

Computer Vision:

5 – Morphological Operators

WS 2019 / 2020

Gunther Heidemann

- Idea: Search image for a (small) pre-defined pattern
- Originally defined for binary images, extension to gray values possible
- Morphological operation is specified by structuring element S
- Operation is translation invariant and nonlinear
- Application examples
 - Smoothing of segmented regions
 - Removal of disruptions
 - Recognition of simple patterns
- Very simple operation
- Well suited for parallel implementation

- Let S be a binary matrix (“*structuring element*”): $S(i,j) \in \{0,1\}$.
- S moves across the image line by line like a filter kernel
- S and the underlying image patch are compared and the resulting similarity value is assigned to a result matrix (same size as the input image) at the location corresponding to the **anchor point** of S . Commonly the center of S is the anchor point.
- S must be shaped according to expected patterns in the image.
- Two ways to apply S :
 - Erosion
 - Dilation
- First only binary images and binary S .

1. Erosion:

- Assign 1 to the result pixel if and only if **all 1-elements** of S cover **1-pixels** of image g , else assign 0:

$$g'(x,y) = \Theta\left(\left(\sum_{k \in [-m,m]} \sum_{l \in [-n,n]} S(k+m,l+n) \cdot g(x+k,y+l)\right) - N + \frac{1}{2}\right)$$

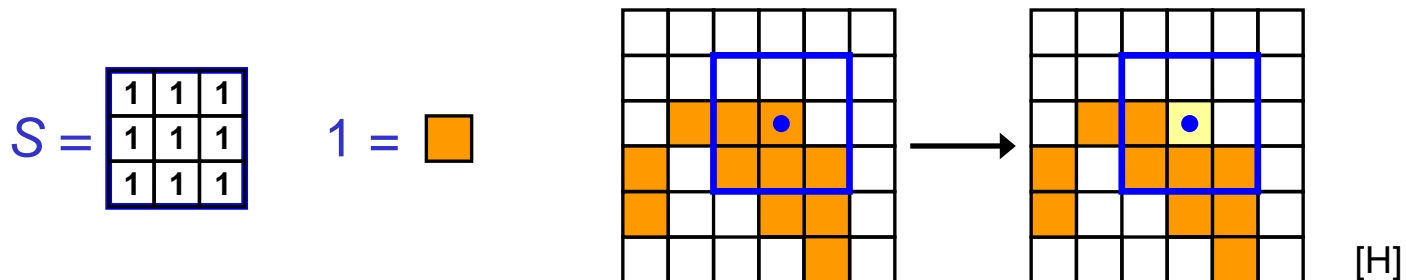
where $N = \sum_{k \in [0,2m+1]} \sum_{l \in [0,2n+1]} S(k,l) = \# \text{ 1s in } S$

- Alternative notation:

$$g'(x,y) = \bigwedge_{k \in [-m,m]} \bigwedge_{l \in [-n,n]} (S(k+m,l+n) \rightarrow g(x+k,y+l)),$$

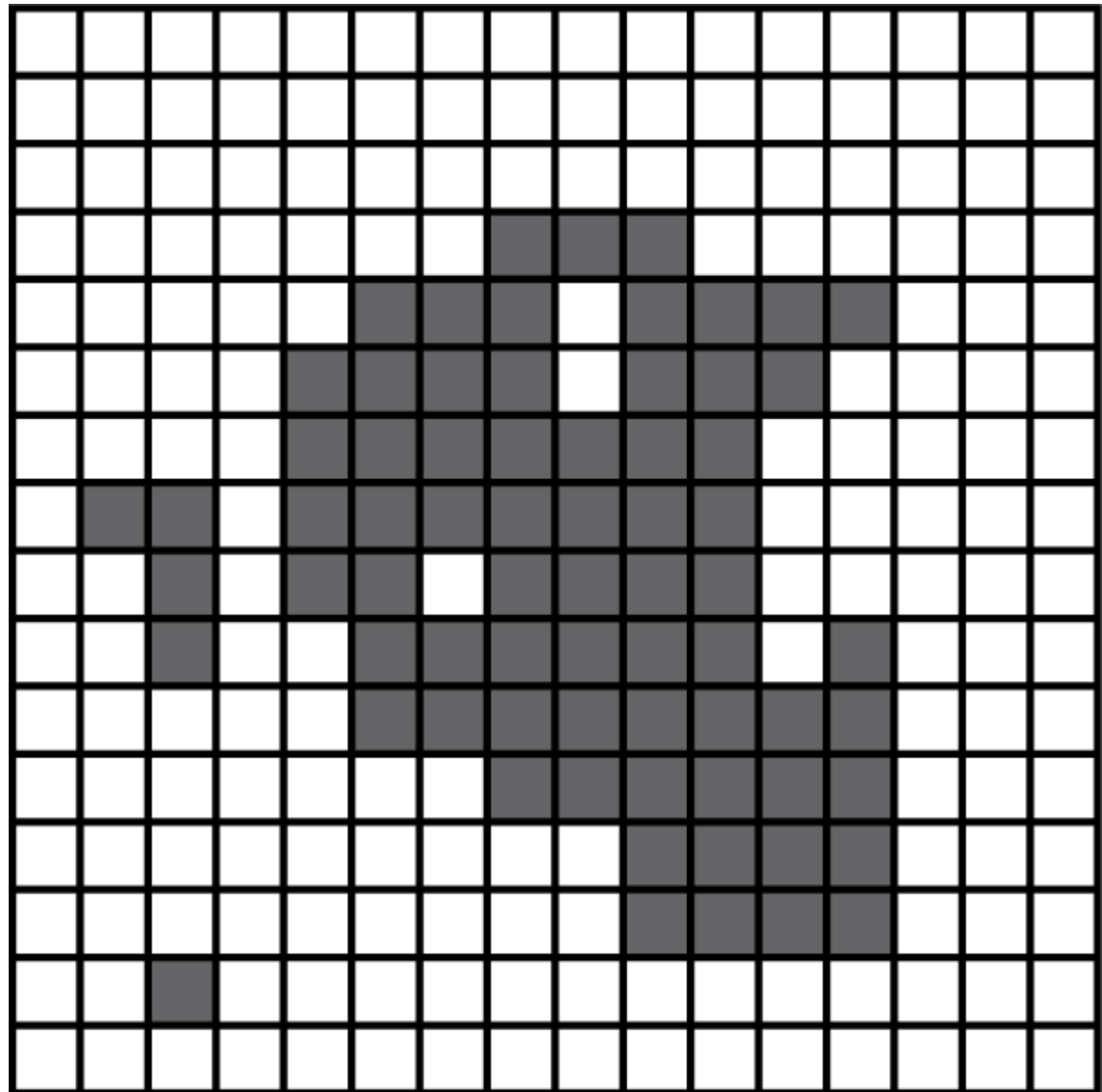
where \rightarrow denotes the (logical) implication.

- Short: $g' = g \ominus S$
- Erosion cuts off fringe of objects

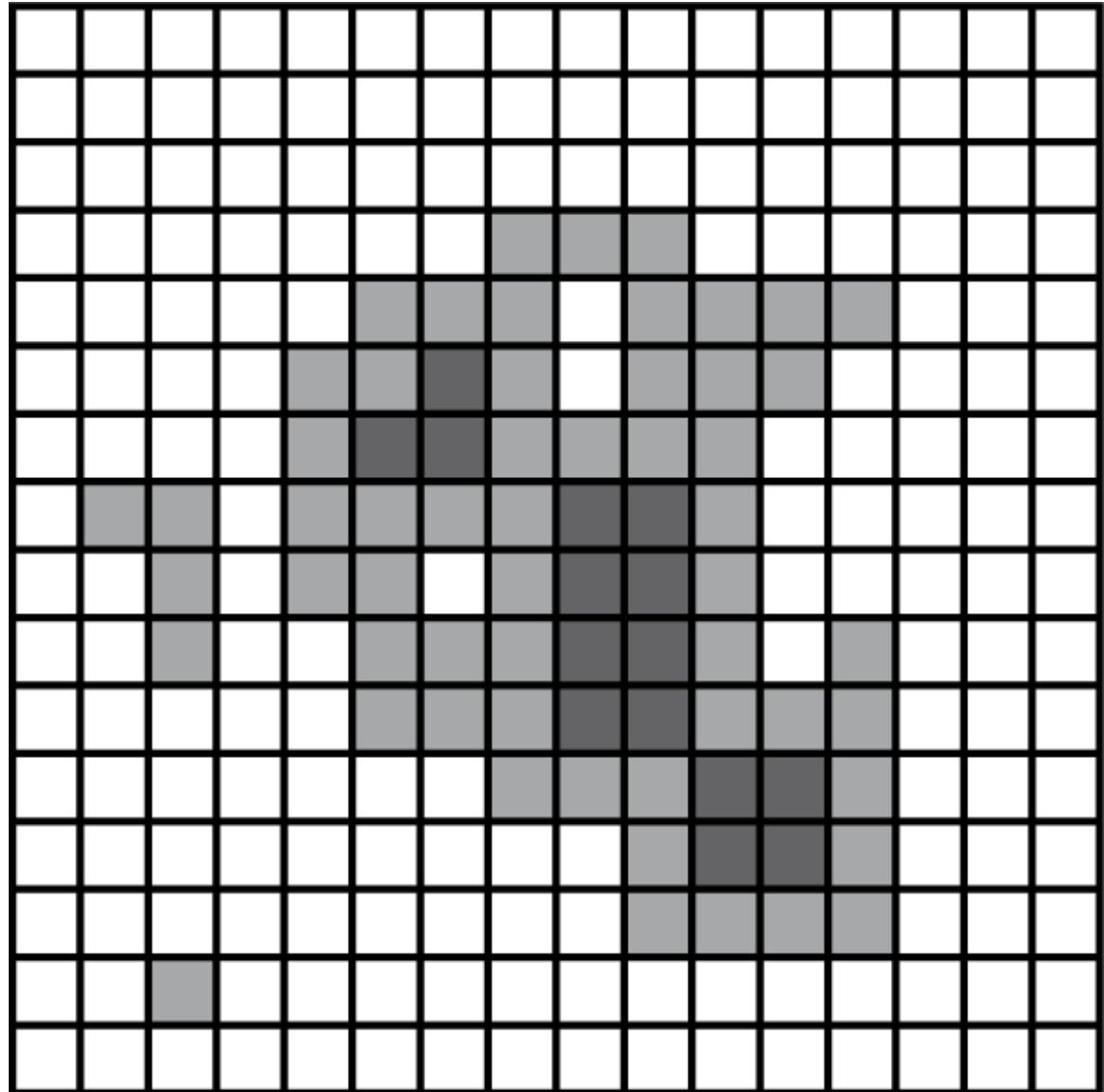


[H]

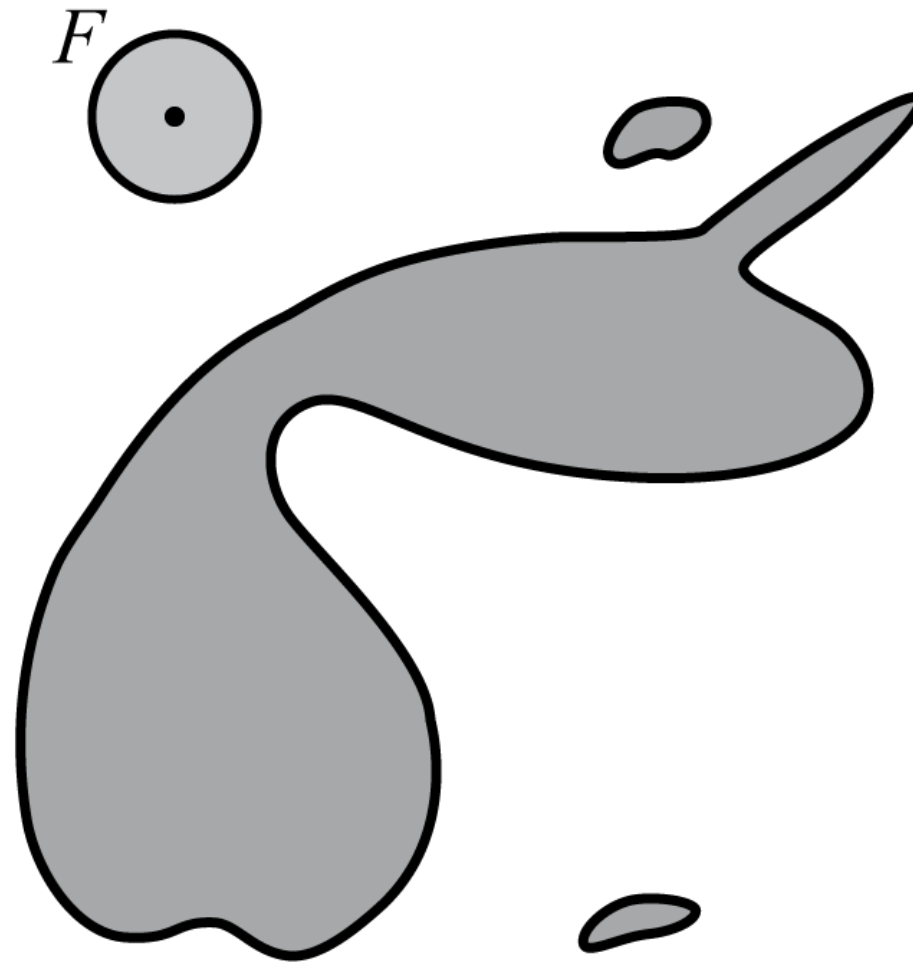
Binary
object



Erosion using
3x3 structuring
element of 1s.

