

Introduction to Computer Vision

Michael J. Black

Sept 2009

Lecture 9:

Image gradients, feature detection,
correlation

Goals

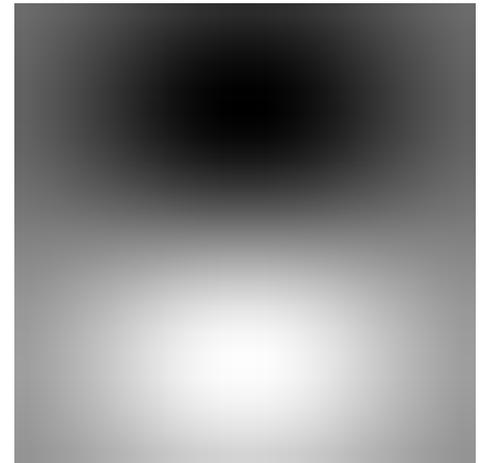
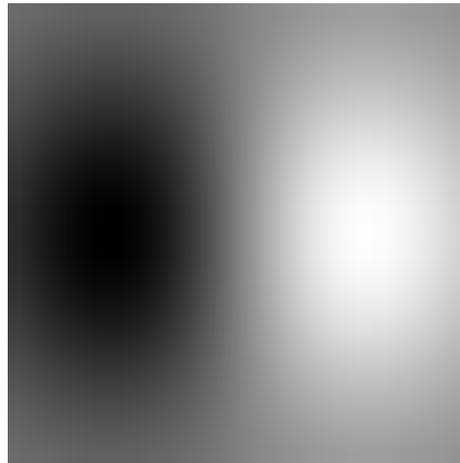
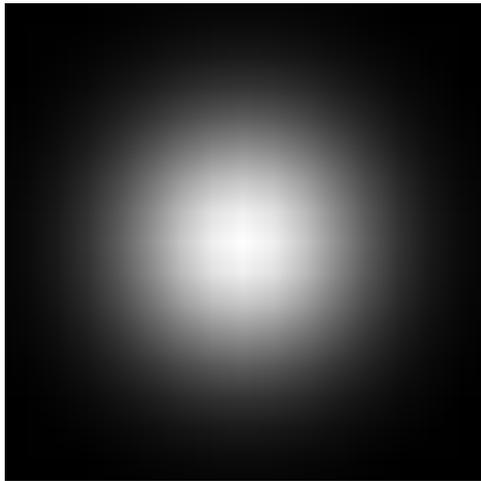
- Image gradient
- Filtering as feature detection
- Convolution vs correlation
- Time permitting: images as vectors

Next week

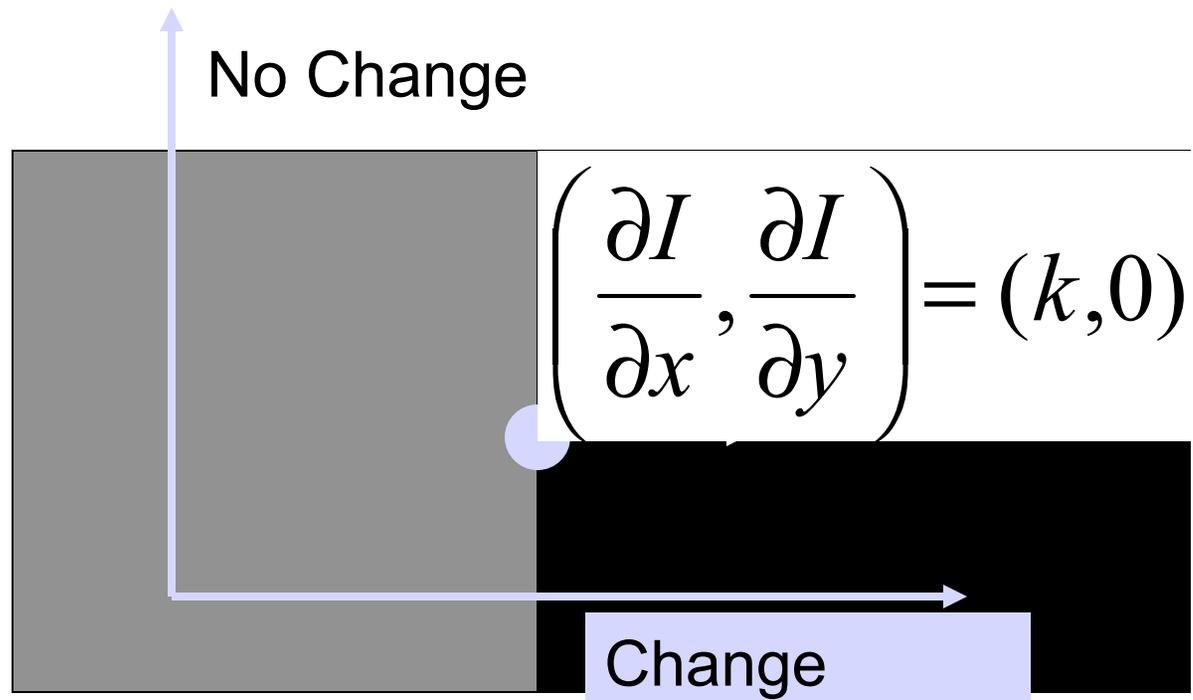
- Wednesday: data for assignment 2. important that you attend.
- Friday: Silvia Zuffi – color

