

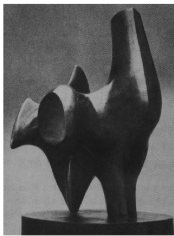


Computer Vision and Image Processing (CSEL-393)

Lecture

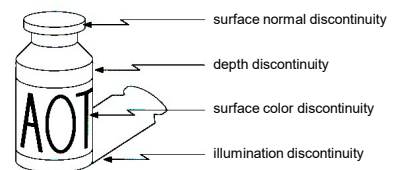
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Edge Detection



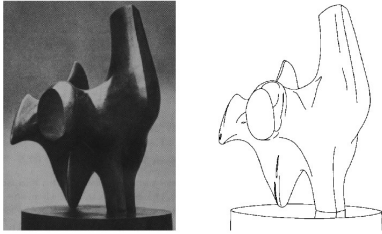
- Convert a 2D image into a set of curves
 - Extracts salient features of the scene
 - More compact than pixels

Origin of Edges

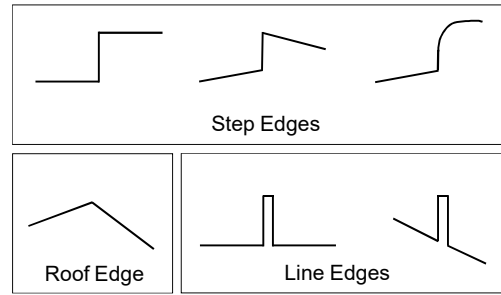


- Edges are caused by a variety of factors

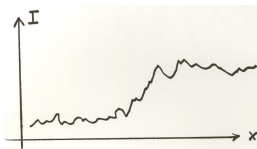
How can you tell that a pixel is on an edge?



Edge Types



Real Edges



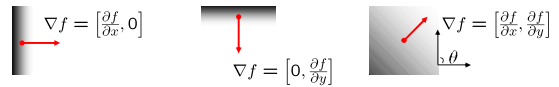
Noisy and Discrete!

We want an **Edge Operator** that produces:

- Edge **Magnitude**
- Edge **Orientation**
- High **Detection Rate** and Good **Localization**

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

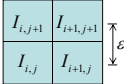
$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

Discrete Edge Operators

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

Finite difference approximations:

$$\frac{\partial I}{\partial x} \approx \frac{1}{2\epsilon} ((I_{i+1,j+1} - I_{i,j+1}) + (I_{i+1,j} - I_{i,j}))$$

$$\frac{\partial I}{\partial y} \approx \frac{1}{2\epsilon} ((I_{i+1,j+1} - I_{i+1,j}) + (I_{i,j+1} - I_{i,j}))$$


Convolution masks :


$$\frac{\partial I}{\partial x} \approx \frac{1}{2\epsilon} \begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix} \quad \frac{\partial I}{\partial y} \approx \frac{1}{2\epsilon} \begin{bmatrix} 1 & 1 \\ -1 & -1 \end{bmatrix}$$

Discrete Edge Operators

- First order partial derivatives:

$$\frac{\partial I}{\partial x} \approx \begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix} \quad \frac{\partial I}{\partial y} \approx \begin{bmatrix} 1 & 1 \\ -1 & -1 \end{bmatrix}$$

- Second order partial derivatives:



- Laplacian :

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

Convolution masks :

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

The Sobel Operators

- Better approximations of the gradients exist

– The *Sobel* operators below are commonly used

$$s_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad s_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

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):

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

Sobel (3 x 3):

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

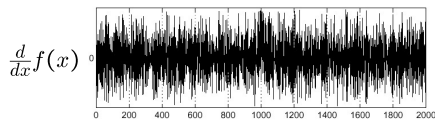
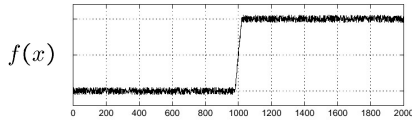
Sobel (5 x 5):

$$\begin{bmatrix} -1 & -2 & 0 & 2 & 1 \\ -2 & -3 & 0 & 3 & 2 \\ -3 & -5 & 0 & 5 & 3 \\ -2 & -3 & 0 & 3 & 2 \\ -1 & -2 & 0 & 2 & 1 \end{bmatrix} \quad \begin{bmatrix} 1 & 2 & 3 & 2 & 1 \\ 2 & 3 & 5 & 3 & 2 \\ 0 & 0 & 0 & 0 & 0 \\ -2 & -3 & -5 & -3 & -2 \\ -1 & -2 & -3 & -2 & -1 \end{bmatrix}$$

