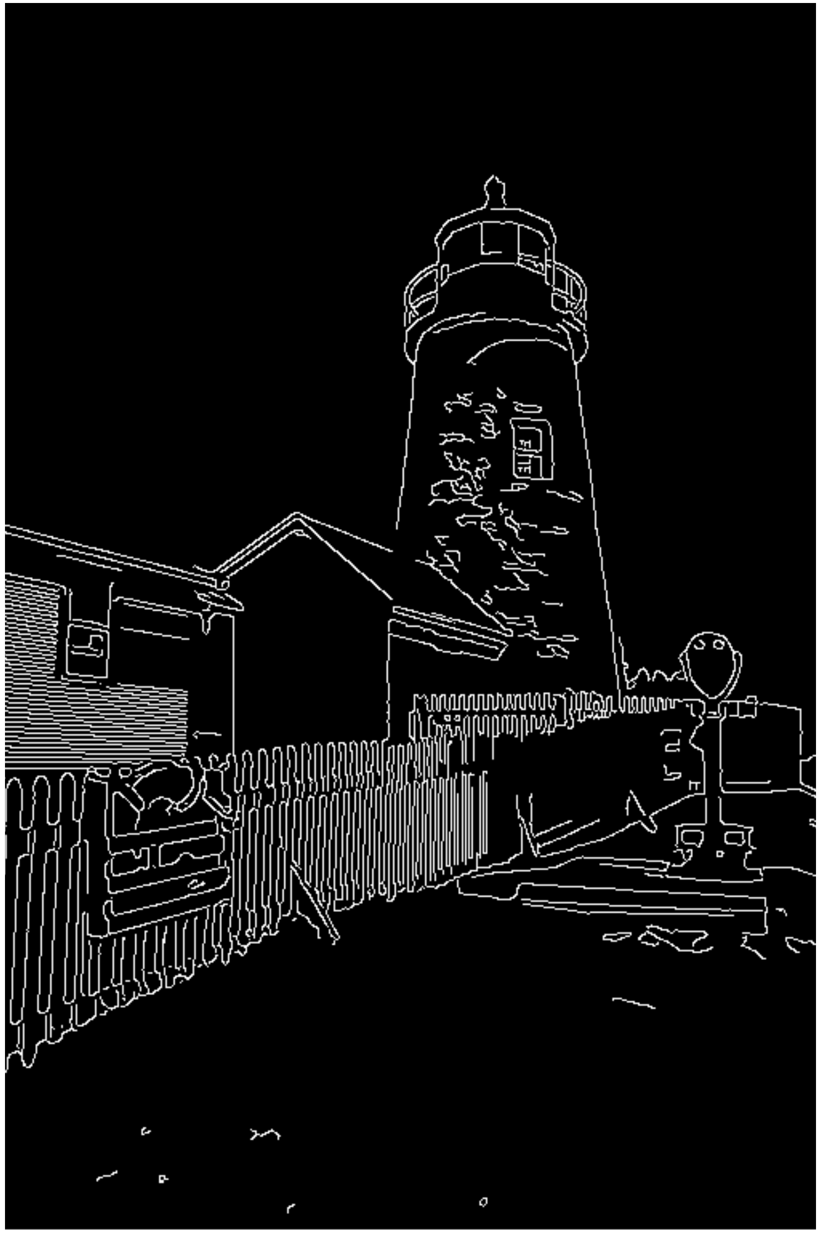


Edge image (Canny)

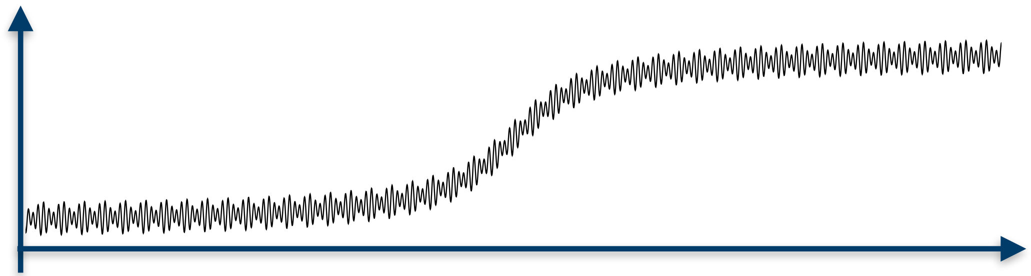
# Canny edge detector

- Calculates a gradient image using the derivative of a Gaussian filter (i.e. Sobel operator)
- Detects local maxima of the gradient
- Thresholding using two thresholds:
  - **High** threshold for detection of strong edges
  - **Low** threshold for detection of weak edges
- Only weak edges connected to strong edges are retained in the output image

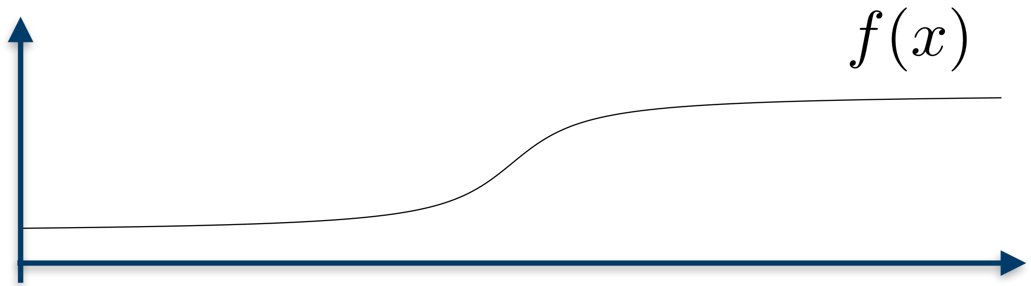
- This method is less likely to be fooled by noise than other methods, and
- More likely to detect true weak edges



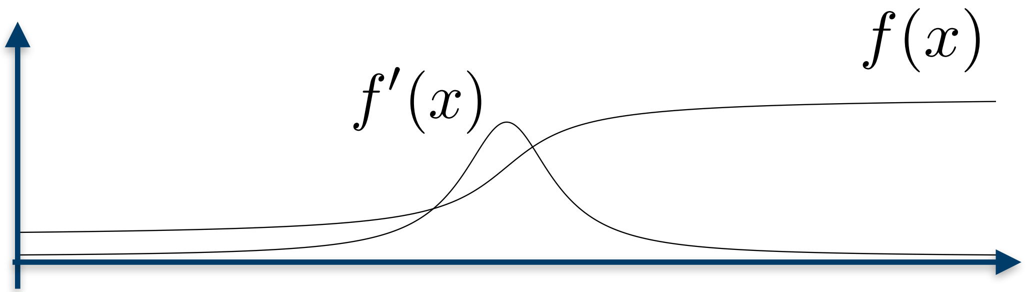
# First and second derivatives



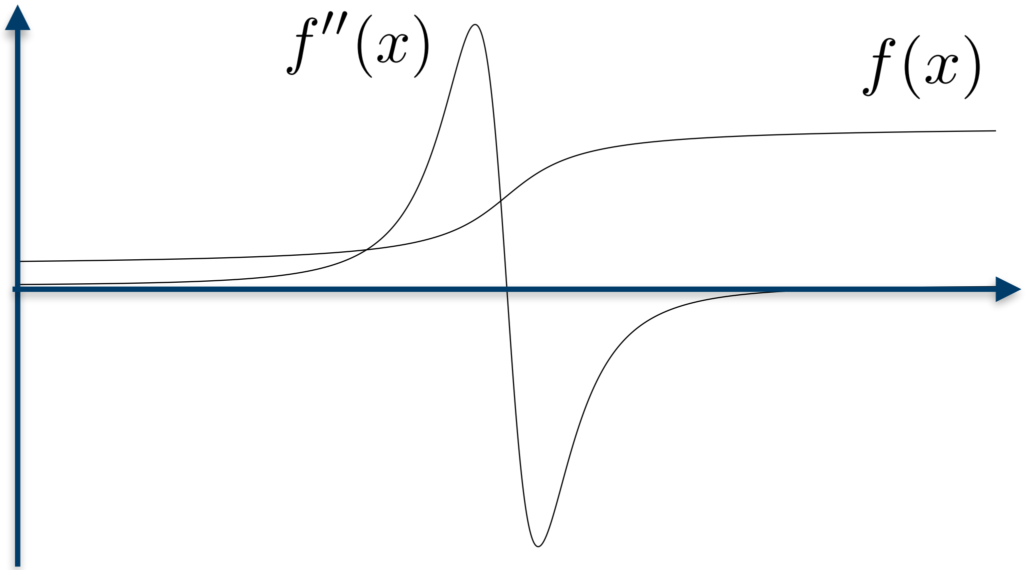
Noisy image function




Low-pass filtered image function




First derivative (Gradient)




Second derivative (Laplacian)

# Laplacian operator

Gradient (in two dimensions):

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

Laplacian:

$$\nabla \cdot \nabla = \nabla^2 = \frac{\partial^2}{\partial^2 x} + \frac{\partial^2}{\partial^2 y}$$

