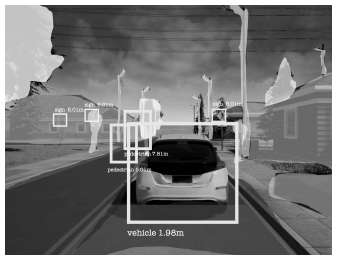
Principles of Safe Autonomy
Lecture 4: Perception, edge detection

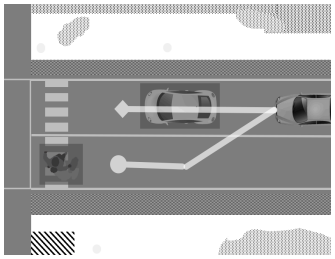
Sayan Mitra

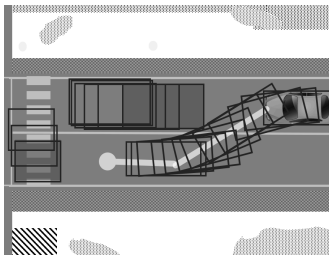
slides from Svetlana Lazebnik

GEM platform

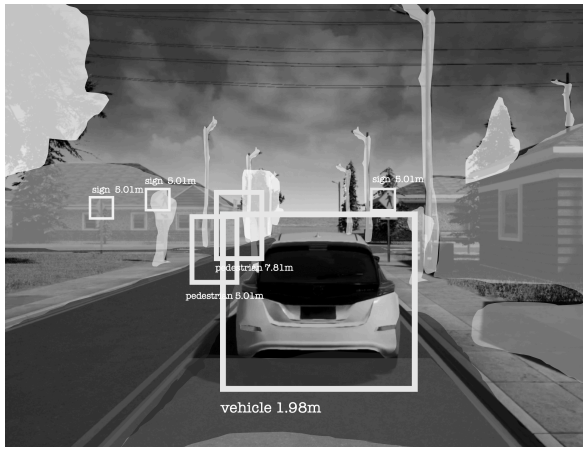
Autonomy pipeline







Sensing	Perception	Decisions and planning	Control
Physics-based models of camera, LIDAR, RADAR, GPS, etc.	Programs for object detection, lane tracking, scene understanding, etc.	Programs and multi-agent models of pedestrians, cars, etc.	Dynamical models of engine, powertrain, steering, tires, etc.

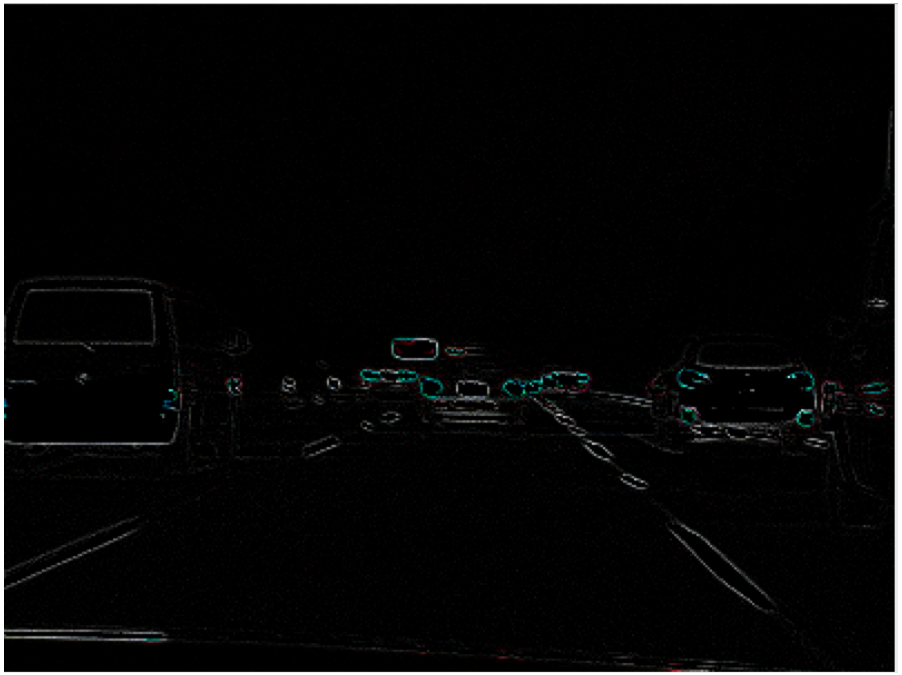


Perception

Programs for object detection, lane tracking, scene understanding, etc.

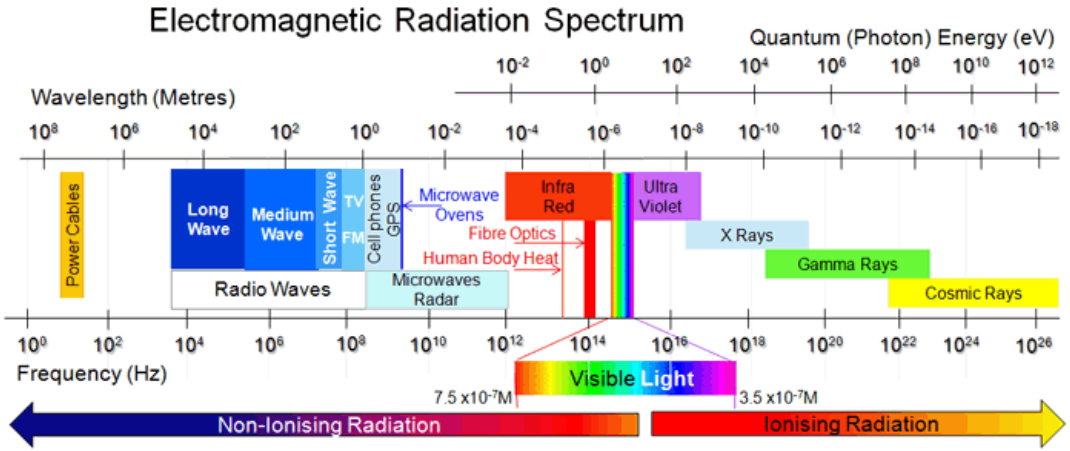
Outline

- Linear filtering
- Edge detection
- Assumptions in simple safety model (read)



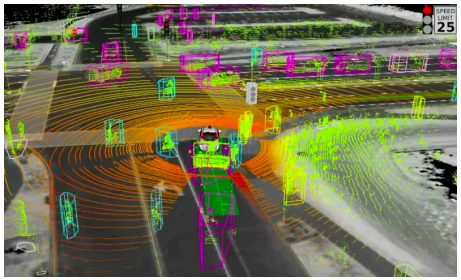
Perception: EM to objects

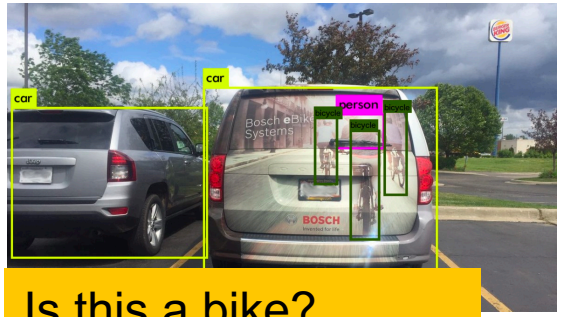
Problem: Process electromagnetic radiation from the environment to construct a *model* of the world, so that the constructed model is close to the real world



Challenging for computers: millions of years of evolution

Ill-defined problem: impossibility of defining meaning “car”, “bicycle”, etc.

