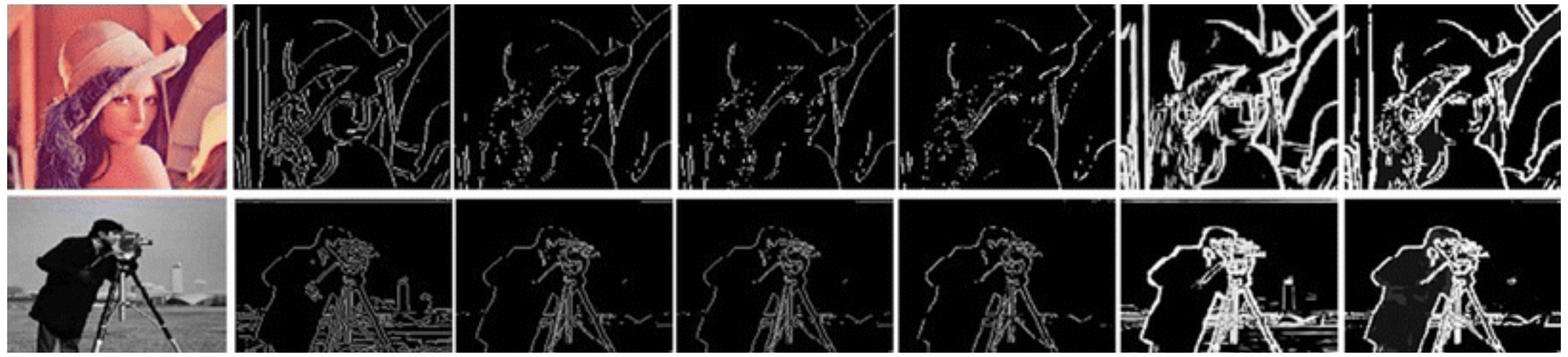
THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision



Lecture 8: Edge Detection (cont.)

(unless otherwise stated slides are taken or adopted from **Bob Woodham, Jim Little** and **Fred Tung**)

Menu for Today (**January 30, 2020**)

Topics:

— Edge **Detection**
— **Marr / Hildreth** and **Canny** Edges
— Image **Boundaries**

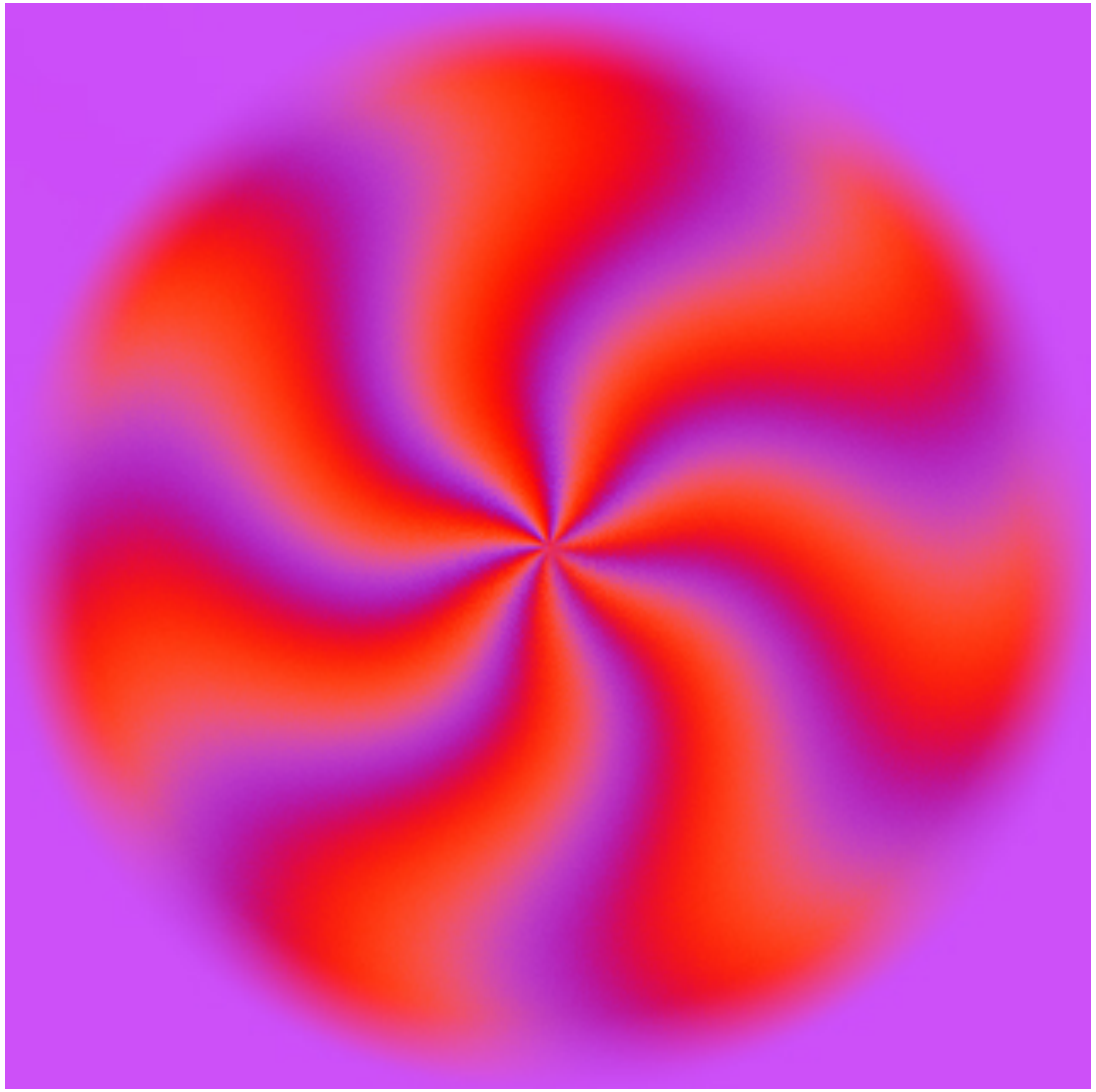
Redings:

— **Today's** Lecture: Forsyth & Ponce (2nd ed.) 5.1 - 5.2
— **Next** Lecture: Forsyth & Ponce (2nd ed.) 5.3.0 - 5.3.1

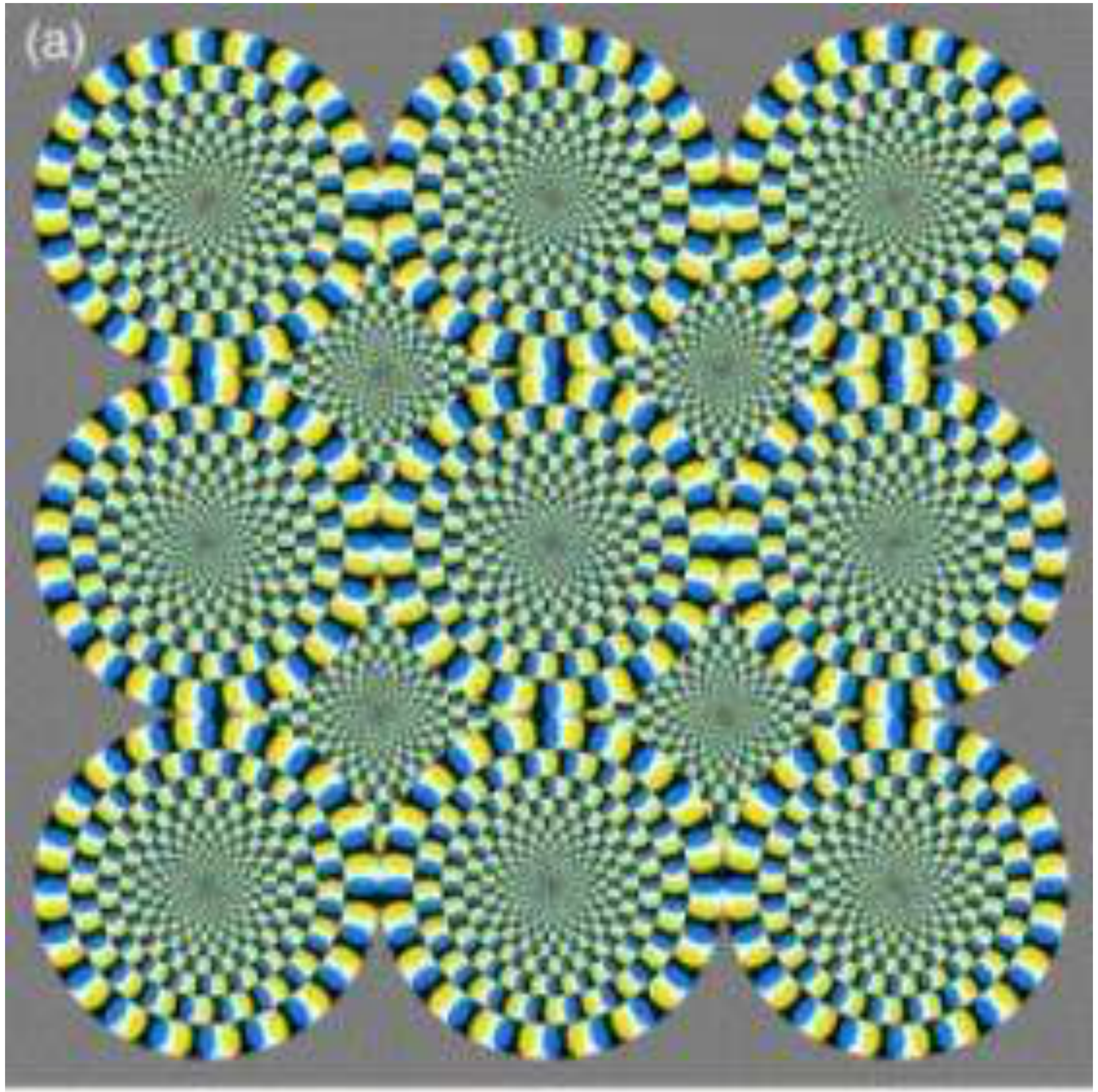
Reminders:

— **Assignment 2**: Scaled Representations, Face Detection and Image Blending

Today’s “**fun**” Example #1: Motion Illusion



Today's "**fun**" Example #1: Rotating Snakes Illusion



Today's "**fun**" Example #2: NCIS

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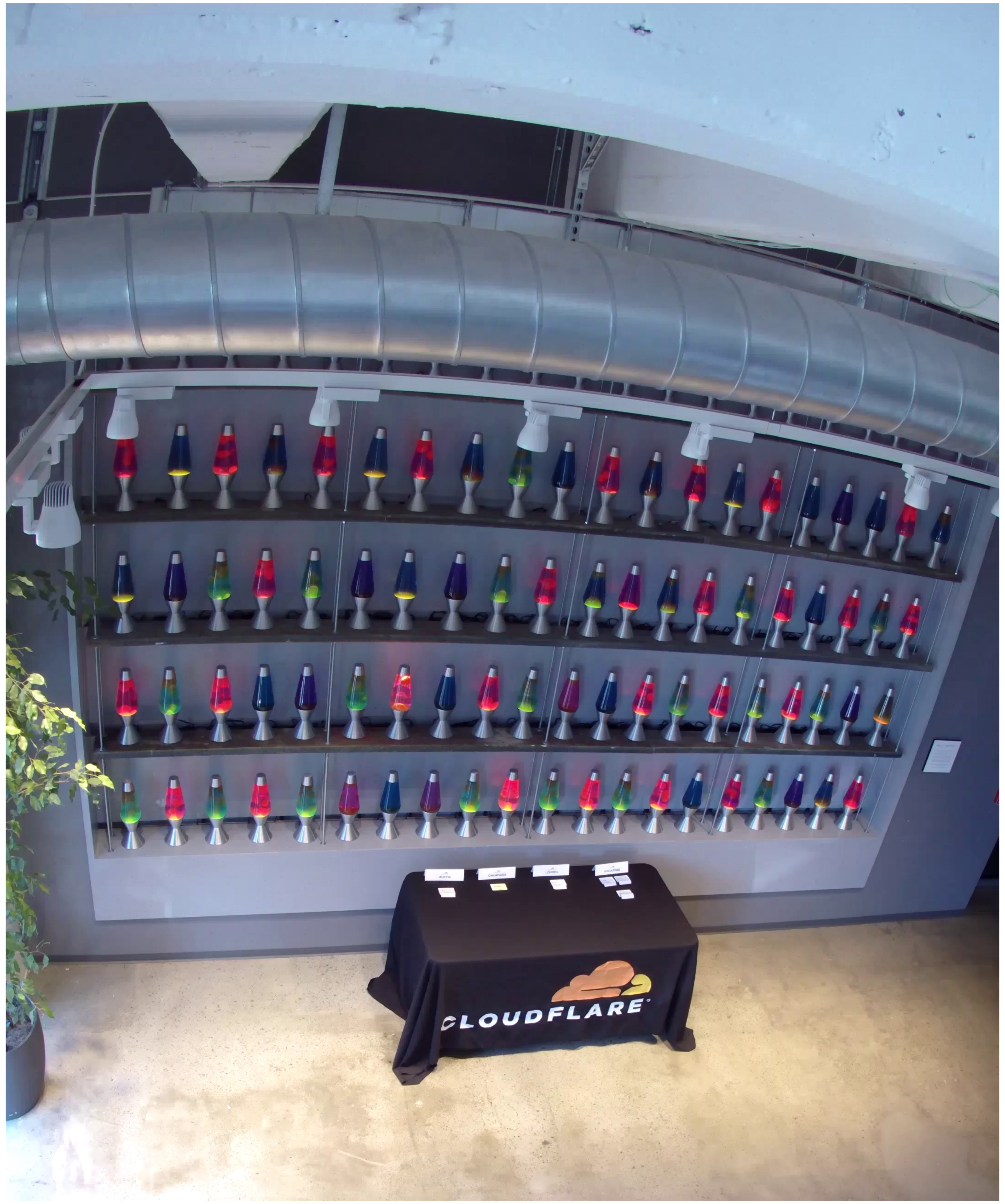
Today's "**fun**" Example #2: LavaRAND

Today's "**fun**" Example #2: LavaRAND



Lecture 7: Re-cap

Template matching as (normalized) correlation

Template matching is **not robust** to changes in
— 2D spatial scale and 2D orientation
— 3D pose and viewing direction
— illumination

Scaled representations facilitate:
— template matching at multiple scales
— efficient search for image-to-image correspondences
— image analysis at multiple levels of detail

A **Gaussian pyramid** reduces artifacts introduced when sub-sampling to coarser scales

Lecture 7: Re-cap

A (**discrete**) approximation is

$$\frac{\partial f}{\partial x} \approx \frac{F(X+1,y) - F(x,y)}{\Delta x}$$

— "First forward difference"

— Can be implemented as a **convolution**

$$\begin{array}{|c|c|}\hline -1 & 1 \\ \hline \end{array} \qquad \begin{array}{|c|}\hline -1 \\ \hline 1 \\ \hline \end{array}$$

Formally

A (**discrete**) approximation is

$$\frac{\partial f}{\partial x} \approx \frac{F(X+1, y) - F(x, y)}{\Delta x}$$

"**forward** difference" implemented as

correlation

-1	1

from **left**

convolution

1	-1

"**backward** difference" implemented as

correlation

-1	1

from **right**

convolution

1	-1

Lecture 7: Re-cap

Use the “first forward difference" to compute the image derivatives in X and Y directions.

(Compute two arrays, one of $\frac{\partial f}{\partial x}$ values and one of $\frac{\partial f}{\partial y}$ values.)

1	1	0.6	0.3	0	0
1	1	0.6	0.3	0	0
0	0	0	0	0	0
0	0	0	0	0	0

A Sort **Exercise**: Derivative in Y Direction

Use the “first forward difference" to compute the image derivatives in X and Y directions.

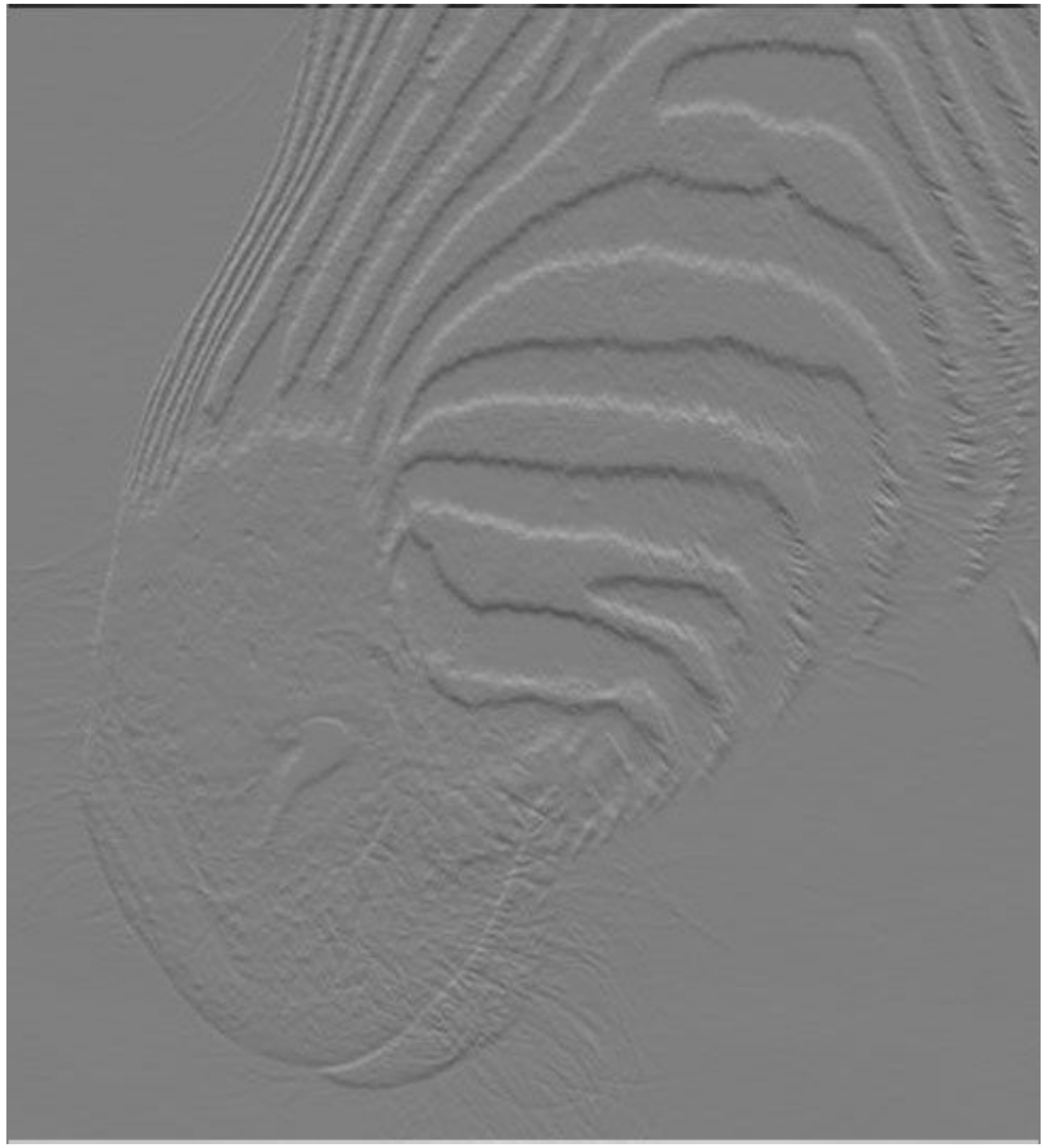
(Compute two arrays, one of $\frac{\partial f}{\partial x}$ values and one of $\frac{\partial f}{\partial y}$ values.)