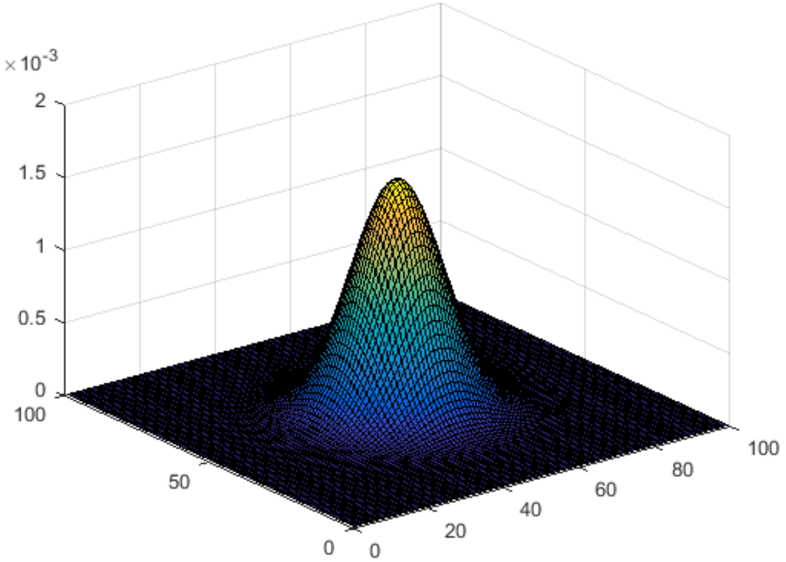
Discrete approximations (3 x3 kernels):

$$\frac{1}{6}\begin{bmatrix} 1 & 4 & 1 \\ 4 & -20 & 4 \\ 1 & 4 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

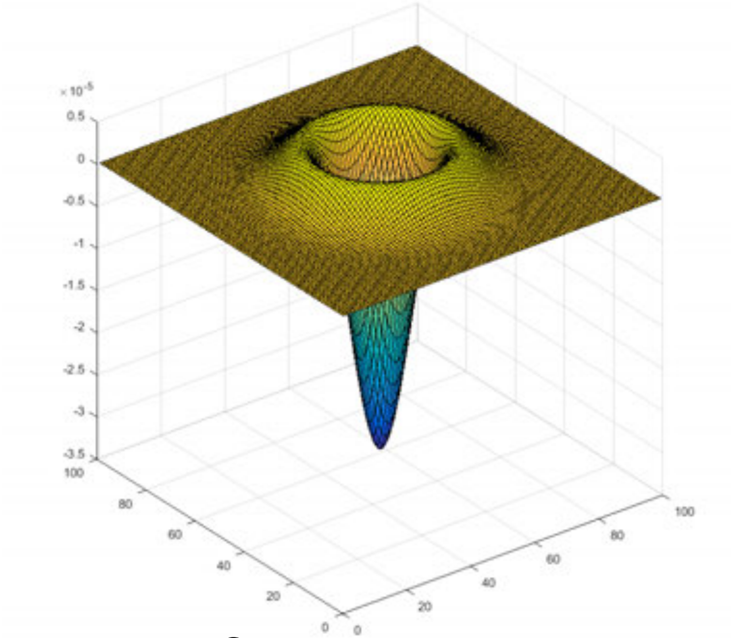
# Laplacian of Gaussian (LoG)

## Gaussian




$$h_\sigma(u,v) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{u^2+v^2}{2\sigma^2}\right)}$$

## Laplacian of Gaussian



$$\nabla^2 h_\sigma(u,v)$$

Edge pixels at zero-crossings in the LoG image!

# Laplacian of Gaussian - example

$$\nabla^2 h_\sigma(u,v)$$

Laplace

| | | |
|---|---|---|
| 0 | 1 | 0 |
| 1 | -4 | 1 |
| 0 | 1 | 0 |

*

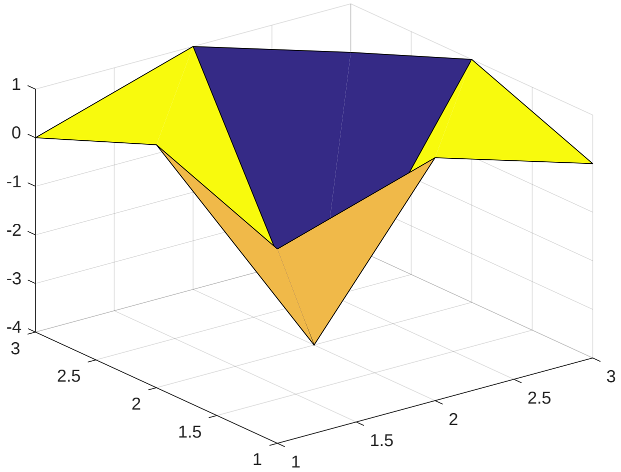
Gauss

| | | |
|---|---|---|
| 0.0113 | 0.0838 | 0.0113 |
| 0.0838 | 0.6193 | 0.0838 |
| 0.0113 | 0.0838 | 0.0113 |

=

LoG

| | | | | |
|---|---|---|---|---|
| 0.0000 | 0.0113 | 0.0838 | 0.0113 | 0.0000 |
| 0.0113 | 0.1223 | 0.3068 | 0.1223 | 0.0113 |
| 0.0838 | 0.3068 | -2.1421 | 0.3068 | 0.0838 |
| 0.0113 | 0.1223 | 0.3068 | 0.1223 | 0.0113 |
| 0.0000 | 0.0113 | 0.0838 | 0.0113 | 0.0000 |



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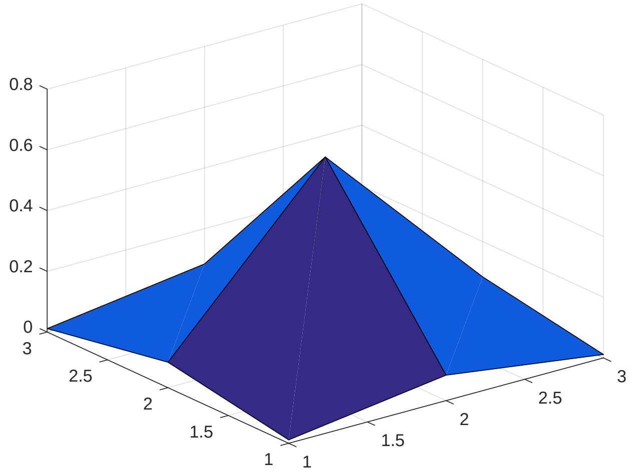