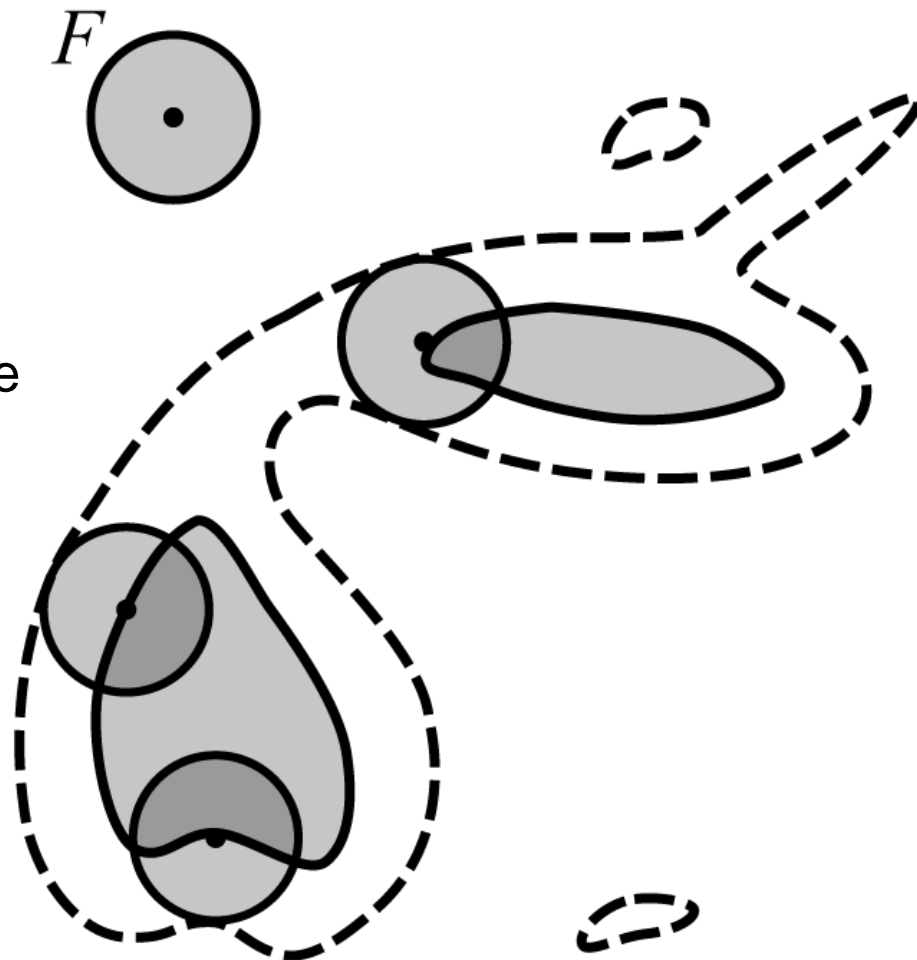


Input



Erosion using structuring element F :

Roll wheel on the inside of the figure, axis is a knife cutting away the outer layer.



2. Dilation

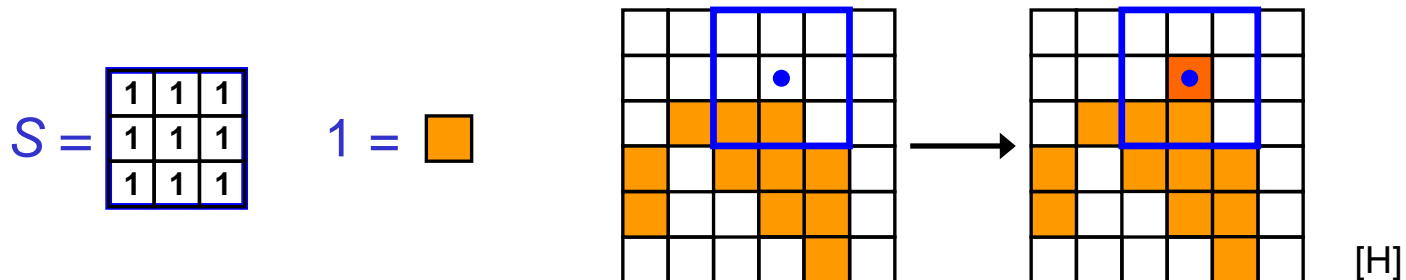
- Assign 1 to result pixel if *at least* one 1-element of S covers a 1-pixel of g , else assign 0:

$$g'(x,y) = \Theta\left(\left(\sum_{k \in [-m,m]} \sum_{l \in [-n,n]} S(k+m,l+n) \cdot g(x+k,y+l)\right) - \frac{1}{2}\right)$$

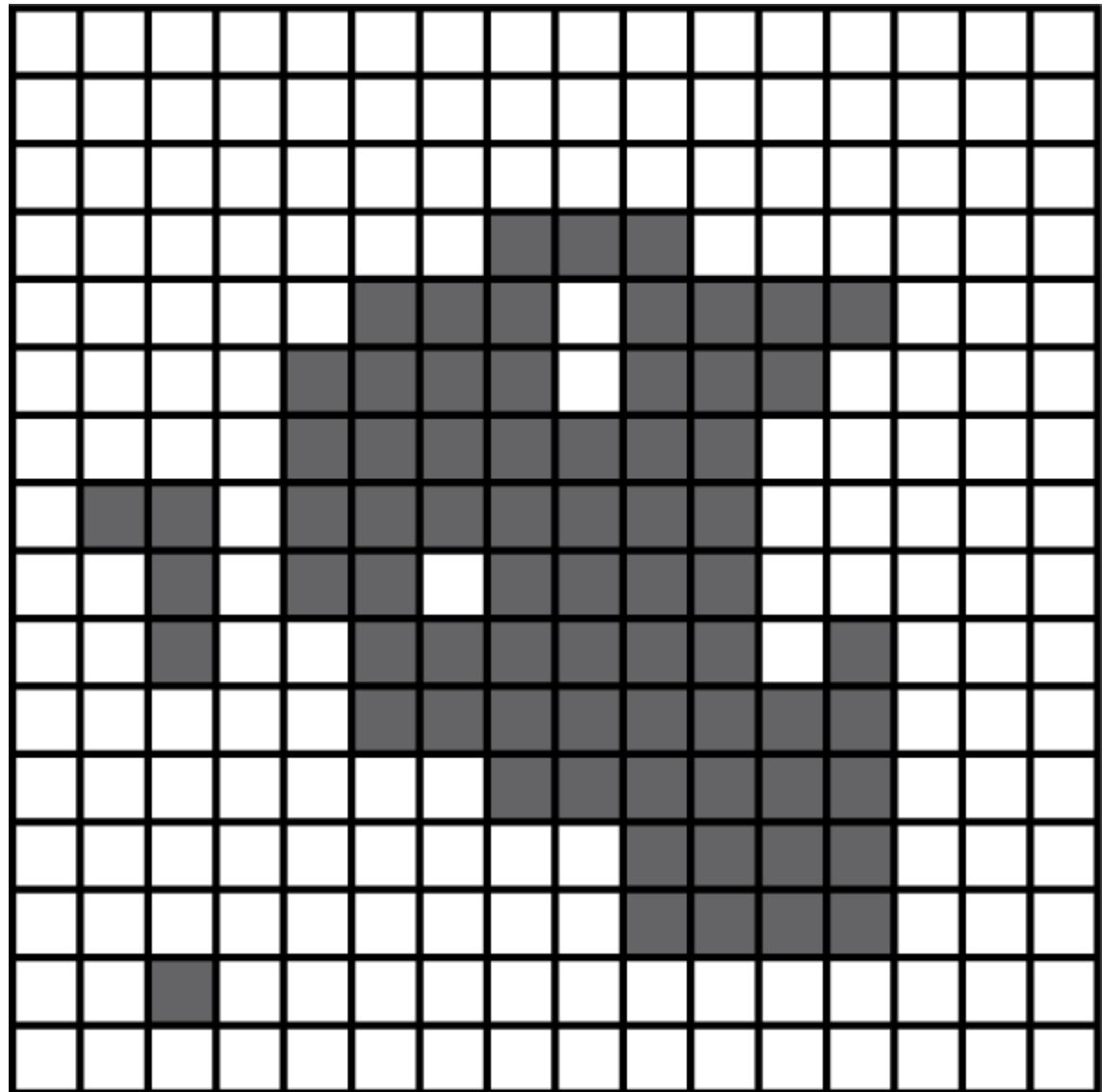
- Alternative notation:

$$g'(x,y) = \bigvee_{k \in [-m,m]} \bigvee_{l \in [-n,n]} S(k+m,l+n) \wedge g(x+k,y+l)$$

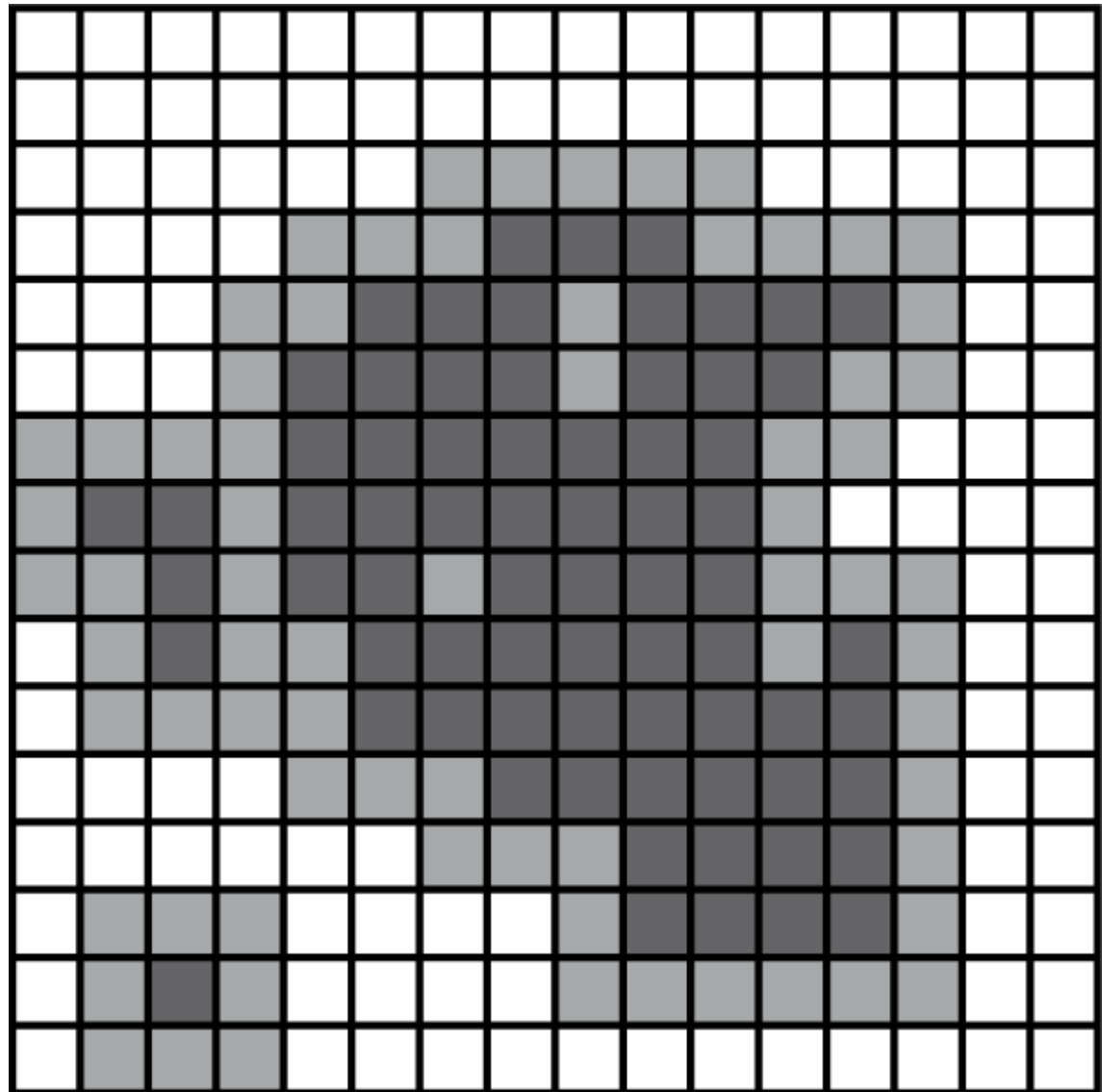
- Short: $g' = g \oplus S$
- Dilation adds pixels at the fringe of objects and fills in holes