1	1	0.6	0.3	0	0
1	1	0.6	0.3	0	0
0	0	0	0	0	0
0	0	0	0	0	0

1					
0	0	0	0	0	0

Lecture 7: Re-cap

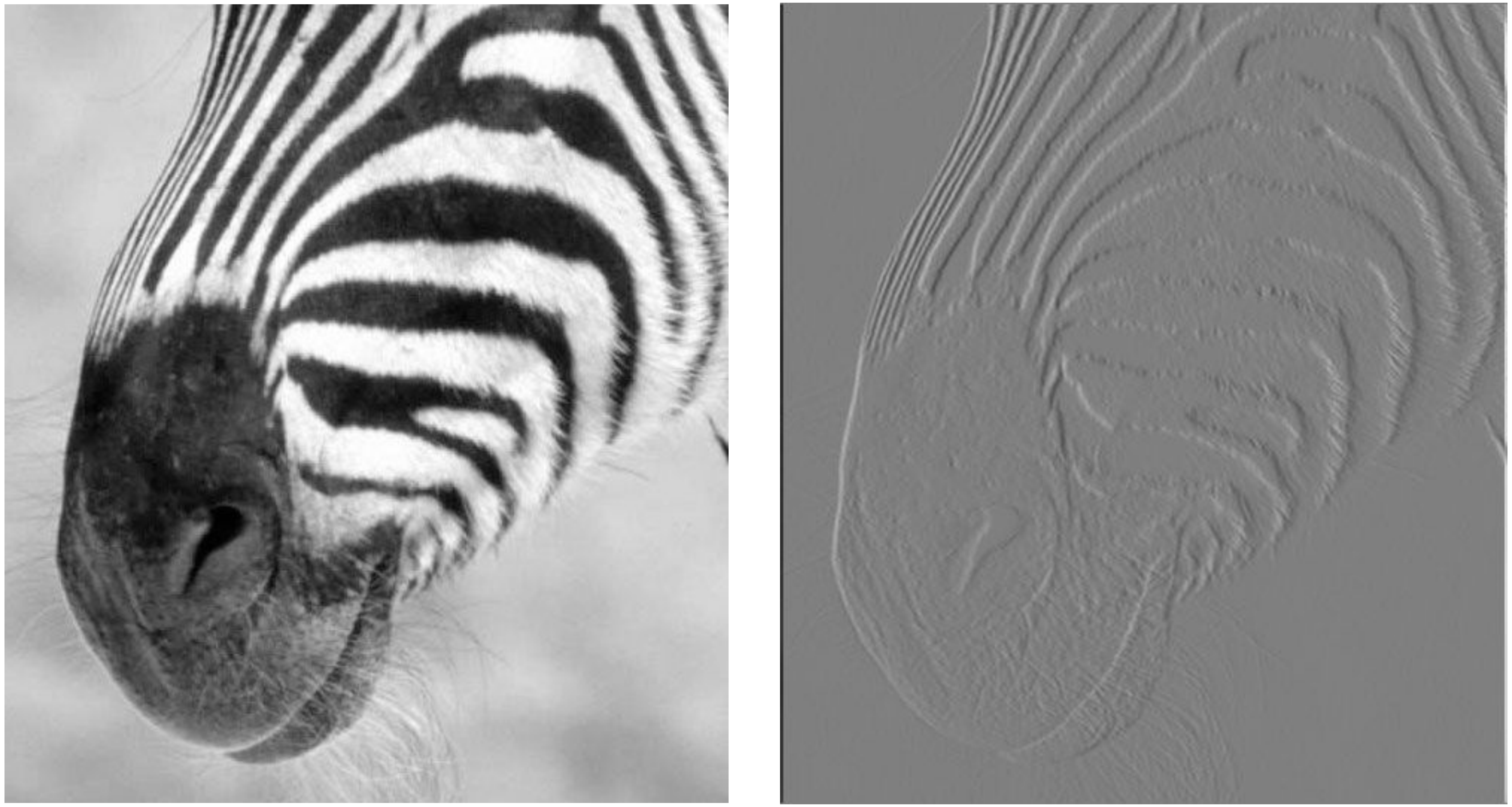
Derivative in Y (i.e., vertical) direction



Forsyth & Ponce (1st ed.) Figure 7.4 (top left & top middle)

Lecture 7: Re-cap

Derivative in X (i.e., horizontal) direction



Forsyth & Ponce (1st ed.) Figure 7.4 (top left & top right)

Edge Detection

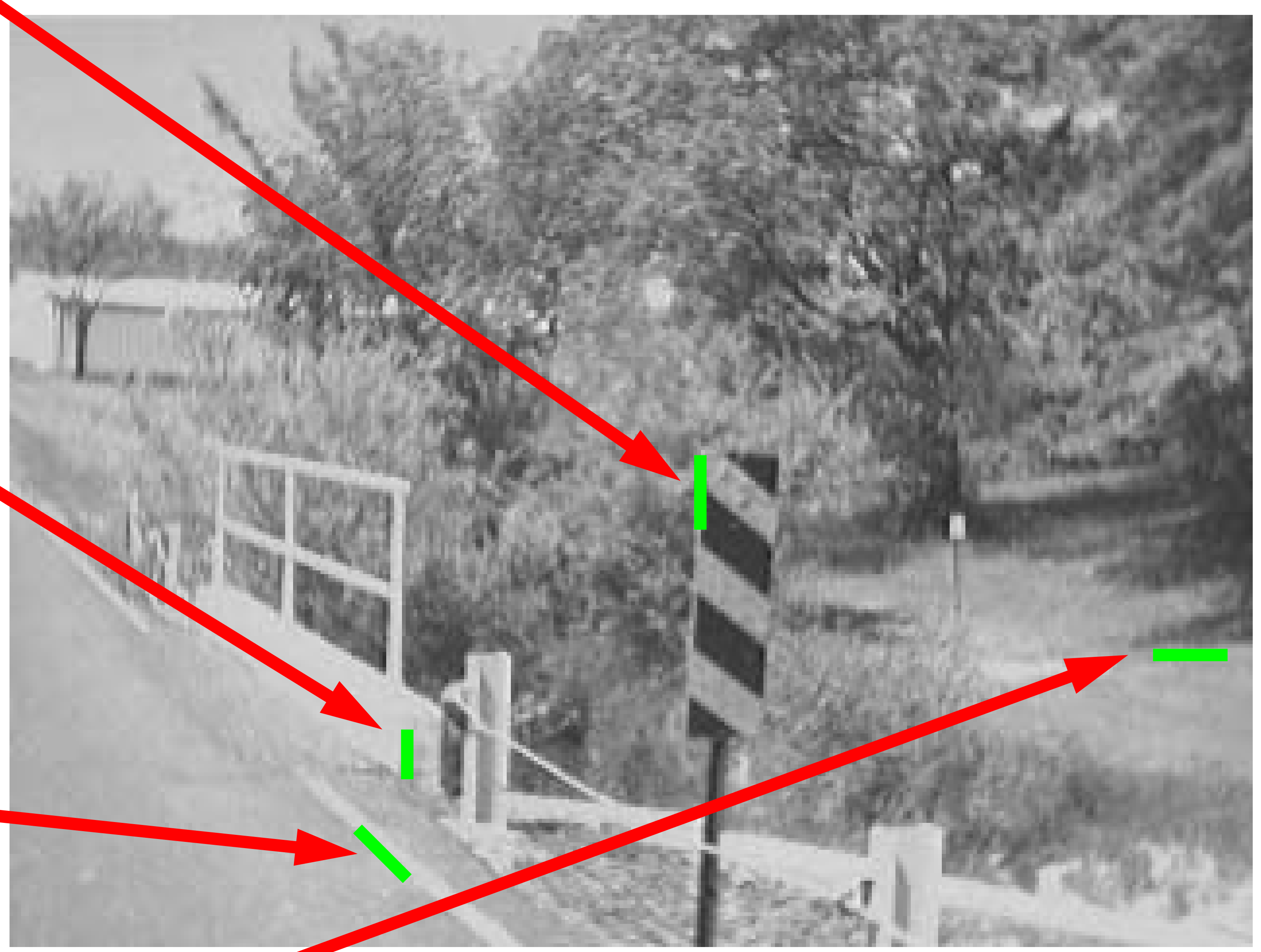
Goal: Identify sudden changes in image intensity

This is where most shape information is encoded

Example: artist's line drawing (but artist also is using object-level knowledge)

What Causes **Edges**?

- Depth discontinuity
- Surface orientation discontinuity
- Reflectance discontinuity (i.e., change in surface material properties)
- Illumination discontinuity (e.g., shadow)



Slide Credit: Christopher Rasmussen

Smoothing and Differentiation

Edge: a location with high gradient (derivative)

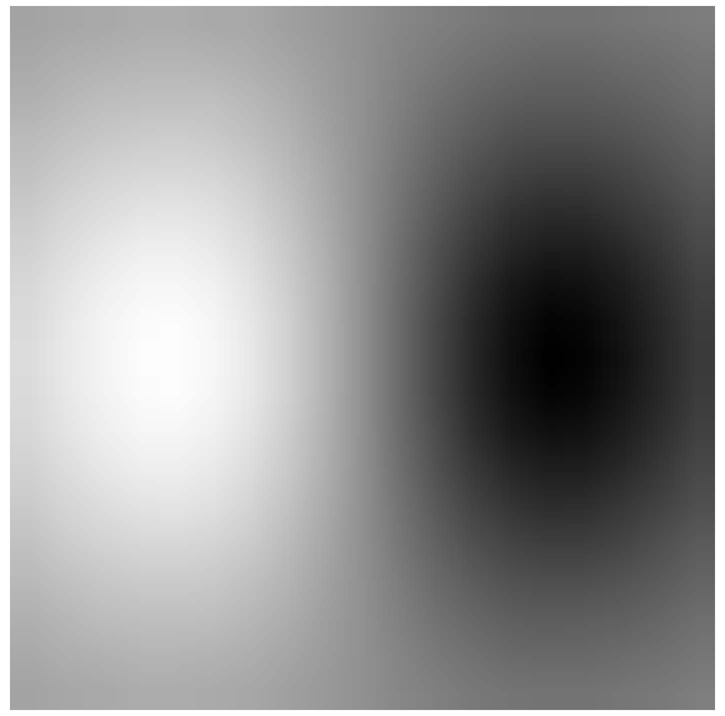
Need smoothing to reduce noise prior to taking derivative

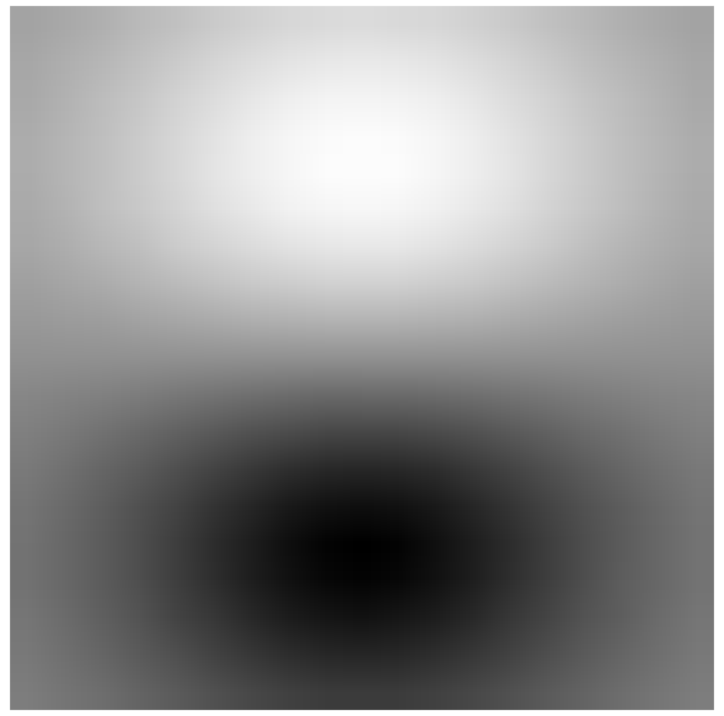
Need two derivatives, in x and y direction

We can use **derivative of Gaussian** filters
— because differentiation is convolution, and
— convolution is associative

Let $\otimes$ denote convolution

$$D \otimes (G \otimes I(X,Y)) = (D \otimes G) \otimes I(X,Y)$$

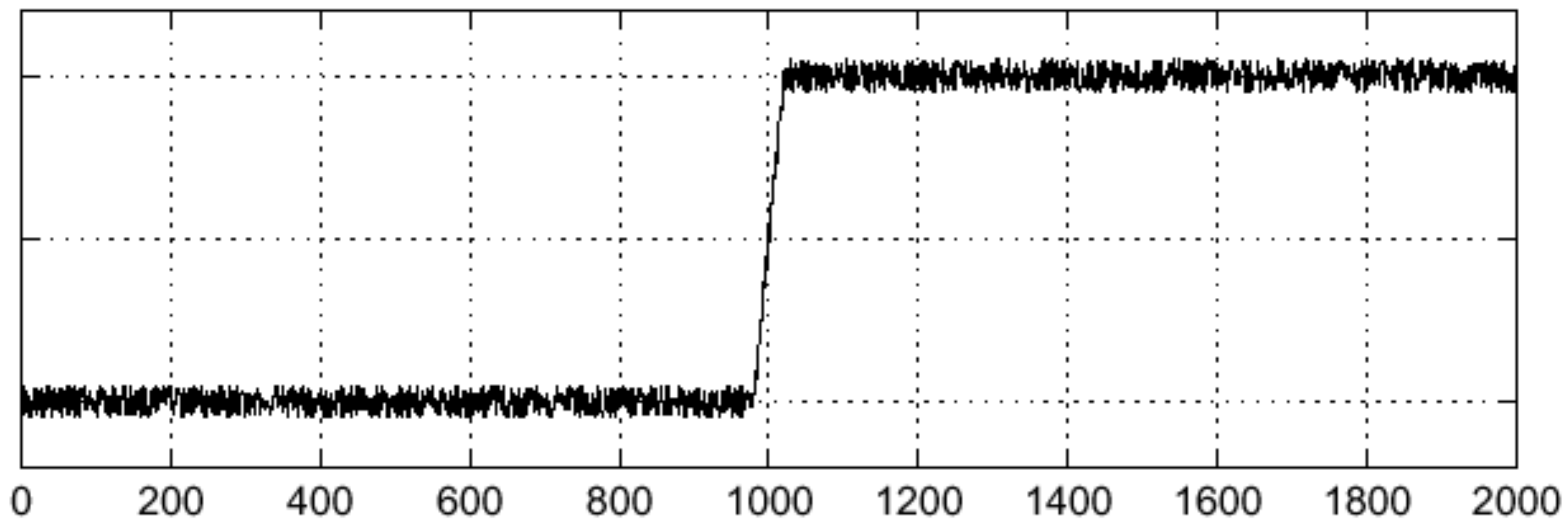




1D **Example**

Lets consider a row of pixels in an image:

$I(X, 245)$

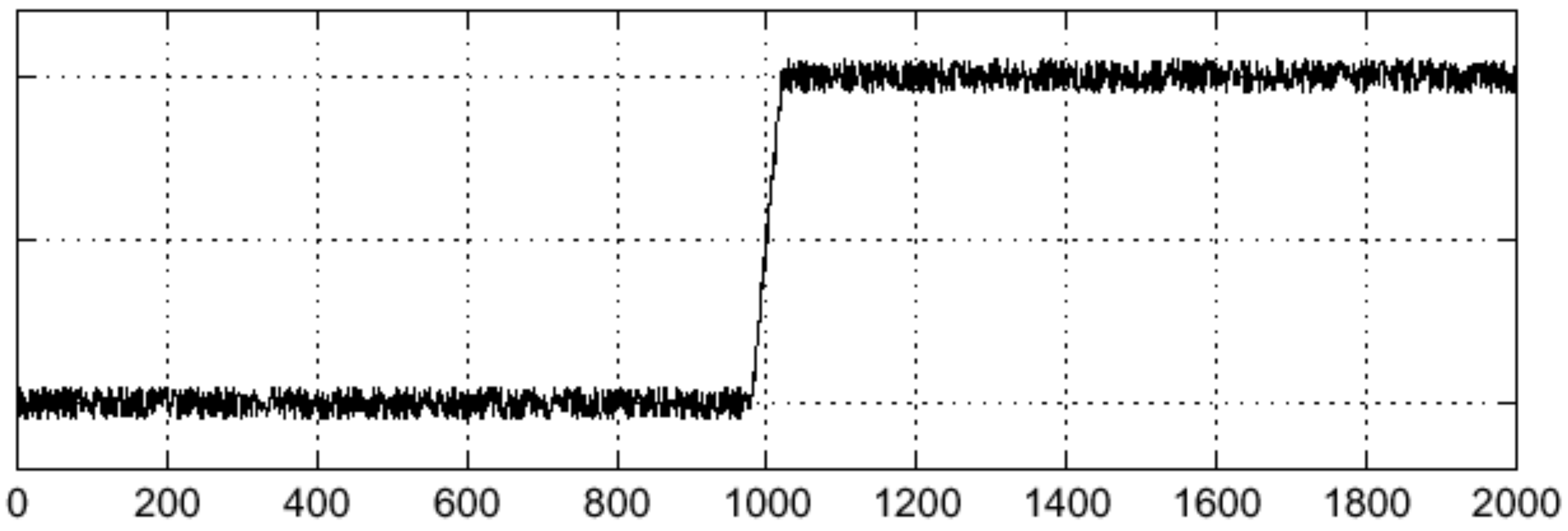


Where is the edge?

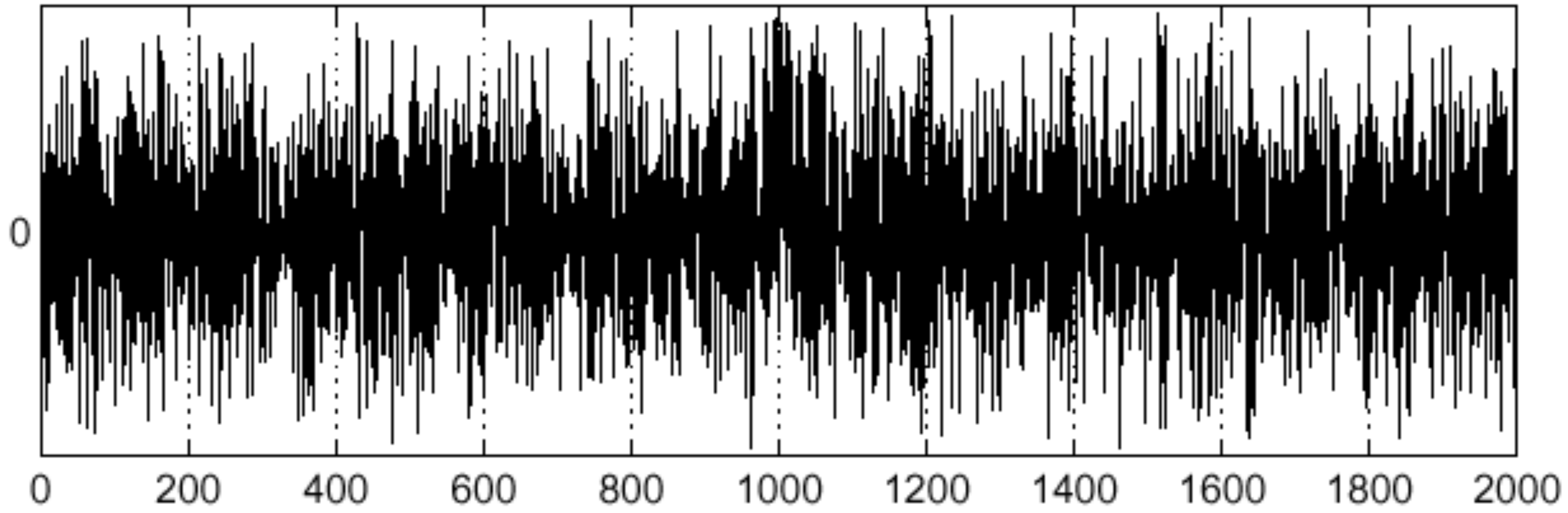
1D **Example**: Derivative

Lets consider a row of pixels in an image:

$$I(X, 245)$$



$$\frac{\partial I(X, 245)}{\partial x}$$



Where is the edge?