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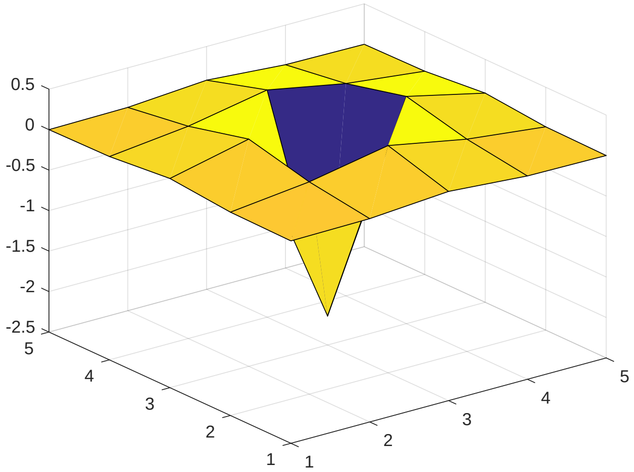
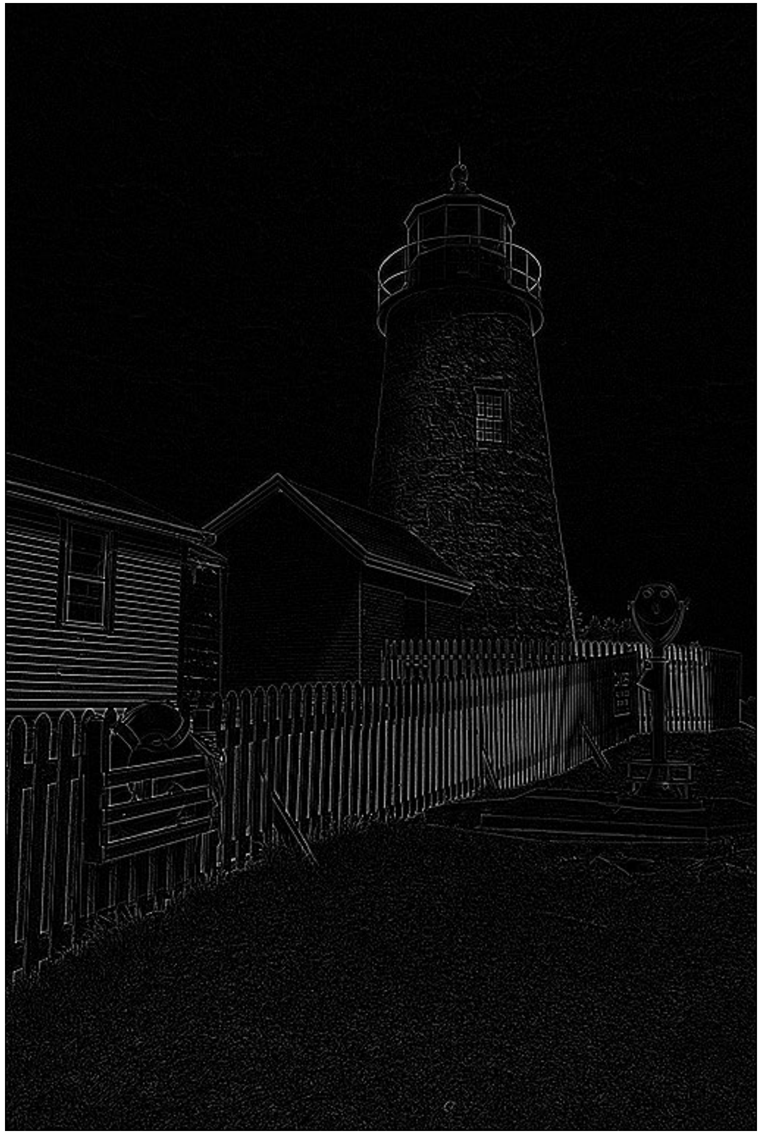
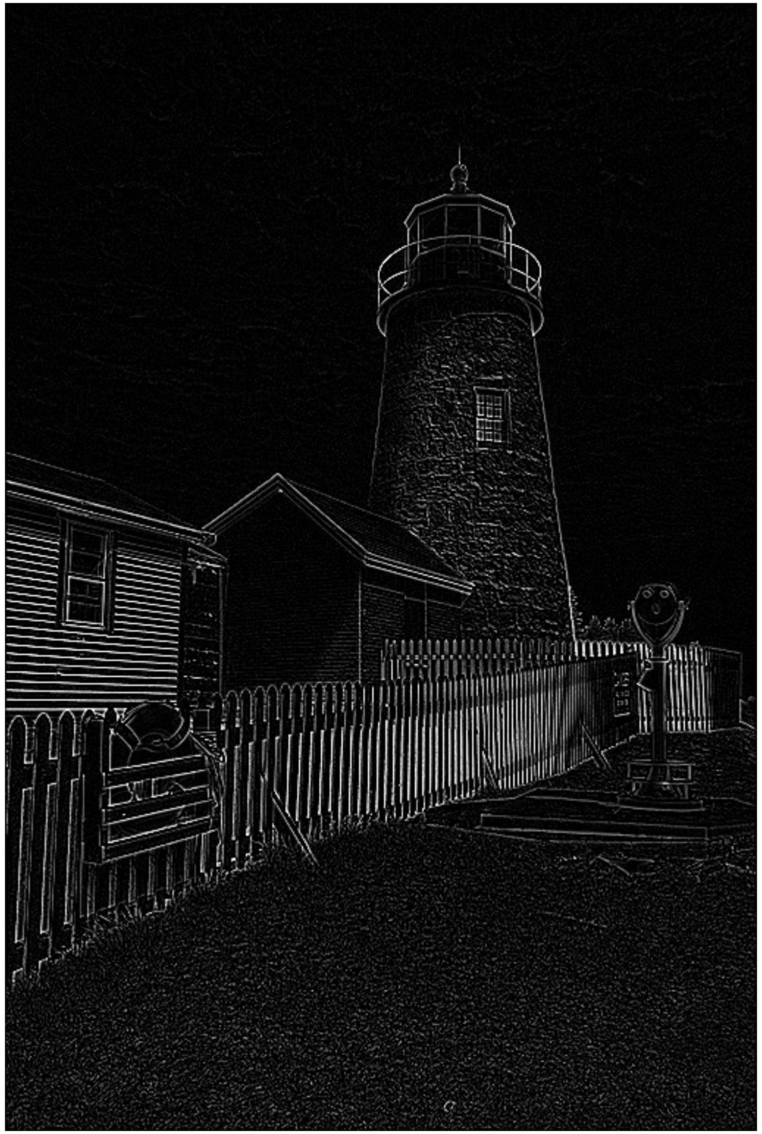


