

Gaussian filter

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

0.0113	0.0838	0.0113
0.0838	0.6193	0.0838
0.0113	0.0838	0.0113

Discretization on a 3x3 mask of a Gaussian with mean=0 and dev.standard =0.5

Derivative properties

$f(x)$	$f'(x)$	$f''(x)$
<i>Constant trend</i>	$= 0$	$= 0$
<i>Discontinuity (begin-end)</i>	$\neq 0$	$\neq 0$
<i>Ramp</i>	$\neq 0$	$= 0$

Objective:

Define 2 discrete operators f' and f'' that verify these properties

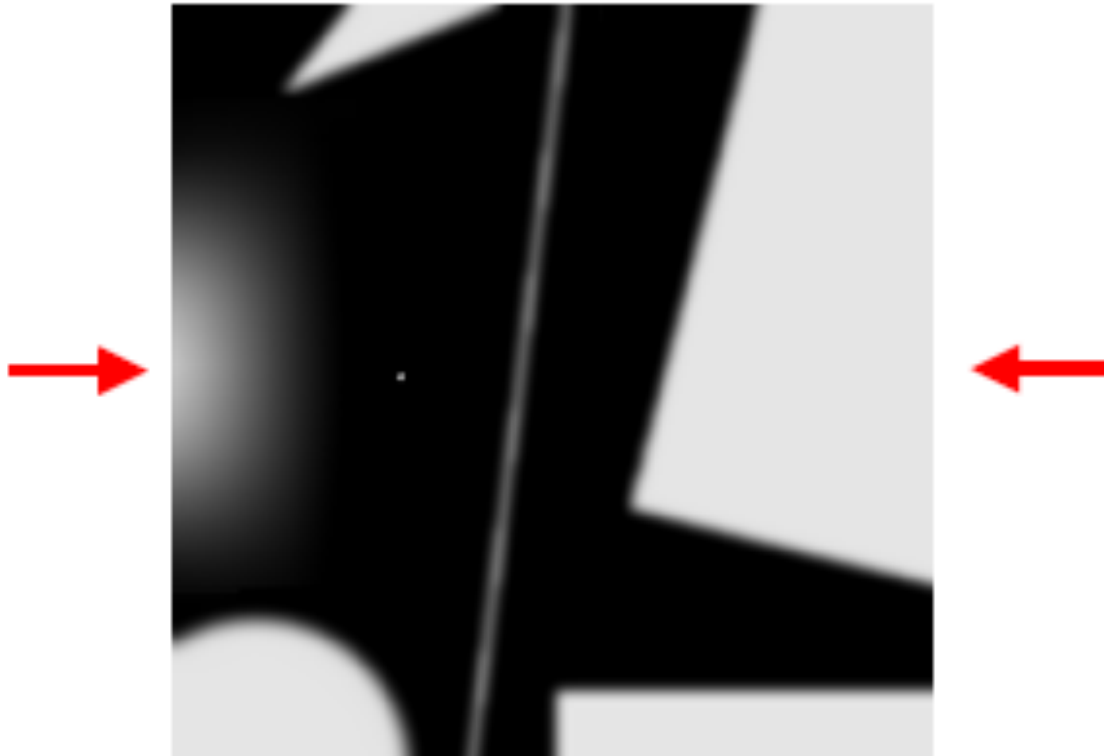
$$f'(x) = f(x+1) - f(x)$$

$$f''(x) = \dots$$

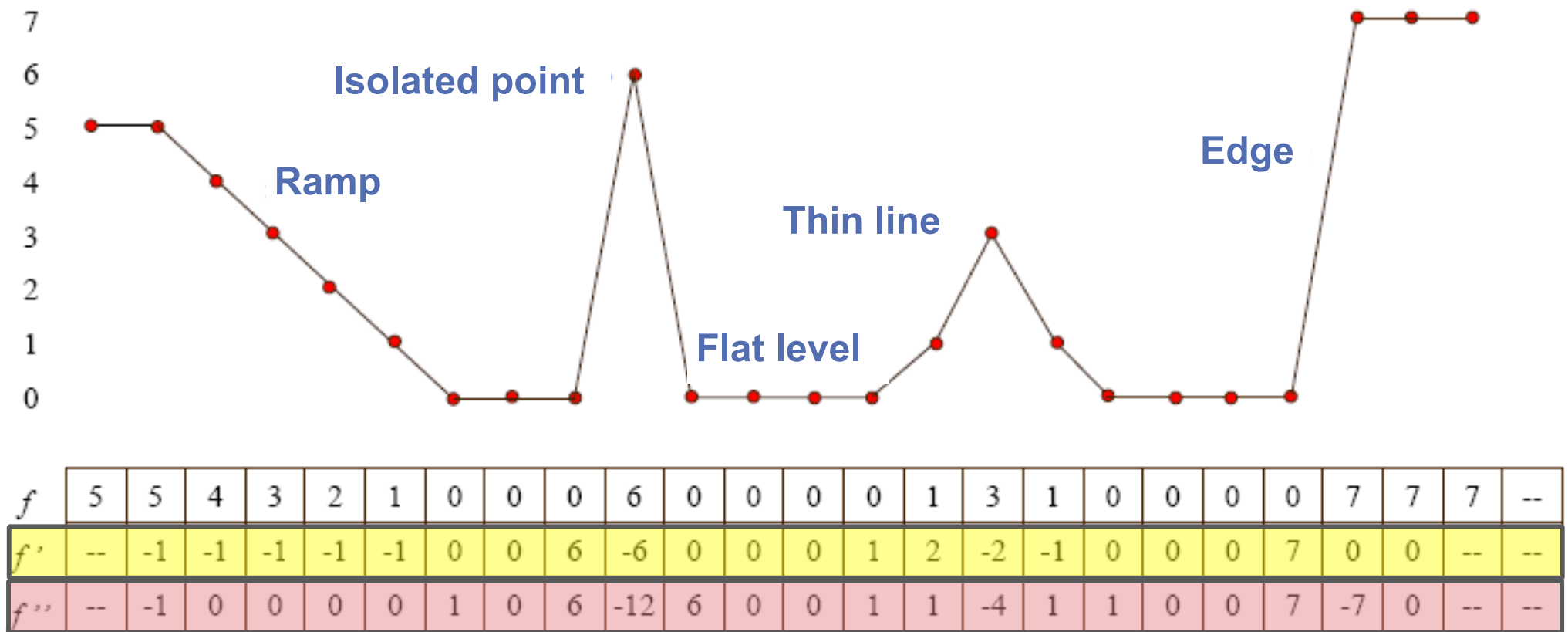
$$= f(x+1) + f(x-1) - 2f(x)$$

Example

- Let apply the derivative operators to the 1D line indicated by the arrows



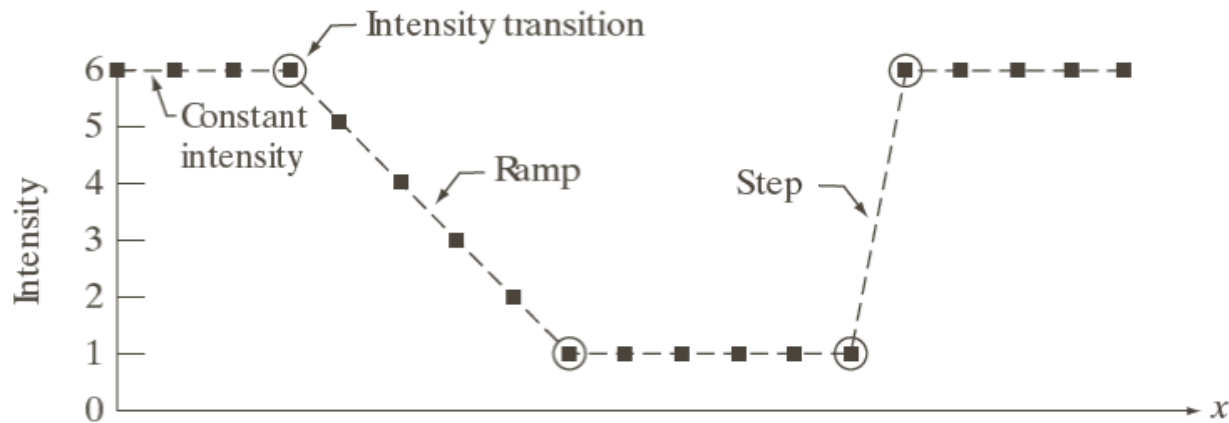
Example (cont.)