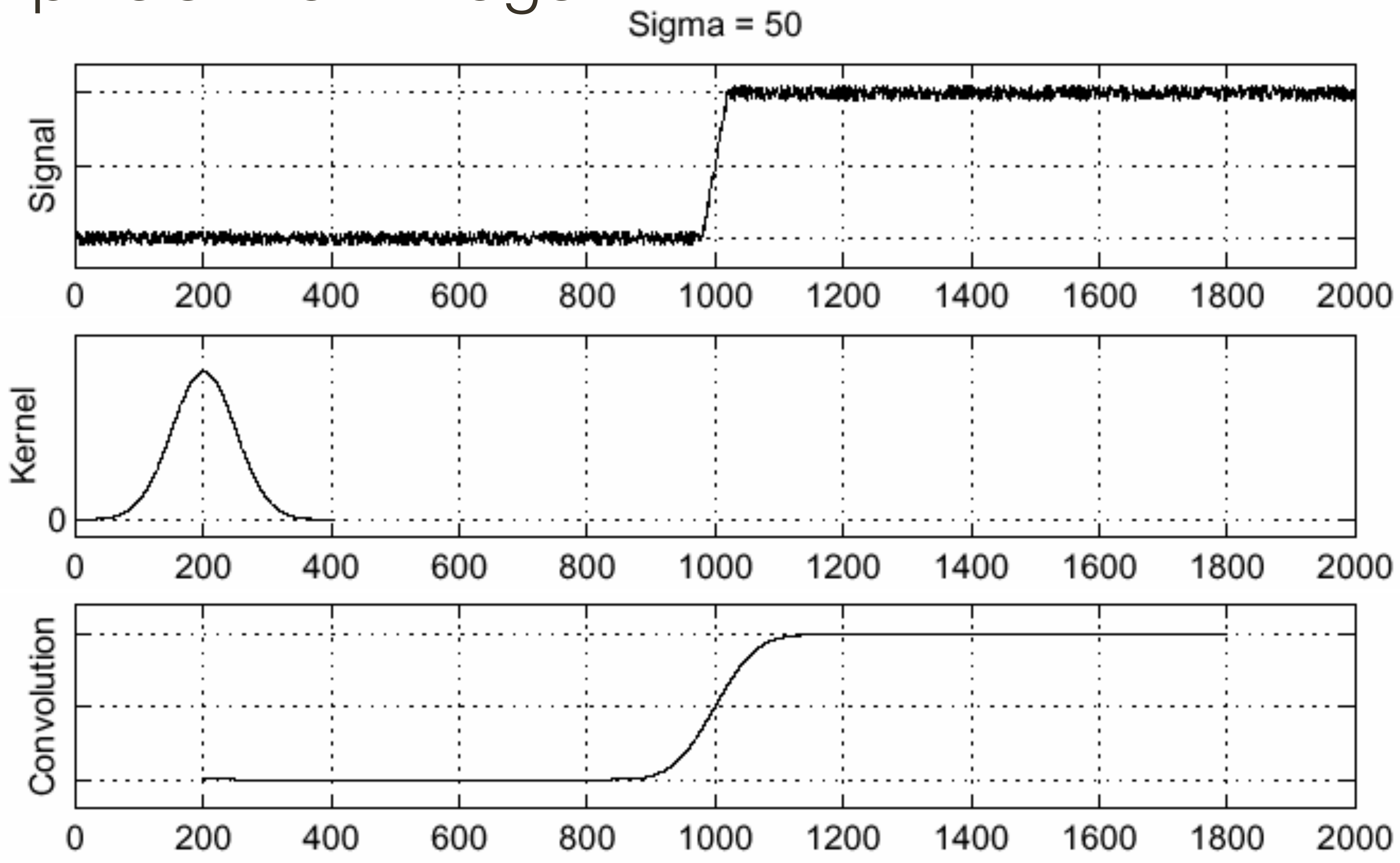
1D **Example**: Smoothing + Derivative

Lets consider a row of pixels in an image:

$I(X, 245)$

G

$G \otimes I(X, Y)$



1D **Example**: Smoothing + Derivative

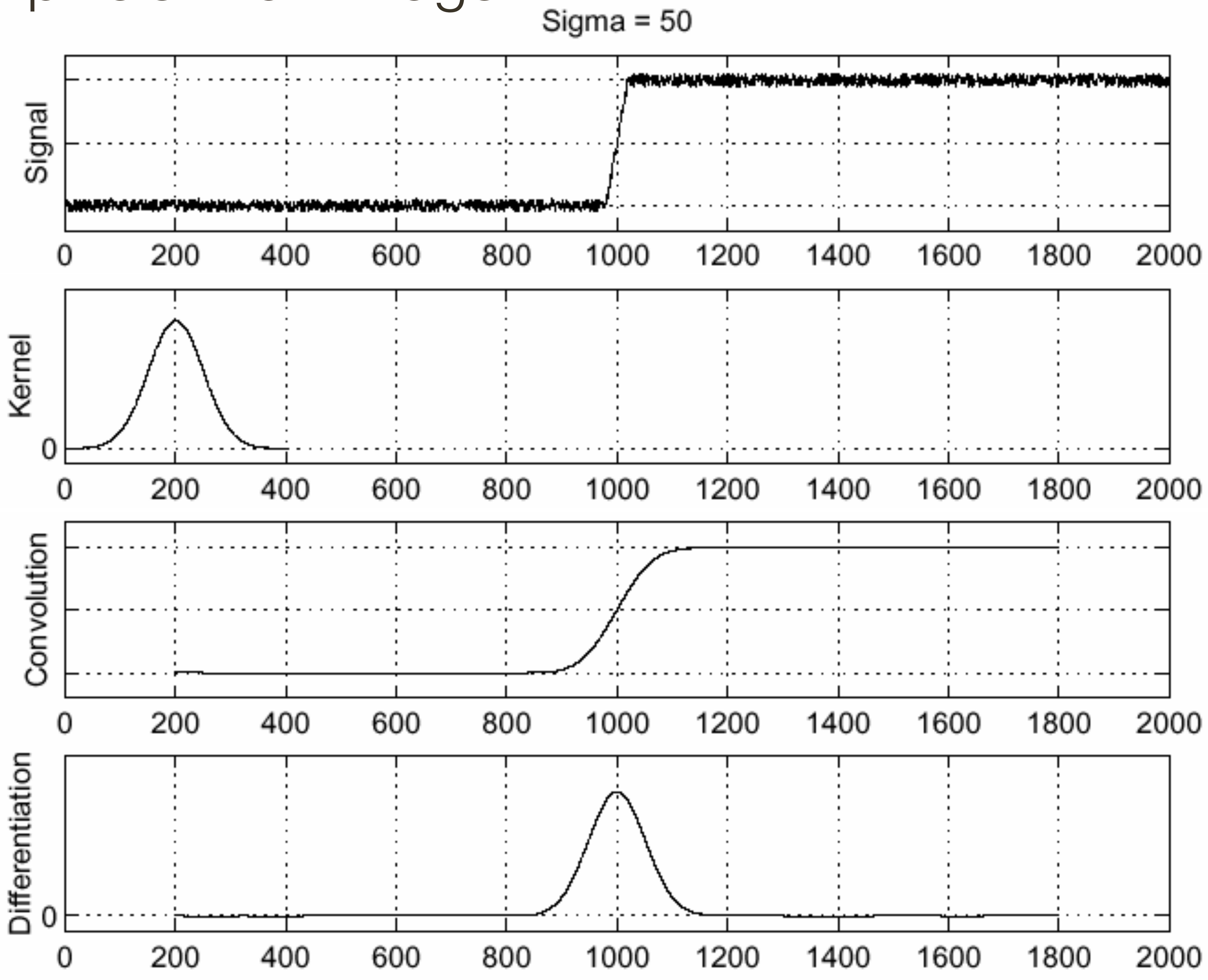
Lets consider a row of pixels in an image:

$I(X, 245)$

G

$G \otimes I(X,Y)$

$$\frac{\partial G \otimes I(X,Y)}{\partial x}$$



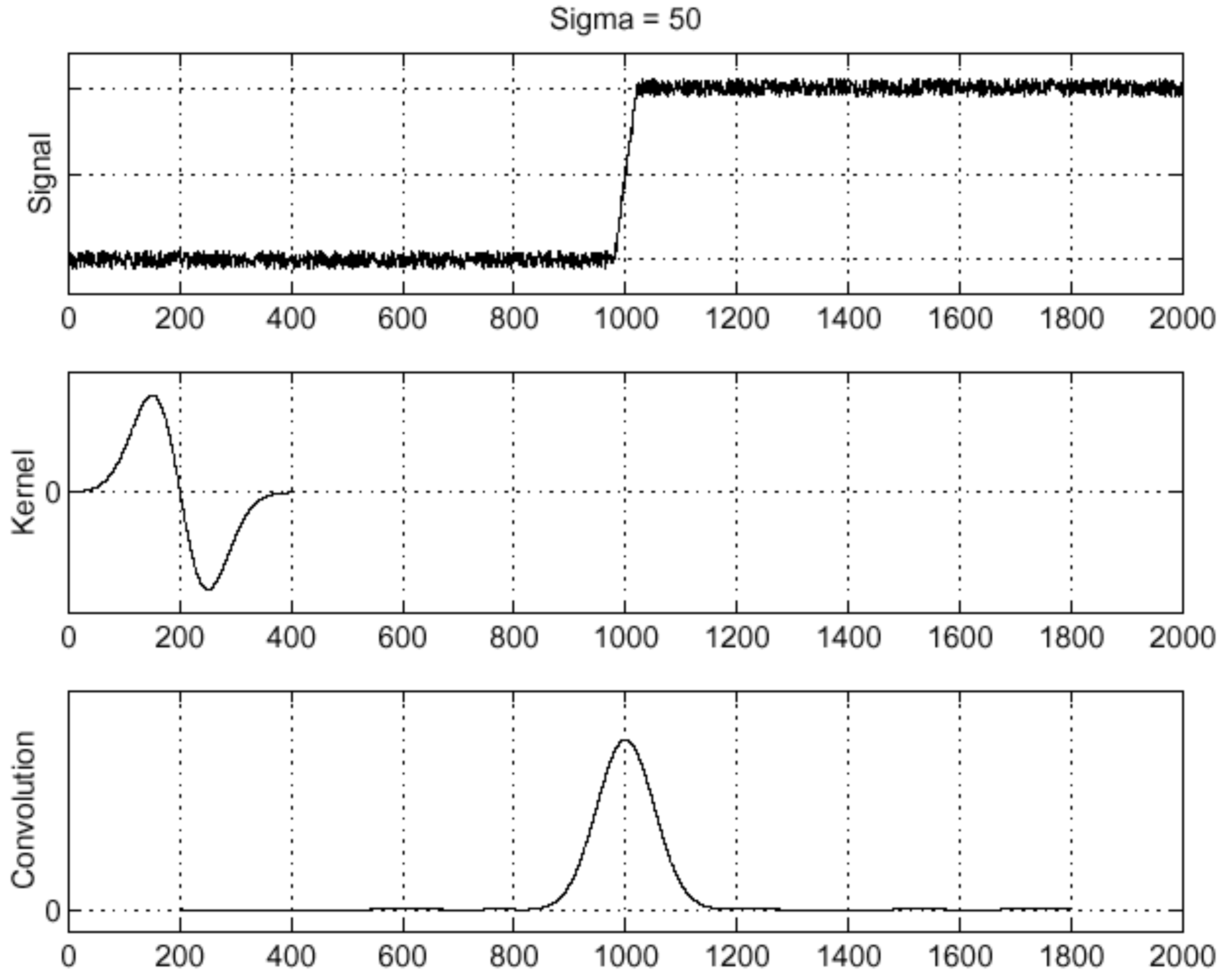
1D **Example**: Smoothing + Derivative (efficient)

Lets consider a row of pixels in an image:

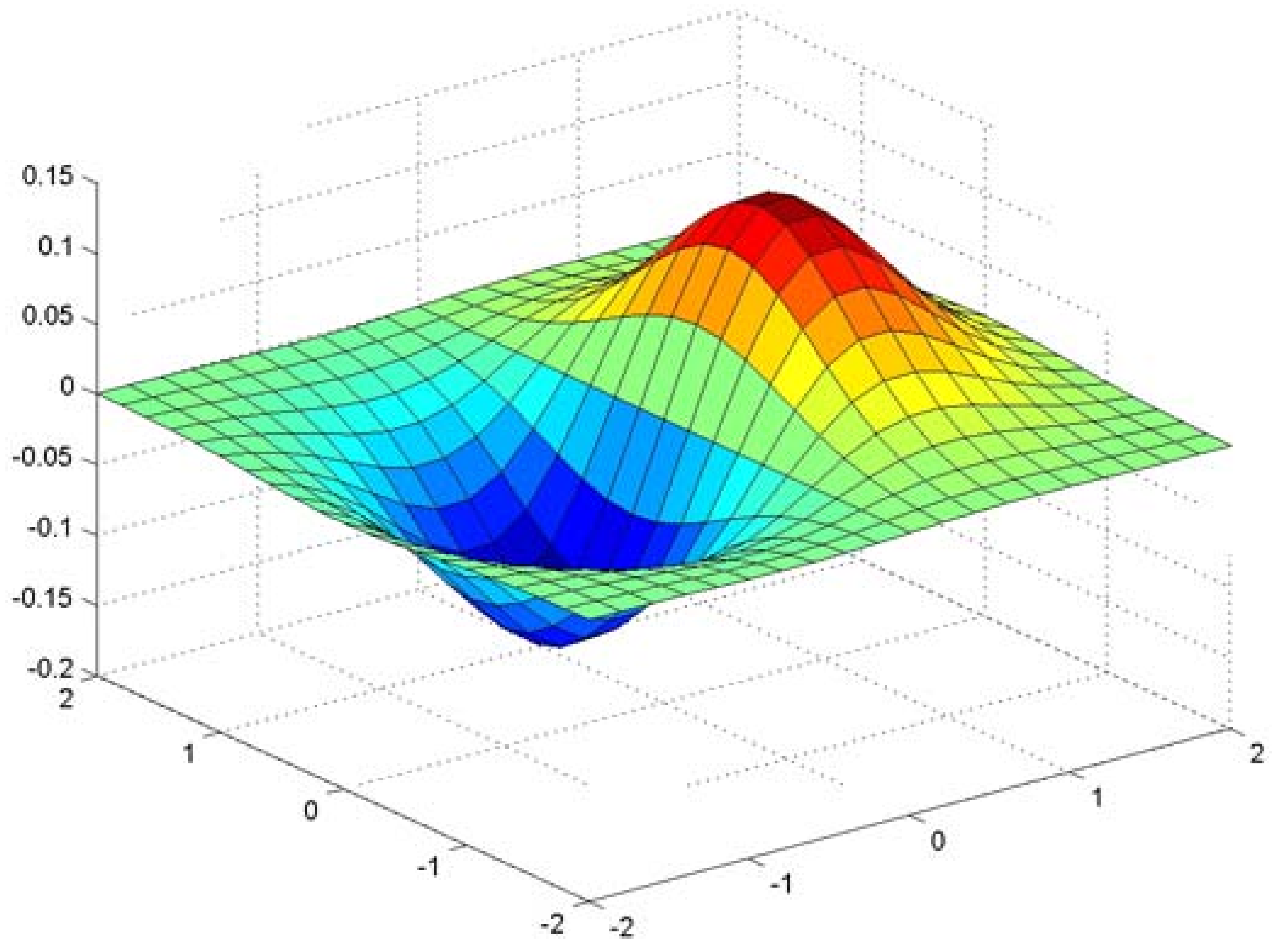
$$I(X, 245)$$

$$\frac{\partial G}{\partial x}$$

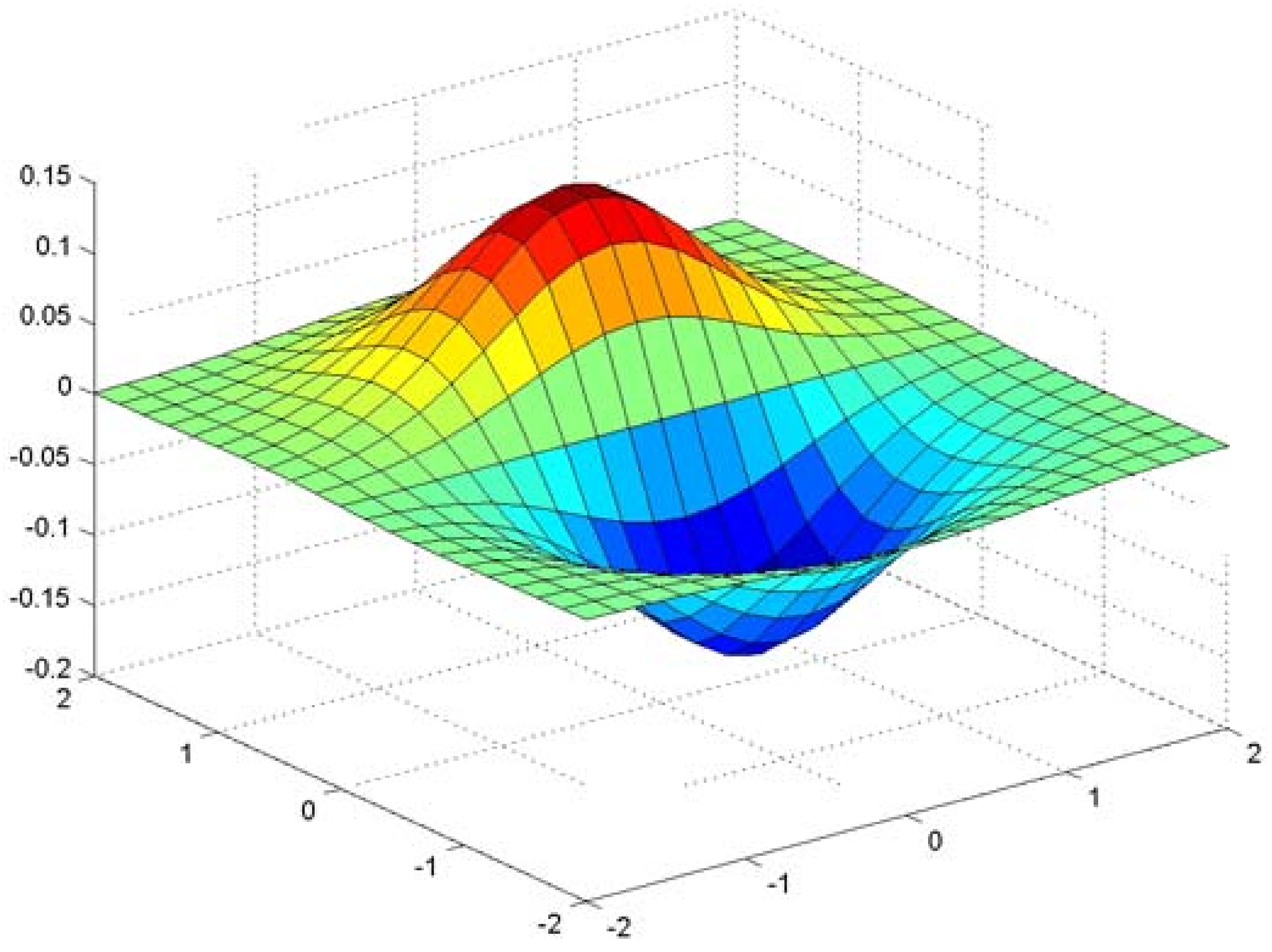
$$\frac{\partial G}{\partial x} \otimes I(X, Y)$$



Partial **Derivatives** of **Gaussian**



$$\frac{\partial}{\partial x} G_\sigma$$



$$\frac{\partial}{\partial y} G_\sigma$$

Slide Credit: Christopher Rasmussen

Gradient **Magnitude**

Let $I(X, Y)$ be a (digital) image

Let $I_x(X, Y)$ and $I_y(X, Y)$ be estimates of the partial derivatives in the x and y directions, respectively.

Call these estimates I_x and I_y (for short) The vector $[I_x, I_y]$ is the **gradient**

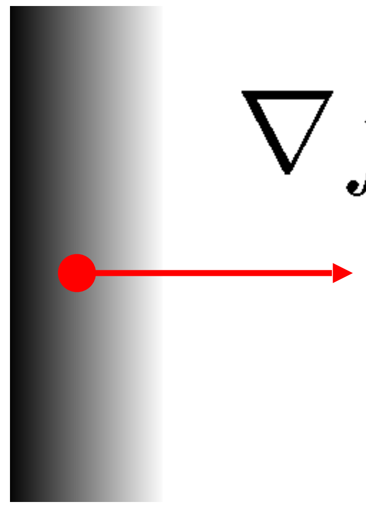
The scalar $\sqrt{I_x^2 + I_y^2}$ is the **gradient magnitude**

Image **Gradient**

The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

Image **Gradient**

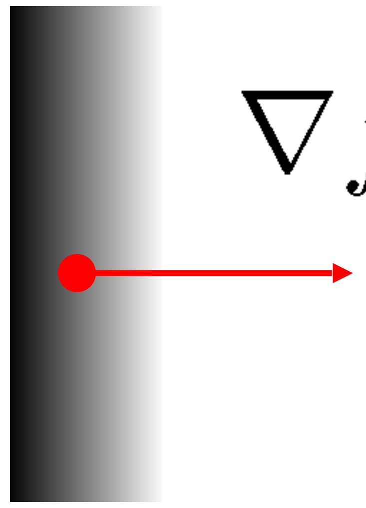
The gradient of an image: $$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$



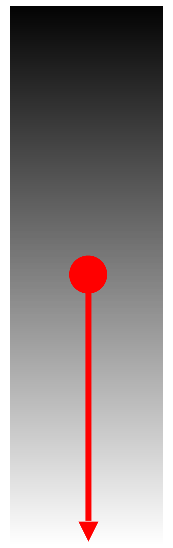
$$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$$

Image **Gradient**

The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$



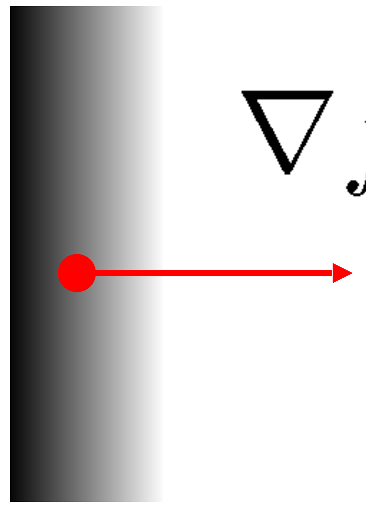
$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$



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

Image **Gradient**

The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$



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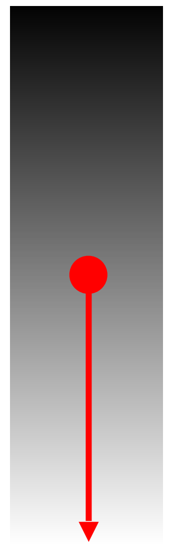
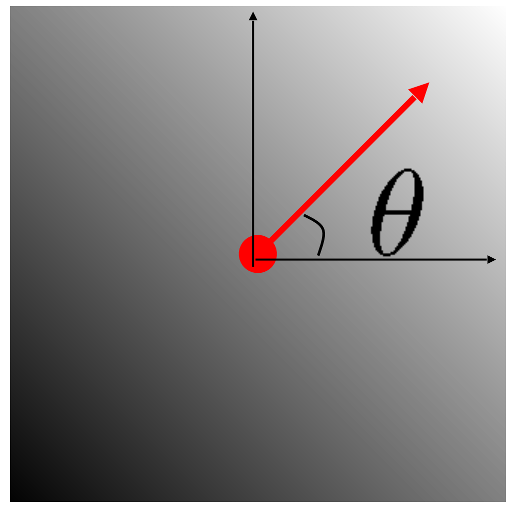


$\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$

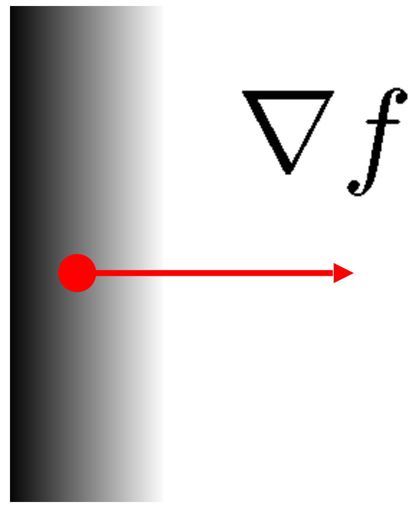


$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

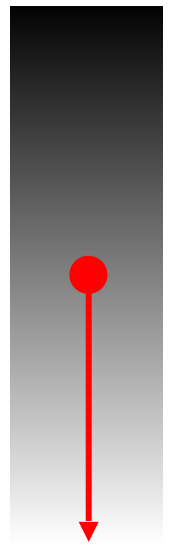
The gradient points in the direction of most rapid **increase of intensity**:

Image **Gradient**

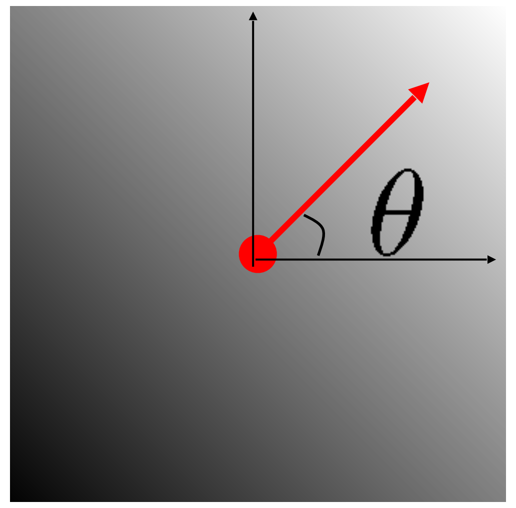
The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$



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



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



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

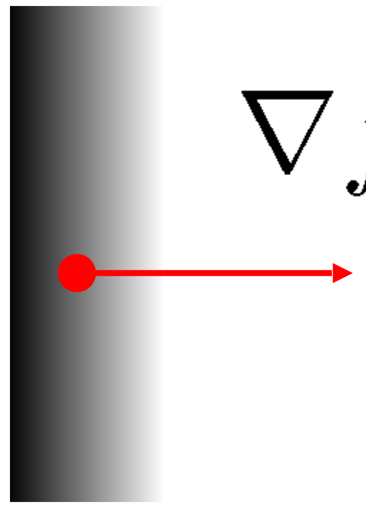
The gradient points in the direction of most rapid **increase of intensity**:

The **gradient direction** is given by:

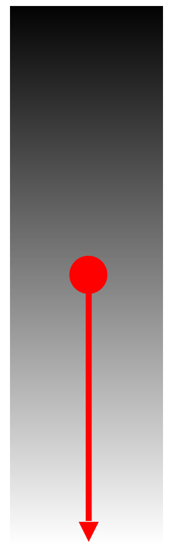
(how is this related to the direction of the edge?)

