# Computational Vision

Lecture 2.1.1: Advanced Edge Detection

Hamid Dehghani
Office: CS 241

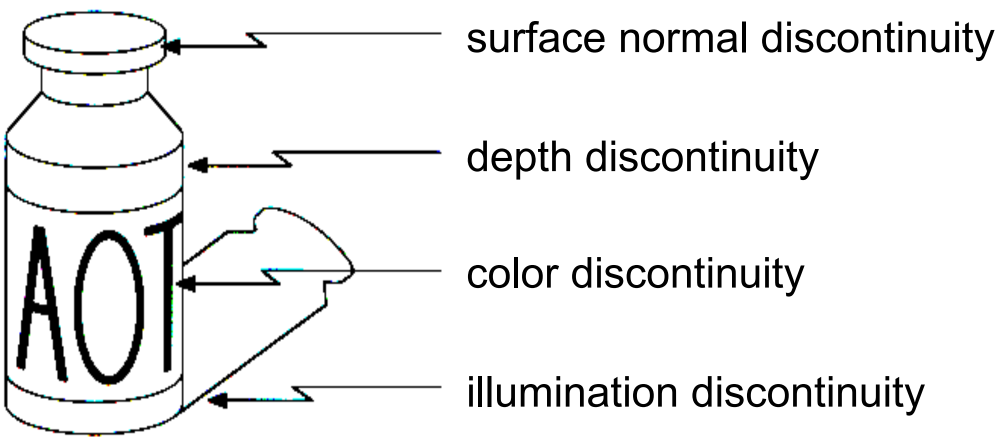
# Labs

- Thursday, see CANVAS for grouping
- Submit report for formal feedback by 29th Jan 2024

# What Causes Intensity Changes?

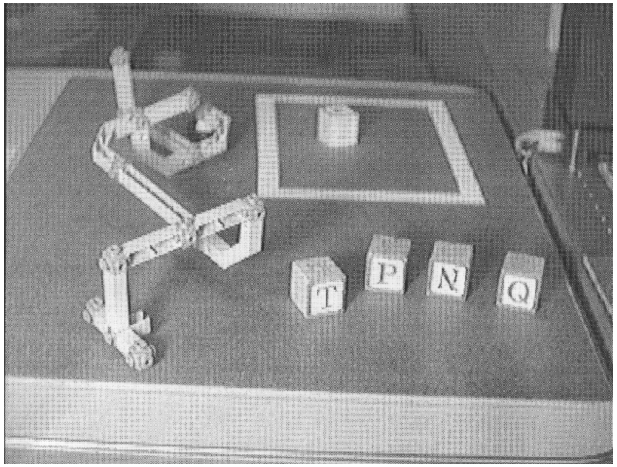
- Geometric events
  - surface orientation (boundary) discontinuities
  - depth discontinuities
  - color and texture discontinuities

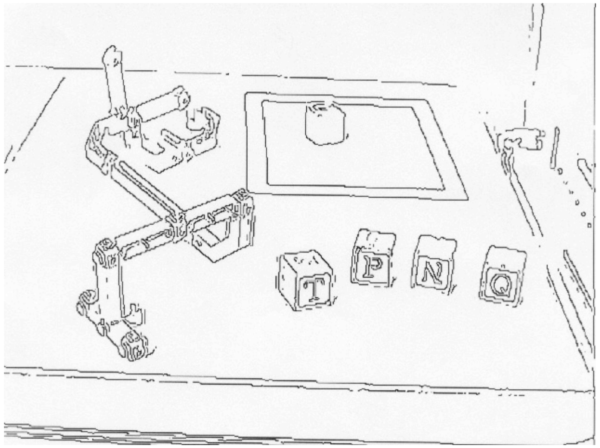
- Non-geometric events
  - illumination changes
  - specularities
  - shadows
  - inter-reflections



# Goal of Edge Detection

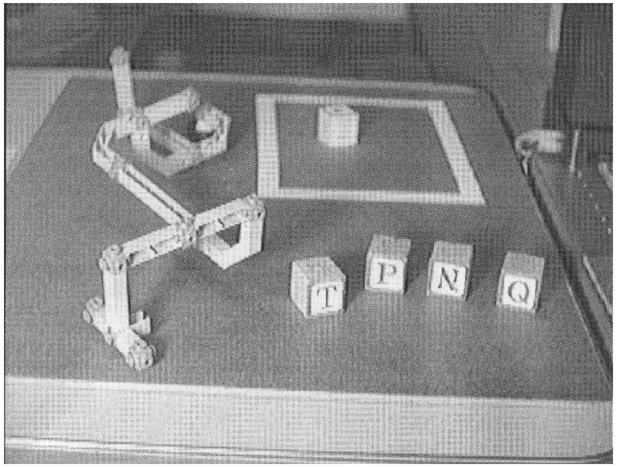
- Produce a line “drawing” of a scene from an image of that scene.