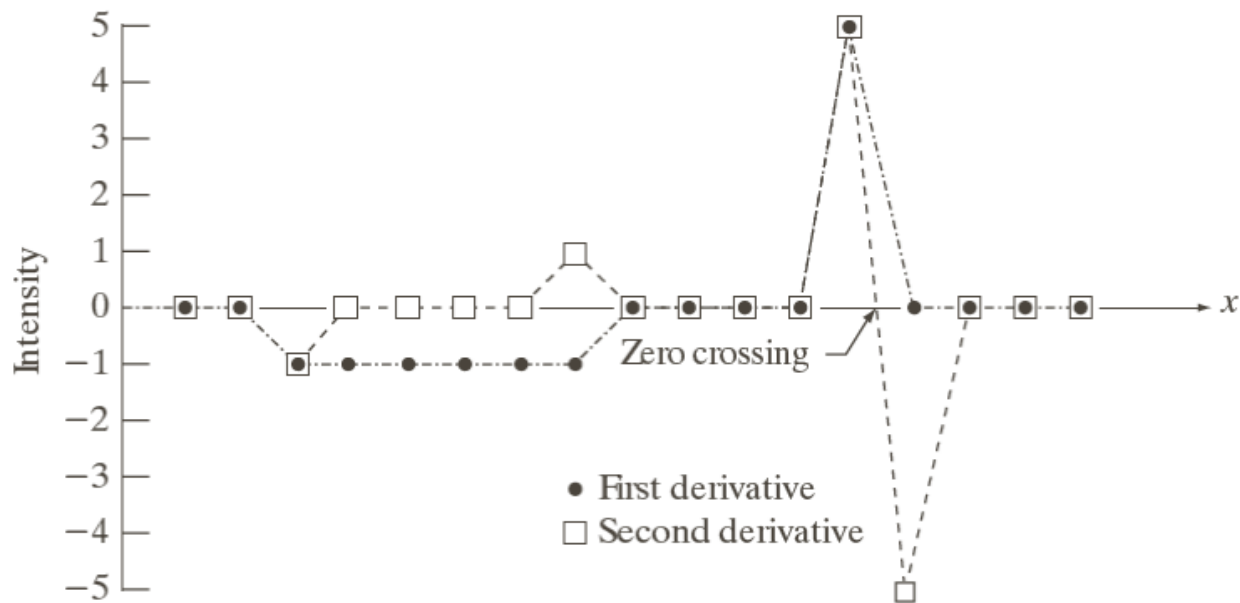
$$f'(x) = f(x+1) - f(x)$$

$$f''(x) = f(x+1) + f(x-1) - 2f(x)$$

Another example



Scan line	6	6	6	6	5	4	3	2	1	1	1	1	1	1	6	6	6	6	6	x
1st derivative	0	0	0	-1	-1	-1	-1	-1	0	0	0	0	0	0	5	0	0	0	0	
2nd derivative	0	0	-1	0	0	0	0	0	1	0	0	0	0	0	5	-5	0	0	0	



Considerations

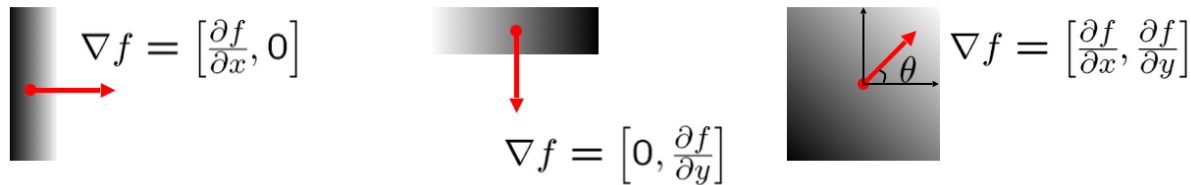
- Properties verified!
- Moreover:
 - f' :
 - Ramp \rightarrow Thick contours
 - Step \rightarrow Strong response in correspondence to steep edges
 - f'' :
 - Point \rightarrow Stronger response to thin details
 - Edges \rightarrow Double response to edges with the zero-crossing
- Conclusion:
 - f'' ideal for sharpening
 - $f' \text{ e } f''$ ideal for edge extraction

Gradient

- The image gradient is defined as:

$$\Delta f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right]$$

- The gradient is a vector oriented toward the direction of maximum intensity variation



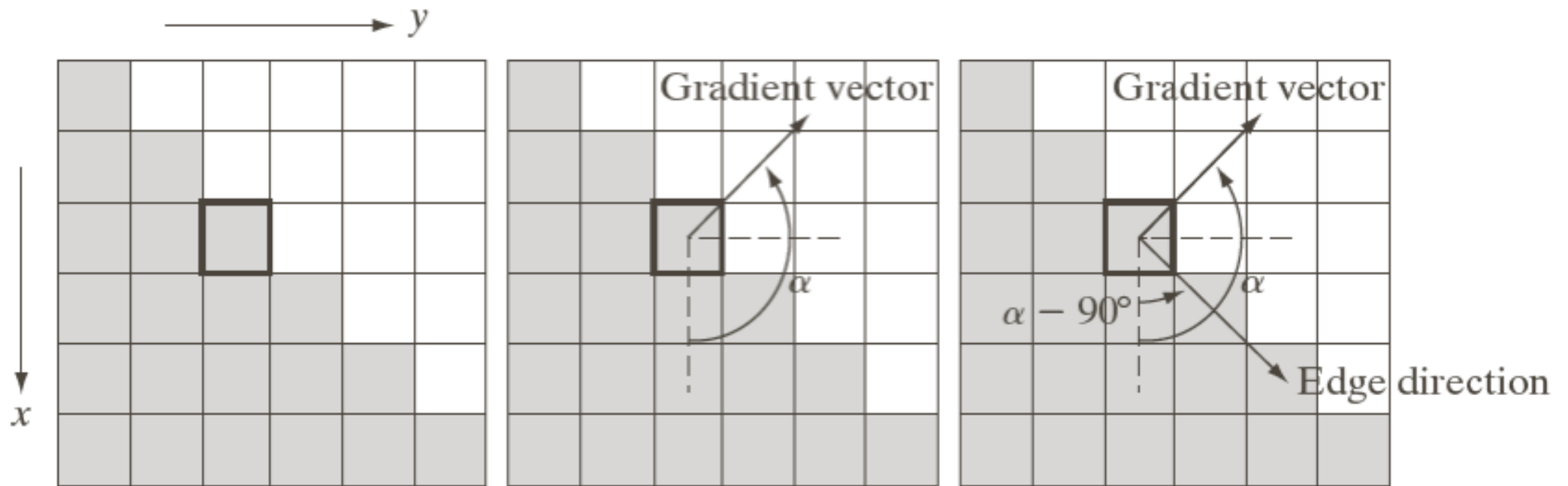
- The direction of the gradient is given by:

$$\Theta = \tan^{-1} \left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x} \right)$$

- What can we conclude about the edge direction?
- The edge intensity is given by the gradient magnitude

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

Gradient



Gradient approximation

Roberts

1	0
0	-1

0	1
-1	0

Prewitt

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

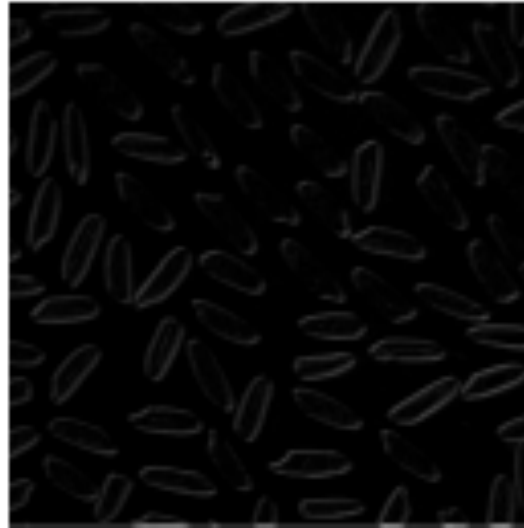
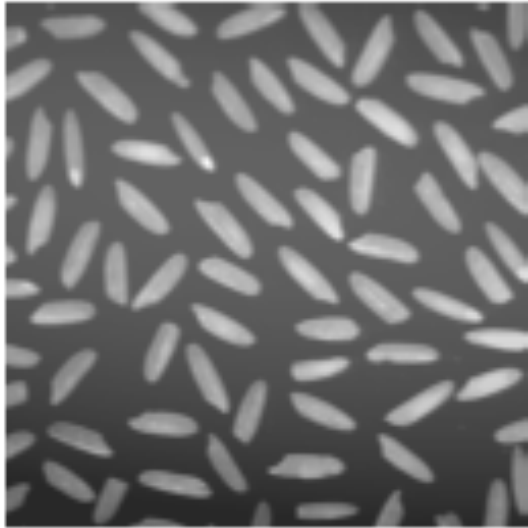
-1	0	1
-1	0	1
-1	0	1