Recall derivatives of Gaussian

$$D_x \otimes (G \otimes I) = (D_x \otimes G) \otimes I$$

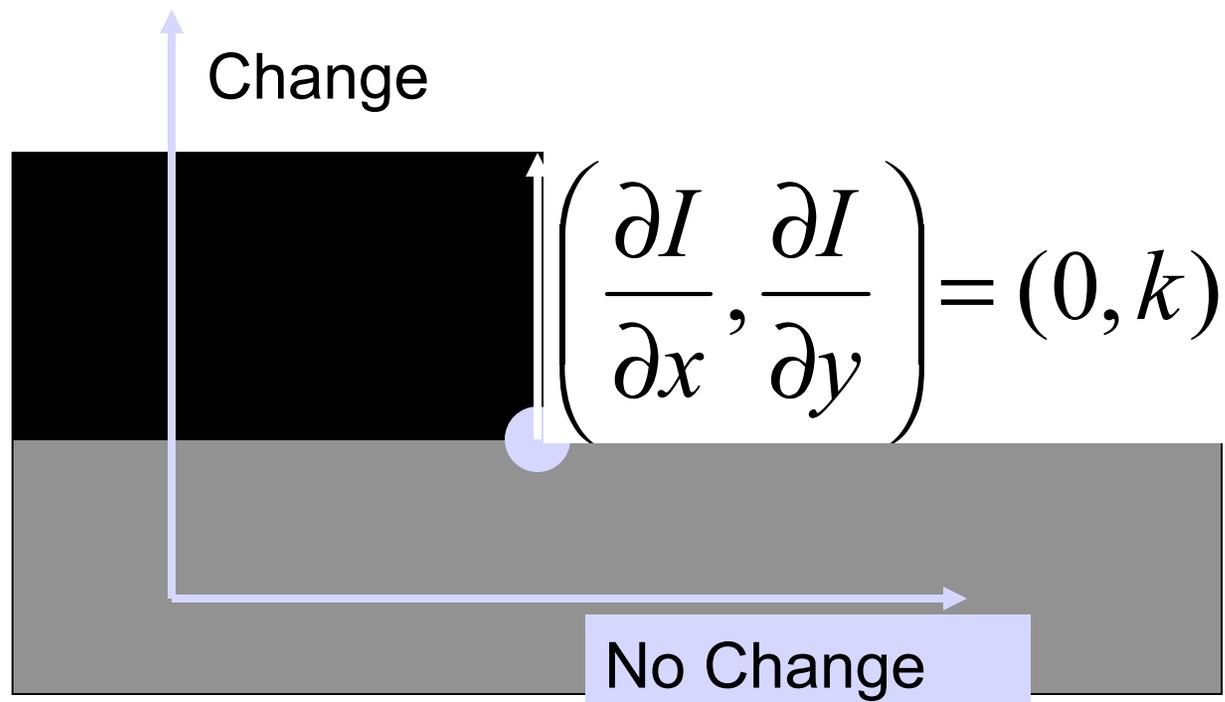


What is the gradient?



Jacobs

What is the gradient?

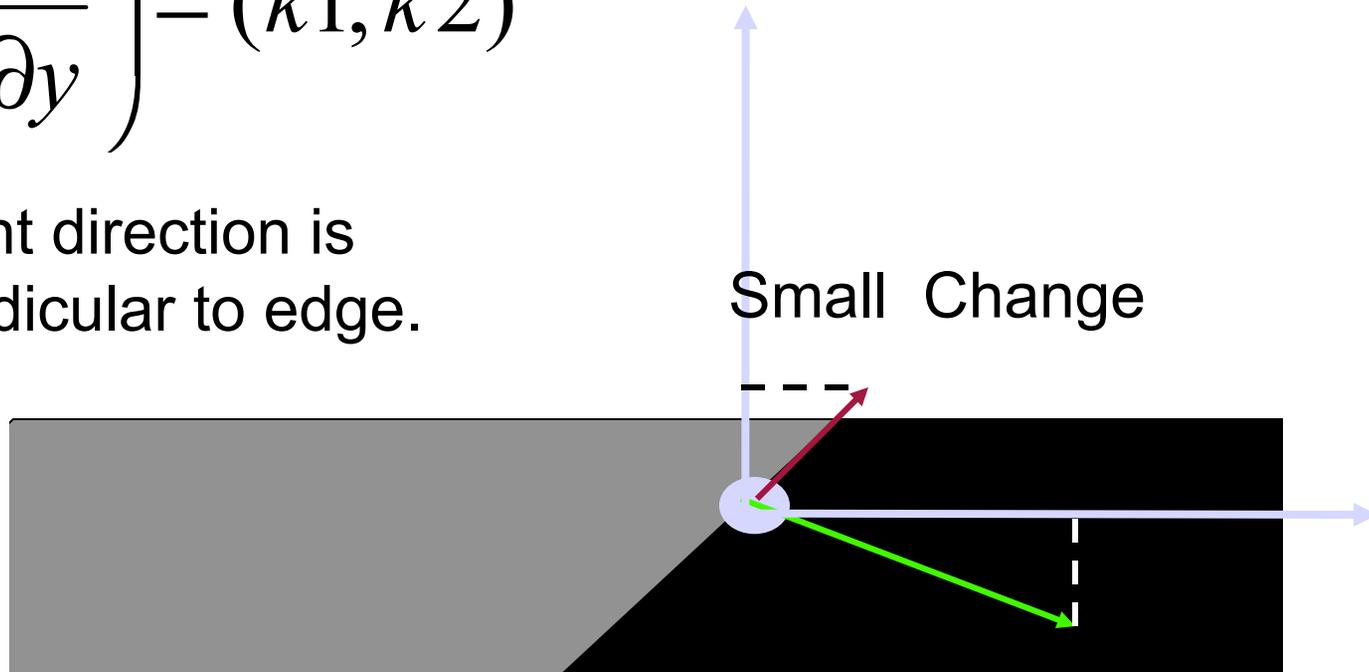


Jacobs

What is the gradient?

$$\left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y} \right) = (k1, k2)$$

Gradient direction is perpendicular to edge.



Gradient Magnitude measures edge strength.