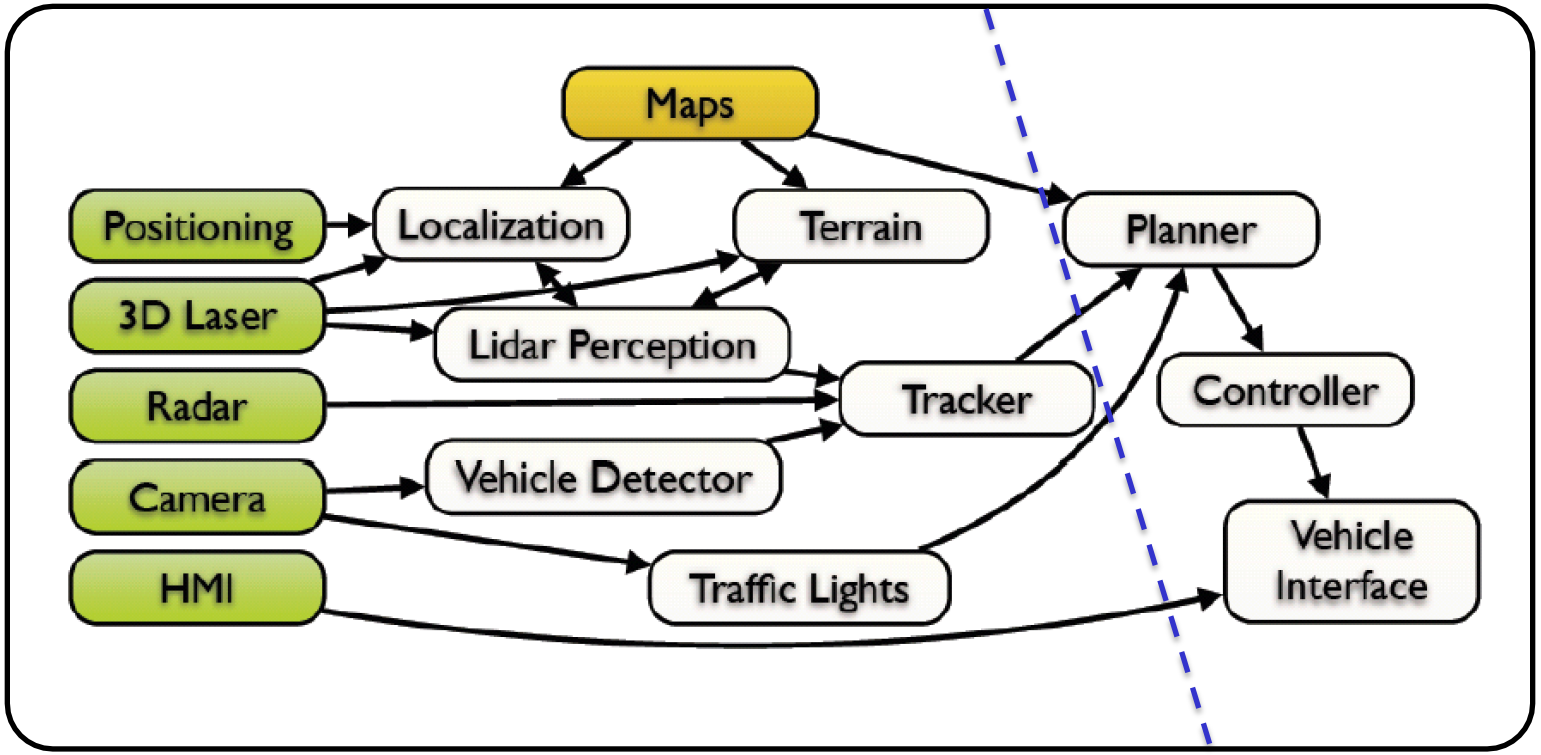




Is this a bike?

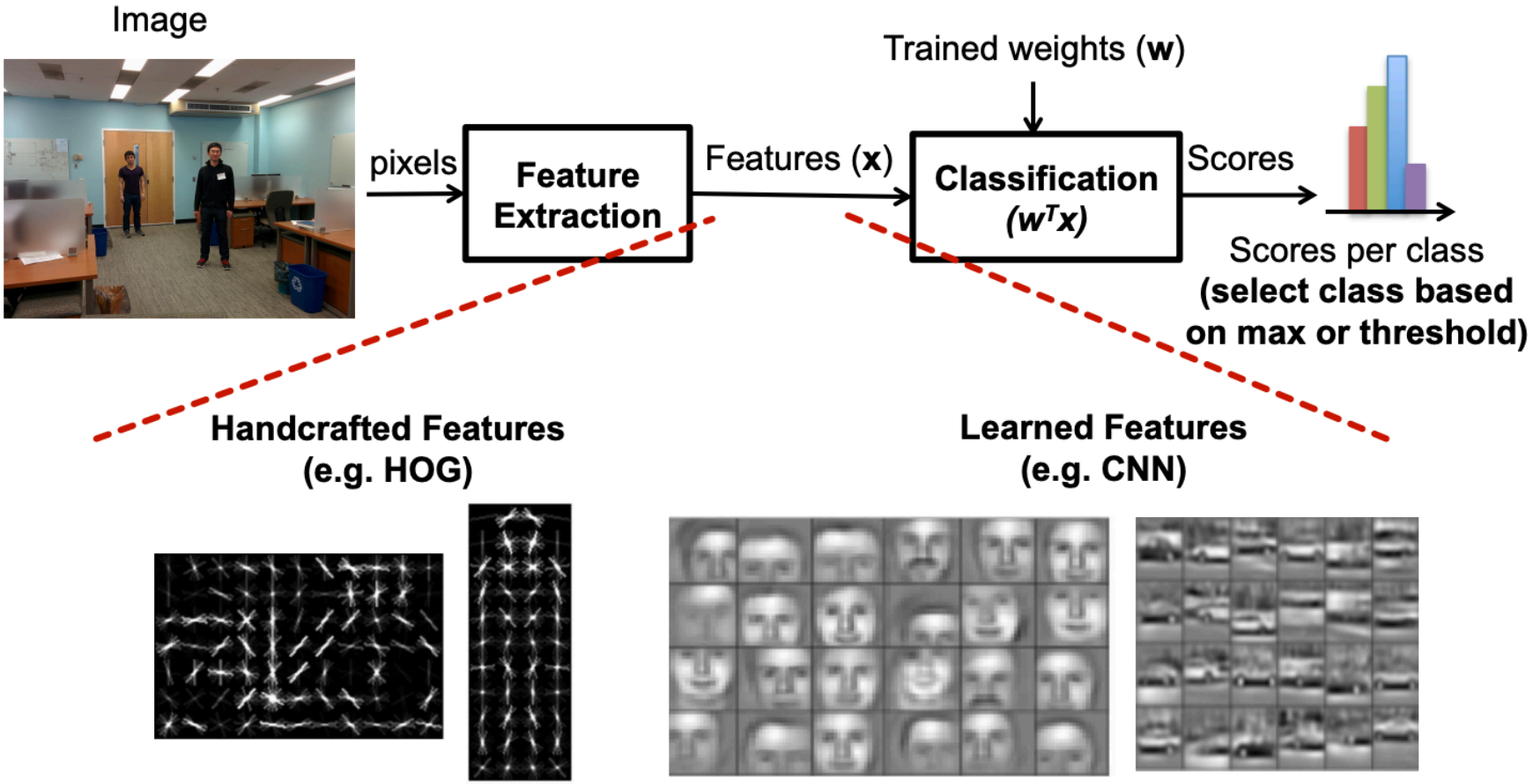
Is this a car?

