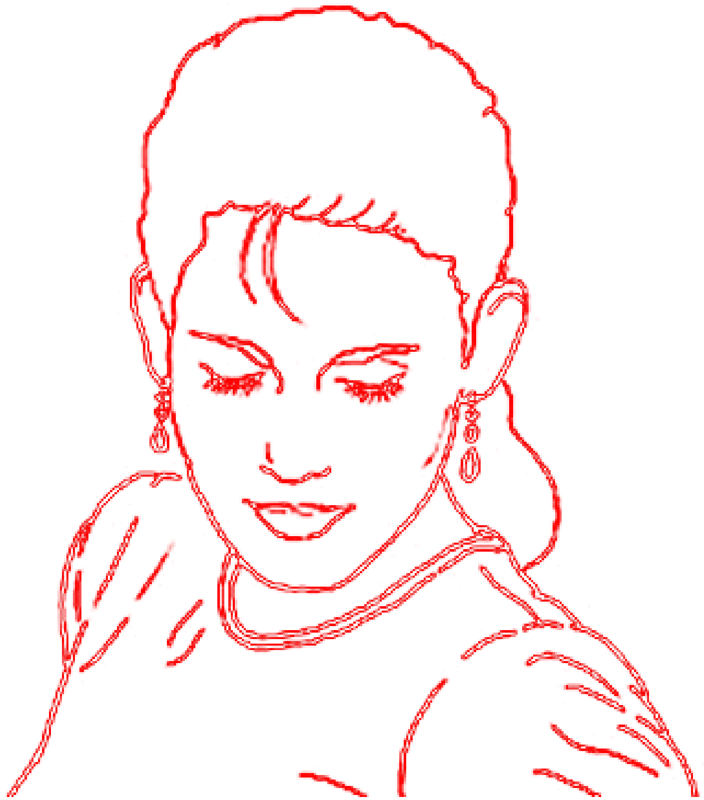
Shape extraction: contour

Edge detection

Edge detection

- **Goal:** Identify sudden changes (discontinuities) in an image
  - Intuitively, most semantic and shape information from the image can be encoded in the edges
  - More compact than pixels
- **Ideal:** artist's line drawing (but artist is also using object-level knowledge)



Source: D. Lowe

Segmentation

- Image segmentation consists into the decomposition of the image in segments (i.e. components)
- This process is based on a given criteria of homogeneity (chromatic, morphologic, motion, depth, etc.)
- From the operational viewpoint, three approach have been proposed:
  - Clustering image data and growing regions
  - Border following
  - Search of borders

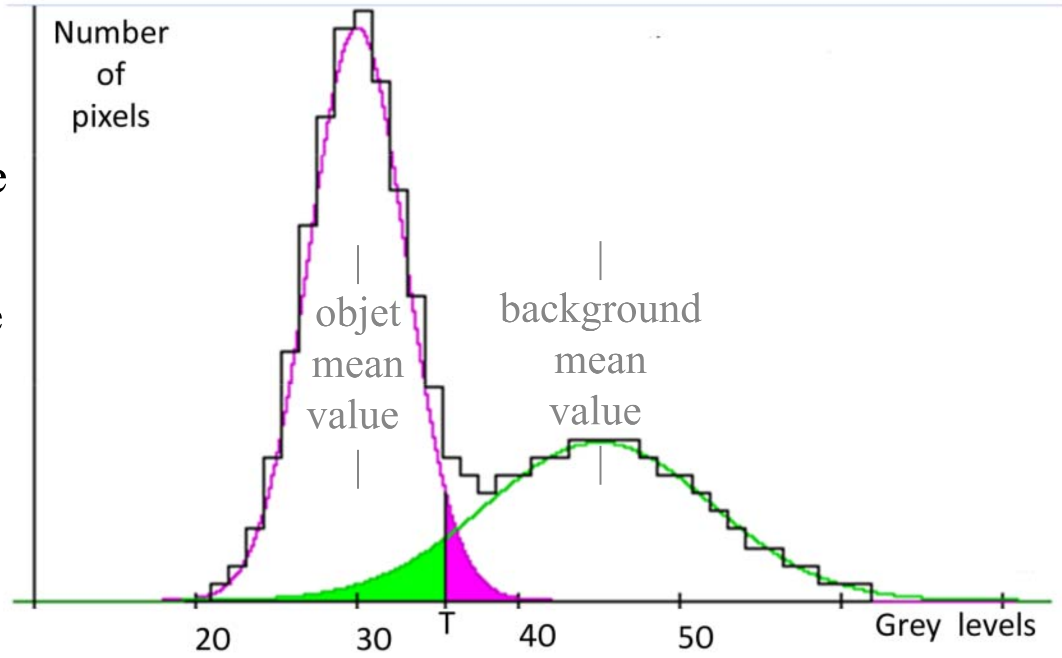
Binary Images

- The segmentation process leads to detect an individual object (foreground) in contrast to the background so it is a binarization process
- Some applications are by nature binary: black and white printing, writing, mechanical parts, bio-imagery like cells or chromosomes, etc. ....
- Often the originals contains various grey levels due to:
  - Electric noise of the camera
  - Non-uniform scene illuminations
  - Shadowing
  - …

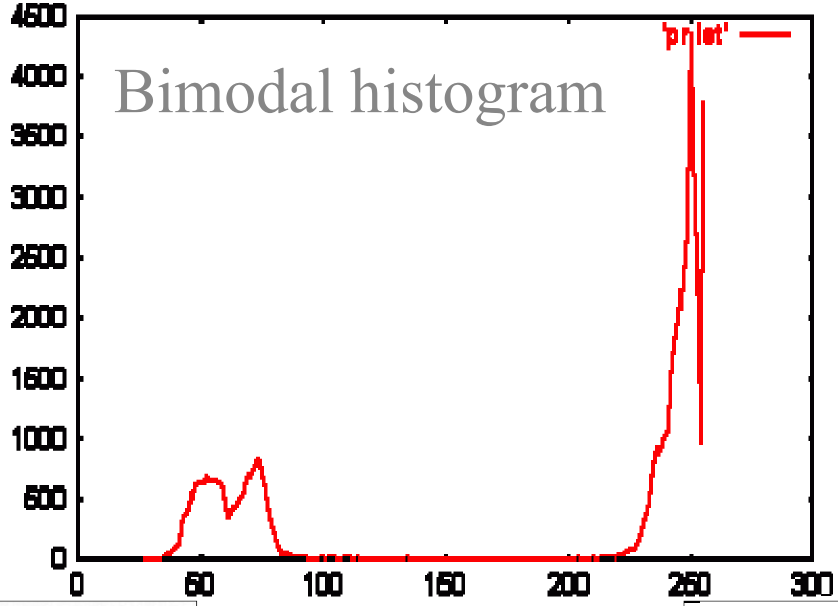
Bimodal Distribution

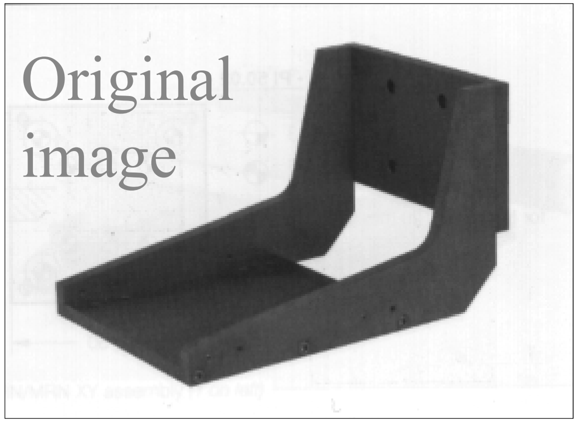
- The easest solution is a threshold applied to the grey levels:
  - O(i, j) = 255 se I(i, j) < S
  - O(i, j) = 0 otherwise
- It is required the evaluation of the optimal threshold S.
- Operating on the histogram, there are two possibilities:
  - Finding the minimum
  - Applying statistic criteria

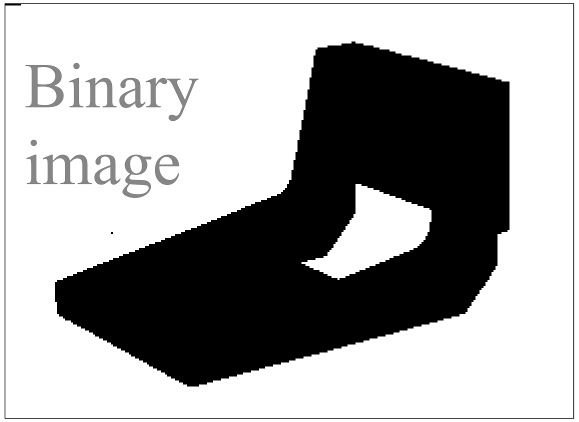
Bimodal histogram



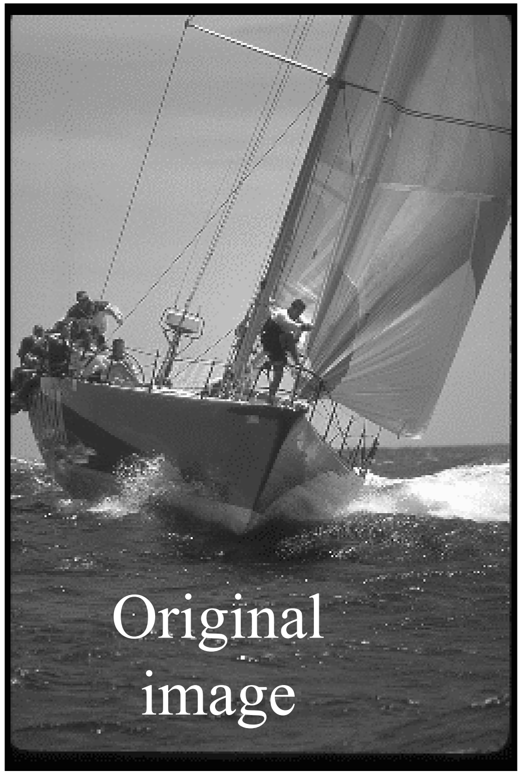
Example: mechanical part

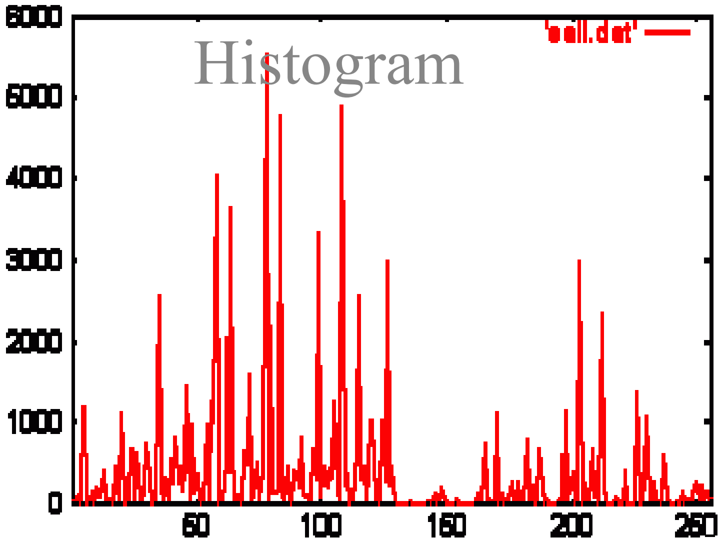




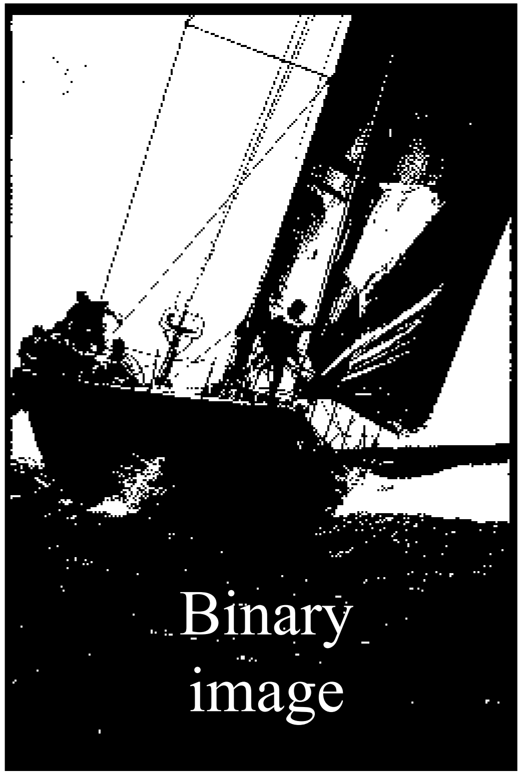


Example: sailing

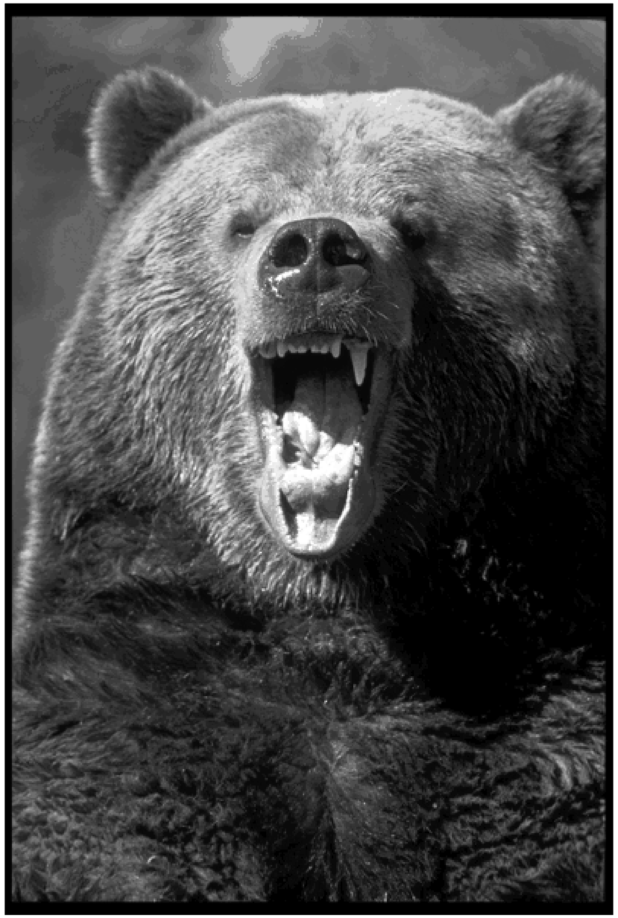




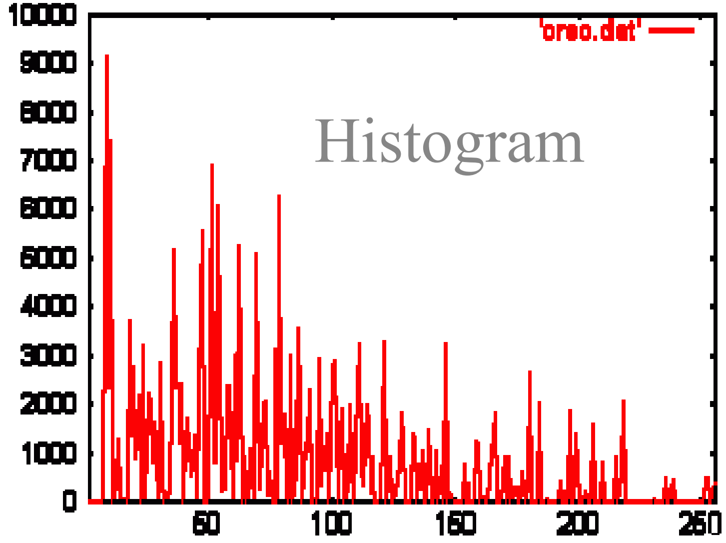
Threshold = 140



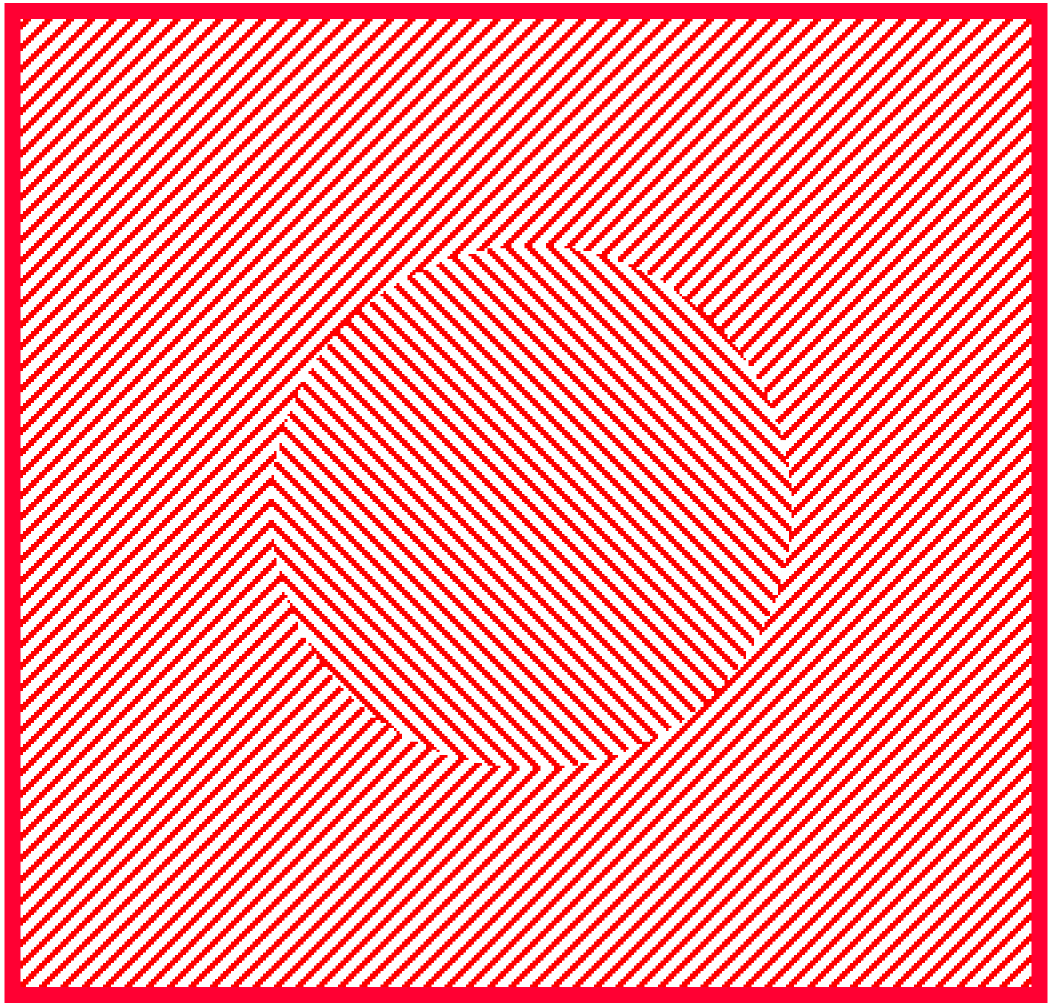
Example: bear



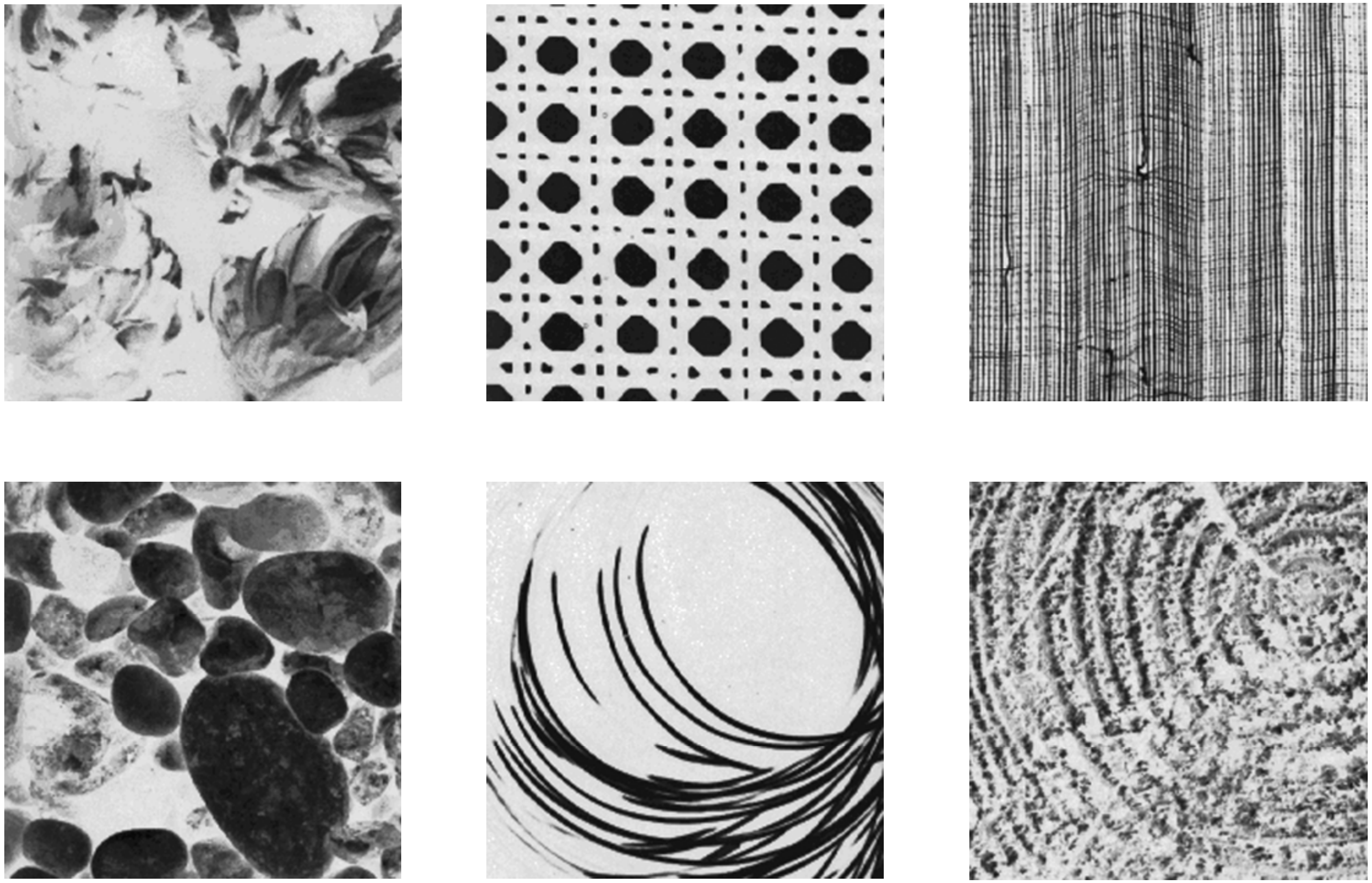
Original image



Example: circle

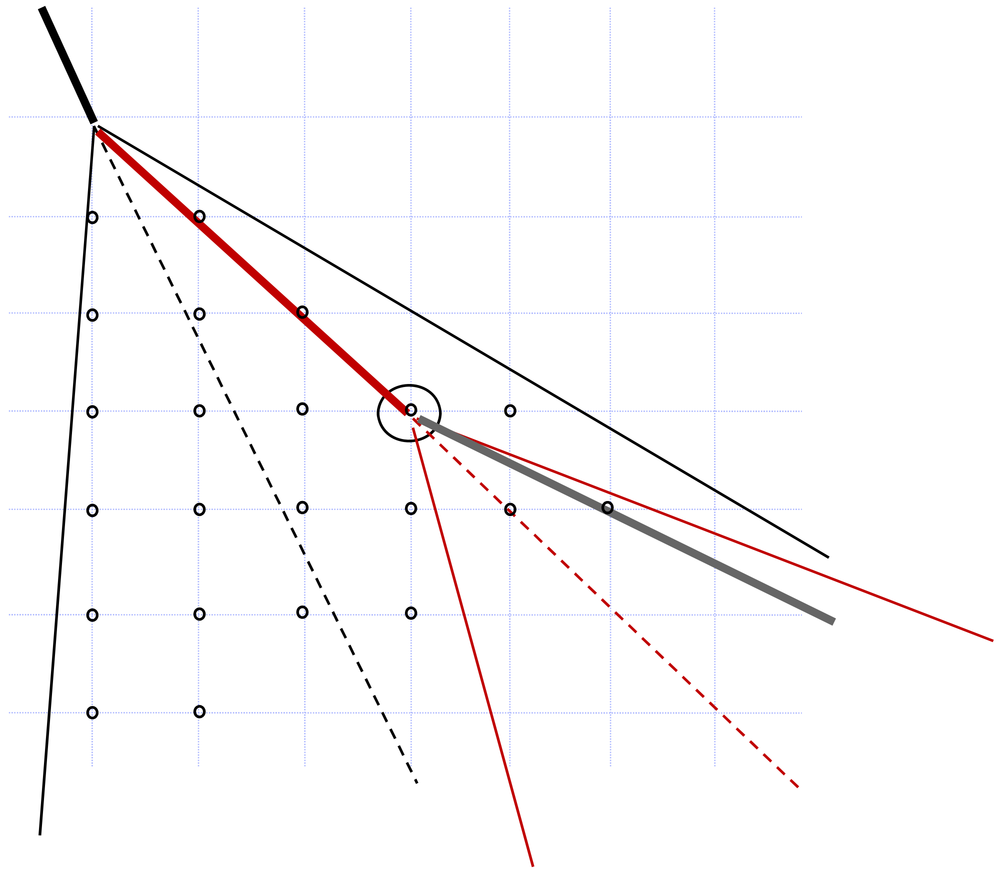


Texture: Brodatz album



Border following

- An example of a recursive walk over the image, following the contour to be exhibited. The horizon of an edge point is the triangle of depth 5 and basis 6, in the direction of the last found edge segment.



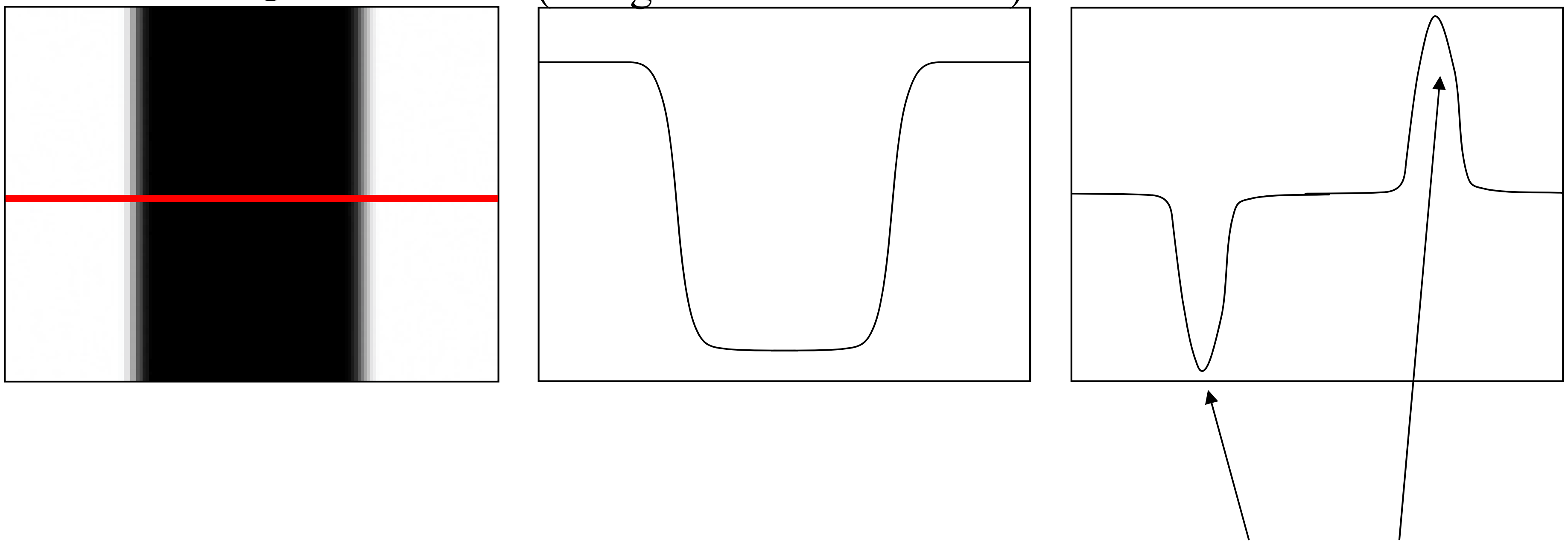
Search of borders

Analytic derivative model

- The border search can be based on the discontinuity of an image feature like the grey level, a texture or a motion parameter, the depth in the scene, etc.
- For operators stemming from first order partial derivatives a maximum response is looked for, either local maximum or over a threshold whether given or adapted
- Note that the second derivative is used too, and among second order operators the Laplacian is peculiarly popular as being scalar then isotropic. There, of course, the zero crossing – inflection points - are looked for.

