Edges, Orientation, HOG and SIFT

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Linear Filters

- Example: smoothing by averaging
  - form the average of pixels in a neighbourhood
- Example: smoothing with a Gaussian
  - form a weighted average of pixels in a neighbourhood
- Example: finding a derivative
  - form a weighted average of pixels in a neighbourhood

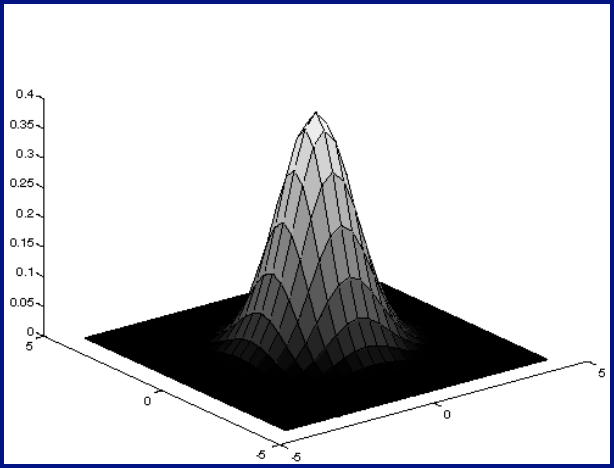
Smoothing by Averaging

$$N_{ij} = \frac{1}{N}\Sigma_{uv}O_{i+u,j+v}$$

where u, v, is a window of N pixels in total centered at 0, 0

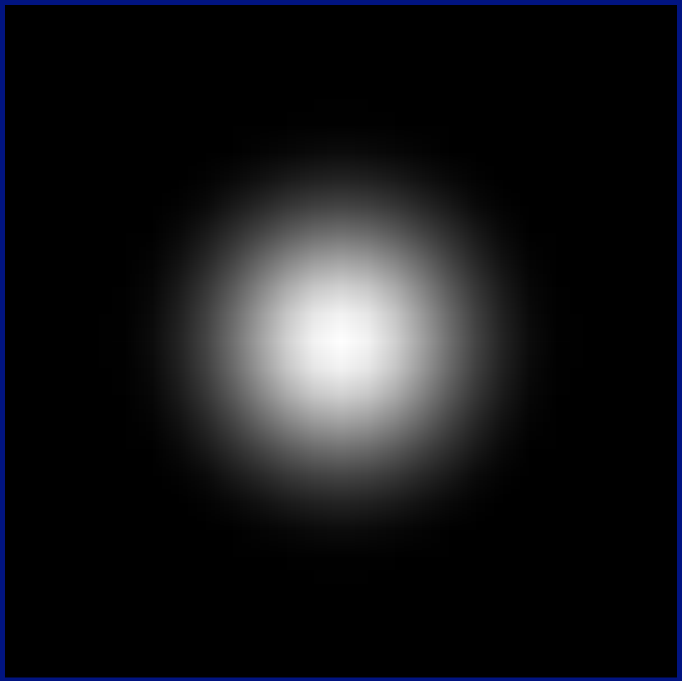
Smoothing with a Gaussian

- Notice "ringing"
  - apparently, a grid is superimposed
- Smoothing with an average actually doesn't compare at all well with a defocussed lens
  - what does a point of light produce?



- A Gaussian gives a good model of a fuzzy blob

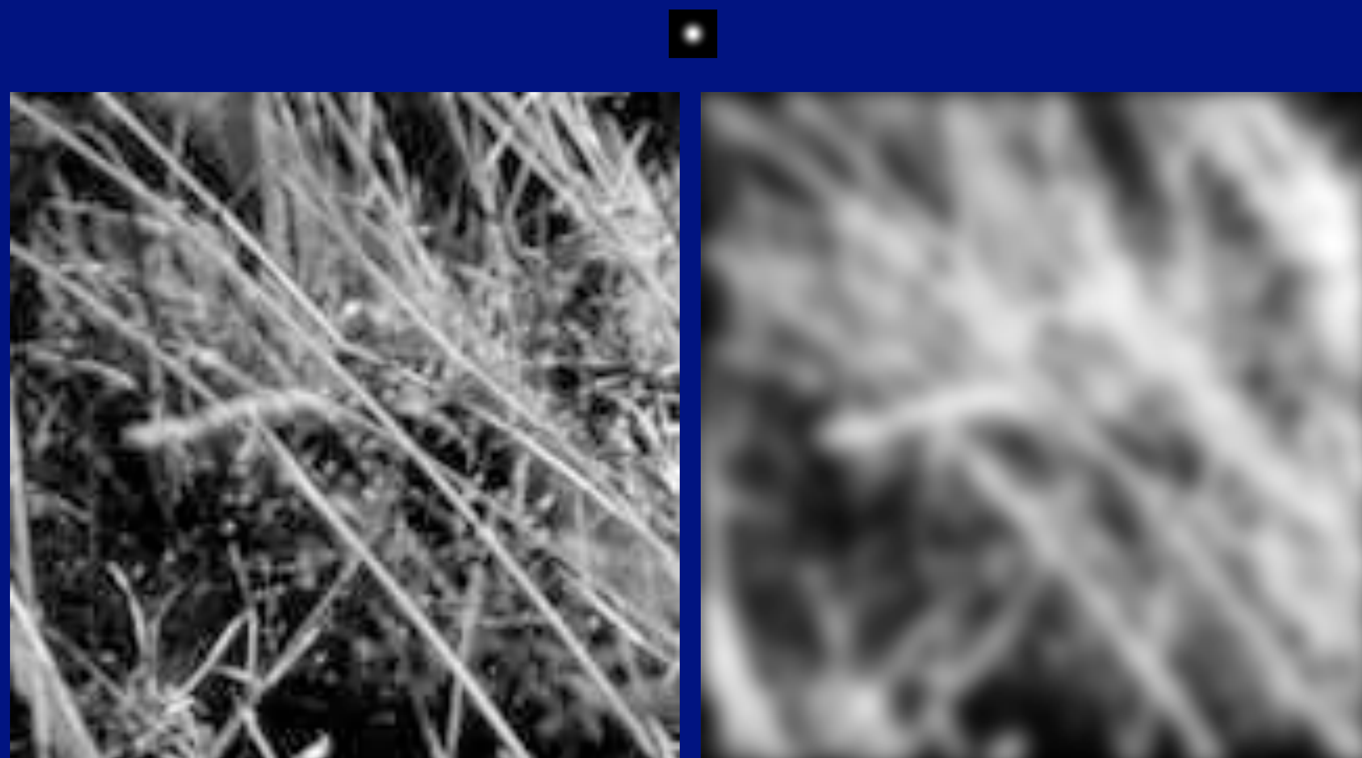
Gaussian filter kernel



$$K_{uv} = \left(\frac{1}{2\pi\sigma^2}\right)\exp\left(\frac{-\left[u^2+v^2\right]}{2\sigma^2}\right)$$

