Computer Vision and Image Processing (CSEL-393)

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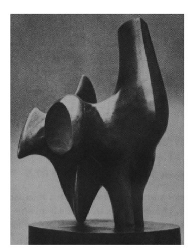
Edge detection

- Goal: Identify sudden changes (discontinuities) in an image
  - Intuitively, most semantic and shape information from the image can be encoded in the edges
  - More compact than pixels
- Ideal: artist's line drawing (but artist is also using object-level knowledge)

Edge Detection



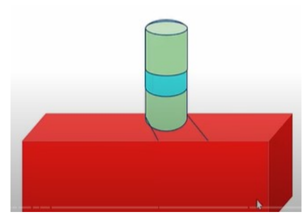
- Convert a 2D image into a set of curves
  - Extracts salient features of the scene
  - More compact than pixels

Application

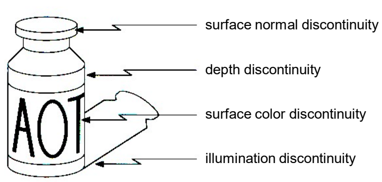
- What is an object
- How can we find it

Edge Detection in images

- At edges intensity or color changes

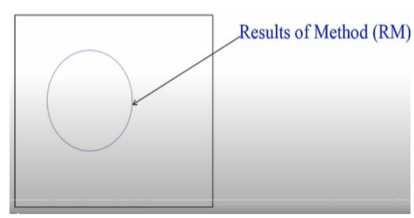


Origin of Edges

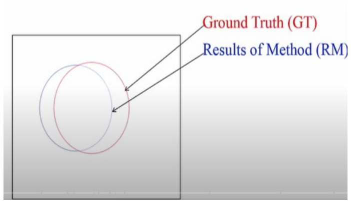


- Edges are caused by a variety of factors

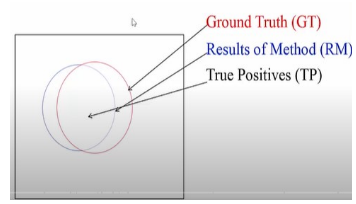
Evaluation Metrics



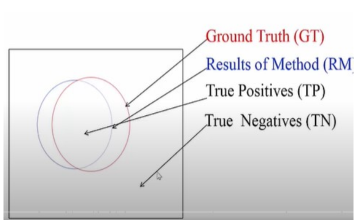
Evaluation Metrics



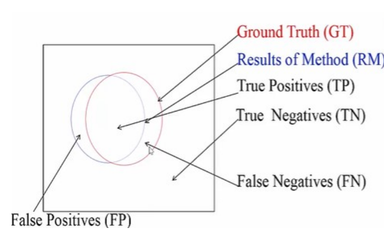
Evaluation Metrics



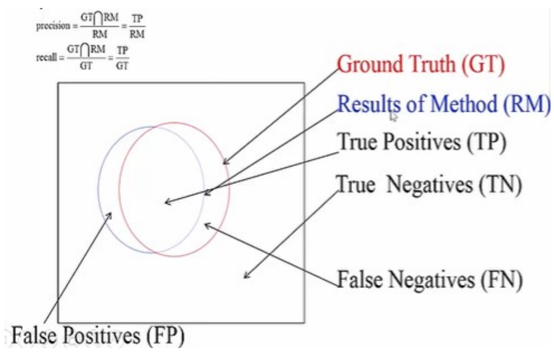
Evaluation Metrics



Evaluation Metrics



Evaluation Metrics

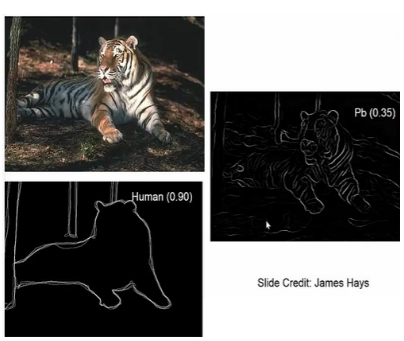


•Given following table, calculate precision and recall.