Sobel

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

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

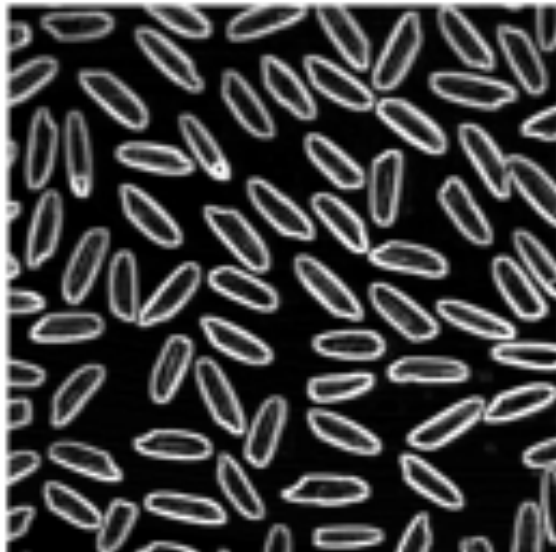
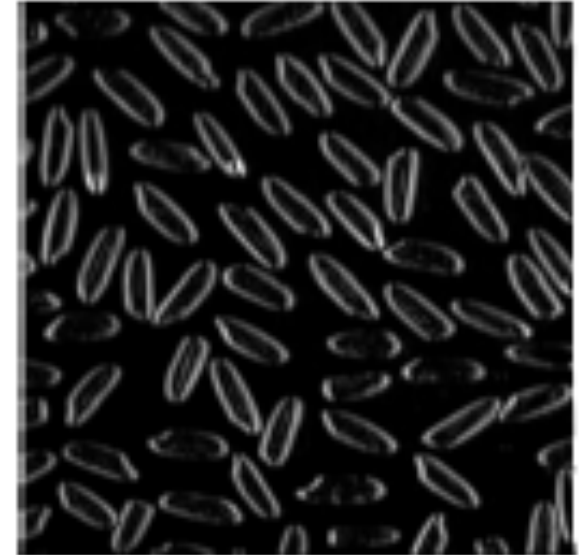
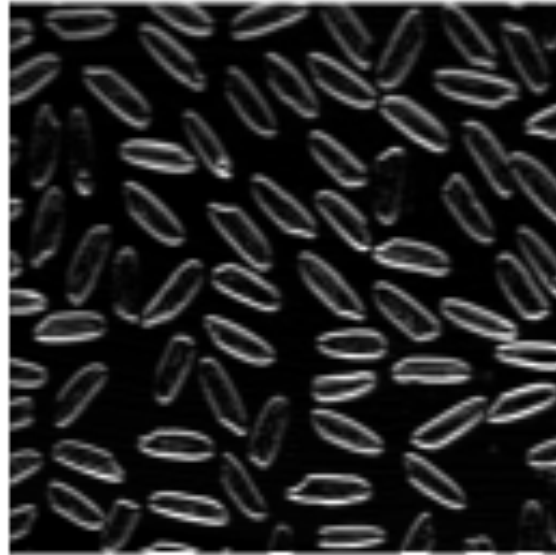
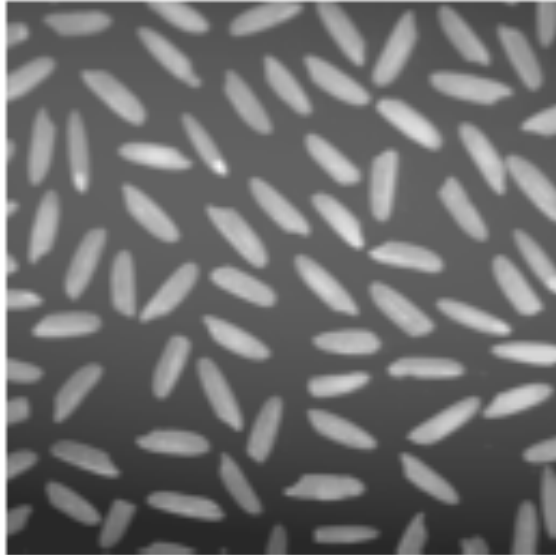
Roberts operator



1	0
0	-1

0	1
-1	0

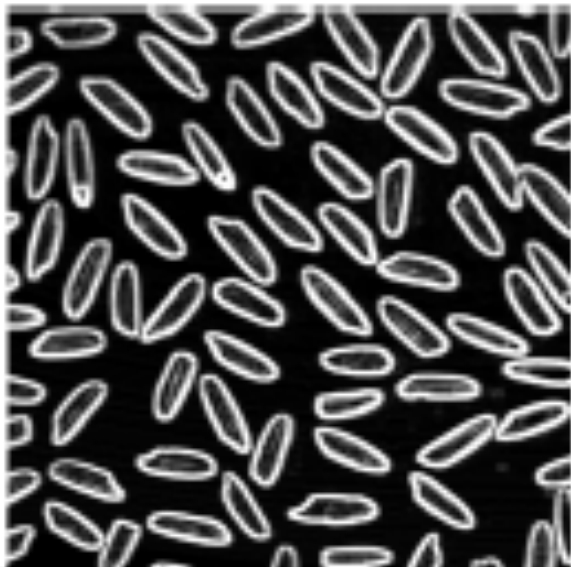
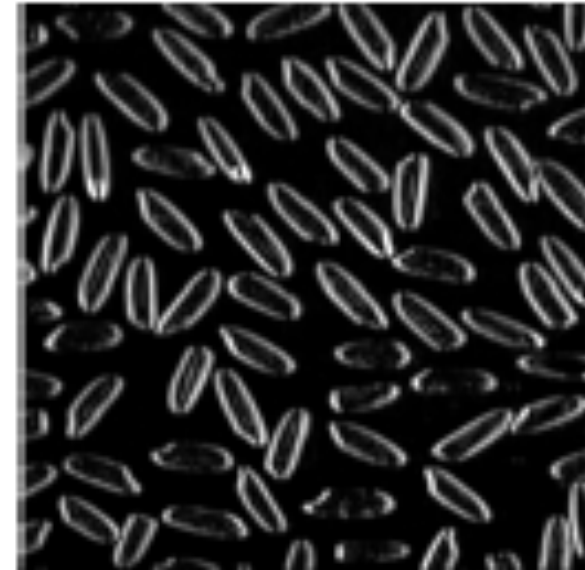
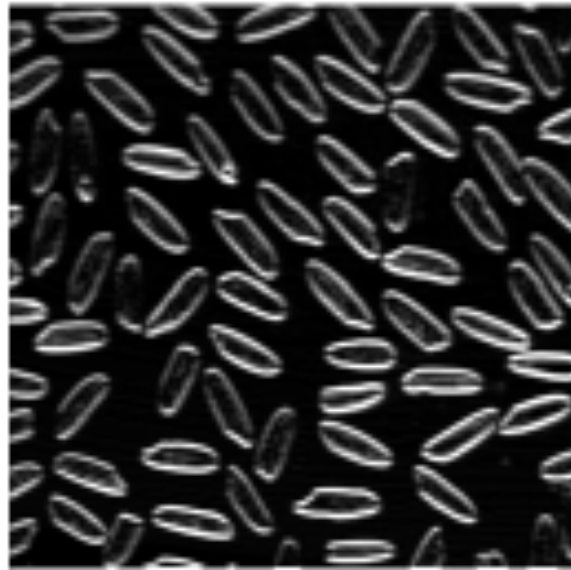
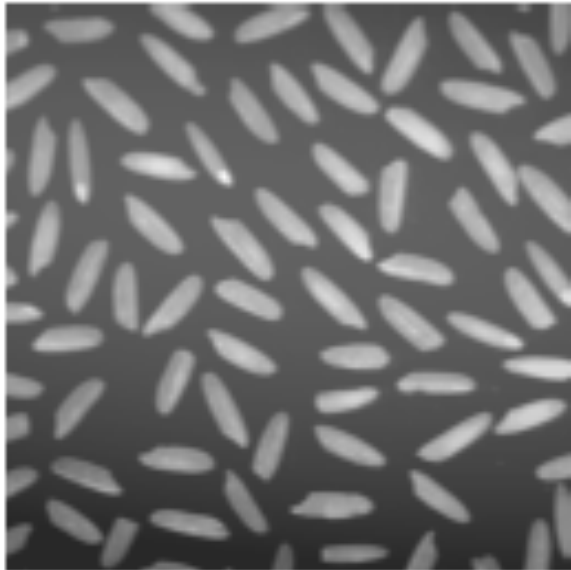
Prewitt operator