A practical perception pipeline in an AV



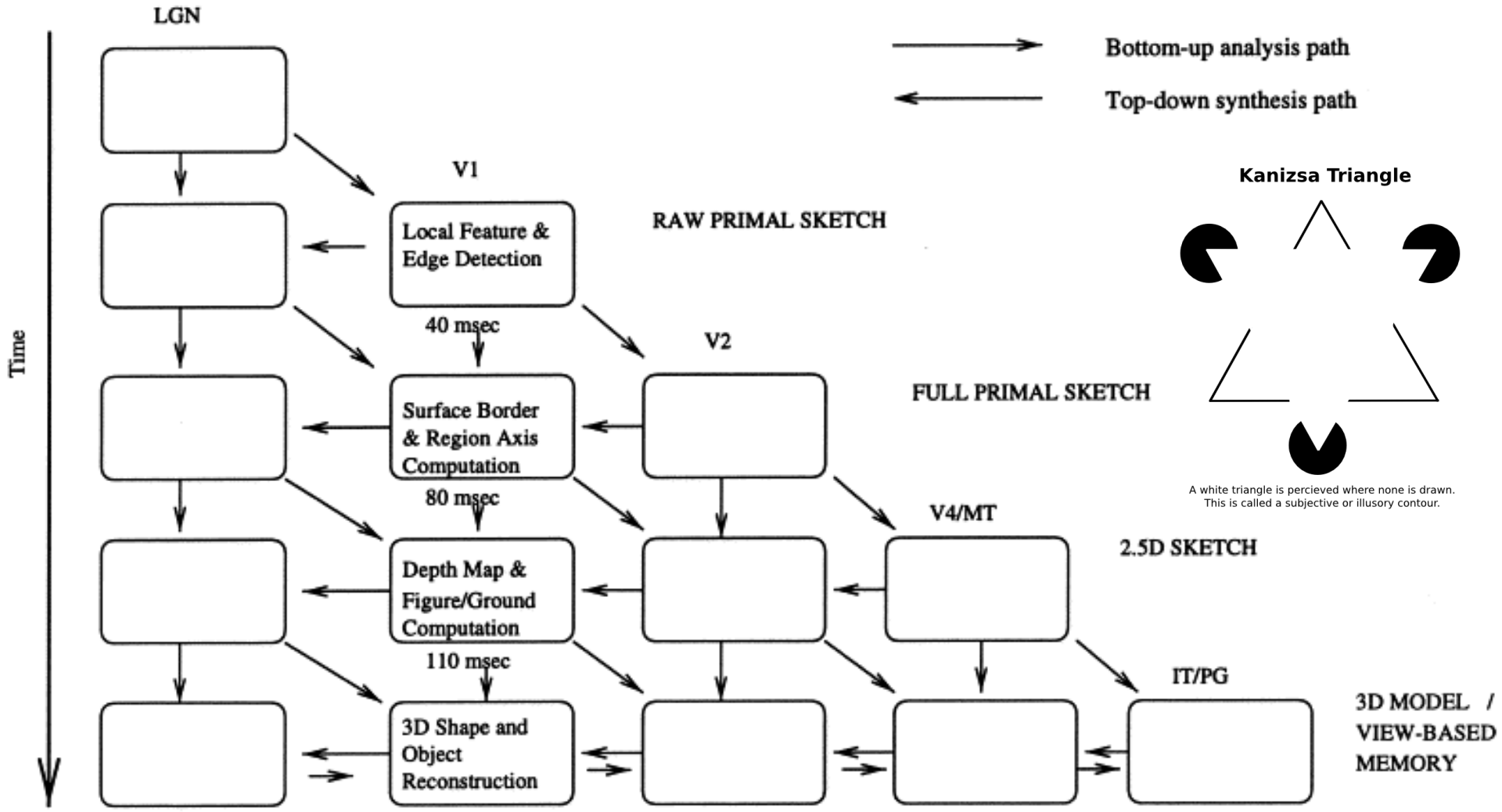
This architecture from a slide from M. James of Toyota Research Institute, North America

Recognition pipeline (more details in next lecture)



Towards Closing the Energy Gap Between HOG and CNN Features for Embedded Vision, Amr Suleiman, Yu-Hsin Chen, Joel Emer, Vivienne Sze

Natural vision “pipeline”



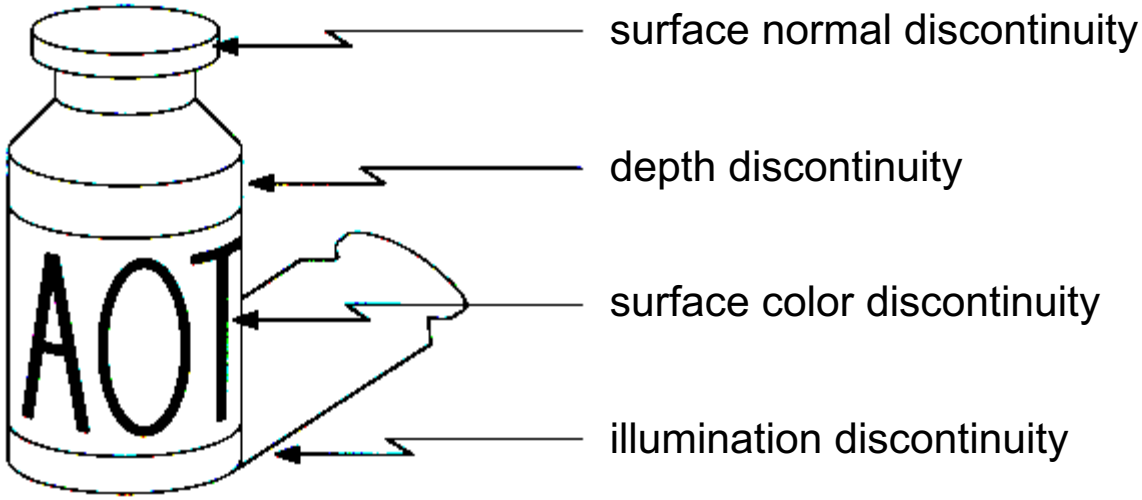
The role of the primary visual cortex in higher level vision, Tai Sing Lee, David Mumford, Richard Romero, Victor A.F.Lamme

Edge detection

Winter in Kraków photographed by Marcin Ryczek

Edge detection

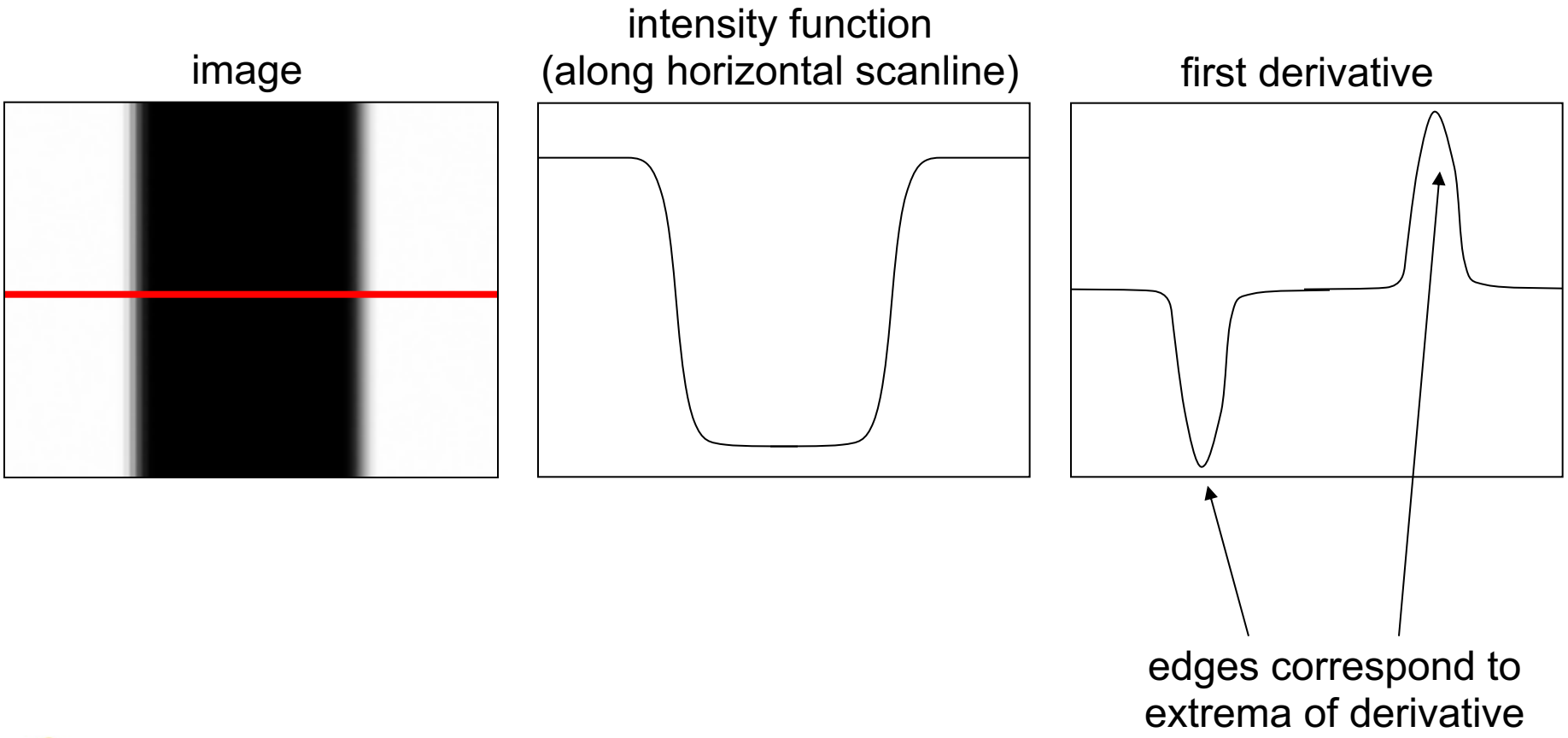
- **Goal:** Identify sudden changes (discontinuities) in an image
- Intuitively, edges carry most of the semantic and shape information from the image
  - E.g., Lanes, traffic signs, cars