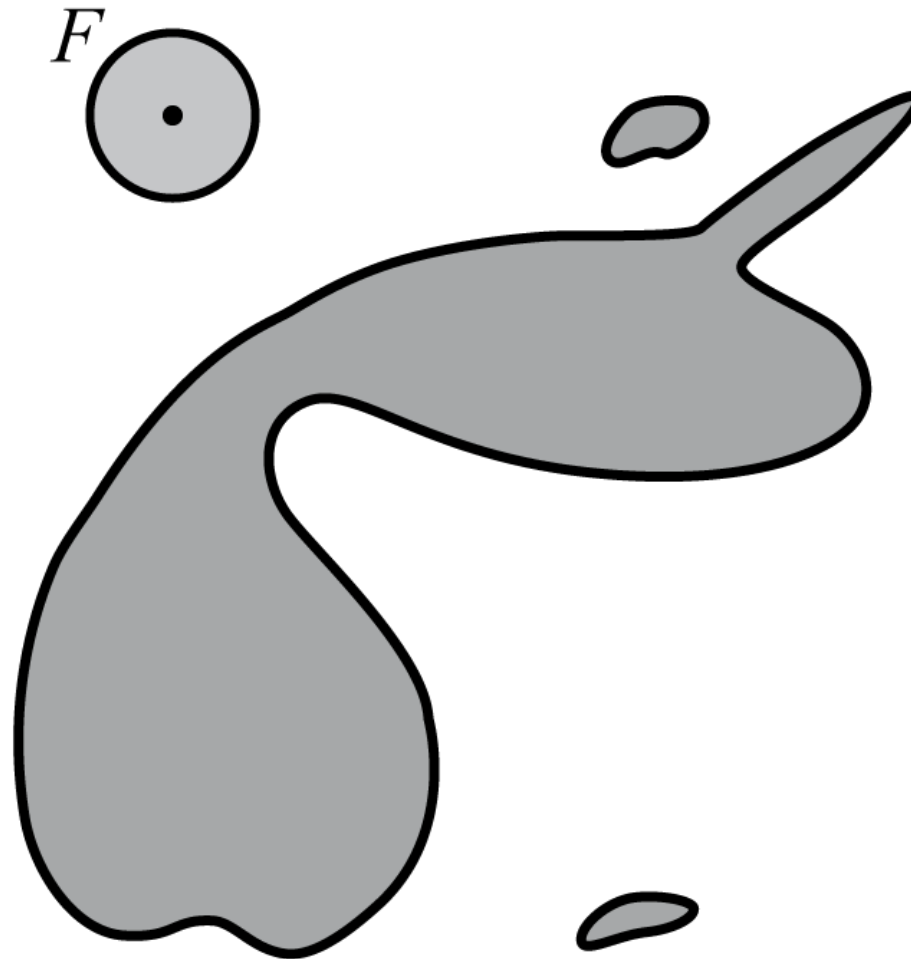
Binary
object



Dilation using
3x3 structuring
element of 1s

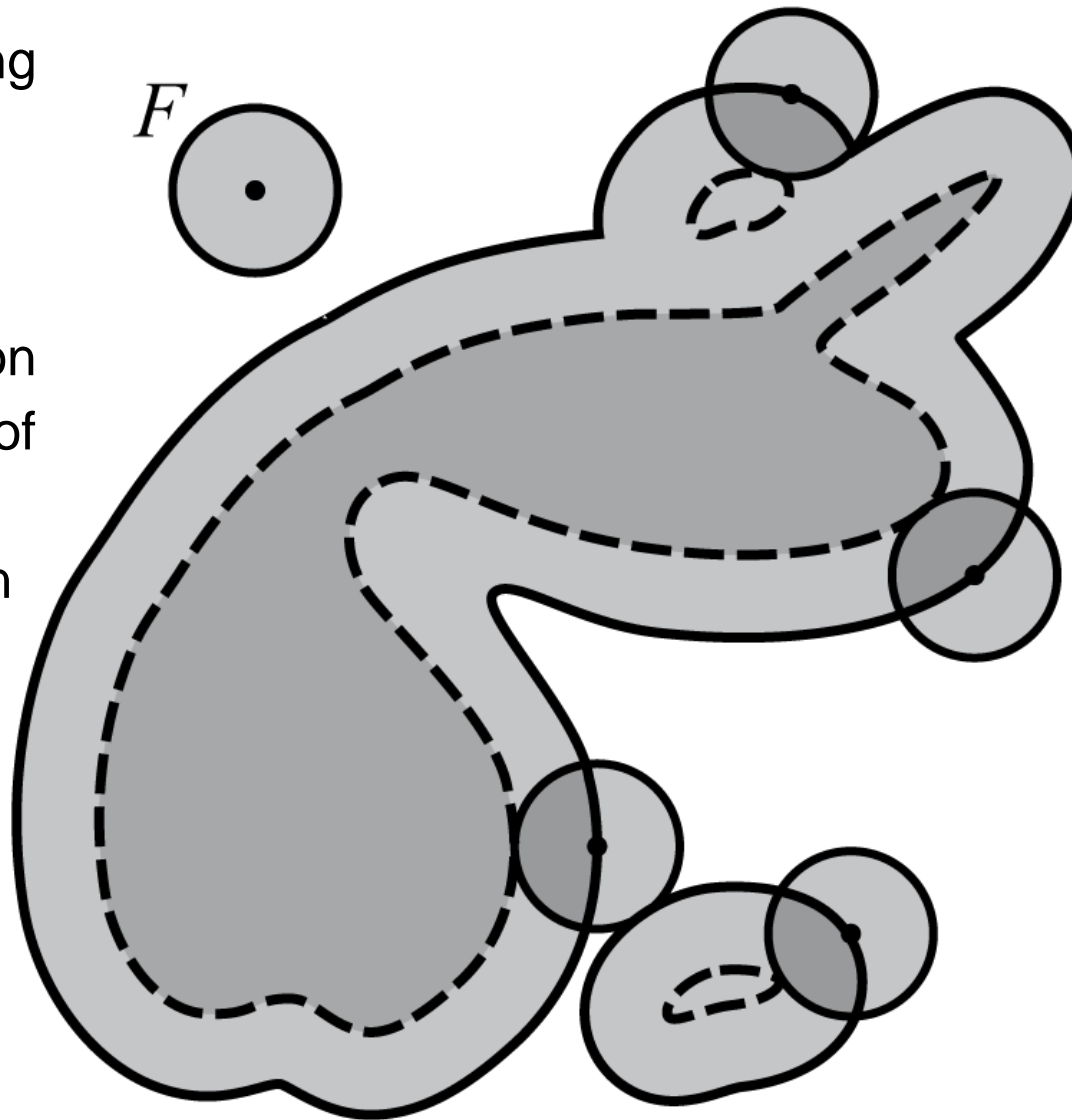


Input

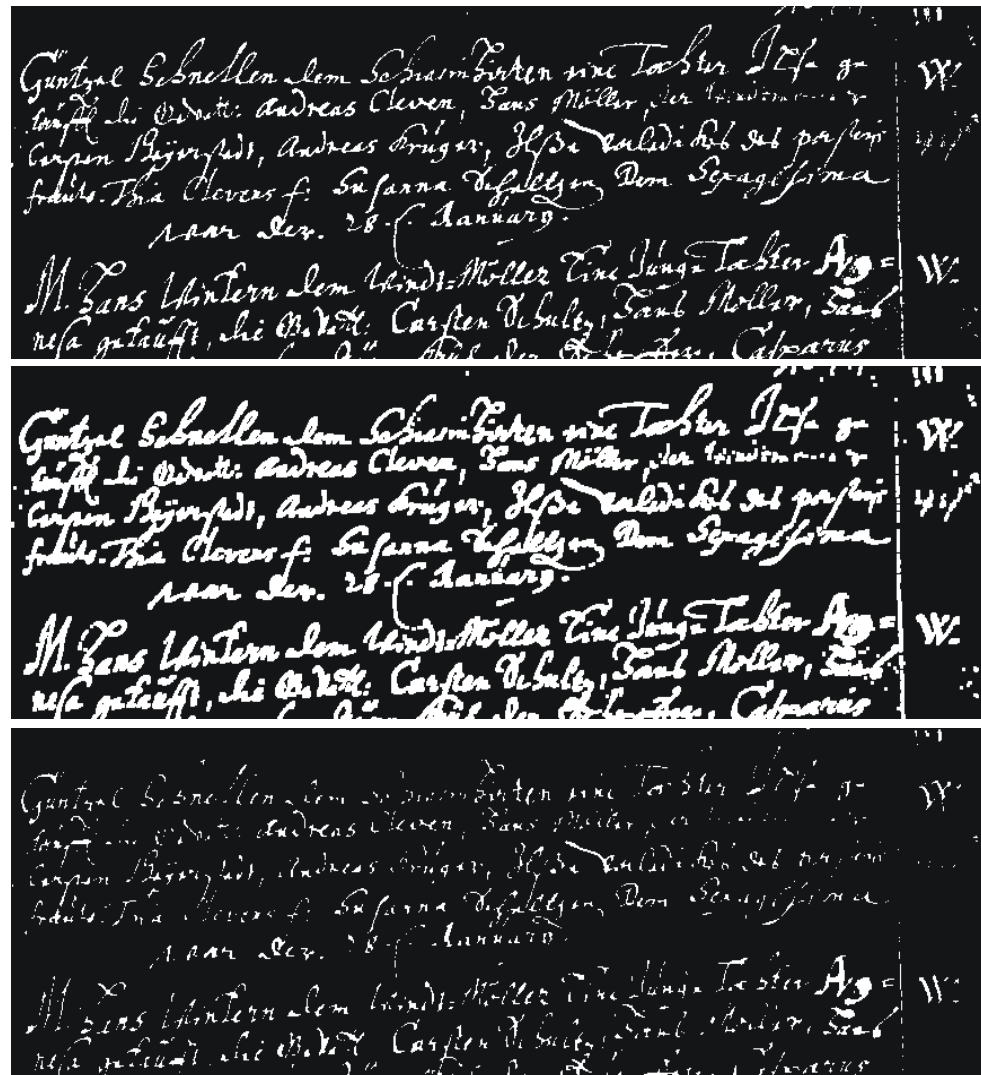


Dilation using structuring element F :

Roll wheel on the outside of the figure, axis is a pen marking the new boundary.



Comparison erosion / dilation



[T]

Above: Input — Center: Dilation — Below: Erosion

By choice of S selected structures can be removed or filled up.

- Problems:

1. Erosion removes not only irregularities but also a smooth fringe, making objects smaller
2. Dilation enlarges objects

- Solution: Combine both

1. Opening = Erosion using S + dilation using S' :

$$g' = (g \ominus S) \oplus S'$$

E.g., removes irregularities at object boundary without making object smaller

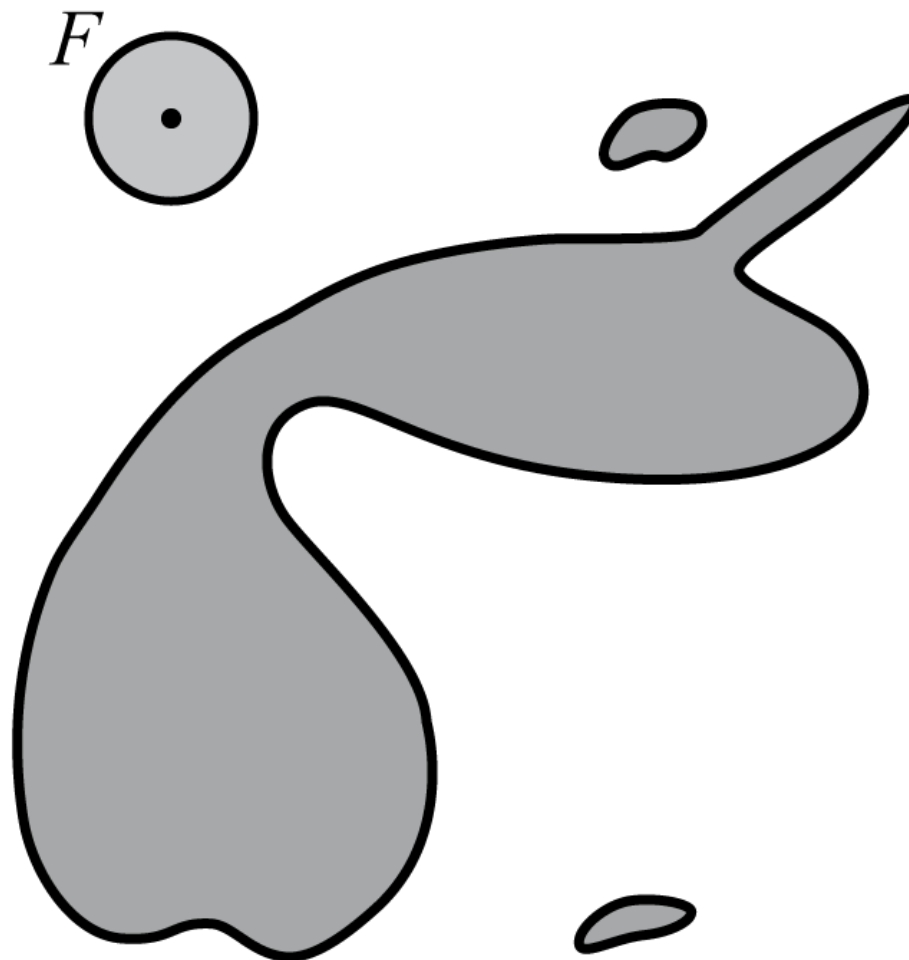
2. Closing = Dilation using S + erosion using S' :