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

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

Sobel operator

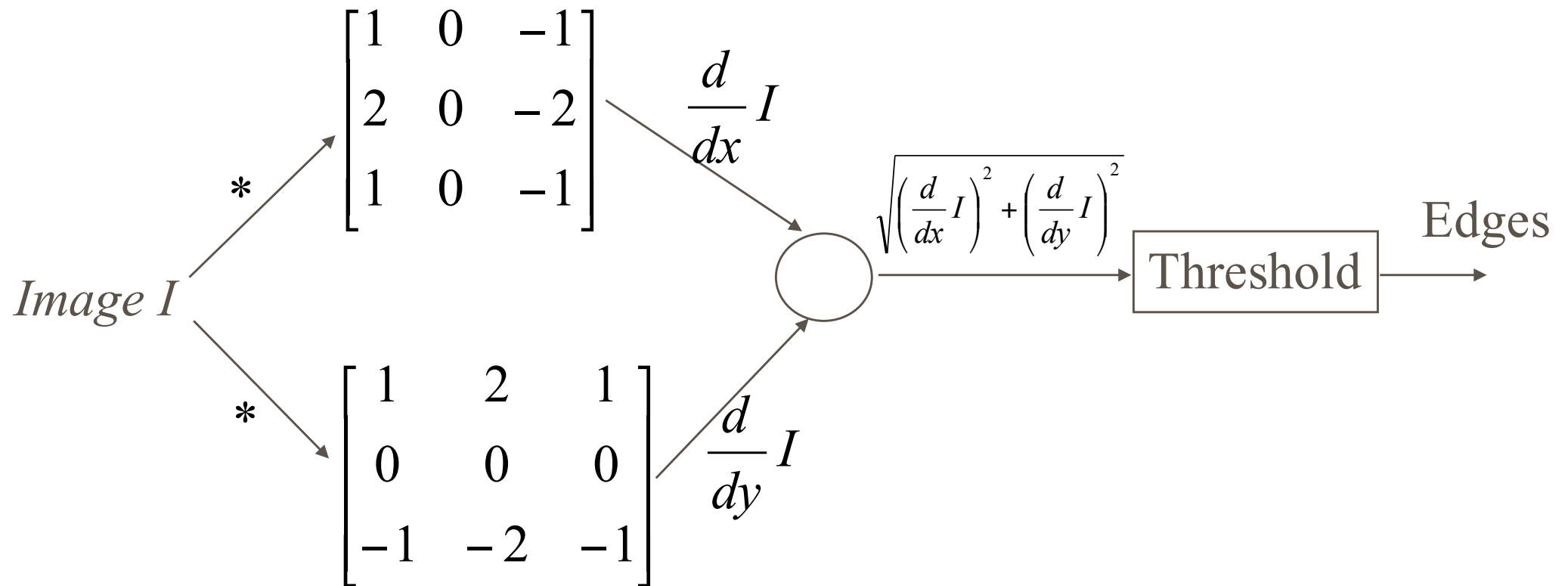


-1	-2	-1
0	0	0
1	2	1

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

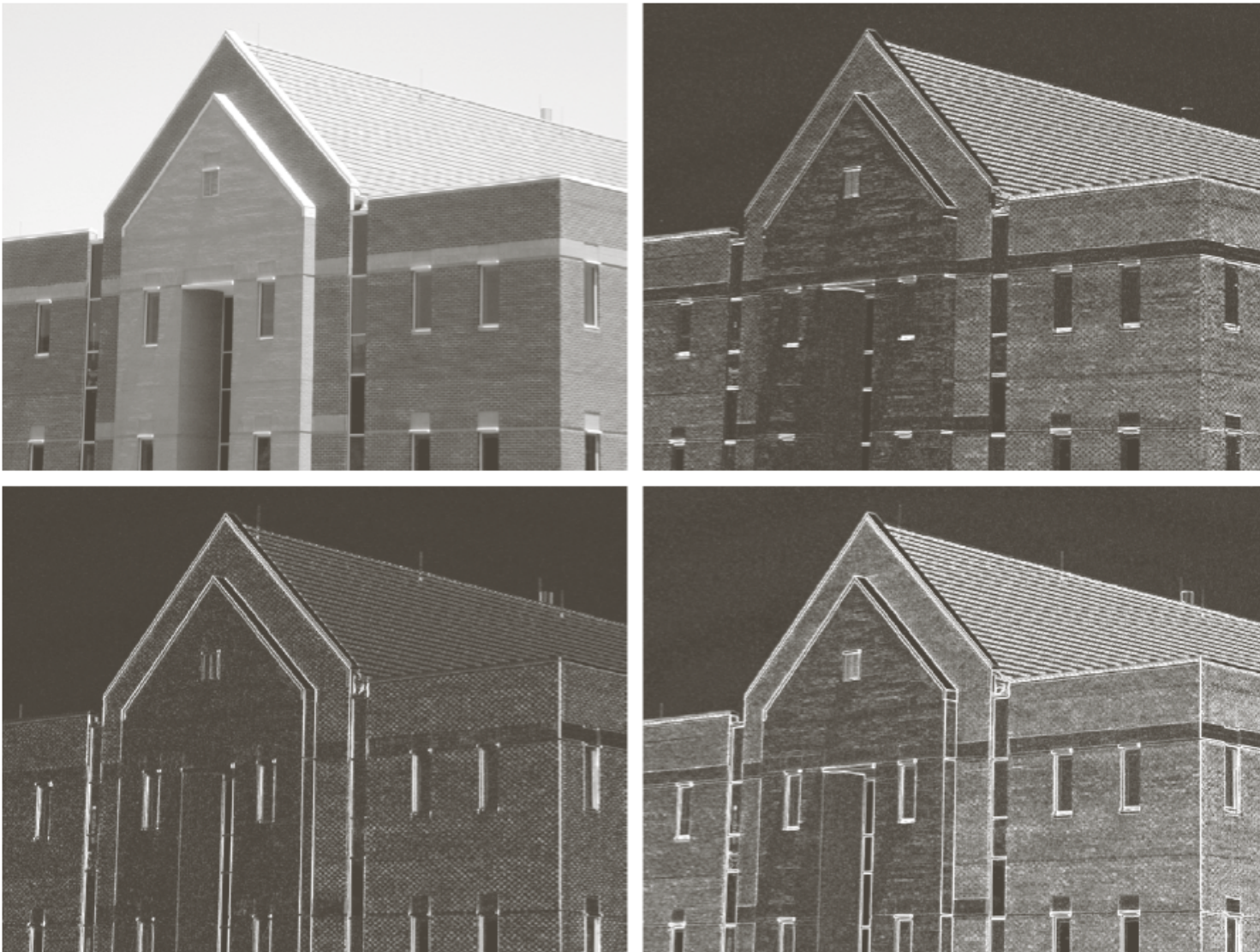
Sobel Edge detector

■ Sobel Edge Detector



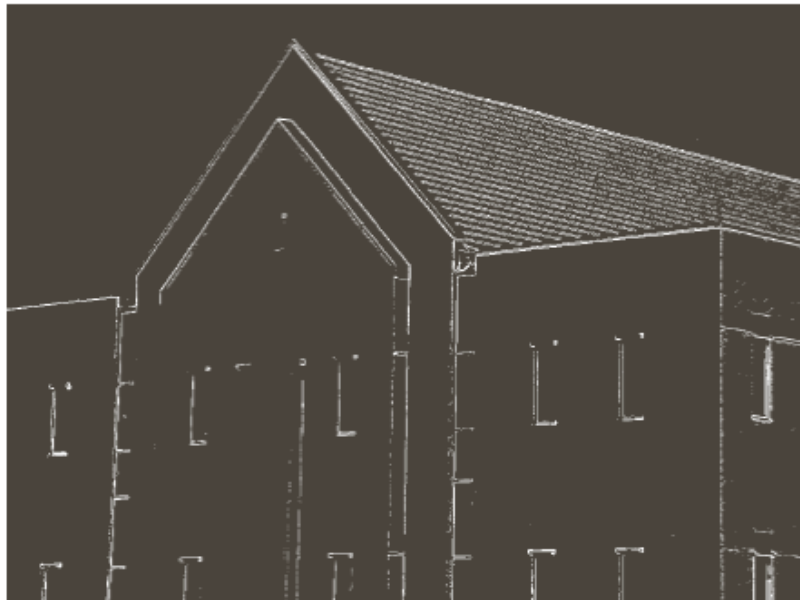
Sobel application

Original image, partial derivatives, and magnitude

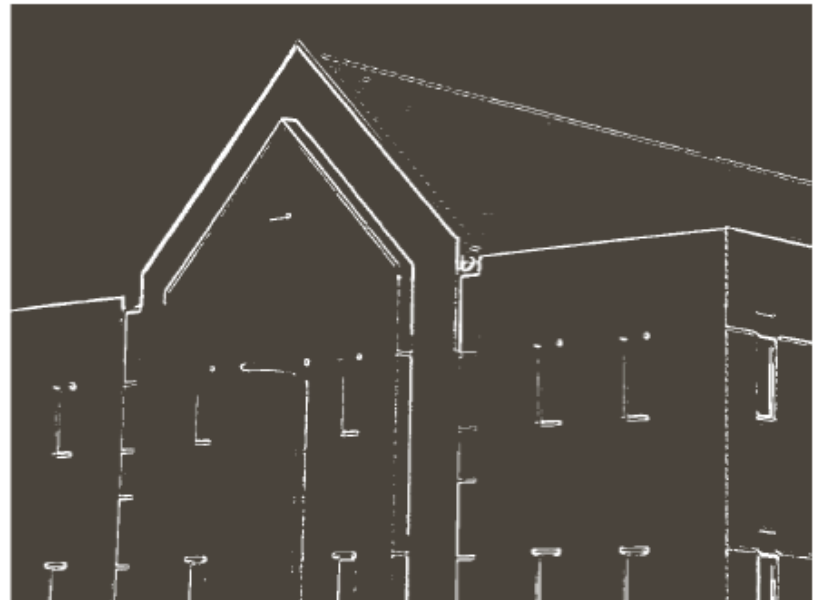


Alternative: Gradient magnitude Thresholding

Let maintain the 33% of the edges with the highest magnitude



Starting from the original
image (NOT BLURRED)



Starting from a BLURRED
version of the original image

Laplacian

- *def*: $L(x, y) = \frac{d^2 f}{dx^2} + \frac{d^2 f}{dy^2}$

We have already derived:

$$\frac{d^2 f}{dx^2} = f(x + 1, y) - 2f(x, y) + f(x - 1, y)$$

Analogously we have:

$$\frac{d^2 f}{dy^2} = f(x, y + 1) - 2f(x, y) + f(x, y - 1)$$

Laplacian, cont.

$$\frac{d^2 f}{dx^2} = f(x+1, y) - 2f(x, y) + f(x-1, y)$$

$$\frac{d^2 f}{dy^2} = f(x, y+1) - 2f(x, y) + f(x, y-1)$$

Adding the two components we have:

$$\begin{aligned} L(x, y) &= \frac{d^2 f}{dx^2} + \frac{d^2 f}{dy^2} = \\ &= f(x+1, y) + f(x-1, y) + \\ &\quad + f(x, y+1) + f(x, y-1) - 4f(x, y) \end{aligned}$$

Masks:

0	1	0
1	-4	1
0	1	0

Isotropic to 90° rotations

1	1	1
1	-8	1
1	1	1

Isotropic to 45° rotations

Masks, cont.:

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

Sign changes

-1	-1	-1
-1	8	-1
-1	-1	-1

Observation

