DTU

Perception for Autonomous Systems 31392:

Edge Detection

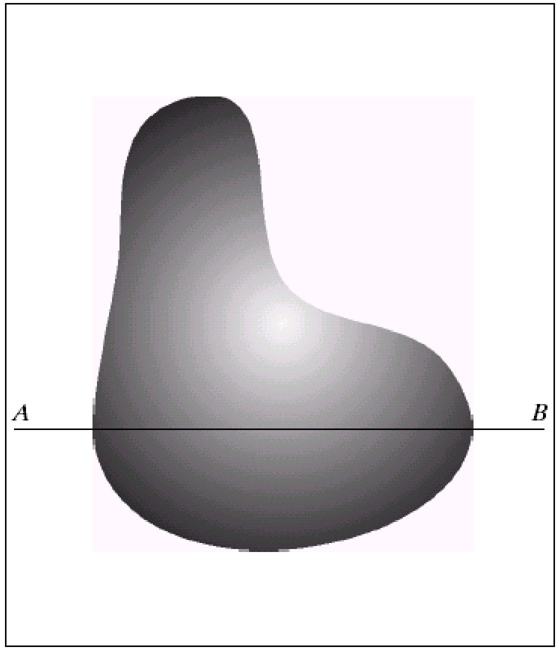
Lecturer: Evangelos Boukas—PhD

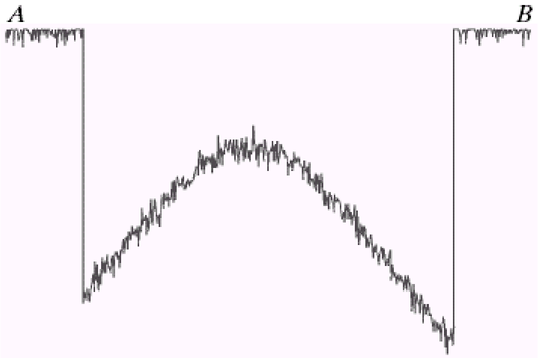
Edge Detection

- What is an Edge?
- Image Derivative
- Gradient
- Sobel
- Laplacian
- Canny

Edge Detection

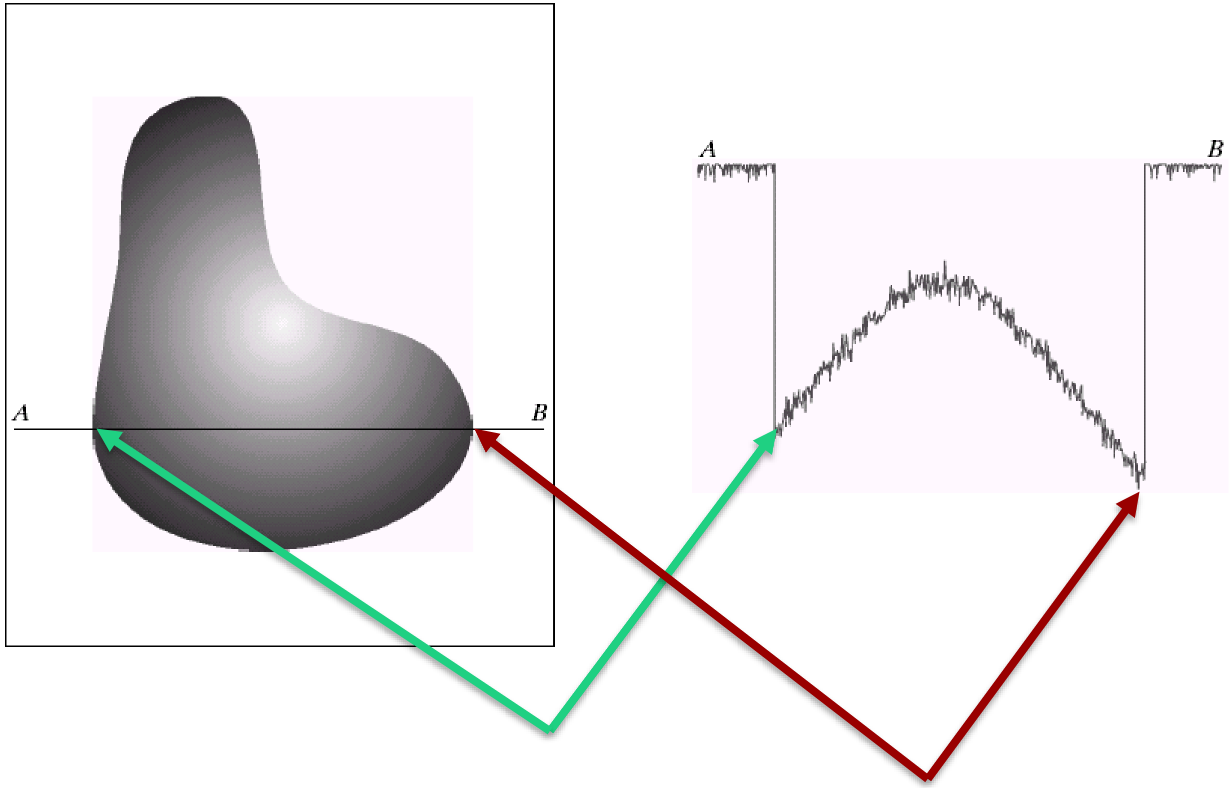
- What is and edge?