Large Change

Jacobs

2D Edge Detection

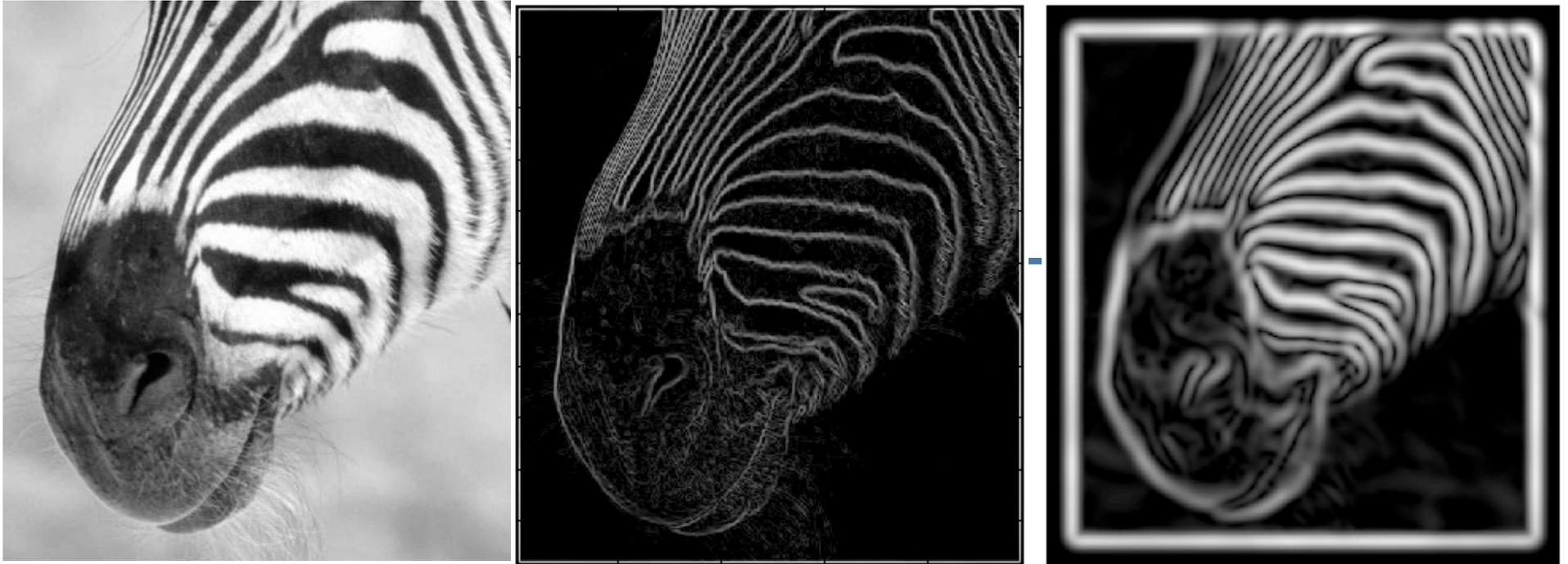
Take a derivative

- Compute the magnitude of the gradient:

$$\nabla I = (I_x, I_y) = \left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y} \right) \text{ is the Gradient}$$

$$\|\nabla I\| = \sqrt{I_x^2 + I_y^2}$$

Jacobs

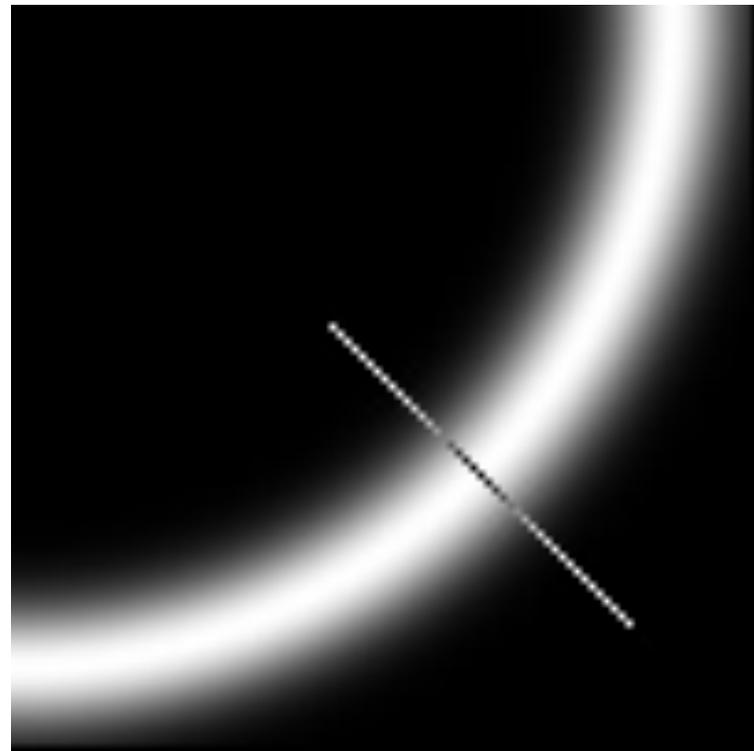


There are three major issues:

- 1) The gradient magnitude at different scales is different; which should we choose?
- 2) The gradient magnitude is large along a thick trail; how do we identify the significant points?
- 3) How do we link the relevant points up into curves?

Ponce & Forsyth

Non-Maxima Suppression



Look in a neighborhood along the direction of the gradient.

Choose the largest gradient magnitude in this neighborhood..