We're assuming the index can take negative values

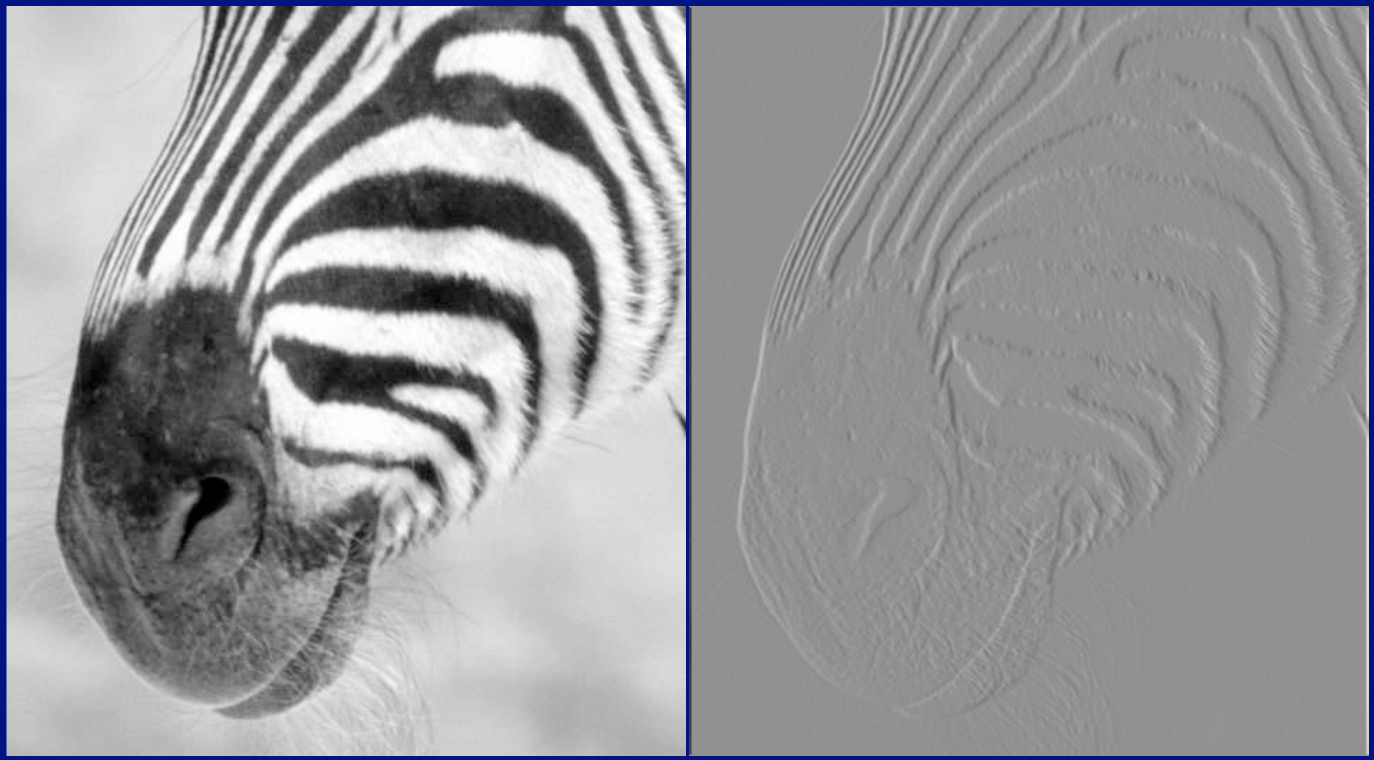
Smoothing with a Gaussian



$$N_{ij} = \sum_{uv} O_{i-u,j-v} K_{uv}$$

Notice the curious looking form

Finding derivatives



$$N_{ij} = \frac{1}{\Delta x}(I_{i+1,j} - I_{ij})$$

Convolution

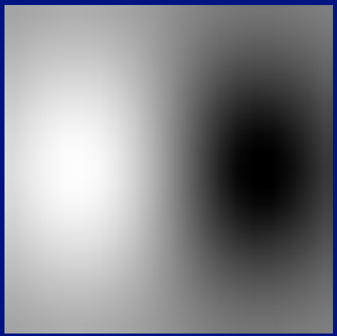
- Each of these involves a weighted sum of image pixels
- The set of weights is the same
  - we represent these weights as an image, H
  - H is usually called the kernel
- Operation is called convolution
  - it's associative
- Any linear shift-invariant operation can be represented by convolution
  - linear: G(k f)=k G(f)
  - shift invariant: G(Shift(f))=Shift(G(f))
  - Examples:
    - smoothing, differentiation, camera with a reasonable, defocussed lens system

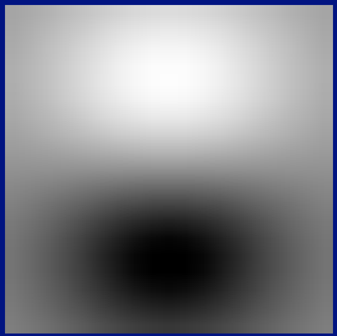
$$N_{ij} = \sum_{uv} H_{uv} O_{i-u,j-v}$$

Filters are templates

$$N_{ij} = \sum_{uv} H_{uv} O_{i-u,j-v}$$

- At one point
  - output of convolution is a (strange) dot-product
- Filtering the image involves a dot product at each point
- Insight
  - filters look like the effects they are intended to find
  - filters find effects they look like

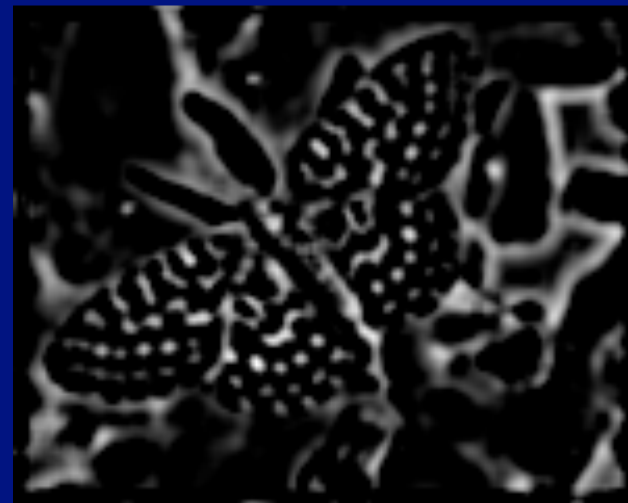




Normalised correlation

- Think of filters of a dot product
  - now measure the angle
  - i.e normalised correlation output is filter output, divided by root sum of squares of values over which filter lies
  - Tricks:
    - ensure that filter has a zero response to a constant region
      - helps reduce response to irrelevant background
    - subtract image average when computing the normalising constant
    - absolute value deals with contrast reversal