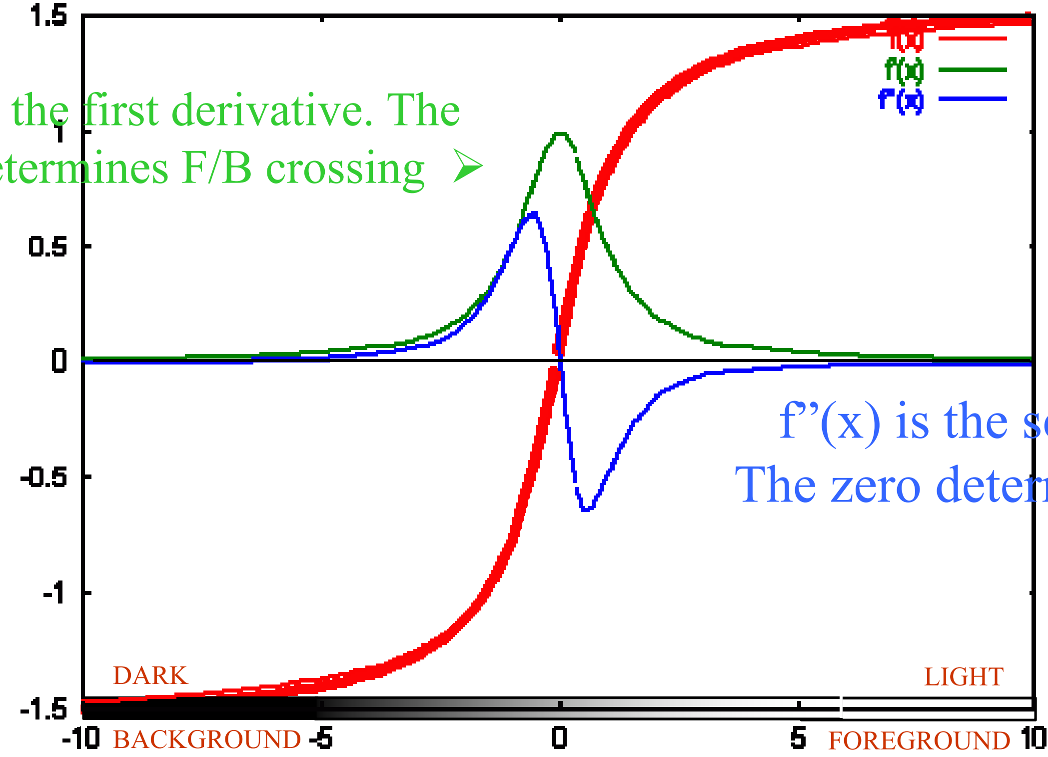
Derivatives and edges

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



Source: L. Lazebnik

Analytic derivative model



f’(x) is the first derivative. The max determines F/B crossing ➢

f’’(x) is the second derivative
The zero determines F/B crossing

f(x) is the grey level, here representing the image in one dimension

Analytic derivative model

- The first derivative is given by:

$$f'(x) \approx \frac{f(x+h) - f(x-h)}{2h}$$

- The second derivative is given by:

$$f''(x) \approx \frac{f(x+h) - 2f(x) + f(x-h)}{h^2}$$

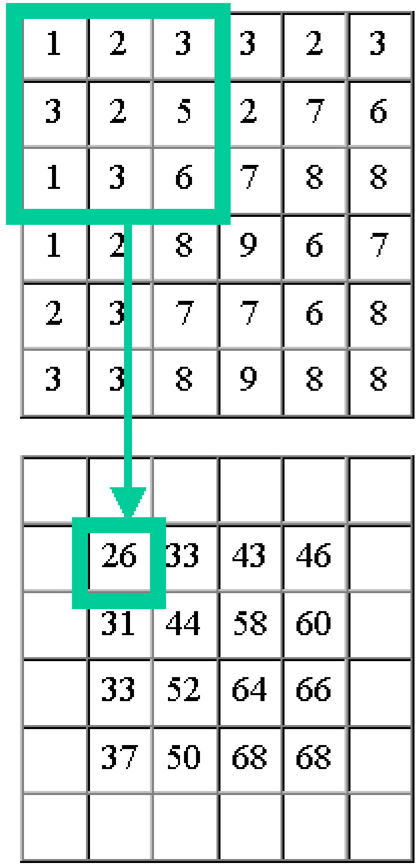
- In 2D the derivate is substituted by the vector gradient

Convolution

- The convolution is a linear operator, that is applied when the image I(x, y) is continue. To the digital image I(i, j) a filter is applied represented by the mask:

$$O(x_0,y_0) = \iint f(x_0-x, y_0-y)\, I(x,y)\, dx\, dy$$

$$O(x,y) = \sum\sum f(x-i, y-j)\, I(i,j)$$



Example: box filter

$$g[\cdot\,,\cdot\,]$$

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Slide credit: David Lowe (UBC)

Image filtering

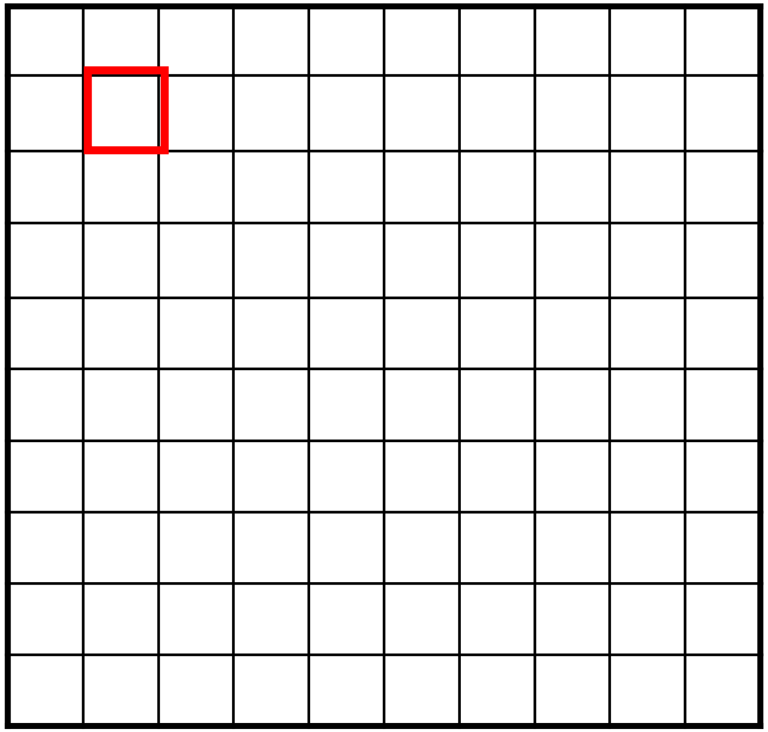
g[· ,·] $\frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$



$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k, n+l]$$

Credit: S. Seitz

Image filtering

$g[\cdot\,,\cdot\,]\ \frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10							

$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k,n+l]$$

Credit: S. Seitz

Image filtering

$g[\cdot,\cdot]\ \frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20						

$$h[m,n] = \sum_{k,l} g[k,l]\ f[m+k,n+l]$$

Credit: S. Seitz

Image filtering

$g[\cdot,\cdot]\ \frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20	30					

$$h[m,n] = \sum_{k,l} g[k,l]\ f[m+k, n+l]$$

Credit: S. Seitz

Image filtering

$g[\cdot,\cdot]$ $\frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20	30	30				

$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k, n+l]$$

Credit: S. Seitz

Image filtering

$g[\cdot,\cdot]$ $\frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20	30	30				
				?					

$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k, n+l]$$

Credit: S. Seitz

Image filtering

$g[\cdot,\cdot]$ $\frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20	30	30				
						?			
				50					

$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k, n+l]$$

Credit: S. Seitz

Image filtering

$g[\cdot,\cdot]\ \frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20	30	30	30	20	10	
	0	20	40	60	60	60	40	20	
	0	30	60	90	90	90	60	30	
	0	30	50	80	80	90	60	30	
	0	30	50	80	80	90	60	30	
	0	20	30	50	50	60	40	20	
	10	20	30	30	30	30	20	10	
	10	10	10	0	0	0	0	0	

$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k, n+l]$$

Credit: S. Seitz

Box Filter

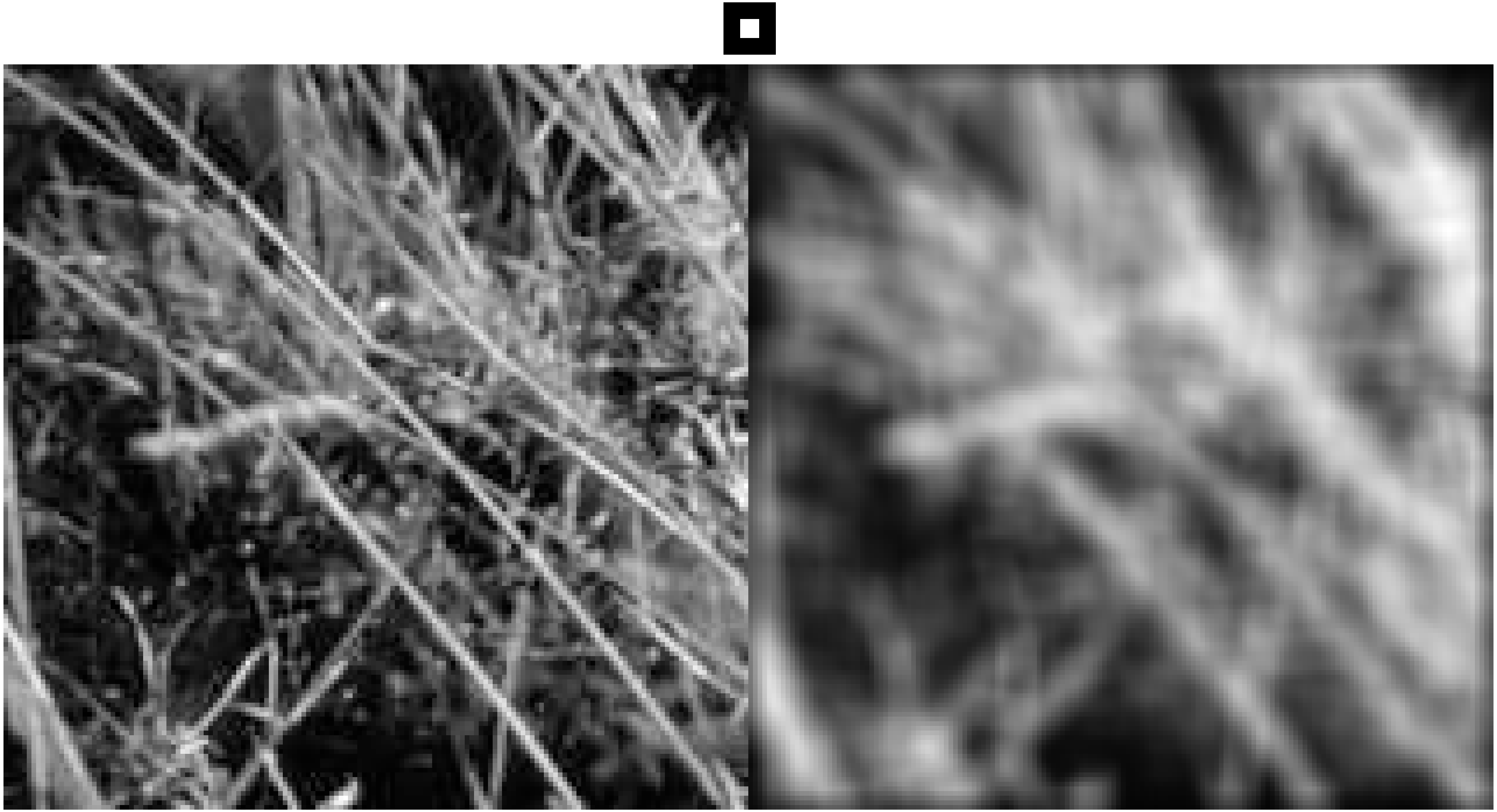
What does it do?

- Replaces each pixel with an average of its neighborhood
- Achieve smoothing effect (remove sharp features)

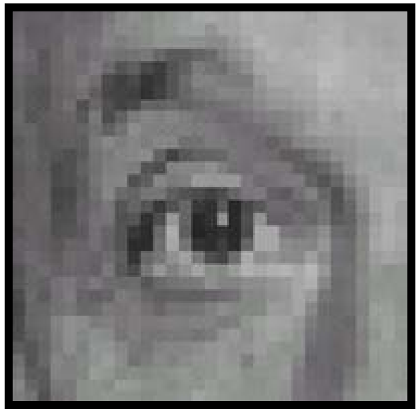
$$g[\cdot\,,\cdot\,] = \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Slide credit: David Lowe (UBC)

Smoothing with box filter



Practice with linear filters



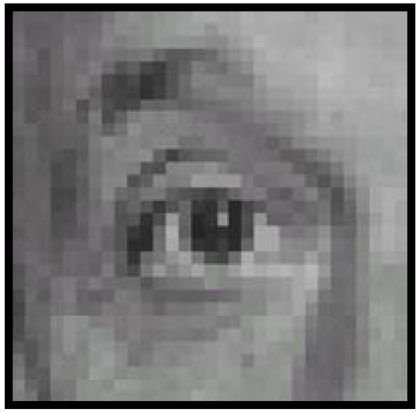
Original

0	0	0
0	1	0
0	0	0

?

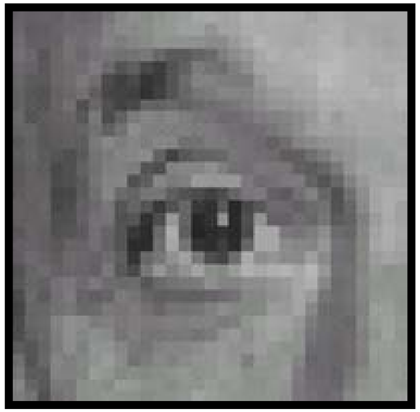
Source: D. Lowe

Practice with linear filters



Original

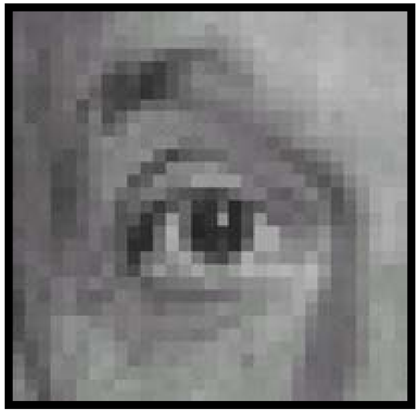
0	0	0
0	1	0
0	0	0



Filtered
(no change)

Source: D. Lowe

Practice with linear filters



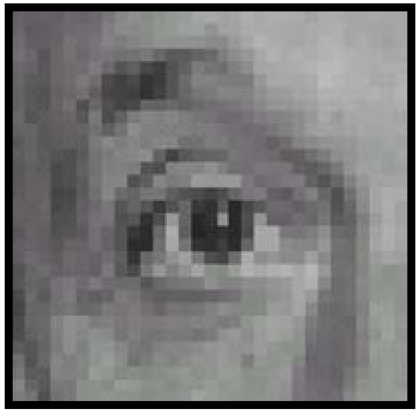
Original

0	0	0
0	0	1
0	0	0

?

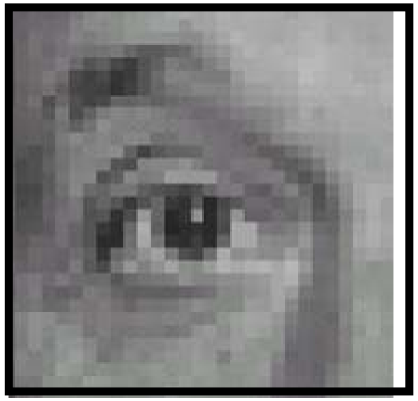
Source: D. Lowe

Practice with linear filters



Original

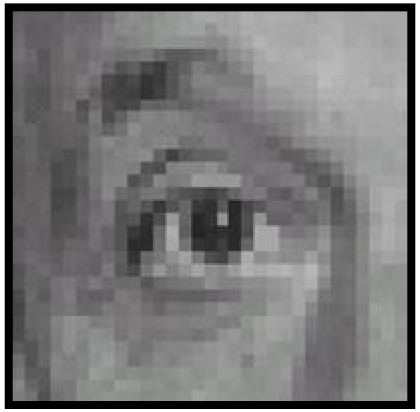
0	0	0
0	0	1
0	0	0



Shifted left
By 1 pixel

Source: D. Lowe

Practice with linear filters



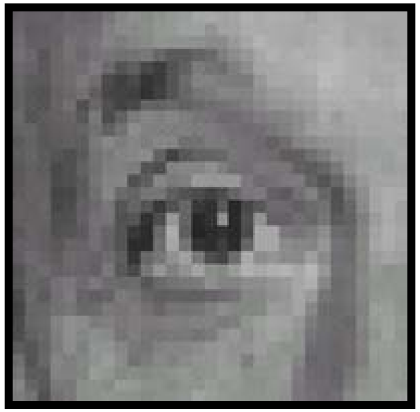
Original

$$\begin{bmatrix}0&0&0\\0&2&0\\0&0&0\end{bmatrix} - \frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix} \quad ?$$

(Note that filter sums to 1)

Source: D. Lowe

Practice with linear filters



Original

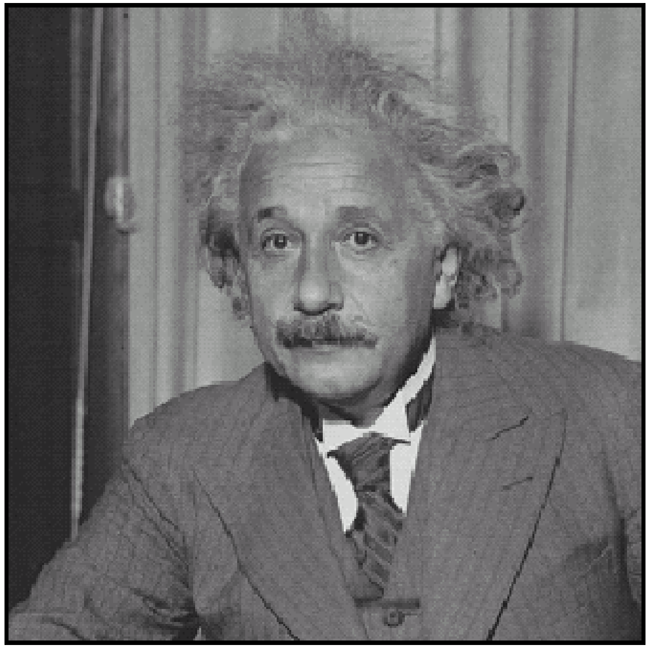
$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} - \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Sharpening filter

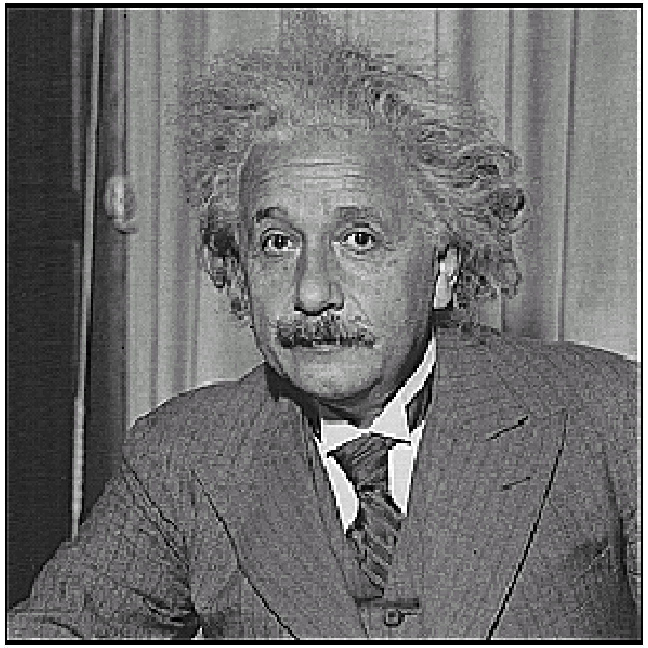
- Accentuates differences with local average