# Examples - Laplacian and LoG

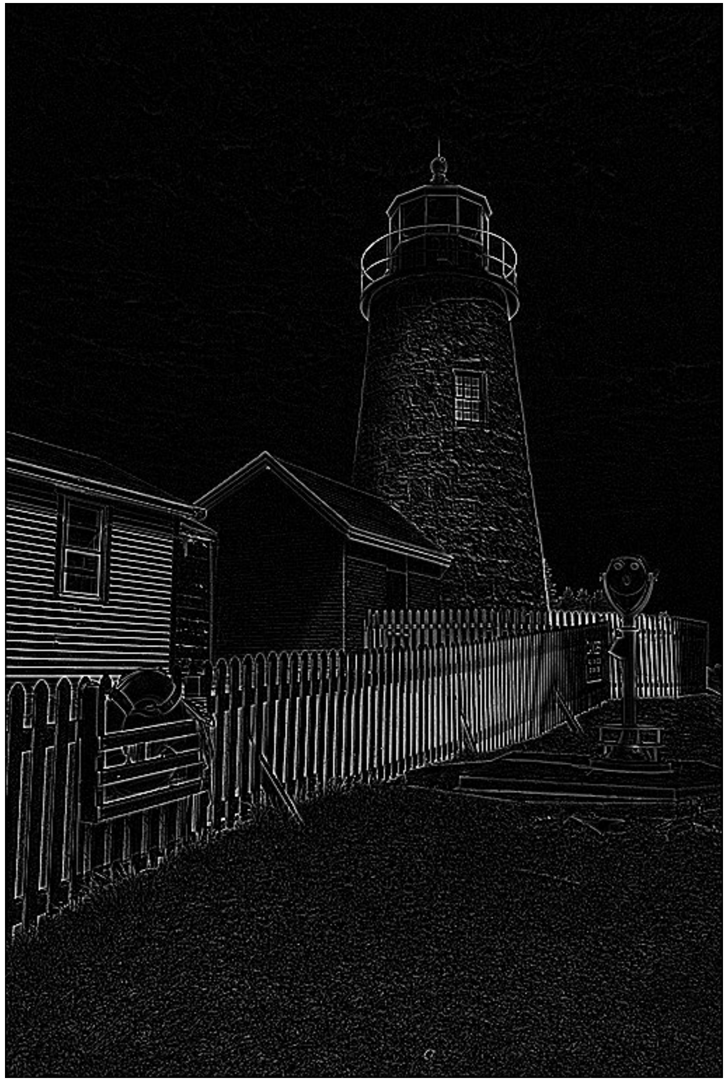


Laplace

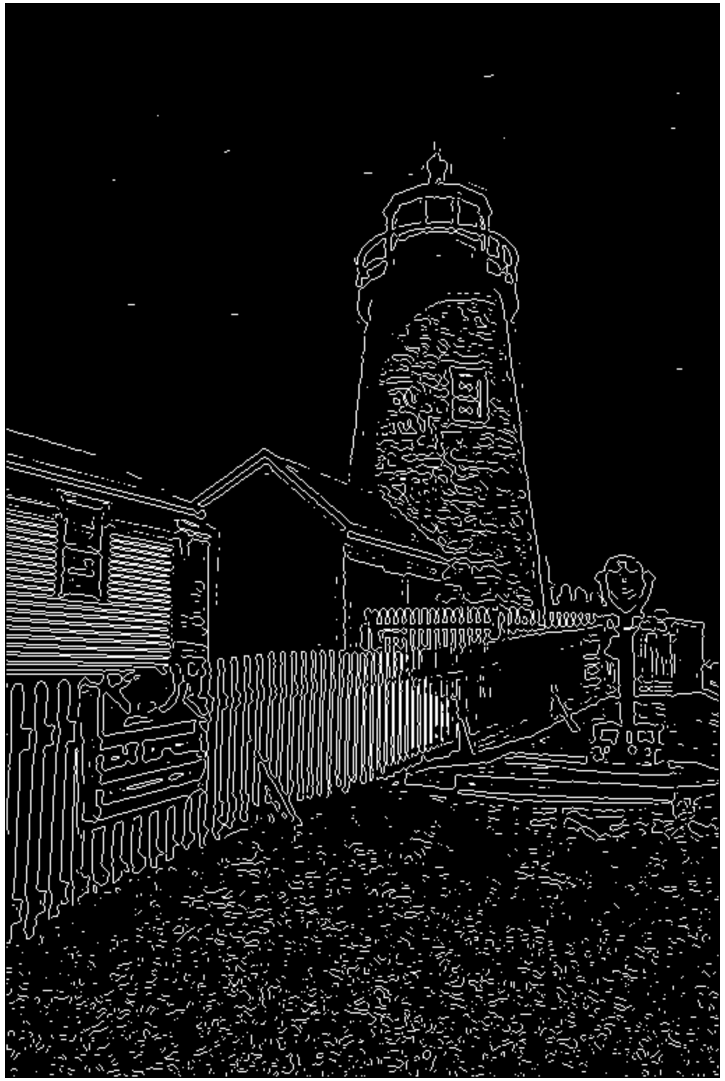


Laplacian of Gaussian

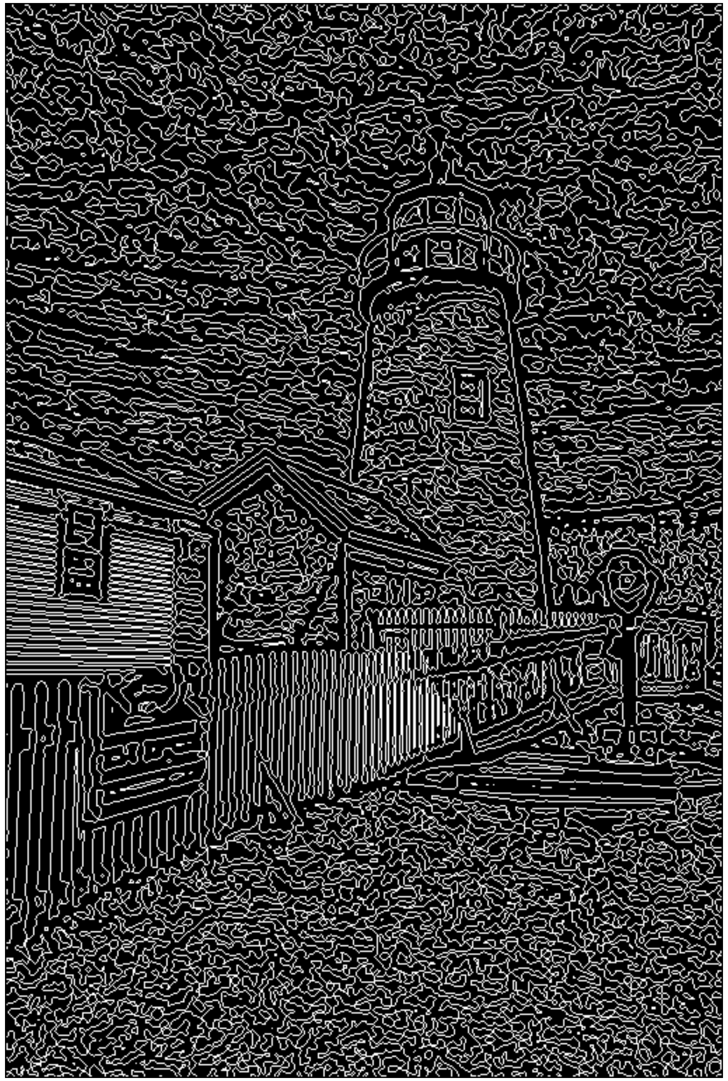
# Edge detection - Laplacian of Gaussian (LoG)



LoG (gray level)

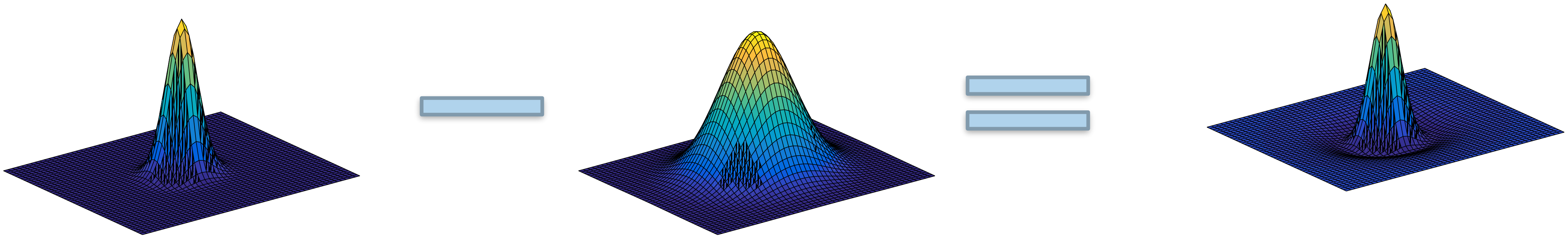


Thresholded (binary)



Zero crossing (binary)

# Difference of Gaussians (DoG)

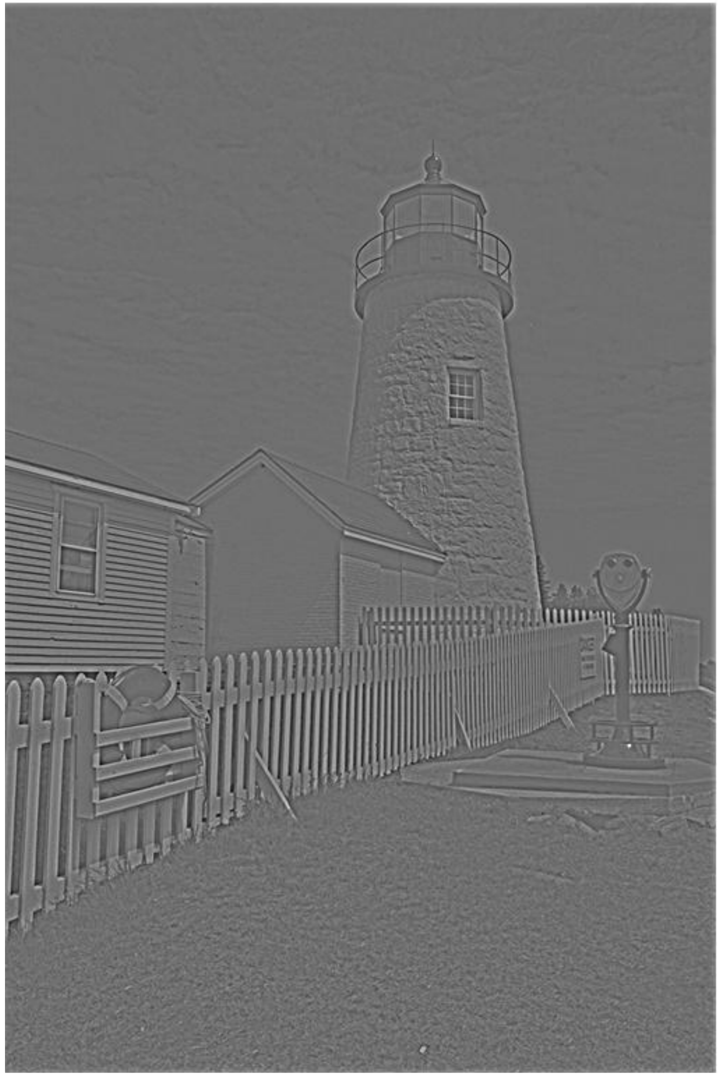


Small variance

Large variance

DoG (approximation to LoG)

