

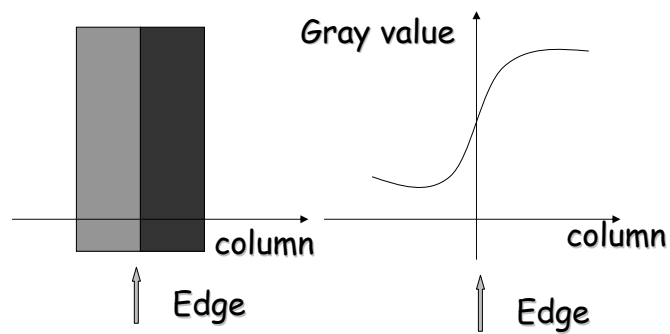
Image Features

Local, meaningful, detectable parts of the image.
We will look at edges and corners

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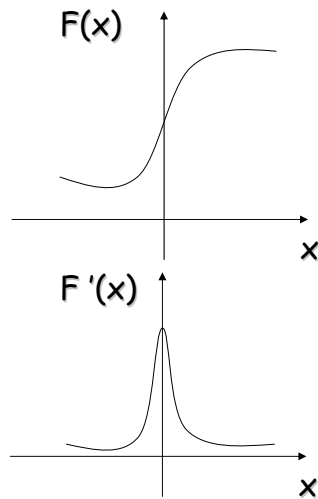
Edges

- They happen at places where the image values exhibit sharp variation



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Edge detection (1D)



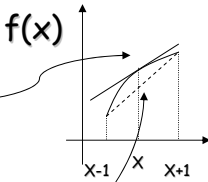
Edge= sharp variation



Large first derivative

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Digital Approximation of 1st derivatives

$$\frac{df(x)}{dx} = \lim_{\Delta x \rightarrow 0} \frac{f(x + \Delta x) - f(x)}{\Delta x}$$

$$\frac{df(x)}{dx} \cong \frac{f(x+1) - f(x-1)}{2}$$



Convolve with:

-1	0	1
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Edge Detection (2D)

Vertical Edges:

Convolve with:

-1	0	1
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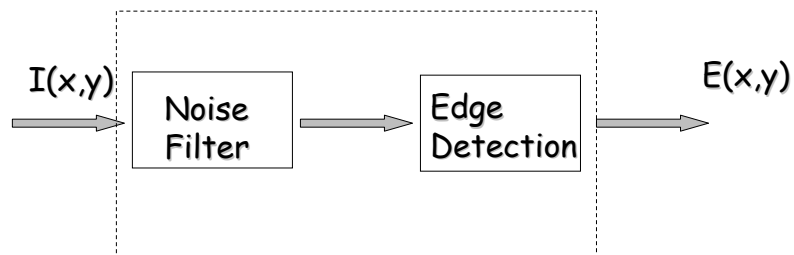
Horizontal Edges:

Convolve with:

-1
0
1

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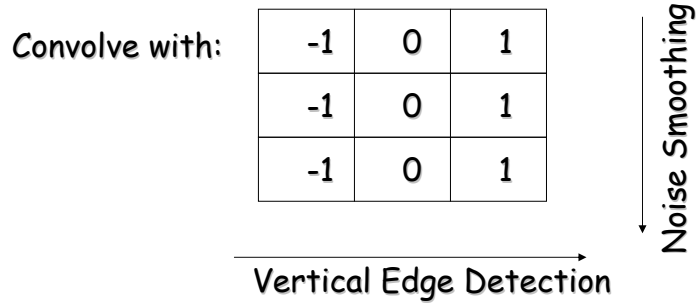
Noise cleaning and Edge Detection



We need to also deal with noise
Combine Linear Filters

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Noise Smoothing & Edge Detection