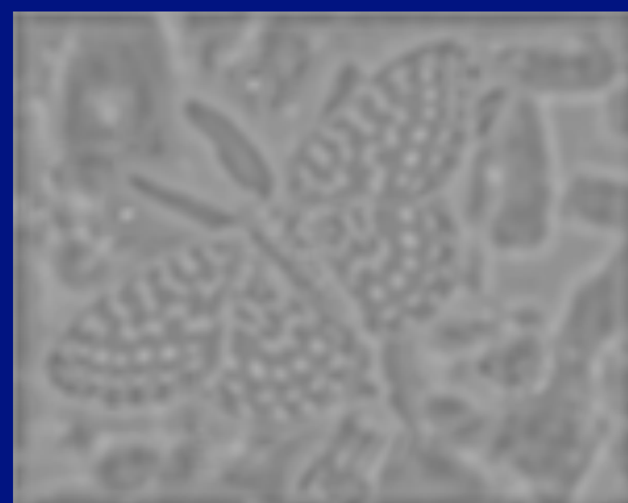
normalised correlation
with non-zero mean filter

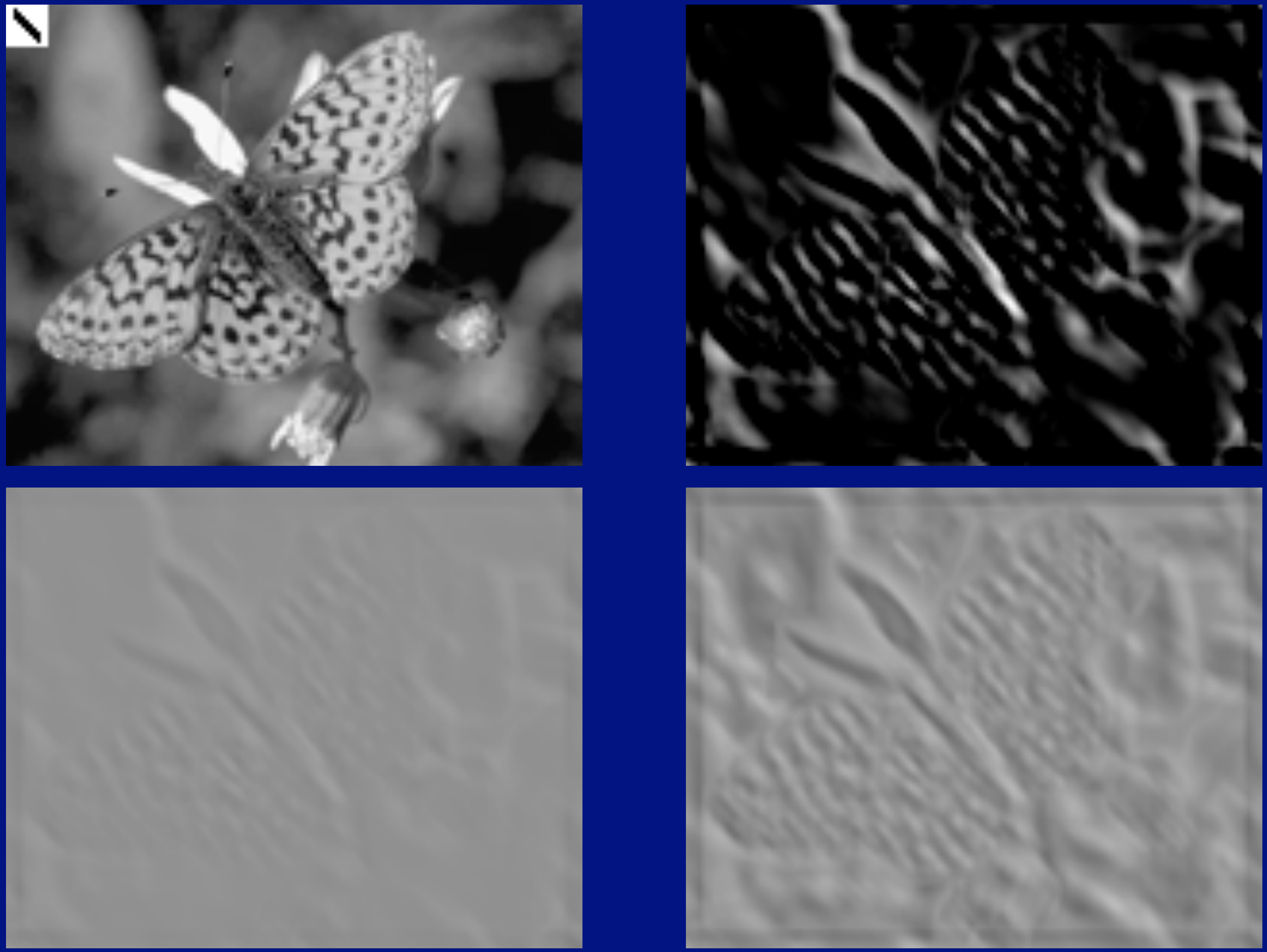


Positive responses

Zero mean image, -1:1 scale

Zero mean image, -max:max scale





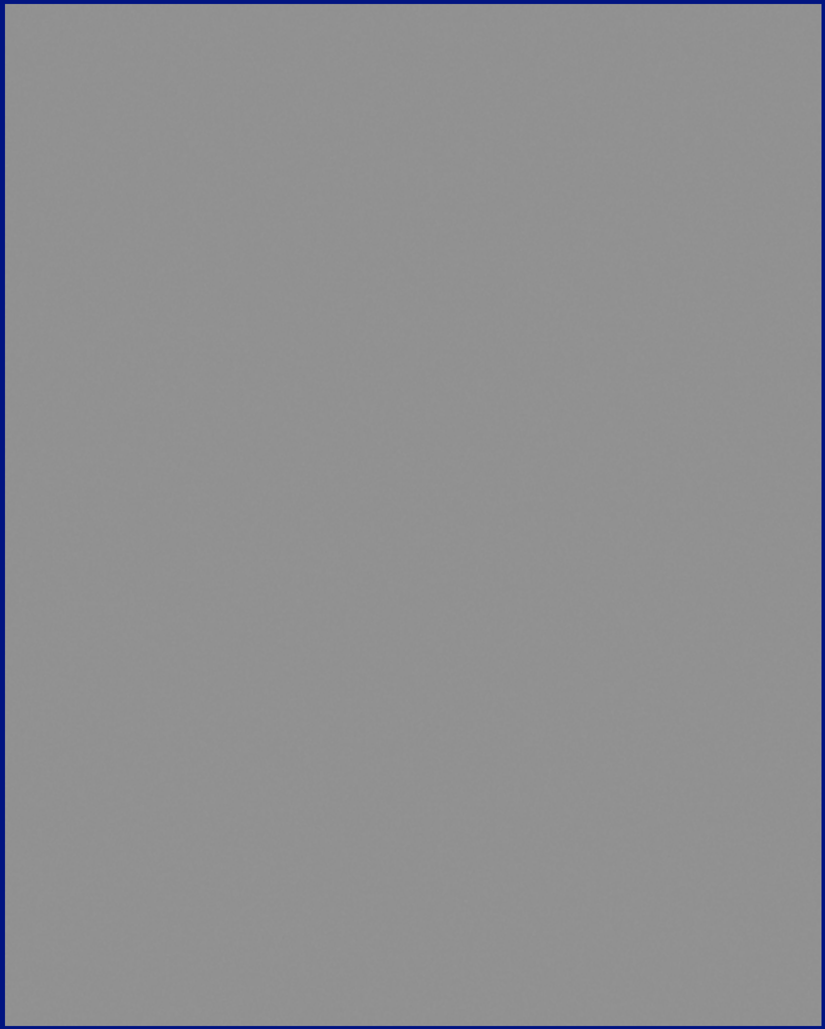
Finding hands

Figure from "Computer Vision for Interactive Computer Graphics," W.Freeman et al, IEEE Computer Graphics and Applications, 1998