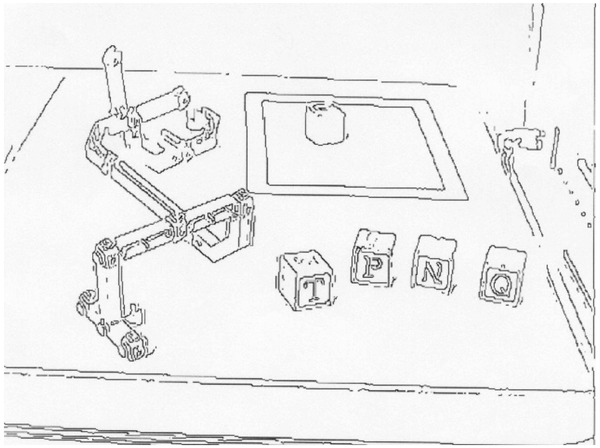




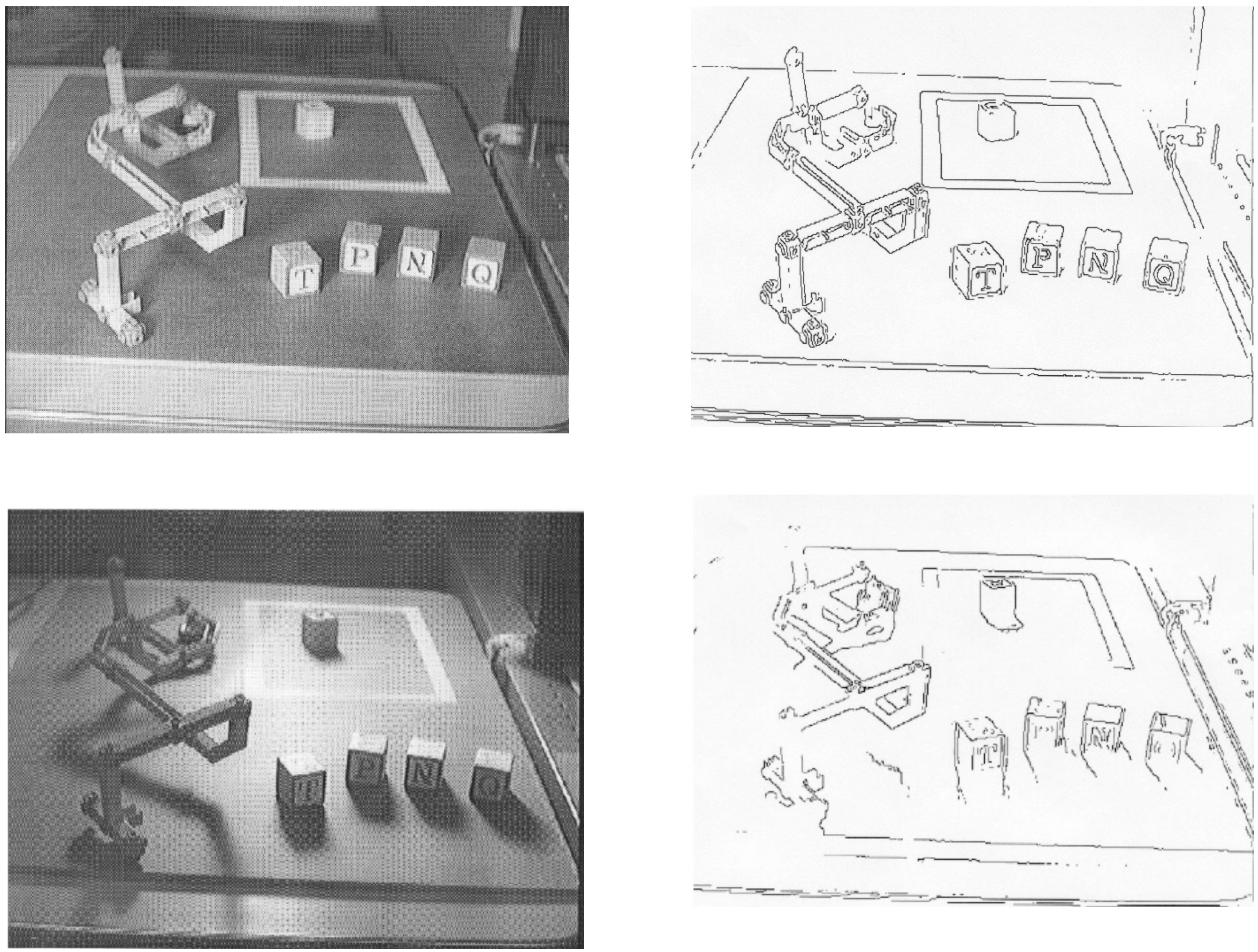
# Why is Edge Detection Useful?

- Important features can be extracted from the edges of an image (e.g., corners, lines, curves).
- These features are used by higher-level computer vision algorithms (e.g., recognition).



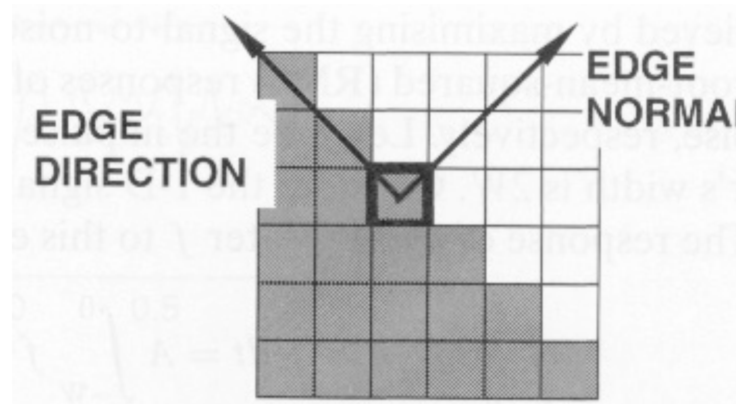


# Effect of Illumination



# Edge Descriptors

- **Edge direction:** perpendicular to the direction of maximum intensity change (i.e., edge normal)
- **Edge strength:** related to the local image contrast along the normal.
- **Edge position:** the image position at which the edge is located.