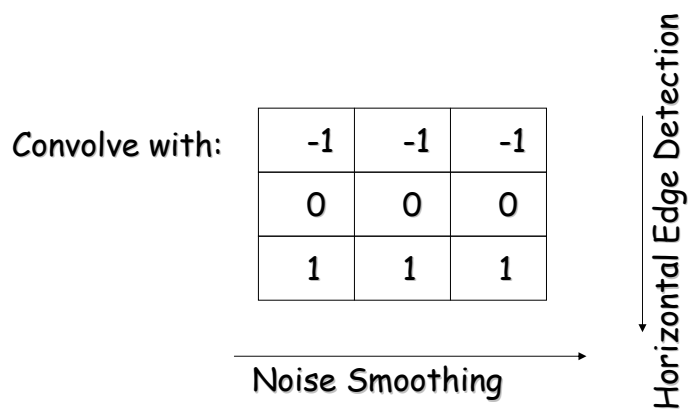


This mask is called the (vertical) Prewitt Edge Detector

Outer product of box filter $[1\ 1\ 1]^T$ and $[-1\ 0\ 1]$

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Noise Smoothing & Edge Detection



This mask is called the (horizontal) Prewitt Edge Detector

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Sobel Edge Detector

Convolve with:

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

and

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

Gives more weight to the 4-neighbors

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Example

0	0	0	0	0
0	0	0	0	0
0	0	50	50	50
0	0	50	50	50
0	0	50	50	50

$I_x =$

0	0	0	0	0
0	50	100	150	150
0	50	100	150	150
0	0	0	0	0
0	0	0	0	0

$I_y =$

0	0	0	0	0
0	50	50	0	0
0	100	100	0	0
0	150	150	0	0
0	150	150	0	0

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

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

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Image Derivatives

We know better alternative to smoothing

Smooth using Gaussian filter

$g(x)$ is a 1-D gaussian kernel, $g(x,y)$ - 2-D gaussian kernel

$$\tilde{I}[x, y] = I[x, y] * g[x, y] = \sum_{k=-\frac{w}{2}}^{\frac{w}{2}} \sum_{l=-\frac{w}{2}}^{\frac{w}{2}} I[k, l] g[x - k] g[y - l]$$

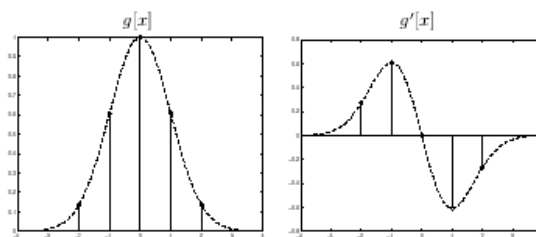
Taking a derivative - linear operation (take the derivative of the filter)

$$I_x[x, y] = I[x, y] * g'[x] * g[y] = \sum_{k=-\frac{w}{2}}^{\frac{w}{2}} \sum_{l=-\frac{w}{2}}^{\frac{w}{2}} I[k, l] g'[x - k] g[y - l],$$

$$I_y[x, y] = I[x, y] * g[x] * g'[y] = \sum_{k=-\frac{w}{2}}^{\frac{w}{2}} \sum_{l=-\frac{w}{2}}^{\frac{w}{2}} I[k, l] g[x - k] g'[y - l].$$

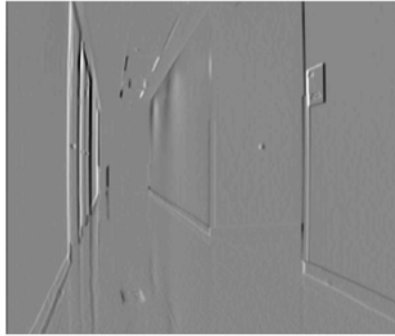
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Gaussian and its derivative