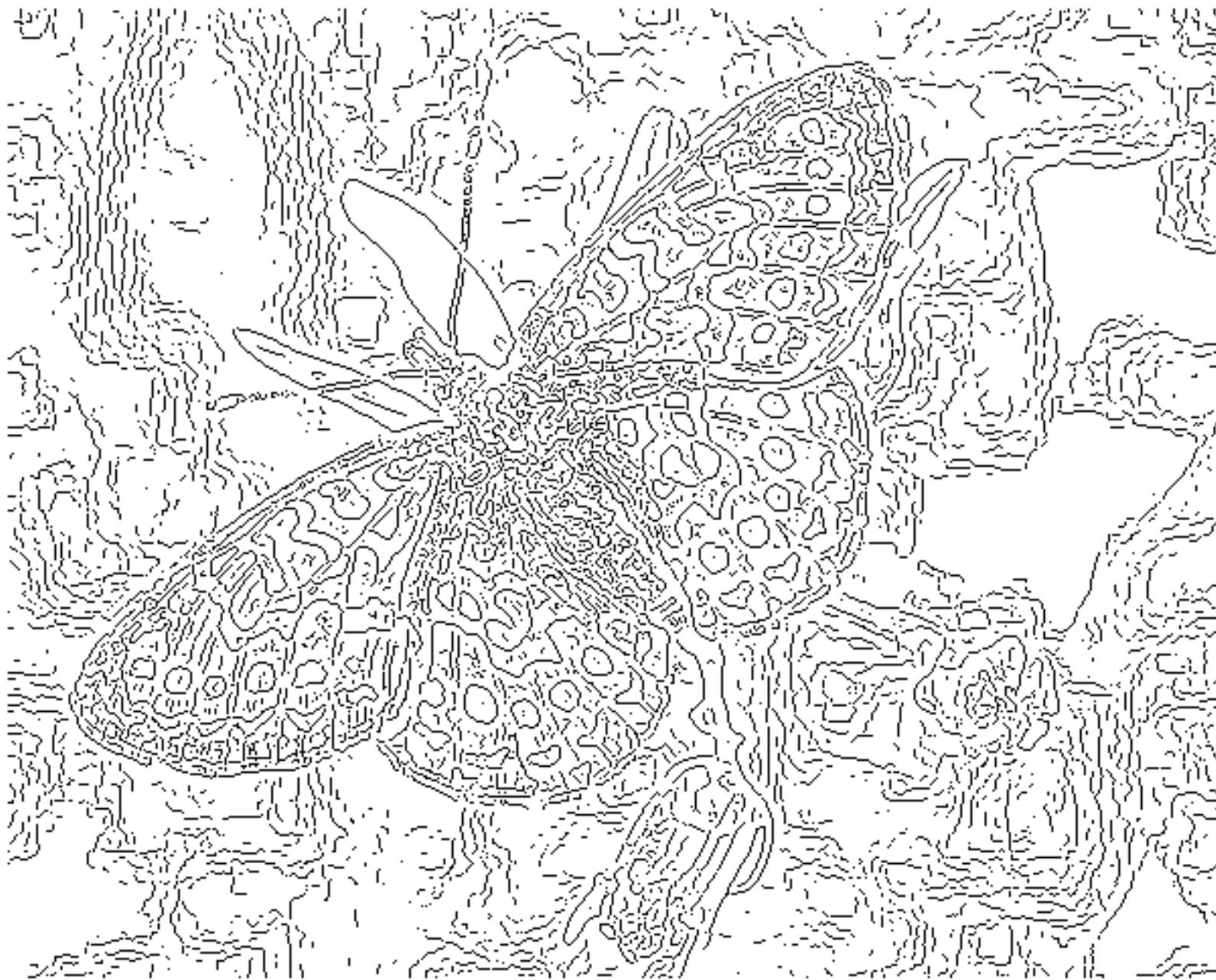
Ponce & Forsyth



Ponce & Forsyth

CS143 Intro to Computer Vision

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fine scale
high
threshold

Ponce & Forsyth



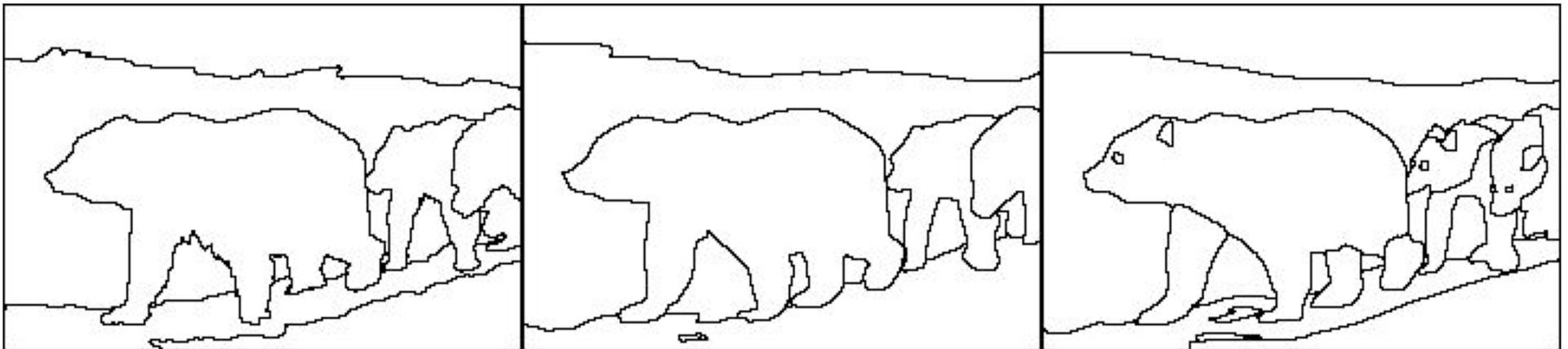
coarse
scale,
high
threshold

Ponce & Forsyth



coarse
scale
low
threshold

Ponce & Forsyth

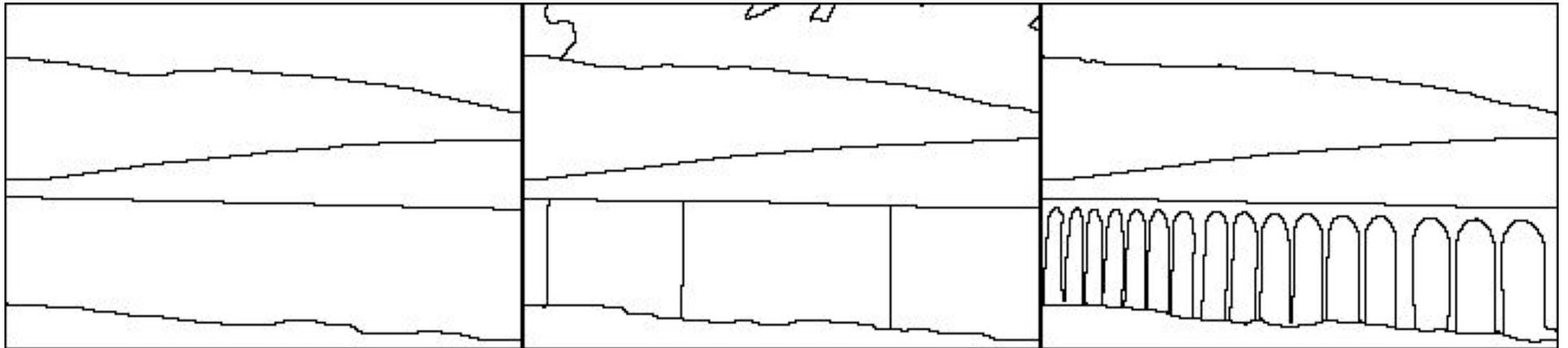
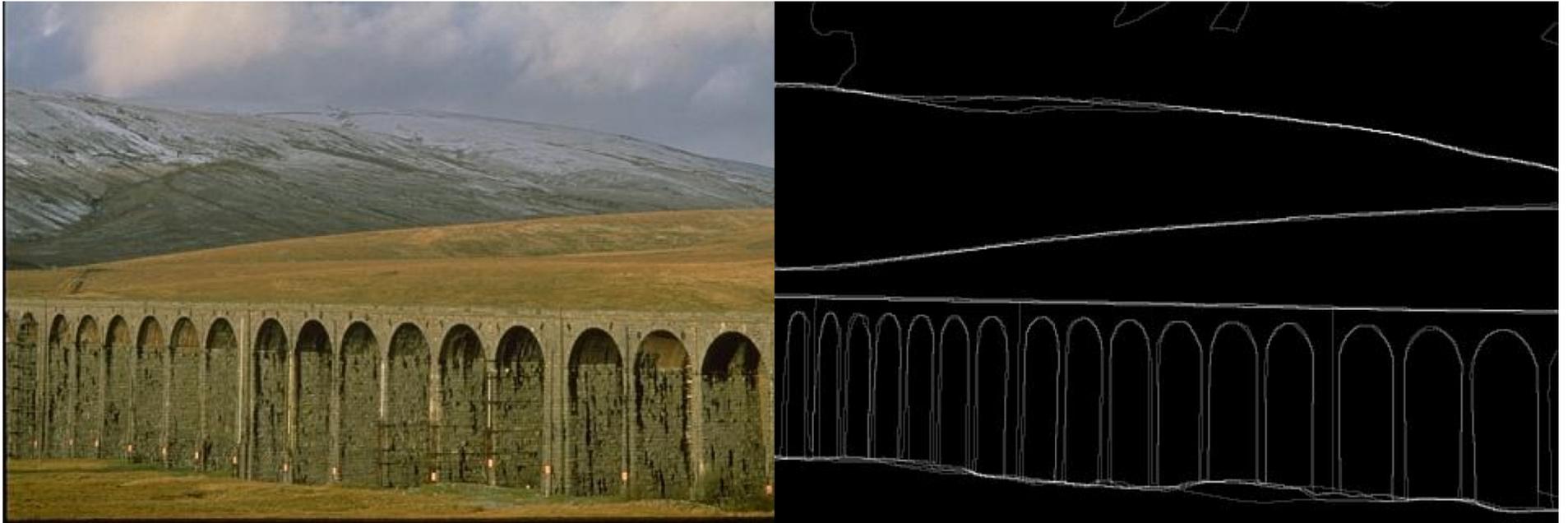


Compare these detected edges to human marked edges:

Humans focus on semantic edges and they don't always agree.

Berkeley Segmentation Dataset and Benchmark

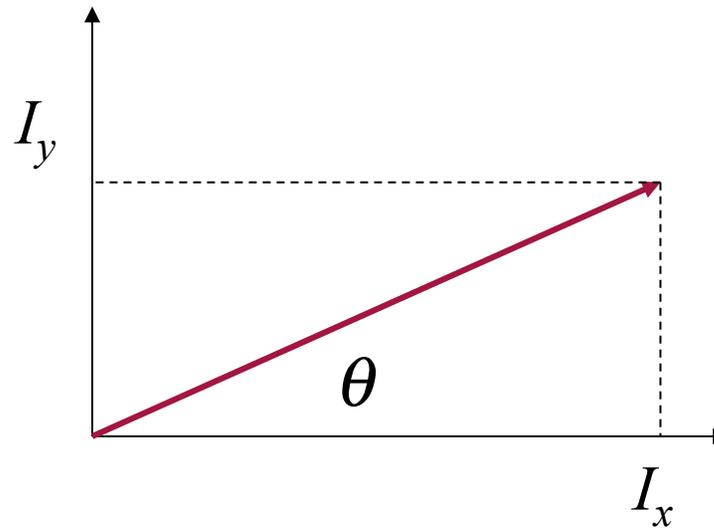
<http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/>



Berkeley Segmentation Dataset and Benchmark

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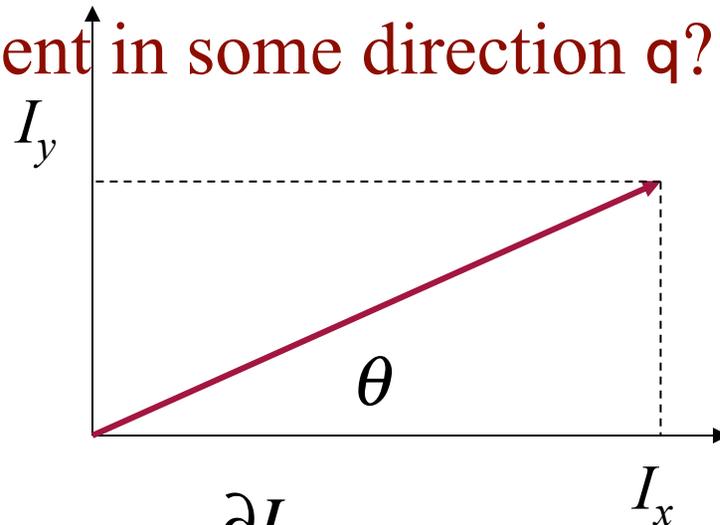
Direction of the Gradient



$$\theta(x, y) = \arctan(I_y(x, y), I_x(x, y))$$

Steerable filters

What is the gradient in some direction θ ?