Image **Gradient**

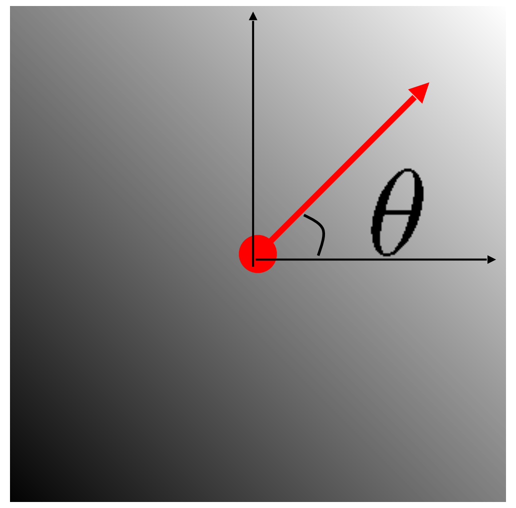
The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$



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



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



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

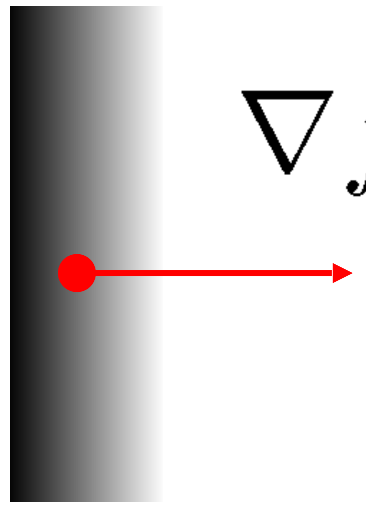
The gradient points in the direction of most rapid **increase of intensity**:

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

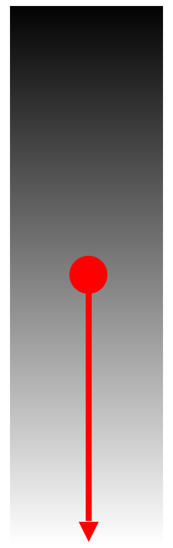
(how is this related to the direction of the edge?)

Image **Gradient**

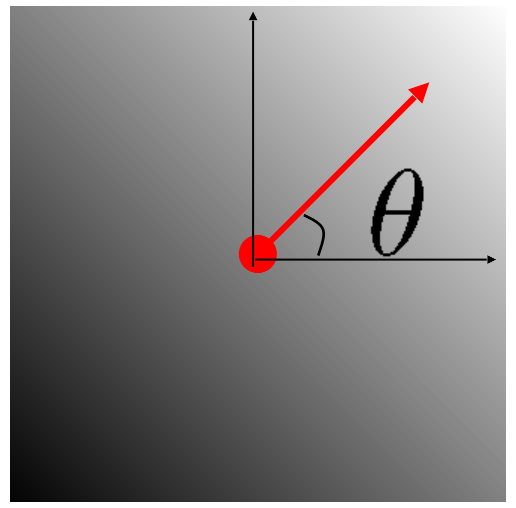
The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$



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



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



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

The gradient points in the direction of most rapid **increase of intensity**:

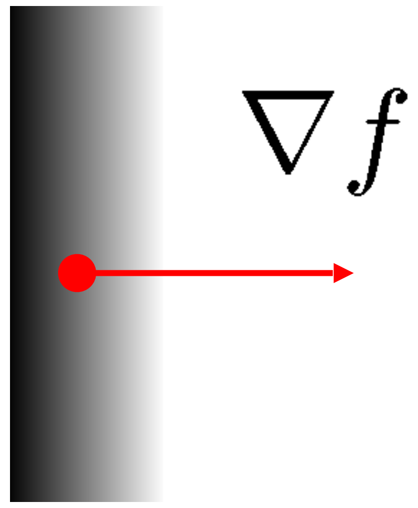
The **gradient direction** is given by:

(how is this related to the direction of the edge?)

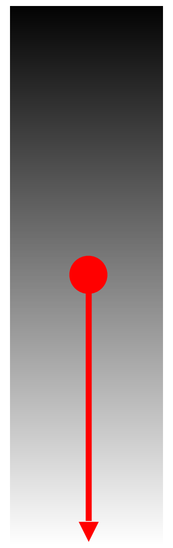
The edge strength is given by the **gradient magnitude**:

Image **Gradient**

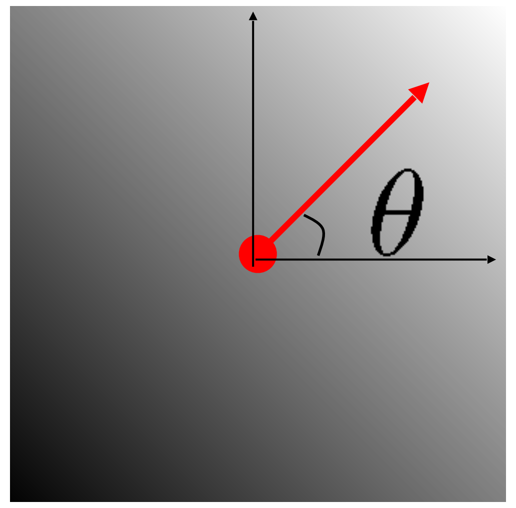
The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$



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



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



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

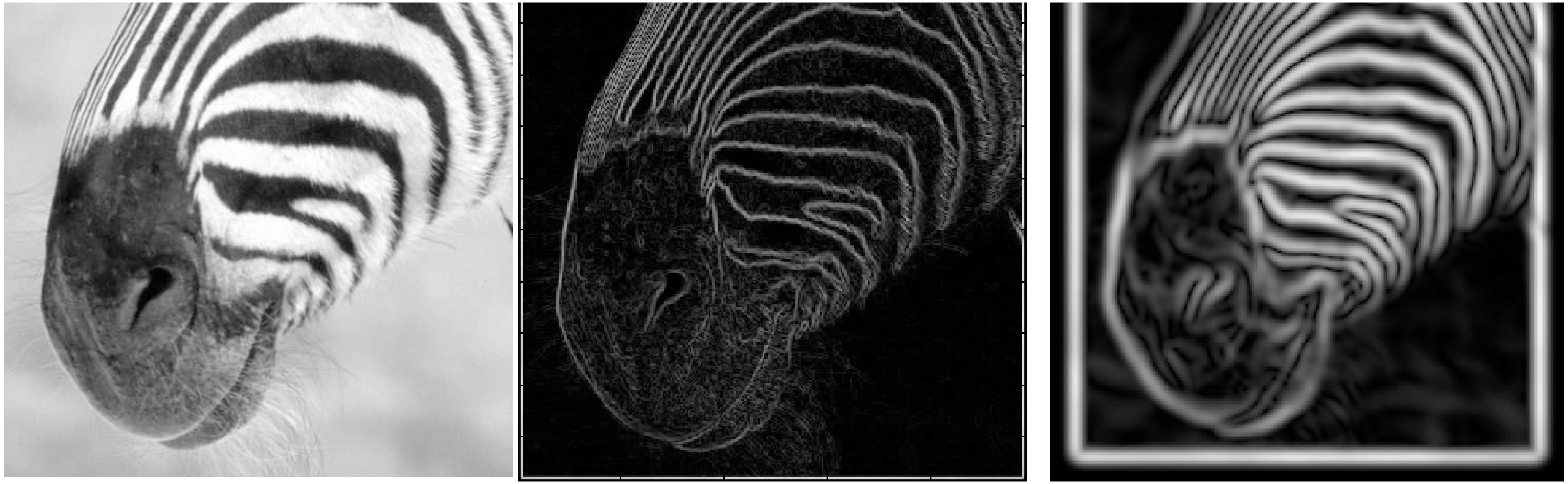
The gradient points in the direction of most rapid **increase of intensity**:

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

(how is this related to the direction of the edge?)

The edge strength is given by the **gradient magnitude**: $\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$

Gradient **Magnitude**



$\sigma = 1$ $\sigma = 2$

Forsyth & Ponce (2nd ed.) Figure 5.4

Increased **smoothing**:

— eliminates noise edges

— makes edges smoother and thicker

— removes fine detail

Sobel Edge Detector

1. Use **central differencing** to compute gradient image (instead of first forward differencing). This is more accurate.

2. **Threshold** to obtain edges

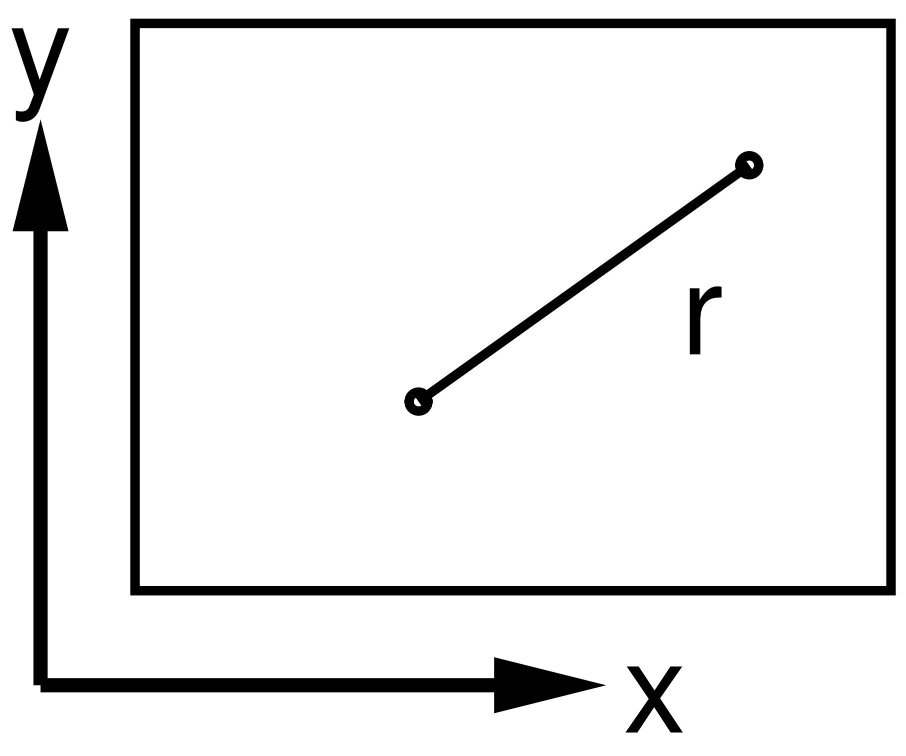
Original Image

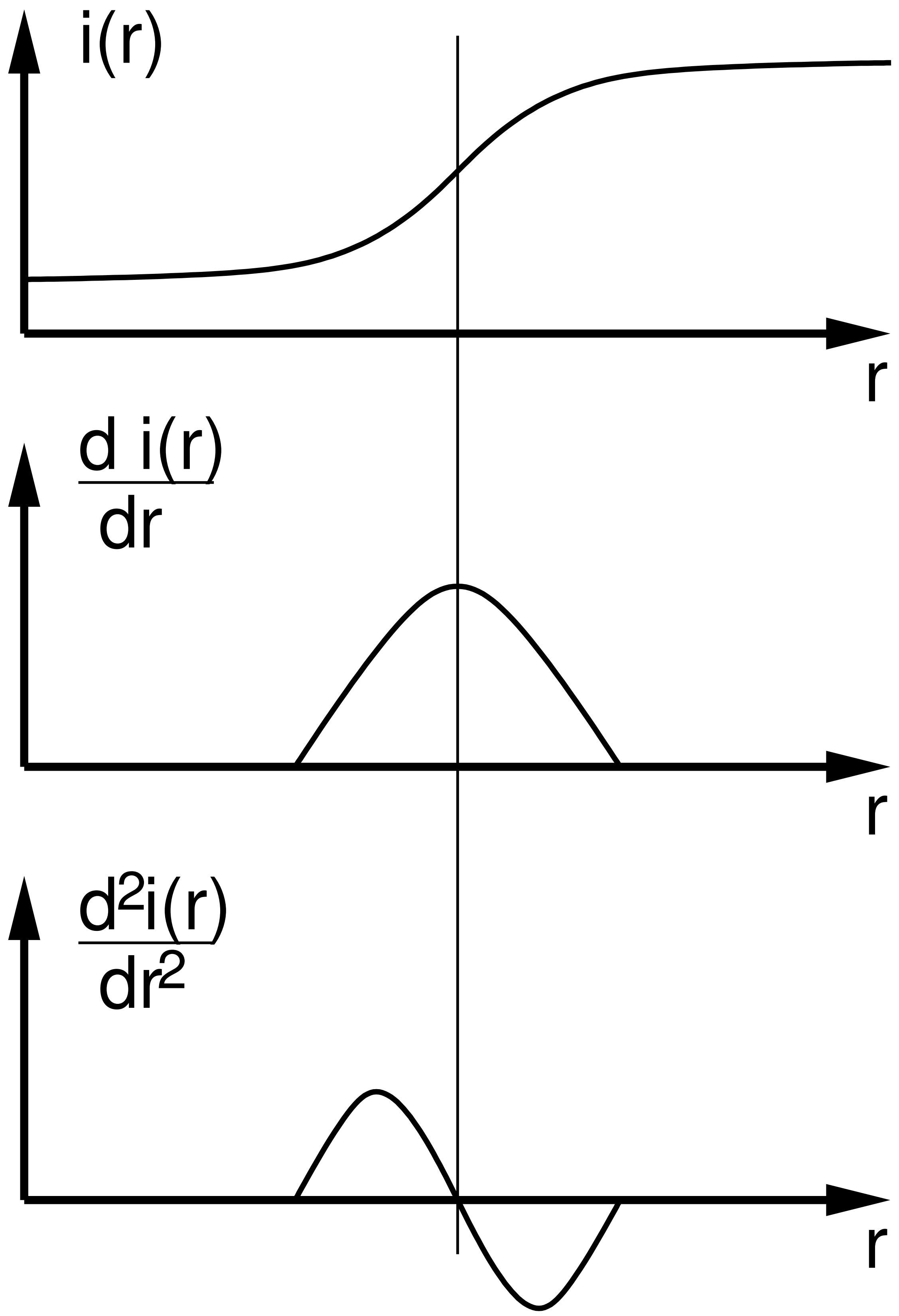
Sobel Gradient

Sobel Edges

Thresholds are brittle, we can do better!

Two Generic Approaches for **Edge** Detection





Two generic approaches to **edge point detection**:

— (significant) local extrema of a first derivative operator

— zero crossings of a second derivative operator

Marr / Hildreth **Laplacian of Gaussian**

A "**zero crossings** of a second derivative operator" approach

Design Criteria:

1. localization in space

2. localization in frequency

3. rotationally invariant

Marr / Hildreth **Laplacian of Gaussian**

A "**zero crossings** of a second derivative operator" approach

Steps:

1. Gaussian for smoothing

2. Laplacian (∇^2) for differentiation where

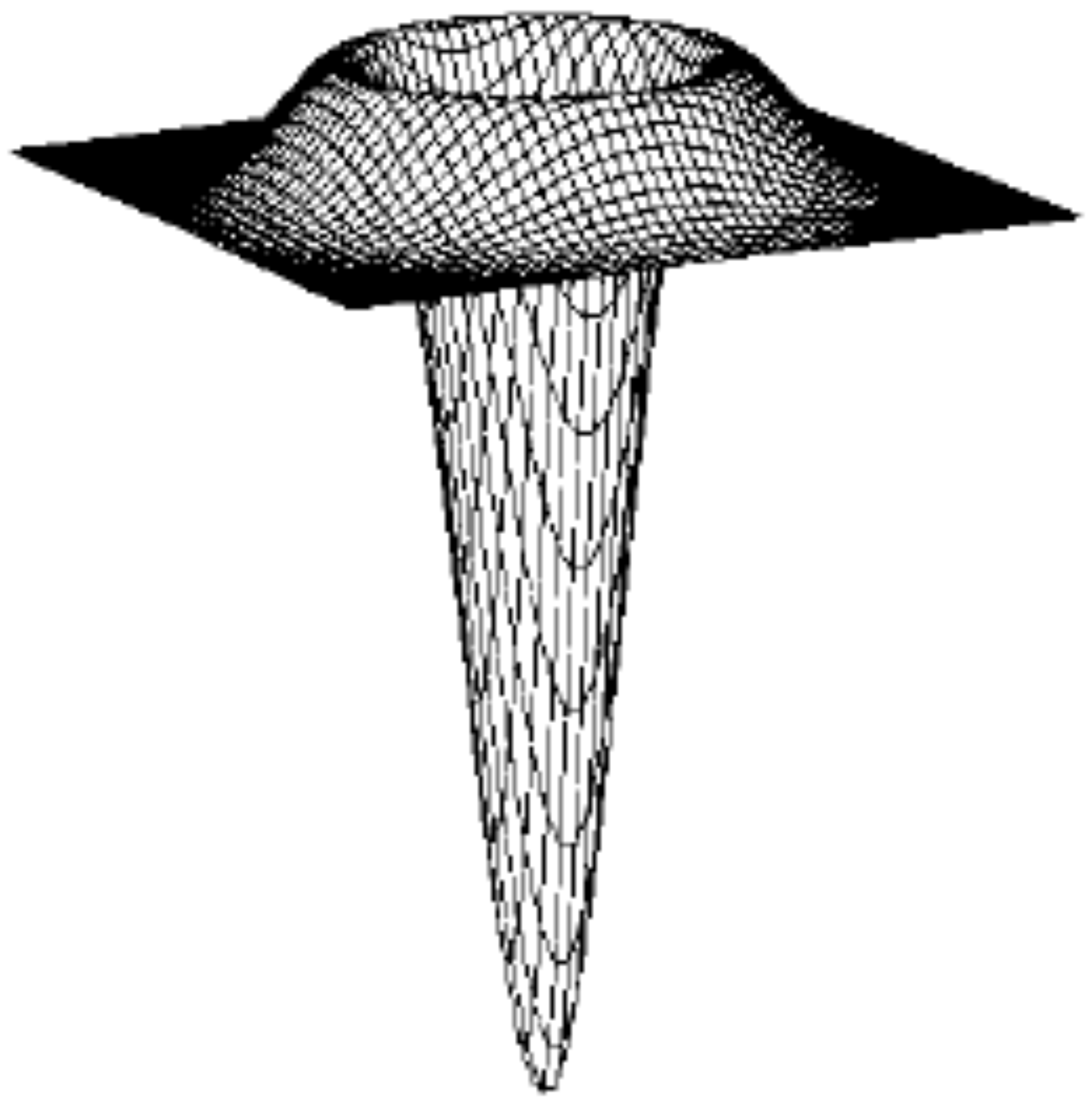
$$\nabla^2 f(x,y) = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2}$$

3. Locate zero-crossings in the Laplacian of the Gaussian ($\nabla^2 G$) where

$$\nabla^2 G(x,y) = \frac{-1}{2\pi\sigma^4}\left[2 - \frac{x^2+y^2}{\sigma^2}\right]\exp^{-\frac{x^2+y^2}{2\sigma^2}}$$

Marr / Hildreth **Laplacian of Gaussian**

Here's a 3D plot of the Laplacian of the Gaussian ($\nabla^2 G$)