Source: D. Lowe

Sharpening



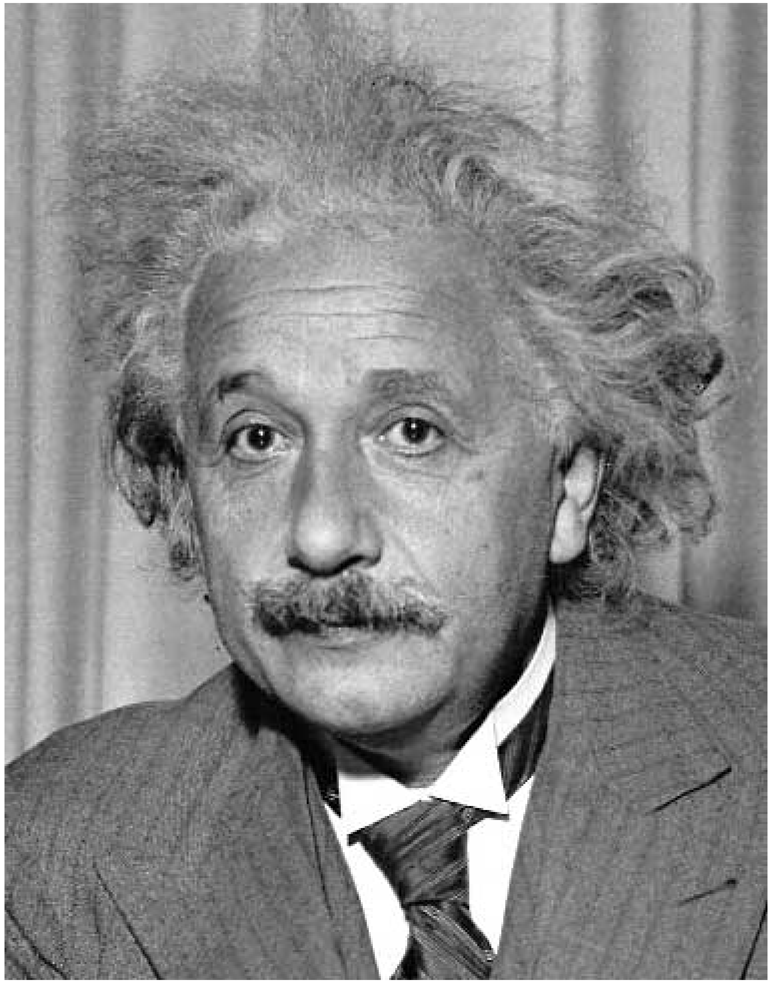
before



after

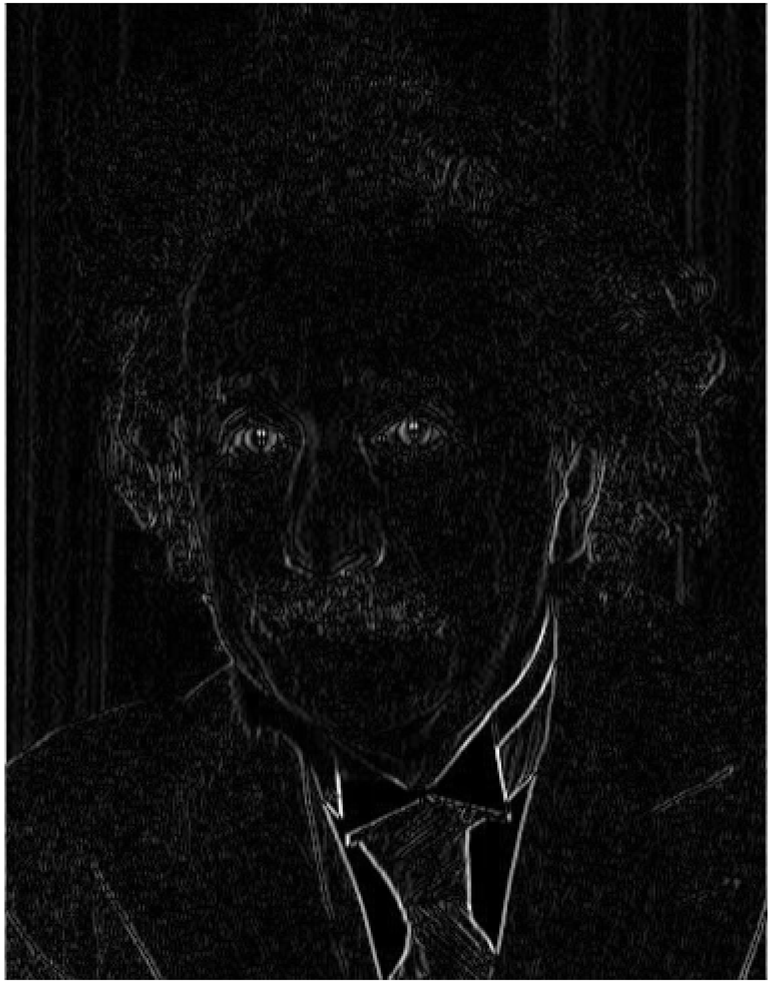
Source: D. Lowe

Other filters



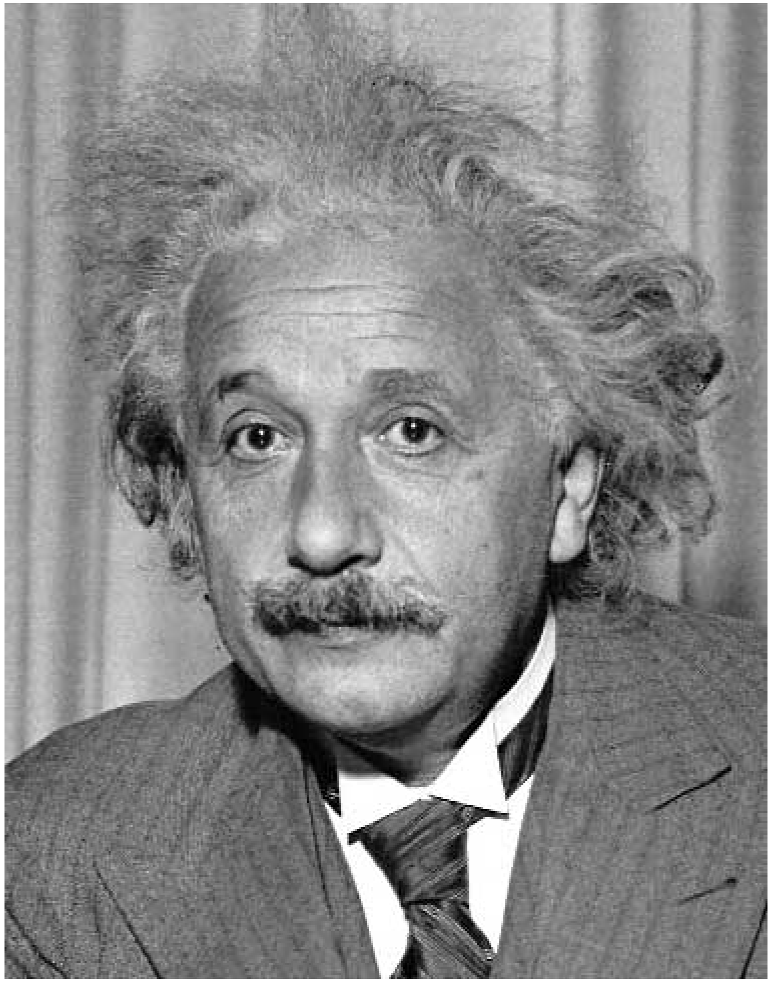
1	0	-1
2	0	-2
1	0	-1

Sobel



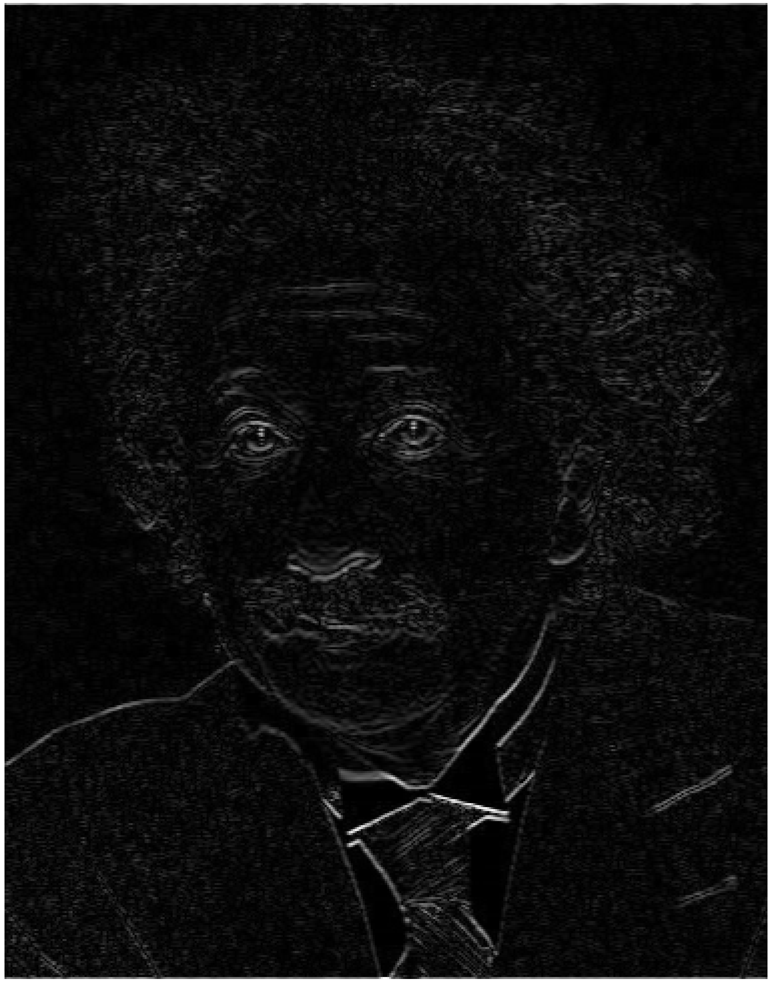
Vertical Edge
(absolute value)

Other filters



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

Sobel



Horizontal Edge
(absolute value)

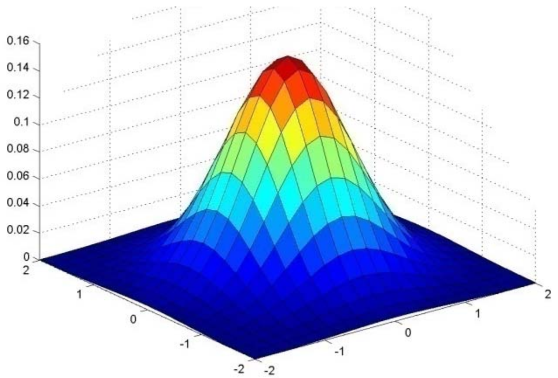
More properties

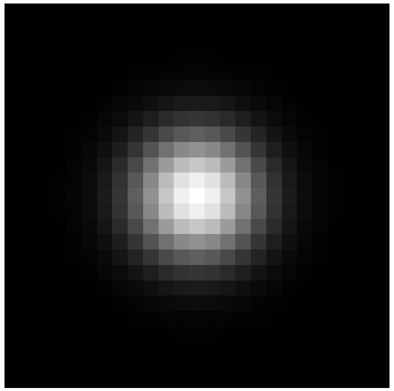
- Commutative: $a * b = b * a$
  - Conceptually no difference between filter and signal
  - But particular filtering implementations might break this equality
- Associative: $a * (b * c) = (a * b) * c$
  - Often apply several filters one after another: $(((a * b_1) * b_2) * b_3)$
  - This is equivalent to applying one filter: a * $(b_1 * b_2 * b_3)$
- Distributes over addition: $a * (b + c) = (a * b) + (a * c)$
- Scalars factor out: $ka * b = a * kb = k (a * b)$
- Identity: unit impulse $e = [0, 0, 1, 0, 0]$, $a * e = a$

Source: S. Lazebnik

Important filter: Gaussian

- Weight contributions of neighboring pixels by nearness



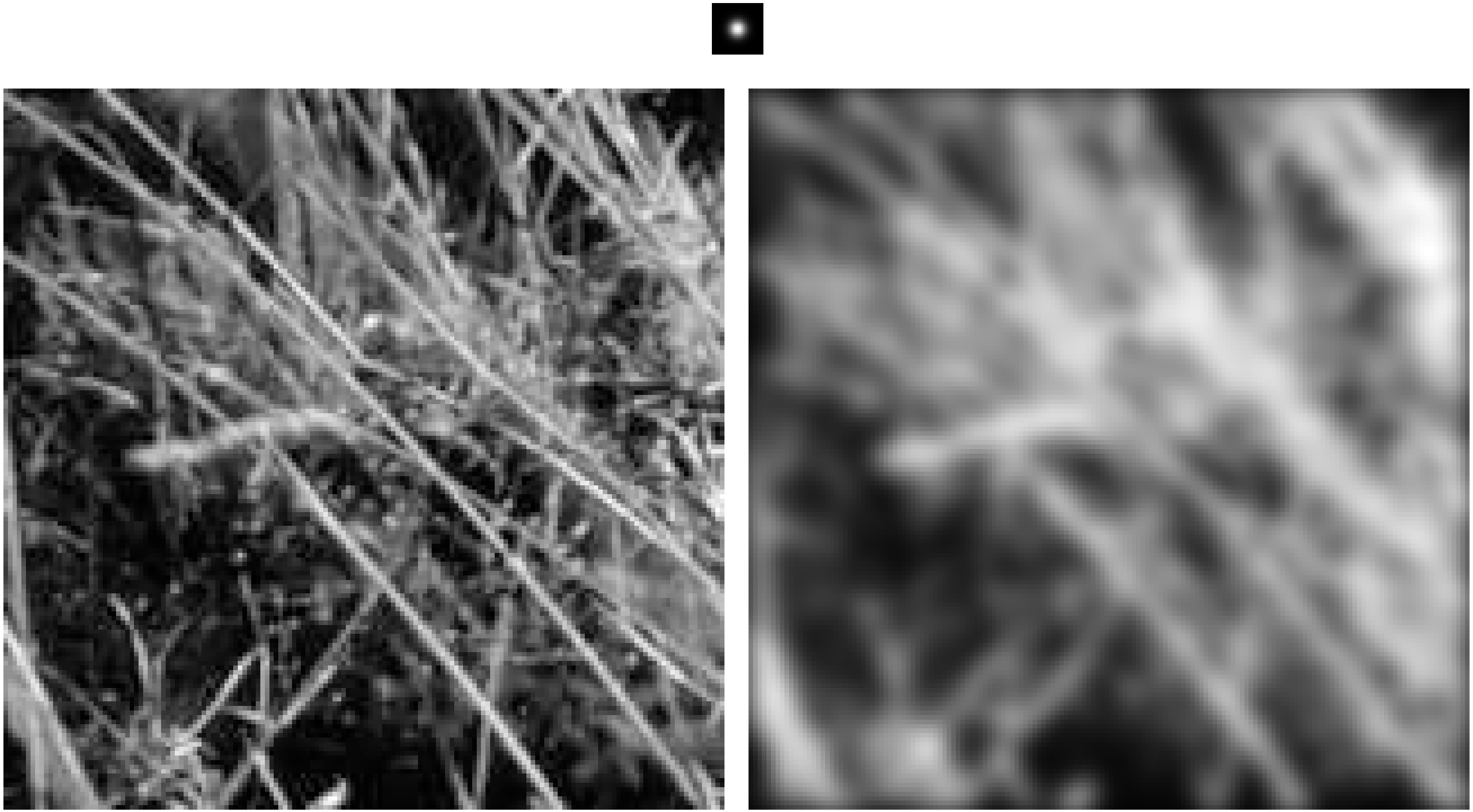


0.003	0.013	0.022	0.013	0.003
0.013	0.059	0.097	0.059	0.013
0.022	0.097	0.159	0.097	0.022
0.013	0.059	0.097	0.059	0.013
0.003	0.013	0.022	0.013	0.003

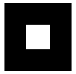
5 x 5, σ = 1

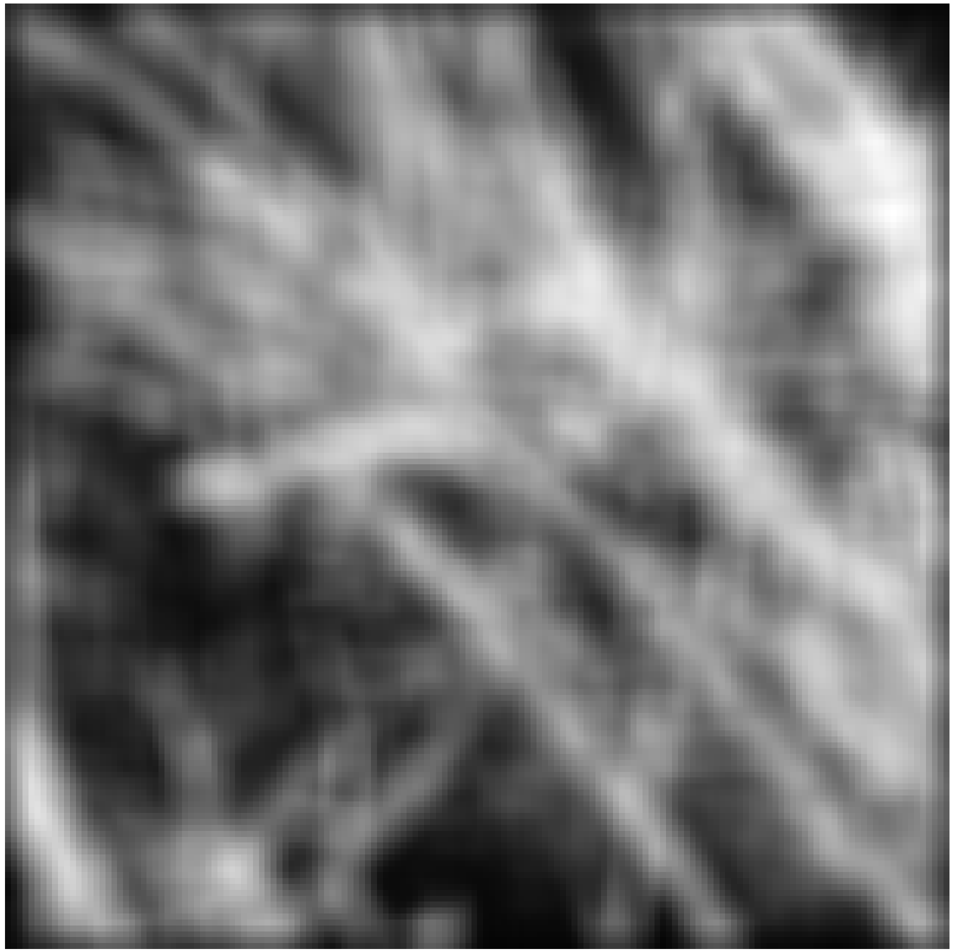
$$G_\sigma = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

Smoothing with Gaussian filter



Smoothing with box filter





Gaussian filters

- Remove "high-frequency" components from the image (low-pass filter)
  - Images become more smooth
- Convolution with self is another Gaussian
  - So can smooth with small-width kernel, repeat, and get same result as larger-width kernel would have
  - Convolving two times with Gaussian kernel of width σ is same as convolving once with kernel of width $\sigma\sqrt{2}$
- *Separable* kernel
  - Factors into product of two 1D Gaussians

Source: K. Grauman

Separability of the Gaussian filter

$$
\begin{aligned}
G_\sigma(x,y) &= \frac{1}{2\pi\sigma^2}\exp^{-\frac{x^2+y^2}{2\sigma^2}} \\
&= \left(\frac{1}{\sqrt{2\pi}\sigma}\exp^{-\frac{x^2}{2\sigma^2}}\right)\left(\frac{1}{\sqrt{2\pi}\sigma}\exp^{-\frac{y^2}{2\sigma^2}}\right)
\end{aligned}
$$

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

Practical matters

How big should the filter be?

- Values at edges should be near zero
- Rule of thumb for Gaussian: set filter half-width to about 3 σ

Boundary issues

- What about near the edge?
  - the filter window falls off the edge of the image
  - need to extrapolate
  - methods:
    - clip filter (black)
    - wrap around
    - copy edge
    - reflect across edge

Source: S. Marschner

Filtering basics

Say the averaging window size is 2k+1 x 2k+1:

$$G[i,j] = \underbrace{\frac{1}{(2k+1)^2}}_{\text{Attribute uniform weight to each pixel}} \underbrace{\sum_{u=-k}^{k} \sum_{v=-k}^{k} F[i+u, j+v]}_{\text{Loop over all pixels in neighborhood around image pixel } F[i,j]}$$

Attribute uniform weight to each pixel

Loop over all pixels in neighborhood around image pixel F[i,j]

Now generalize to allow different weights depending on neighboring pixel's relative position:

$$G[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} \underbrace{H[u,v]}_{\text{Non-uniform weights}} F[i+u, j+v]$$

Non-uniform weights

Correlation filtering

$$G[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u,v]F[i+u,j+v]$$

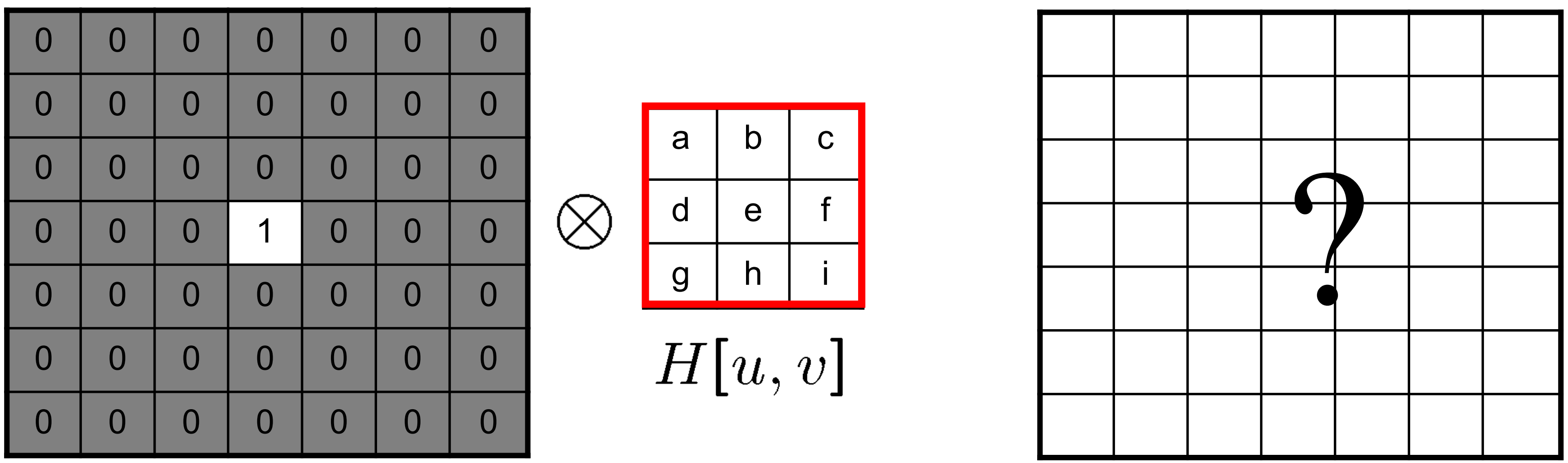
This is called cross-correlation, denoted $G = H \otimes F$

Filtering an image: replace each pixel with a linear combination of its neighbors.

The filter "kernel" or "mask" $H[u,v]$ is the prescription for the weights in the linear combination.

Filtering an impulse signal

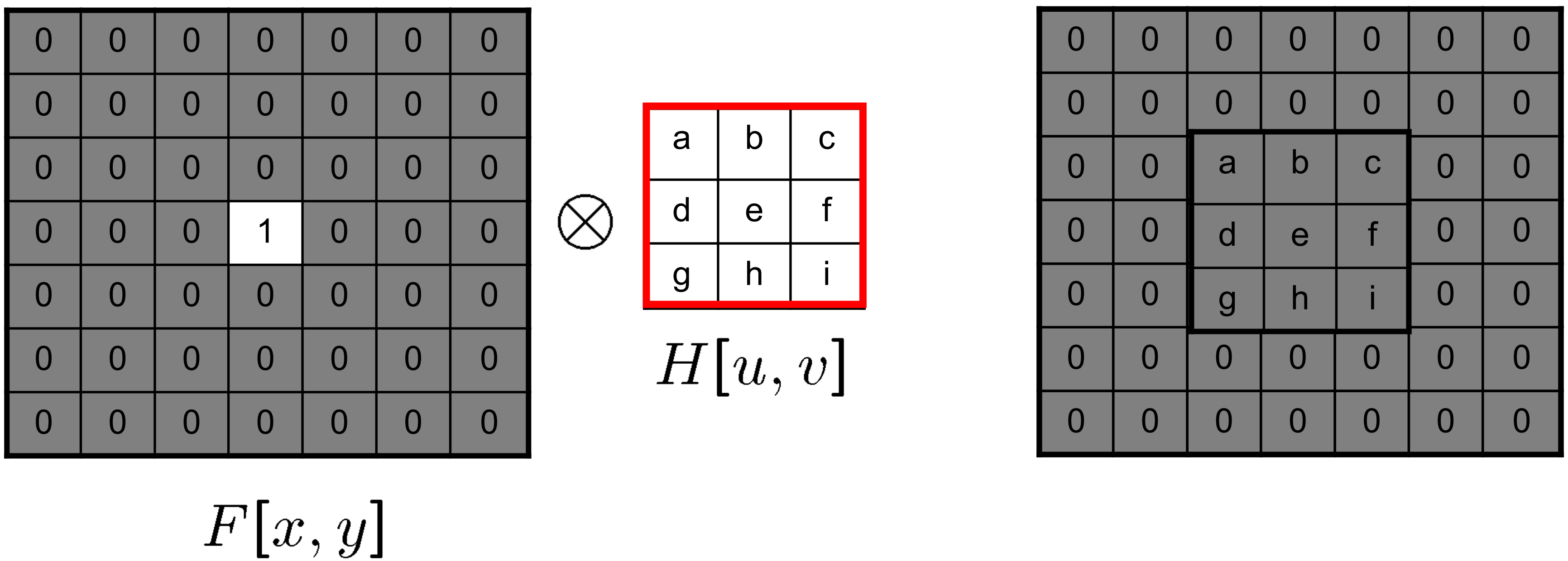
What is the result of filtering the impulse signal (image) *F* with the arbitrary kernel *H*?



$F[x,y]$ $\otimes$ $H[u,v]$ $G[x,y]$

Filtering an impulse signal

What is the result of filtering the impulse signal (image) *F* with the arbitrary kernel *H*?



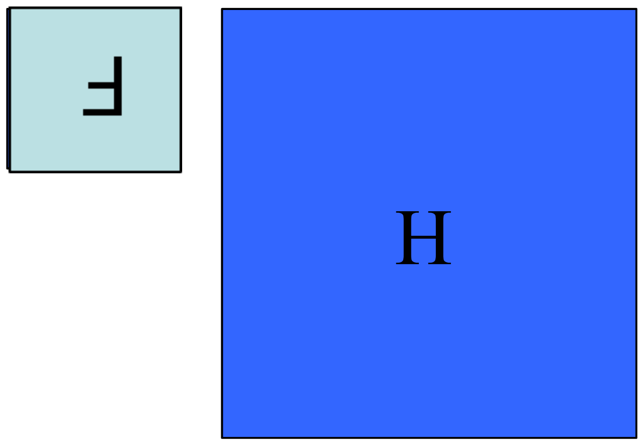
Convolution

- Convolution:
  - Flip the filter in both dimensions (bottom to top, right to left)
  - Then apply cross-correlation

$$G[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u,v] F[i-u, j-v]$$

$$G = H \star F$$

Notation for convolution operator



Convolution vs. correlation

Convolution

$$G[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u,v]F[i-u,j-v]$$

$$G = H \star F$$

Cross-correlation

$$G[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u,v]F[i+u,j+v]$$

$$G = H \otimes F$$

For a Gaussian or box filter, how will the outputs differ?

If the input is an impulse signal, how will the outputs differ?

Separability example

2D convolution
(center location only)

$$\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} * \begin{bmatrix} 2 & 3 & 3 \\ 3 & 5 & 5 \\ 4 & 4 & 6 \end{bmatrix}$$

The filter factors
into a product of 1D
filters:

$$\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \times \begin{bmatrix} 1 & 2 & 1 \end{bmatrix}$$

Perform convolution
along rows:

$$\begin{bmatrix} 1 & 2 & 1 \end{bmatrix} * \begin{bmatrix} 2 & 3 & 3 \\ 3 & 5 & 5 \\ 4 & 4 & 6 \end{bmatrix} = \begin{bmatrix} & 11 & \\ & 18 & \\ & 18 & \end{bmatrix}$$

Followed by convolution
along the remaining column:

Source: K. Grauman

Convolution (decomposition)

- In general the convolution is a computer demanding operator, e.g. the 5x5 template:

1	4	6	4	1
4	16	24	16	4
6	24	36	24	6
4	16	24	16	4
1	4	6	4	1

  is implemented by 25 multiplications for each pixel; note that often complex template may be decomposed in simple 1D operators (e. g. the isotropic, monotonic decreasing template)

- The previous convolution can be decomposed in the following two 1D operators:

```
1  4  6  4  1                       1
   et                                4
                                    6
                                    4
                                    1
```

  in this implementation only10 (5+5) multiplications per pixel are required

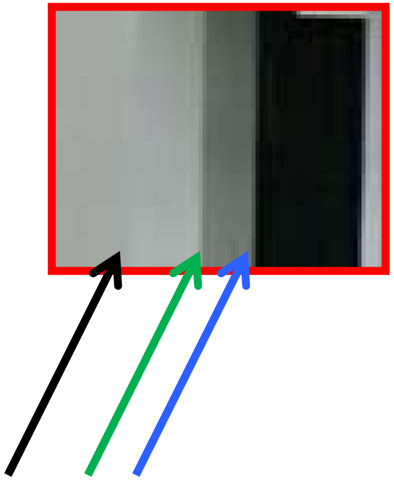
- Note that applying several filters one after another (((a * b1) * b2) * b3) is equivalent to applying one filter a * b4 where b4=(b1 * b2 * b3). If this three templates are 3x3 arrays b4 is a 7x7 template.

- Each 3x3 kernel has 9 independent values for a total of 27 values meanwhile a general 7x7 templates has 49 independent values: Not al templates are decomposable in a short sequence of smaller ones! Fortunately in important practical cases (e.g. circular symmetric and monotonic decreasing) they are.