# Difference of Gaussians - example



# Another example

RGB original

Gray level

# Laplace and LoG images

Laplace

LoG

# DoG images

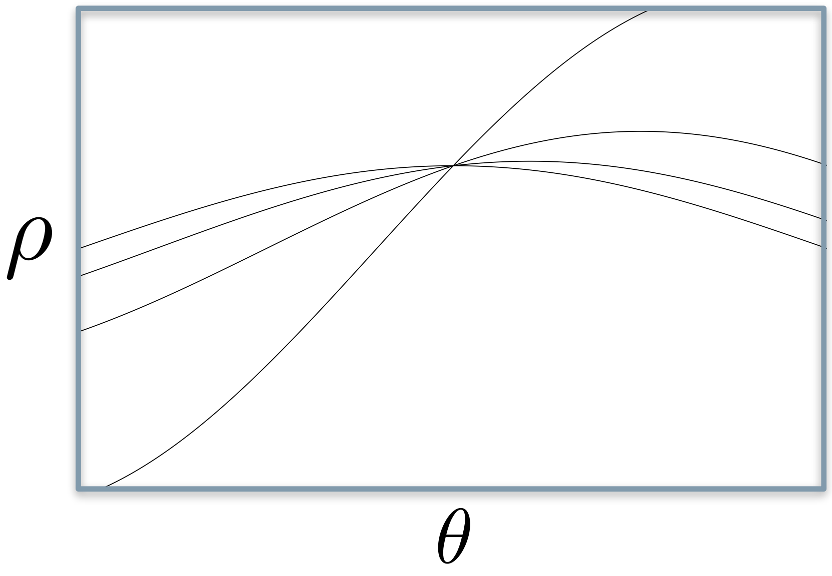
3 x 3 Gaussian kernel

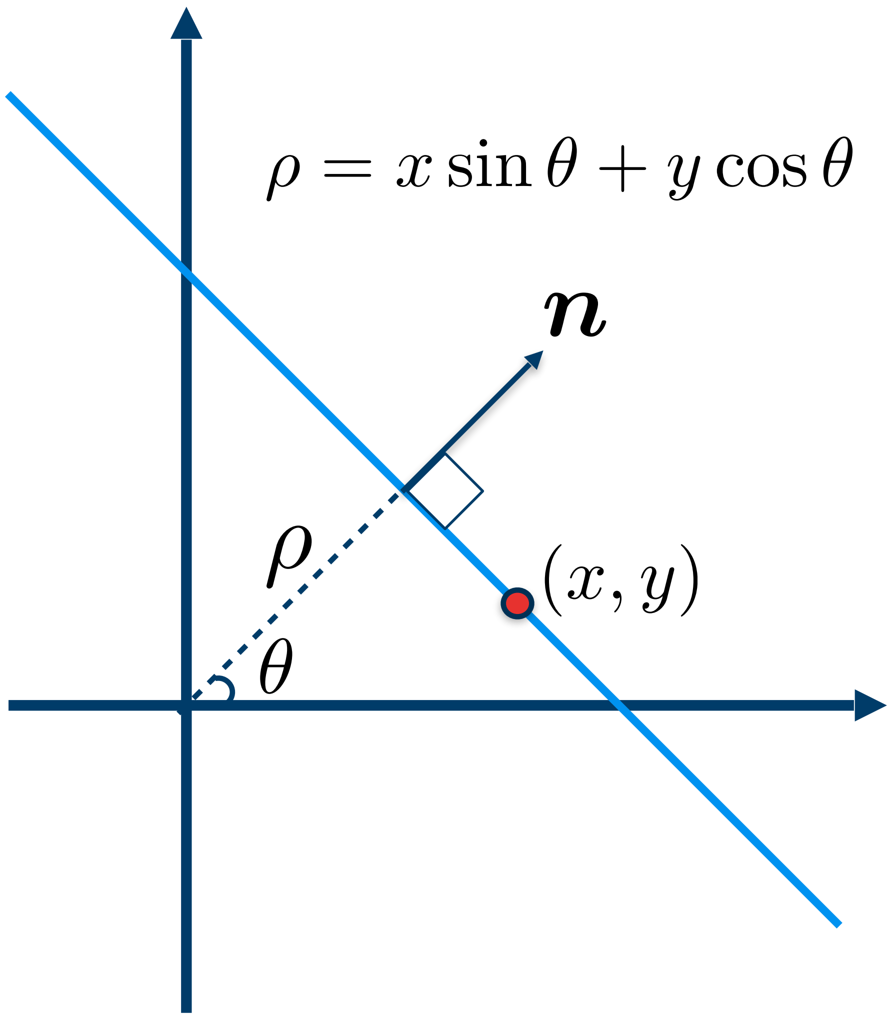
7 x 7 Gaussian kernel

# Line detection - Hough transform

The set of all lines going through a given point corresponds to a sinusoidal curve in the $(\rho, \theta)$ plane.

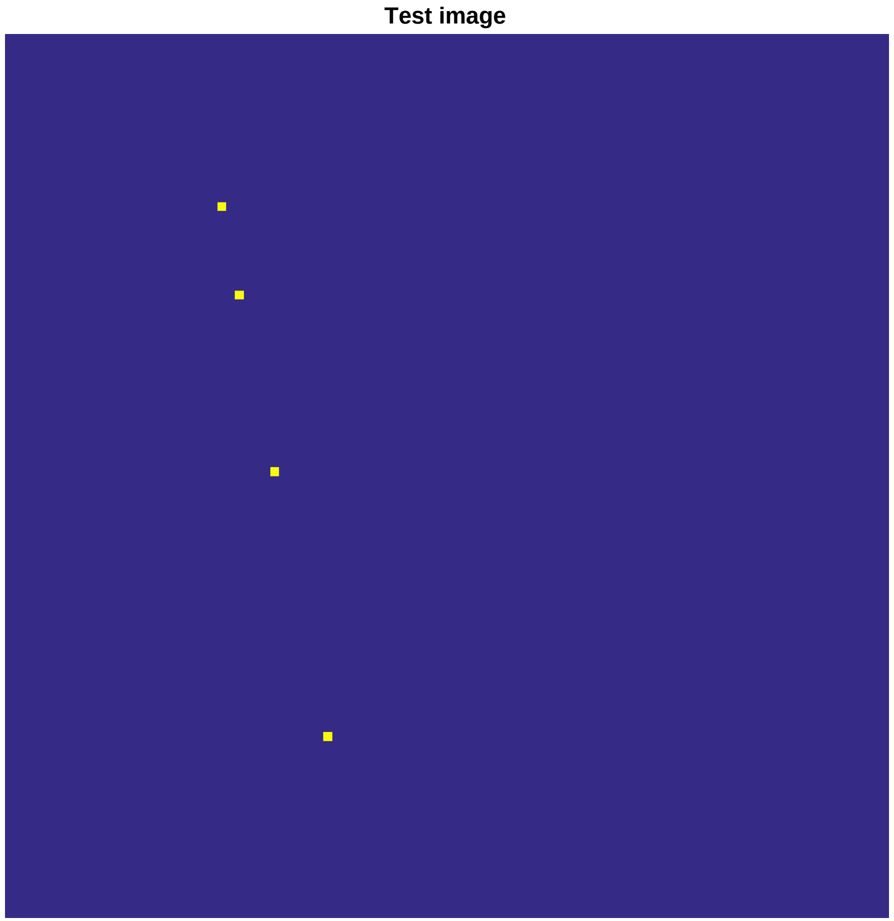
Two or more points on a straight line will give rise to sinusoids intersecting at the point $(\rho, \theta)$ for that line.

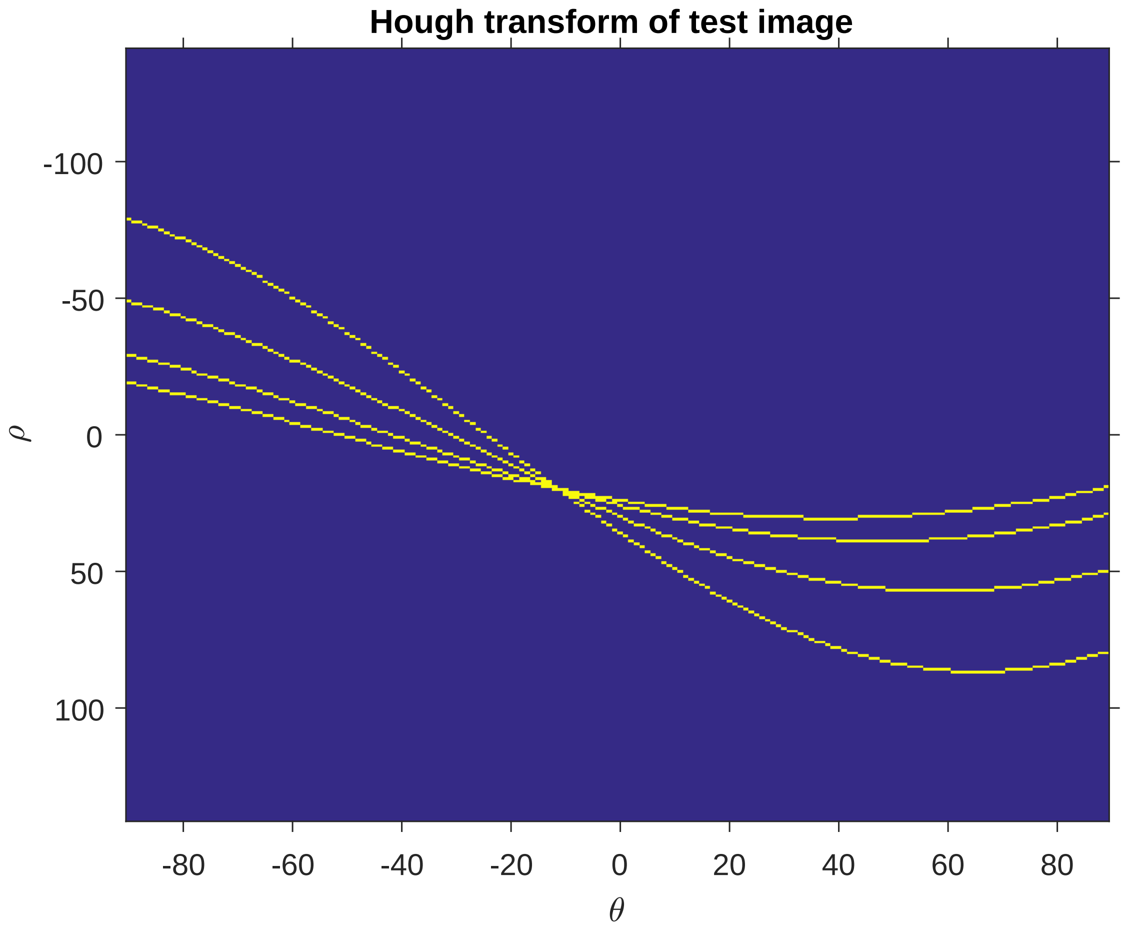



The Hough transform can be generalized to other shapes.