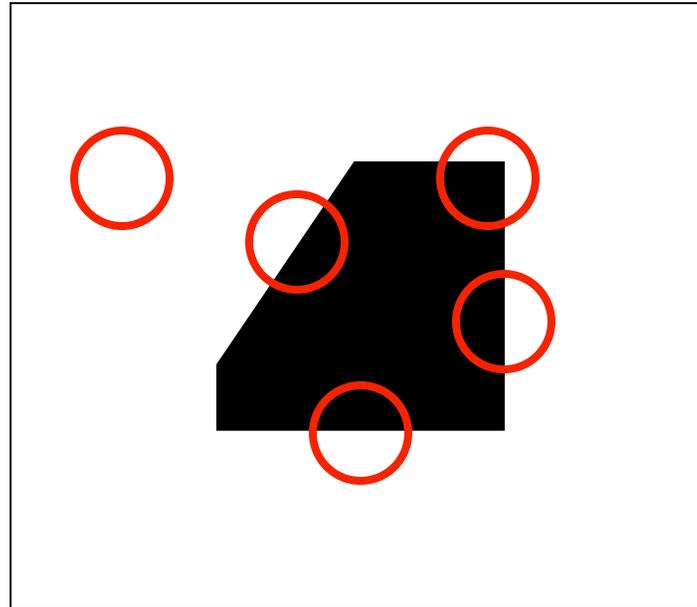
$$I_{\theta}(x, y) = \frac{\partial I}{\partial x} \cos \theta + \frac{\partial I}{\partial y} \sin \theta = I_x \cos \theta + I_y \sin \theta$$

In the direction of the gradient:

$$\|\nabla I\| = I_x \frac{I_x}{\|\nabla I\|} + I_y \frac{I_y}{\|\nabla I\|} = \frac{I_x^2 + I_y^2}{\sqrt{I_x^2 + I_y^2}} = \sqrt{I_x^2 + I_y^2}$$

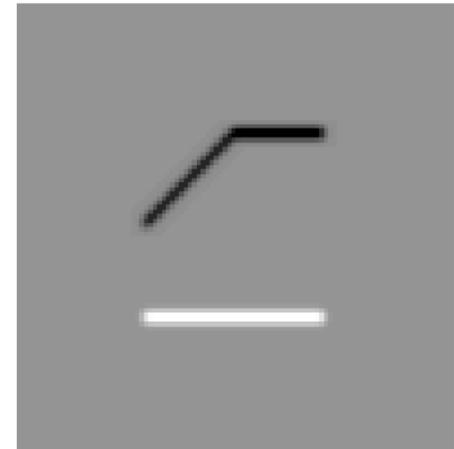
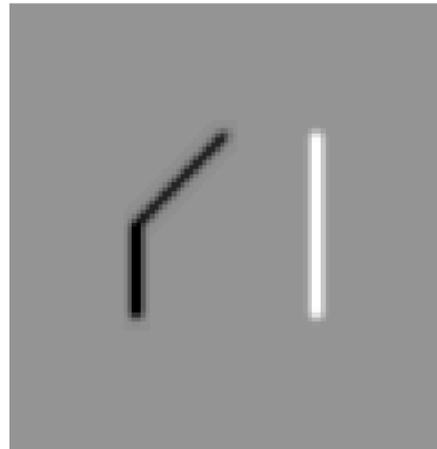
Features (problem 3)

What do the derivatives look like in these neighborhoods?

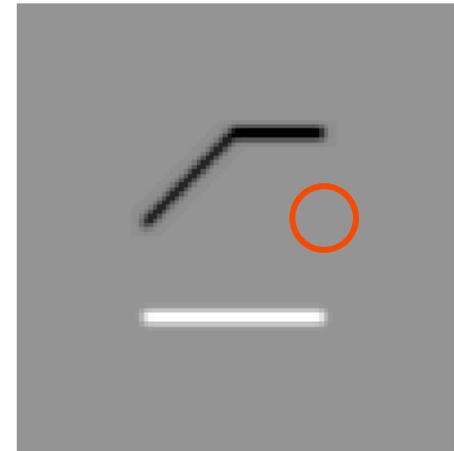
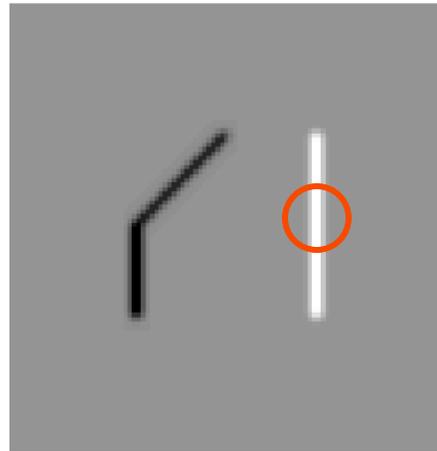


What can you tell about an image neighborhood from the local image derivatives?

Partial derivatives

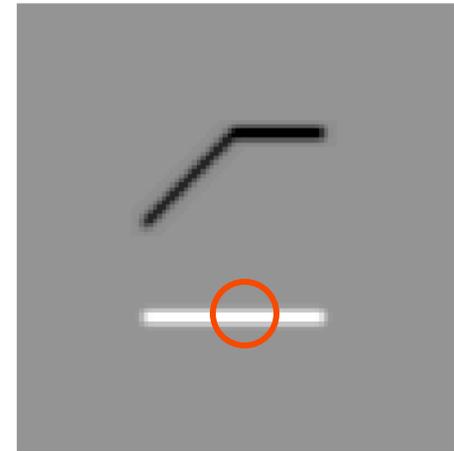
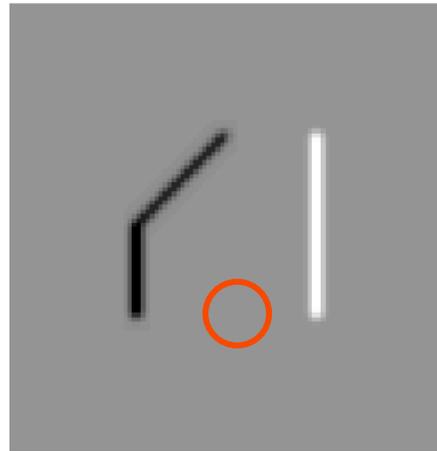
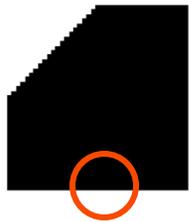