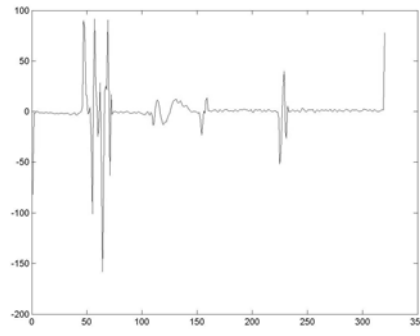


$$g(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}, \quad g'(x) = -\frac{x}{\sigma^2\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}.$$

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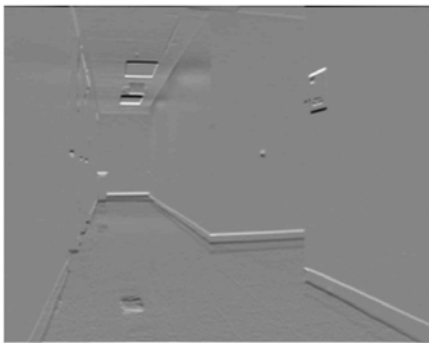
Vertical edges



First derivative

$$I_x(x, y) = \frac{\partial I}{\partial x}$$

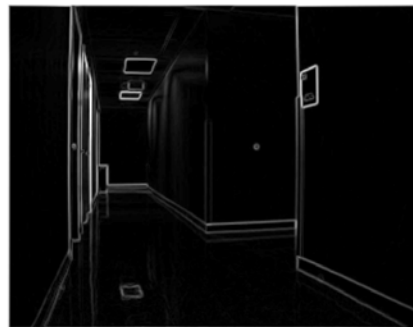
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Horizontal edges $I_y(x, y) = \frac{\partial I}{\partial y}$

• Convolution along columns

• Image Gradient $\nabla I = \left[\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y} \right]$

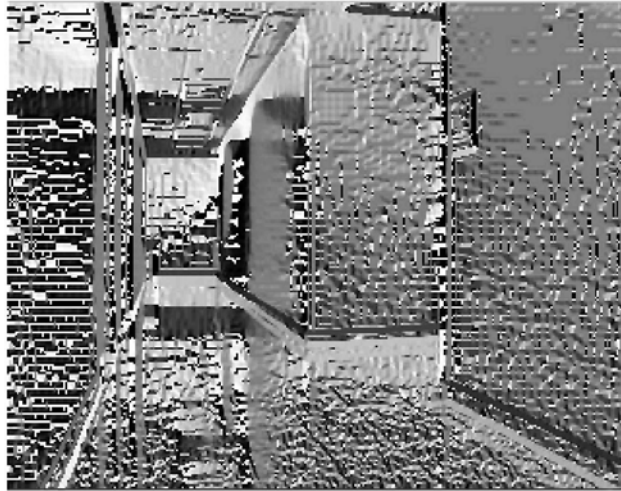


Gradient Magnitude

$$m = \sqrt{\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2}$$

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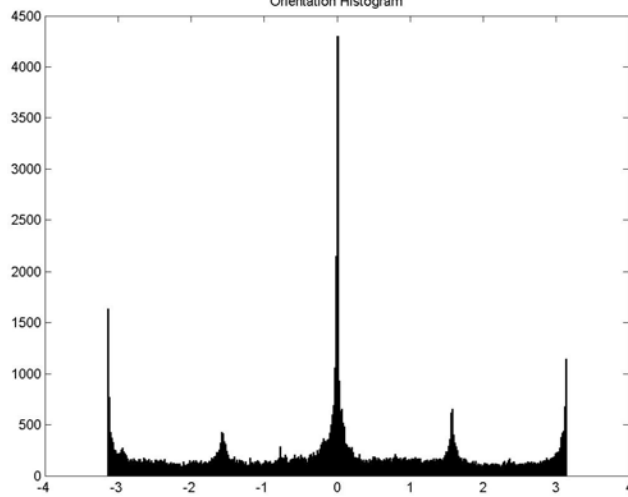
Gradient orientation



Gradient Orientation $\theta = \tan^{-1}\left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right)$

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Orientation Histogram



Orientation histogram

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