Sources: D. Lowe and S. Seitz

Edge detection

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



Derivatives with convolution

For 2D function f(x,y), the partial derivative w.r.t *x* is:

$$\frac{\partial f(x,y)}{\partial x} = \lim_{\varepsilon \to 0} \frac{f(x+\varepsilon, y) - f(x,y)}{\varepsilon}$$

For discrete data, we can approximate using finite differences:

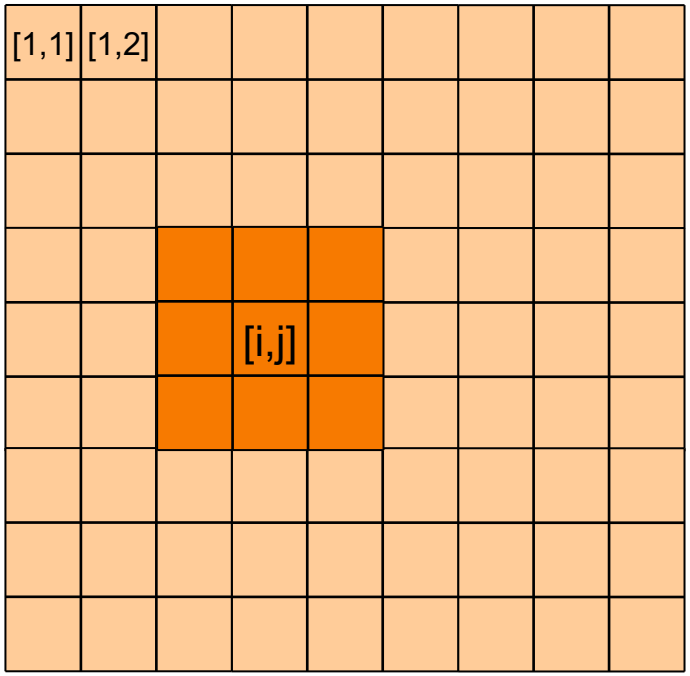
$$\frac{\partial f(x,y)}{\partial x} \approx \frac{f(x+1, y) - f(x,y)}{1}$$

To implement the above as convolution, what would be the associated filter?

Source: K. Grauman

Convolution

image[i,j]



convolution mask g[,]

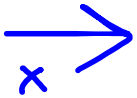
-1	1

Output or convolved image

f = g * img

f[i,j] = -1.img[i,j-1] + 1. img[i,j]

Partial derivatives of an image



$$\frac{\partial f(x,y)}{\partial x}$$

-1	1

$$\frac{\partial f(x,y)}{\partial y}$$

-1
1

1
-1

Which shows changes with respect to x?

Finite difference filters

Other approximations of derivative filters exist:

Prewitt: $M_x =$

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

; $M_y =$

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

Sobel: $M_x =$

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

; $M_y =$

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

Roberts: $M_x =$

0	1
-1	0

; $M_y =$

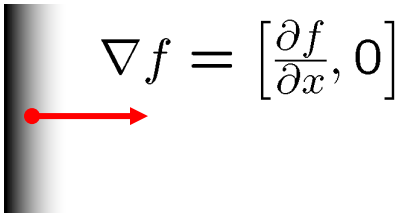
1	0
0	-1

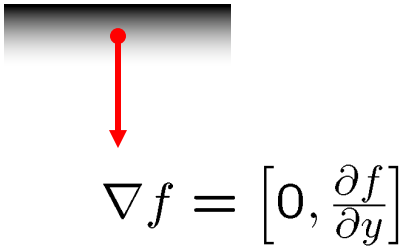
Source: K. Grauman

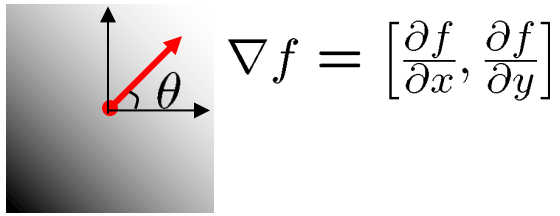
Kahoot!

Image gradient

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







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

- How does this direction relate to the direction of the edge?

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

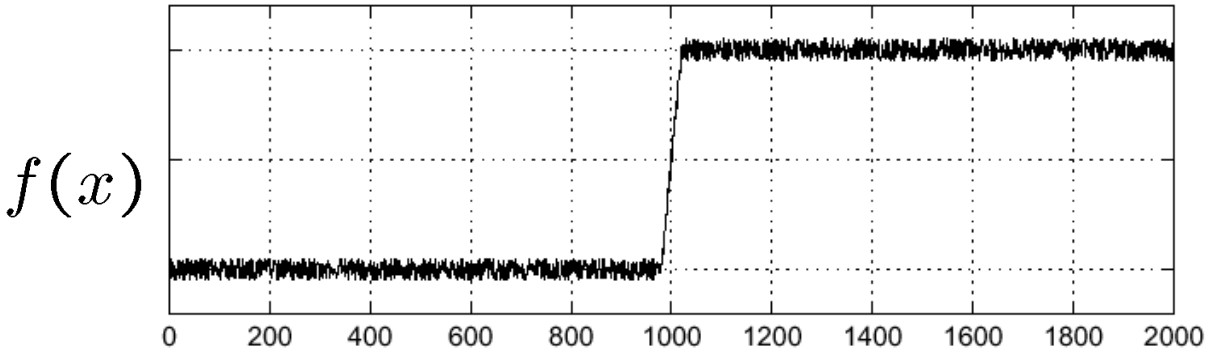
The edge strength is given by the gradient magnitude (norm)

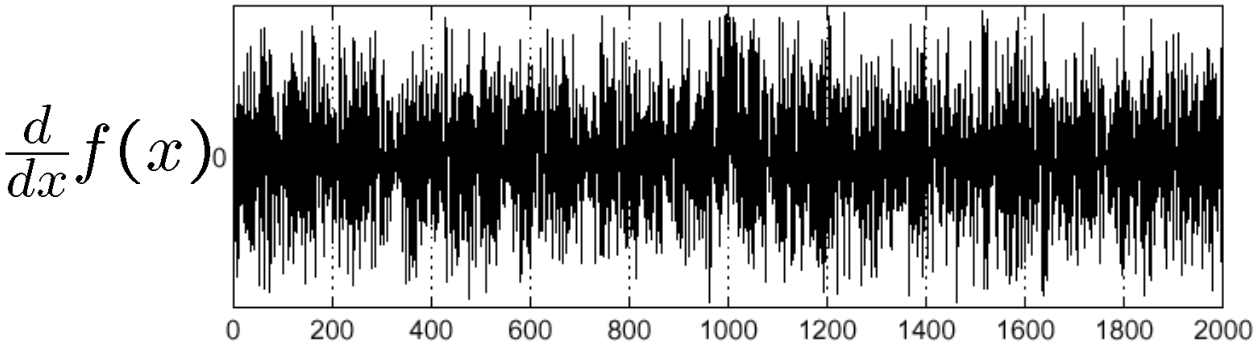
$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