# Example




Accumulator

# Hough transform

1. Clear the accumulator array

2. For each detected edgel (edge pixel) at location $(x, y)$ and each orientation $\theta = \tan^{-1}(n_y/n_x)$, compute the value of:

$$\rho = x \sin\theta + y \cos\theta$$

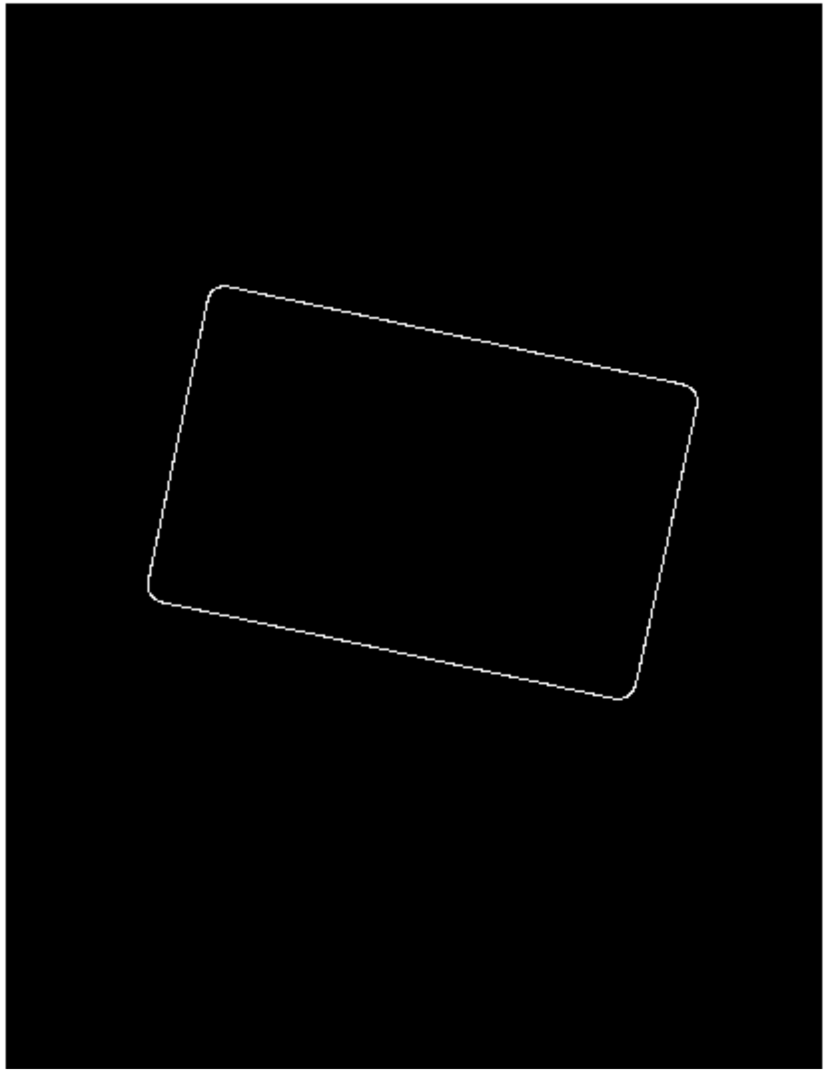
   and increment the accumulator bin corresponding to $(\rho, \theta)$