Edge Detection

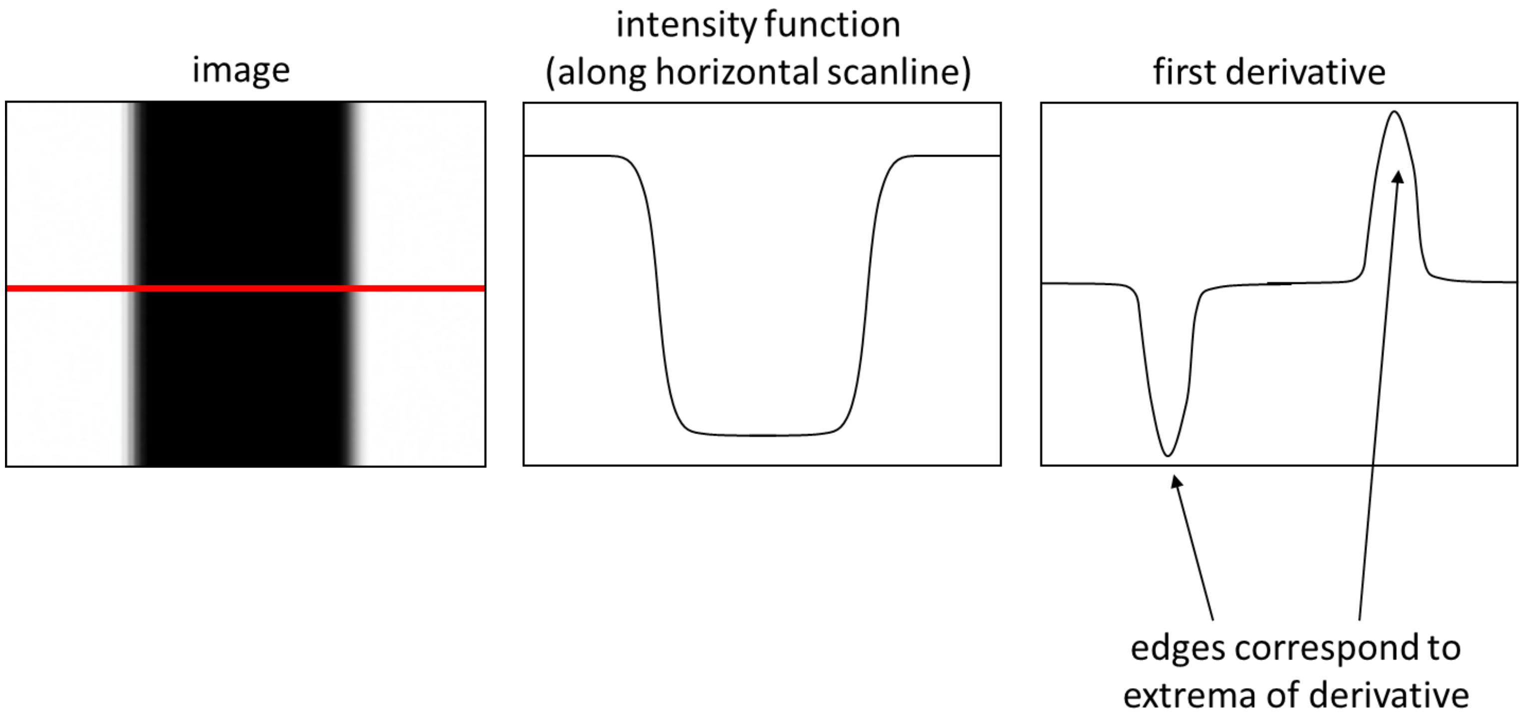
- What is and edge?