$$g' = (g \oplus S) \ominus S'$$

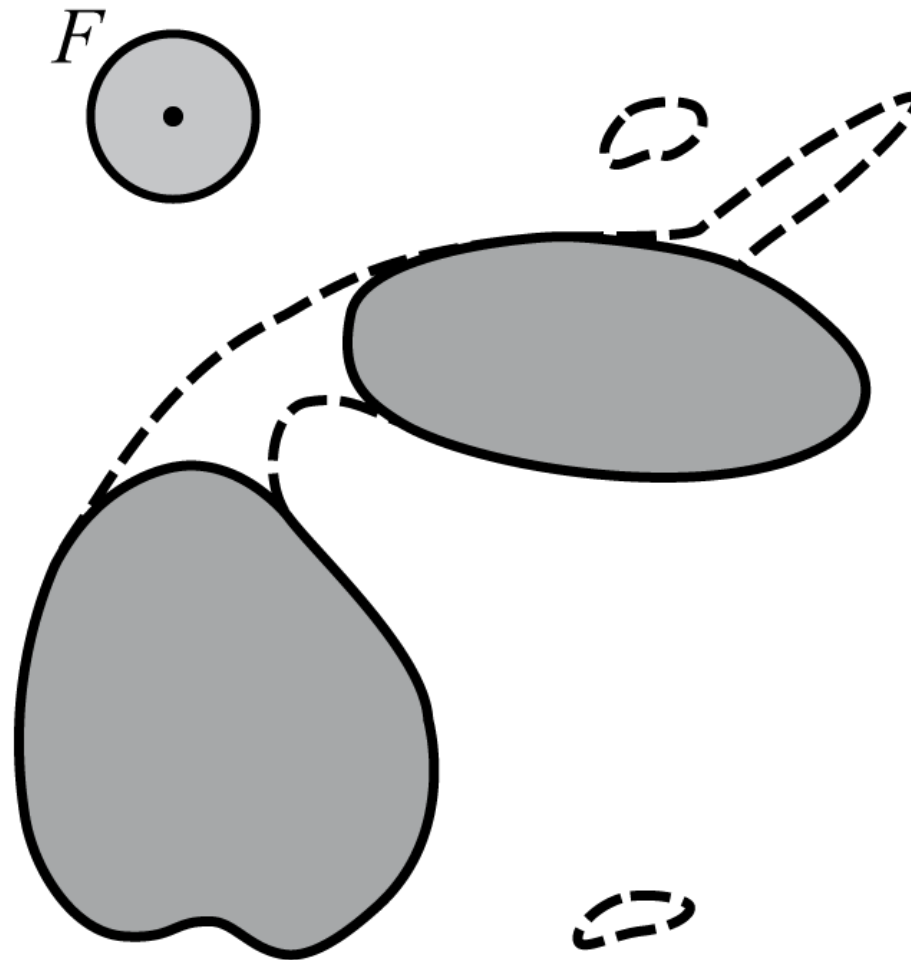
E.g., fills in holes without making object larger

S' is a version of the structuring element **mirrored** at the anchor point

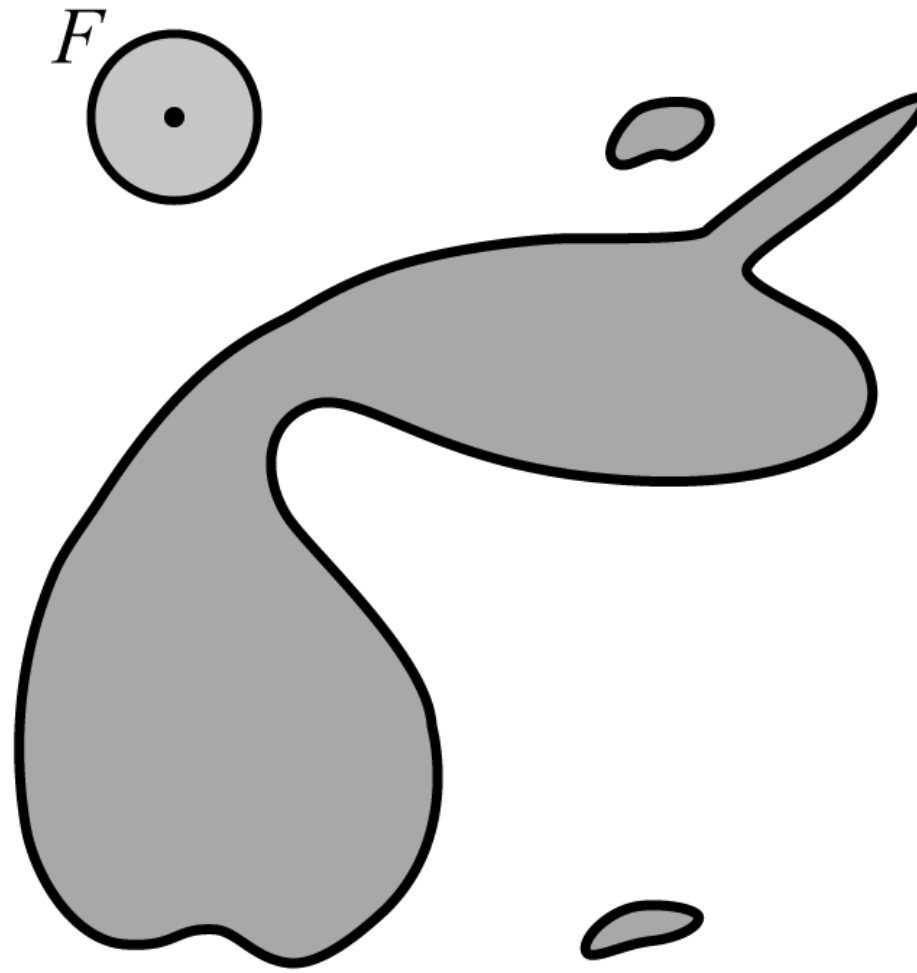
Input



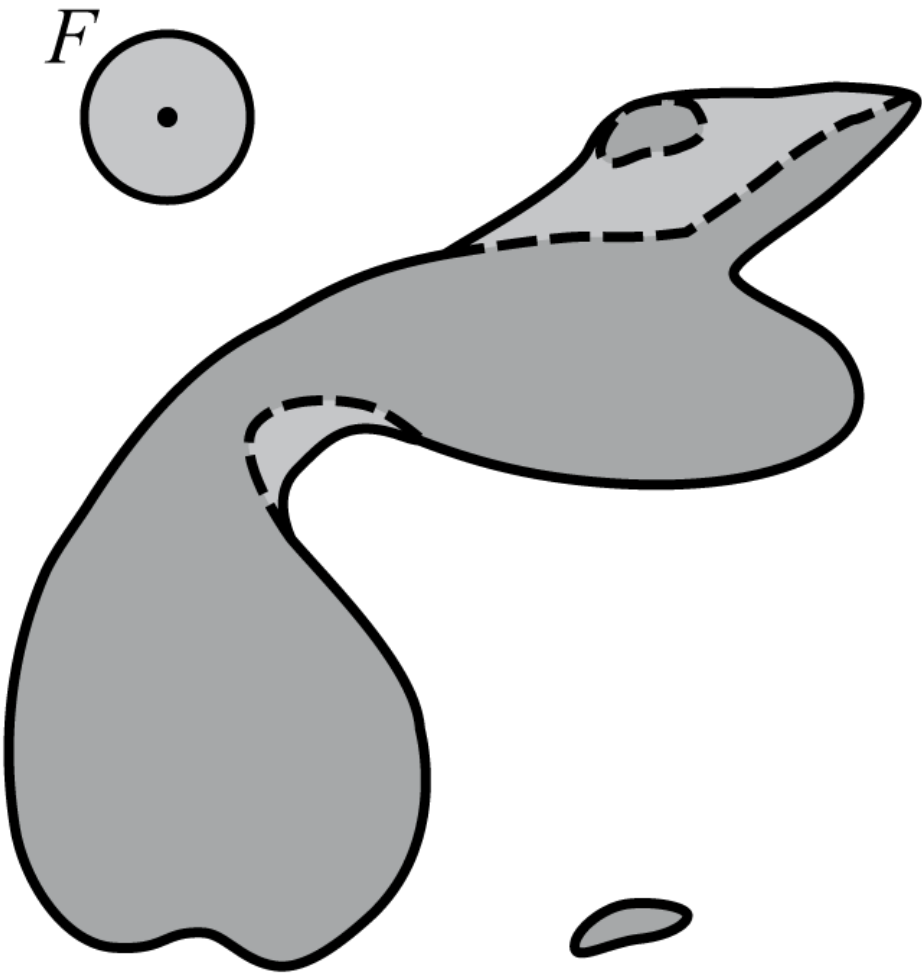
Opening using
structuring
element F

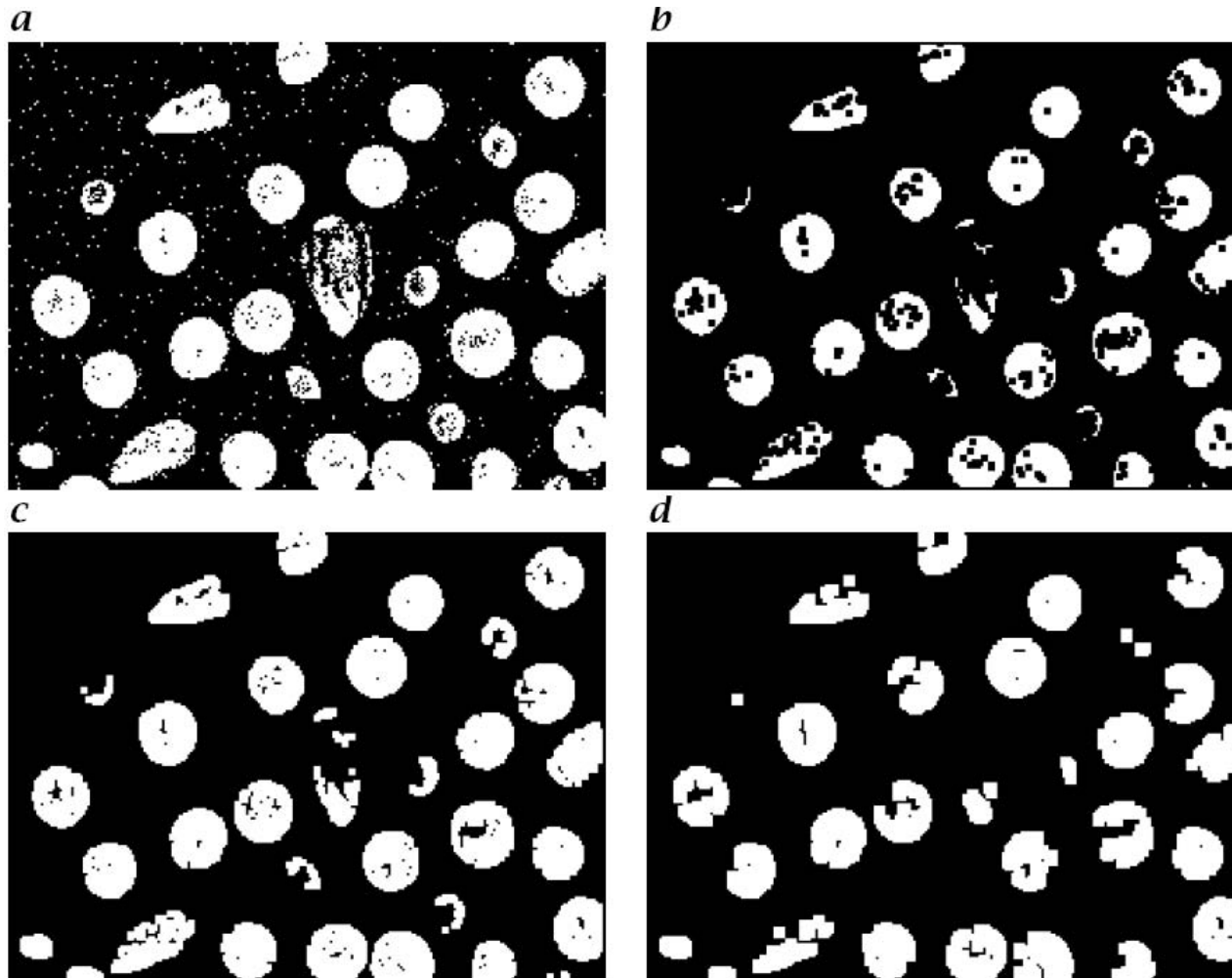


Input



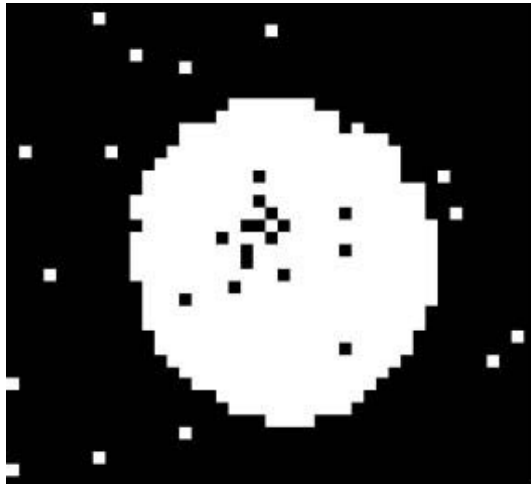
Closing using
structuring
element F





[J]