3. Find the peaks (local maxima) in the accumulator corresponding to lines

4. Optional post-processing to fit the lines to the constituent edgels.

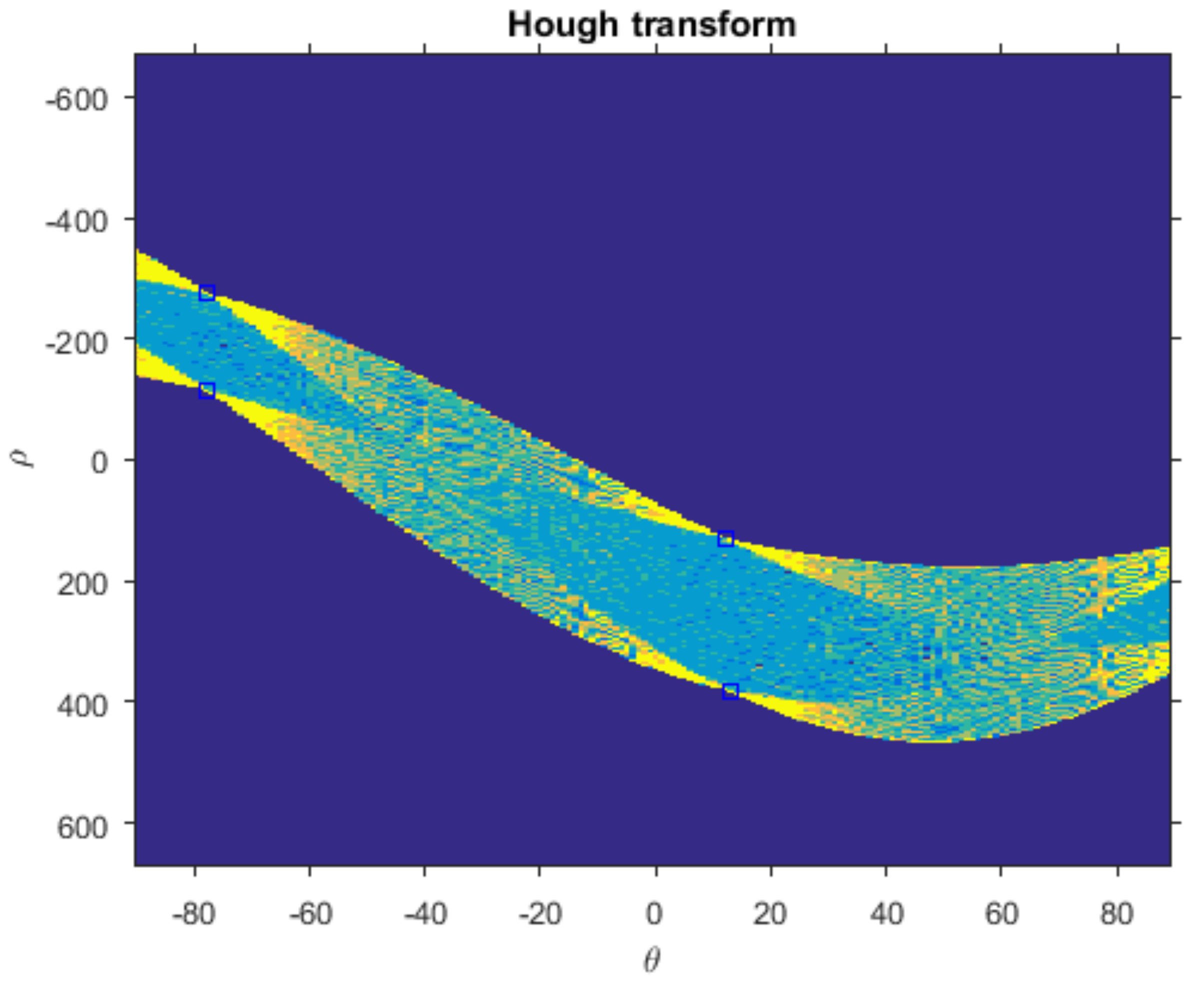
# Example 1

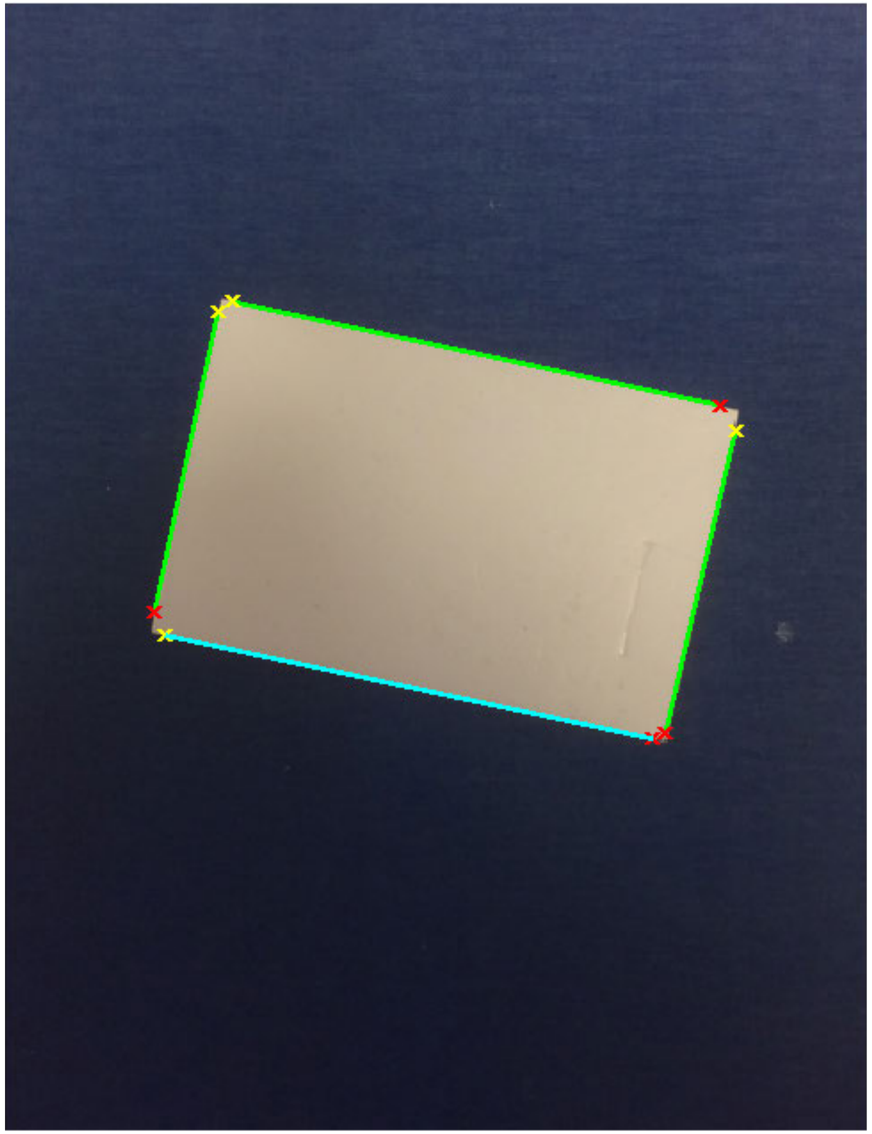
Original



Edge image (Canny)

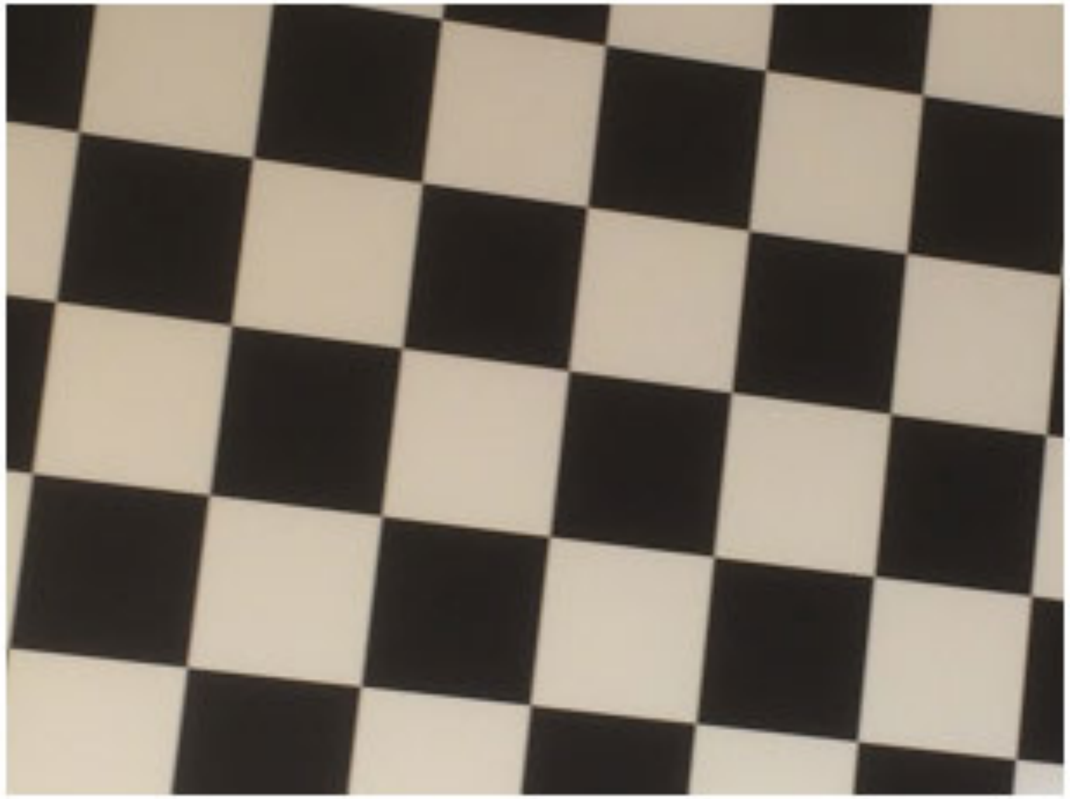
# Example 1 (2)