. . . with its characteristic "Mexican hat" shape

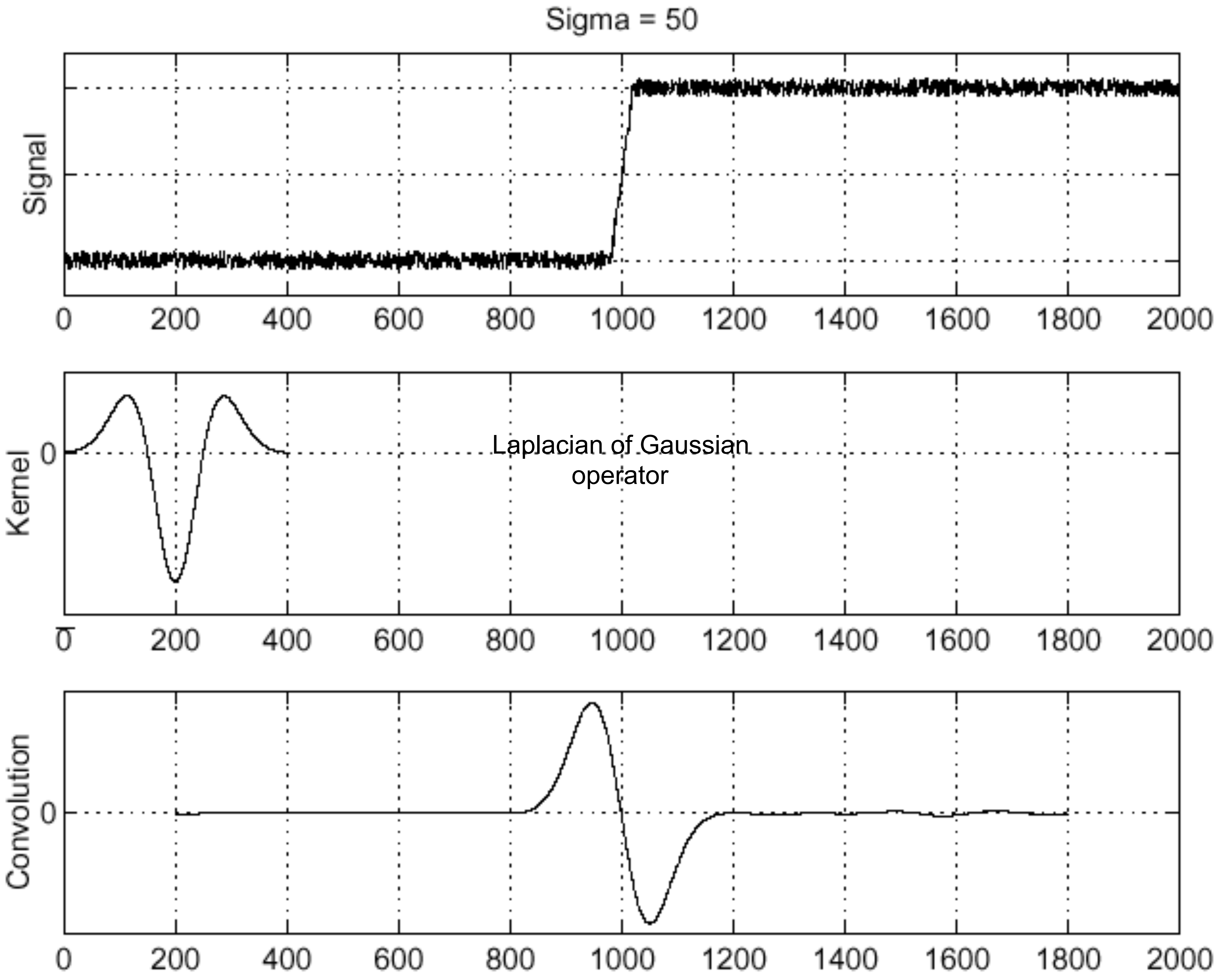
1D **Example**: Continued

Lets consider a row of pixels in an image:

$$I(X, 245)$$

$$\nabla^2 G$$

$$\nabla^2 G \otimes I(X, Y)$$



Where is the edge?

Zero-crossings of bottom graph

Marr / Hildreth **Laplacian of Gaussian**

5 x 5 LoG filter

0	0	-1	0	0
0	-1	-2	-1	0
-1	-2	16	-2	-1
0	-1	-2	-1	0
0	0	-1	0	0

17 x 17 LoG filter

0	0	0	0	0	0	-1	-1	**-1**	-1	-1	0	0	0	0	0
0	0	0	0	-1	-1	-1	-1	**-1**	-1	-1	-1	-1	0	0	0
0	0	-1	-1	-1	-2	-3	-3	**-3**	-3	-3	-2	-1	-1	-1	0
0	0	-1	-1	-2	-3	-3	-3	**-3**	-3	-3	-3	-2	-1	-1	0
0	-1	-1	-2	-3	-3	-3	-2	**-3**	-2	-3	-3	-3	-2	-1	-1
0	-1	-2	-3	-3	-3	0	2	**4**	2	0	-3	-3	-3	-2	-1
-1	-1	-3	-3	-3	0	4	10	**12**	10	4	0	-3	-3	-3	-1
-1	-1	-3	-3	-2	2	10	18	**21**	18	10	2	-2	-3	-3	-1
-1	**-1**	**-3**	**-3**	**-3**	**4**	**12**	**21**	**24**	**21**	**12**	**4**	**-3**	**-3**	**-3**	**-1**
-1	-1	-3	-3	-2	2	10	18	**21**	18	10	2	-2	-3	-3	-1
-1	-1	-3	-3	-3	0	4	10	**12**	10	4	0	-3	-3	-3	-1
0	-1	-2	-3	-3	-3	0	2	**4**	2	0	-3	-3	-3	-2	-1
0	-1	-1	-2	-3	-3	-3	-2	**-3**	-2	-3	-3	-3	-2	-1	-1
0	-1	-1	-2	-3	-3	-3	-2	**-3**	-2	-3	-3	-3	-2	-1	-1
0	0	-1	-1	-1	-2	-3	-3	**-3**	-3	-3	-2	-1	-1	-1	0
0	0	0	0	-1	-1	-1	-1	**-1**	-1	-1	-1	-1	0	0	0

Scale (σ)

Image From: A. Campilho

Marr / Hildreth **Laplacian of Gaussian**

Image From: A. Campilho

Assignment 1: High Frequency Image

original

-

smoothed
(5x5 Gaussian)

=

original - smoothed
(scaled by 4, offset +128)

Assignment 1: High Frequency Image

original

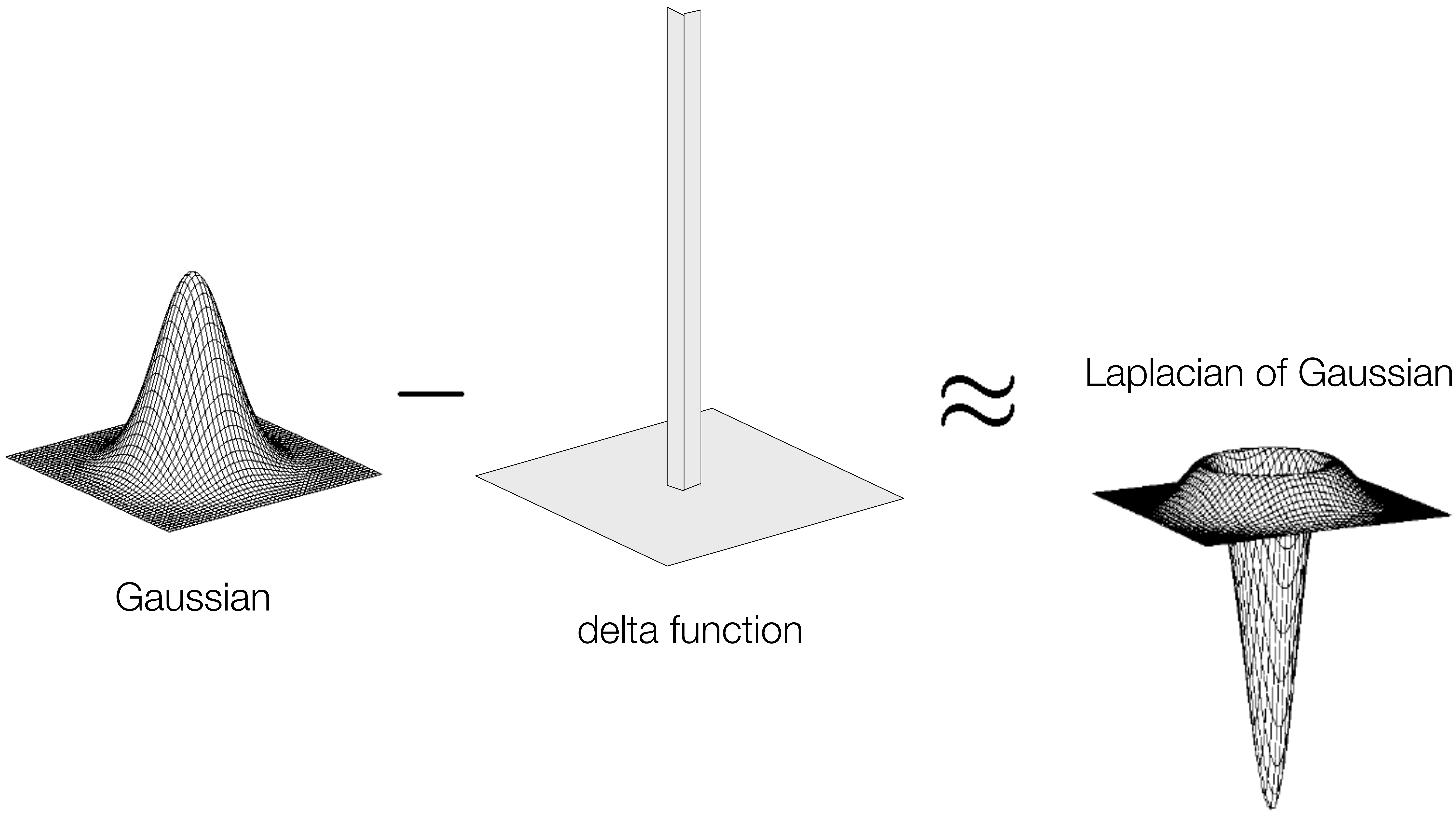
-

smoothed
(5x5 Gaussian)

=

smoothed - original
(scaled by 4, offset +128)

Assignment 1: High Frequency Image



Canny Edge Detector

A “**local extrema of a first derivative operator**” approach

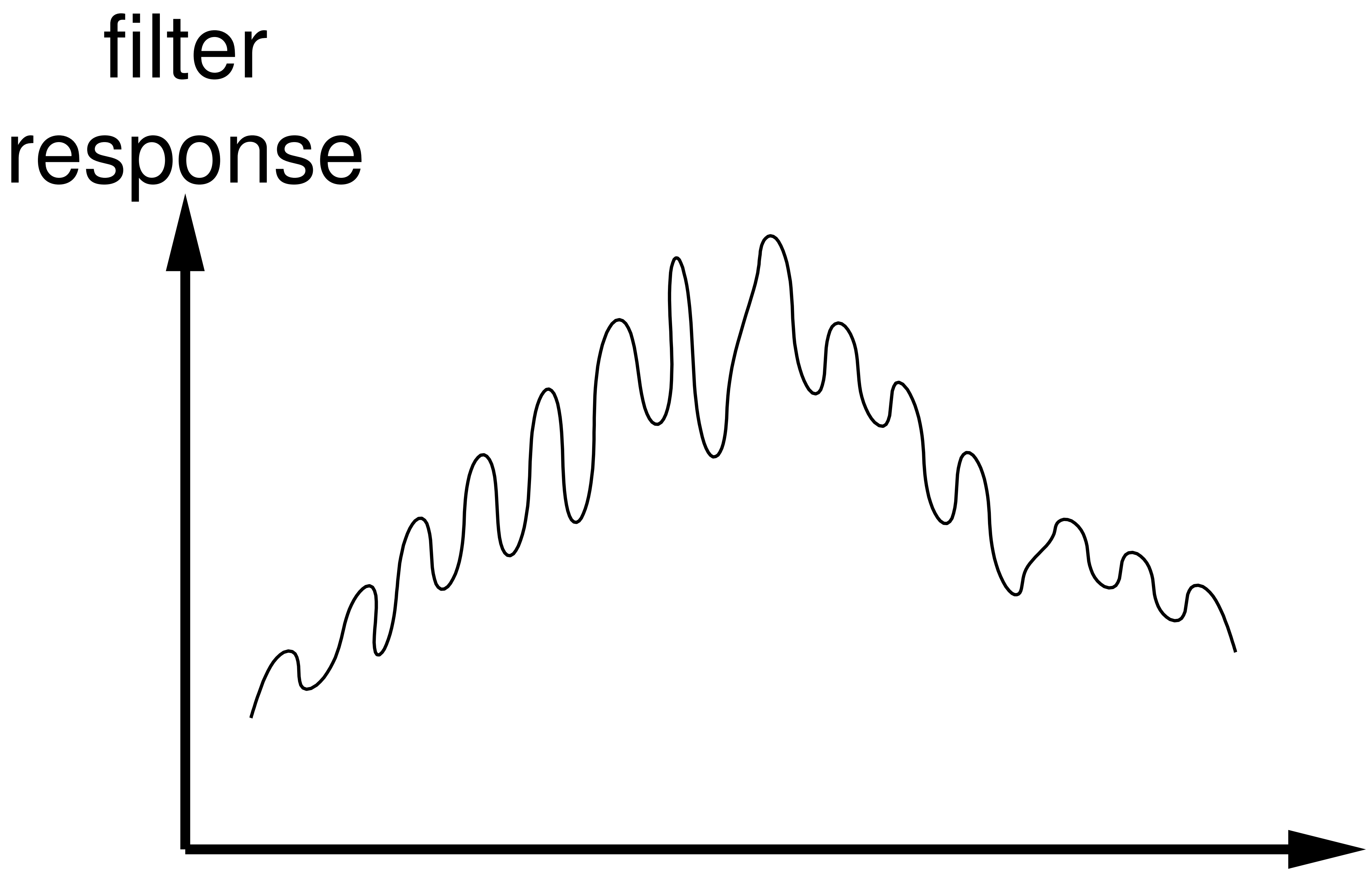
Design Criteria:

1. good detection
   — low error rate for omissions (missed edges)
   — low error rate for commissions (false positive)

2. good localization

3. one (single) response to a given edge
   — (i.e., eliminate multiple responses to a single edge)

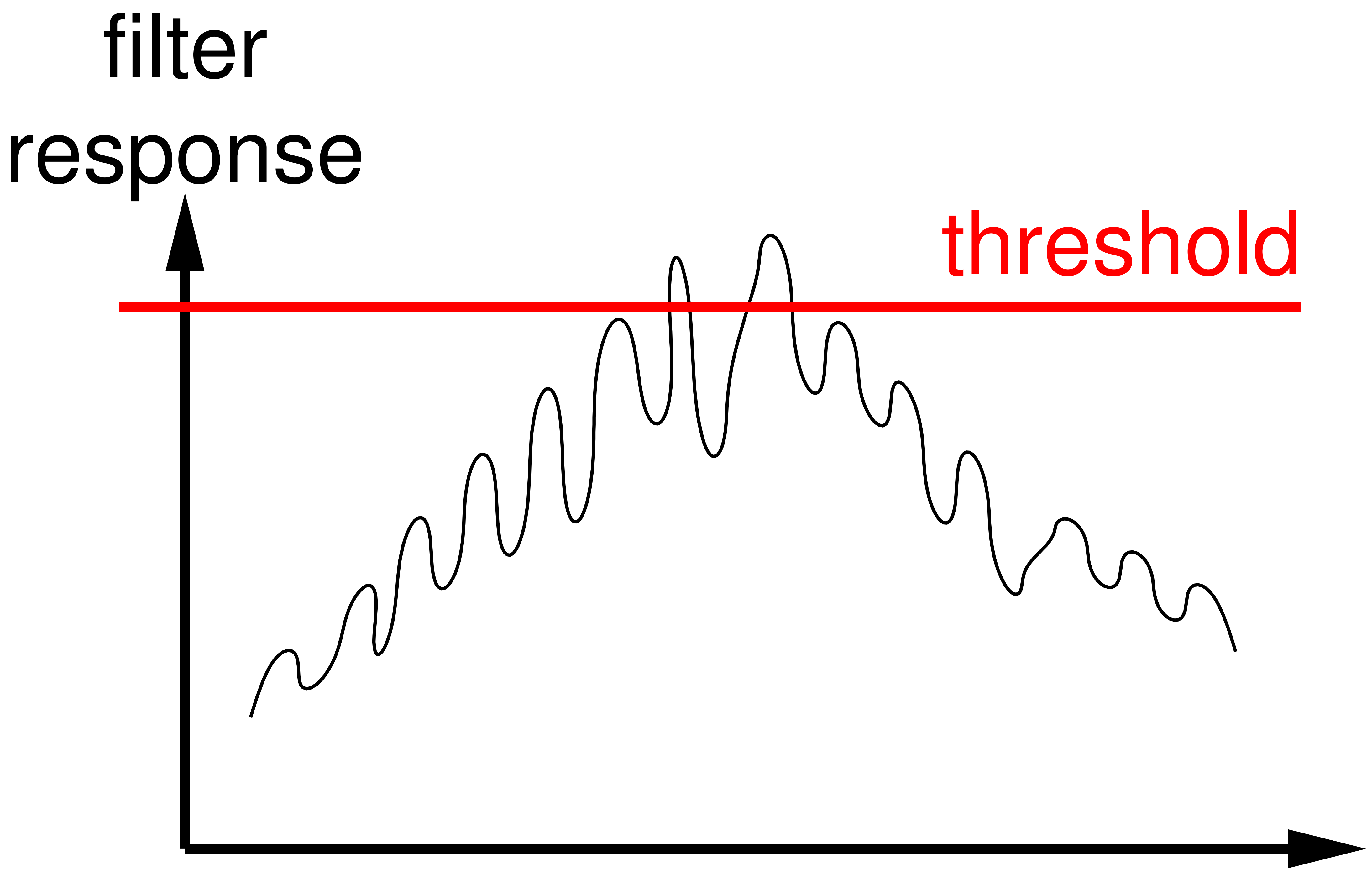
Example: Edge Detection



Question: How many edges are there?

Question: What is the position of each edge?

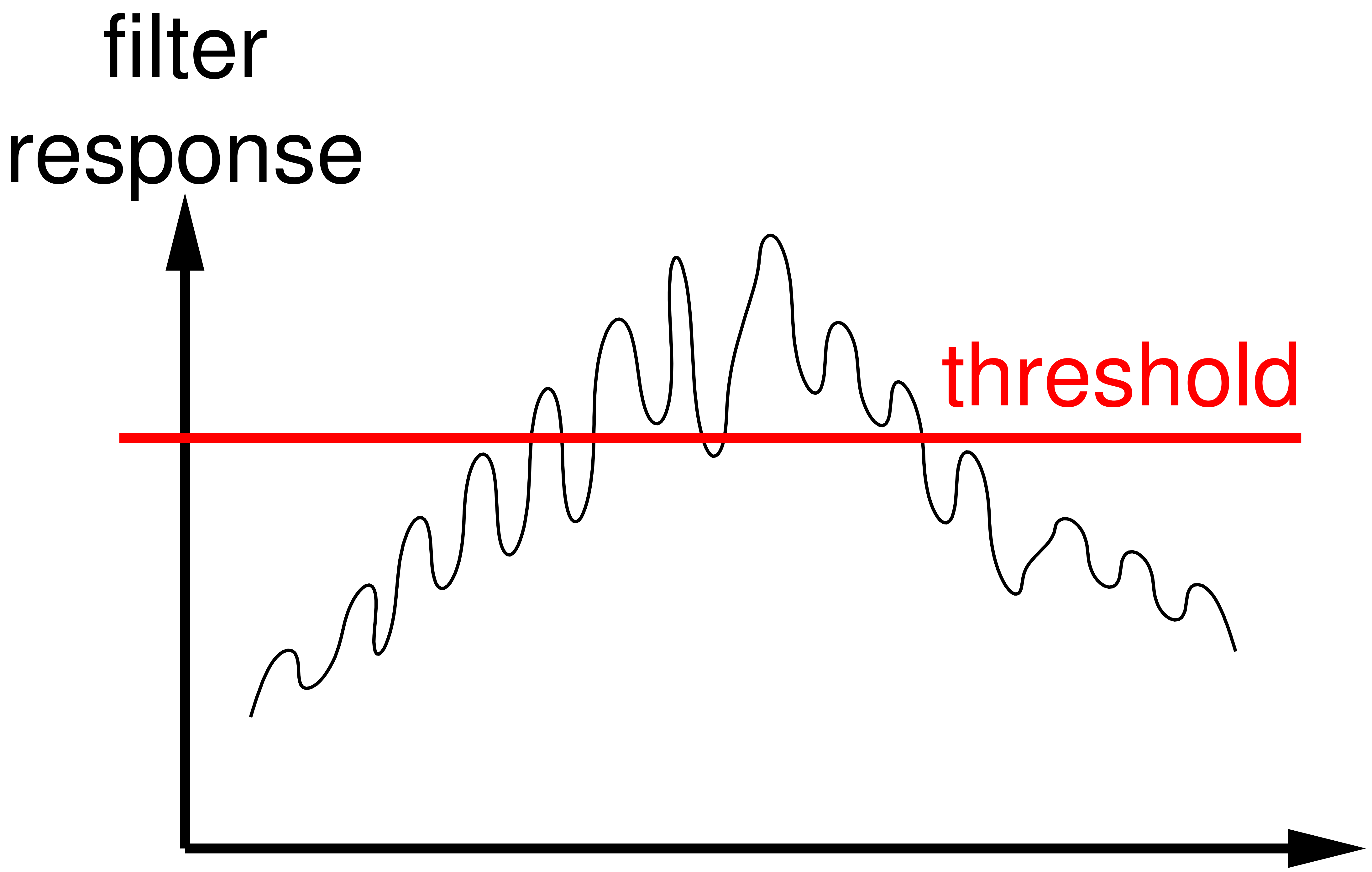
Example: Edge Detection



Question: How many edges are there?