Source: Steve Seitz

Effects of noise

Consider a single row or column of the image

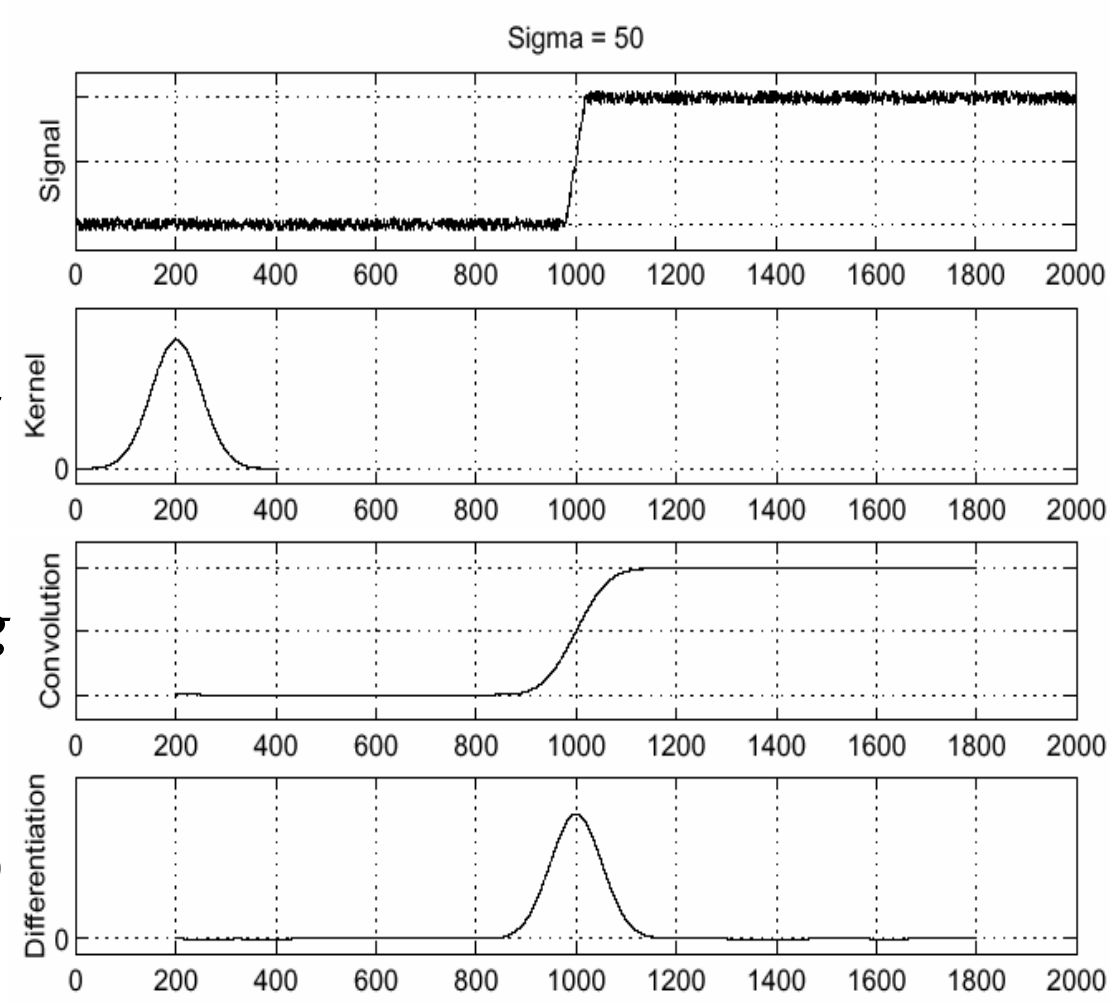




Where is the edge?