Noise

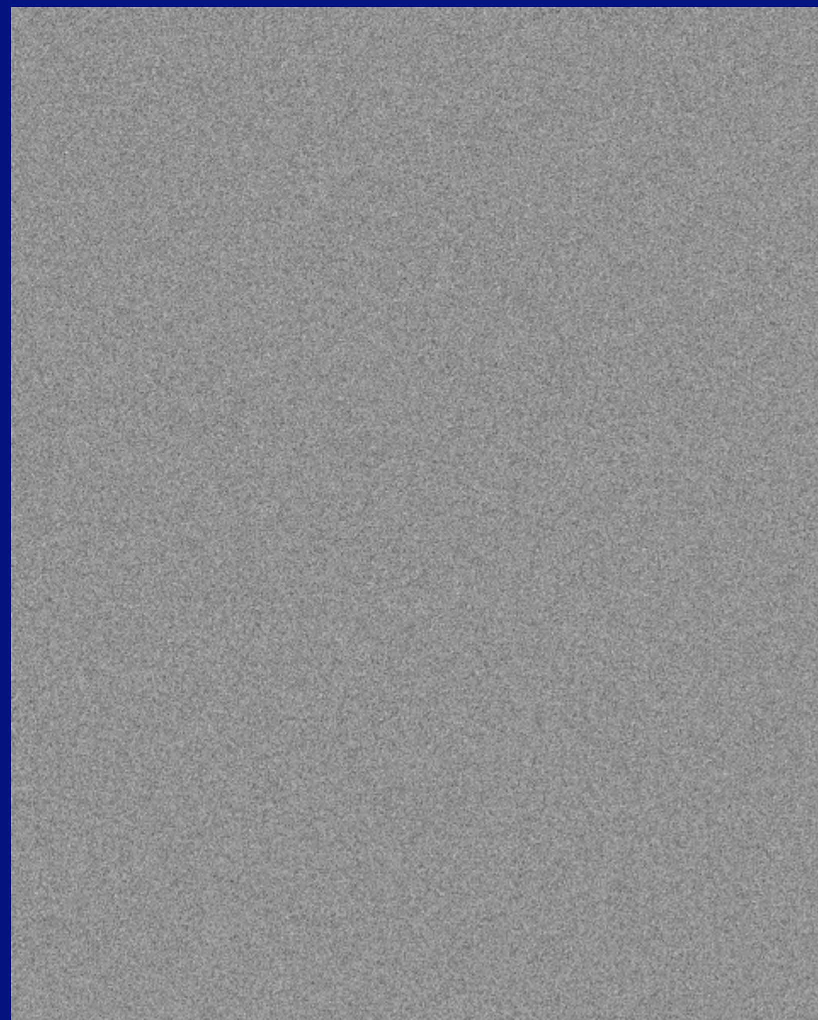
- Simplest noise model
  - independent stationary additive Gaussian noise
  - the noise value at each pixel is given by an independent draw from the same normal probability distribution
- Issues
  - allows values greater than maximum camera output or less than zero
    - for small standard deviations, this isn't too much of a problem
  - independence may not be justified (e.g. damage to lens)
  - may not be stationary (e.g. thermal gradients in the ccd)