(a) Input, (b) Erosion using 3x3 S ,
(c) Opening using 3x3 S , (d) Opening using 5x5 S



Input



Erosion using 3x3 S

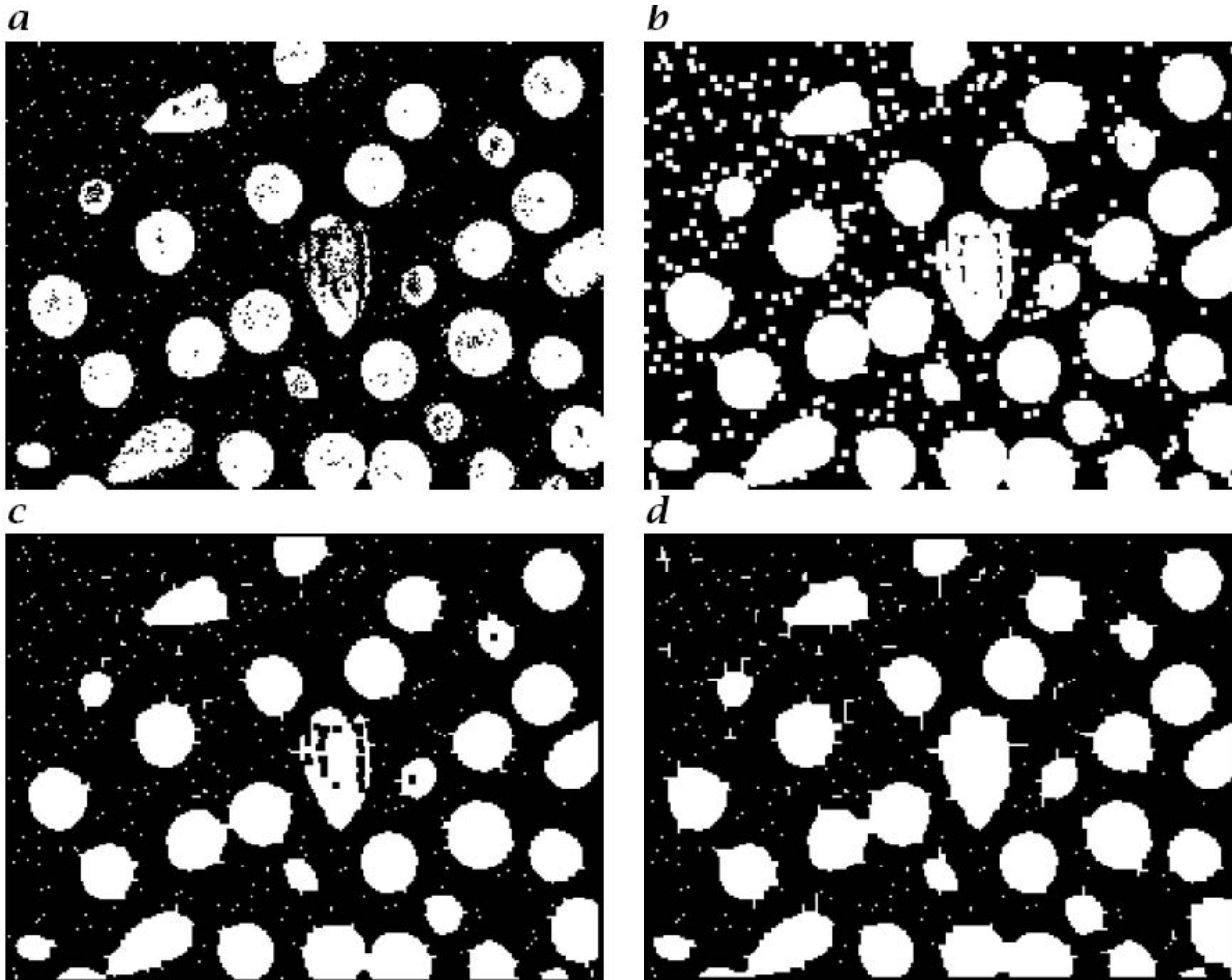


Opening using 5x5 S



Opening using 3x3 S

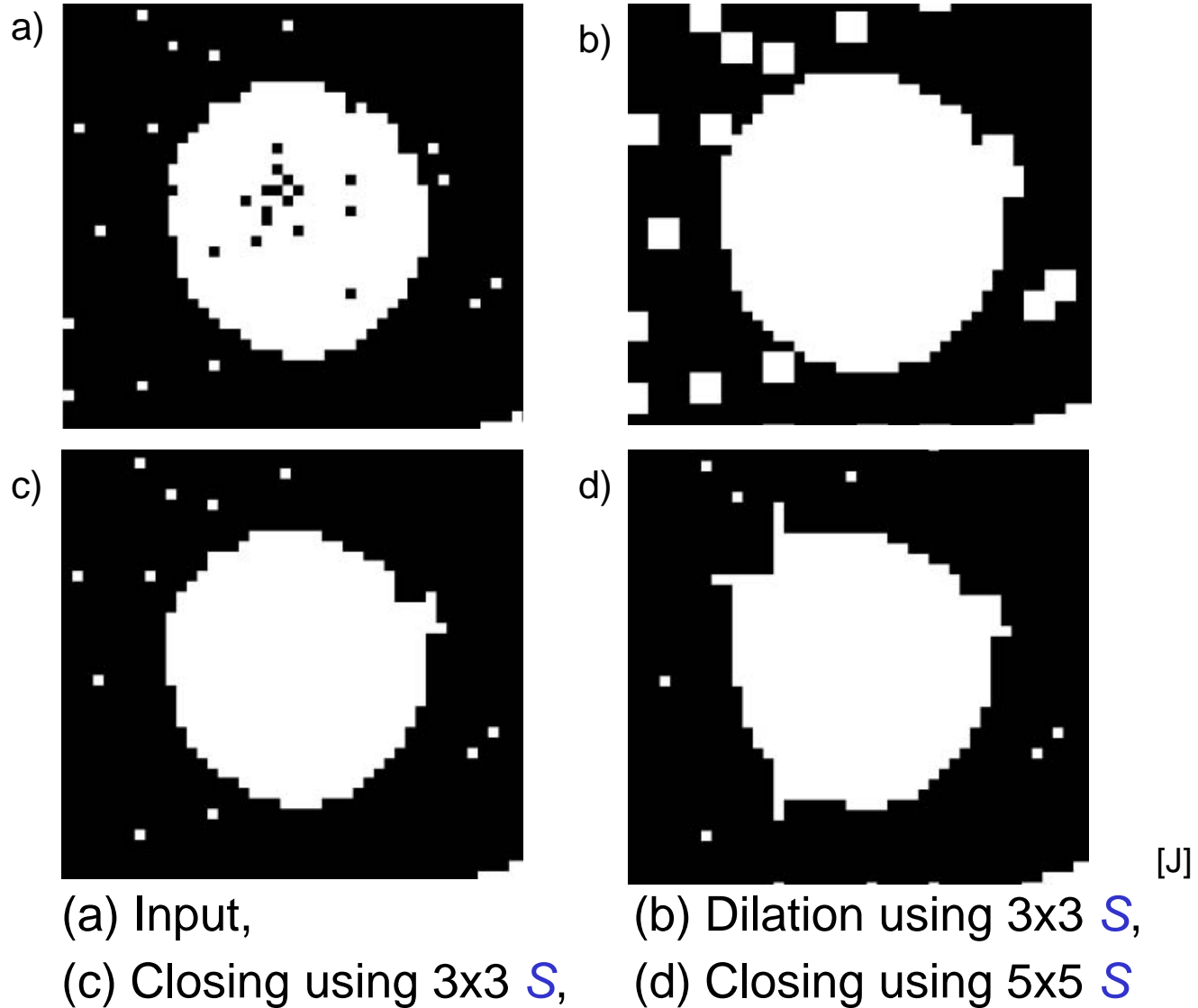
[J]



[J]

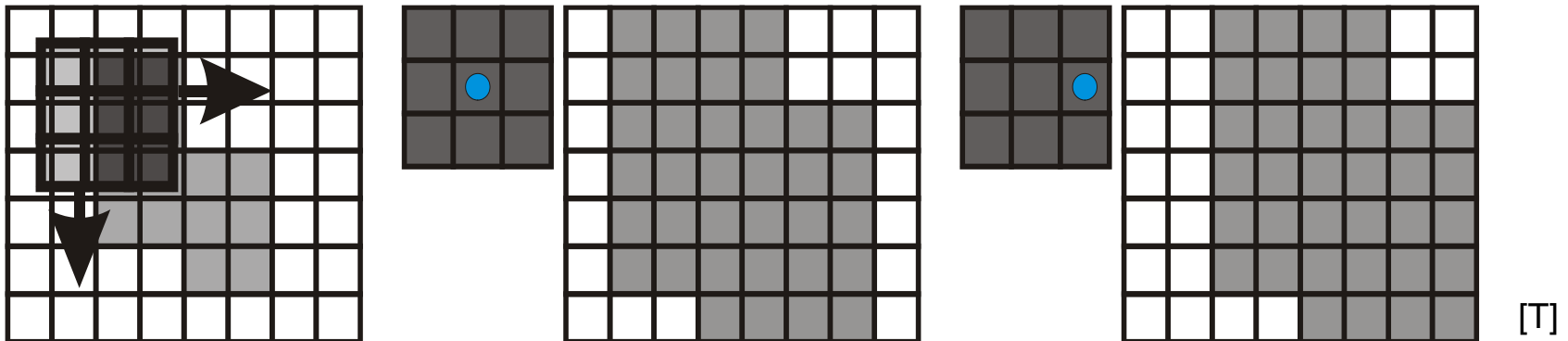
(a) Input,
(c) Closing using 3x3 S ,

(b) Dilation using 3x3 S ,
(d) Closing using 5x5 S



- So far, we have used only “unstructured” structuring elements, i.e., *nxn* structuring elements filled with 1.
- So far, the center was the anchor point.
- Useful as long as
 - there is no a priori knowledge about the image,
 - no special tasks are to be solved.
- Using specialized structuring elements it is possible
 - to fill gaps of a particular shape,
 - to detect patterns (hit-or-miss operation).

Note the anchor point needs not to be in the center of the structuring element:



This is current driver circuit.

Phil.

22-9-71

Special problems can be solved using structuring elements of a customized shape

Undisturbed binary image

[T]

W1
This is current driver circuit.

Phil.

22-9-71

Erased stripe

Special problems can be solved using structuring elements of a customized shape



Structuring element to fill in the erased stripe

[T]

This is current driver circuit.

Phil.

22-9-71

Special problems can be solved using structuring elements of a customized shape



Structuring element to fill in the eroded stripe

Result after dilation:
Stripe closed

[T]

This is current driver circuit.

Phil.