Closeup of edges

Source: D. Hoiem

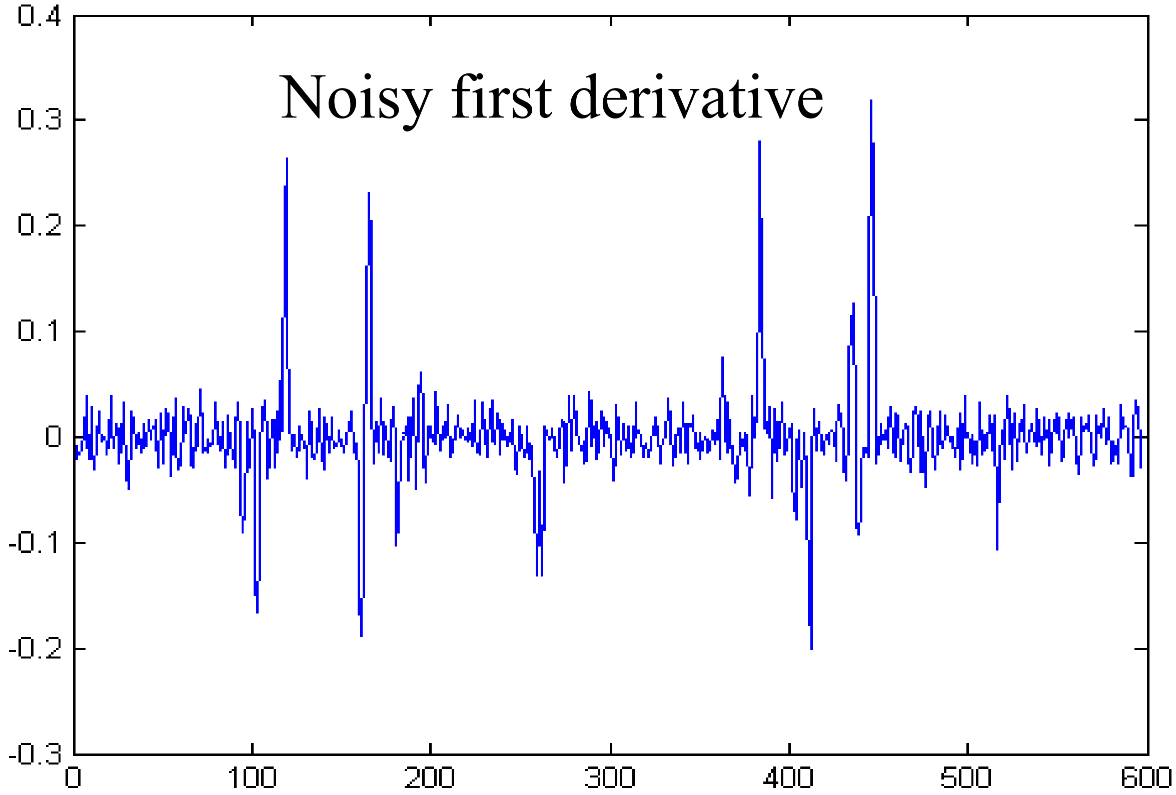
Closeup of edges



Source: D. Hoiem

Closeup of edges

Source: D. Hoiem



Source: D. Hoiem

Gradient approximations

- The gradient is a 2D vector
- The digital differential operators are implemented by template in which the sum of the kernel parameters is null: in a uniform area the result must be zero (no variation)
- The basic and historical convolution kernels have an extension limited to 2x2 and 3x3, for each of the two components

Roberts Operator

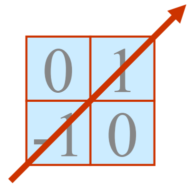
- It is the simplest solution
  - Two templates are applied M_1 and M_2, obtaining the two orthogonal gradient components:
  - $G_1=M_1*I, \quad G_2=M_2*I$
  - It is very sensible to noise

- The gradient module and phase are:

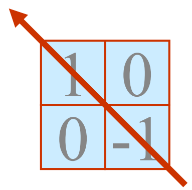
$$G_m = \sqrt{G_1^2 + G_2^2}$$

$$G_\phi = \mathrm{arctg}(G_2/G_1)+\pi/4$$

G_1



G_2



Isotropic operator

- Two templates are applied M_1 and M_2, obtaining the two orthogonal gradient components:

  $G_x = M_x * I,\ G_y = M_y * I$

- The gradient module and phase are:

  $G_m = \sqrt{G_1^2 + G_2^2}$

  $G_\phi = \mathrm{arctg}(G_y / G_x)$

- In C:
  - phi = atan2(gy, gx)

G_x

-1	0	1
$-\sqrt{2}$	0	$\sqrt{2}$
-1	0	1

G_y

1	$\sqrt{2}$	1
0	0	0
-1	$-\sqrt{2}$	-1

Prewitt and Sobel operators

- To simplify the computation often the isotropic filter is implemented by these two simplified solutions:
  - Prewitt

G_x

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

G_y

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

  - Sobel

G_x

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

G_y

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

Example Sobel

Original image

Module

Phase

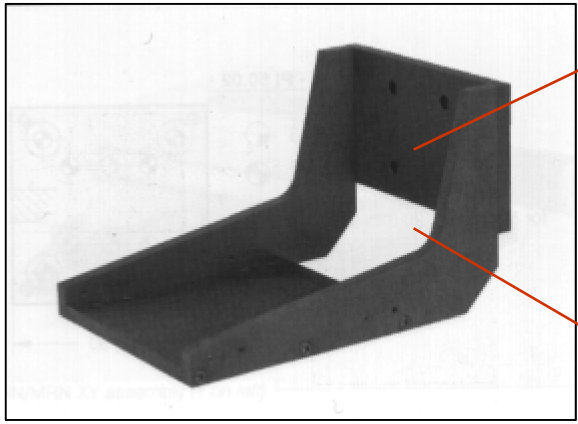
Example Sobel

Original image

Module

Phase

Sobel operator

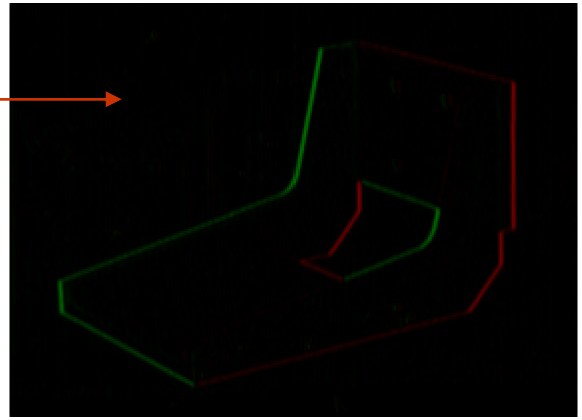


Original image

horizontal gradient

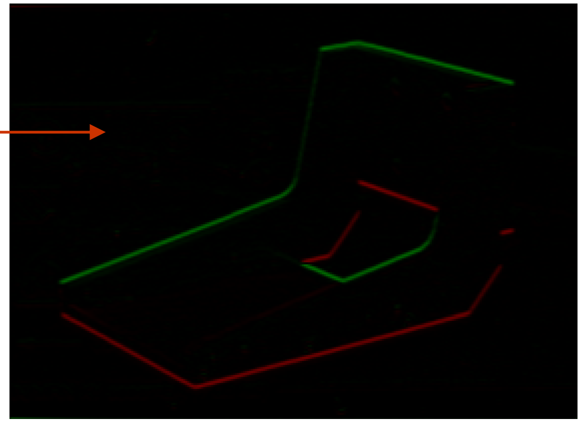
$$G_1 = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

vertical contour



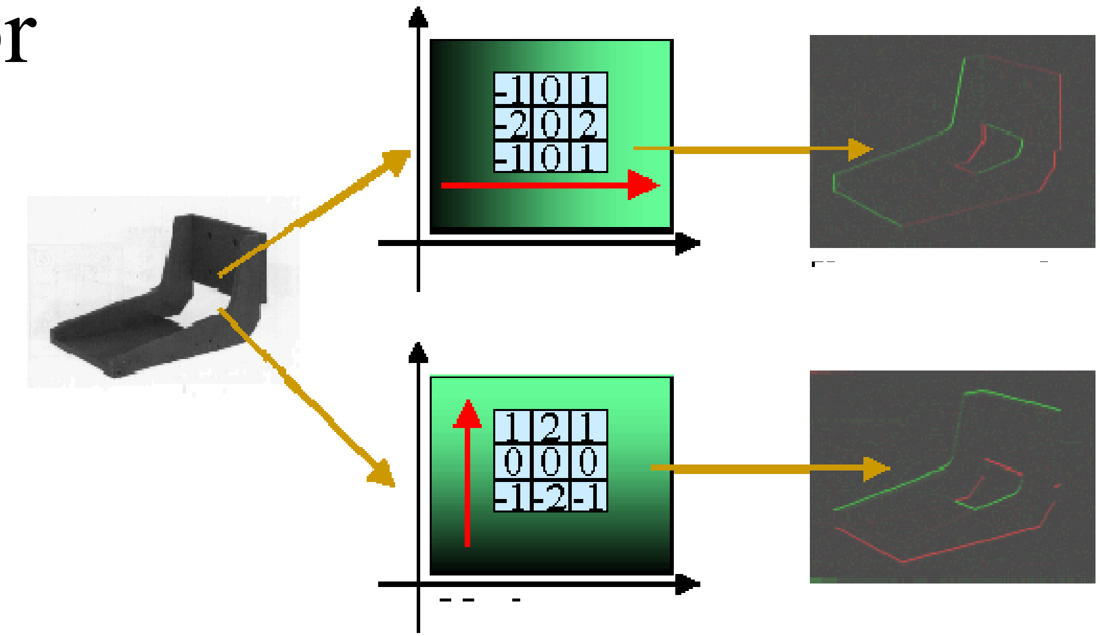
$$G_2 = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

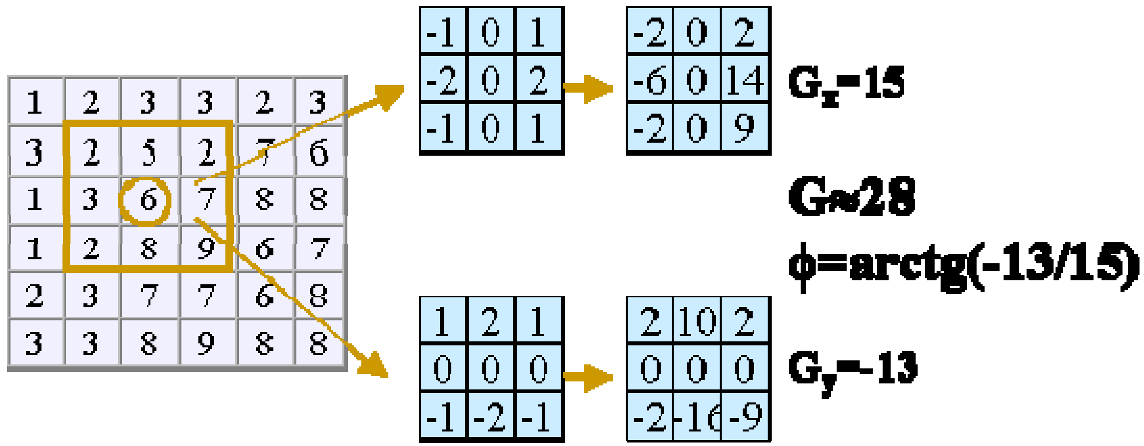
vertical gradient



horizontal contour

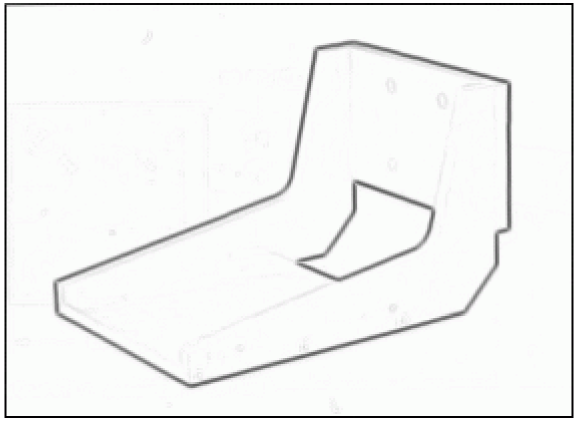
Sobel operator



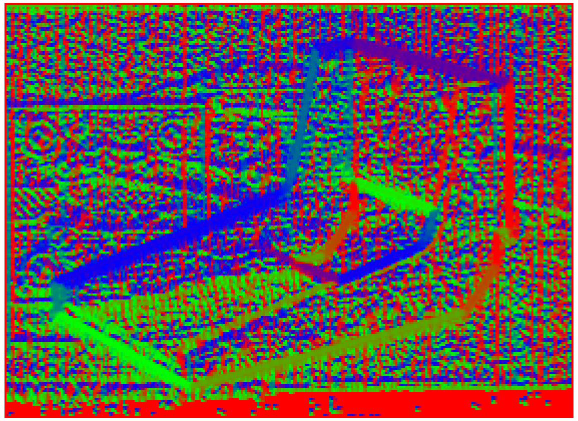


Sobel operator

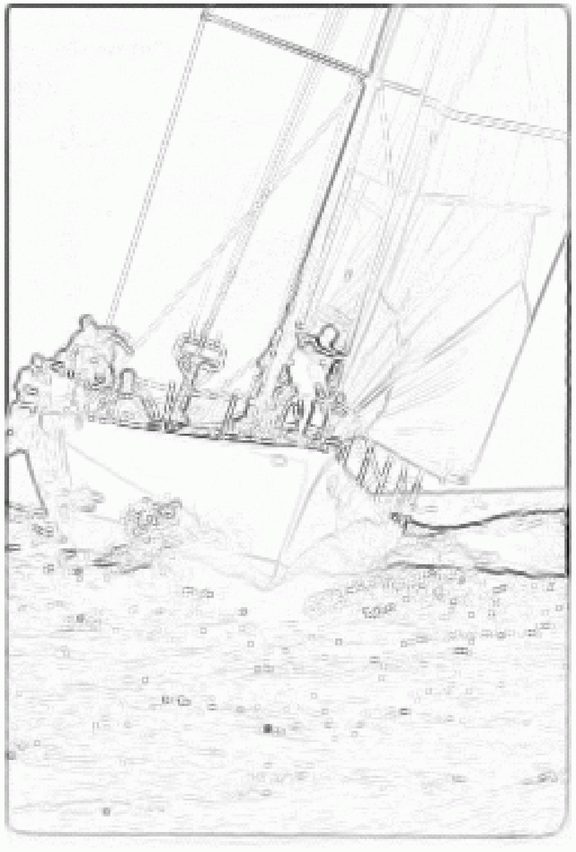
Module

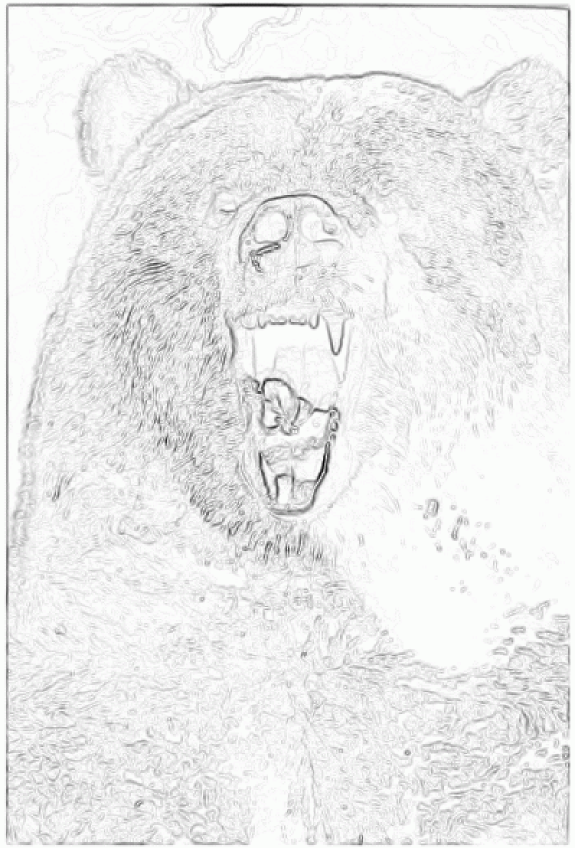


Phase

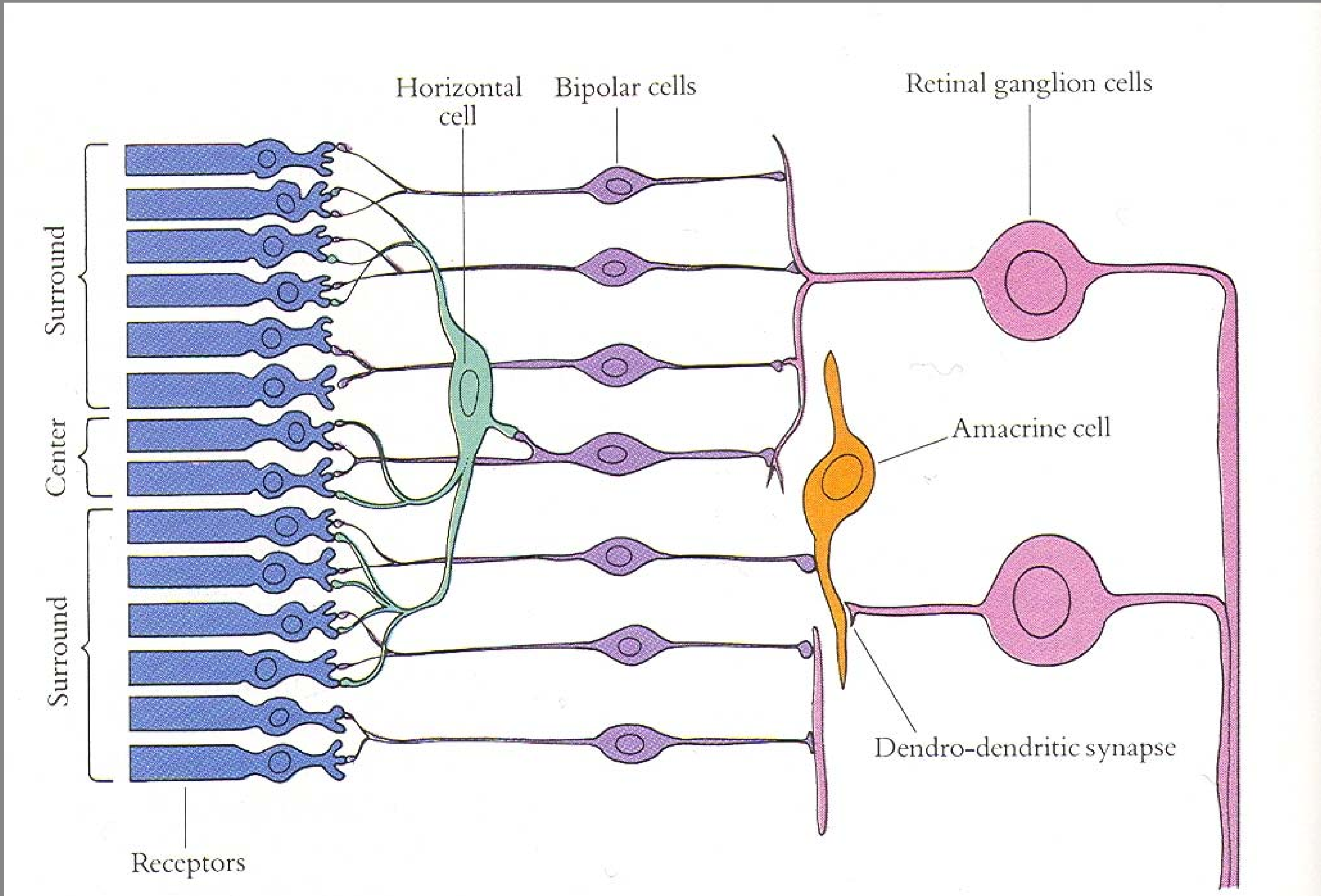


Example (module)





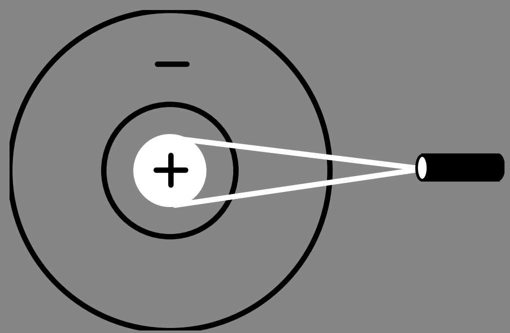
Lateral inhibition

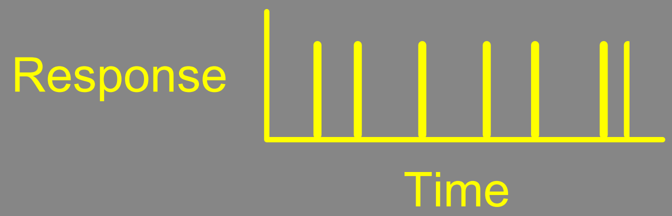


Retinal Receptive Fields

Receptive field structure in ganglion cells:

On-center Off-surround





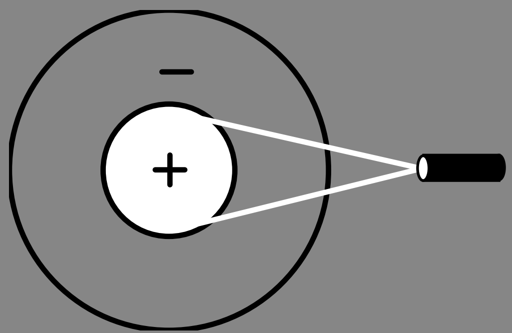
Stimulus condition

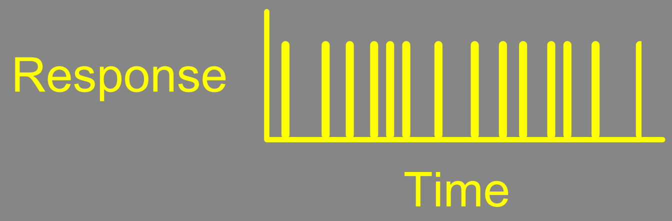
Electrical response

Retinal Receptive Fields

Receptive field structure in ganglion cells:

On-center Off-surround





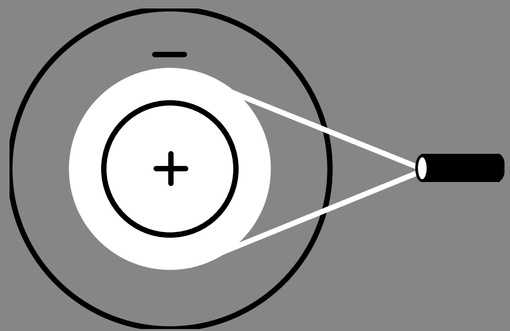
Stimulus condition

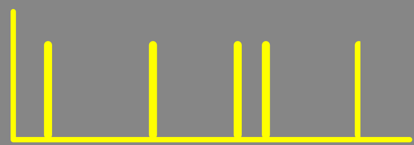
Electrical response

Retinal Receptive Fields

Receptive field structure in ganglion cells:

On-center Off-surround





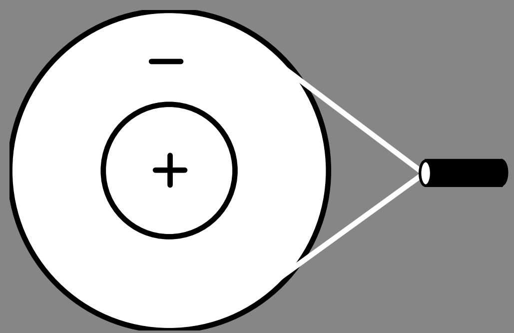
Stimulus condition

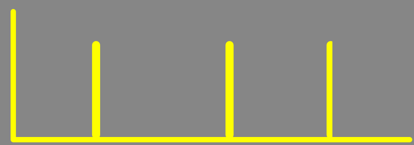
Electrical response

Retinal Receptive Fields

Receptive field structure in ganglion cells:

On-center Off-surround





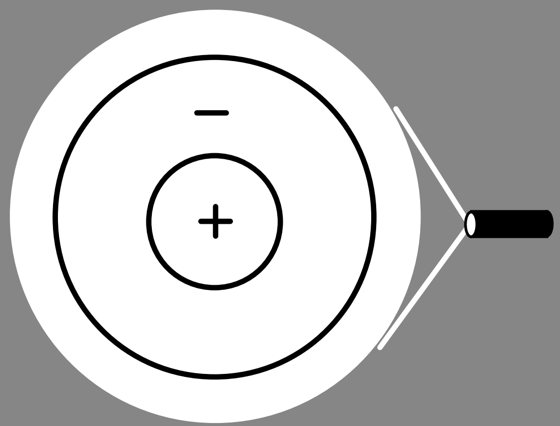
Stimulus condition

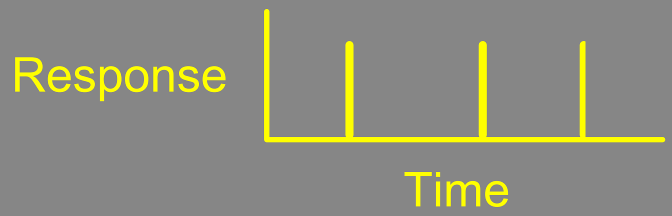
Electrical response

Retinal Receptive Fields

Receptive field structure in ganglion cells:

On-center Off-surround





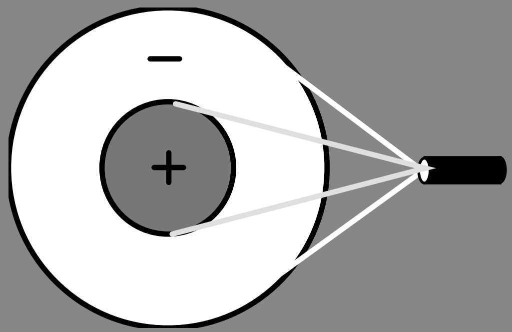
Stimulus condition

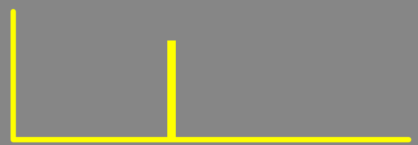
Electrical response

Retinal Receptive Fields

Receptive field structure in ganglion cells:

On-center Off-surround

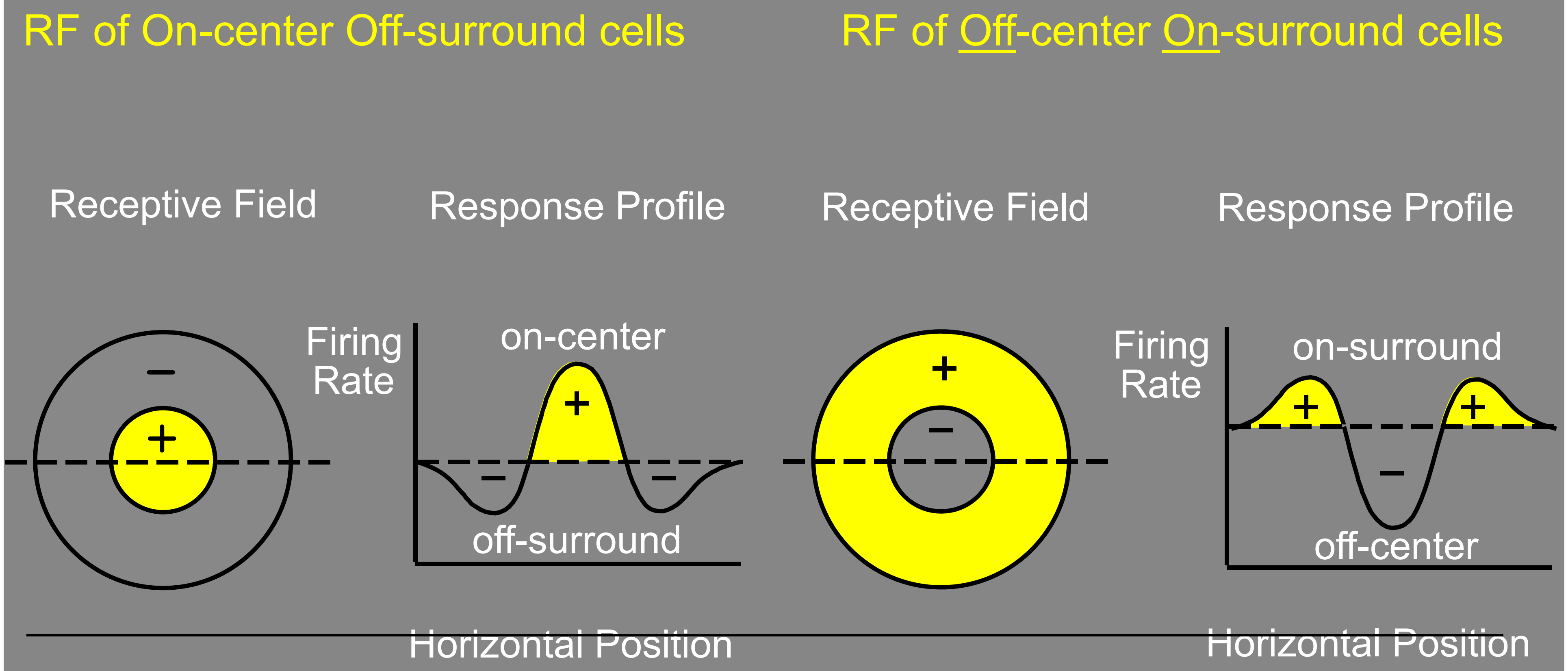




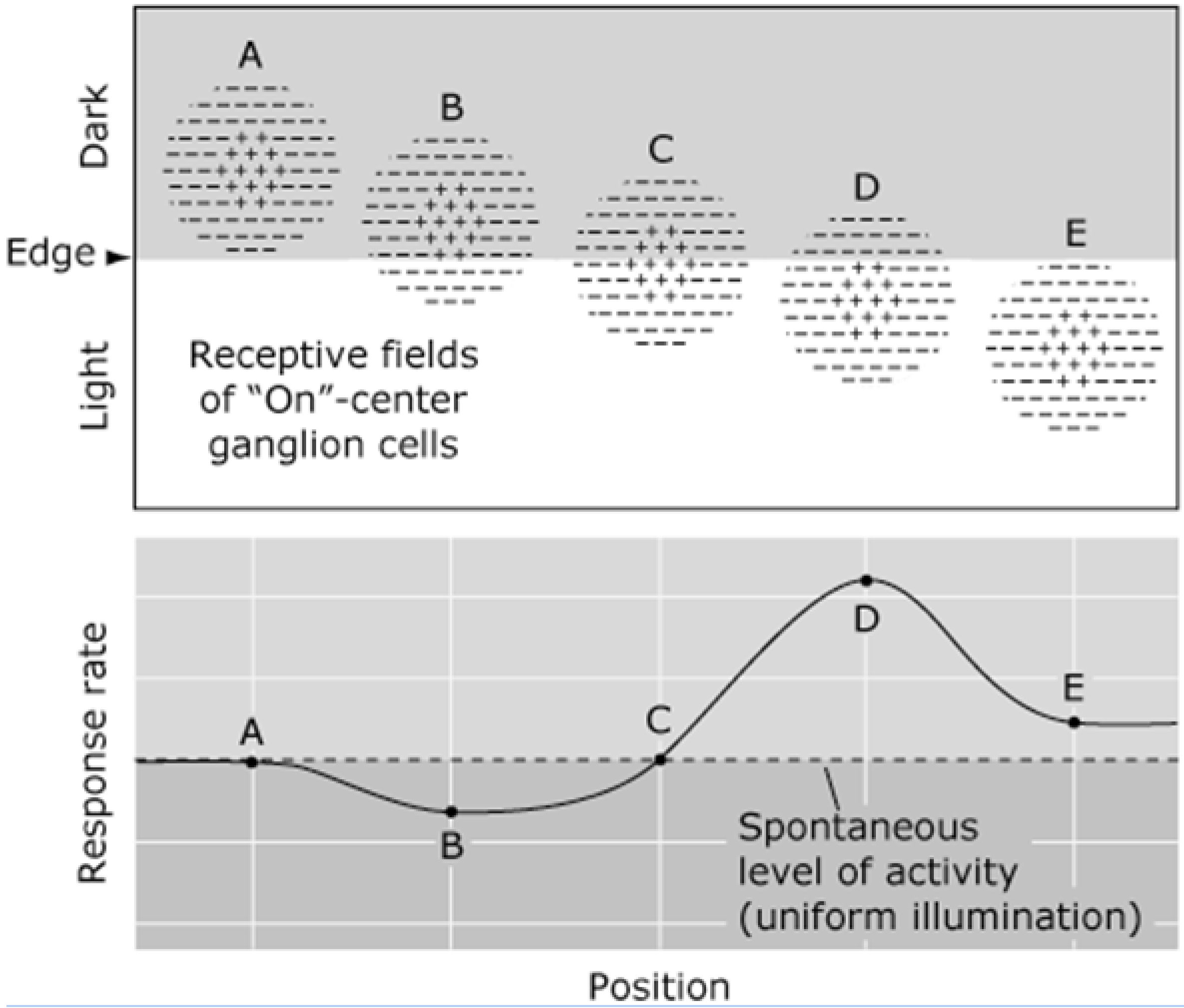
Stimulus condition

Electrical response

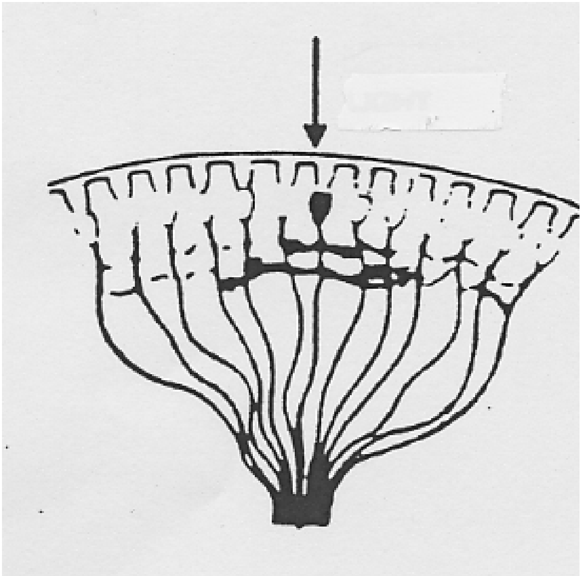
Retinal Receptive Fields

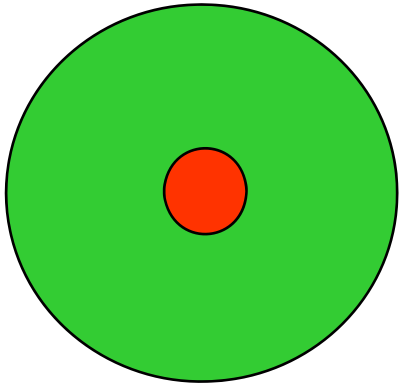


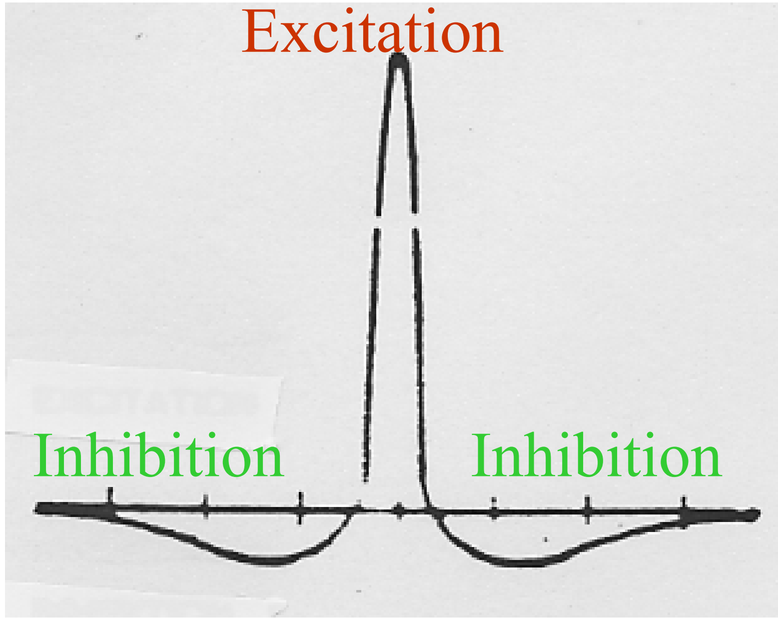
Lateral inhibition



Lateral inhibition







Lateral inhibition

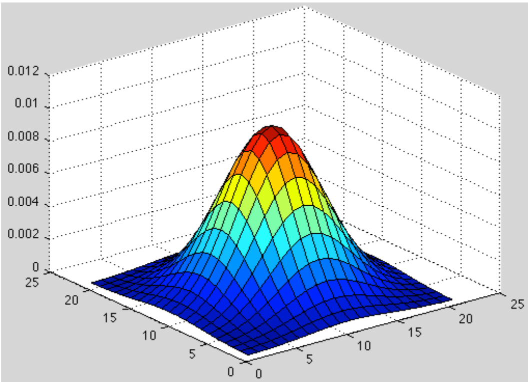
- The retina receptor apply a lateral inhibition mechanism.
- The implementation of this mechanism can be done by a filter obtained by the difference of two Gaussian of equal area, having different σ (and amplitude):

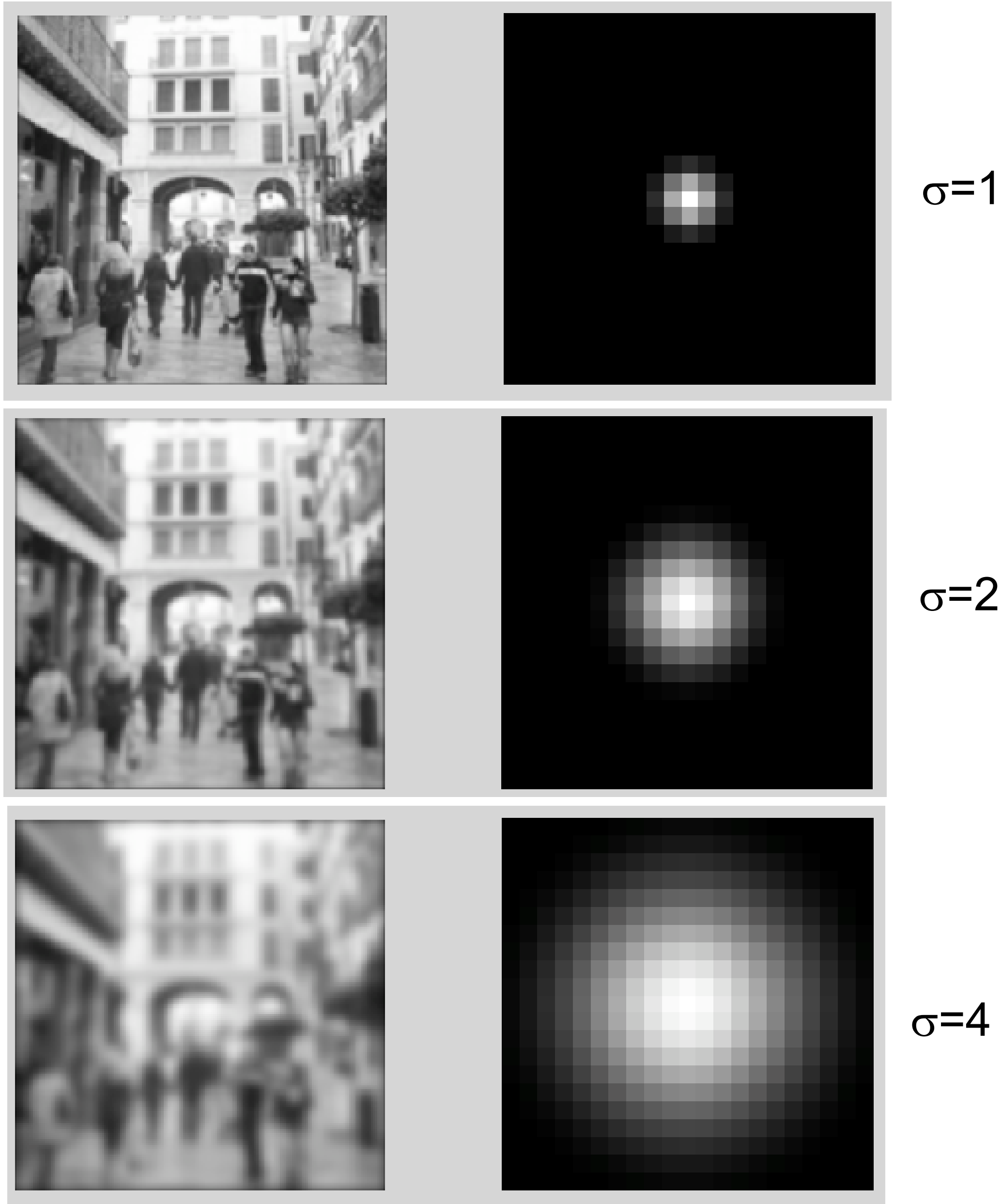
$$\frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

- The 'zero-crossing' correspond to the border points. An advantage of this technique is that the produced contour are closed.

Gaussian filter

$$G(x,y;\sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$



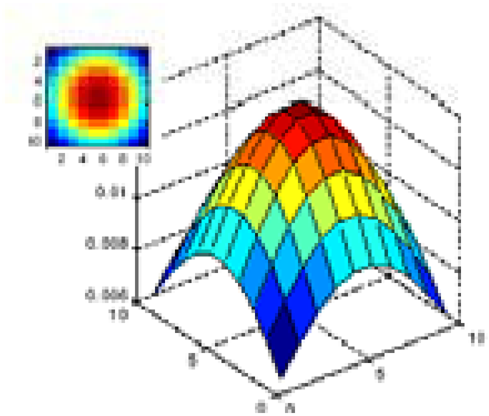


Gaussian filters

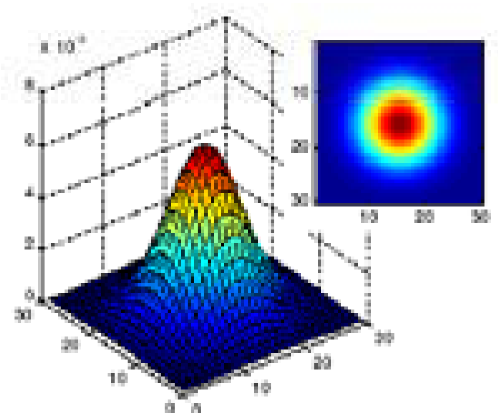
- What parameters matter here?

  Size of kernel or mask

  Note, Gaussian function has infinite support, but discrete filters use finite kernels



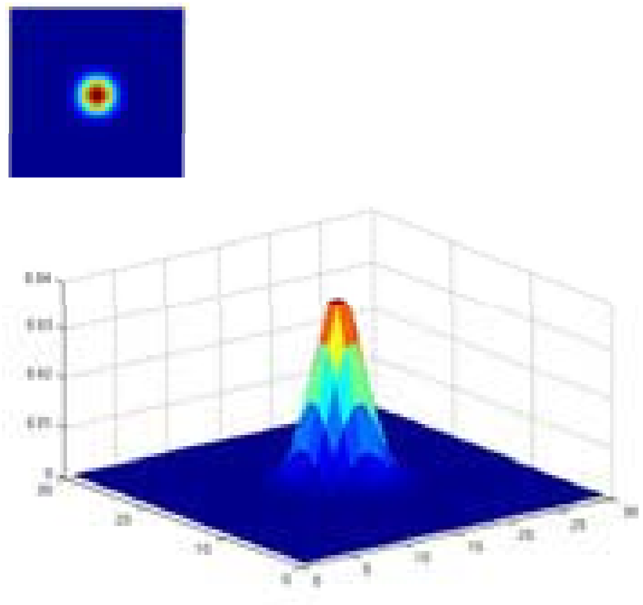
σ = 5 with 10 x 10 kernel



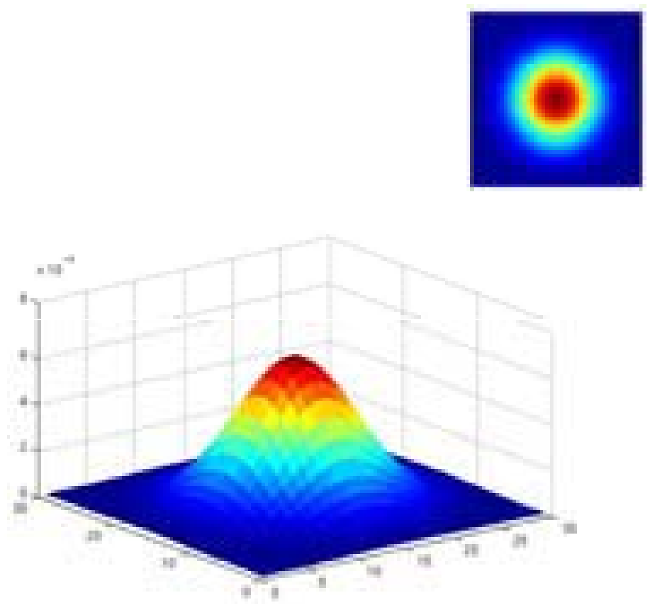
σ = 5 with 30 x 30 kernel

Gaussian filters

- What parameters matter here?
- **Variance** of Gaussian: determines extent of smoothing



$\sigma = 2$ with 30 x 30 kernel



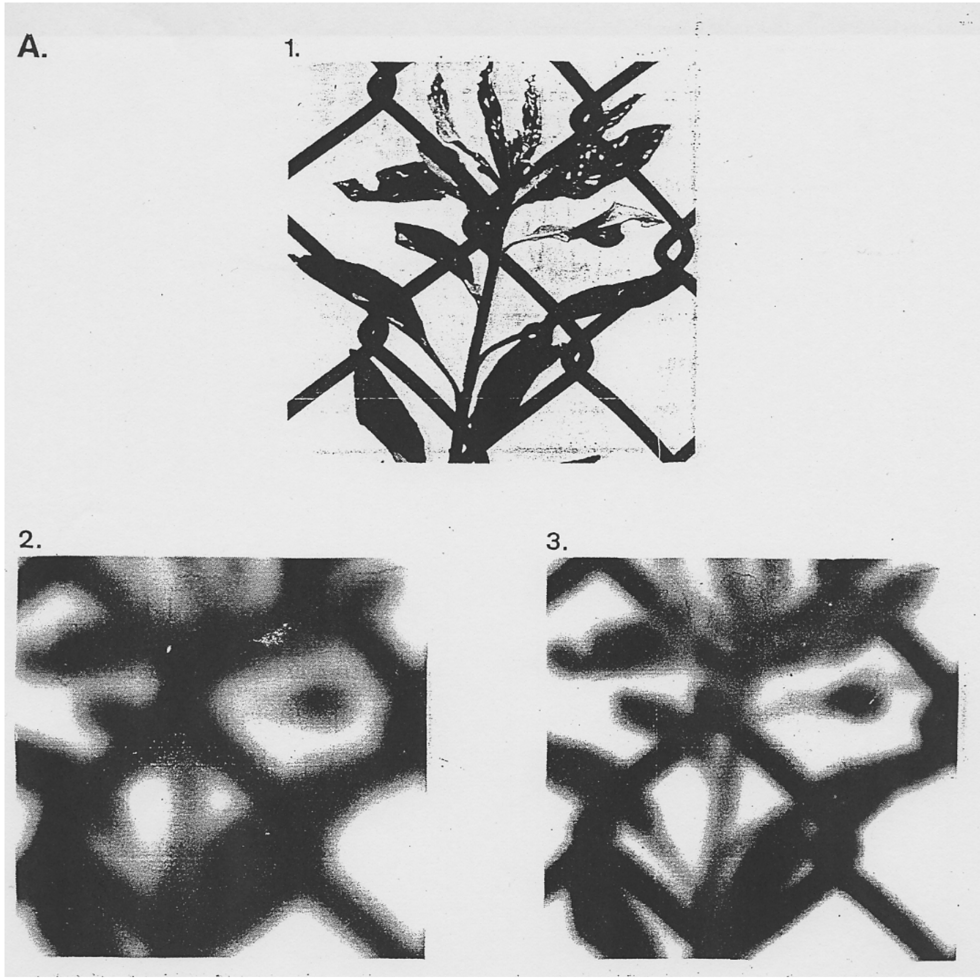
$\sigma = 5$ with 30 x 30 kernel

Gaussian Filter

1 Original image

2 Filtered image σ=8

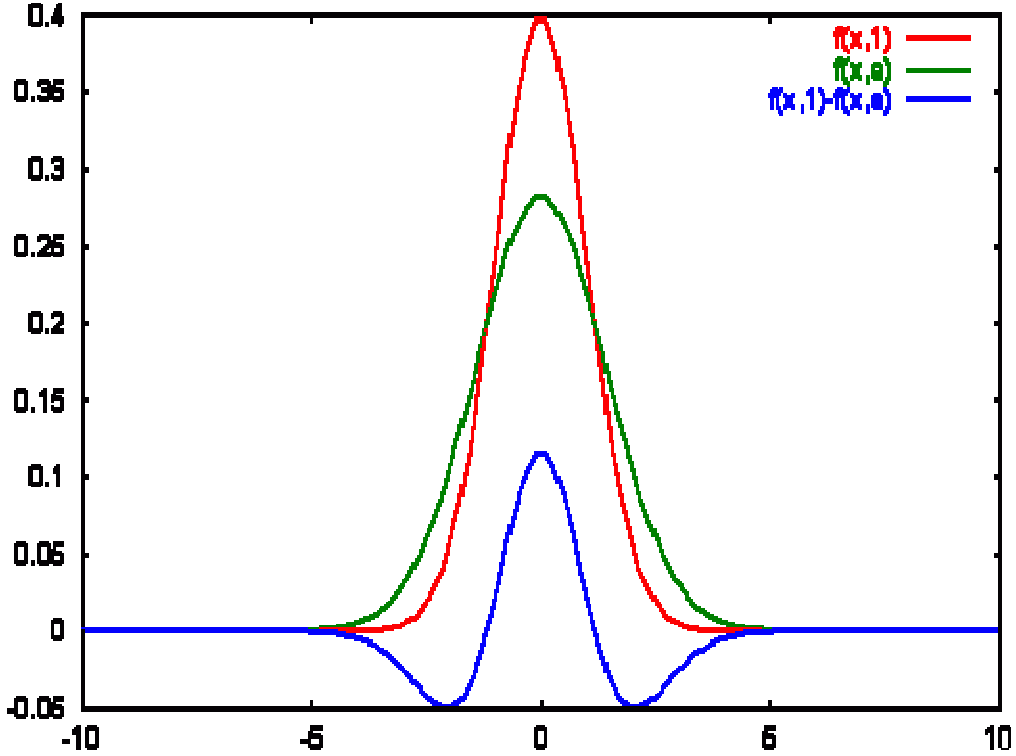
3 Filtered image σ=4



The DoG operator

- This operator is called usually Difference of Gaussians (DoG)
- The best results are obtained maintaining the external Gaussian as large as possible but avoiding to include more than one border
- The internal Gaussian is optimized if it covers just the transition area
- Complex scene are better analyzed if a set of different DoG filters with various σ are applied.