Question: What is the position of each edge?

Example: Edge Detection



Question: How many edges are there?

Question: What is the position of each edge?

Canny Edge Detector

Steps:

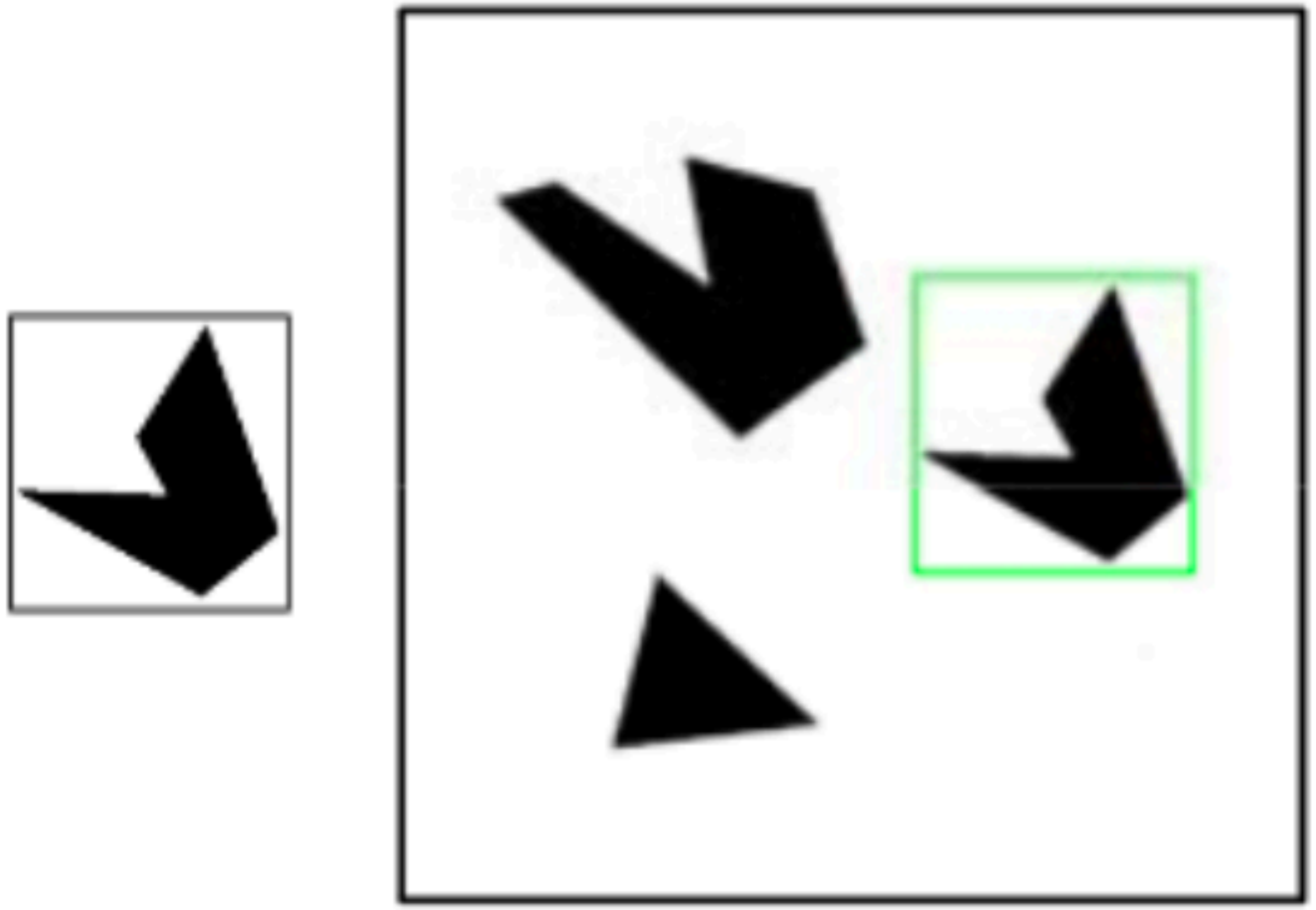
1. Apply **directional derivatives** of Gaussian
2. Compute **gradient magnitude** and **gradient direction**
3. **Non-maximum** suppression
   — thin multi-pixel wide "ridges" down to single pixel width
4. **Linking** and thresholding
   — Low, high edge-strength thresholds
   — Accept all edges over low threshold that are connected to edge over high threshold

Non-maxima Suppression

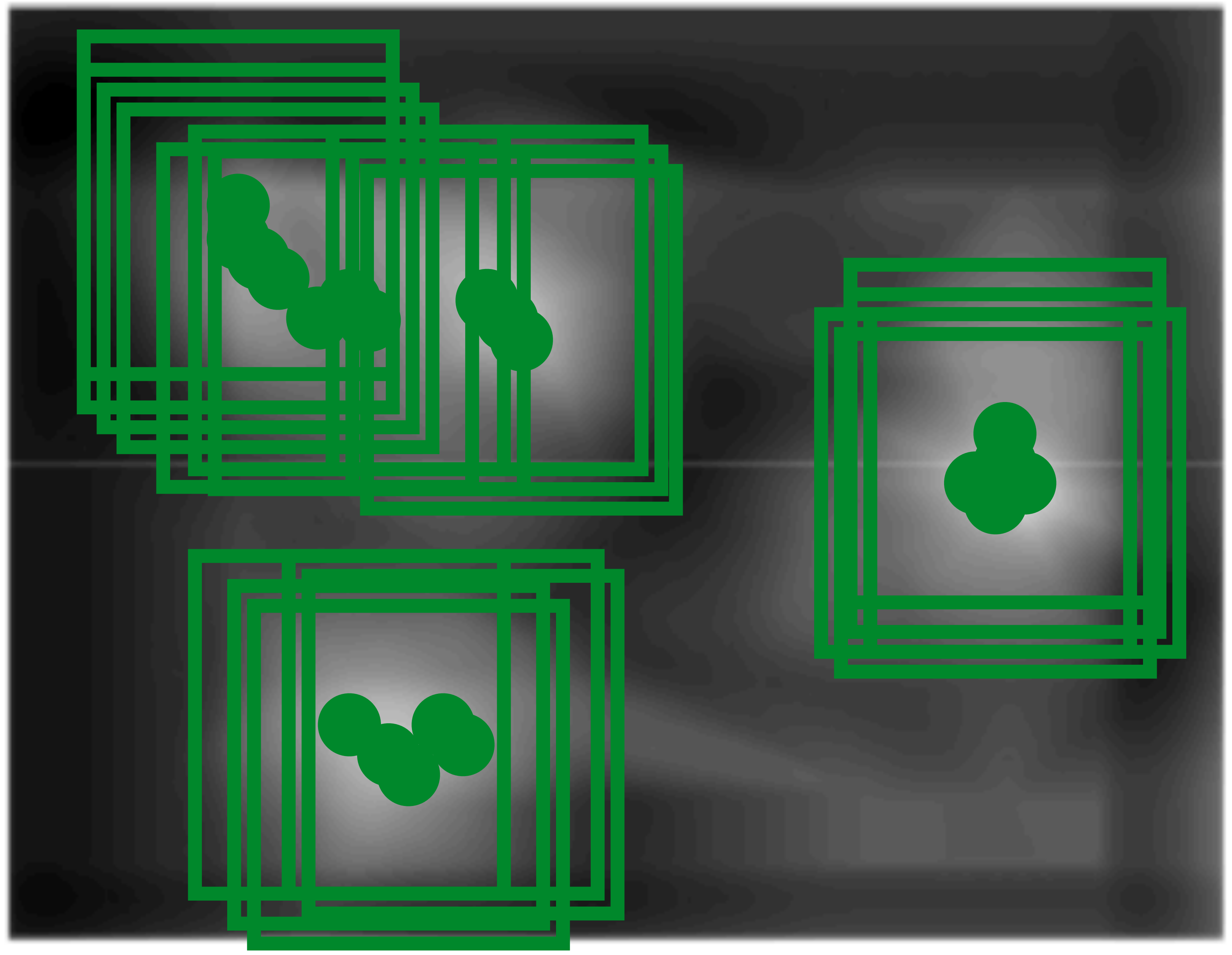
Idea: suppress near-by similar detections to obtain one “true” result