# Main Steps in Edge Detection

**(1) Smoothing:** suppress as much noise as possible, without destroying true edges.

**(2) Enhancement:** apply differentiation to enhance the quality of edges (i.e., sharpening).

# Main Steps in Edge Detection (cont' d)

**(3) Thresholding:** determine which edge pixels should be discarded as noise and which should be retained (i.e., threshold edge magnitude).

**(4) Localization:** determine the exact edge location.

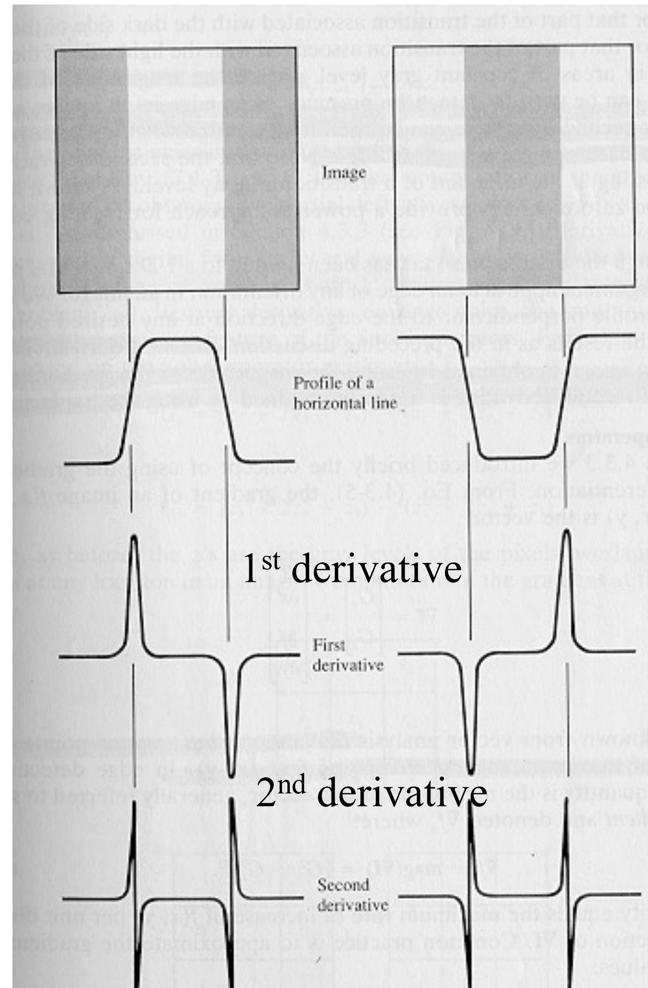
*sub-pixel* resolution might be required for some applications to estimate the location of an edge to better than the spacing between pixels.

# Edge Detection Using Derivatives

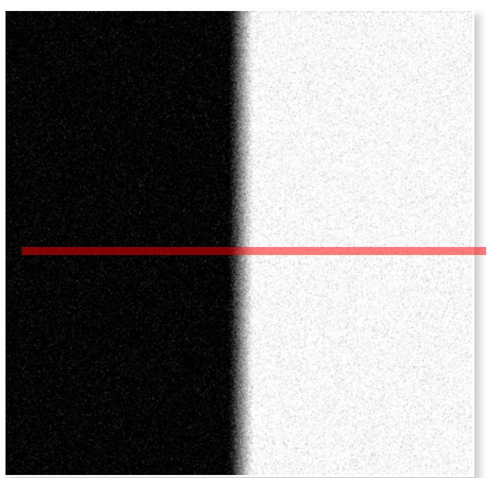
- Often, points that lie on an edge are detected by:

  **(1)** Detecting the local <u>**maxima**</u> or <u>**minima**</u> of the first derivative.

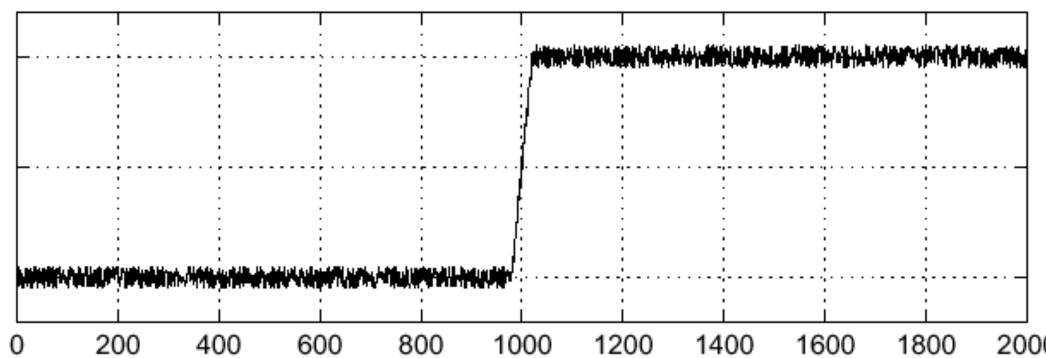
  **(2)** Detecting the <u>**zero-crossings**</u> of the second derivative.