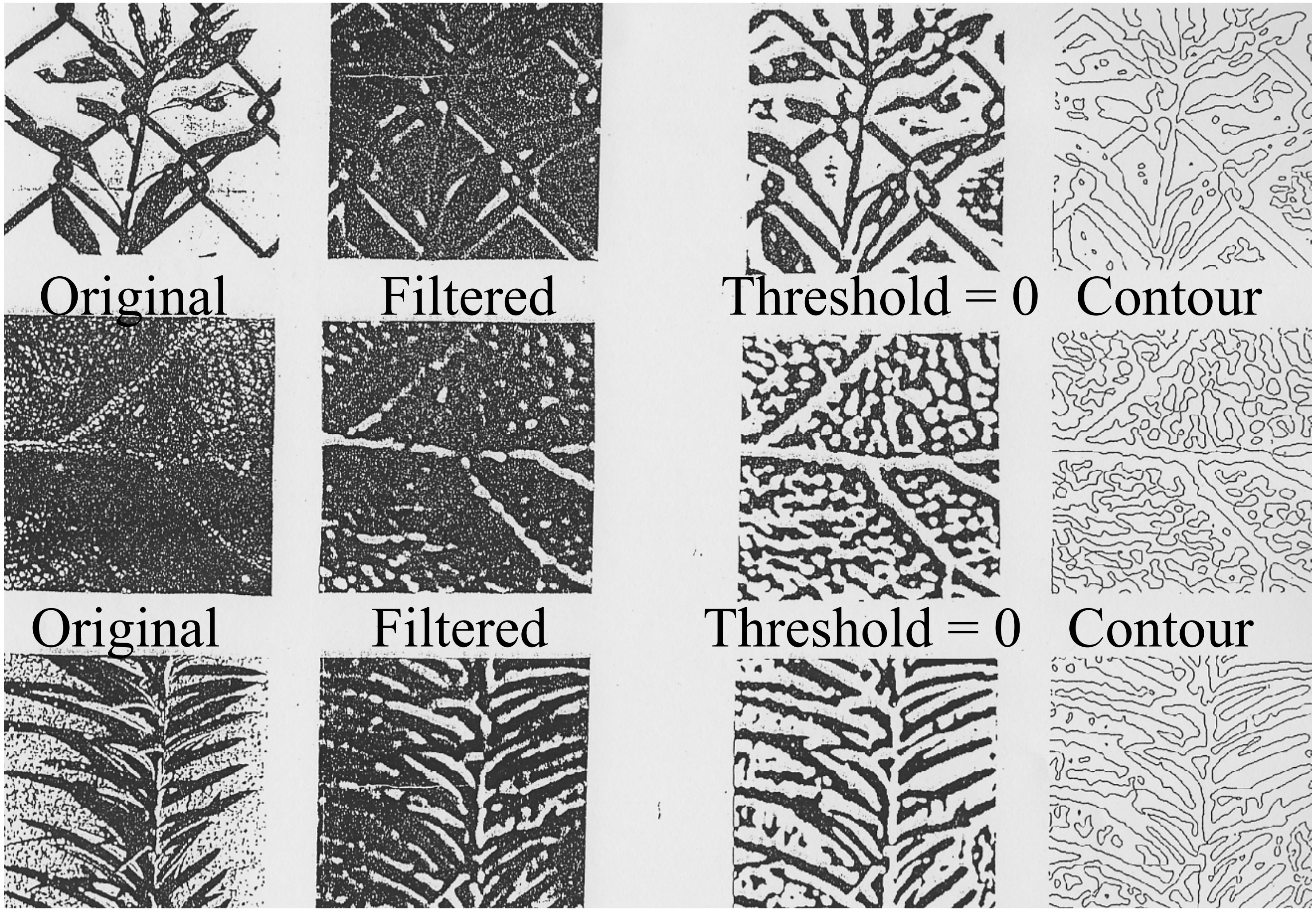
The DoG operator



DoG Example

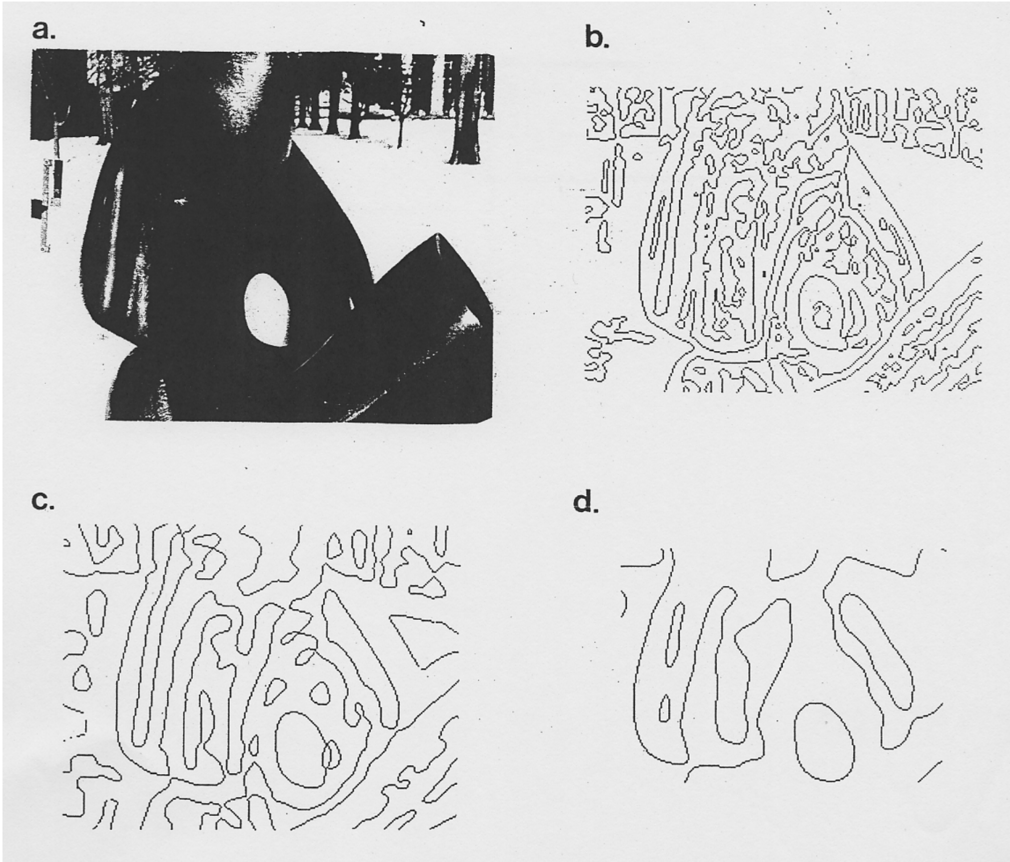
DoG Example

DoG Filter


Original
Filtered
Threshold = 0
Contour
Original
Filtered
Threshold = 0
Contour

DoG: σ dependence

Original

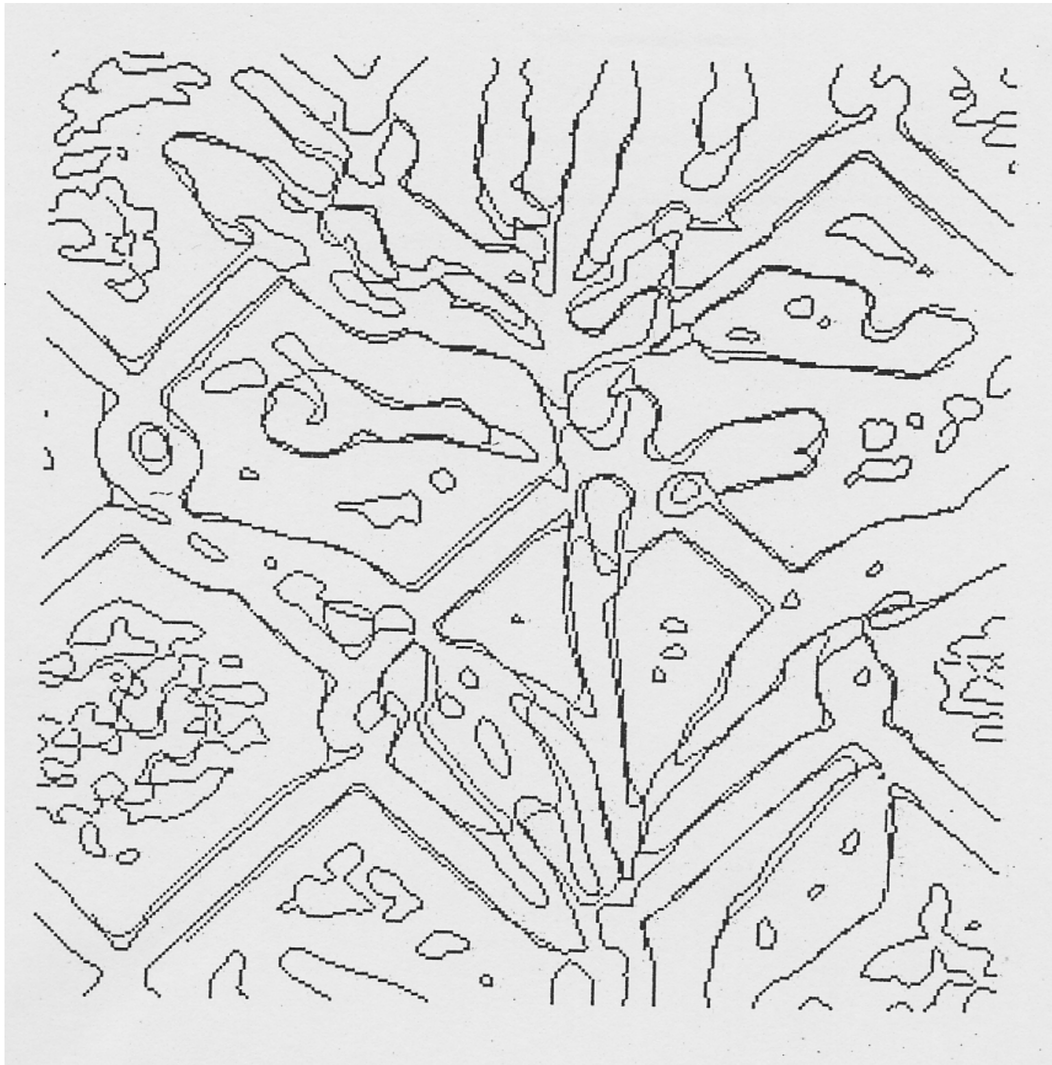


$\sigma = 6$

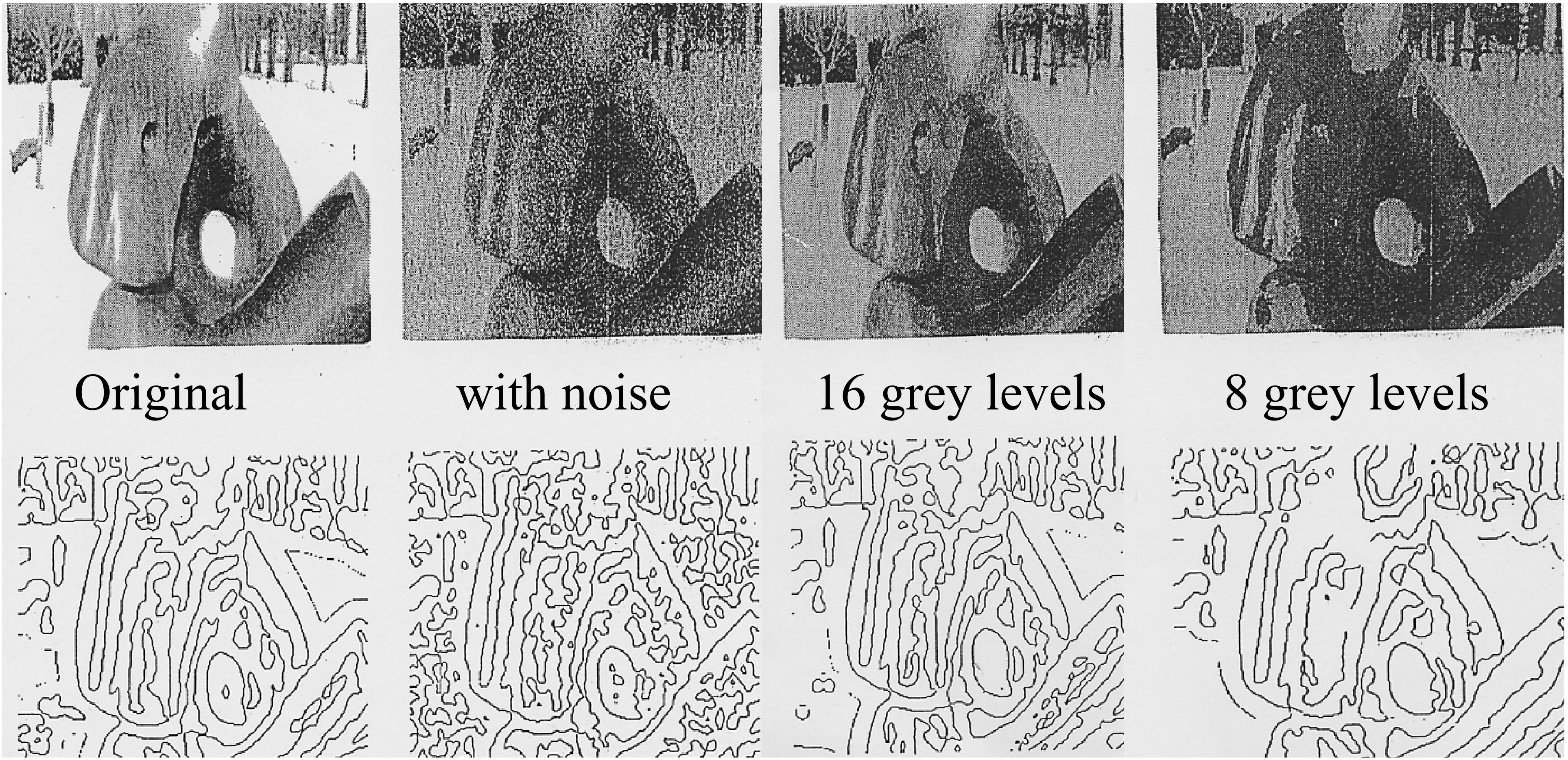
$\sigma = 12$

$\sigma = 24$

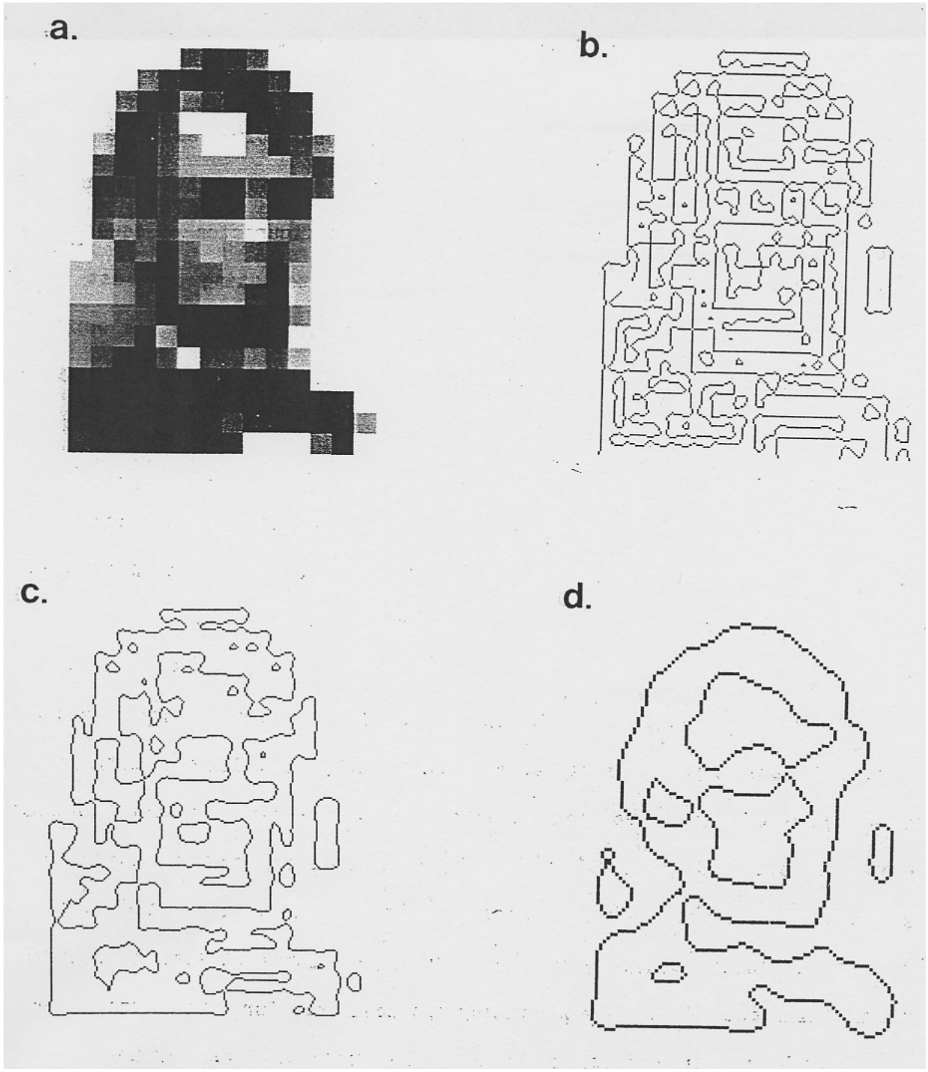
DoG: contour robustness



DoG: discretization of grey level and noise

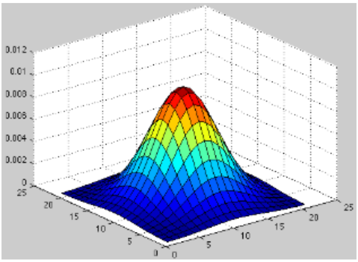


DoG: spatial discretization



Laplacian

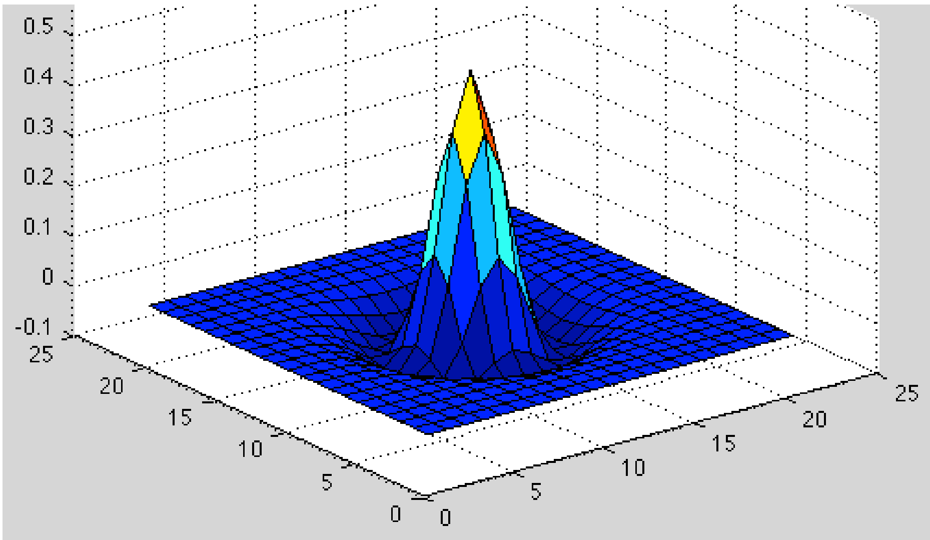
$$h(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}}$$



$$\nabla^2 g\otimes h=\left(\frac{\partial^2 g(x,y)}{\partial x^2}+\frac{\partial^2 g(x,y)}{\partial y^2}\right)\otimes h(x,y)$$

$$\nabla^2 g\otimes h=g\otimes\nabla^2 h$$

$$\nabla^2 h(x,y)=\left(\frac{x^2+y^2}{\sigma^4}-\frac{2}{\sigma^2}\right)h(x,y)$$



John Canny, Rachid Deriche, etc operators





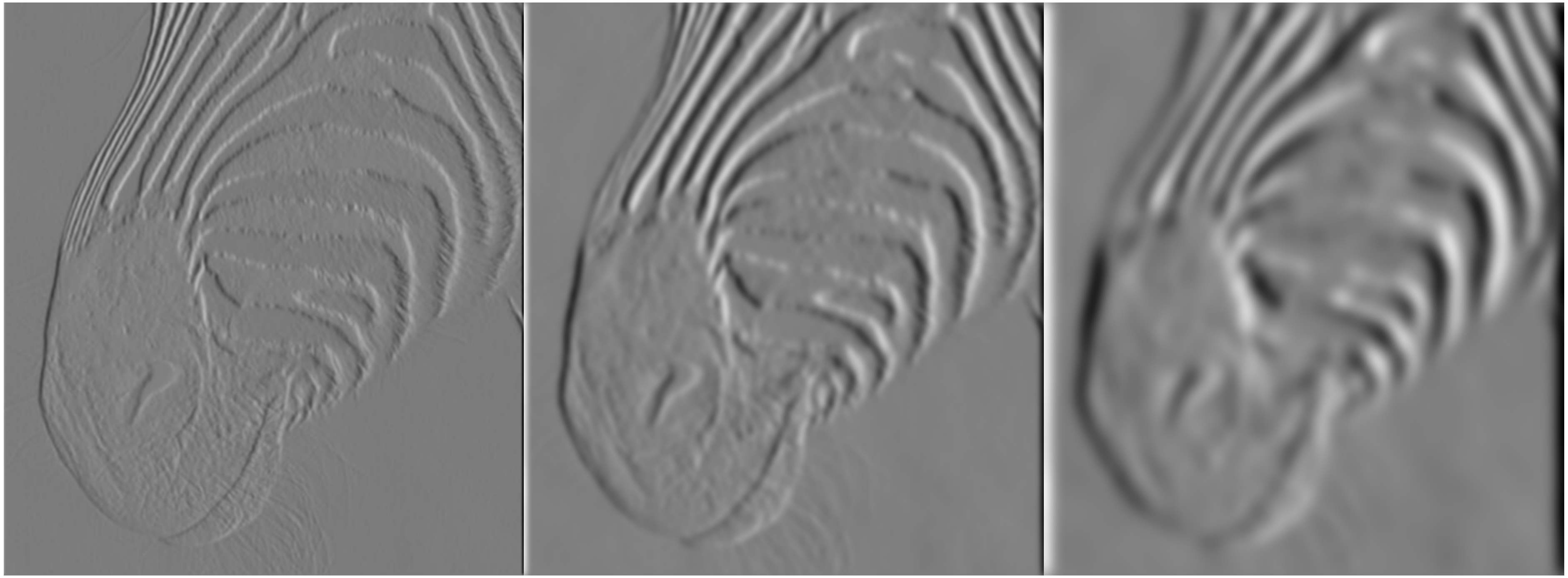
Canny edge detector (CED)

a) Filter image with derivative of Gaussian
b) Find magnitude and orientation of gradient
c) **Non-maximum suppression**:
    a) Thin multi-pixel wide “ridges” down to single pixel width
d) Linking and thresholding (**hysteresis**):
    a) Define two thresholds: low and high
    b) Use the high threshold to start edge curves and the low threshold to continue them

- MATLAB: **`edge(image, ‘canny’);`**
- **`>>help edge`**

Source: D. Lowe, L. Fei-Fei

CED: a) derivative of Gaussian

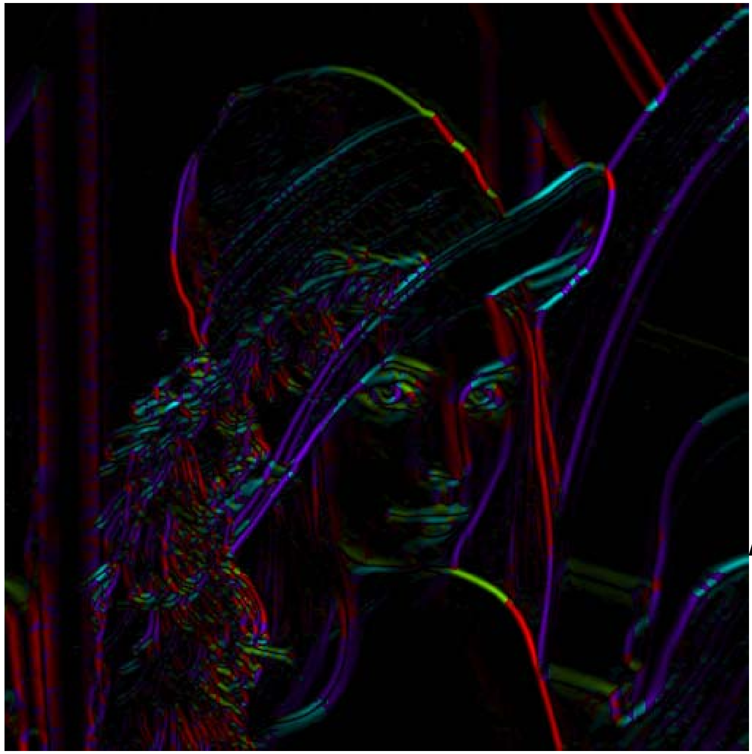


1 pixel 3 pixels 7 pixels

The scale of the smoothing filter affects derivative estimates, and also the semantics of the edges recovered.

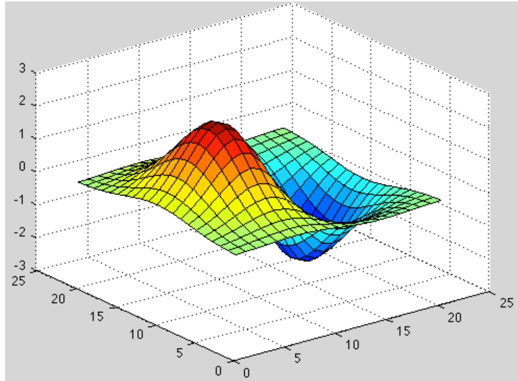
Forsyth, 2002

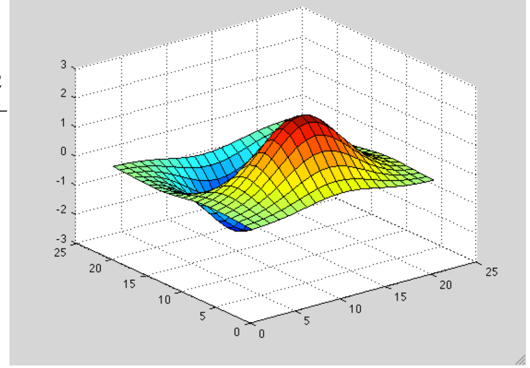
CED: b) magnitude and orientation of gradient



$$h_x(x,y) = \frac{\partial h(x,y)}{\partial x} = \frac{-x}{2\pi\sigma^4} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

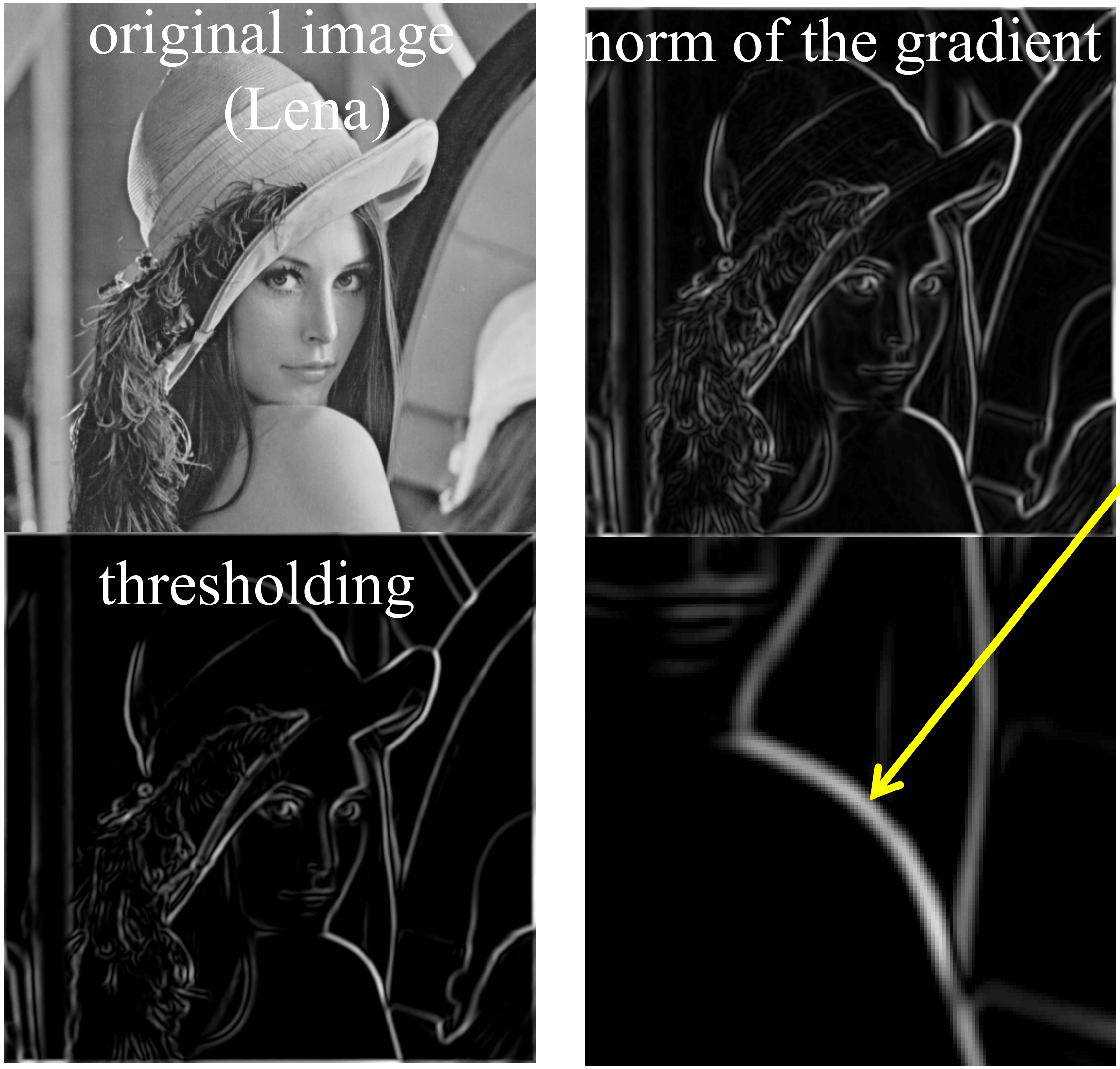
$$h_y(x,y) = \frac{\partial h(x,y)}{\partial y} = \frac{-y}{2\pi\sigma^4} e^{-\frac{x^2+y^2}{2\sigma^2}}$$



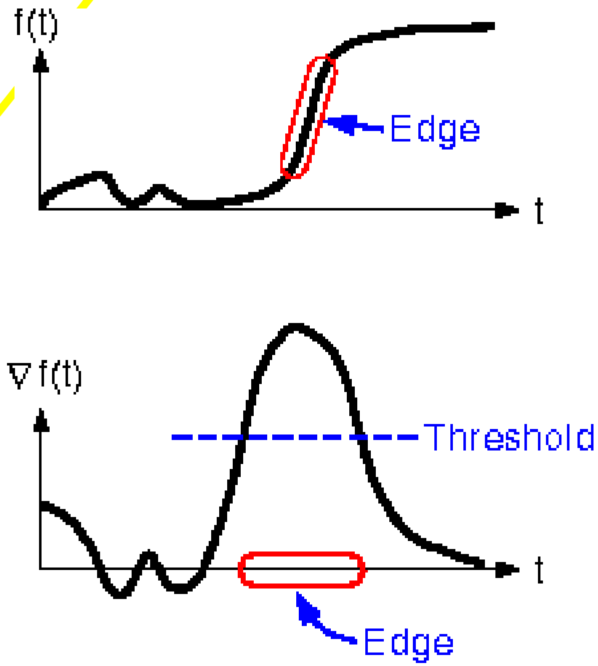


Magnitude: *Edge strength* $\sqrt{h_x(x,y)^2 + h_y(x,y)^2}$ Angle: *Edge normal* $\arctan\left(\frac{h_y(x,y)}{h_x(x,y)}\right)$