Poor Localization
Less Noise Sensitive
Good Detection

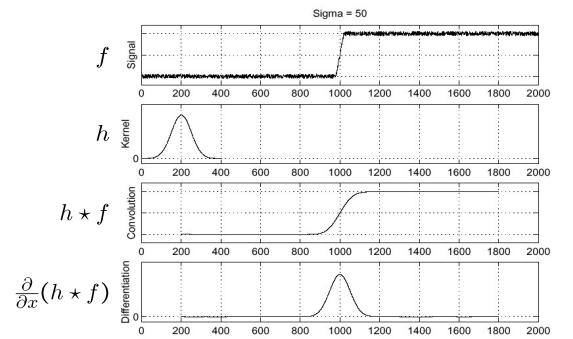
Effects of Noise

- 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

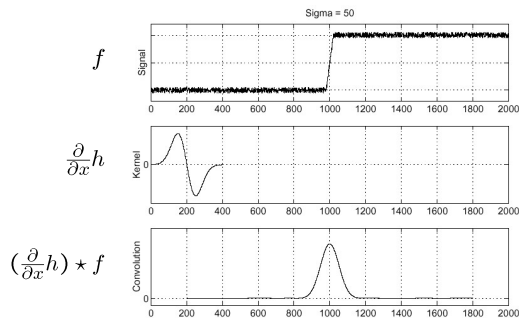


Where is the edge?

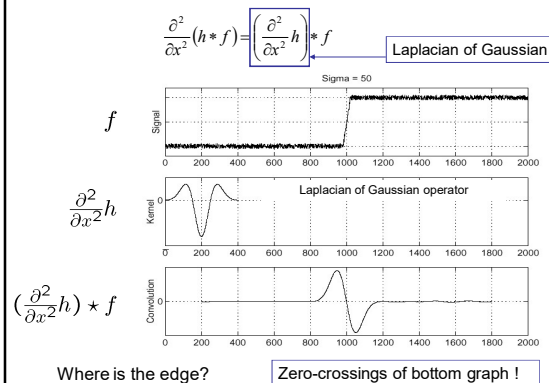
Look for peaks in $\frac{\partial}{\partial x}(h * f)$

Derivative Theorem of Convolution

$$\frac{\partial}{\partial x}(h * f) = \left(\frac{\partial}{\partial x}h\right) * f \quad \dots \text{saves us one operation.}$$



Laplacian of Gaussian (LoG)



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**)

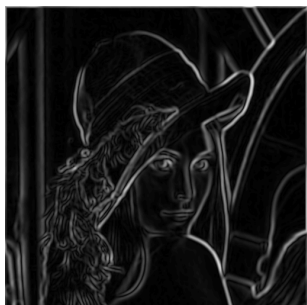
$$\frac{\partial^2(G * I)}{\partial \bar{\mathbf{n}}^2} = 0$$

The Canny Edge Detector



original image (Lena)

The Canny Edge Detector



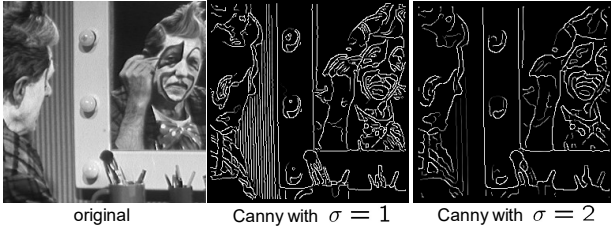
magnitude of the gradient

The Canny Edge Detector



After non-maximum suppression

Canny Edge Operator



- The choice of σ depends on desired behavior
 - large σ detects large scale edges
 - small σ detects fine features