Non-maxima Suppression

Idea: suppress near-by similar detections to obtain one “true” result



Detected template

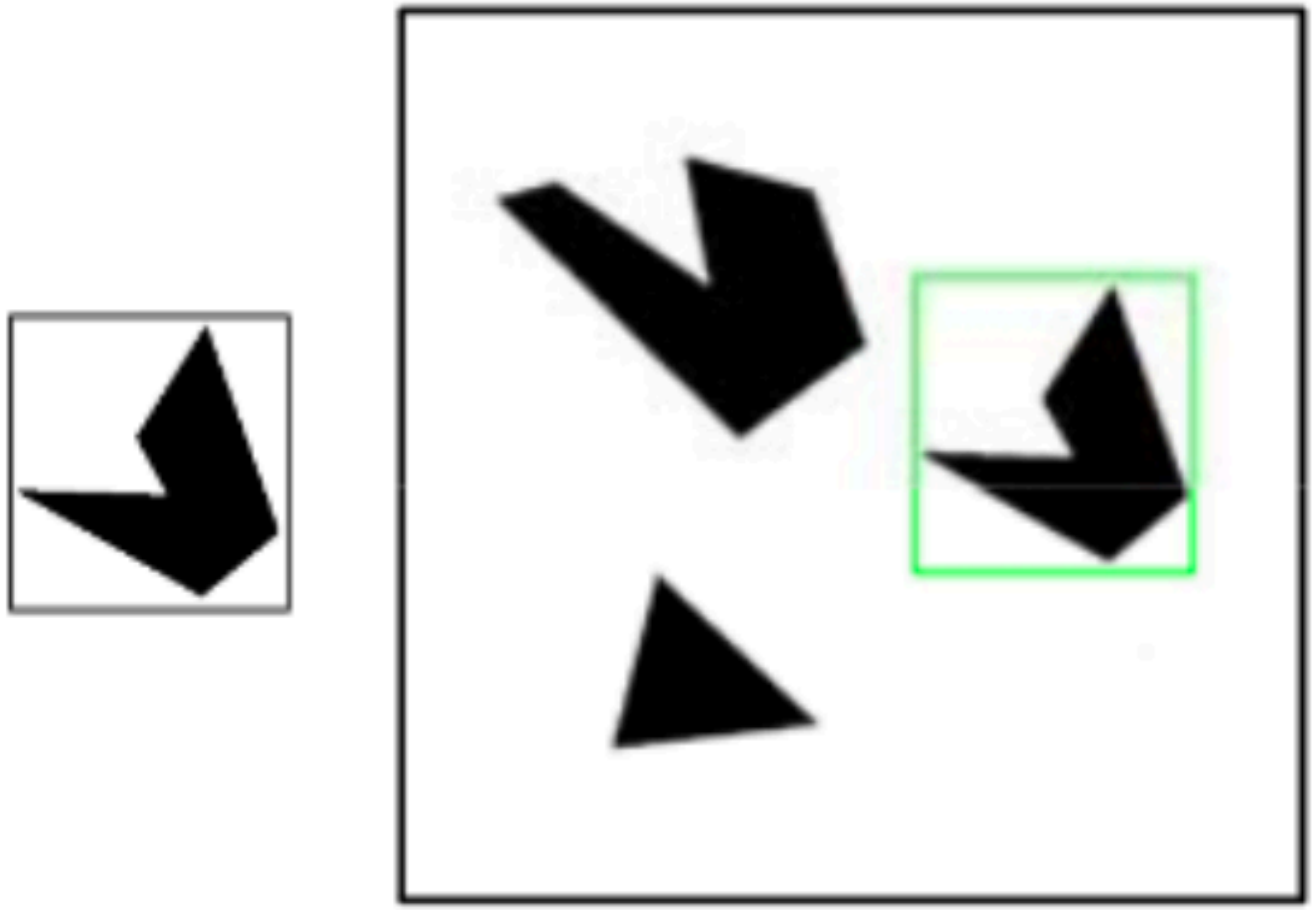


Correlation map

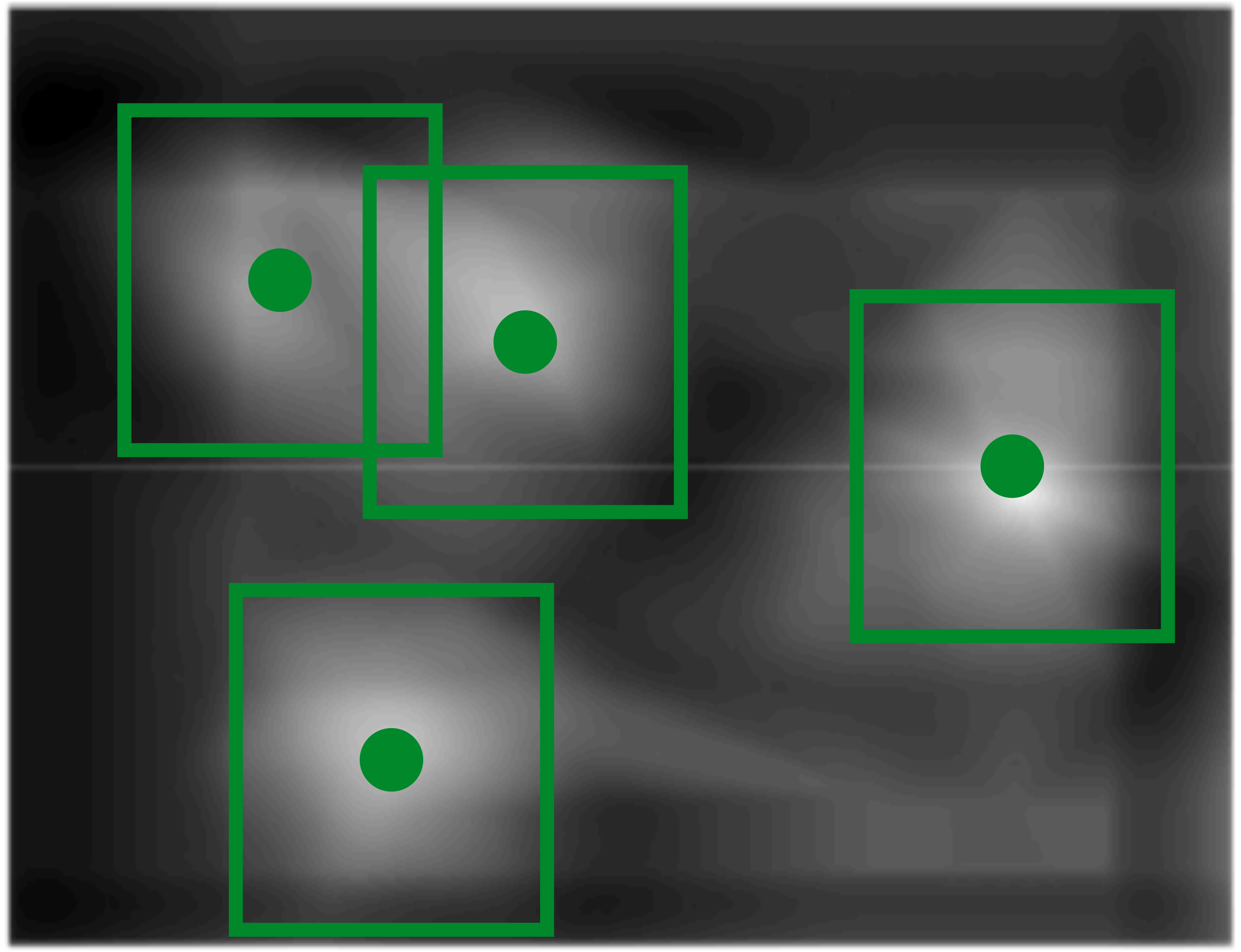
Slide Credit: Kristen Grauman

Non-maxima Suppression

Idea: suppress near-by similar detections to obtain one "true" result



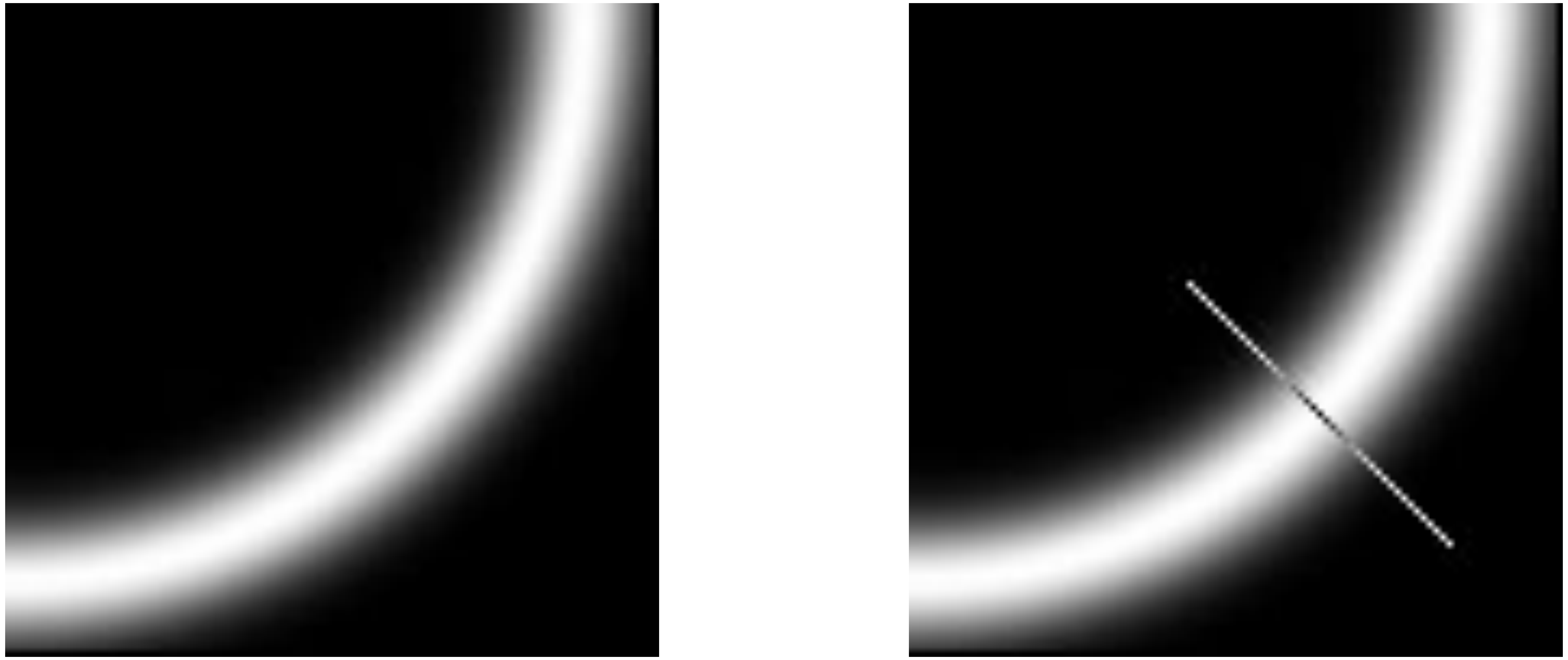
Detected template



Correlation map

Slide Credit: Kristen Grauman

Non-maxima Suppression

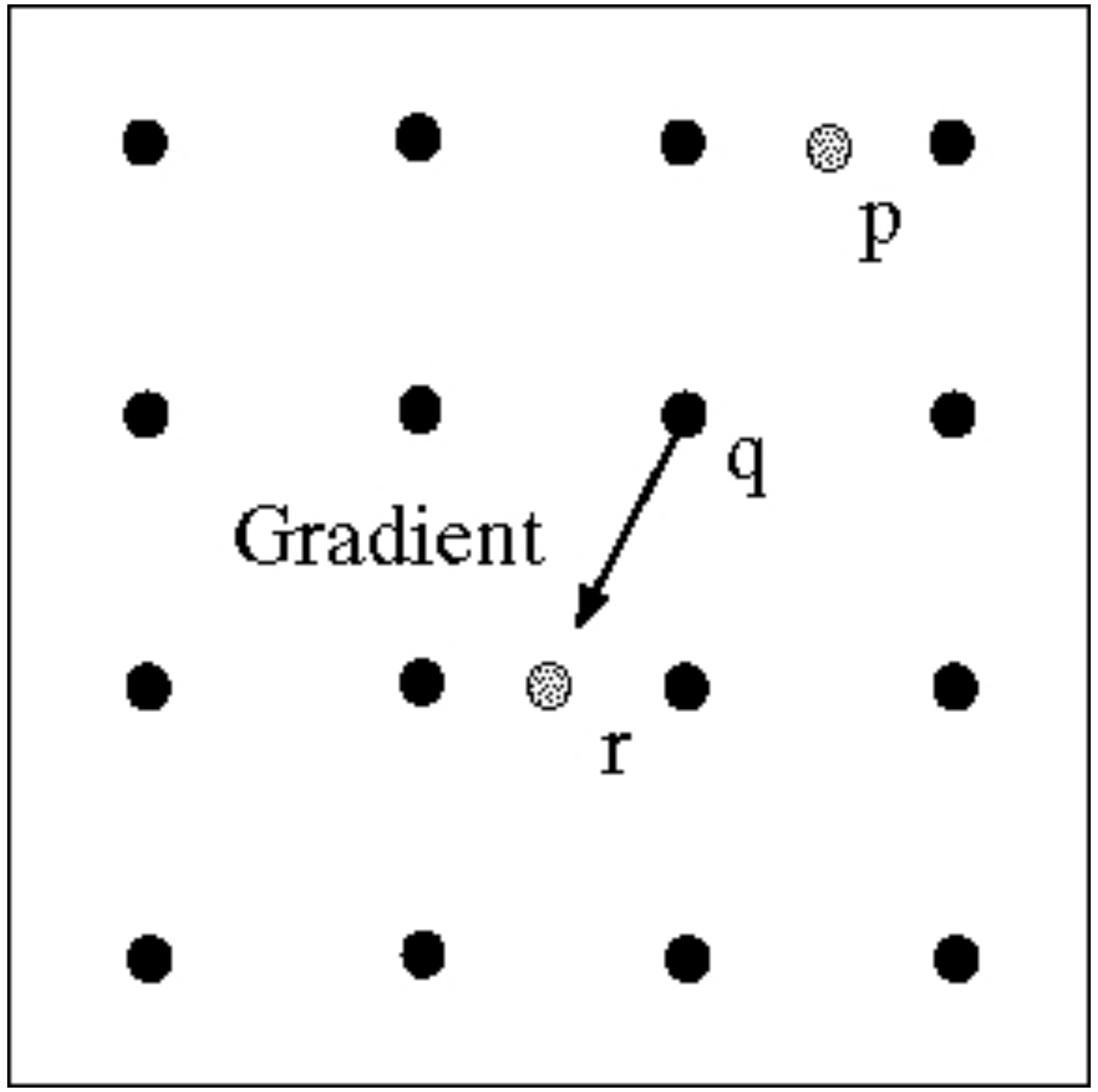


Forsyth & Ponce (1st ed.) Figure 8.11

Select the image **maximum point** across the width of the edge

Non-maxima Suppression

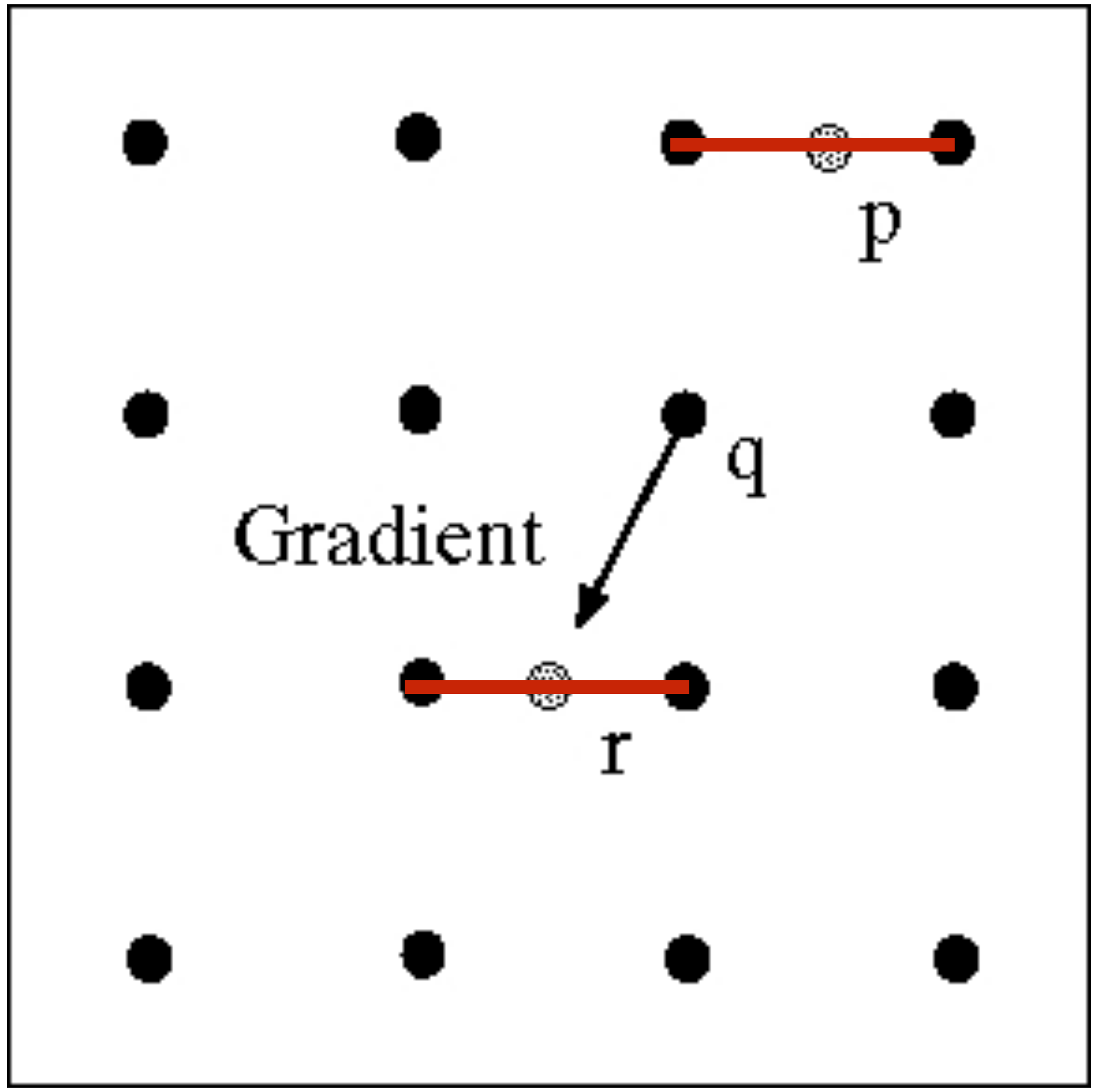
Value at *q* must be larger than interpolated values at *p* and *r*



Forsyth & Ponce (2nd ed.) Figure 5.5 left

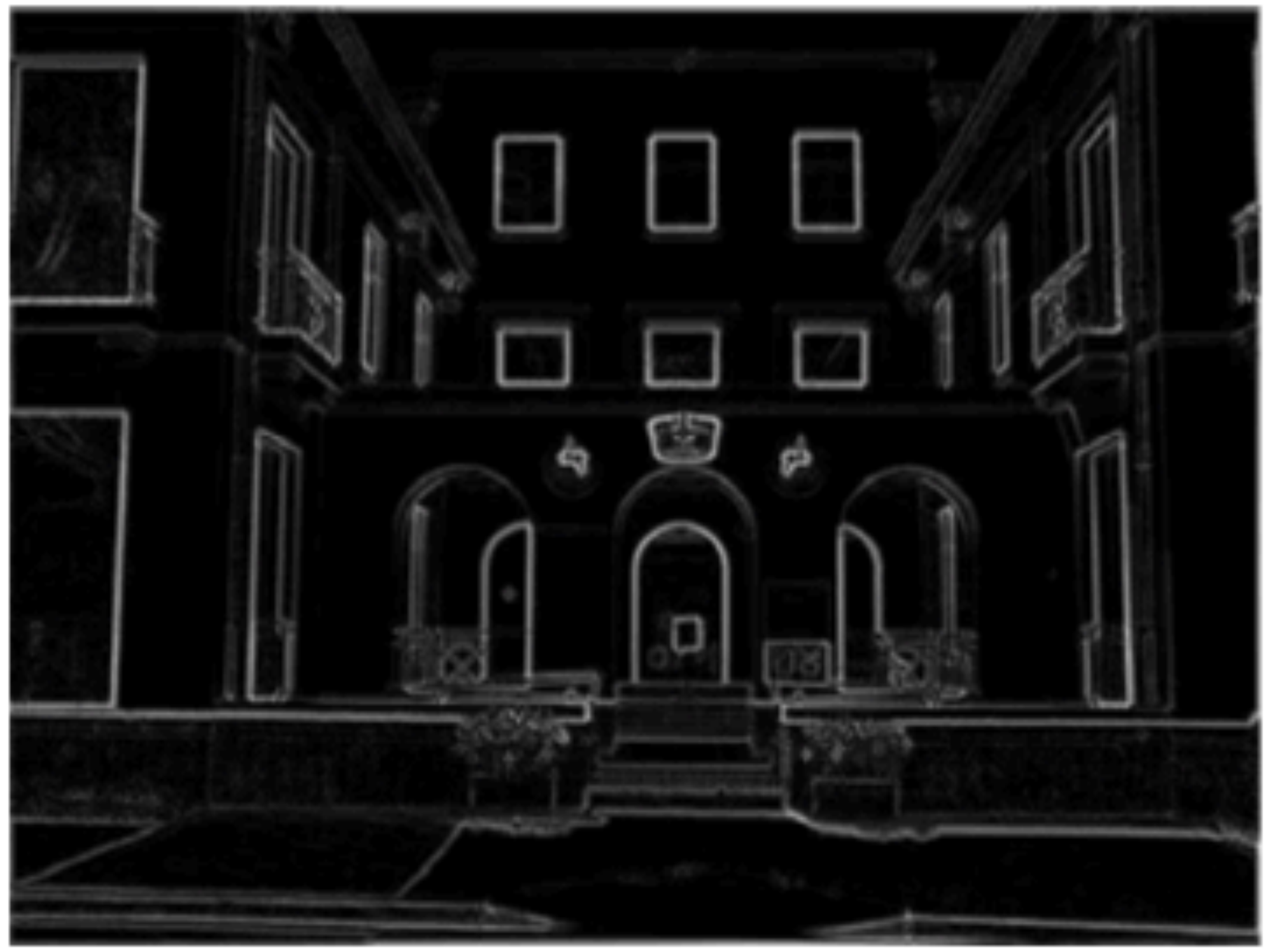
Non-maxima Suppression

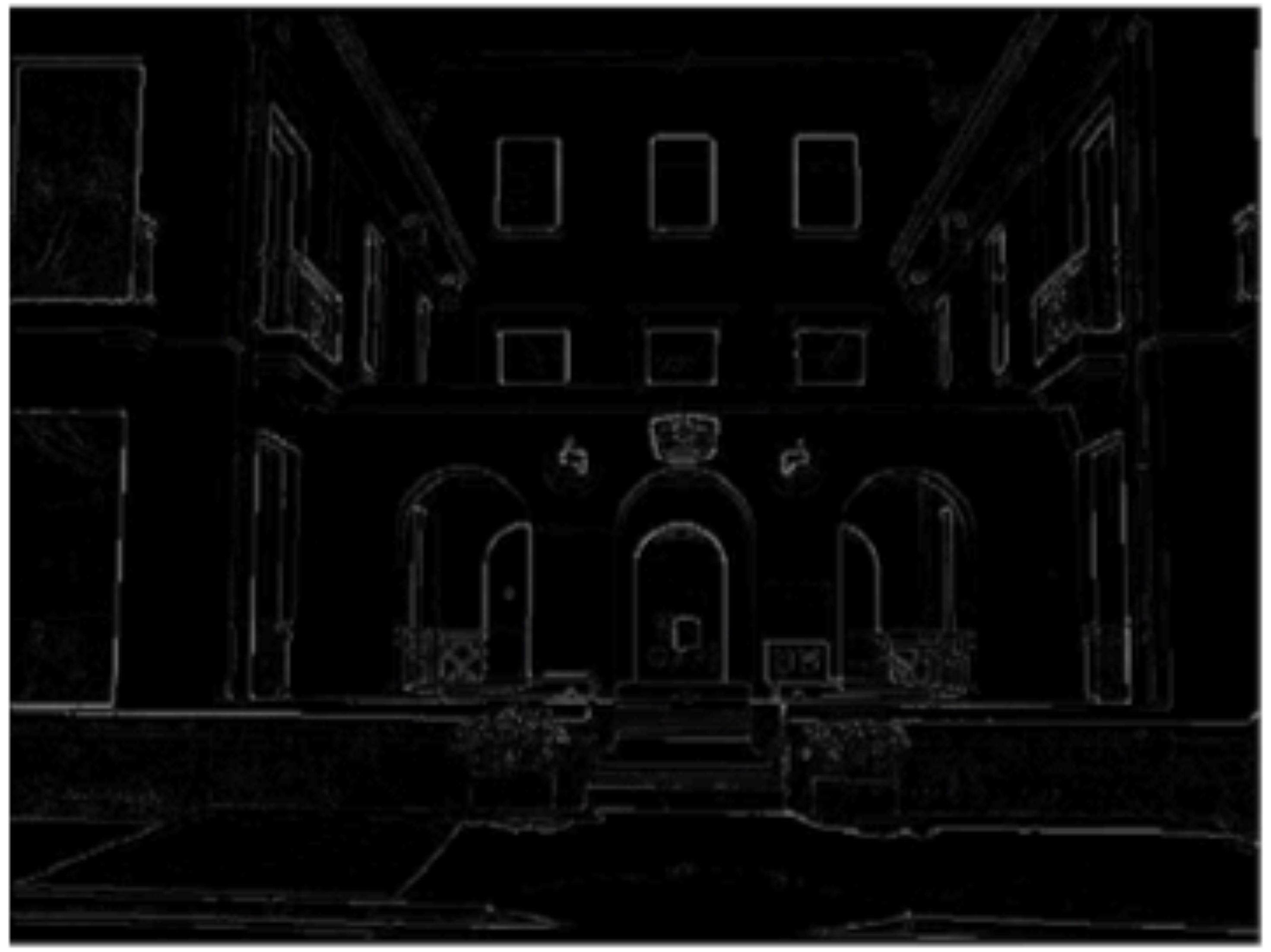
Value at q must be larger than interpolated values at p and r



Forsyth & Ponce (2nd ed.) Figure 5.5 left

Example: Non-maxima Suppression





courtesy of G. Loy

Original Image

Gradient Magnitude

Non-maxima Suppression

Slide Credit: Christopher Rasmussen

Example

Forsyth & Ponce (1st ed.) Figure 8.13 top

Example

Forsyth & Ponce (1st ed.) Figure 8.13 top

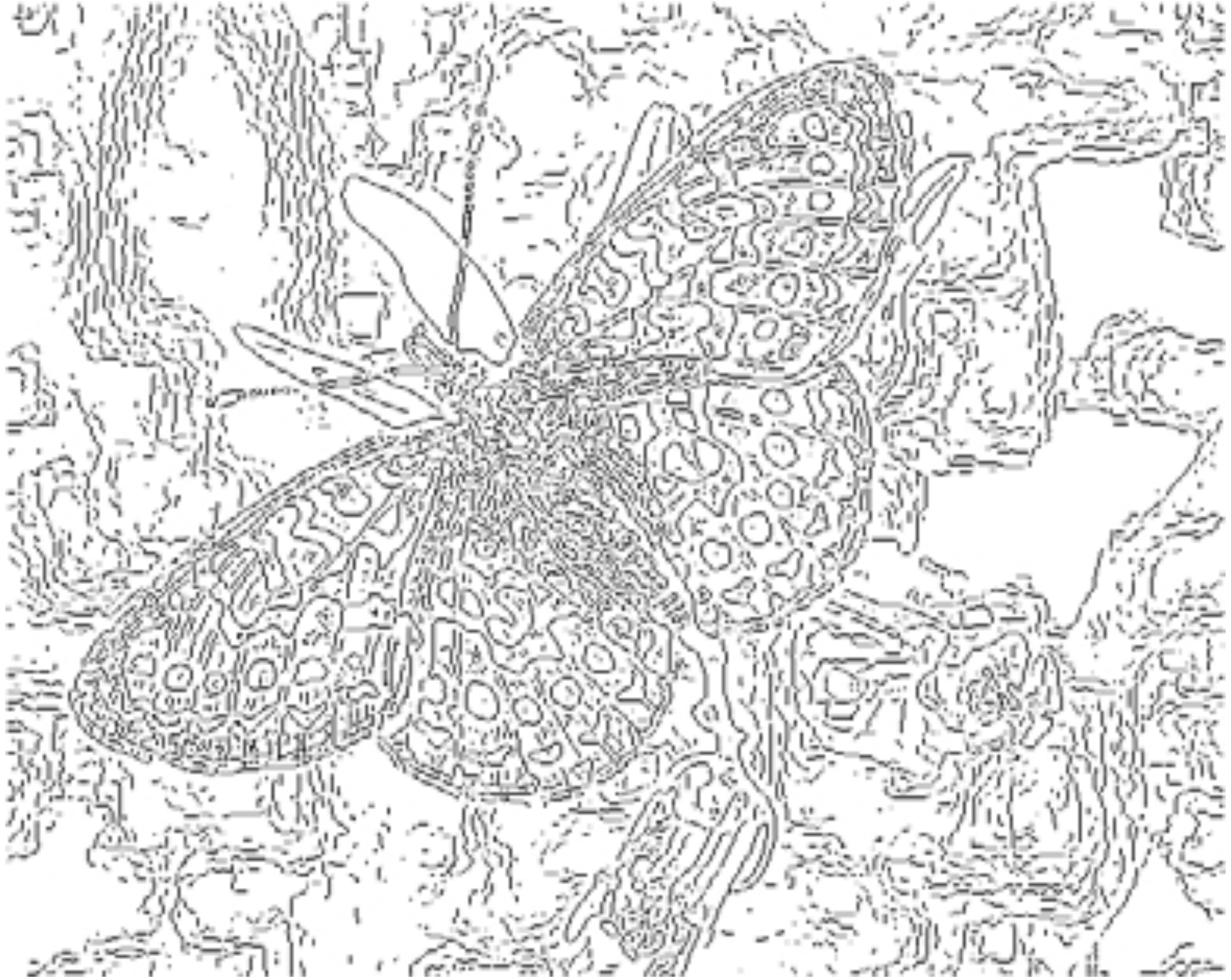


Figure 8.13 bottom left

Fine scale ($\sigma = 1$), high threshold

Example

Forsyth & Ponce (1st ed.) Figure 8.13 top

Figure 8.13 bottom middle

Fine scale ($\sigma = 4$), high threshold

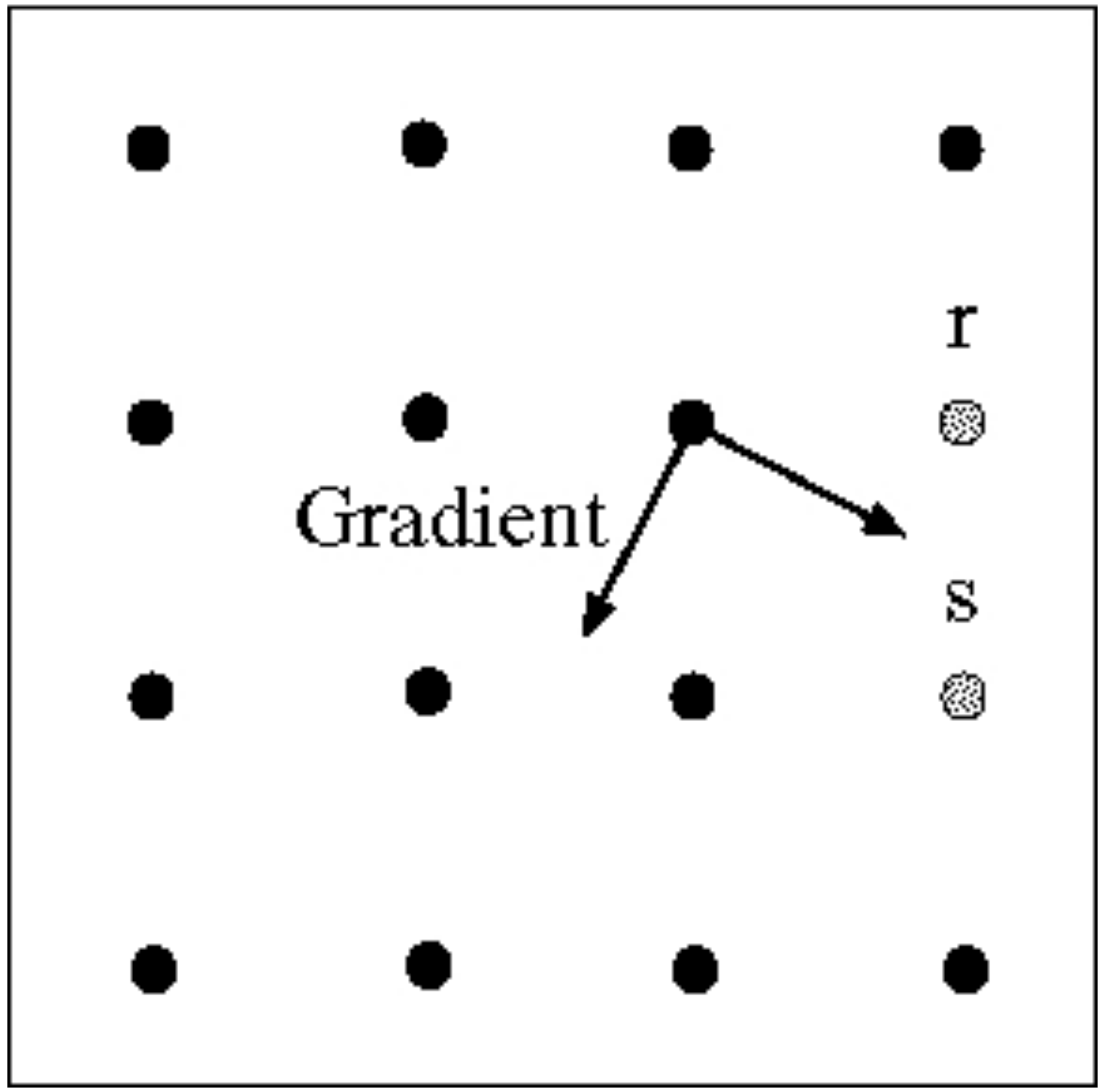
Example

Forsyth & Ponce (1st ed.) Figure 8.13 top

Figure 8.13 bottom right

Fine scale ($\sigma = 4$), low threshold

Linking Edge Points



Forsyth & Ponce (2nd ed.) Figure 5.5 right

Assume the marked point is an **edge point**. Take the normal to the gradient at that point and use this to predict continuation points (either *r* or *s*)