Source: S. Seitz

Solution: smooth first



f

g

$f * g$

$\frac{d}{dx}(f * g)$

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

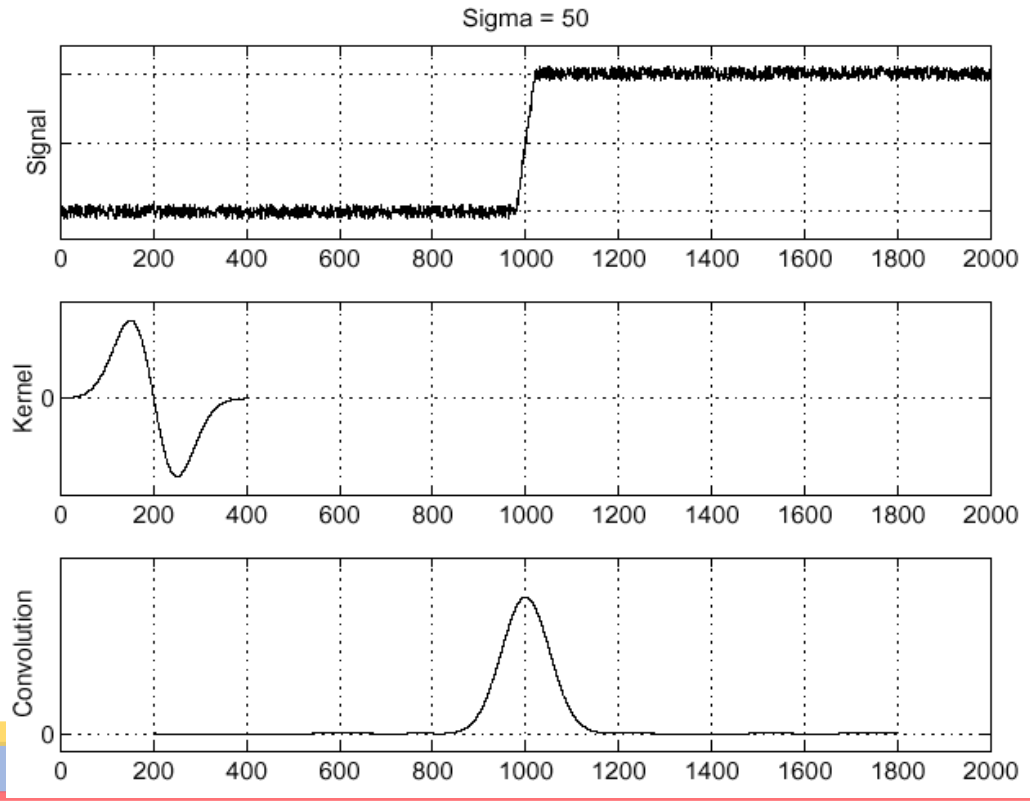
Derivative theorem of convolution

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

f

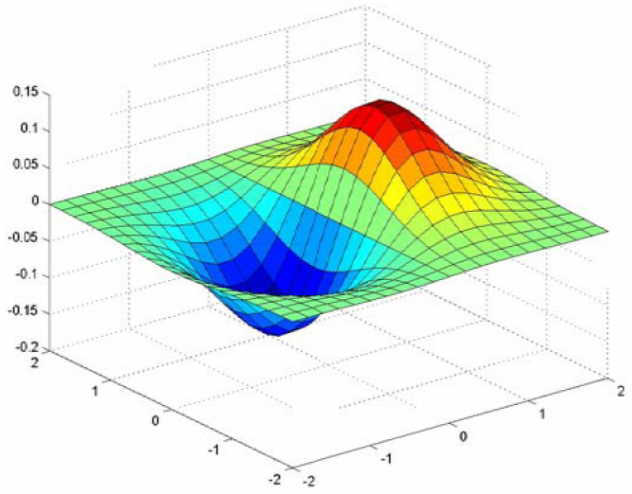
$\frac{d}{dx} g$

$f * \frac{d}{dx} g$

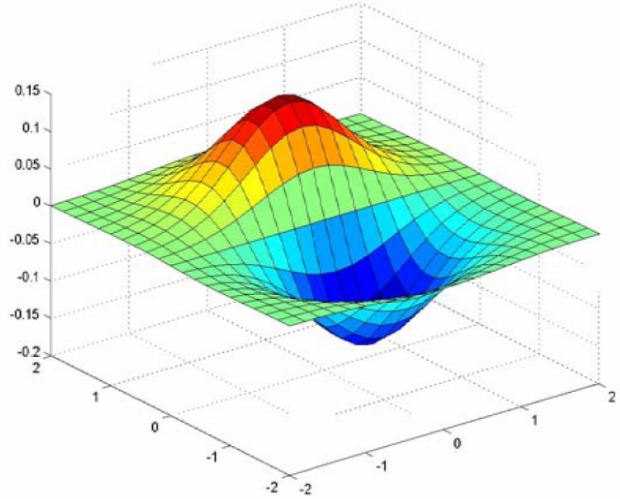


Source: S. Seitz

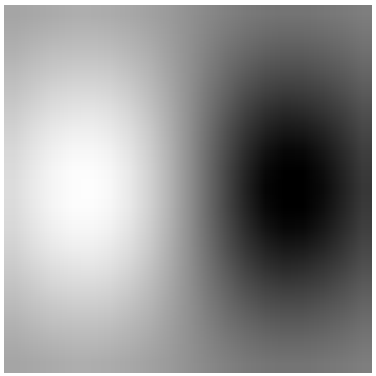
Derivative of Gaussian filters

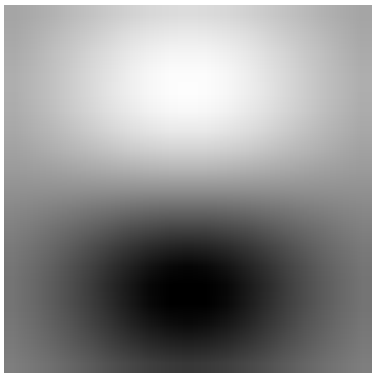


x-direction



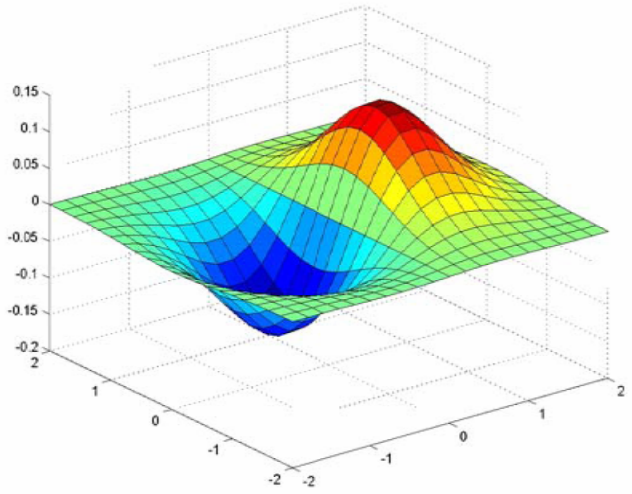
y-direction



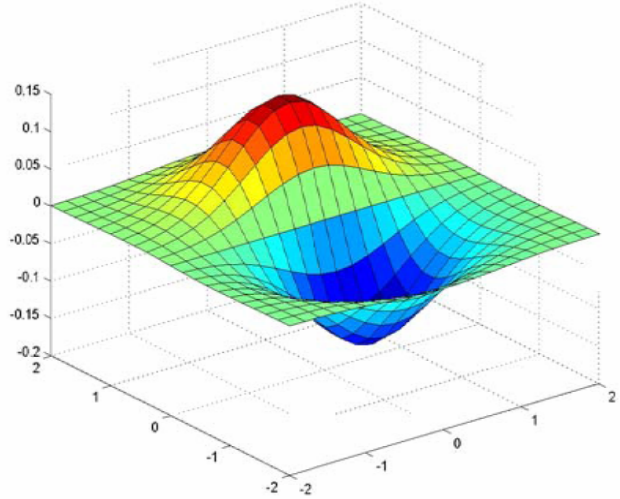


Which one finds horizontal/vertical edges?

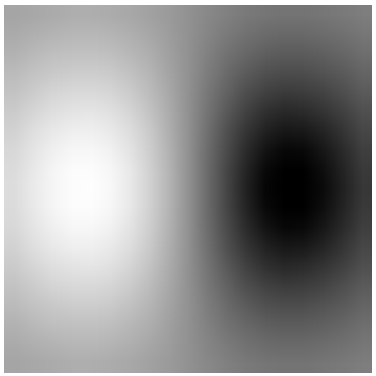
Derivative of Gaussian filters

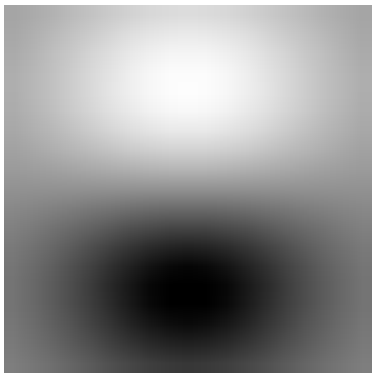


x-direction



y-direction





Are these filters separable?

Recall: Separability of the Gaussian filter

$$G_\sigma(x,y) = \frac{1}{2\pi\sigma^2}\exp^{-\frac{x^2+y^2}{2\sigma^2}}$$

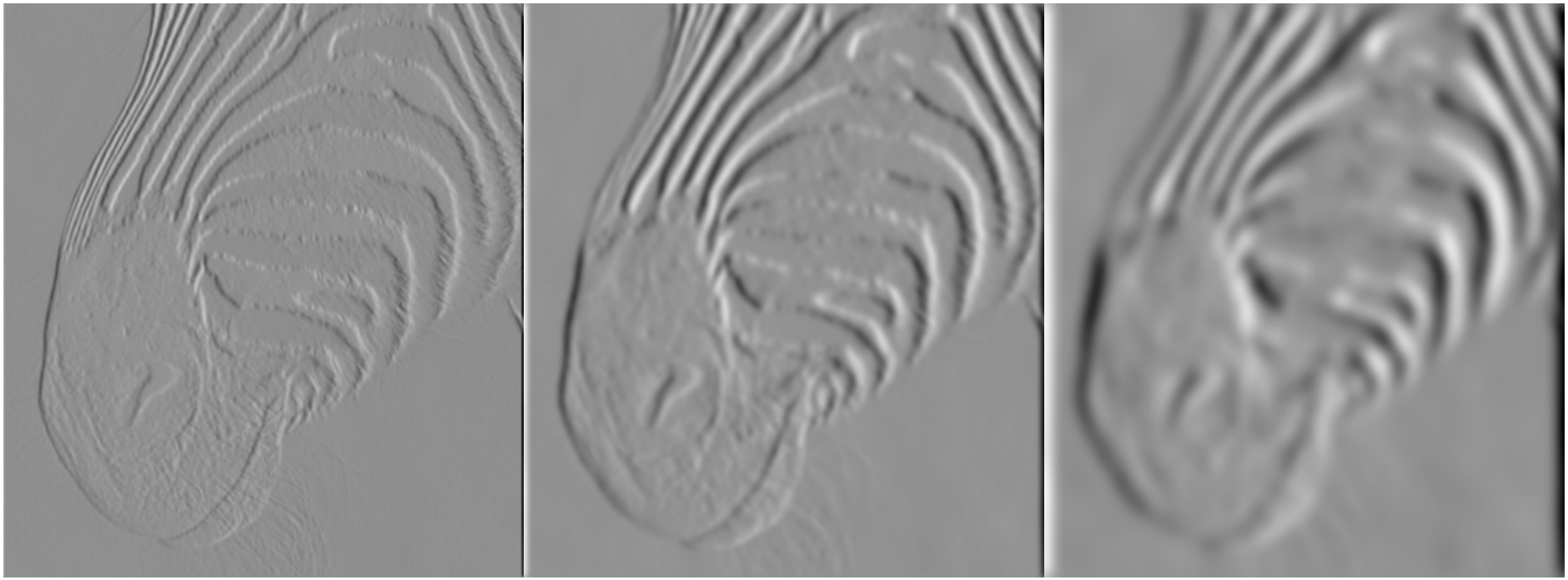
$$= \left(\frac{1}{\sqrt{2\pi}\sigma}\exp^{-\frac{x^2}{2\sigma^2}}\right)\left(\frac{1}{\sqrt{2\pi}\sigma}\exp^{-\frac{y^2}{2\sigma^2}}\right)$$