- Coefficient sum = 0 \Rightarrow constant areas = 0
- To maintain the image information:

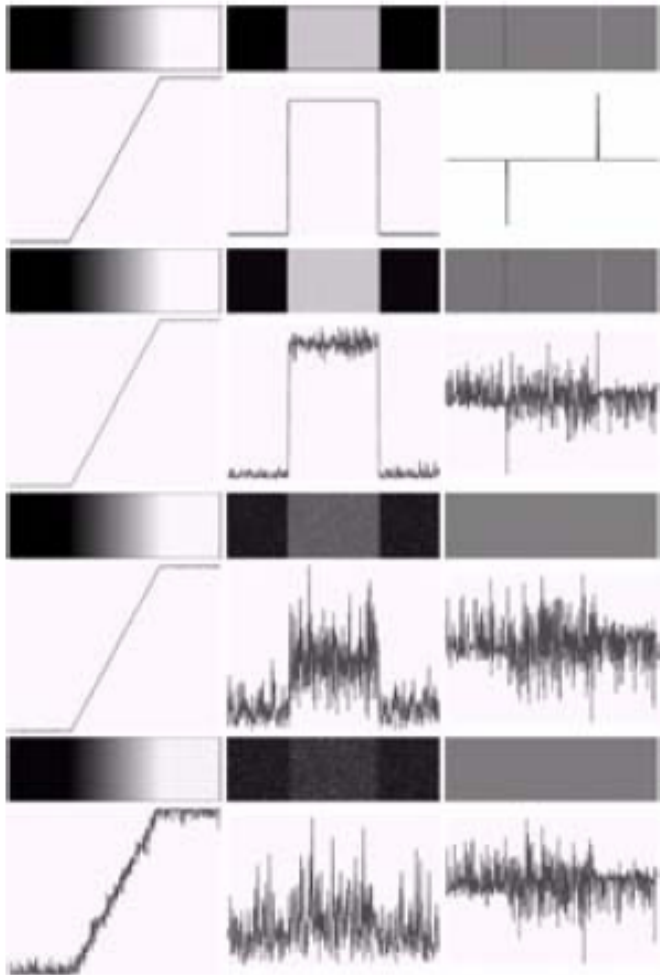
$$g(x, y) = \begin{cases} f(x, y) - L(x, y) & \text{se coeff centrale} < 0 \\ f(x, y) + L(x, y) & \text{se coeff centrale} > 0 \end{cases}$$

0	-1	0
-1	5	-1
0	-1	0

-1	-1	-1
-1	9	-1
-1	-1	-1

\rightarrow Sharpening!

Noise effect



OBS:

Noise obstruct the correct behavior of the derivative filters

→ Remove noise BEFORE applying the derivative filters

Marr model

- **Marr approach:**
Studied the vision mechanisms to reproduce them into the computational systems
 - ***Primal Sketch:*** scene *lowest level* description given by the vision system
 - **Obs:** the *edges* are a component of the primal sketch

Marr model

- **Marr conclusions**
 1. **Characteristics at different details levels**
→ operators at different scales
 2. Smoothing to remove non interesting details
→ Gaussian filter optimal for smoothing
 3. Edge = zero-crossing of the second derivative
 4. Laplacian optimal to this end (isotropic)

Marr-Hildreth Algorithm (1980)

- Image smoothing by means of a Gaussian filter
- Edge extraction by means of the Laplacian filter
- Localization of the zero-crossing points

Marr-Hildreth Algorithm

- Let call I the input image and $G(x,y)$ the bidimensional Gaussian filter
- Following the steps, we should proceed as:

$$\nabla^2(I * G(x, y))$$

- where $\nabla^2 = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}$ is the Laplacian,
- and $I * G(x, y)$ applies the Gaussian filtering