Edge **Hysteresis**

One way to deal with broken edge chains is to use hysteresis

Hysteresis: A lag or momentum factor

Idea: Maintain two thresholds $\mathbf{k}_{high}$ and $\mathbf{k}_{low}$
— Use khigh to find strong edges to start edge chain
— Use klow to find weak edges which continue edge chain

Typical ratio of thresholds is (roughly):

$$\frac{\mathbf{k}_{high}}{\mathbf{k}_{low}} = 2$$

Canny Edge Detector

Original Image

Strong + connected **Weak** Edges

Strong Edges

Weak Edges

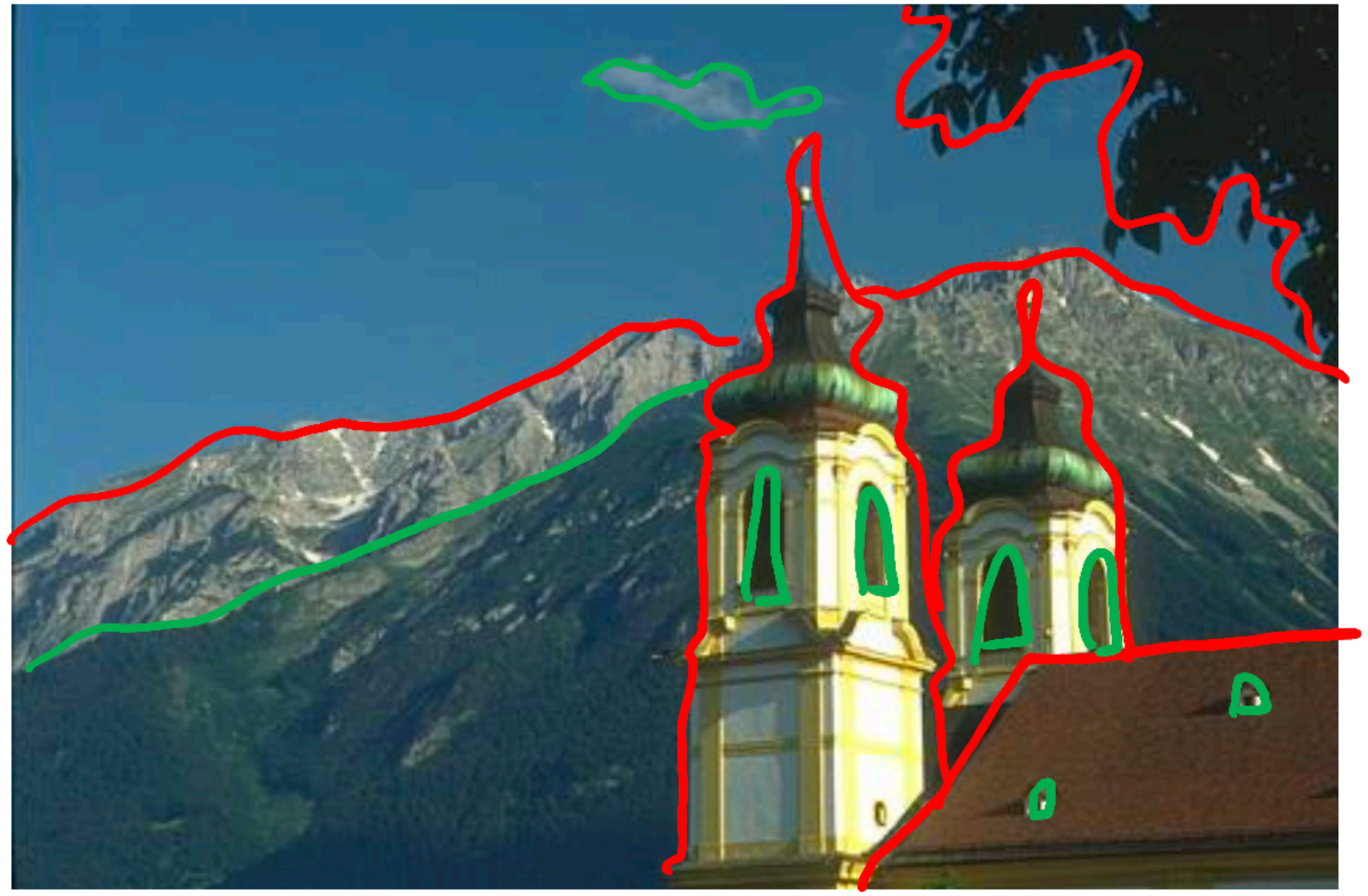
courtesy of G. Loy

How do humans perceive **boundaries**?

Edges are a property of the 2D image.

It is interesting to ask: How closely do image edges correspond to boundaries that humans perceive to be salient or significant?

How do humans perceive **boundaries**?



"Divide the image into some number of segments, where the segments represent 'things' or 'parts of things' in the scene. The number of segments is up to you, as it depends on the image. Something between 2 and 30 is likely to be appropriate. It is important that all of the segments have approximately equal importance."

(Martin et al. 2004)

How do humans perceive **boundaries**?

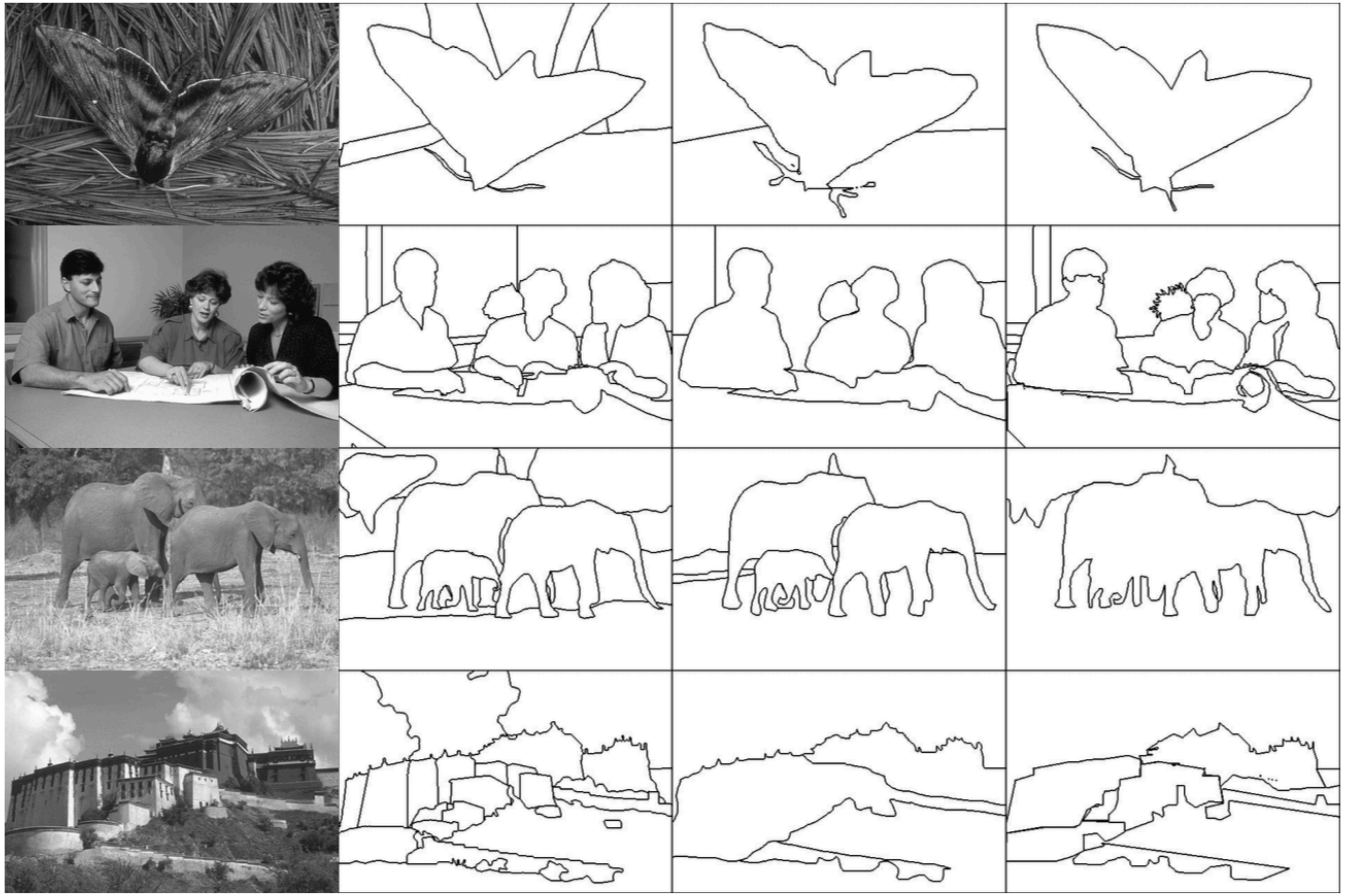


Figure Credit: Martin et al. 2001

How do humans perceive **boundaries**?

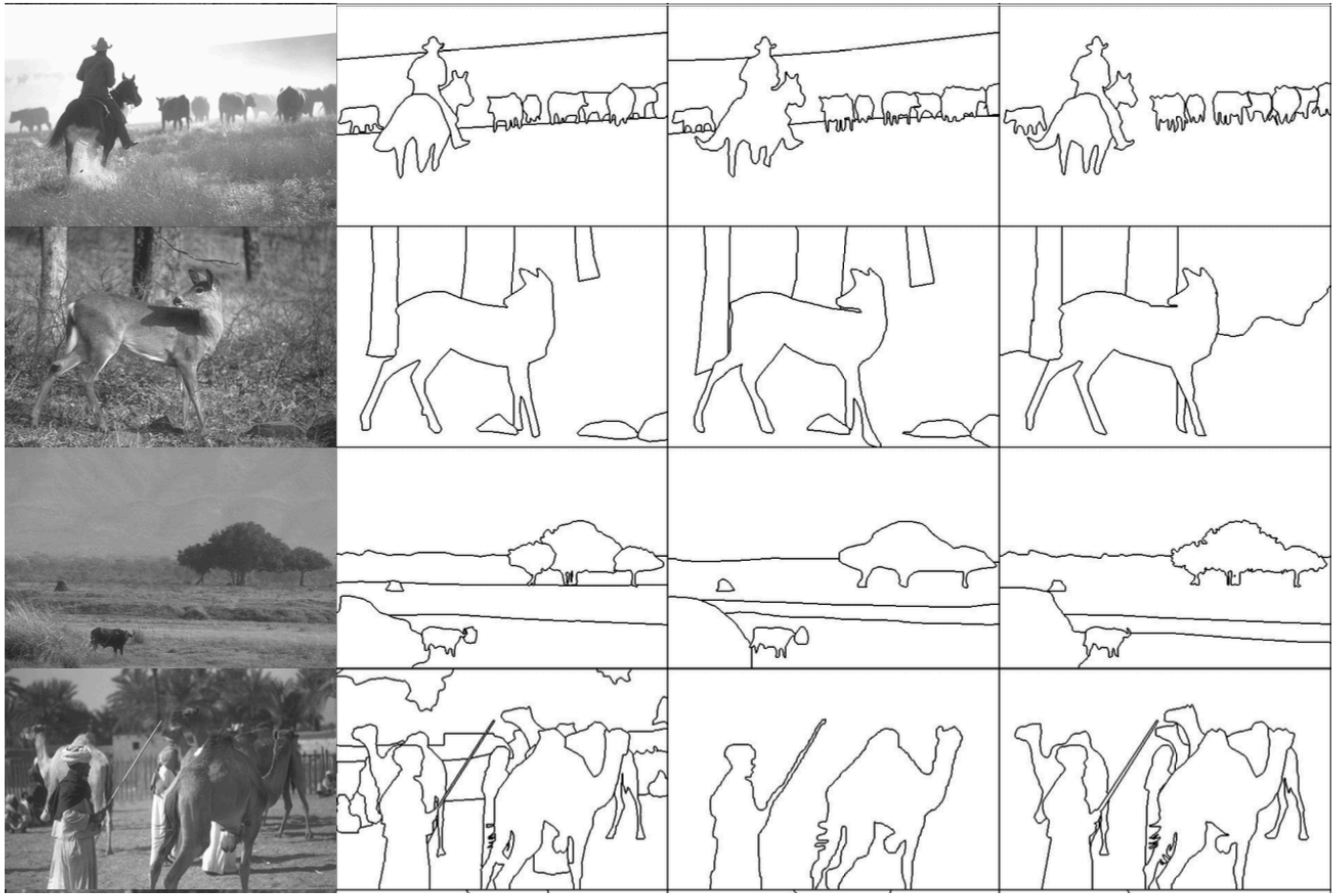
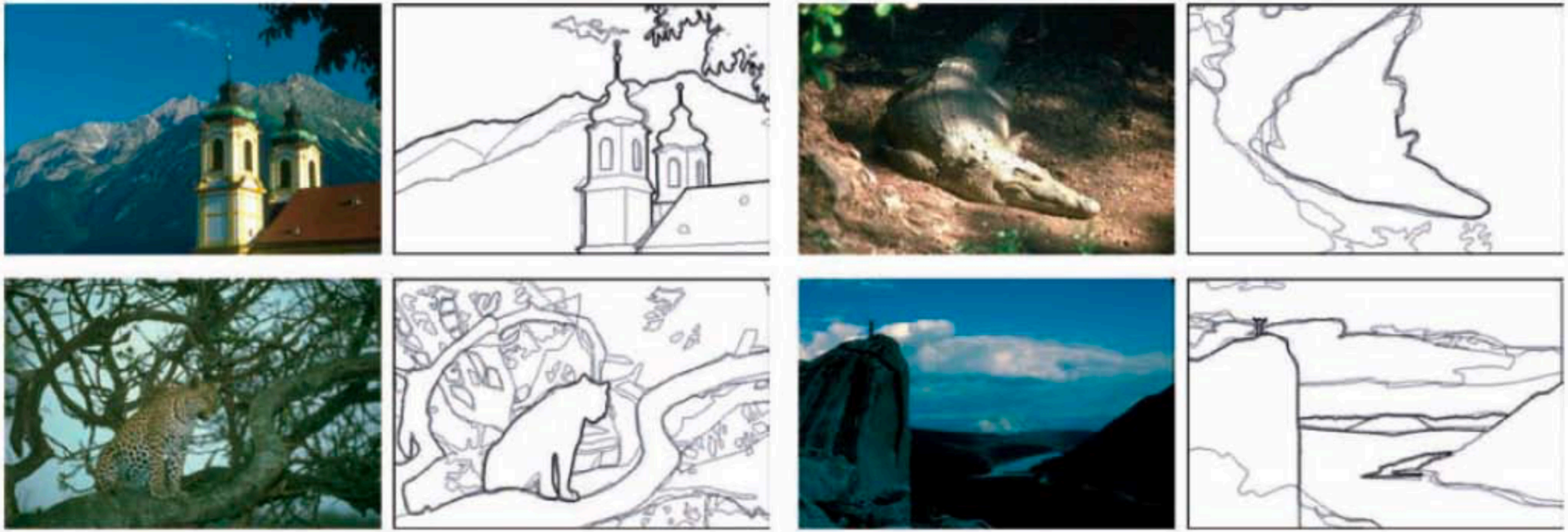


Figure Credit: Martin et al. 2001

How do humans perceive **boundaries**?



Each image shows multiple (4-8) human-marked boundaries. Pixels are darker where more humans marked a boundary.

Figure Credit: Szeliski Fig. 4.31. **Original**: Martin et al. 2004

Boundary Detection

We can formulate **boundary detection** as a high-level recognition task

— Try to learn, from sample human-annotated images, which visual features or cues are predictive of a salient/significant boundary

Many boundary detectors output a **probability or confidence** that a pixel is on a boundary

Boundary Detection: Example Approach

— Consider circular windows cut in half by an oriented line through the middle

— Compare visual features on both sides of the cut line

— If features are very different on the two sides, the cut line probably corresponds to a boundary

— Notice this gives us an idea of the orientation of the boundary as well

Boundary Detection:

Features:

— Raw Intensity

— Orientation Energy

— Brightness Gradient

— Color Gradient

— Texture gradient

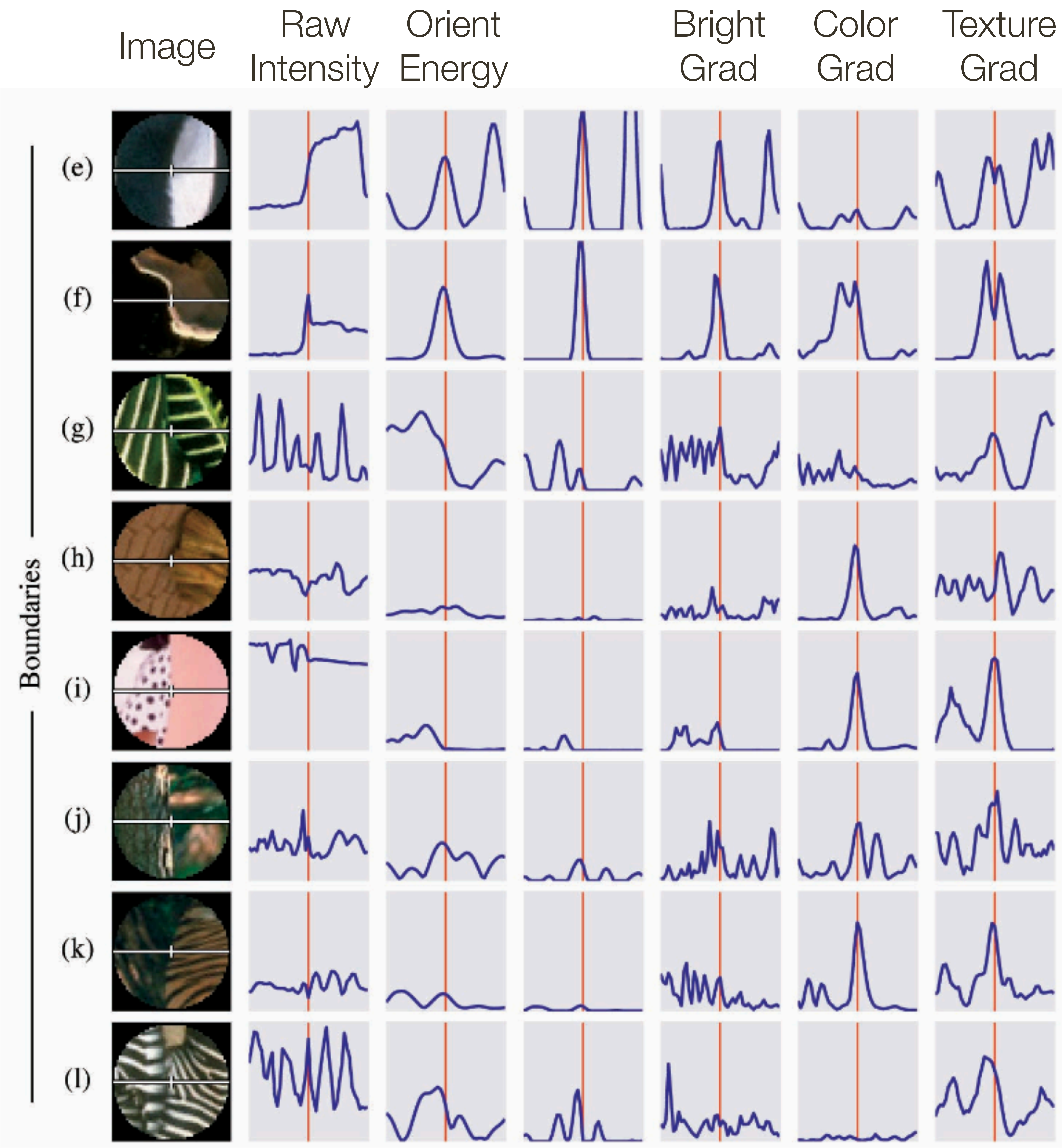


Figure Credit: Martin et al. 2004

Boundary Detection: Example Approach

Figure Credit: Szeliski Fig. 4.33. **Original**: Martin et al. 2004

Summary

Physical properties of a 3D scene cause “**edges**” in an image:

— depth discontinuity

— surface orientation discontinuity

— reflectance discontinuity

— illumination boundaries

Two generic approaches to **edge detection**:

— local extrema of a first derivative operator → **Canny**

— zero crossings of a second derivative operator → **Marr/Hildreth**

Many algorithms consider “**boundary detection**” as a high-level recognition task and output a probability or confidence that a pixel is on a human-perceived boundary