The 2D Gaussian can be expressed as the product of two functions, one a function of x and the other a function of y

In this case, the two functions are the (identical) 1D Gaussian

Source: D. Lowe

Scale of Gaussian derivative filter



1 pixel 3 pixels 7 pixels

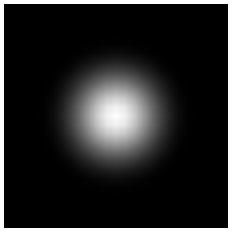
Smoothed derivative removes noise, but blurs edge

Also finds edges at different “scales”

Source: D. Forsyth

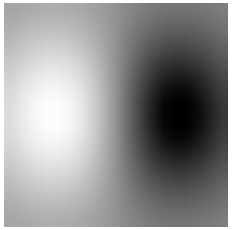
Review: Smoothing vs. derivative filters

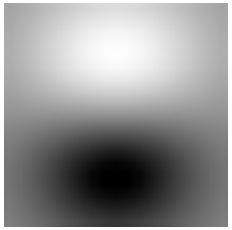
Smoothing filters



- Gaussian: remove “high-frequency” components; “low-pass” filter
- Can the values of a smoothing filter be negative?
- What should the values sum to?
  - **One:** constant regions are not affected by the filter

Derivative filters



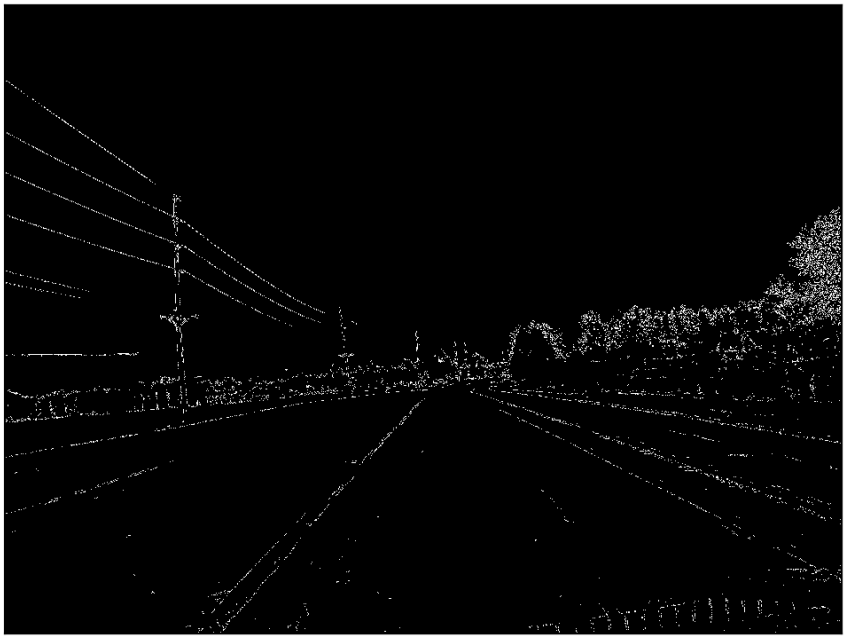


- Derivatives of Gaussian
- Can the values of a derivative filter be negative?
- What should the values sum to?
  - **Zero:** no response in constant regions

Building an edge detector

Original Image

Edge Image



original image

final output

norm of the gradient $\|\nabla f\| = \sqrt{(\frac{\partial f}{\partial x})^2 + (\frac{\partial f}{\partial y})^2}$

Building an edge detector

How to turn these thick regions of the gradient into curves?

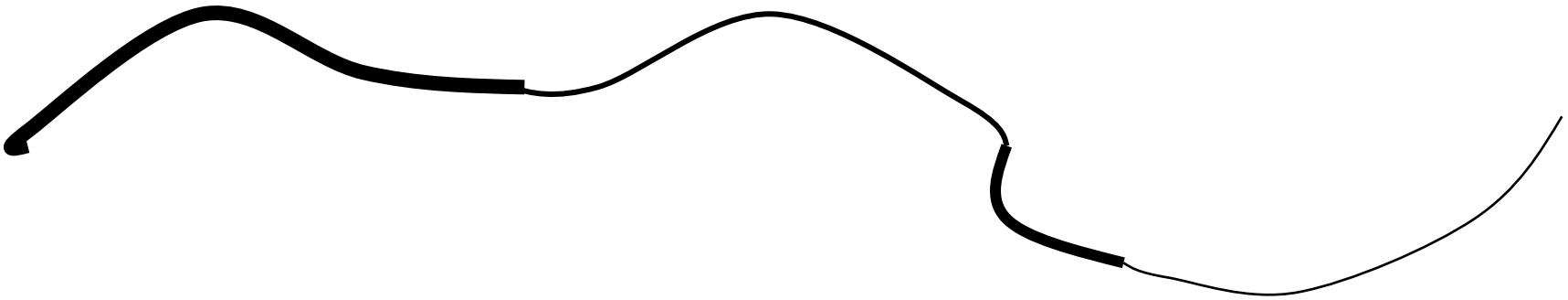
Thresholded norm of the gradient

Non-maximum suppression

Another problem: pixels along this edge didn't survive thresholding

Hysteresis thresholding

Use a high threshold to start edge curves, and a low threshold to continue them.



Source: Steve Seitz

Hysteresis thresholding

original image

high threshold
(strong edges)

low threshold
(weak edges)

hysteresis threshold

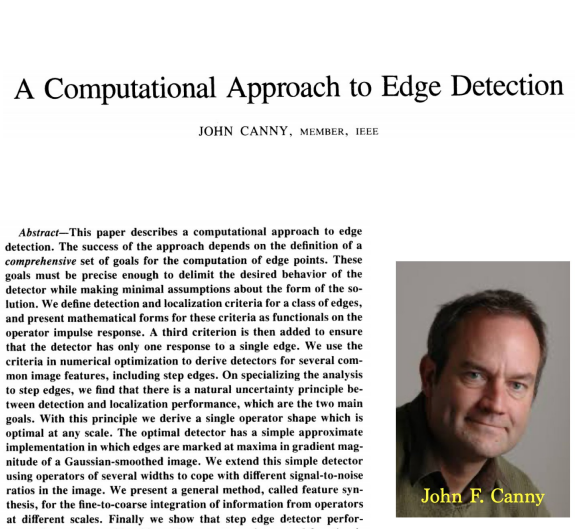
Source: L. Fei-Fei

Recap: Canny edge detector

1. Compute x and y gradient images
2. Find magnitude and orientation of gradient
3. **Non-maximum suppression**:
   - Thin wide “ridges” down to single pixel width
4. **Linking and thresholding** (**hysteresis**):
   - Define two thresholds: low, high
   - Use the high threshold to start edge curves and the low threshold to continue them

opencv: `canny(image,th1,th2)`

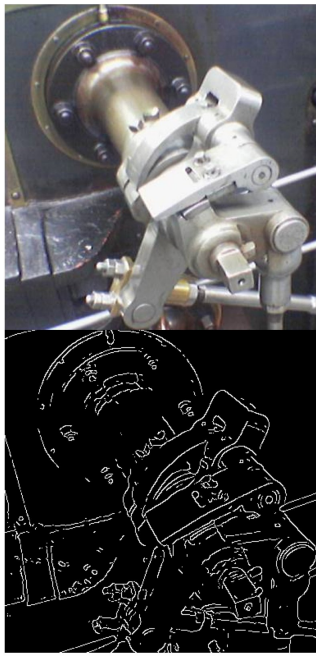
J. Canny, A Computational Approach To Edge Detection, IEEE Trans. Pattern Analysis and Machine Intelligence, 8:679-714, 1986.