sigma=1



sigma=4

sigma=
16



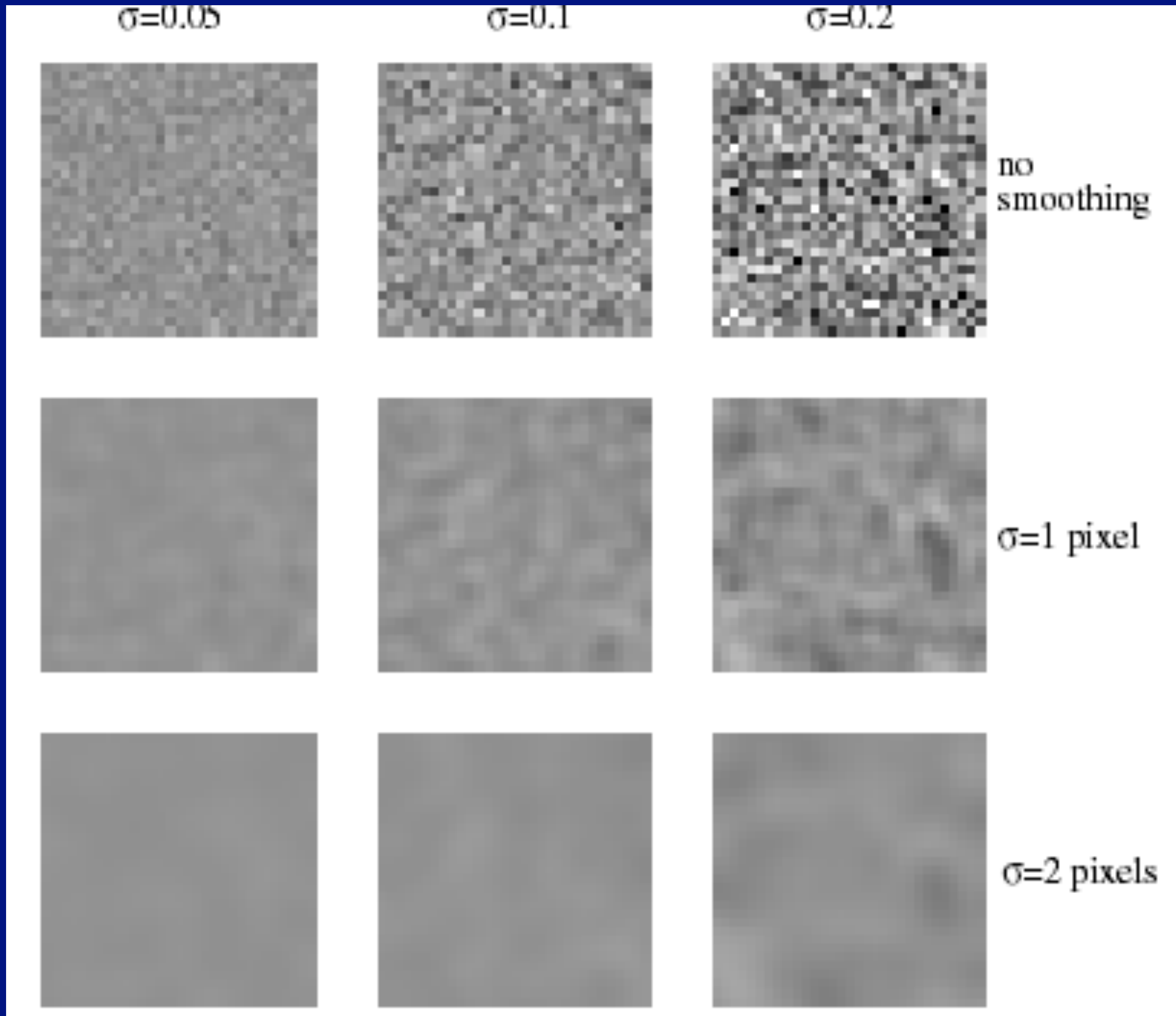
sigma=1

sigma=16

Smoothing reduces noise

- Generally expect pixels to “be like” their neighbours
  - surfaces turn slowly
  - relatively few reflectance changes
- Expect noise to be independent from pixel to pixel
  - Implies that smoothing suppresses noise, for appropriate noise models
- Scale
  - the parameter in the symmetric Gaussian
  - as this parameter goes up, more pixels are involved in the average
  - and the image gets more blurred
  - and noise is more effectively suppressed

$$K_{uv} = \left(\frac{1}{2\pi\sigma^2}\right)\exp\left(\frac{-\left[u^2+v^2\right]}{2\sigma^2}\right)$$

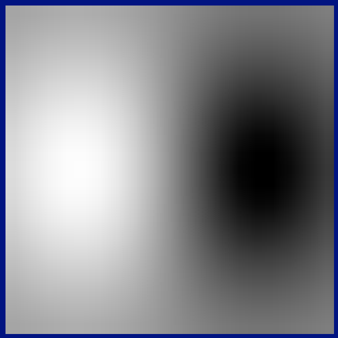

σ=0.05
σ=0.1
σ=0.2
no smoothing
σ=1 pixel
σ=2 pixels

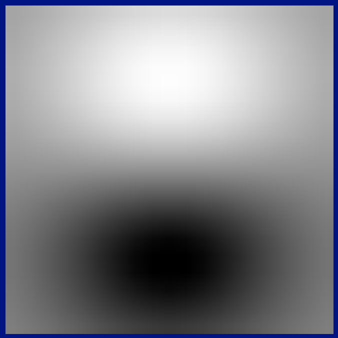
Representing image changes: Edges

- Idea:
  - points where image value change very sharply are important
    - changes in surface reflectance
    - shadow boundaries
    - outlines
- Finding Edges:
  - Estimate gradient magnitude using appropriate smoothing
  - Mark points where gradient magnitude is
    - Locally biggest and
    - big

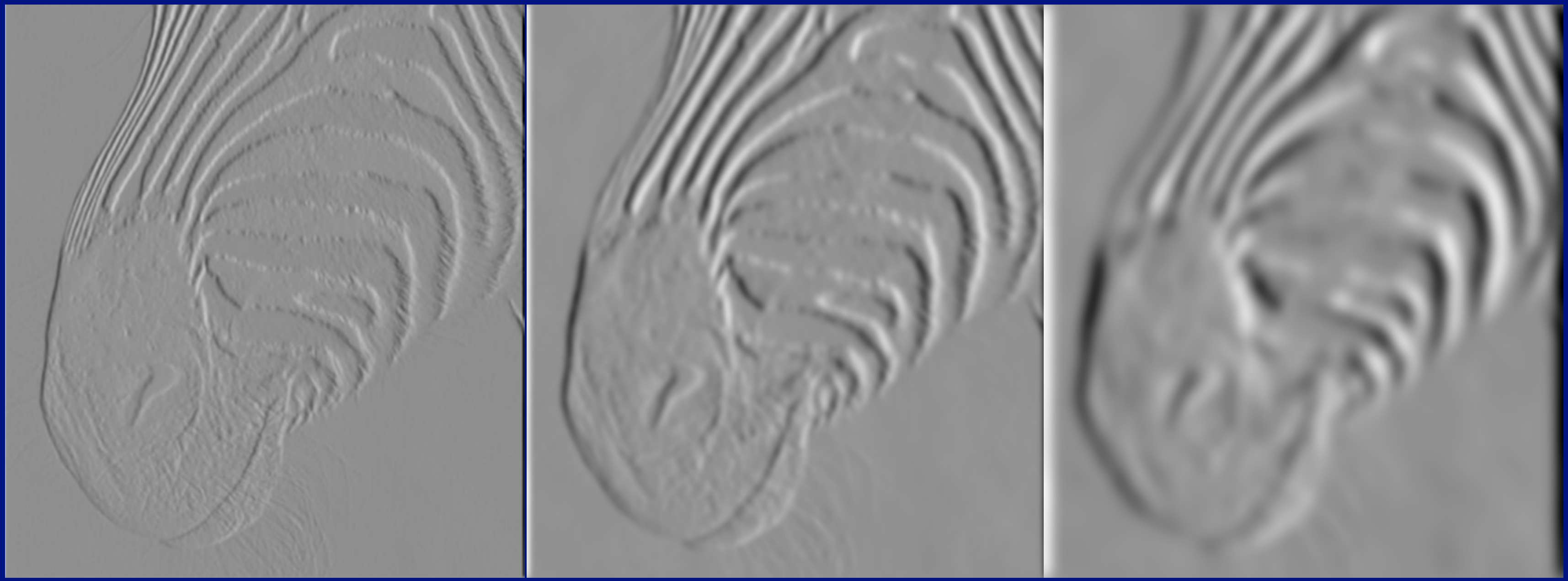
Smoothing and Differentiation

- Issue: noise
  - smooth before differentiation
  - two convolutions to smooth, then differentiate?
  - actually, no - we can use a derivative of Gaussian filter