Partial derivatives



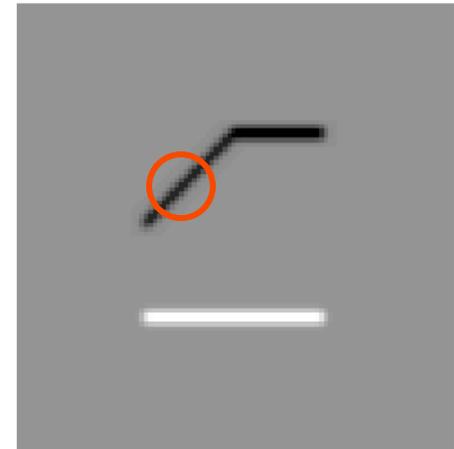
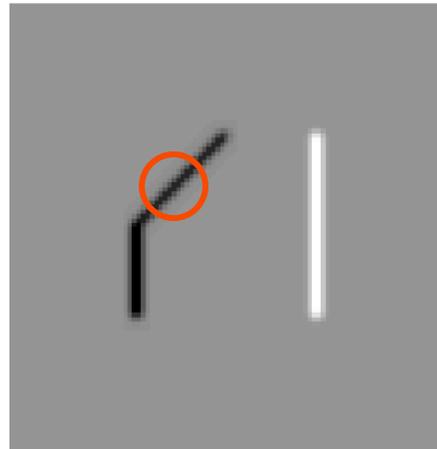
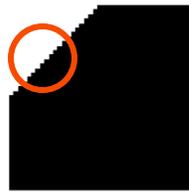
$$\begin{bmatrix} I_x & 0 & I_x & \dots \\ 0 & 0 & 0 & \dots \end{bmatrix}$$

Partial derivatives



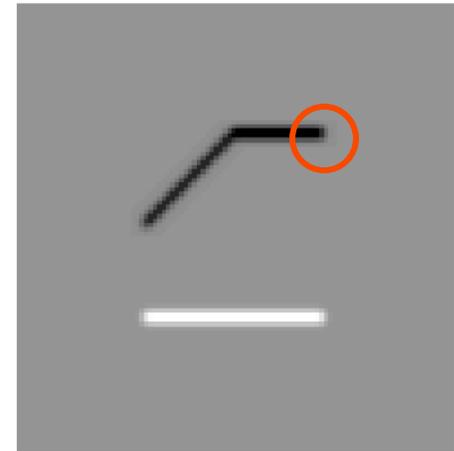
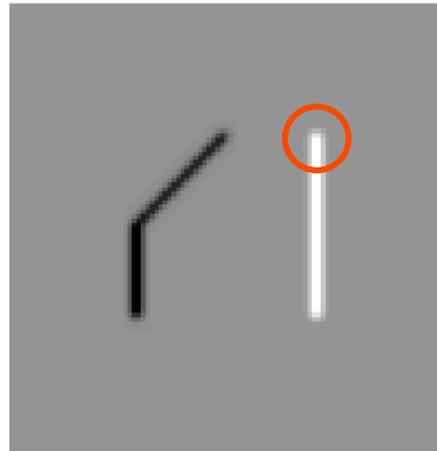
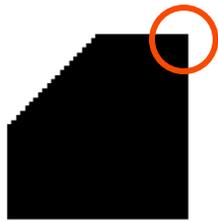
$$\begin{bmatrix} 0 & 0 & 0 & \dots \\ I_y & I_y & 0 & \dots \end{bmatrix}$$

Partial derivatives



$$\begin{bmatrix} 0 & I_x & I_x & \dots \\ 0 & I_y & I_y & \dots \end{bmatrix}$$

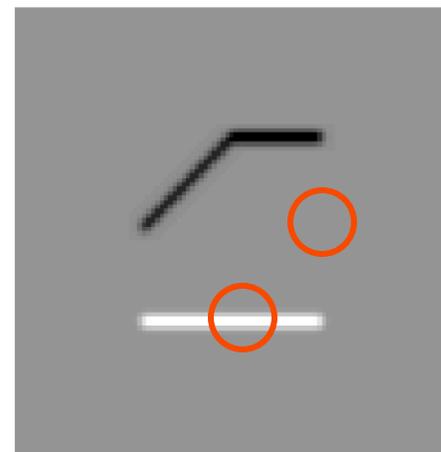
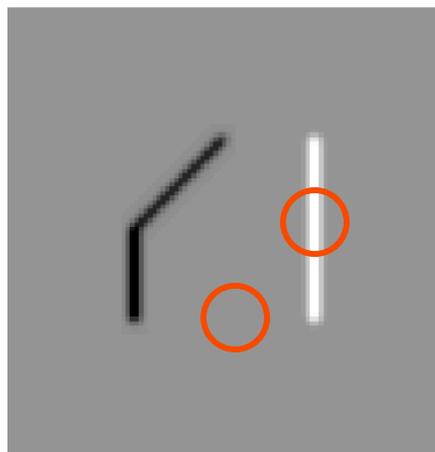
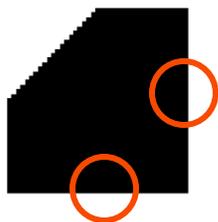
Partial derivatives



$$\begin{bmatrix} I_x & 0 & I_x & \dots \\ 0 & I_y & I_y & \dots \end{bmatrix}$$

Rank of these matrices?

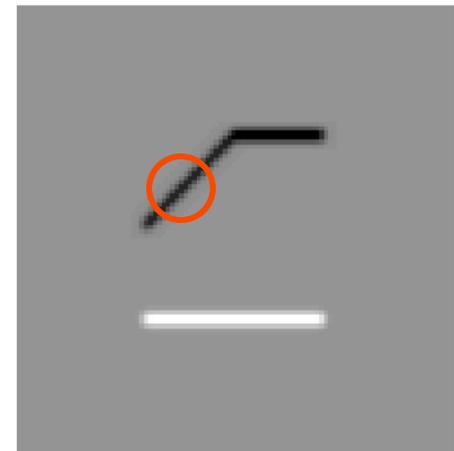
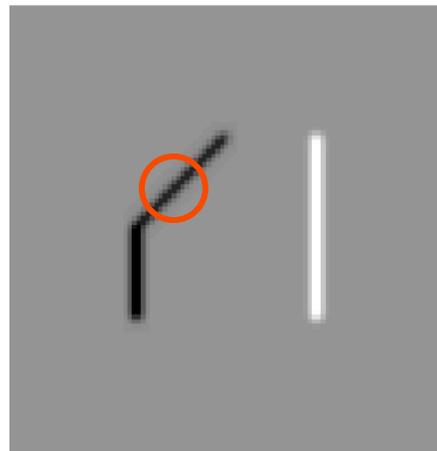
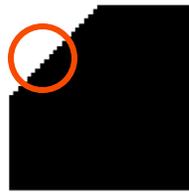
(ie maximum number of linearly independent columns)