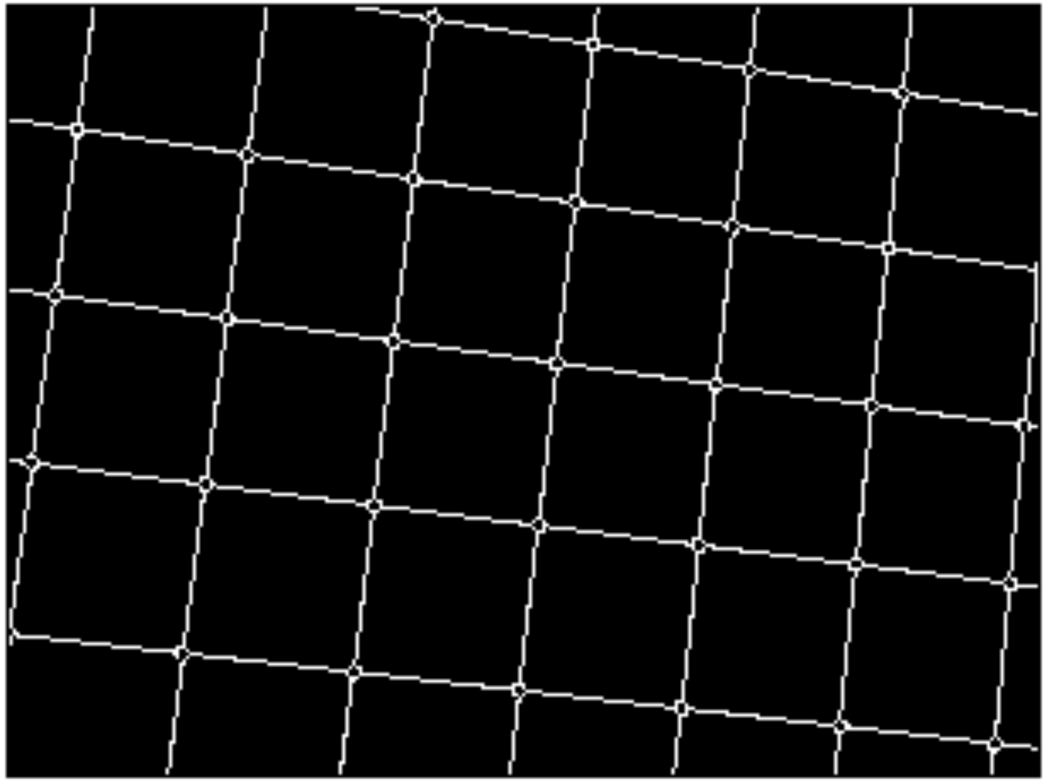



Detected lines

# Example 2

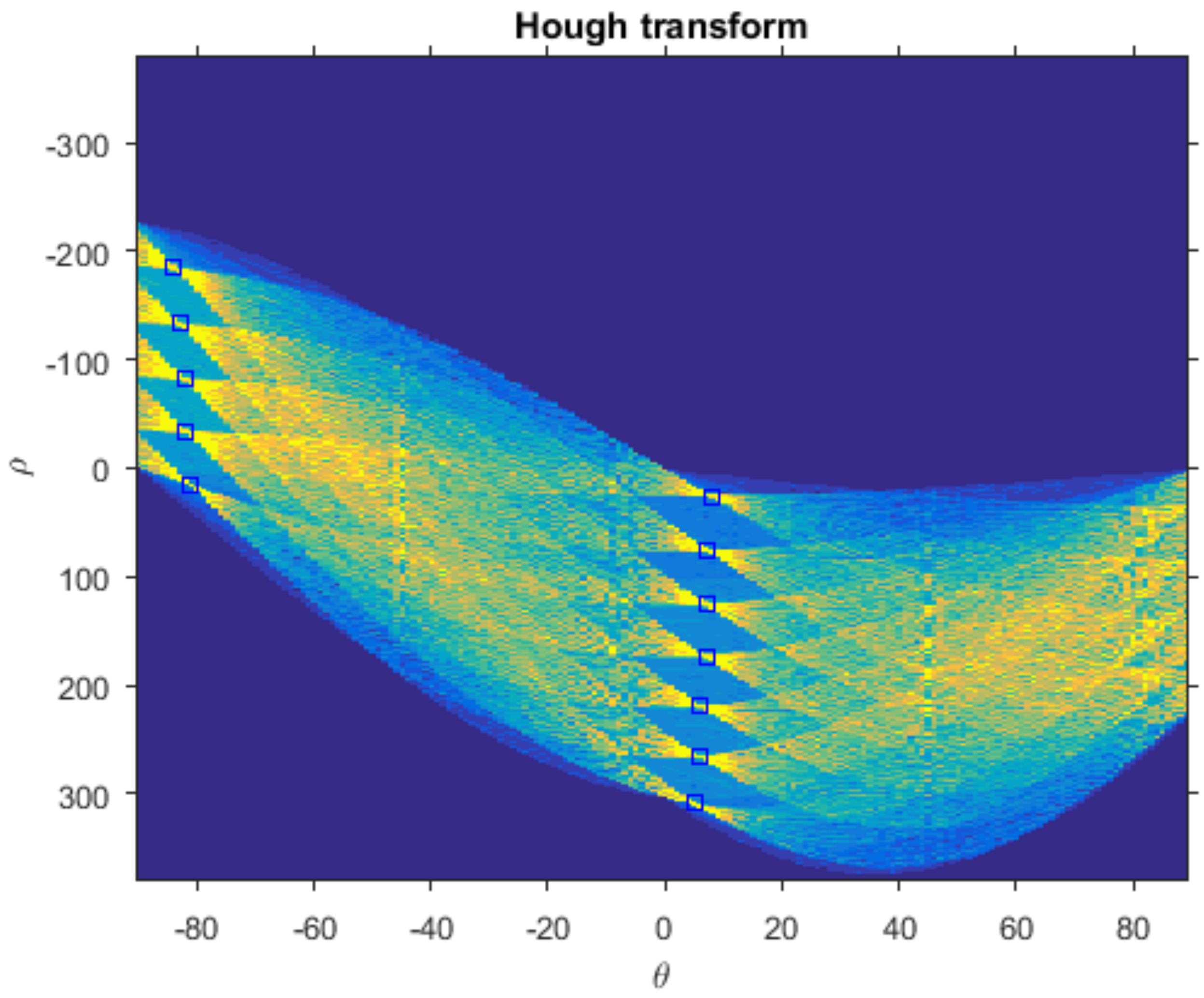


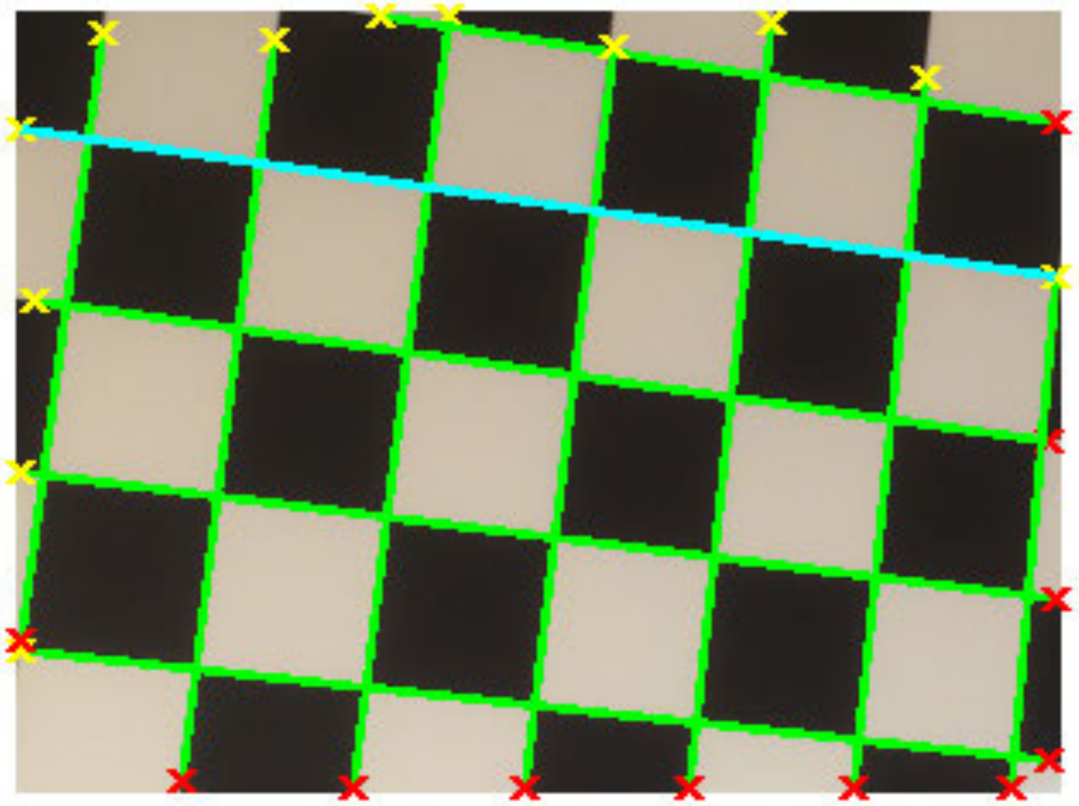
Original



Edge image (Canny)

# Example 2 (2)



Detected lines

# Example 3

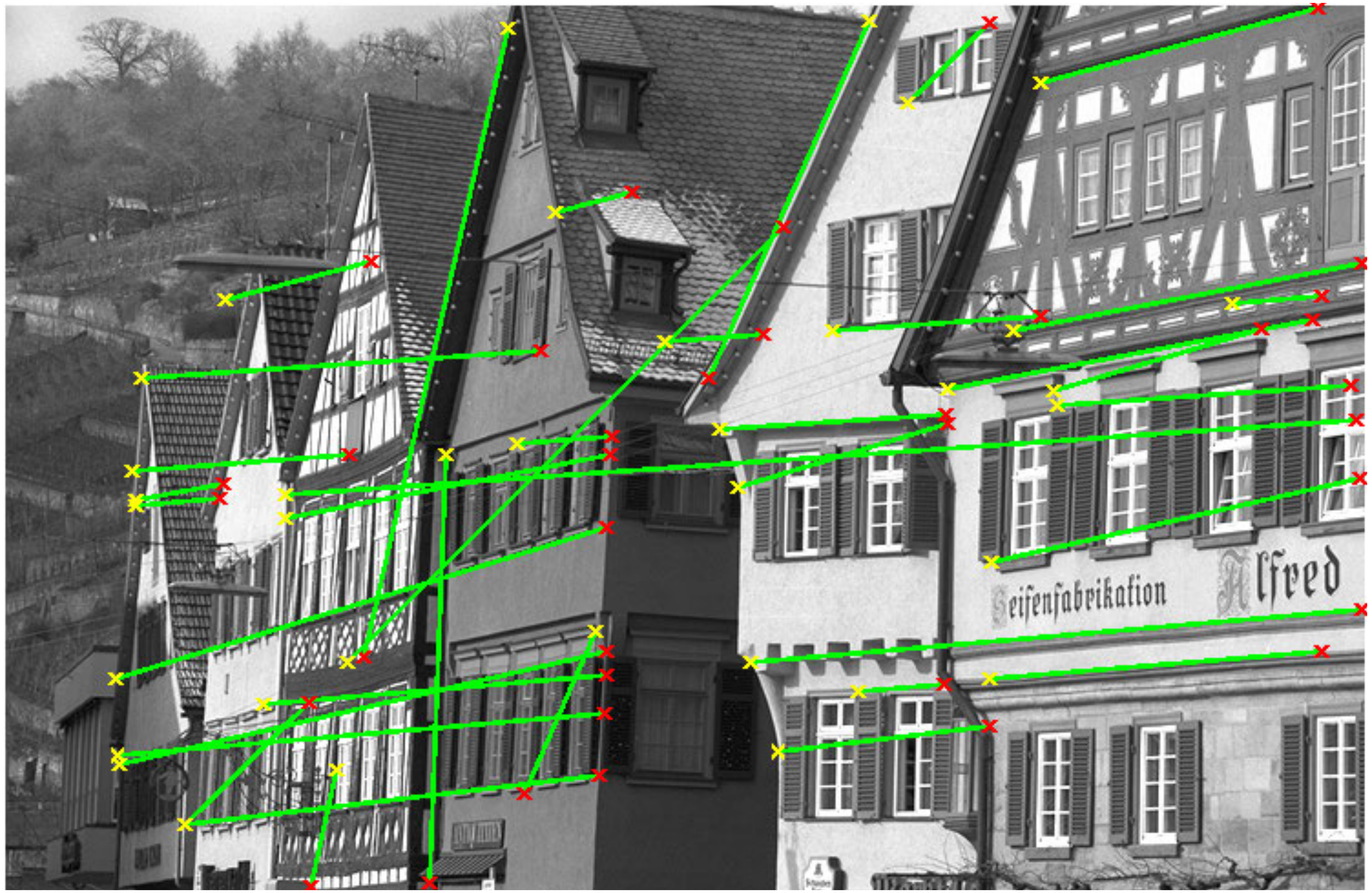
Original

Edge image (Canny)

# Example 3 - some results




# Line detection - complicated scene



# Summary

**Line features:**

- Edge detectors
- Line detection with the Hough transform

**More information:** Szeliski 4.2 - 4.3.