Marr-Hildreth Algorithm

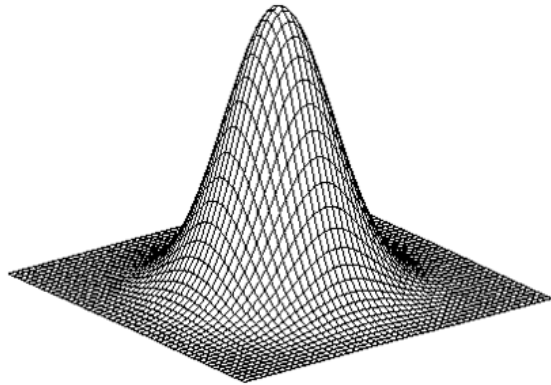
- Given the linearity, we can invert the operators order:

$$\nabla^2(I * G(x, y)) = I * (\nabla^2 G(x, y))$$

- That is, we construct the *Laplacian of the Gaussian* (**LoG**) and apply it only once to the image.
- LoG:

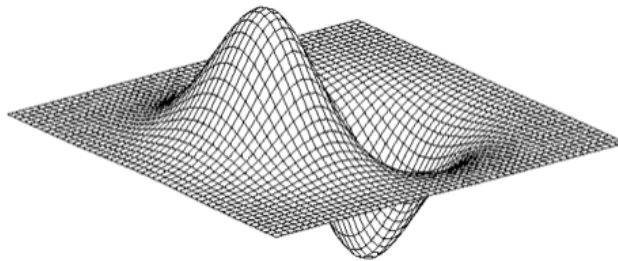
$$\nabla^2 G(x, y) = \frac{x^2 + y^2 - 2\sigma^2}{2\pi\sigma^6} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

LoG filter



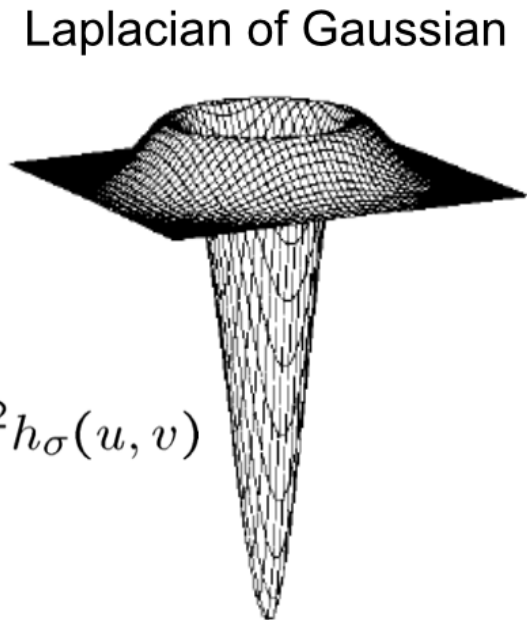
Gaussian

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



derivative of Gaussian

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



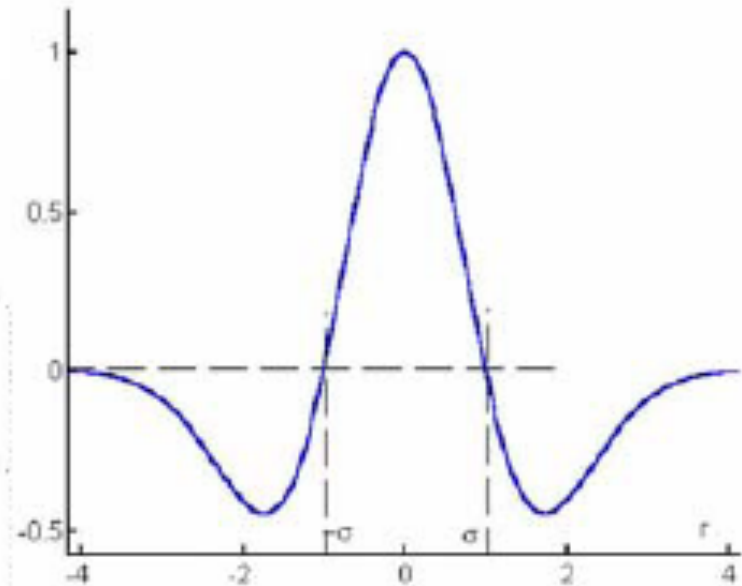
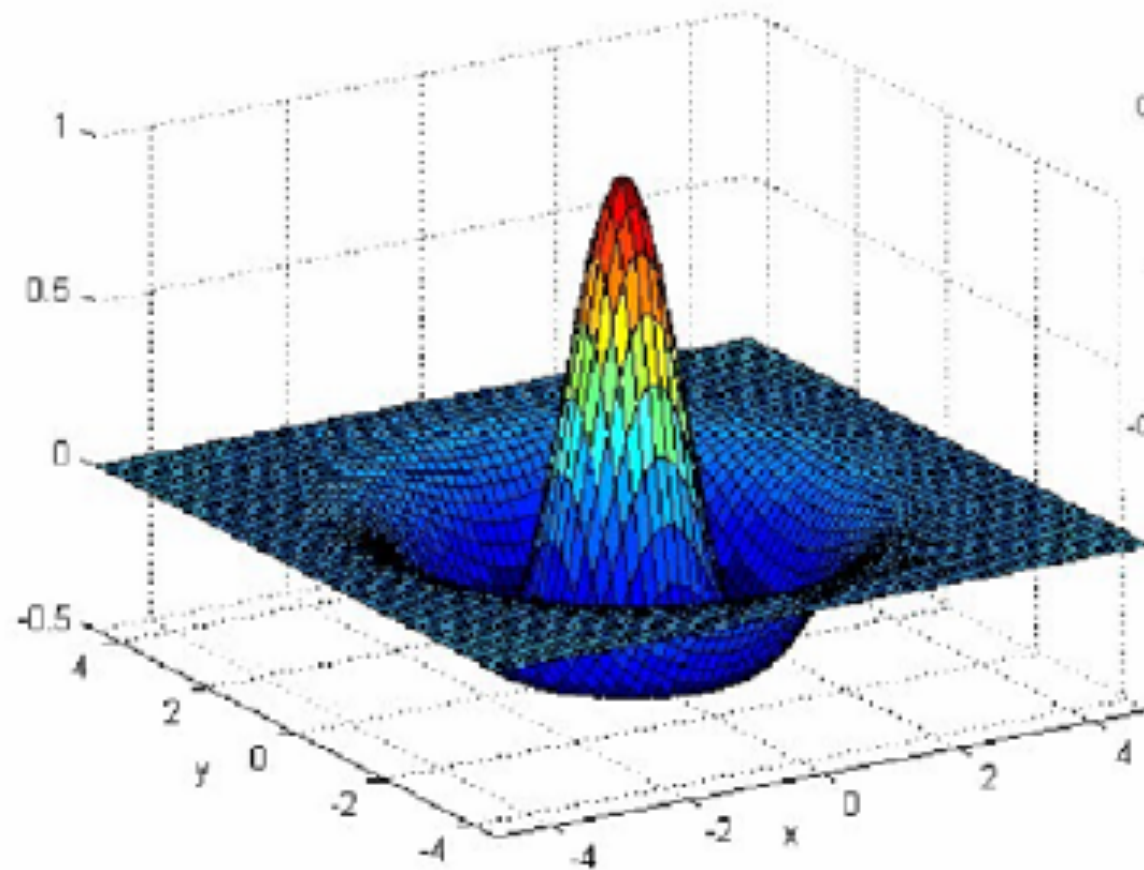
Laplacian of Gaussian

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

∇^2 is the **Laplacian** operator:

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

LoG filter



LoG filter is also called *Mexican Hat* for its shape

Mask example

Example of a 5x5 mask approximating the LoG function shape: central positive value, surrounded by negative values augmenting going far away from the center till becoming 0