$$\begin{bmatrix} I_x & 0 & I_x & \dots \\ 0 & 0 & 0 & \dots \end{bmatrix}$$

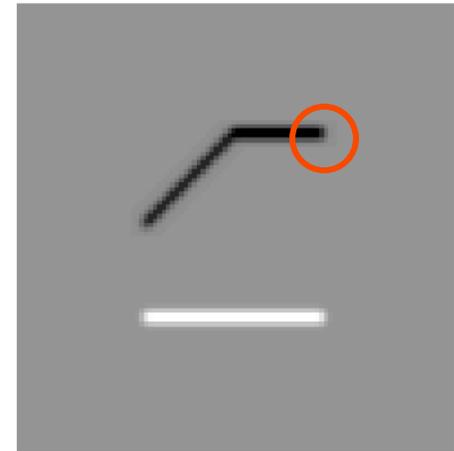
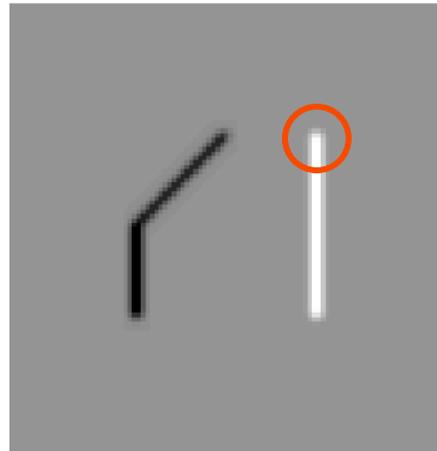
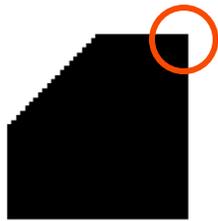
$$\begin{bmatrix} 0 & 0 & 0 & \dots \\ I_y & I_y & 0 & \dots \end{bmatrix}$$

Rank?



$$\begin{bmatrix} 0 & I_x & I_x & \dots \\ 0 & I_y & I_y & \dots \end{bmatrix}$$

Rank?



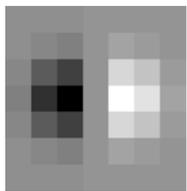
$$\begin{bmatrix} I_x & 0 & I_x & \dots \\ 0 & I_y & I_y & \dots \end{bmatrix}$$

Let's step back a moment...

Convolution

Correlation

Feature detection



f



I



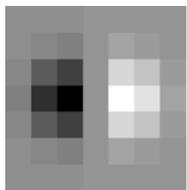
H

$$H[m, n] = f \otimes I = \sum_{k, l} f[k, l] I[m - k, n - l]$$

Notice the “flipping” of the filter.

Let's step back a moment...

Convolution



I

Correlation



H

Feature detection

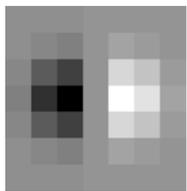
$H = \text{imfilter}(I, f, \text{'symmetric'}, \text{'conv'});$

Let's step back a moment...

Convolution

Correlation

Feature detection



f



I

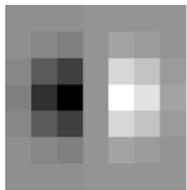


H

$$H[m, n] = f * I = \sum_{k, l} f[k, l] I[m + k, n + l]$$

Let's step back a moment...

Convolution



Correlation



Feature detection

```
dBarb=imfilter(im, dGx, 'symmetric', 'corr');
```

What's the difference?

Convolution:

$$H[m, n] = f \otimes I = \sum_{k, l} f[k, l] I[m - k, n - l]$$

Correlation:

$$H[m, n] = f * I = \sum_{k, l} f[k, l] I[m + k, n + l]$$

Convolution is associative:

$$F \otimes (G \otimes I) = (F \otimes G) \otimes I$$

Correlation is not.

For symmetric filters, there is no difference.

Example: Correlation

$$\begin{array}{c} [-1 \ 3 \ -3 \ 1] \\ \underbrace{\hspace{10em}} \\ [1 \ -2 \ 1] \\ \underbrace{\hspace{10em}} \\ [-1 \ 1] \ [1 \ -1] \ [-1 \ 1] \\ \underbrace{\hspace{10em}} \\ [1 \ -2 \ 1] \\ \underbrace{\hspace{10em}} \\ [1 \ -3 \ 3 \ -1] \end{array}$$

Example: Convolution

$$\begin{array}{c} [1 \ -3 \ 3 \ -1] \\ \underbrace{\hspace{10em}} \\ [-1 \ 2 \ -1] \\ \underbrace{\hspace{10em}} \\ [-1 \ 1] \ [1 \ -1] \ [-1 \ 1] \\ \underbrace{\hspace{10em}} \\ [-1 \ 2 \ -1] \\ \underbrace{\hspace{10em}} \\ [1 \ -3 \ 3 \ -1] \end{array}$$

Strange, eh?

- In the Fourier domain this is easy to explain (convolution is multiplication in the Fourier domain and is hence associative but correlation involves taking the complex conjugate of the filter – if the order is reversed, you take the complex conjugate of the image which changes the result).
- For this class this can essentially be ignored. From now on we'll mostly use correlation.
- If you don't believe it, try out the Matlab script on the web for this lecture.

Convolution vs Correlation

$$x' = u - x, dx' = -dx$$

substitute $x' = x + u$

$$\begin{aligned} C(u) &= \int_{-\infty}^{\infty} f(x)g(u-x)dx \\ &= - \int_{\infty}^{-\infty} f(u-x')g(x')dx' \\ &= \int_{-\infty}^{\infty} g(x')f(u-x')dx' \\ &= \int_{-\infty}^{\infty} g(x)f(u-x)dx \end{aligned}$$

$$\begin{aligned} f \circ g &= \int_{-\infty}^{\infty} f(x)g(x+u)dx; \\ &= \int_{-\infty}^{\infty} f(x'-u)g(x')dx' \\ &= \int_{-\infty}^{\infty} f(x-u)g(x)dx \end{aligned}$$

<http://www-structmed.cimr.cam.ac.uk/Course/Convolution/convolution.html>