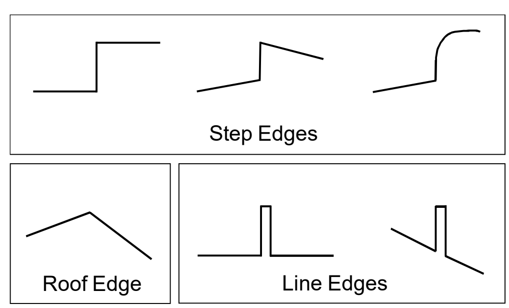
TP: 8	FP: 2
FN: 3	TN: 17

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{8}{8+2} = 0.8$$

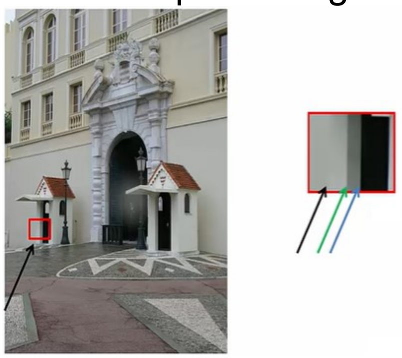
$$\text{Recall} = \frac{TP}{TP + FN} = \frac{8}{8+3} = 0.73$$



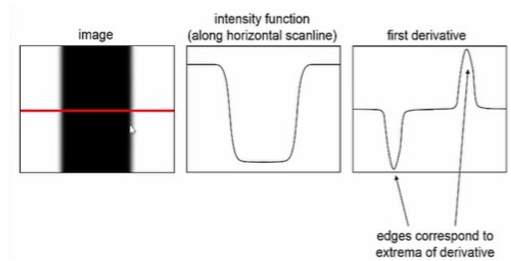
Edge Types



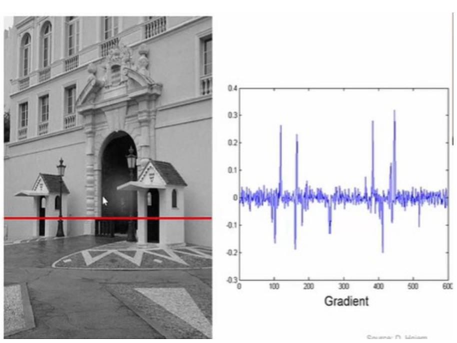
Example of Edges



- An edge is a place of rapid change in the image intensity function

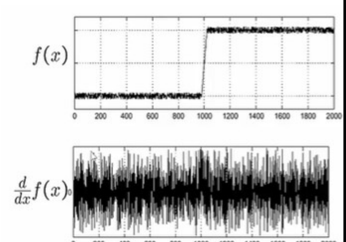


Effect of noise



Effect of Noise

- Consider a single row or column of the image
- Plotting intensity as a function of position gives a signal
- Where is the edge

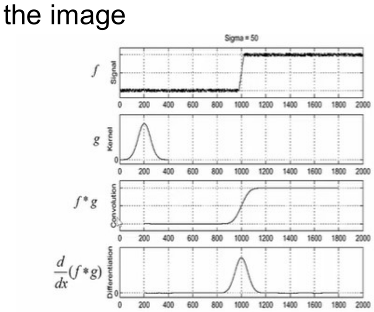


Effects of Noise

- Different filters respond strongly to noise
  - Image noise results in pixels that look very different from their neighbors
  - Generally, the larger the noise the stronger the response
- What can we do about it?

Solution

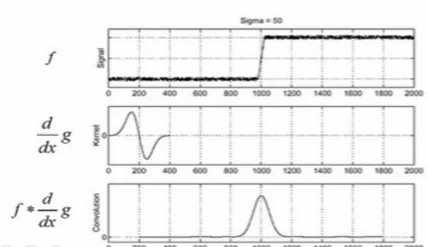
- First Smooth the image



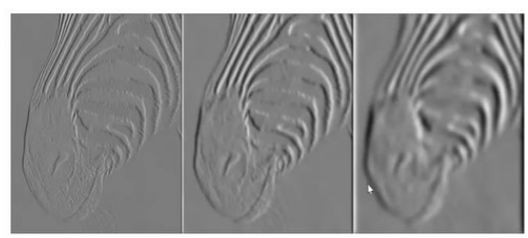
- To find edges, look for peaks in $\frac{d}{dx}(f*g)$

Derivative Theorem of Smoothing

- Differentiation is convolution, and convolution is associative: $\frac{d}{dx}(f*g)=f*\frac{d}{dx}g$
- This saves us one operation:



Tradeoff between smoothing and localization



1 pixel | 3 pixels | 7 pixels

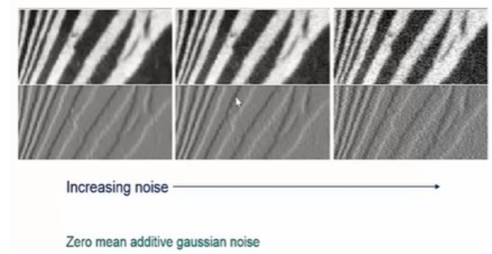
- Smoothed derivative removes noise, but blurs edge. Also finds edges at different "scales".