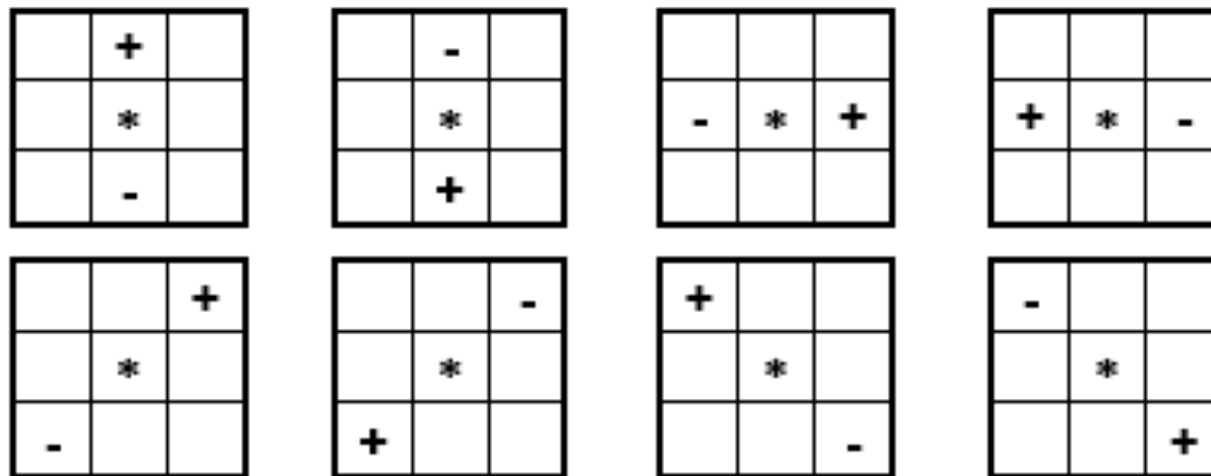
0	0	-1	0	0
0	-1	-2	-1	0
-1	-2	16	-2	-1
0	-1	-2	-1	0
0	0	-1	0	0

Obs: to produce masks of arbitrary dimensions:

- sample the Log eq.
- Or sample the $G(x,y)$ and then apply the Laplacian

Zero crossing

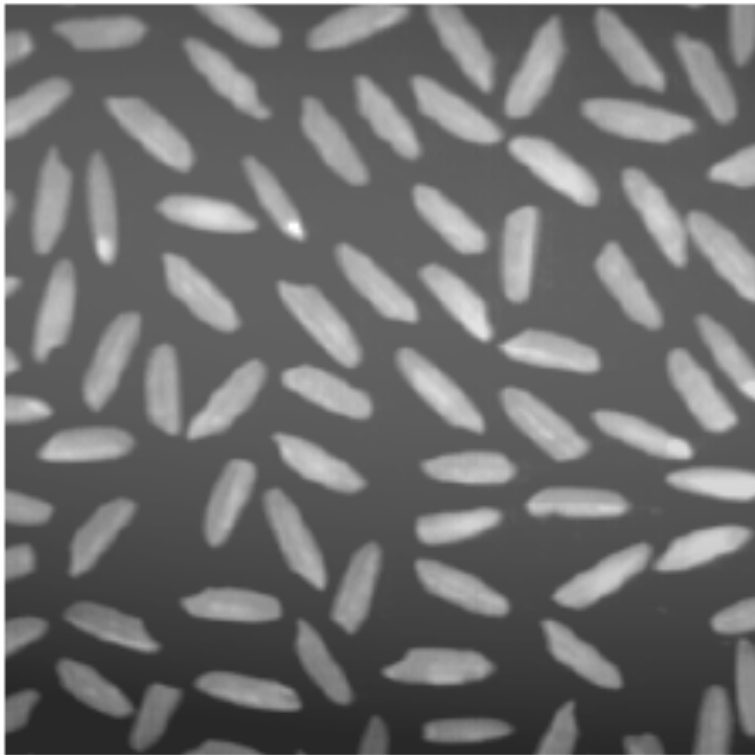
- **Zero crossing search:** we have to take into account the fact that the edge could be in any of the 8 possible directions in the digital plane
- This corresponds to one of these **configurations**:



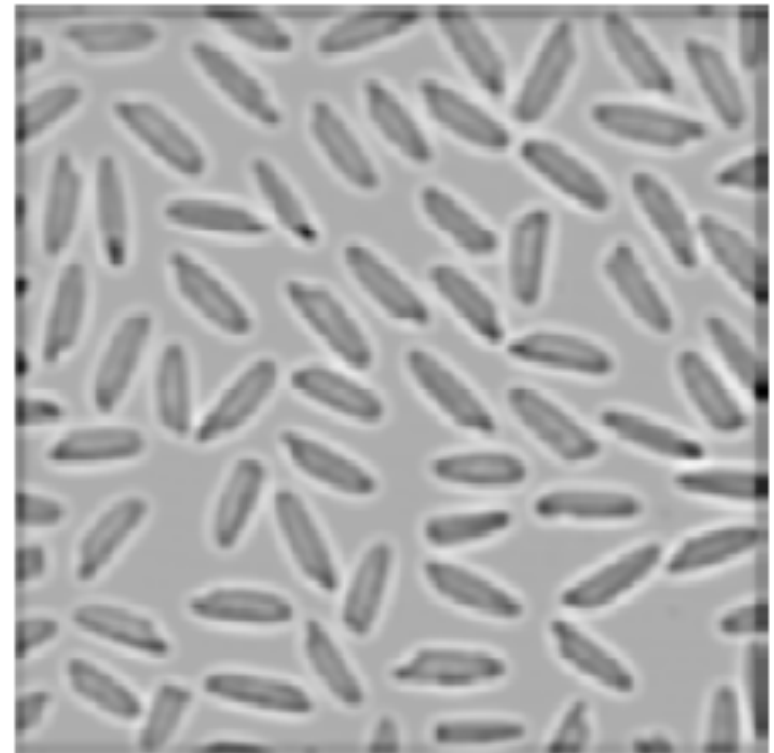
Further considerations

- The value of σ determines the highlighted level of detail
- To have more robust results, we could evaluate the LoG filter at different scales (different σ), finding the different zero crossing, and combining the results
- To describe the whole LoG shape, the mask should have dimensions $W \times W$, with $W > 3c$, where $c = 2\sqrt{2}\sigma$ is the centrale lobe amplitude. Alternatively, we could adopt
$$W = \lceil 3\sigma \rceil * 2 + 1$$