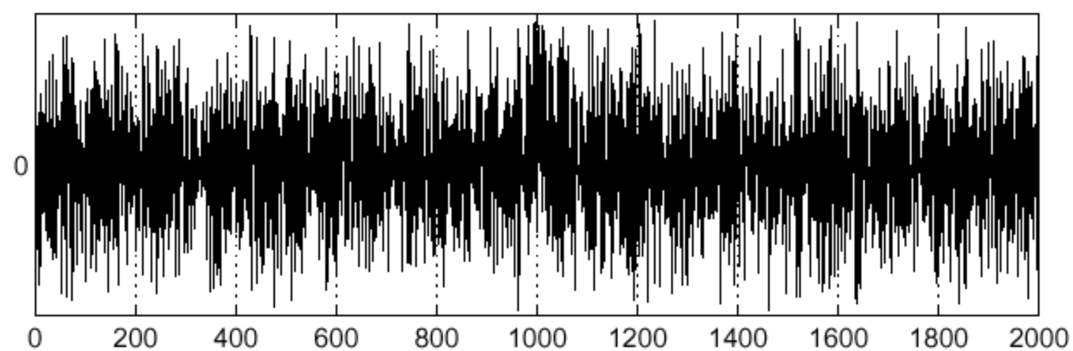
# Effect Smoothing on Derivates



$f(x)$

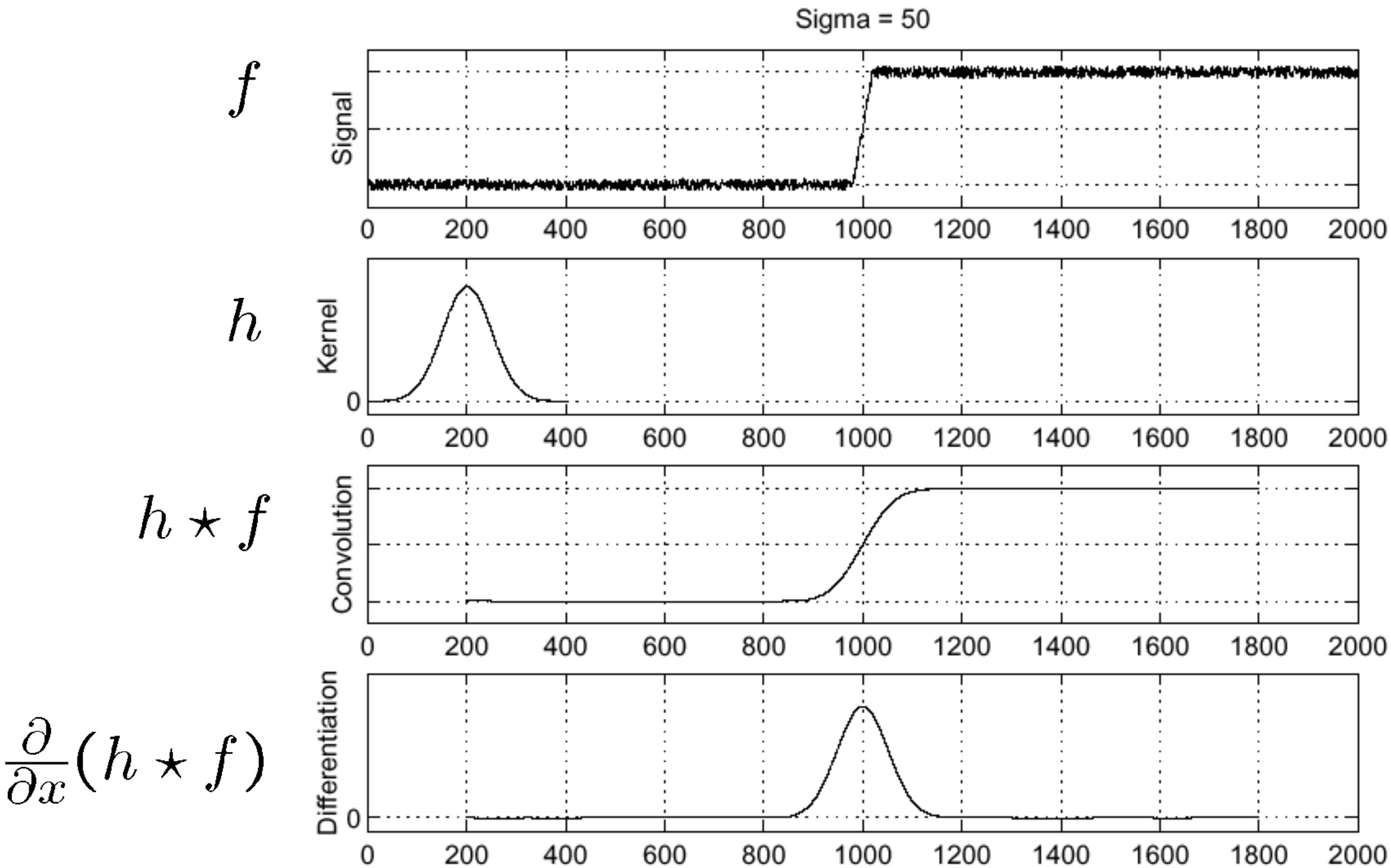



$\frac{d}{dx}f(x)$




Where is the edge??