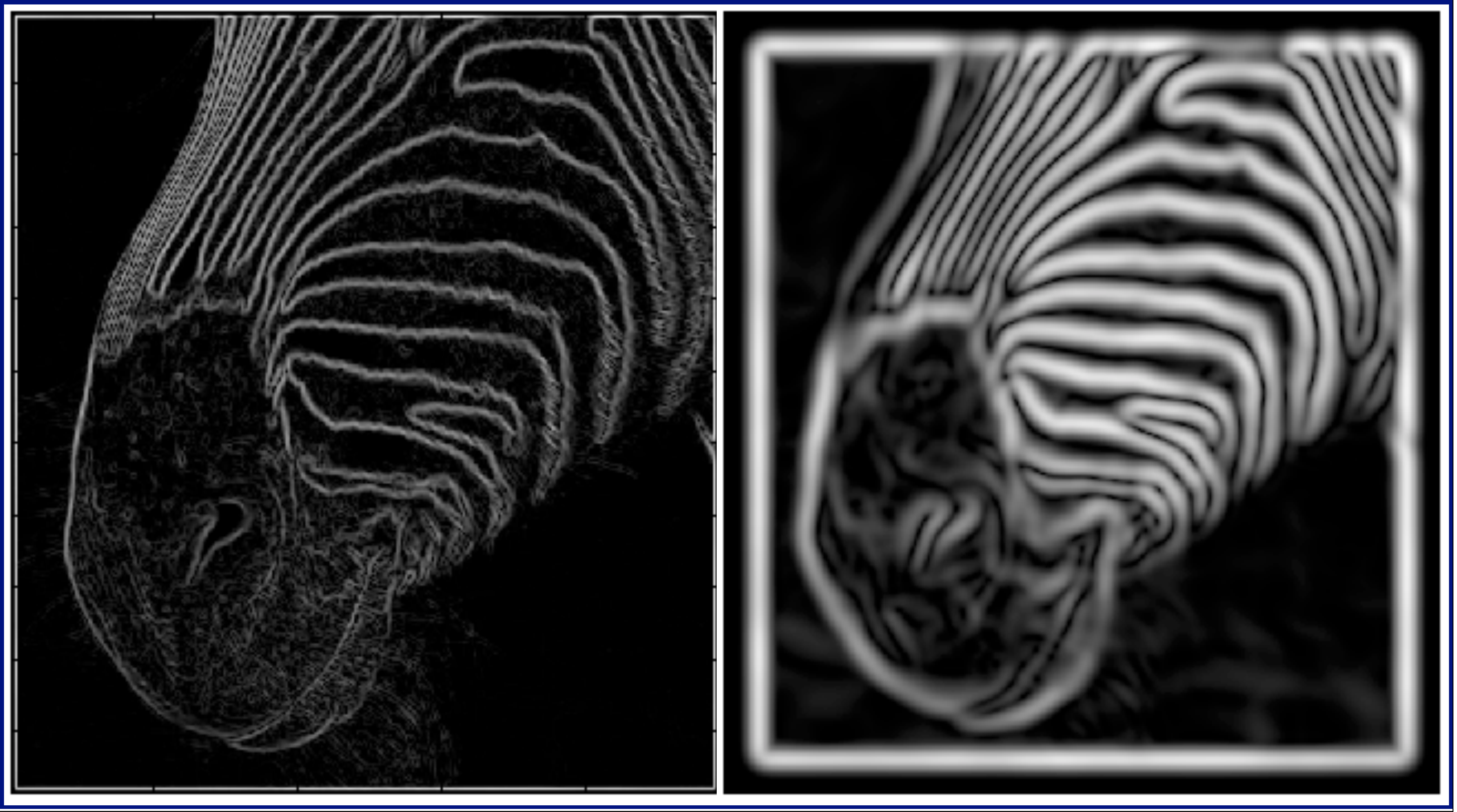


Scale affects derivatives

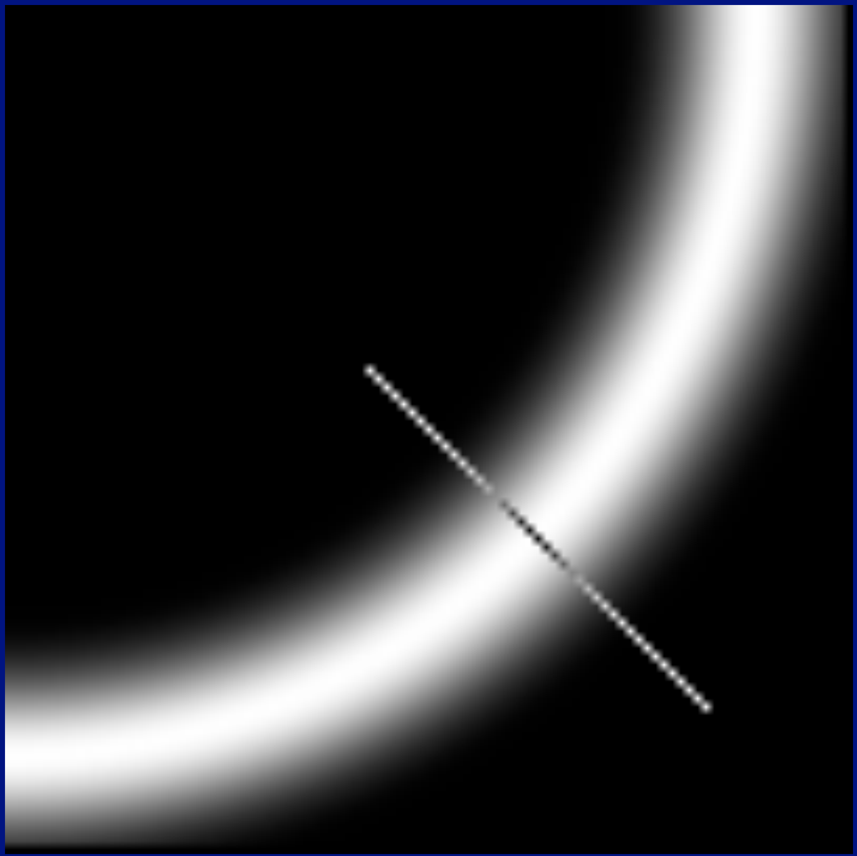


1 pixel   3 pixels   7 pixels

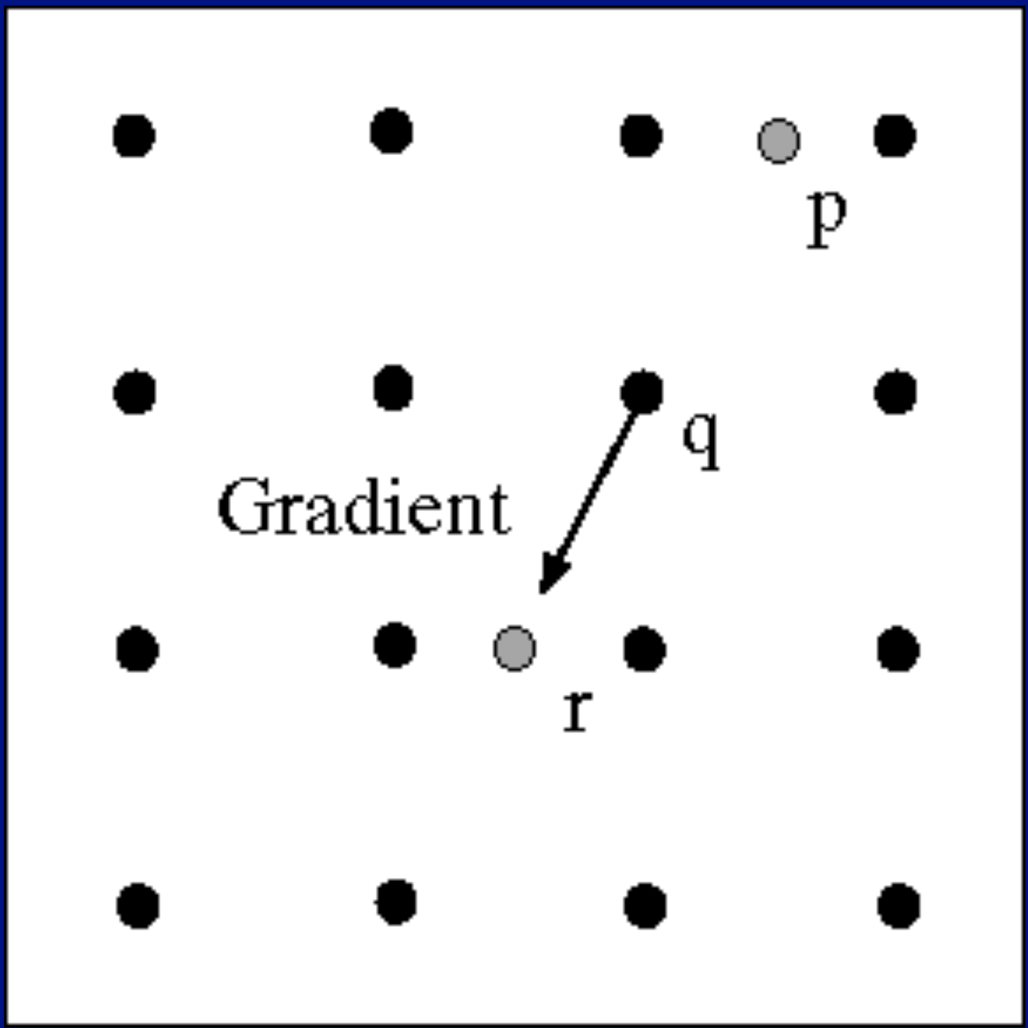
Scale affects gradient magnitude

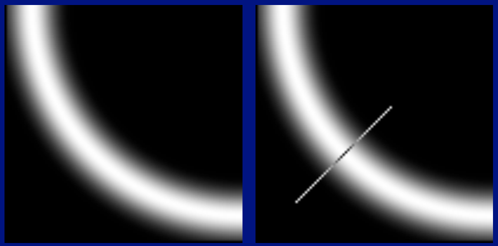


Marking the points

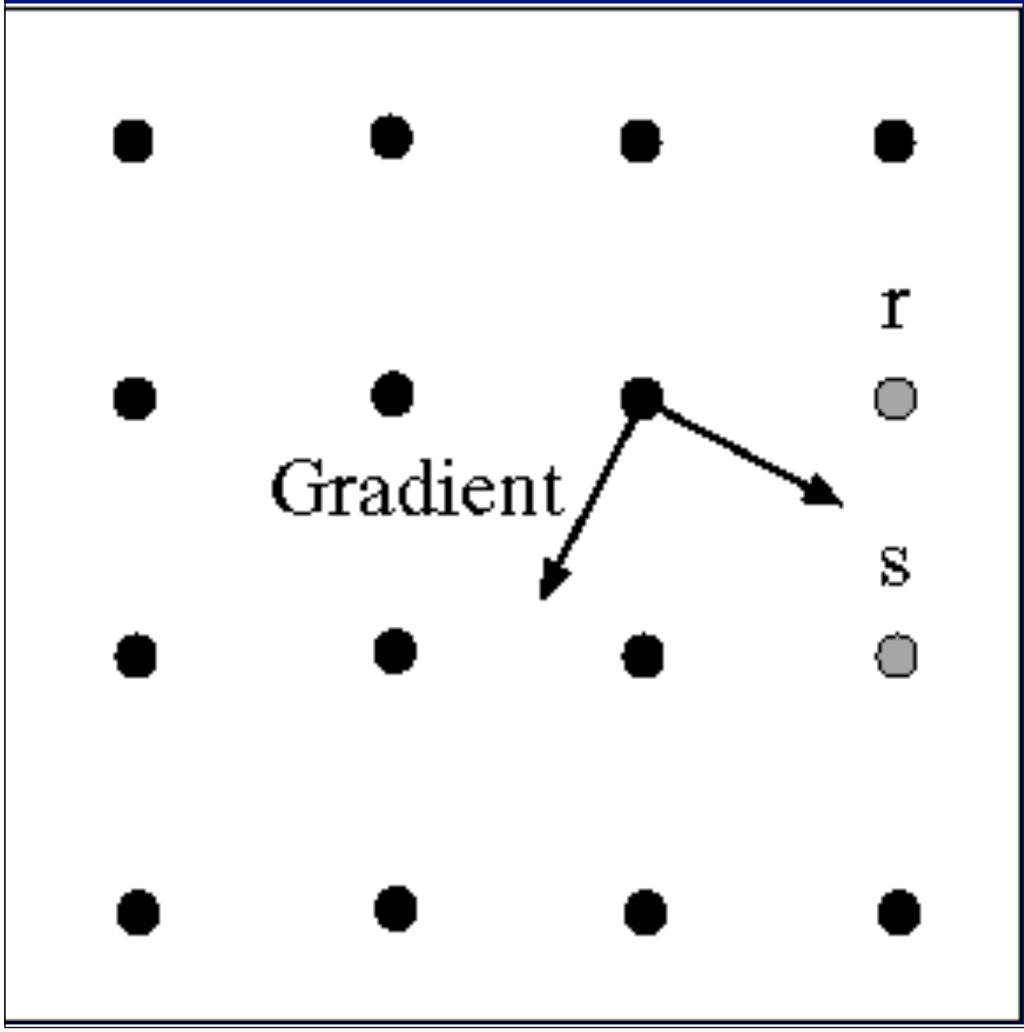


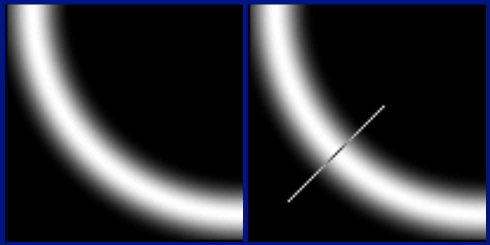
Non-maximum suppression





Predicting the next edge point



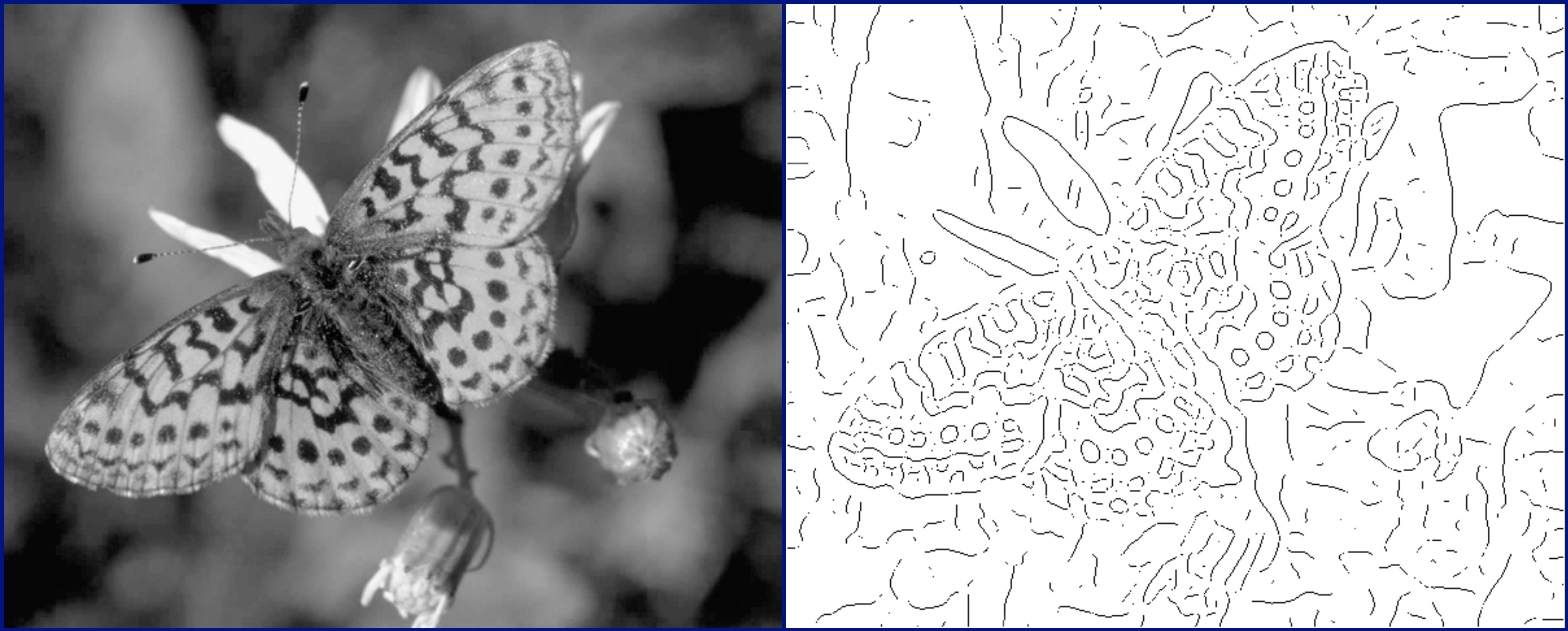


Remaining issues