Derivatives and Noise

- Strongly affected by noise
  - obvious reason: image noise results in pixels that look very different from their neighbors
- The larger the noise is the stronger the response

- What is to be done?
  - Neighboring pixels look alike
  - Pixel along an edge look alike
  - Image smoothing should help
    - Force pixels different from their neighbors (possibly noise) to look like neighbors

Derivatives and Noise



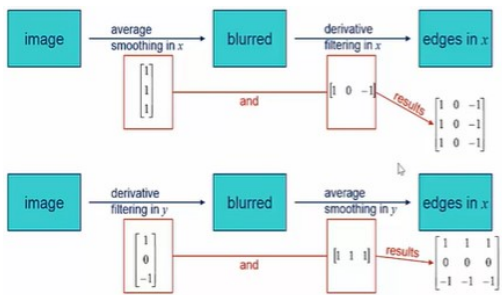
Edge Detectors

- Gradient Operator
  - Prewitt
  - Sobel
- Laplacian of Gaussian
- Gradient of Gaussian (Canny Edge Detector)

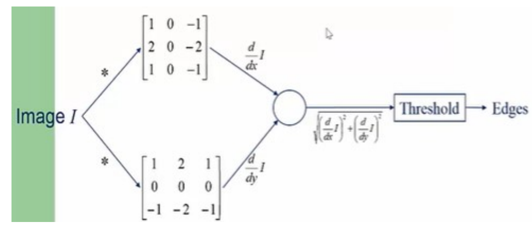
Prewitt and Sobel Edge Detector

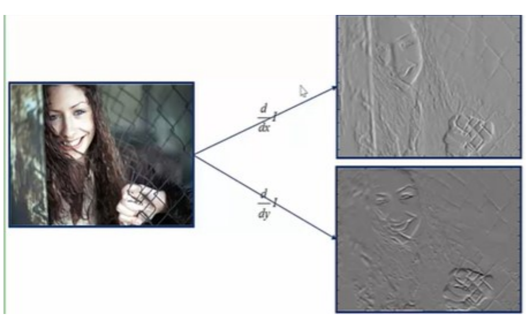
- Compute derivatives in x and y directions
- Find gradient magnitude
- Threshold gradient magnitude

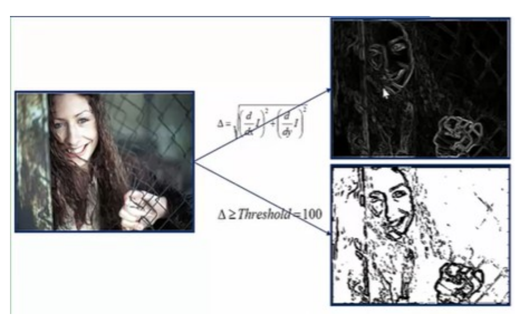
Prewitt Edge Detector



Sobel Edge Detector







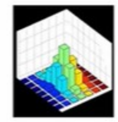
Marr Hildreth Edge Detector

- Smooth image by Gaussian filter → S
- Apply Laplacian to S
- Find zero crossings
  - Scan along each row, record an edge point at the location of zero-crossing
  - Repeat above step along each column

Marr Hildreth Edge Detector

- Gaussian smoothing

$$\overbrace{S}^{\text{smoothed image}} = \overbrace{g}^{\text{Gaussian filter}} * \overbrace{I}^{\text{image}} \qquad g = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}}$$



- Find Laplacian

$$\Delta^2 S = \overbrace{\frac{\partial^2}{\partial x^2} S}^{\text{secondorder derivative in } x} + \overbrace{\frac{\partial^2}{\partial y^2} S}^{\text{secondorder derivative in } y}$$

- ∇ is used for gradient (first derivative)
- Δ^2 is used for Laplacian (Secondt derivative

Laplacian of Gaussian

- Deriving the Laplacian of Gaussian (LoG)

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

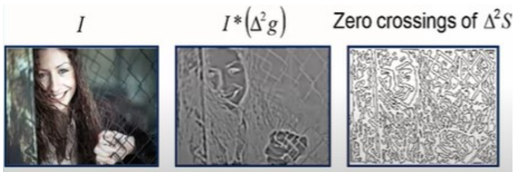
$$g_x = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}} \left(-\frac{2x}{2\sigma^2}\right)$$

$$\Delta^2 g = -\frac{1}{\sqrt{2\pi}\sigma^3} \left(2 - \frac{x^2+y^2}{\sigma^2}\right) e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Finding Zero Crossing