# Effect of Smoothing on Derivatives (cont' d)



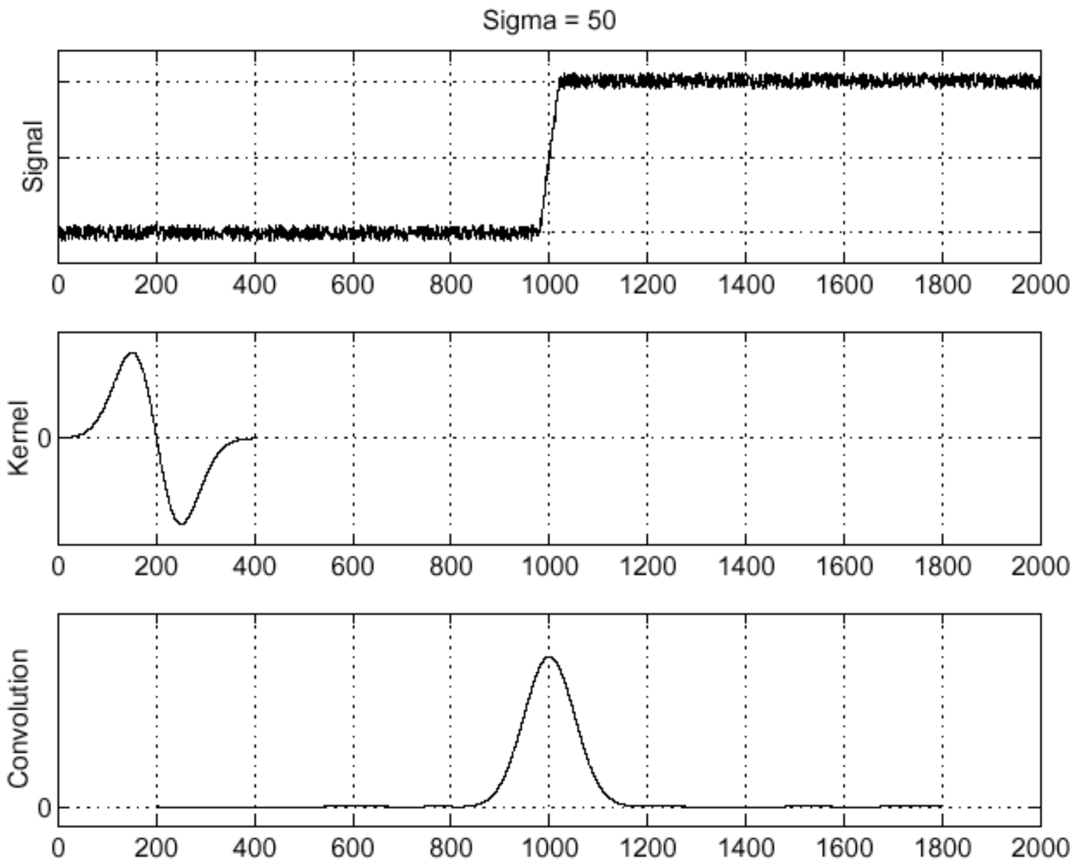
# Combine Smoothing with Differentiation

$$\frac{\partial}{\partial x}(h \star f) = (\frac{\partial}{\partial x}h) \star f$$ (i.e., saves one operation)

$f$

$\frac{\partial}{\partial x}h$

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



# Sobel Operator

$$M_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad M_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

$M_x$ and $M_y$ are approximations at $(i, j)$

# Prewitt Operator

$$M_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \qquad M_y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

$M_x$ and $M_y$ are approximations at $(i, j)$

# Edge Detection Steps Using Gradient

(1) Smooth the input image ($\hat{f}(x, y) = f(x, y) * G(x, y)$)

(2) $\hat{f}_x = \hat{f}(x, y) * M_x(x, y) \longrightarrow \dfrac{\partial f}{\partial x}$

(3) $\hat{f}_y = \hat{f}(x, y) * M_y(x, y) \longrightarrow \dfrac{\partial f}{\partial y}$

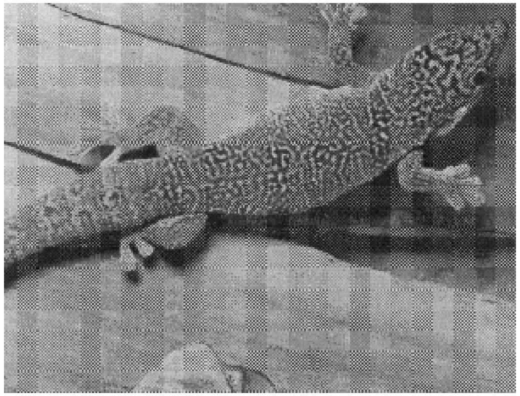
(4) $magn(x, y) = |\hat{f}_x| + |\hat{f}_y|$ (i.e., sqrt is costly!)