22-9-71

Special problems can be solved using structuring elements of a customized shape

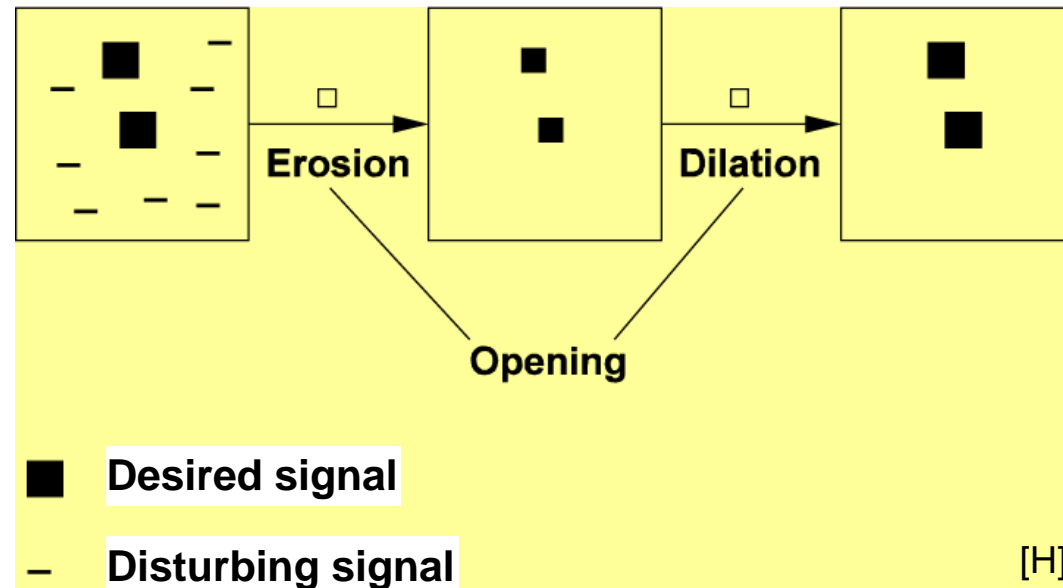


Structuring element to fill in the erased stripe

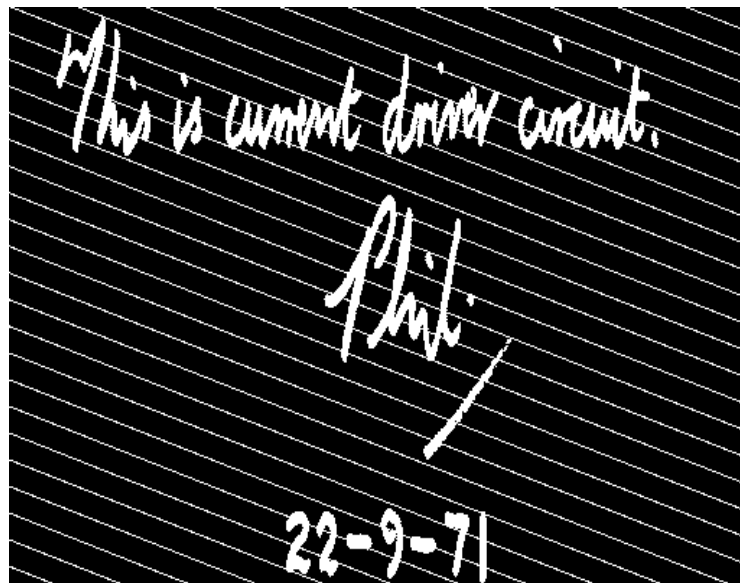
Result after subsequent erosion:
Writing has original size

[T]

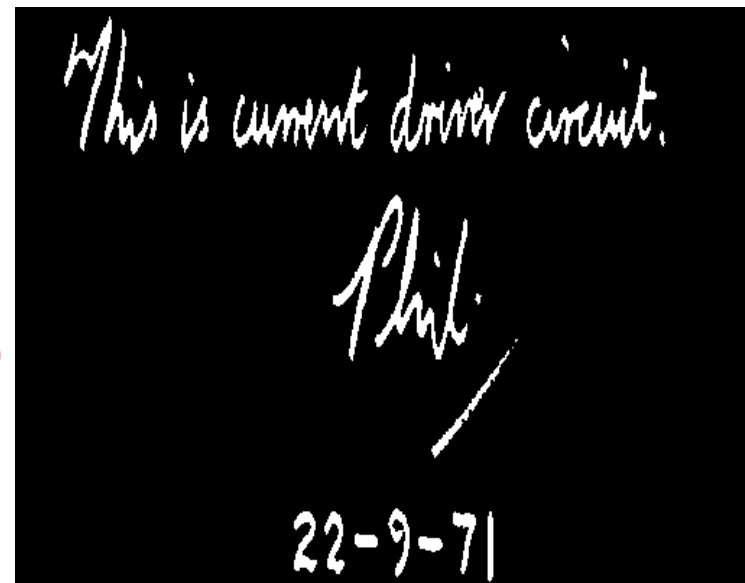
Separation of desired signal and disturbing signal:



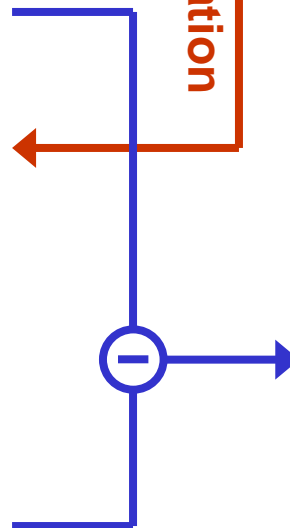
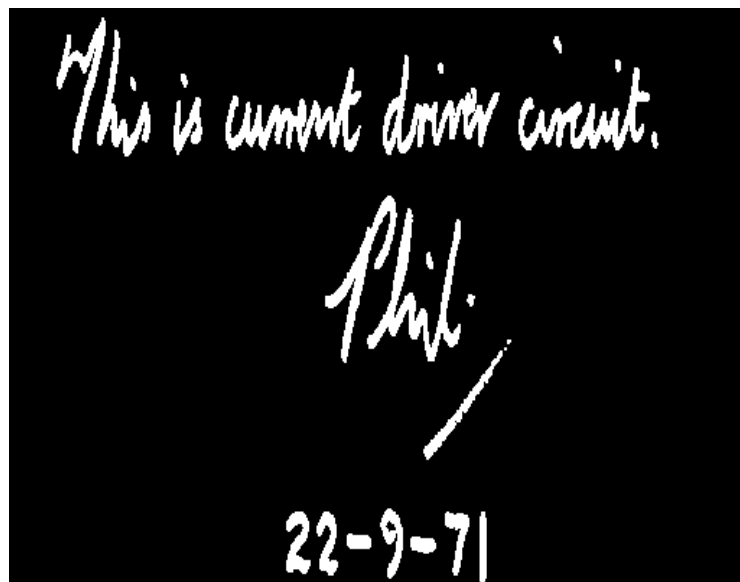
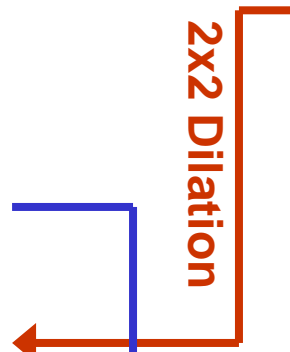
Example: Removal / extraction of lines



2x2 Erosion



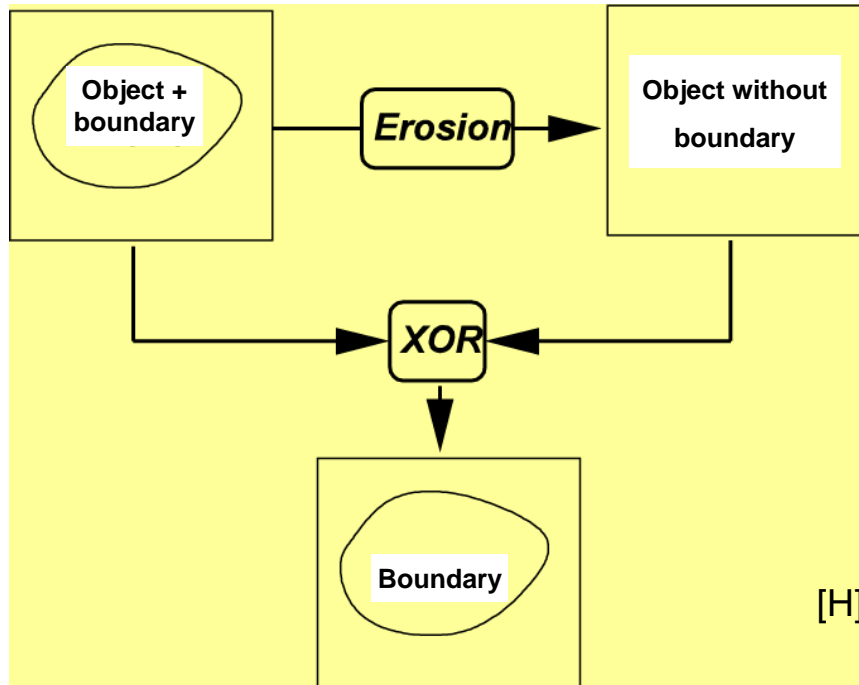
2x2 Dilation



[T]



Boundary extraction: $g_{\text{boundary}} = g \setminus (g \ominus S)$



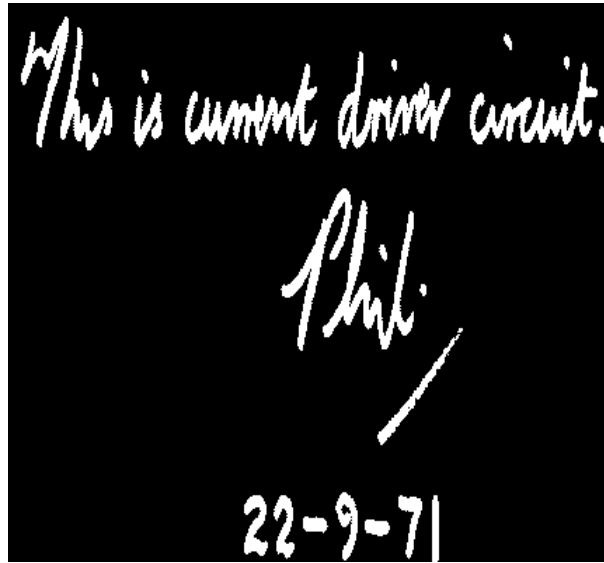
S_4 and S_8 cut off all object pixels in the 4- or 8-neighborhood of which are background pixels.

Structuring elements for 4- and 8-neighborhood:

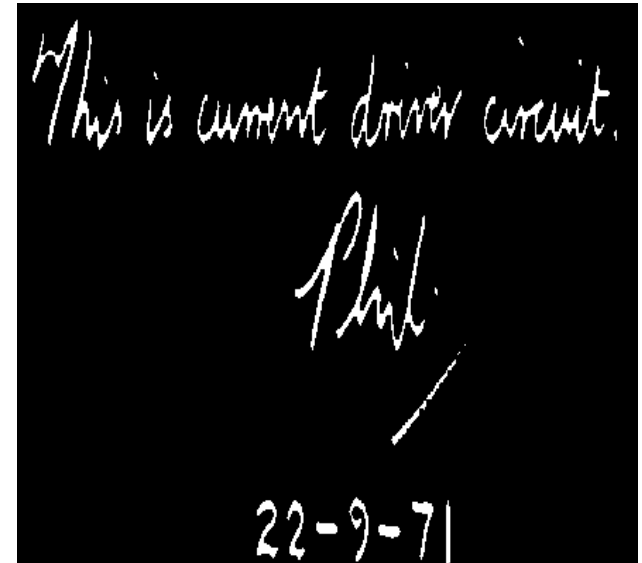
$$S_4 = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{pmatrix}$$

$$S_8 = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}$$

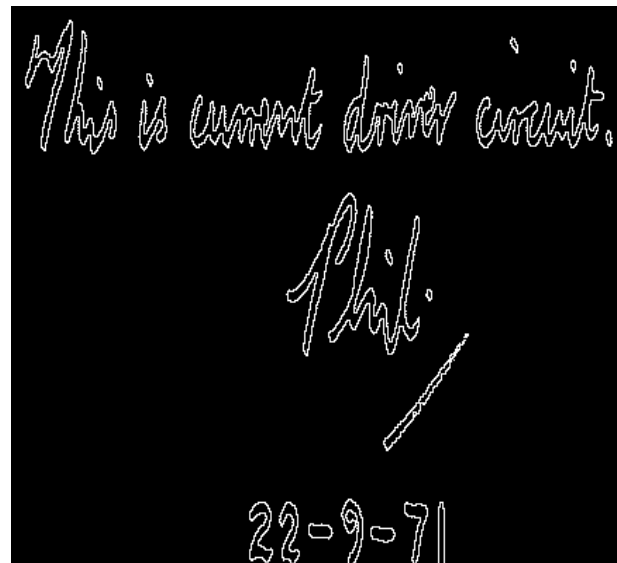
Boundary extraction



g



$g \ominus S$



$g \setminus (g \ominus S)$

[T]

- One-time application of operation $g^0_{boundary} = g \setminus (g \ominus S)$ yields the boundary, i.e., the set of all pixels with **distance 0** to the boundary
- Object without boundary: $g \ominus S$
- Application of this operation to $g \ominus S$ yields $g^1_{boundary}$, i.e., the set of all pixels, with **distance 1** to the boundary:

$$g^1_{boundary} = (g \ominus S) \setminus (g \ominus S \ominus S).$$

- In general:

$$g^n_{boundary} = (g \ominus S)^n \setminus (g \ominus S)^{(n+1)}$$

where $(\ominus S)^n$ is short for the n -time erosion using S .

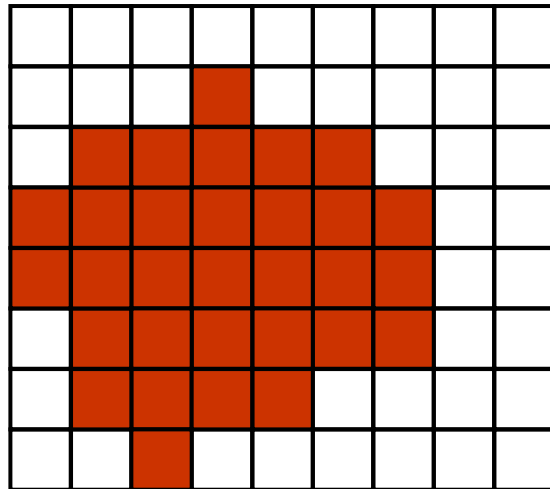
- The **distance image** D is obtained from the union of the boundaries of all distances. In D , the boundary pixels of distance i get gray value i :

$$D = \bigcup_{n=1 \dots \infty} n \cdot g^n_{\text{boundary}}$$

where “ $n \cdot$ ” denotes pixel-wise multiplication, provided g^n_{boundary} is a binary image with 1 for the boundary.