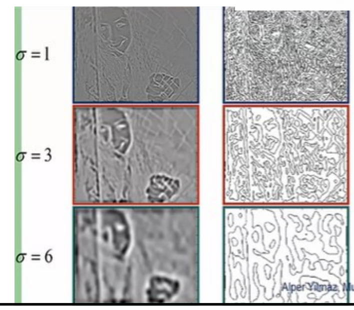
- Four cases of zero-crossings :
  - {+,-}
  - {+,0,-}
  - {-,+}
  - {-,0,+}
- Slope of zero-crossing {a, -b} is |a+b|.
- To mark an edge
  - compute slope of zero-crossing
  - Apply a threshold to slope

Example



Example

$$\Delta^2 G_\sigma = -\frac{1}{\sqrt{2\pi}\sigma^3}\left(2-\frac{x^2+y^2}{\sigma^2}\right)e^{-\frac{x^2+y^2}{2\sigma^2}}$$



LOG Algorithm

- Apply LOG to the image
- Find Zero crossings of each row
- Find slope of zero crossing
- Apply threshold to the slope and mark edges

Canny Edge Detection

- Canny Edge Detector Steps
  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" (use range between low and high)

Home assignment

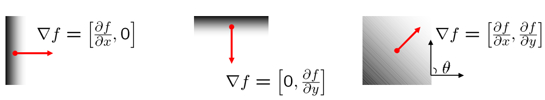
- Write a python code
  - Read an image
  - Find edges using
    1. Prewitt and sobel
    2. Laplacian of Gaussian (LOG)
    3. Canny
- Write image having marked edges on drive

Readings

- Chapter
- Richard Szeliski, Computer Vision, Algorithms and Applications, 2nd Ed, https://szeliski.org/Book/

Gradient

- Gradient equation: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$
- Represents direction of most rapid change in intensity



- Gradient direction: $\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$
- The *edge strength* is given by the gradient magnitude

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

Discrete Edge Operators

- How can we differentiate a ***discrete*** image?

Finite difference approximations:

$$\frac{\partial I}{\partial x} \approx \frac{1}{2\varepsilon}\left(\left(I_{i+1,j+1} - I_{i,j+1}\right) + \left(I_{i+1,j} - I_{i,j}\right)\right)$$
$$\frac{\partial I}{\partial y} \approx \frac{1}{2\varepsilon}\left(\left(I_{i+1,j+1} - I_{i+1,j}\right) + \left(I_{i,j+1} - I_{i,j}\right)\right)$$

$I_{i,j+1}$	$I_{i+1,j+1}$
$I_{i,j}$	$I_{i+1,j}$

ε

Convolution masks :

$\frac{\partial I}{\partial x} \approx \frac{1}{2\varepsilon}$

-1	1
-1	1

$\frac{\partial I}{\partial y} \approx \frac{1}{2\varepsilon}$

1	1
-1	-1

Discrete Edge Operators

- First order partial derivatives:

$$\frac{\partial I}{\partial x} \approx \begin{array}{|c|c|}\hline -1 & 1 \\ \hline -1 & 1 \\ \hline \end{array} \qquad \frac{\partial I}{\partial y} \approx \begin{array}{|c|c|}\hline 1 & 1 \\ \hline -1 & -1 \\ \hline \end{array}$$

-

•Second order partial derivatives:

$I_{i-1,j+1}$	$I_{i,j+1}$	$I_{i+1,j+1}$
$I_{i-1,j}$	$I_{i,j}$	$I_{i+1,j}$
$I_{i-1,j-1}$	$I_{i,j-1}$	$I_{i+1,j-1}$

- **Laplacian** :

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

Convolution masks :

$$\nabla^2 I \approx \begin{array}{|c|c|c|}\hline 0 & 1 & 0 \\ \hline 1 & -4 & 1 \\ \hline 0 & 1 & 0 \\ \hline \end{array} \quad \text{or} \quad \begin{array}{|c|c|c|}\hline 1 & 4 & 1 \\ \hline 4 & -20 & 4 \\ \hline 1 & 4 & 1 \\ \hline \end{array} \quad \text{(more accurate)}$$