(5) $dir(x, y) = \tan^{-1}(\hat{f}_y / \hat{f}_x)$

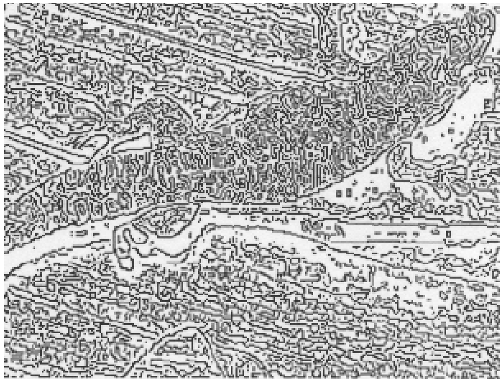
(6) If $magn(x, y) > T$, then possible edge point

# Practical Issues

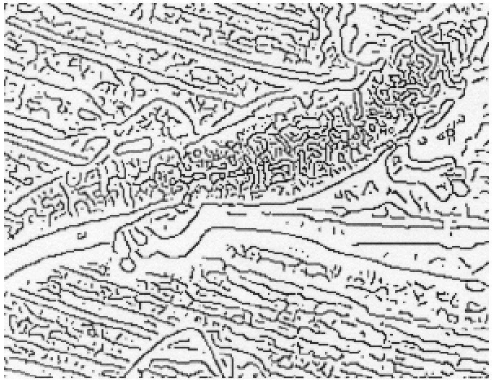
- Noise suppression-localization tradeoff.
  – Smoothing depends on mask size (e.g., depends on $\sigma$ for Gaussian filters).
  – Larger mask sizes reduce noise, but worsen localization (i.e., add uncertainty to the location of the edge) and vice versa.



smaller mask

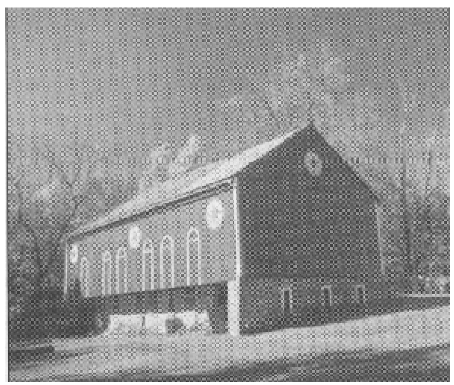


larger mask

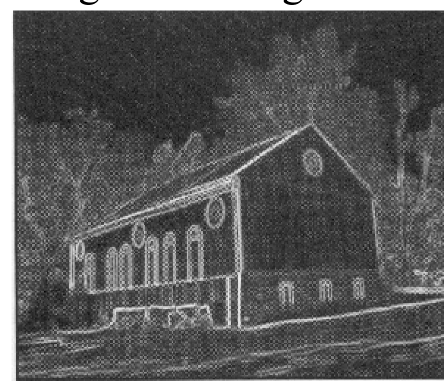


# Practical Issues (cont’d)

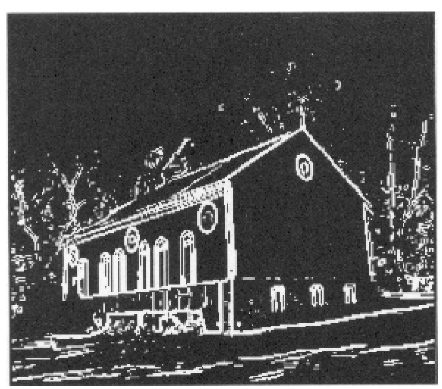
- Choice of threshold.