A Computational Approach to Edge Detection

JOHN CANNY, MEMBER, IEEE

Abstract—This paper describes a computational approach to edge detection. The success of the approach depends on the definition of a *comprehensive* set of goals for the computation of edge points. These goals must be precise enough to delimit the desired behavior of the detector while making minimal assumptions about the form of the solution. We define detection and localization criteria for a class of edges, and present mathematical forms for these criteria as functionals on the operator impulse response. A third criterion is then added to ensure that the detector has only one response to a single edge. We use the criteria in numerical optimization to derive detectors for several common image features, including step edges. On specializing the analysis to step edges, we find that there is a natural uncertainty principle between detection and localization performance, which are the two main goals. With this principle we derive a single operator shape which is optimal at any scale. The optimal detector has a simple approximate implementation in which edges are marked at maxima in gradient magnitude of a Gaussian-smoothed image. We extend this simple detector using operators of several widths to cope with different signal-to-noise ratios in the image. We present a general method, called feature synthesis, for the fine-to-coarse integration of information from operators at different scales. Finally we show that step edge detector performance improves considerably as the operator point spread function is extended along the edge. This detection scheme uses several elongated operators at each point, and the directional operator outputs are integrated with the gradient maximum detector.

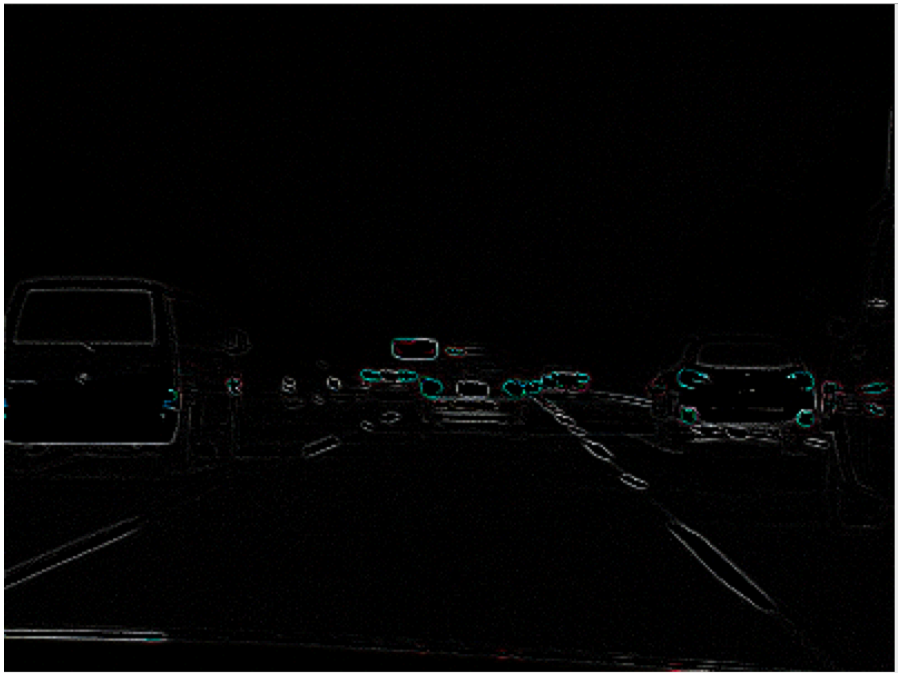


Summary

- Convolution as translation invariant linear operations on signals and images
- Definition of convolution and its properties (associativity, commutativity, etc.)
- Artifacts of of hard-edge kernels
- Gaussian kernel, its definition and properties (separability)
- Median filter, sharpening
- Derivatives as convolution (Sobel, etc.)

Outline

- Linear filtering
- Edge detection
- Assumptions in simple safety model (read)



Sharpening

What does blurring take away?

Let's add it back:

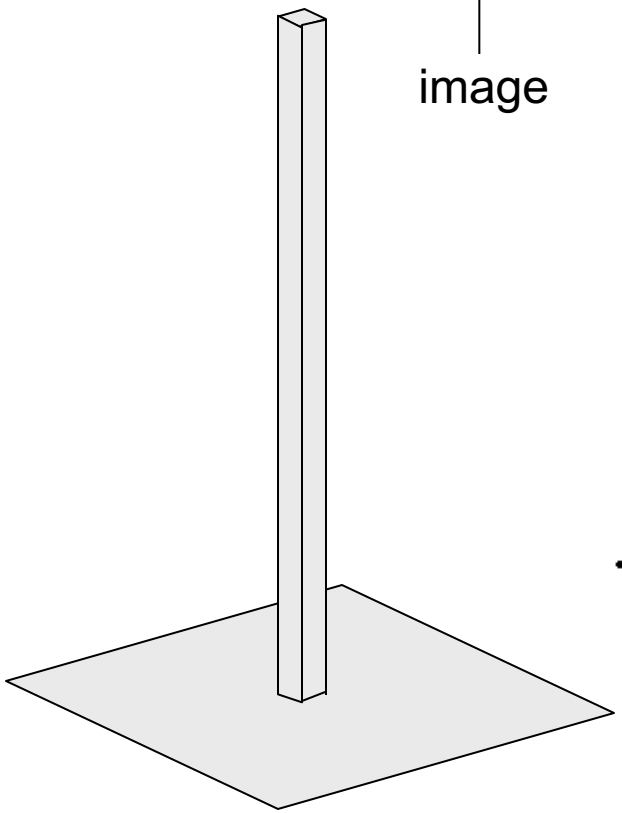
Unsharp mask filter

$$f + \alpha(f - f * g) = (1+\alpha)f - \alpha\, f * g = f * ((1+\alpha)e - g)$$

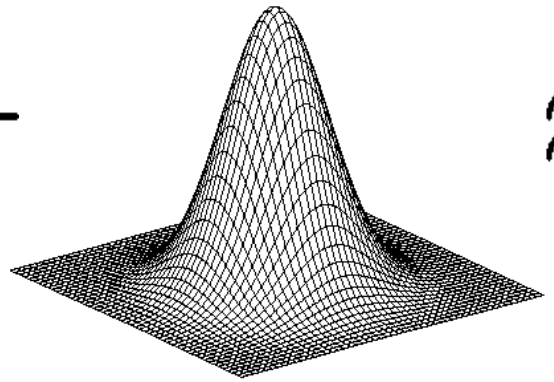
image

blurred image

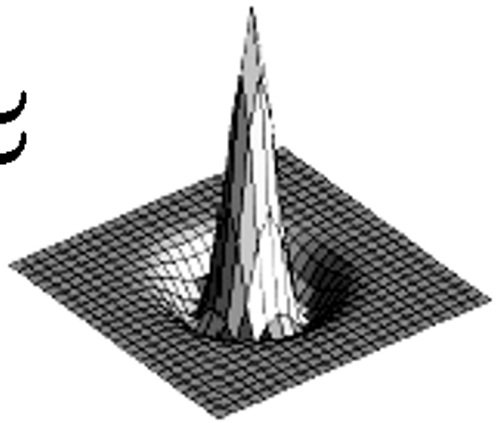
unit impulse (identity)



unit impulse



Gaussian



Laplacian of Gaussian