The Sobel Operators

- Better approximations of the gradients exist
  - The *Sobel* operators below are commonly used

$$\underset{s_x}{\begin{array}{|c|c|c|}\hline -1 & 0 & 1 \\ \hline -2 & 0 & 2 \\ \hline -1 & 0 & 1 \\ \hline \end{array}} \qquad \underset{s_y}{\begin{array}{|c|c|c|}\hline 1 & 2 & 1 \\ \hline 0 & 0 & 0 \\ \hline -1 & -2 & -1 \\ \hline \end{array}}$$

Comparing Edge Operators

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

Good Localization
Noise Sensitive
Poor Detection

Roberts (2 x 2):

0	1
-1	0

1	0
0	-1

Sobel (3 x 3):

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

1	1	1
0	0	0
-1	-1	1

Sobel (5 x 5):

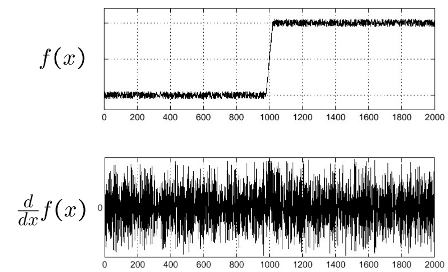
-1	-2	0	2	1
-2	-3	0	3	2
-3	-5	0	5	3
-2	-3	0	3	2
-1	-2	0	2	1

1	2	3	2	1
2	3	5	3	2
0	0	0	0	0
-2	-3	-5	-3	-2
-1	-2	-3	-2	-1

Poor Localization
Less Noise Sensitive
Good Detection

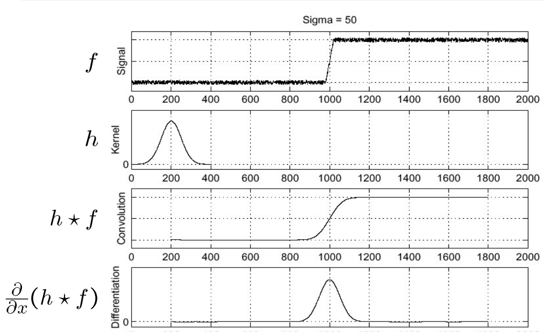
Effects of Noise

- Consider a single row or column of the image
  - Plotting intensity as a function of position gives a signal



Where is the edge??

Solution: Smooth First

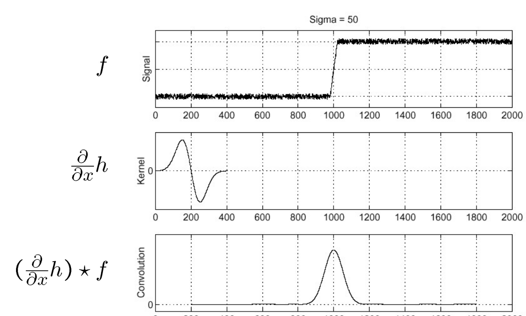


Where is the edge?

Look for peaks in $\frac{\partial}{\partial x}(h \star f)$

Derivative Theorem of Convolution

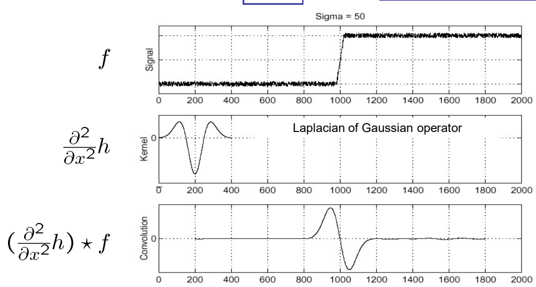
$\frac{\partial}{\partial x}(h \star f) = (\frac{\partial}{\partial x}h) \star f$ …saves us one operation.



Laplacian of Gaussian (LoG)

$$\frac{\partial^2}{\partial x^2}(h * f) = \boxed{\left(\frac{\partial^2}{\partial x^2} h\right)} * f$$

Laplacian of Gaussian



Where is the edge?

Zero-crossings of bottom graph !

Canny Edge Operator

- Smooth image *I* with 2D Gaussian: $G * I$
- Find local edge normal directions for each pixel

$$\bar{\mathbf{n}} = \frac{\nabla(G * I)}{|\nabla(G * I)|}$$

- Compute edge magnitudes $|\nabla(G * I)|$
- Locate edges by finding zero-crossings along the edge normal directions (**non-maximum suppression**)

$$\frac{\partial^2 (G * I)}{\partial \bar{\mathbf{n}}^2} = 0$$

The Canny Edge Detector

original image (Lena)

The Canny Edge Detector

magnitude of the gradient

The Canny Edge Detector

After non-maximum suppression

Canny Edge Operator

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