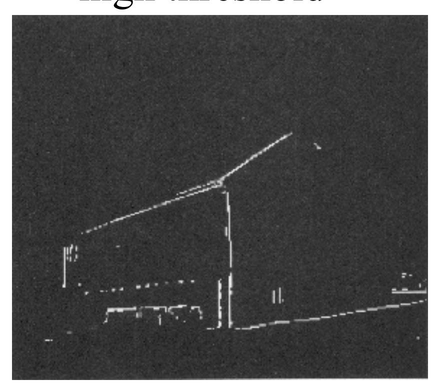
gradient magnitude



low threshold



high threshold



# Criteria for Optimal Edge Detection

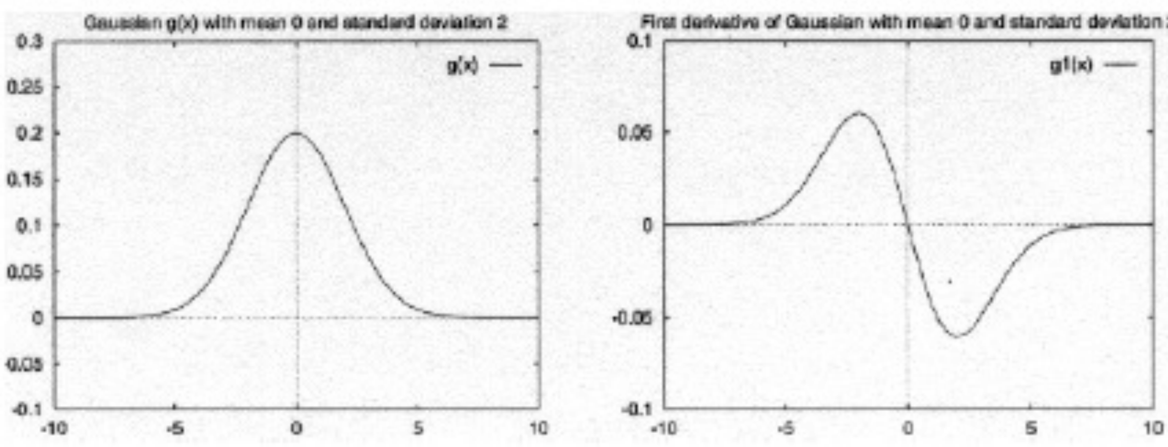
- **(1) Good detection**
  - Minimize the probability of false positives (i.e., spurious edges).
  - Minimize the probability of false negatives (i.e., missing real edges).
- **(2) Good localization**
  - Detected edges must be as close as possible to the true edges.
- **(3) Single response**
  - Minimize the number of local maxima around the true edge.

Event Code:

# Canny edge detector

- Canny has shown that the **first derivative of the Gaussian** closely approximates the operator that optimizes the product of <u>*signal-to-noise* ratio</u> and <u>localization</u>.

  (i.e., analysis based on "step-edges" corrupted by "Gaussian noise")




J. Canny, ***A Computational Approach To Edge Detection***, IEEE Trans. Pattern Analysis and Machine Intelligence, 8:679-714, 1986.

# Steps of Canny edge detector

*Algorithm*

1. Compute $f_x$ and $f_y$

$$f_x = \frac{\partial}{\partial x}(f * G) = f * \frac{\partial}{\partial x} G = f * G_x$$

$$f_y = \frac{\partial}{\partial y}(f * G) = f * \frac{\partial}{\partial y} G = f * G_y$$

$G(x, y)$ is the Gaussian function

$G_x(x, y)$ is the derivate of $G(x, y)$ with respect to $x$: $G_x(x, y) = \dfrac{-x}{\sigma^2} G(x, y)$

$G_y(x, y)$ is the derivate of $G(x, y)$ with respect to $y$: $G_y(x, y) = \dfrac{-y}{\sigma^2} G(x, y)$

# Steps of Canny edge detector (cont' d)

2. Compute the gradient magnitude (and direction)

$$magn(x,y) = |\hat{f}_x| + |\hat{f}_y| \quad dir(x,y) = \tan^{-1}(\hat{f}_y / \hat{f}_x)$$

3. Apply non-maxima suppression.

4. Apply hysteresis thresholding/edge linking.

# Canny edge detector - example

original image

# Canny edge detector – example (cont’d)

Gradient magnitude

# Canny edge detector – example (cont’d)

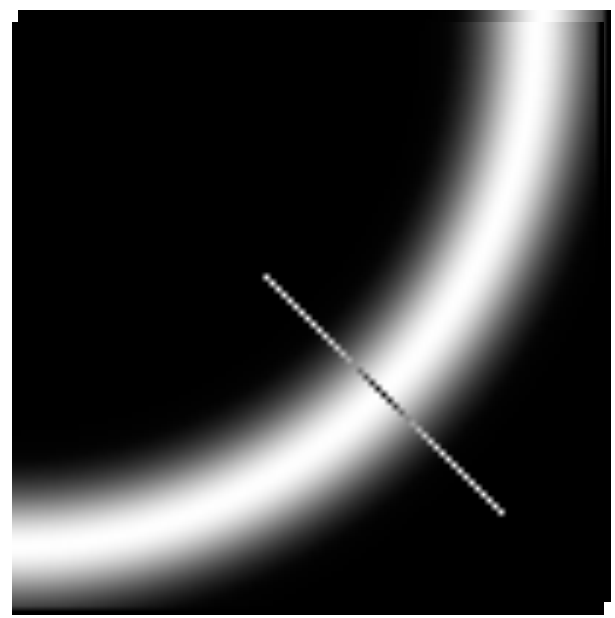
Thresholded gradient magnitude

# Canny edge detector – example (cont' d)

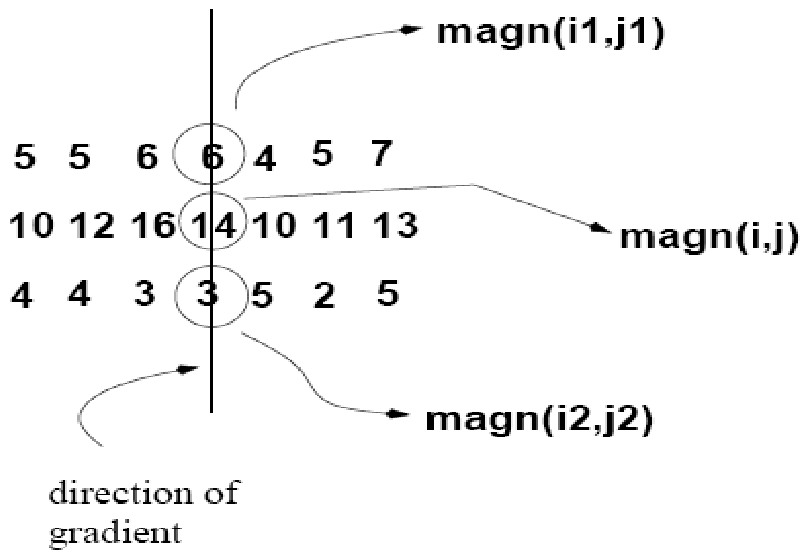
## Thinning (non-maxima suppression)