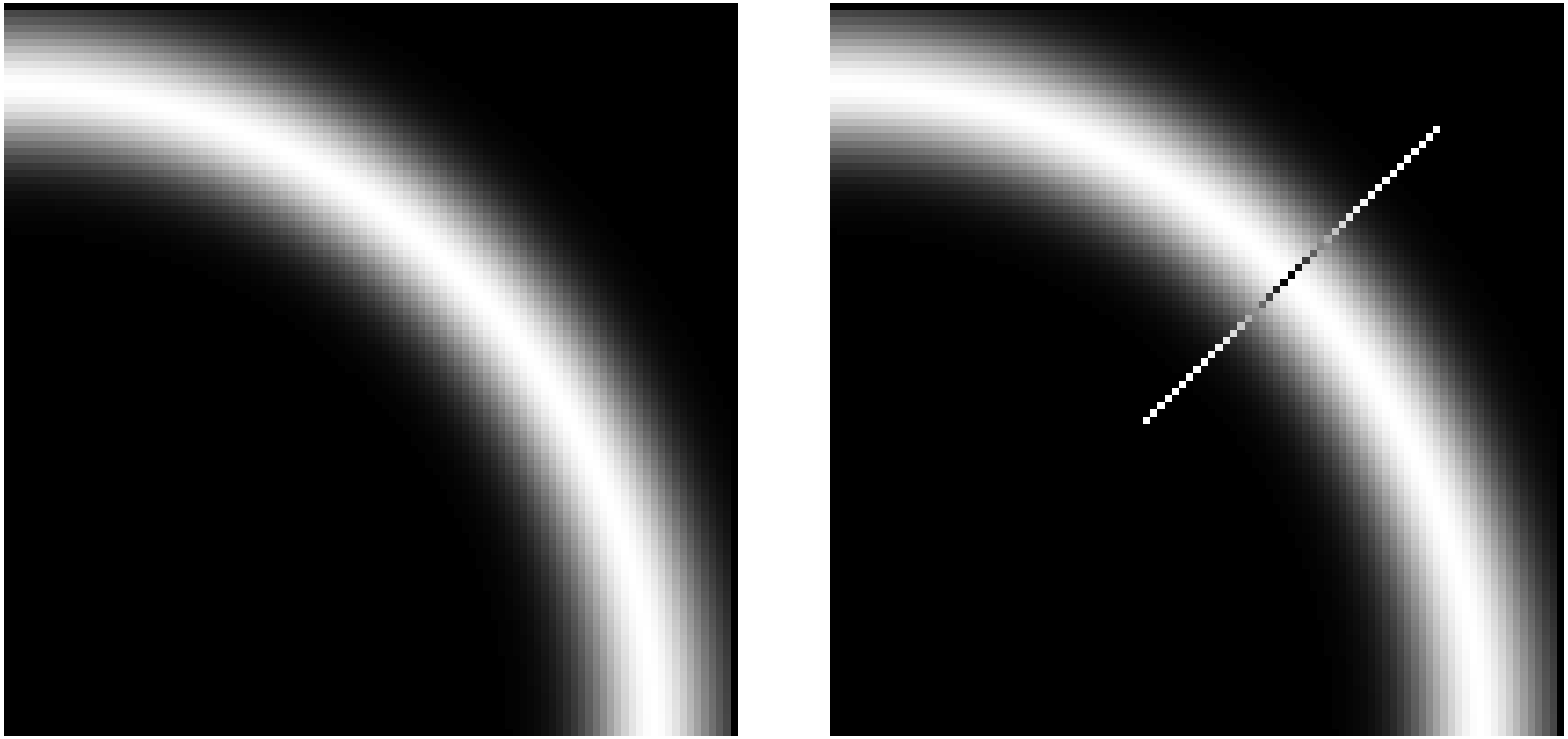
CED: c) Non-maximum suppression



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



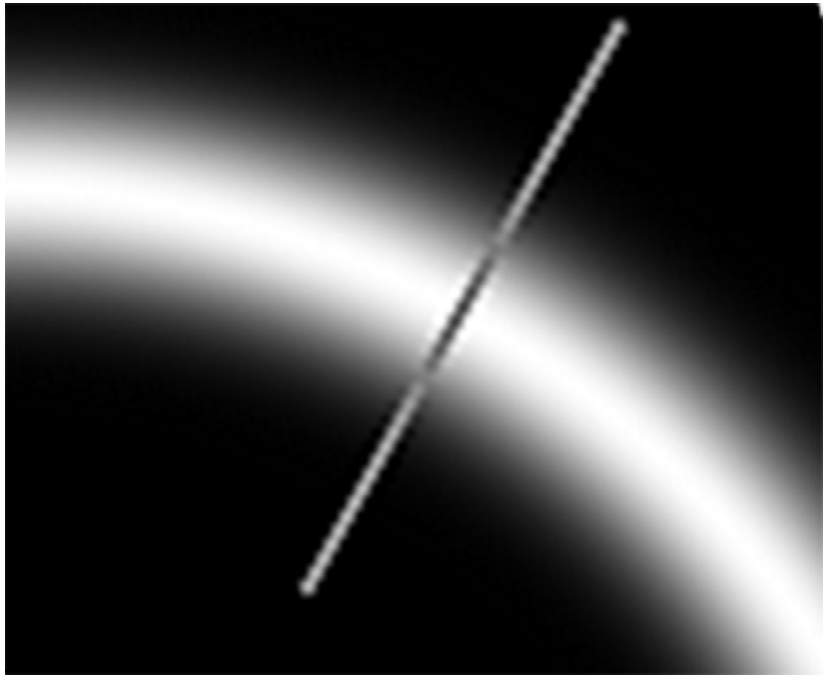
CED: c) Non-maximum suppression

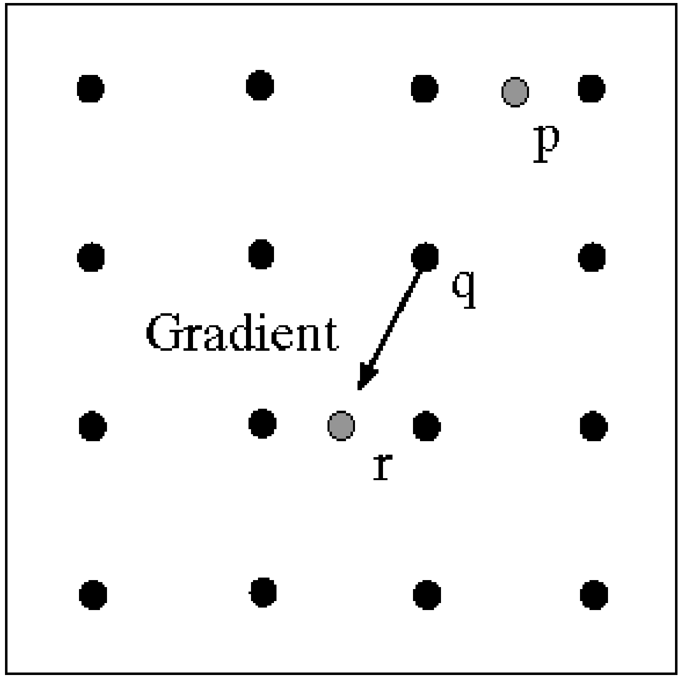


We wish to mark points along the curve where the magnitude is biggest. We can do this by looking for a maximum along a slice normal to the curve (non-maximum suppression). These points should form a curve. There are then two algorithmic issues: at which point is the maximum, and where is the next one?

Forsyth, 2002

CED: Non-maximum suppression





Check if pixel is local maximum along gradient direction, select single max across width of the edge

- requires checking interpolated pixels p and r

Examples: Non-Maximum Suppression

Original image

Gradient magnitude

courtesy of G. Loy

Non-maxima suppressed

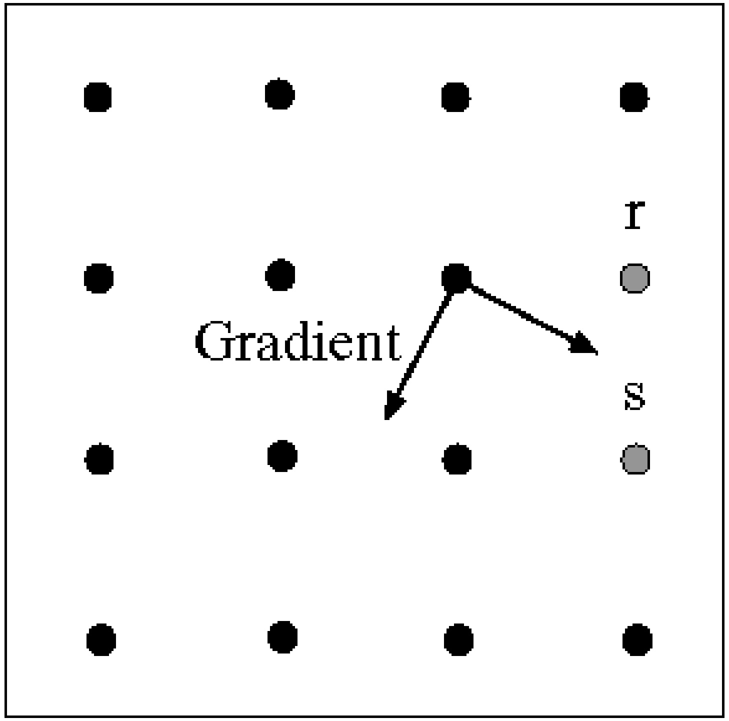
Slide credit: Christopher Rasmussen

CED: d) Linking and thresholding (**hysteresis**)

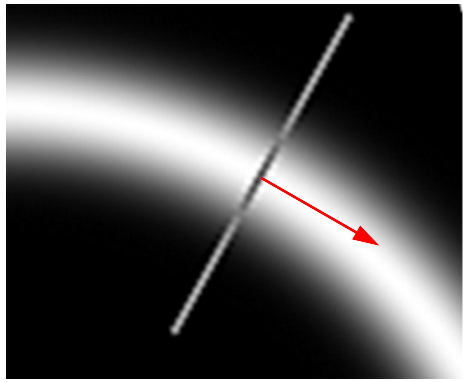
Thinning (non-maximum suppression)

Problem: pixels along this edge didn't survive the thresholding

CED: d_1) Predicting the next edge point



Assume the marked point is an edge point. Then we construct the tangent to the edge curve (which is normal to the gradient at that point) and use this to predict the next points (here either r or s).

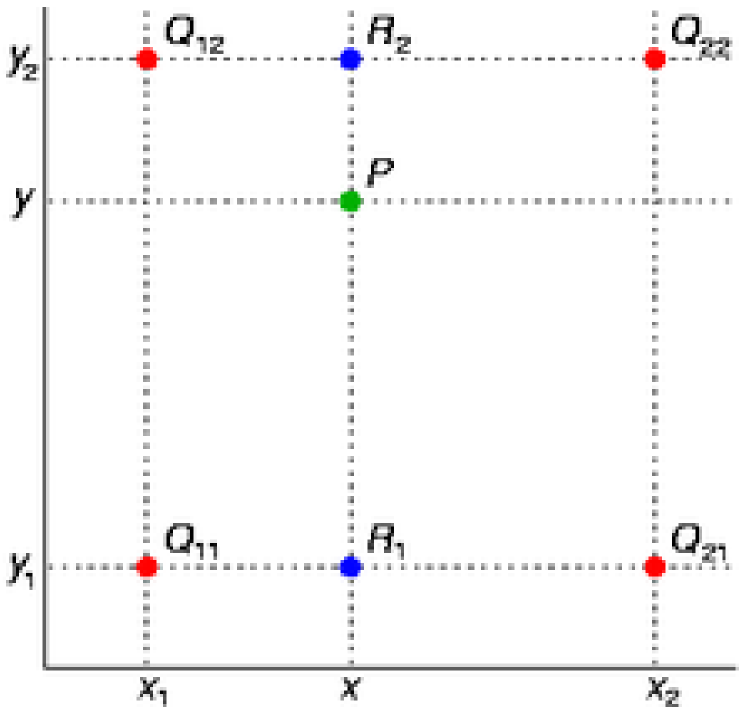


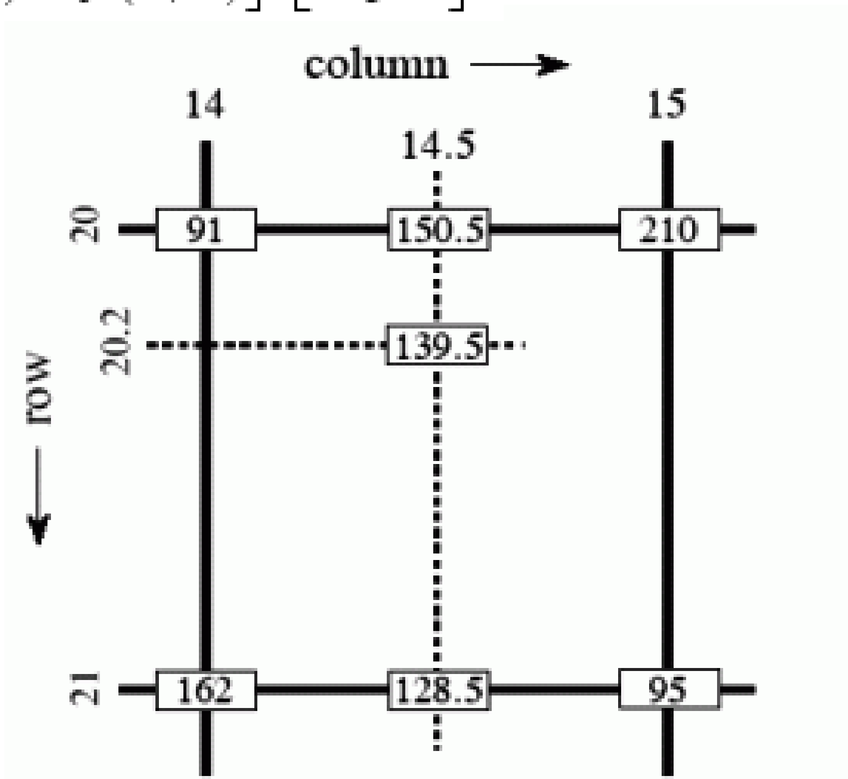
Forsyth, 2002

CED: d_2) Predicting the next edge point

- Sidebar: Bilinear Interpolation

$$f(x,y) \approx \begin{bmatrix}1-x & x\end{bmatrix} \begin{bmatrix} f(0,0) & f(0,1) \\ f(1,0) & f(1,1) \end{bmatrix} \begin{bmatrix} 1-y \\ y \end{bmatrix}.$$

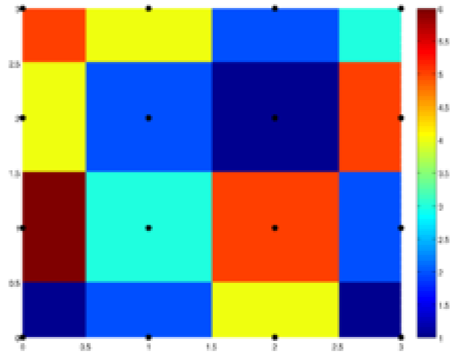




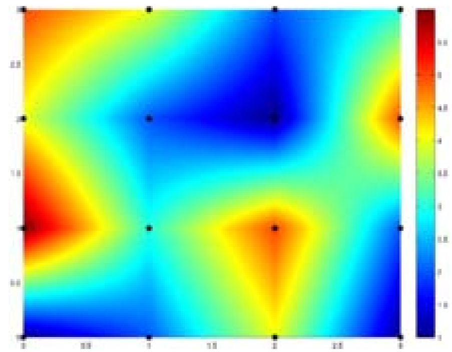
http://en.wikipedia.org/wiki/Bilinear_interpolation

CED: d_3) Predicting the next edge point

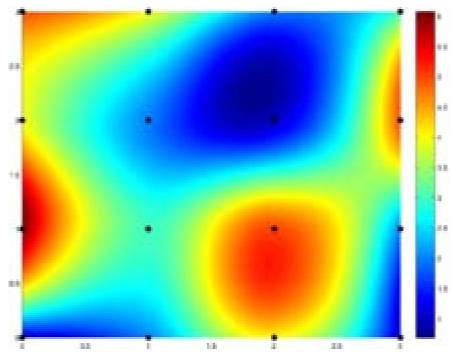
- Sidebar: Interpolation options
- imx2 = imresize(im, 2, interpolation_type)
- 'nearest'
  - Copy value from nearest known
  - Very fast but creates blocky edges



- 'bilinear'
  - Weighted average from four nearest known pixels
  - Fast and reasonable results



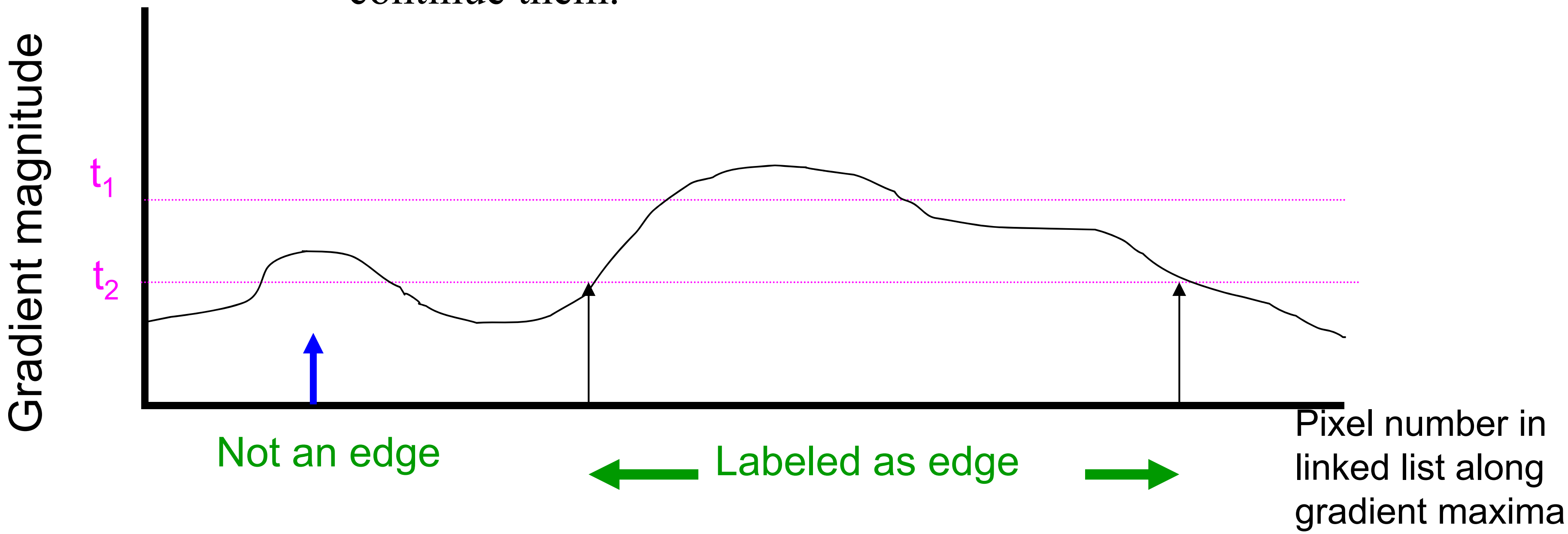
- 'bicubic' (default)
  - Non-linear smoothing over larger area (4x4)
  - Slower, visually appealing, may create negative pixel values



Examples from http://en.wikipedia.org/wiki/Bicubic_interpolation

CED: d_4) Closing edge gaps

- Check that maximum value of gradient value is sufficiently large
  - drop-outs? use **hysteresis**
    - use a high threshold to start edge curves and a low threshold to continue them.



Example: Canny Edge Detection

Original image

gap is gone

Strong + connected weak edges

Strong edges only

Weak edges

courtesy of G. Loy

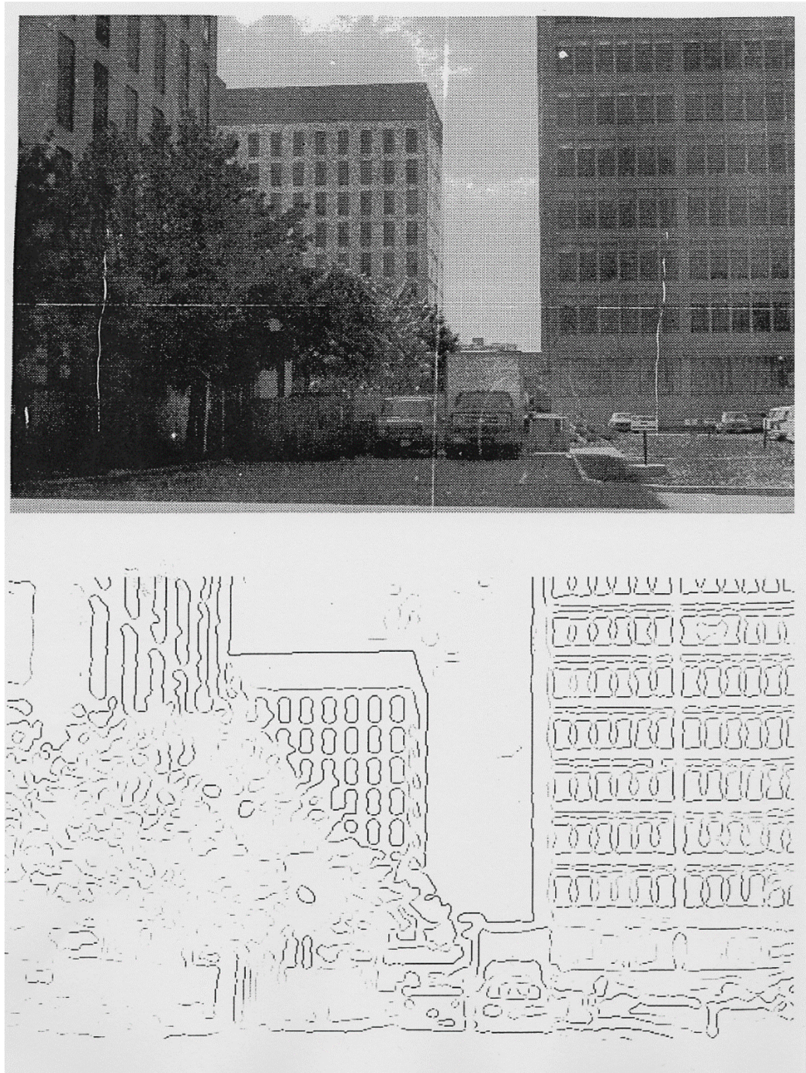
Canny edge detector

1. Filter image with x, y derivatives of Gaussian
2. Find magnitude and orientation of gradient
3. Non-maximum suppression:
   - Thin multi-pixel wide “ridges” down to single pixel width
4. Thresholding and linking (hysteresis):
   - Define two thresholds: low and high
   - Use the high threshold to start edge curves and the low threshold to continue them

- MATLAB: edge(image, ‘canny’)

Source: D. Lowe, L. Fei-Fei

DoG + Sobel



DoG(2, 9)+Sobel

DoG(1, 9)+Sobel

Template Matching

- An alternative method for edge detection computes the closest (over all four/eight directions) approximations of *g(i,j)* in every 3x3 neighborhood, to keep the one with maximum convolution value, provided it is large enough
- Even if the sum of the kernel parameter is null note that starting with grey level images in the range 0:255 the final range is -3825:+3825 and -1275:1275 for Kirsh and compass operators respectively (the equivalent are -255:255, -765:765, -871:871, -1020:1020 for Roberts, Prewitt, isotropic and Sobel respectively)
- Obviously the greater is the number of values different from zero of the kernel parameters the higher is the robustness to noise.

Template Matching

- Kirsh's operator

-3	-3	5
-3	0	5
-3	-3	5

-3	5	5
-3	0	5
-3	-3	-3

5	5	5
-3	0	-3
-3	-3	-3

5	5	-3
5	0	-3
-3	-3	-3

5	-3	-3
5	0	-3
5	-3	-3

-3	-3	-3
5	0	-3
5	5	-3

-3	-3	-3
-3	0	-3
5	5	5

-3	-3	-3
-3	0	5
-3	5	5

- Compass operator

-1	1	1
-1	-2	1
-1	1	1

1	1	1
-1	-2	1
-1	-1	1

1	1	1
1	-2	1
-1	-1	-1

1	1	1
1	-2	-1
1	-1	-1

1	1	-1
1	-2	-1
1	1	-1

1	-1	-1
1	-2	-1
1	1	1

-1	-1	-1
1	-2	1
1	1	1

-1	-1	1
-1	-2	1
1	1	1

3/9 operator

1	1	1
0	0	0
0	0	0

1	1	0
1	0	0
0	0	0

1	0	0
1	0	0
1	0	0

0	0	0
1	0	0
1	1	0

0	0	0
0	0	0
1	1	1

0	0	0
0	0	1
0	1	1

0	0	1
0	0	1
0	0	1

0	1	1
0	0	1
0	0	0

$$P_i = \sum_{j=0}^{8} I_{i,j}$$

3	2	1
4	8	0
5	6	7

$P_{i,j} = I_{i,j} + I_{i,j-1} + I_{i,j+1}$, with $(j=1,8)_{\text{mod } 8}$

Contour extraction

$$P = 1.5\left[\frac{P_{i,k}}{P_i} - 0.333\right]$$

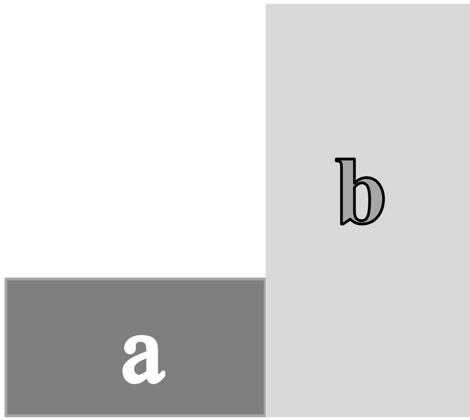
- $P_{i,\,k}$ is the maximum among the 8 parameters $P_{i,j}$
- The coefficients 3/2 et 1/3 are introduced to normalize the result so that monochromatic area has P=0
- The final threshold can be applied depending on the minimum average contrast τ admitted in the neighborhood

Practical aspects of the 3/9 filter

- The filter implements a relative gray level intensity analisys. Also the human eye apply a similir approach.
- It must be payed attention when looking contours in the dark!
- Note that if P_i is low this edge estimation suffers very much for the effect of the noise (if the intensity in the area is 0 then P=0/0).
- Selecting the threshold for P_i note that it is 9 time di average intensity of the area (if the average area intensity is 10 over 255, that is very low, then P_i =90, and edges are looked for in the very dark)

Contrast and threshold

- Let us call ‘contrast’ the ratio $\tau = \frac{a}{b}$, the threshold Th is given by:



$$P_i = \frac{3}{2}\left[\frac{3b}{6a+3b} - \frac{1}{3}\right]$$

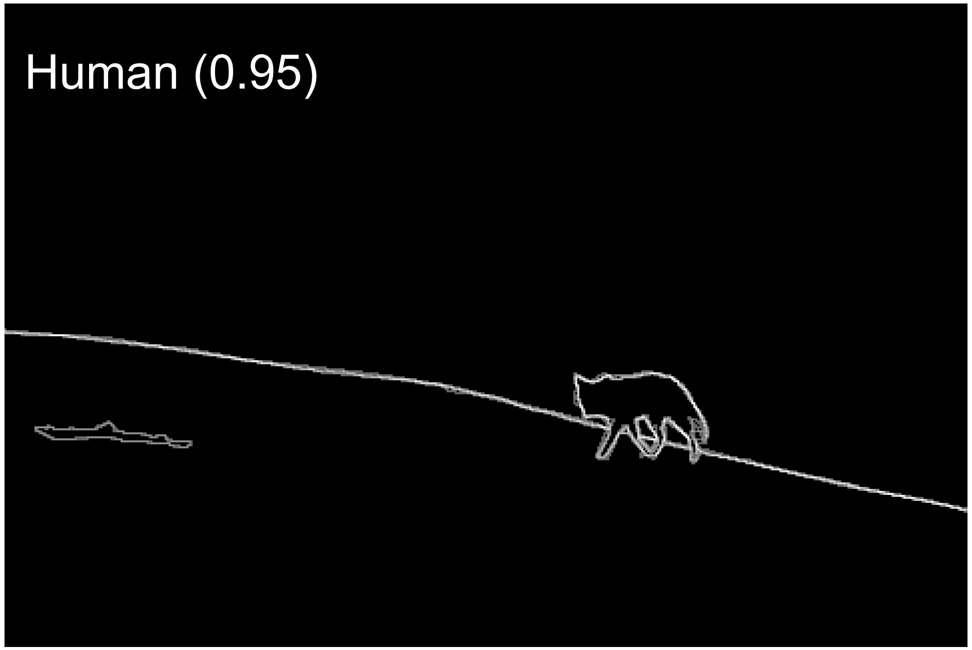
$$P_i = \frac{3}{2}\left[\frac{1}{2\tau+1} - \frac{1}{3}\right]$$