Edge Detection

- What is and edge?
- Derivative of an Image:

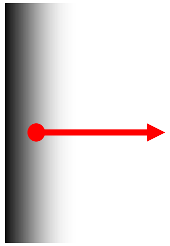
$$f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$



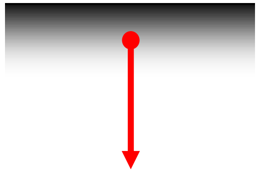
Gradient

- The gradient is a vector which points in the direction of most rapid change in intensity:

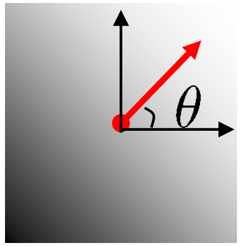
$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$



$$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$$

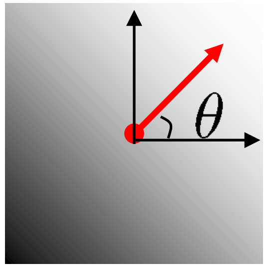


$$\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$$



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

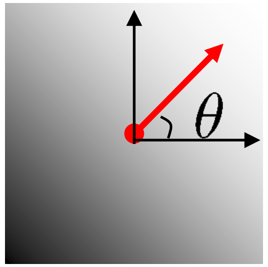
Gradient Simplified



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

$$f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h} \longrightarrow \frac{\partial f}{\partial x} = f(x+1, y) - f(x, y)$$

Gradient Simplified



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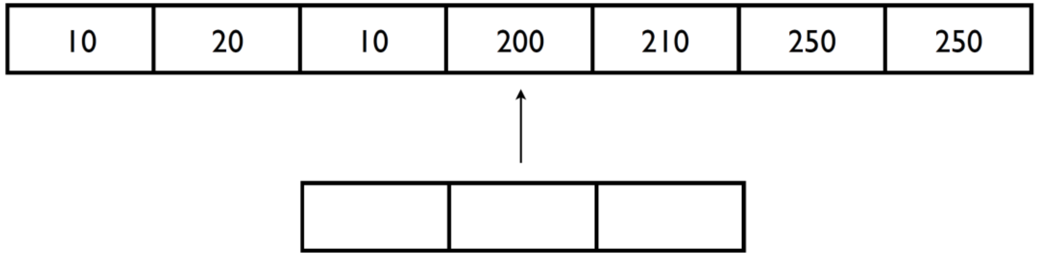
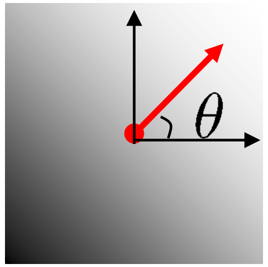
$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

- How would you define the 1D filter of the gradient:



Gradient Simplified



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- How would you define the 1D filter of the gradient:

10	20	10	200	210	250	250

0	-1	1

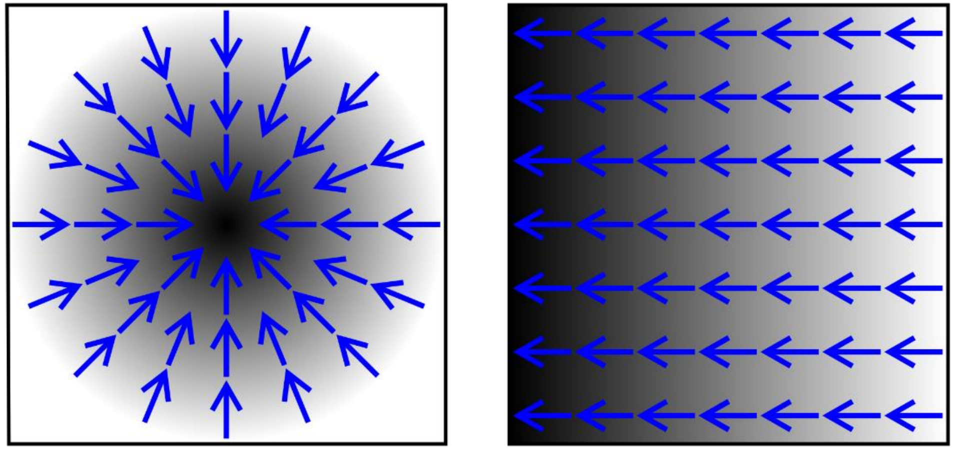
Gradient Simplified

- The gradient is defined by its orientation:

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

- and magnitude:

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



Sobel

- Practically:

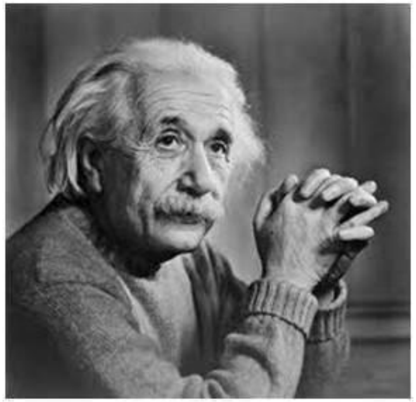
$$g_x = \begin{array}{|c|c|c|} \hline -1 & 0 & 1 \\ \hline -2 & 0 & 2 \\ \hline -1 & 0 & 1 \\ \hline \end{array} \qquad g_y = \begin{array}{|c|c|c|} \hline -1 & -2 & -1 \\ \hline 0 & 0 & 0 \\ \hline 1 & 2 & 1 \\ \hline \end{array}$$

- Magnitude:

$$g = \sqrt{g_x^2 + g_y^2}$$

- Orientation:

$$\Theta = \tan^{-1}\left(\frac{g_y}{g_x}\right)$$



Derivative Filters

Sobel

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

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

Scharr

3	0	-3
10	0	-10
3	0	-3

3	10	3
0	0	0
-3	-10	-3

Prewitt

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

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

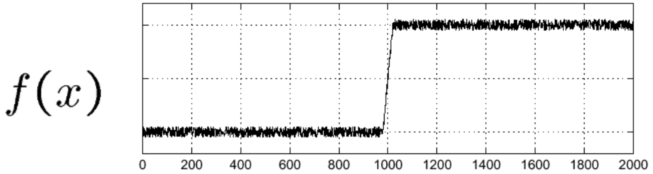
Roberts

0	1
-1	0

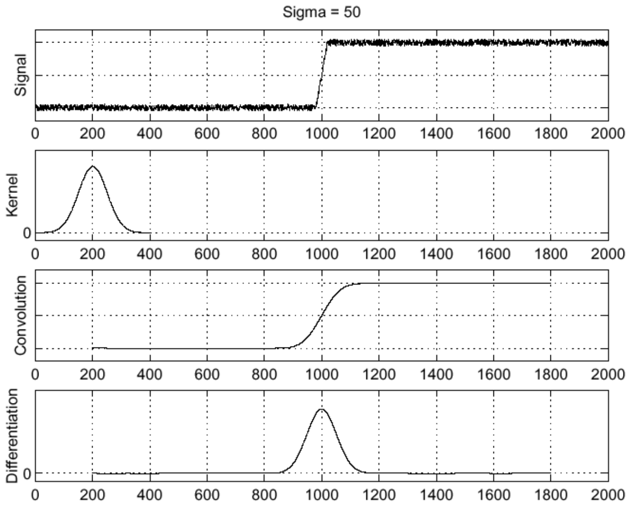
1	0
0	-1

Preprocessing to Edge Detection

- In reality derivatives are very prone to noise
  Consider the following example:



- To overcome this issue we can smooth the signal beforehand



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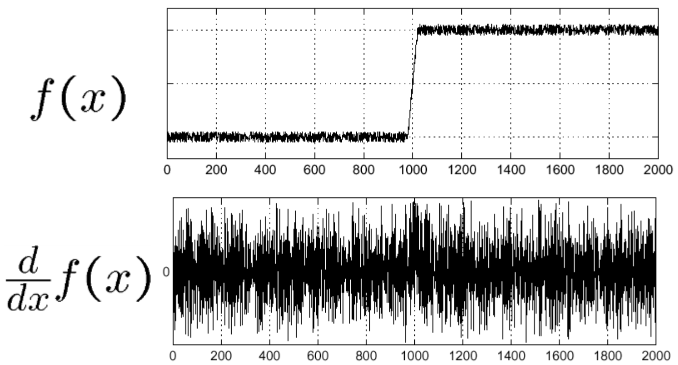

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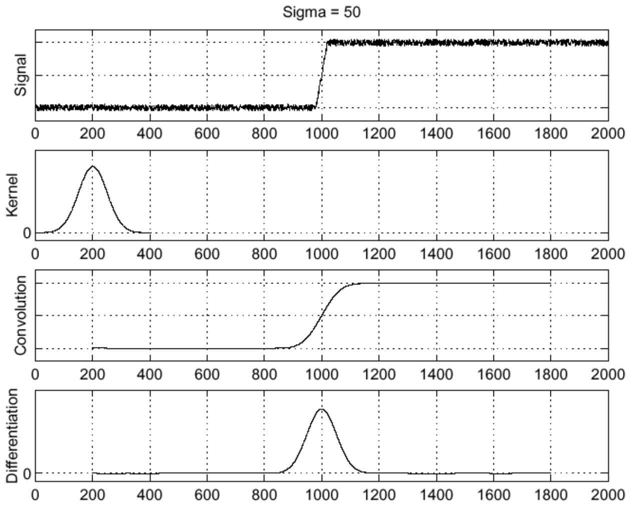
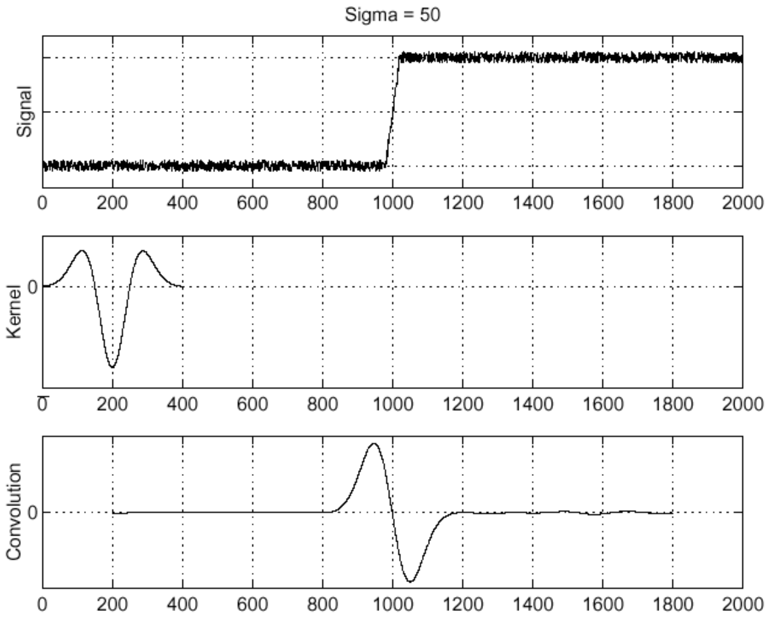


Laplacian of Gaussian

- $\frac{\partial^2}{\partial x^2}(h \star f)$



Canny Edge Detection

Example of a Complex system:

- Noise reduction
- Gradient calculation
- Non-maximum suppression
- Double threshold
- Edge Tracking by Hysteresis.

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