- Each pixel in the distance image indicates the distance to the boundary, however,
 - not the Euclidean distance, but
 - the cityblock- or chessboard-distance
- Problem: Large computational effort
- There are faster algorithms to compute the Euclidean distance transform.

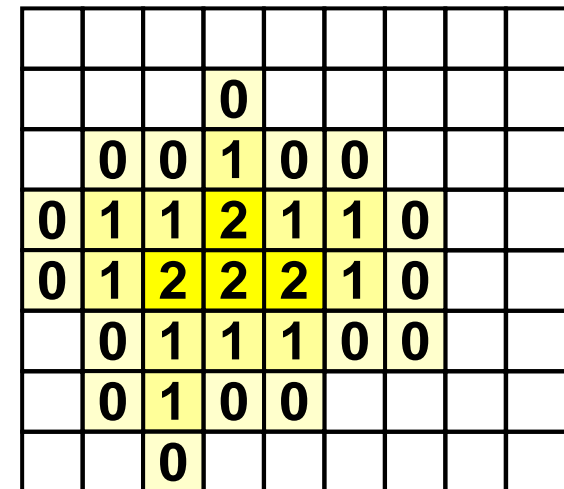
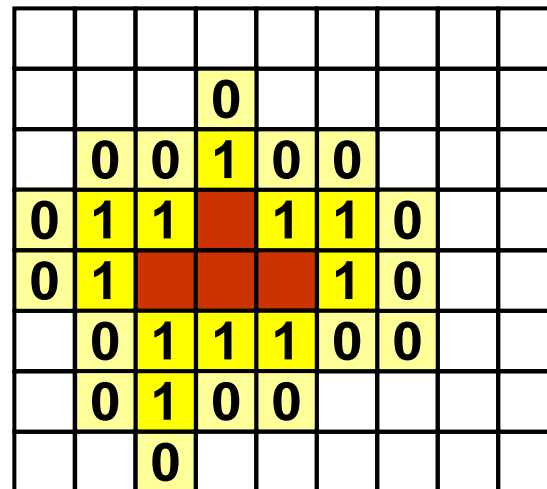
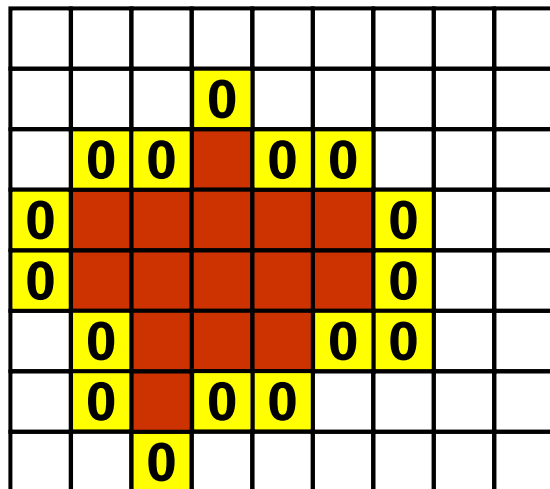
Distance transform



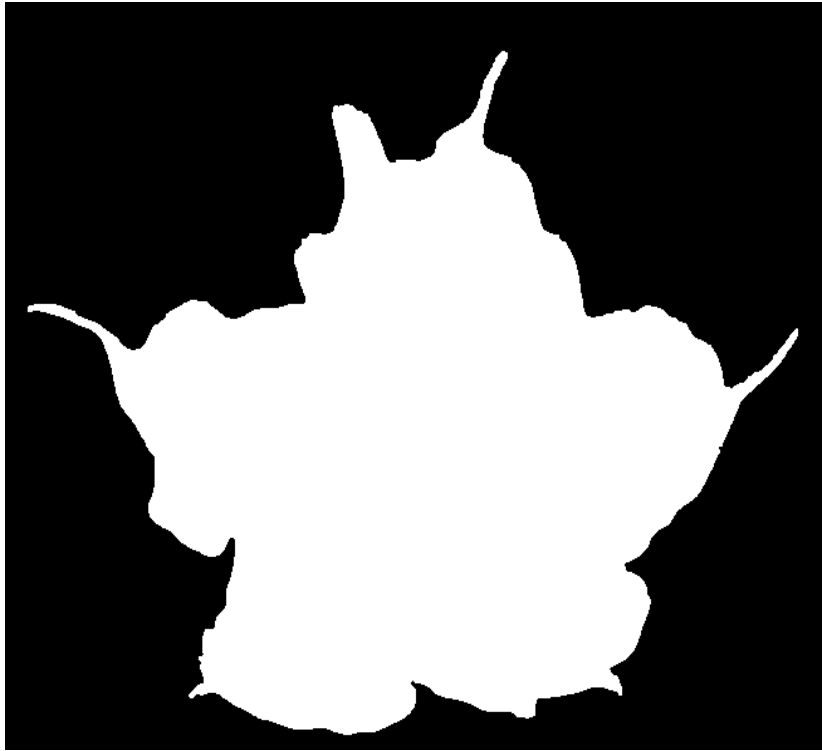
Remaining inside of object



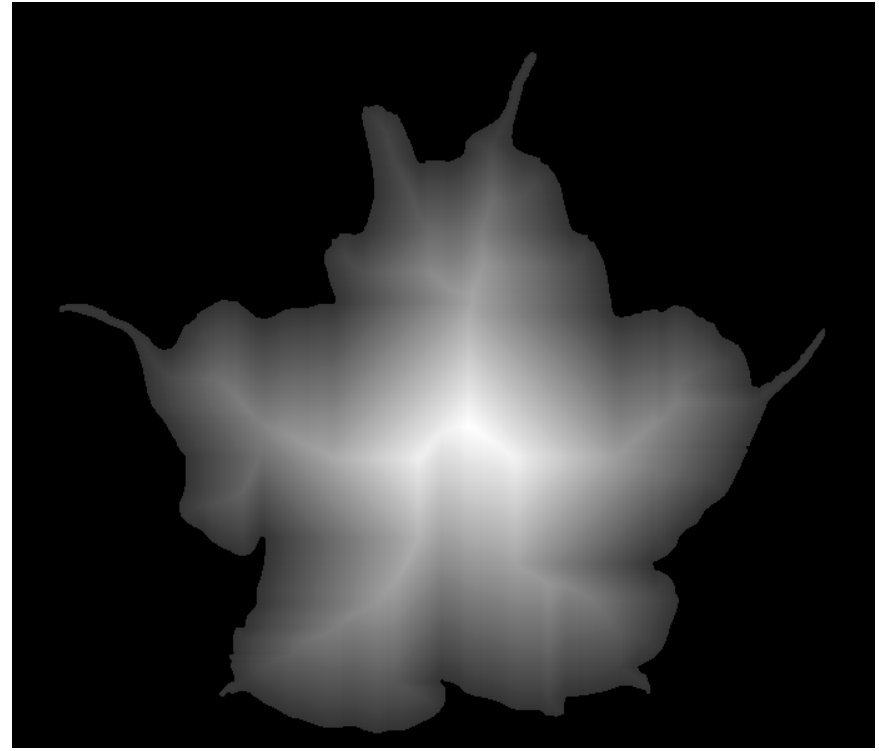
Pixel with distance n to the boundary



[H]



Binary image



Distance transform

[7]

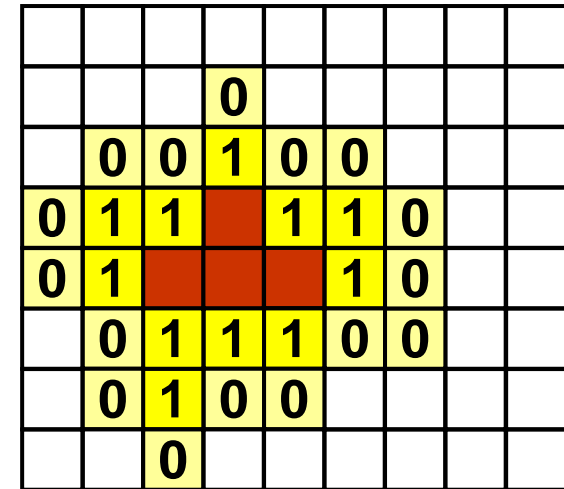
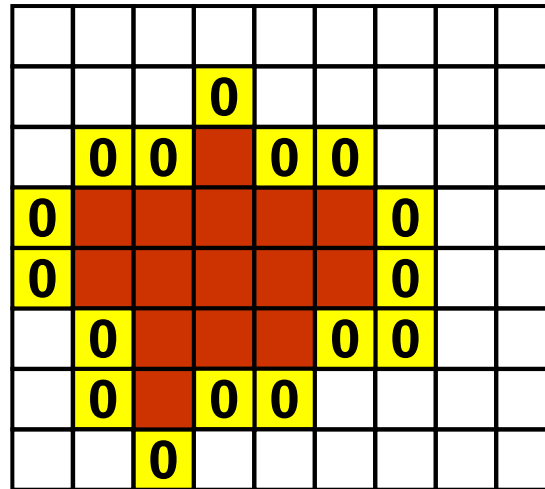
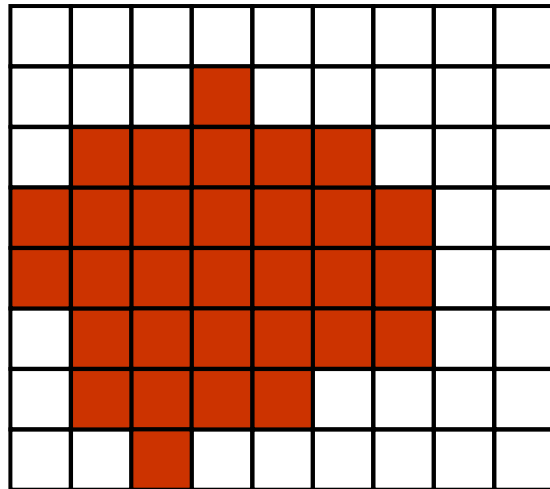
Generalize distance transform beyond the boundary of the object:



1. Input: Binary image b . Compute inverted binary image b^* .
2. Compute D_1 from b
3. Compute D_2 from b^* , i.e., the distances of the background pixels to the boundary of the object
4. Generalized distance transform:

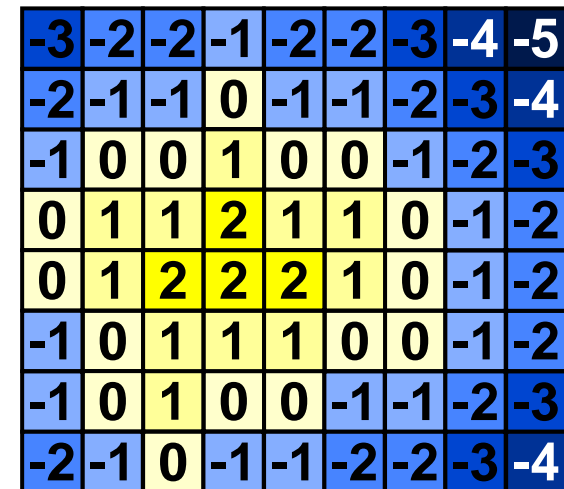
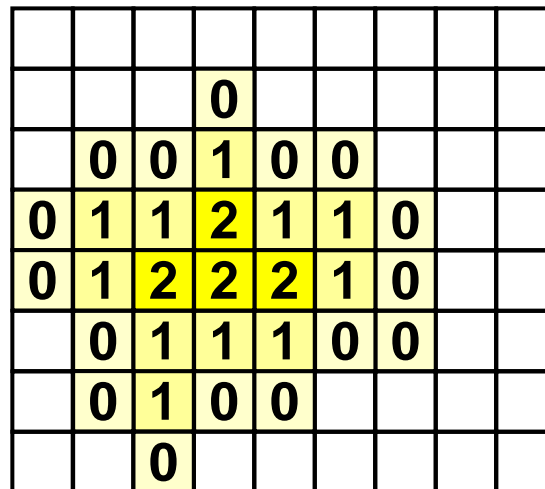
$$D = D_1 - D_2$$

5. Normalization to 0...255 for visualization

Distance transform



 Object
 Boundary

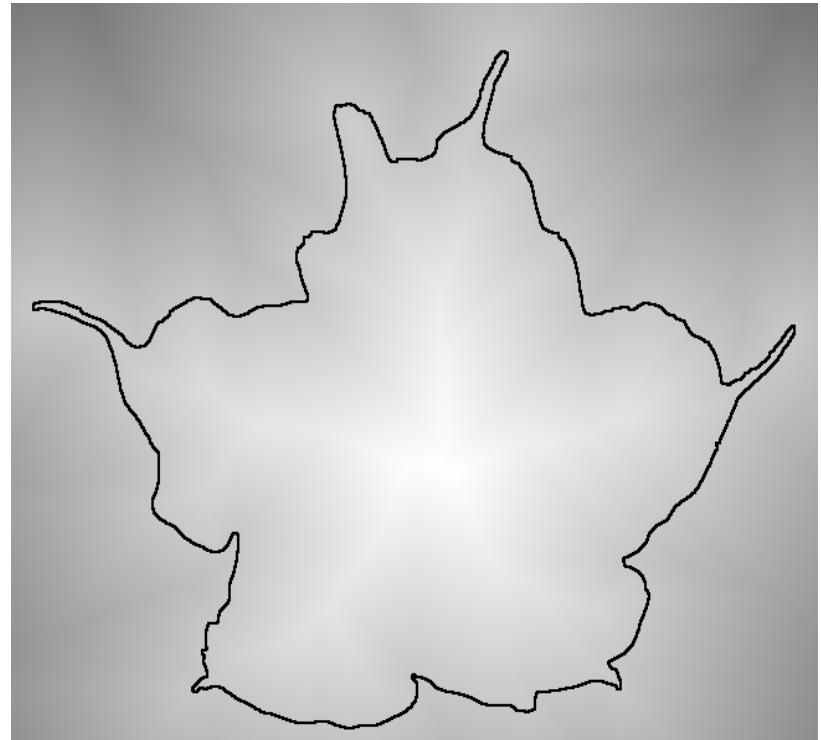


[H]