Marr-Hildreth Algorithm Examples

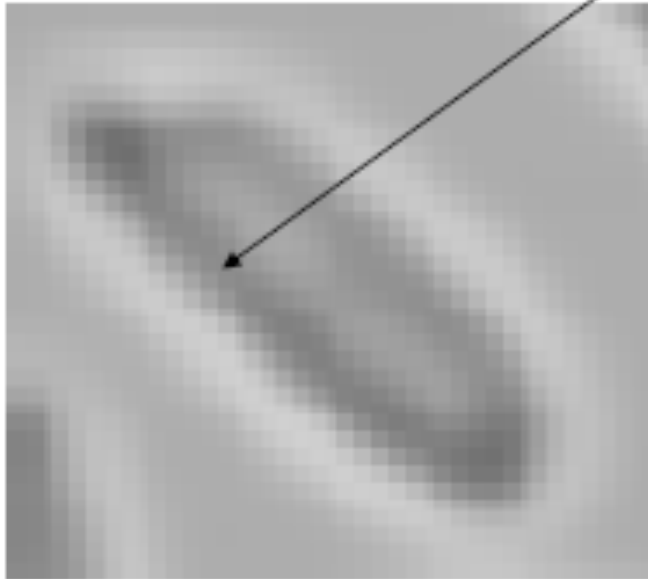


- Image filtered setting:
 $\sigma = 2, \quad W = 13$
- Gray scales rescaled

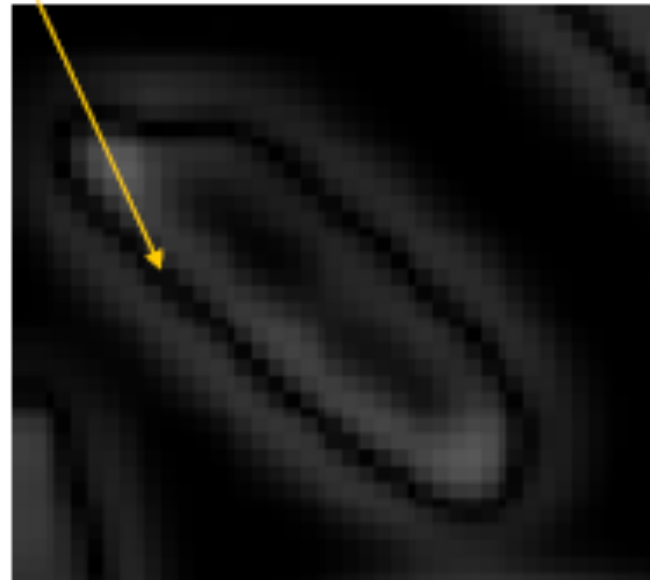


Marr-Hildreth Algorithm Examples

zero crossing



LoG

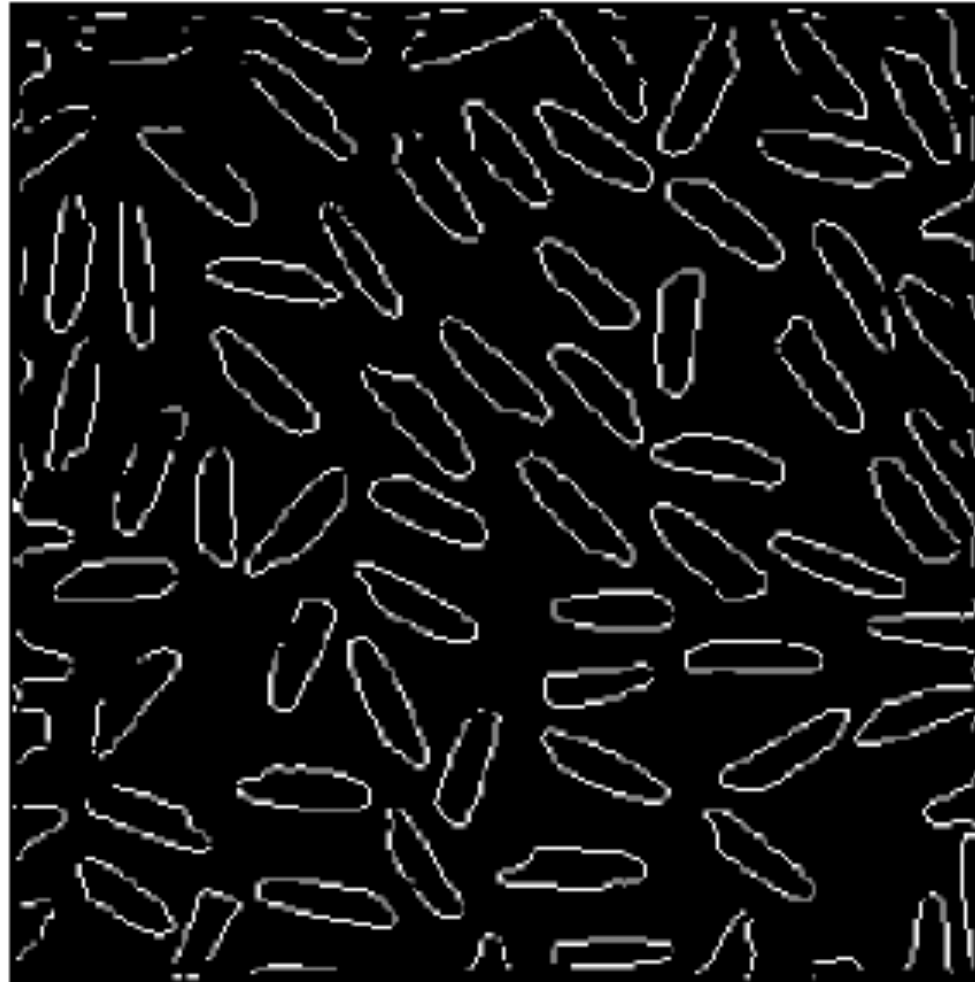


abs(LoG)

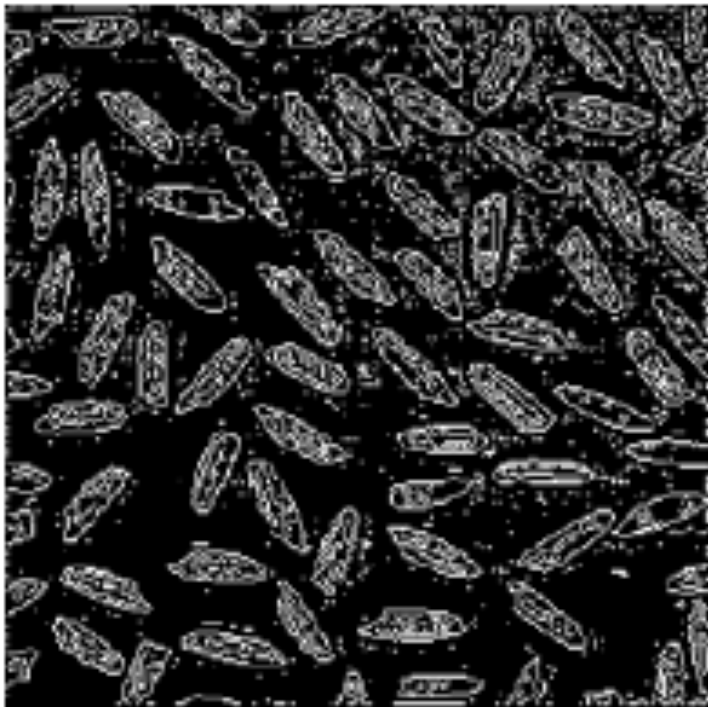
Marr-Hildreth Algorithm Examples

Edge image

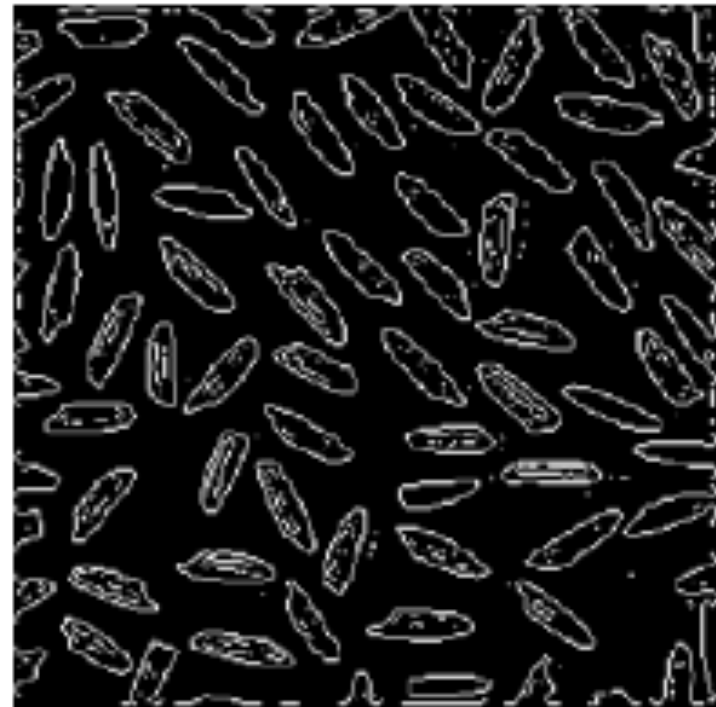
$\sigma=2$



Marr-Hildreth Algorithm, sigma dependency

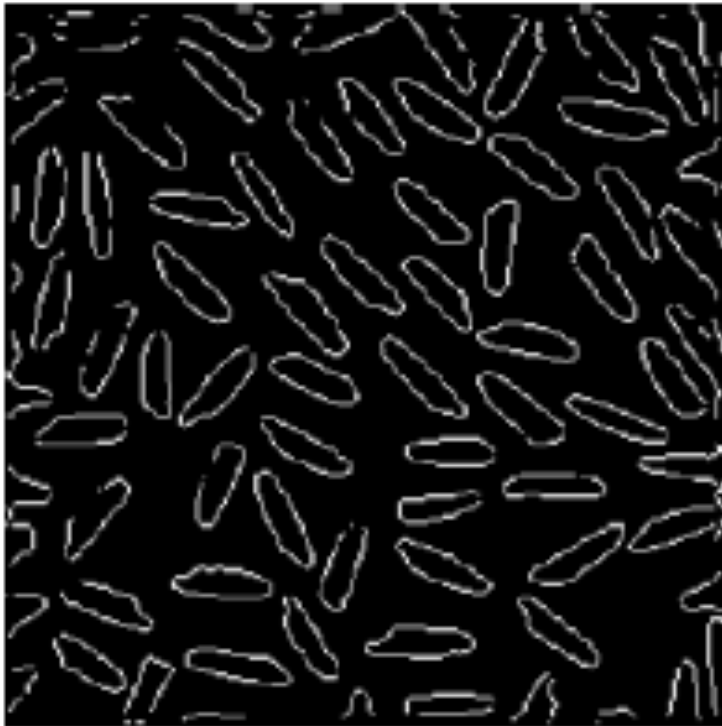


$\sigma=0.5$



$\sigma=1$

Marr-Hildreth Algorithm, sigma dependency



$\sigma=2$



$\sigma=4$