- Check maximum value of gradient value is sufficiently large
    - drop-outs?
        - use hysteresis

Notice

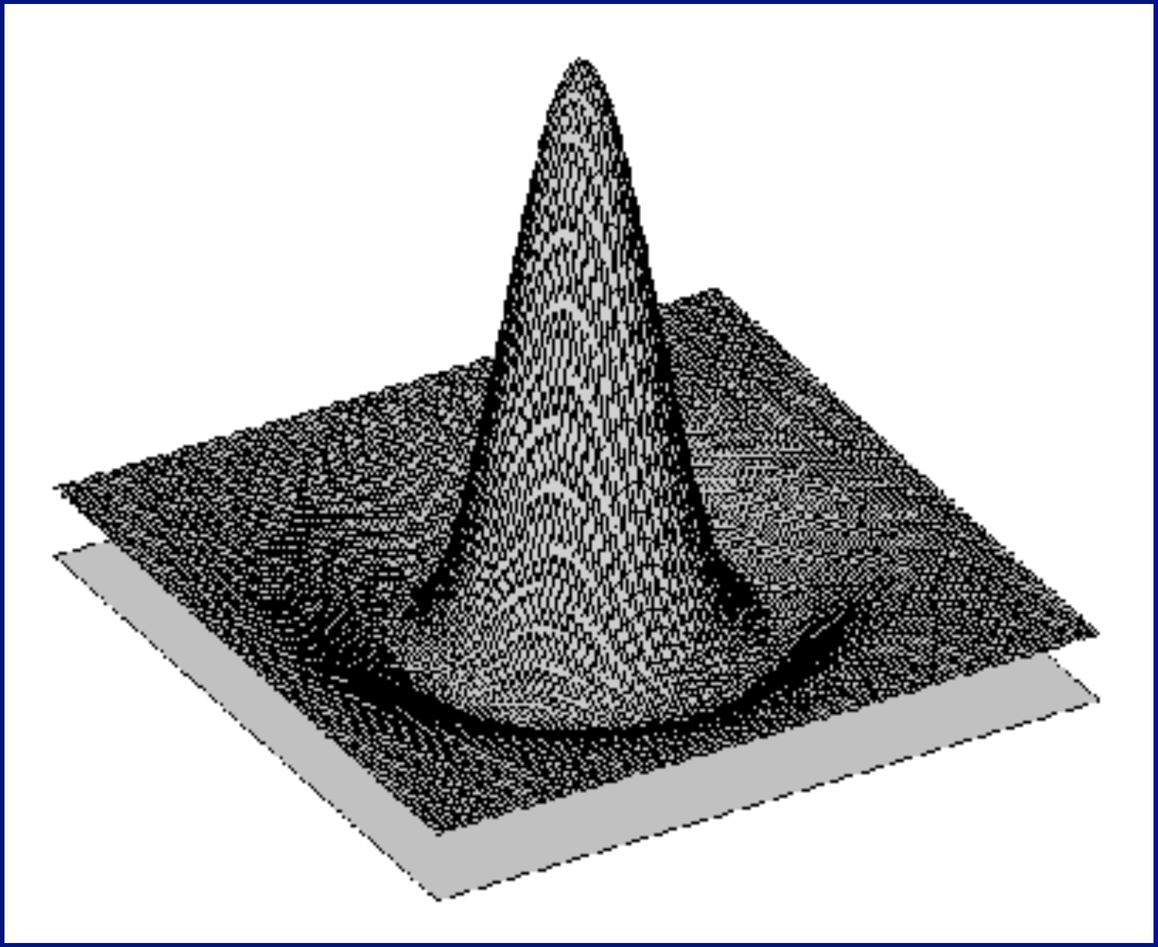
- Something nasty is happening at corners
- Scale affects contrast
- Edges aren’t bounding contours



The Laplacian of Gaussian

- Another way to detect an extremal first derivative is to look for a zero second derivative
- Appropriate 2D analogy is rotation invariant
  - Laplacian
- Edges are zero crossings
  - Bad idea to apply a Laplacian without smoothing
  - smooth with Gaussian, apply Laplacian
  - this is the same as filtering with a Laplacian of Gaussian filter
  - Now mark the zero points where
    - there is a sufficiently large derivative,
    - and enough contrast

The Laplacian of Gaussian



Crucial points

- Filters are simple detectors
  - they look like patterns they find
- Smoothing suppresses noise
  - because pixels tend to agree
- Sharp changes are interesting
  - because pixels tend to agree
  - easy to find - edges