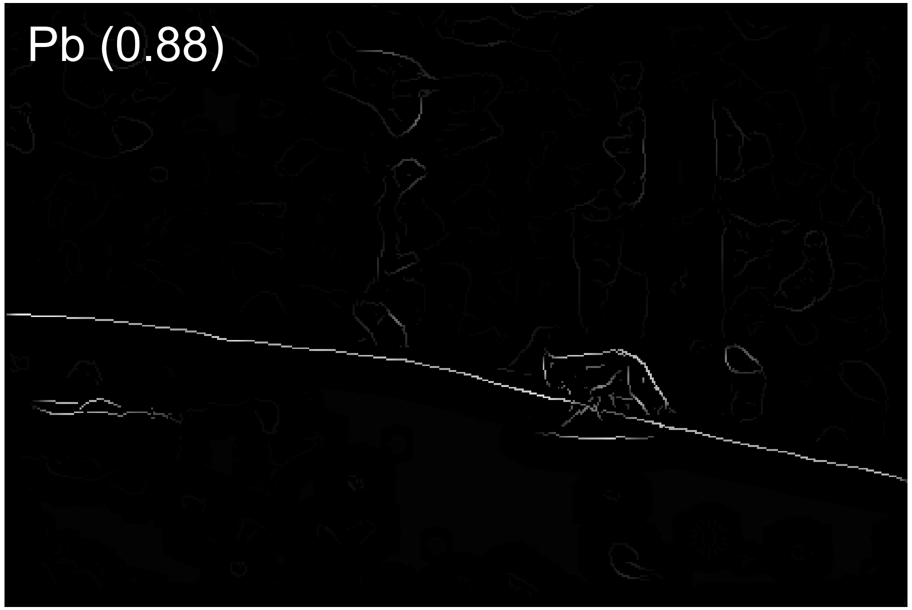
$$Th = \frac{1-\tau}{2\tau+1}$$

Example: Op. 3 / 9

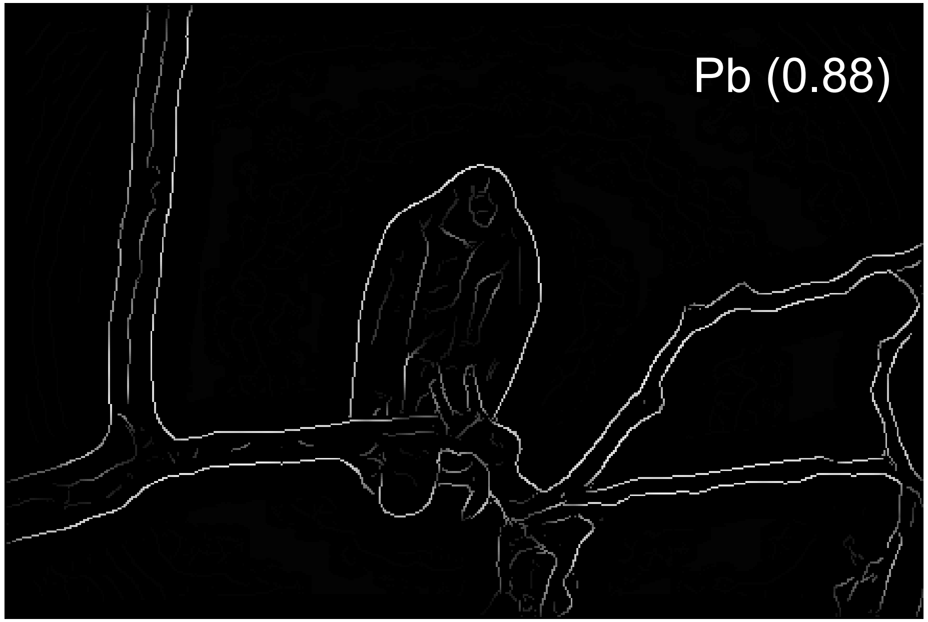
Example: Op. 3 / 9

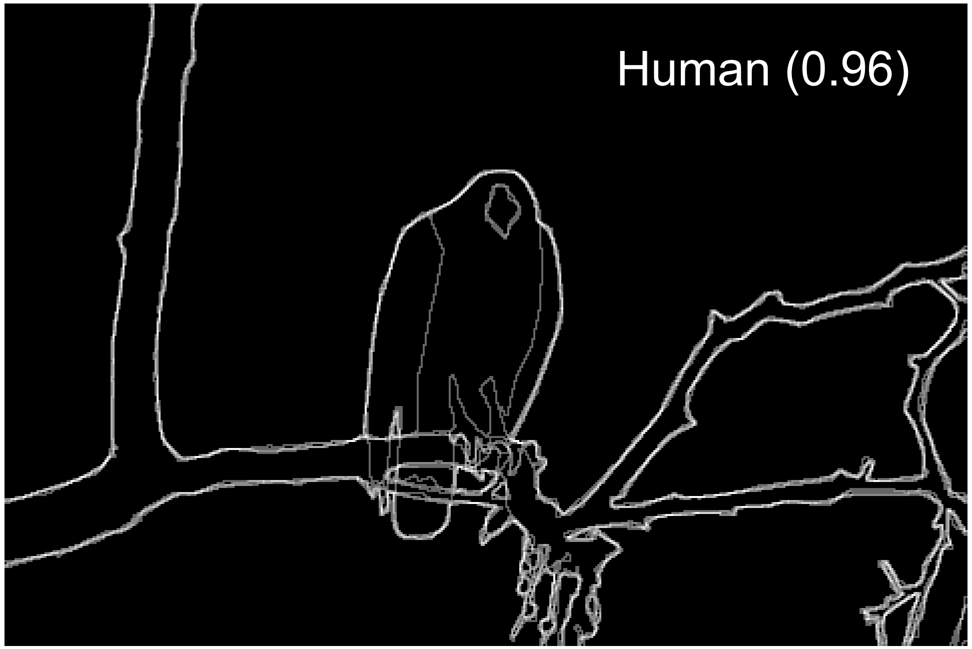
Results





Results





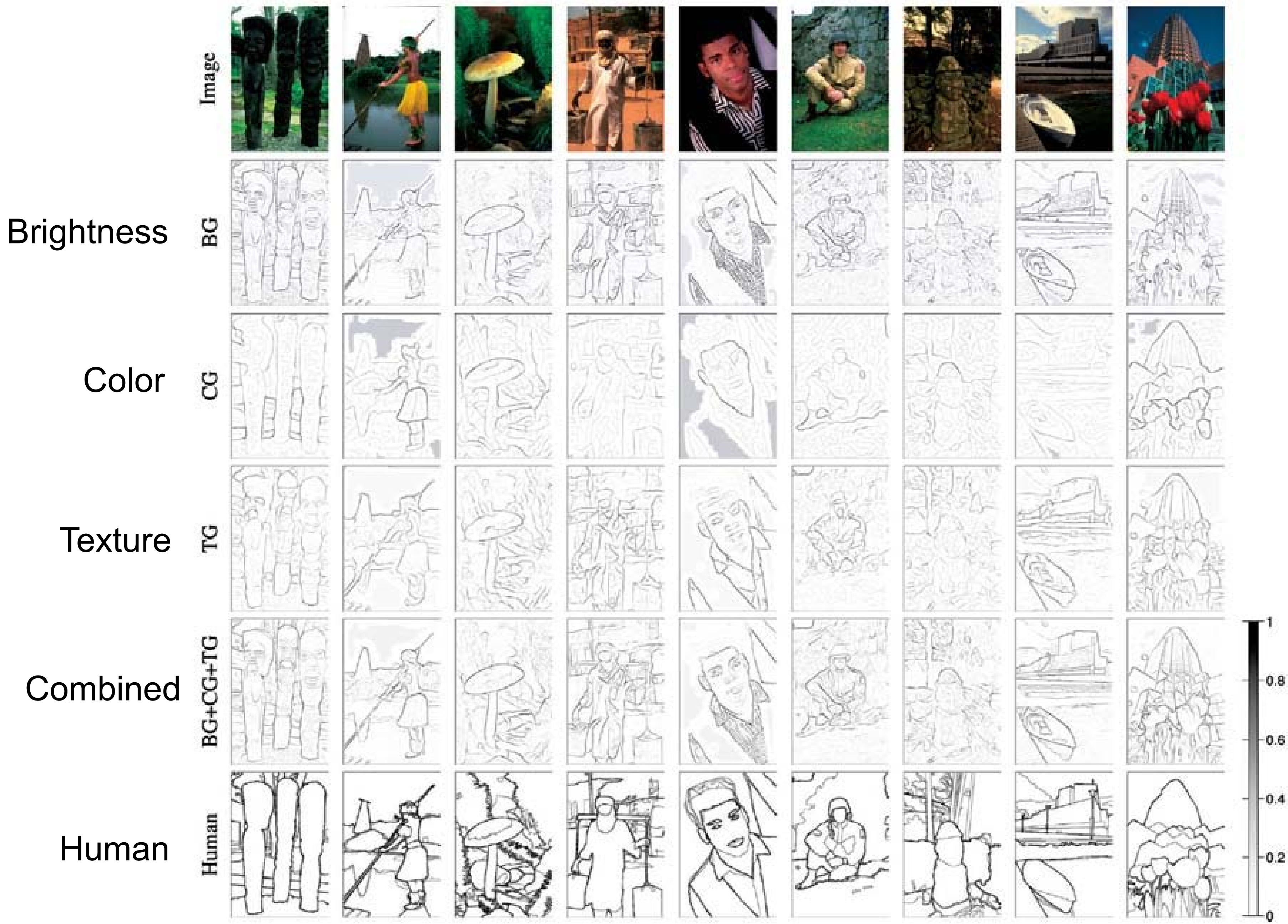


Image
Brightness
BG
Color
CG
Texture
TG
Combined
BG+CG+TG
Human
1
0.8
0.6
0.4
0.2
0

Common types of noise

- **Salt and pepper noise**: random occurrences of black and white pixels
- **Impulse noise:** random occurrences of white pixels
- **Uniform noise**: constant probability density in a given range ±k
- **Gaussian noise**: variations in intensity drawn from a Gaussian normal distribution

Original

Salt and pepper noise

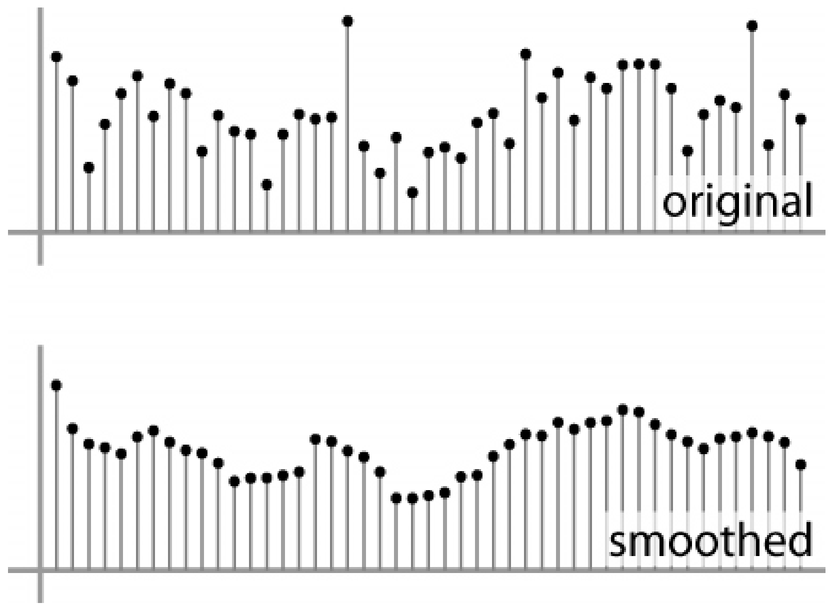
Impulse noise

Gaussian noise

Source: S. Seitz

First attempt at a solution

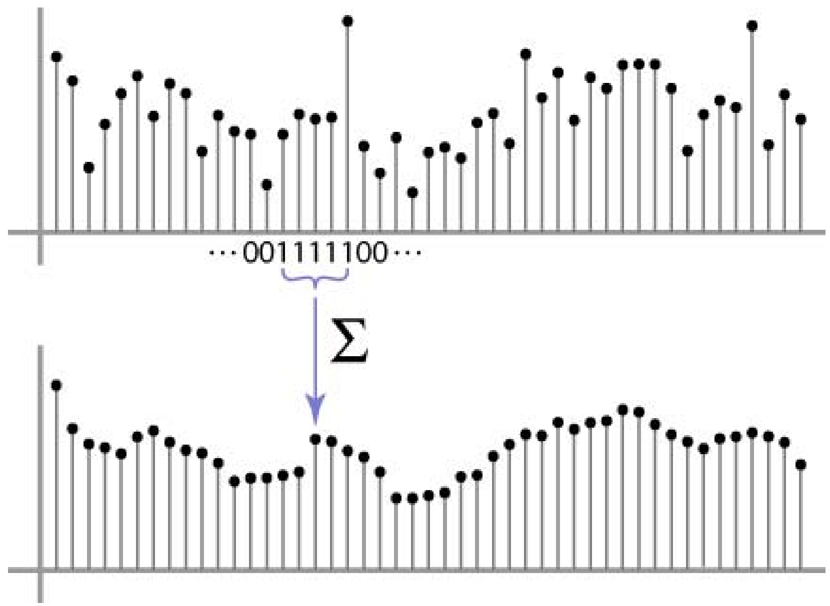
- Let's replace each pixel with an average of all the values in its neighborhood
- Moving average in 1D:



Source: S. Marschner

Weighted Moving Average

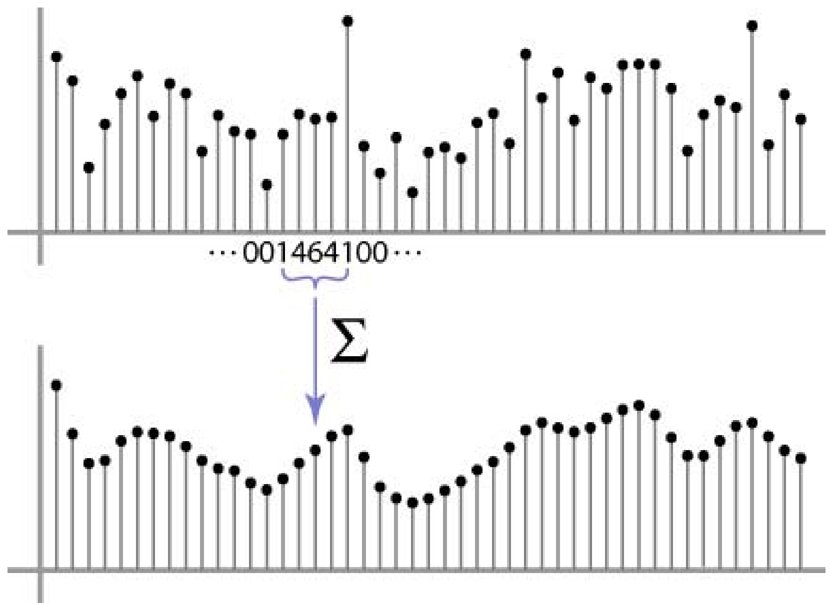
- Can add weights to our moving average
- *Weights* [1, 1, 1, 1, 1] / 5



Source: S. Marschner

Weighted Moving Average

- Non-uniform weights [1, 4, 6, 4, 1] / 16



Source: S. Marschner

Degraded image: uniform noise

- The standard model of this noise is additive, independent at each pixel and independent of the signal intensity with continuous uniform distribution in a given interval**.** The noise caused by quantizing the pixels to discrete levels has an approximately uniform distribution.

This noise can be simulated adding in each pixel $n=2k(rnd - 0,5)$ being k the noise max intensity and *rnd* a random number with $0 \le rnd \le 1$

Degraded image: ‘salt and pepper’

- This is an impulsive or spike noise for which the image has dark pixels and bright pixels randomly distributed.

This noise can be simulated for each pixel in this way:

if $rnd \geq Th_1$ I(i,j) = 255

if $rnd \leq Th_2$ I(i,j) = 0

else $n=2[(K- Th_2)/(Th_1- Th_2)](rnd-0,5)$ and if I(i,j)+n>255: I(i,j)=255, if I(i,j)+n<0:I(i,j)=0

being K the uniform component noise intensity, $0 \leq rnd \leq 1$, and Th_1 and Th_2 two suitable thresholds ($1-Th_1$ and Th_2 are the percentage of extra white and black pixels respectively)

Average value filter

- Each pixel takes the average value over the neighbors (3x3 in the example)
- Example - given the neighborhood:

3	6	8
3	4	2
5	8	3

the central pixel will take the new value:

(3+6+8+3+4+2+5+8+3)/9 = 4.67

Average value filter: uniform noise

Noisy image

Filtered image

Second iteration

Average value filter: uniform noise

Noisy image

Filtered image

Second iteration

Average value filter: salt and pepper

Noisy image

Filtered image

Second iteration

Average value filter: salt and pepper

Noisy image

Filtered image

Second iteration

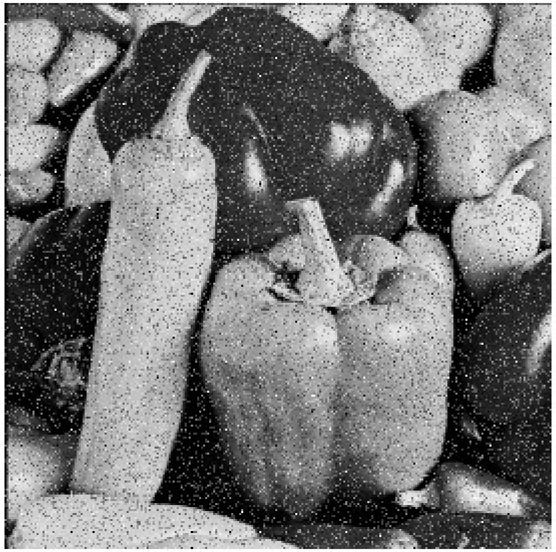
Median filters

- A **Median Filter** operates over a window by selecting the median intensity in the window.
- What advantage does a median filter have over a mean filter?
- Is a median filter a kind of convolution?

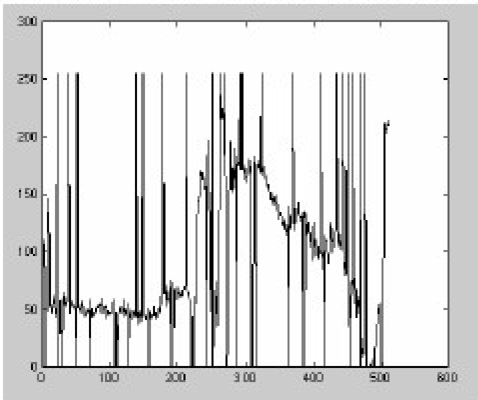
Slide by Steve Seitz

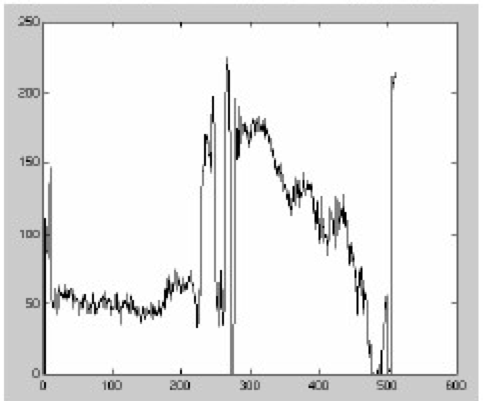
Median filter

Salt and pepper noise →



← Median filtered





Plots of a row of the image

Source: M. Hebert

Median and rank filters

- The median filter assigns to pixel the median value of neighborhood
- It is a particular case of the *rank filters* family, in which to the pixel is assigned the average value over a predefined range of the neighbors histogram.
- The average excluding the extremes is suited for impulse or spike noise such as the salt and pepper case.

- Example - given the neighborhood:

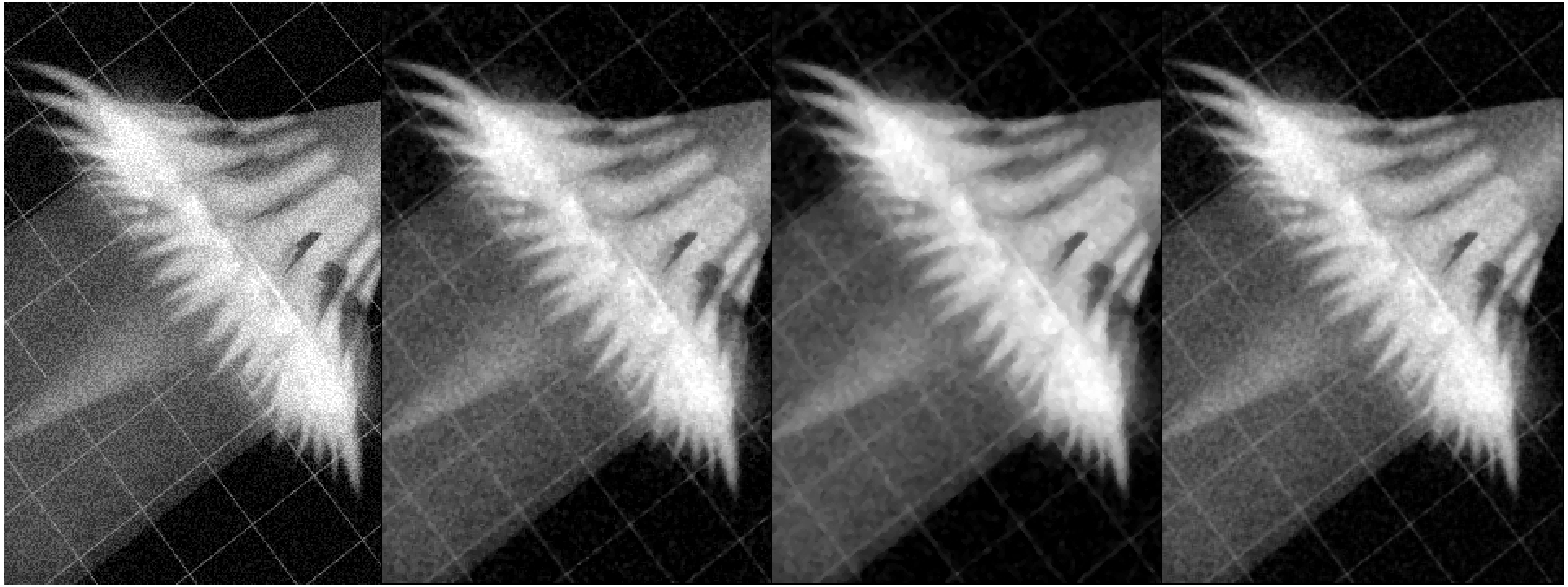
3	6	8
3	4	2
5	8	3

the correspondent values are:

2	3	3	3	4	5	6	8	8

median value: 4;
over three values: 4;
over five values: 4,2;
over seven values: 4,57
over nine values: 4,66

Median filter: uniform noise



Noisy image　　Filtered image　　Second iteration　　Rank 3

Median filter: uniform noise

Noisy image

Filtered image

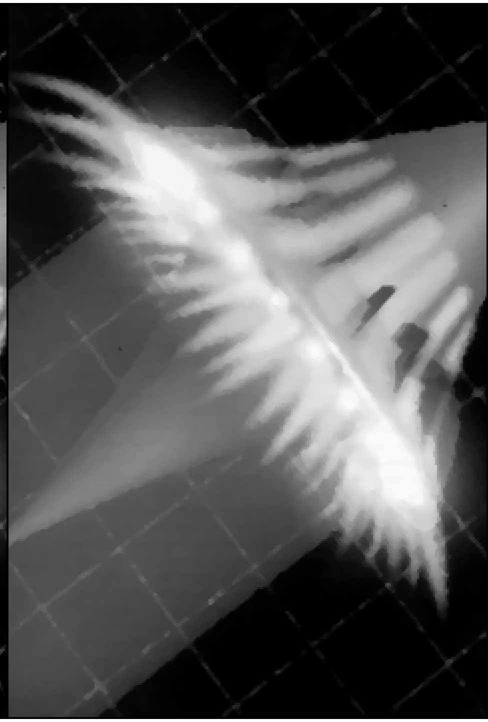
Second iteration

Rank 3

Median filter: salt and pepper

Noisy image

Filtered image



Second iteration

Rank 3

Median filter: salt and pepper

Noisy image

Filtered image

Second iteration

Rank 3

Comparison: salt and pepper noise

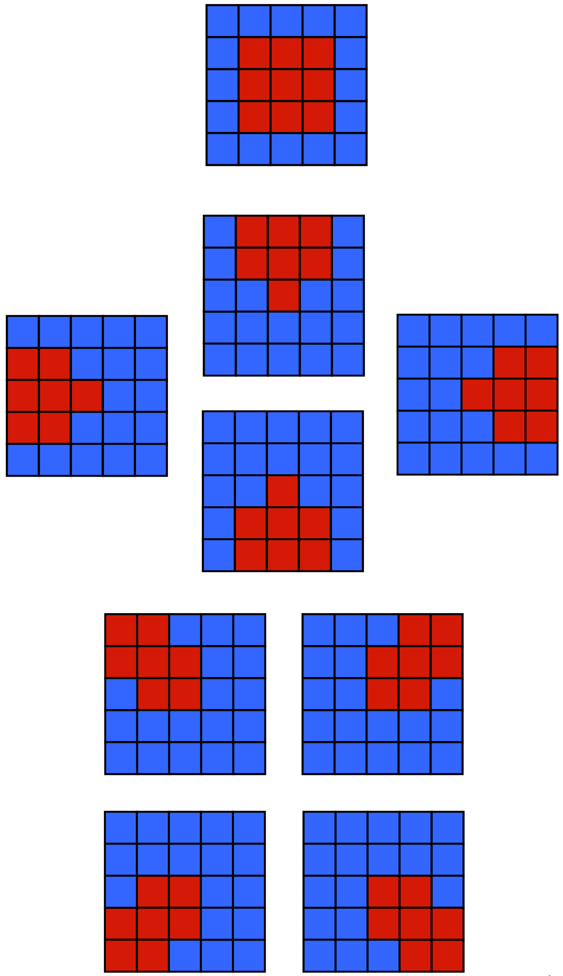
Slide by Steve Seitz

The Nagao-Matsuyama Filter

This filter selects for the centre pixel the average for the orientation with the least variation. Hence, the steps are as follows:

1. Calculate the variance for each of the nine sub-groups shown to the right (including the centre pixel).
2. Determine the sub-group with the lowest variance.
3. Assign the mean of this sub-group to the centre pixel.

Nagao-Matsuyama improves the borders, and is effective at reducing the edges smoothing. Clearly there is a cost in terms of computation due to the calculation of nine variances for each pixel.



Nagao filter: uniform noise

Noisy image

Filtered image

Nagao filter: uniform noise

Noisy image

Filtered image

Nagao filter: salt and pepper

Noisy image

Filtered image

Nagao filter: salt and pepper

Noisy image

Filtered image