# Non-maxima suppression

- Check if gradient magnitude at pixel location (i,j) is local maximum along gradient direction



# Non-maxima suppression (cont'd)




*Algorithm*

For each pixel (i,j) do:

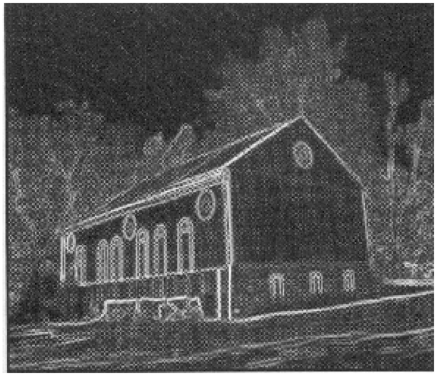
if $magn(i, j) < magn(i_1, j_1)$ or $magn(i, j) < magn(i_2, j_2)$
  then $I_N(i, j) = 0$
else $I_N(i, j) = magn(i, j)$

# Hysteresis thresholding

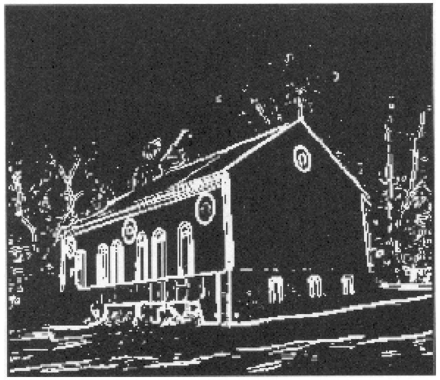
- Standard thresholding:

$$E(x,y) = \begin{cases} 1 & \text{if } \|\nabla f(x,y)\| > T \text{ for some threshold } T \\ 0 & \text{otherwise} \end{cases}$$

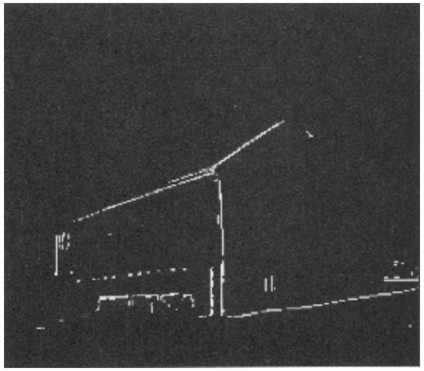
 - Can only select “strong” edges.
 - Does not guarantee “continuity”.



gradient magnitude



low threshold



high threshold

# Hysteresis thresholding (cont'd)

- Hysteresis thresholding uses two thresholds:

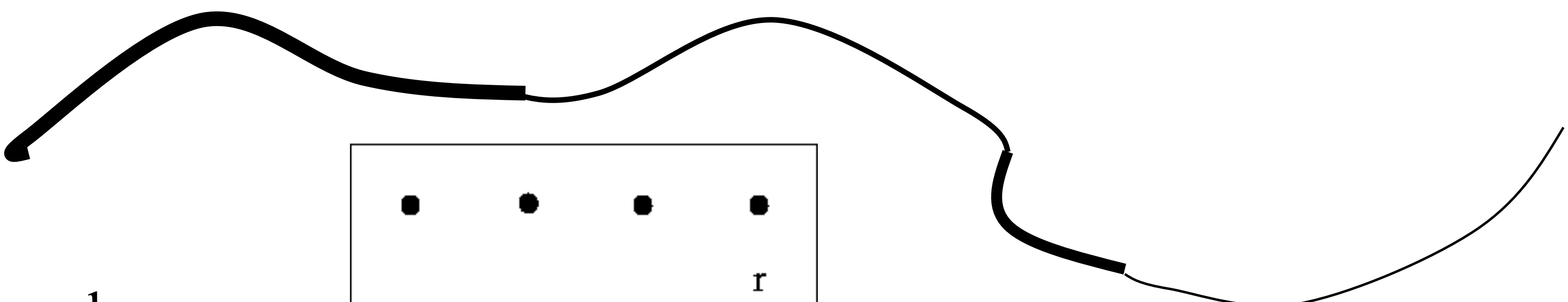
  - low threshold $t_l$
  - high threshold $t_h$ (usually, $t_h = 2t_l$)

$$
\begin{array}{rll}
 & \|\nabla f(x,y)\| \geq t_h & \text{definitely an edge} \\
t_l \geq & \|\nabla f(x,y)\| < t_h & \text{maybe an edge, depends on context} \\
 & \|\nabla f(x,y)\| < t_l & \text{definitely not an edge}
\end{array}
$$

- For "maybe" edges, decide on the edge if neighboring pixel is a strong edge.

# Hysteresis thresholding/Edge Linking

<u>Idea:</u> use a **high** threshold to start edge curves and a **low** threshold to continue them.



Use edge "direction" for linking edges