Binary image

[T]



Generalized distance transform
with normalized gray values

- Task: Morphing from binary image b_a to b_b .
- Generalized distance transform provides a solution:
 1. Compute distance transforms D_a und D_b of b_a and b_b .
 2. Compute the $N-1$ intermediate distance images D_i between D_a and D_b by linear interpolation:

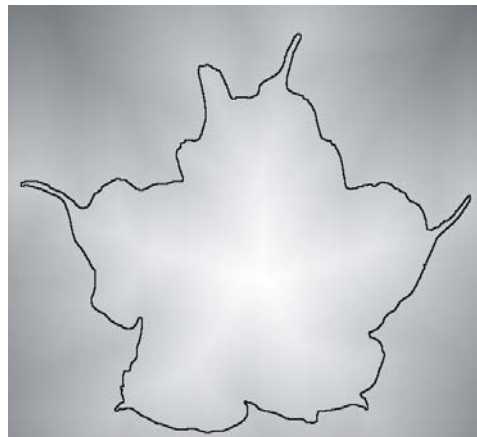
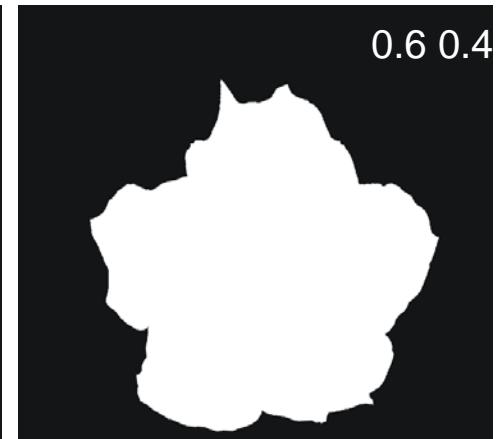
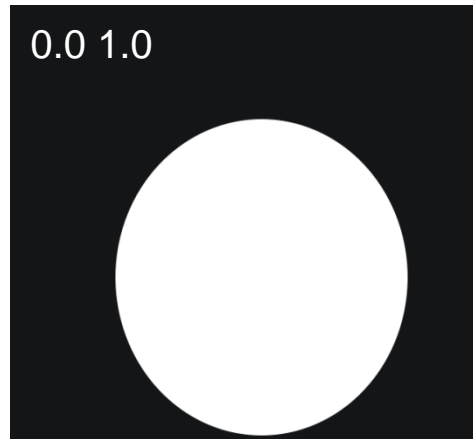
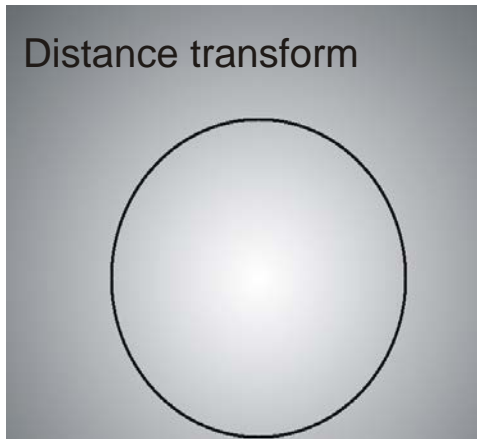
$$D_i = (i \cdot D_b + (N-i) D_a) / N \quad \text{with } i = 0 \dots N,$$

where $D_a = D_0$ and $D_b = D_N$.

3. Binarize the intermediate images to obtain b_i :

$$b_i(x,y) = \Theta(D_i(x,y)),$$

with $b_a = b_0$ and $b_b = b_N$.

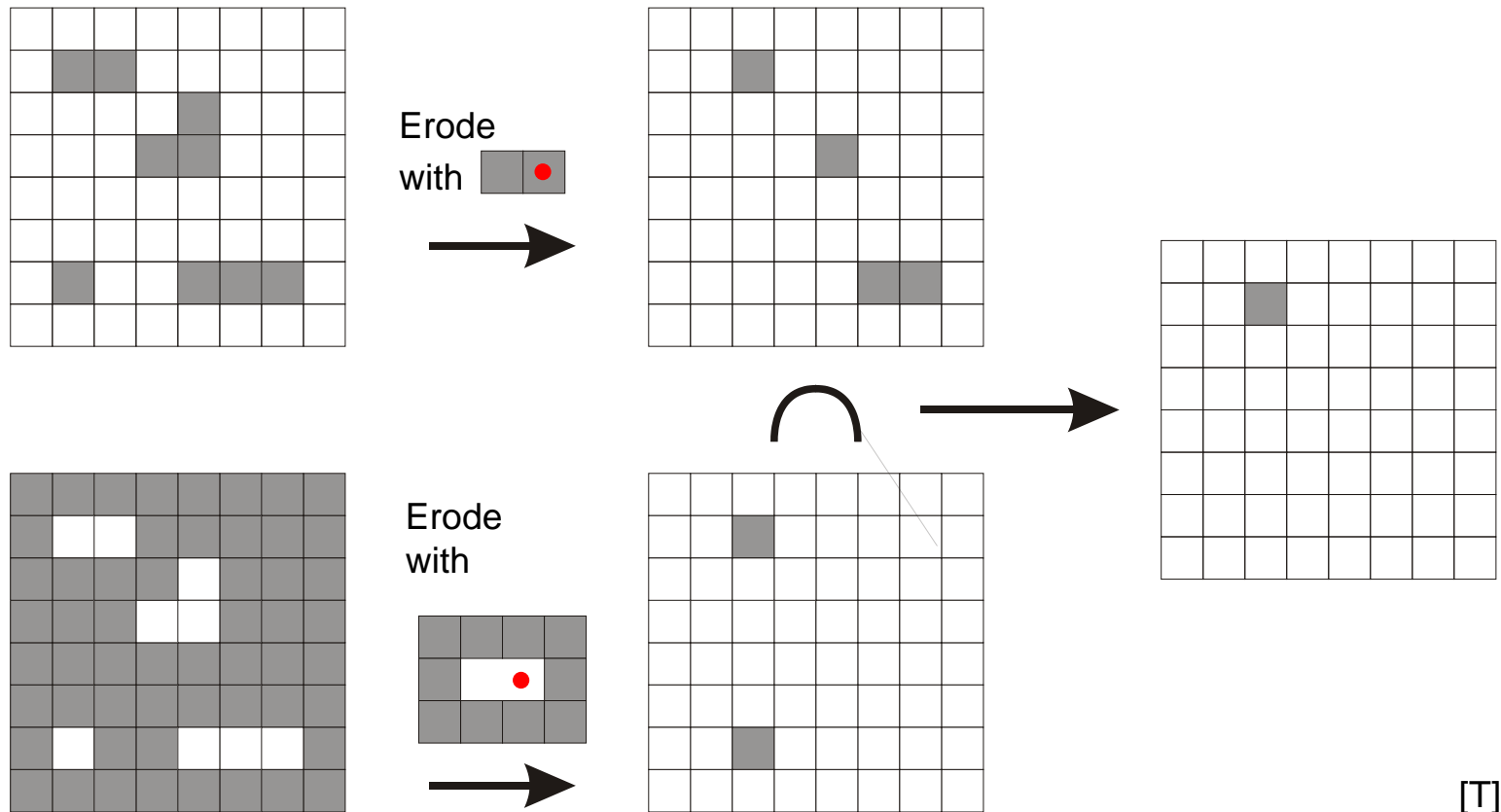


[T]

Intermediate images with mixtures i/N and $(N-i)/N$

- Hit-or-miss operation for explicit definition of a pattern
- Detects all image patches which exhibit the exact shape of S
- Principle:
 1. Hit: Find all *candidate locations* where the pattern might be by erosion using S . Erosion removes all “islands” smaller than S .
 2. Miss: Remove all locations where the pattern can *not* be. For this the inverted binary input image is eroded using the disjoint structuring element S^* to remove all segments larger than S . Note S^* is not the mirrored structuring element S' .
 3. Intersection of the *hits* and the pixels remaining after the *miss* operation are anchors of the pattern S

Hit-or-miss operation

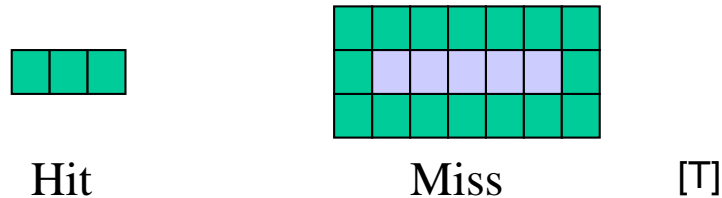


[T]

• Anchor point

Problem: So far, only the *exact* pattern can be found

Hit-or-miss operation for **variable structure**:



Accepts horizontal lines of 3, 4, and 5 pixels.

Notation for variable hit-or-miss operation:

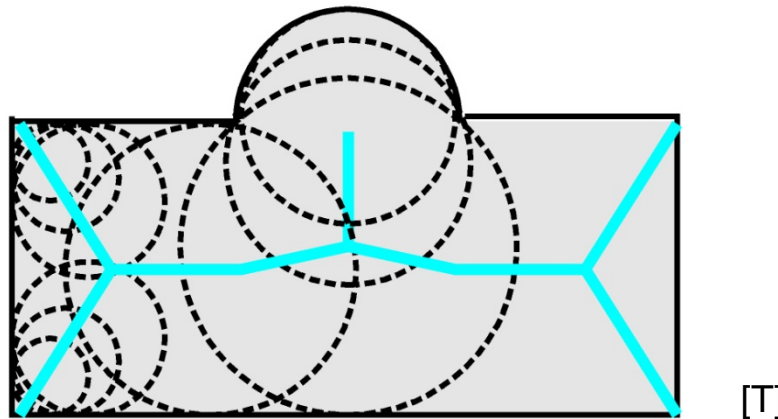
$$M = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & X & 1 & 1 & 1 & X & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Variable hit-or-miss operation facilitates search for patterns as parts of segments:

$$\begin{pmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad \text{Detects single pixels}$$

$$\begin{pmatrix} 0 & 1 & X \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix} \quad \text{Detects lower left corners}$$

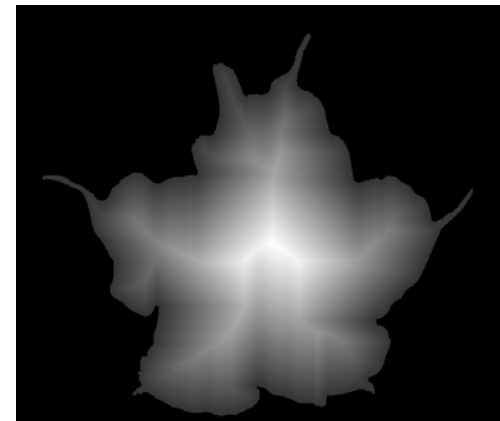
- Aim: Get a meaningful, compact description of the shape of binary segments that facilitates classification.
- **Skeleton** of a segment =
Set of centers of all bi-tangent circles (circles within the segment that touch the boundary at least at two points).
- Skeleton is always connected.



- Application, e.g., in OCR (optical character recognition): Skeletonization of characters filters information relevant for classification such as branching properties out of irrelevant information (font).

Compute skeleton of a binary segment:

- We need to find all bi-tangent circles, which have the following properties:
 - Circle is completely inside the segment
 - Circle touches a boundary pixel
 - For this boundary pixel, there is no larger circle inside the segment
- Idea 1: Ridges of the **distance transform** are the skeleton
- Idea 2: Find ridges using the hit-or-miss operation



- Shape of ridges is a priori unknown.
- Therefore remove iteratively all pixels of the distance transformed image which are not ridges.
- In each iteration apply the following eight hit-or-miss operations, which remove the boundary pixels for directions left, right, up, down and the four diagonals:

$$S_l = \begin{pmatrix} 0 & X & 1 \\ 0 & 1 & 1 \\ 0 & X & 1 \end{pmatrix}$$

$$S_r = \begin{pmatrix} 1 & X & 0 \\ 1 & 1 & 0 \\ 1 & X & 0 \end{pmatrix}$$

$$S_o = \begin{pmatrix} 0 & 0 & 0 \\ X & 1 & X \\ 1 & 1 & 1 \end{pmatrix}$$

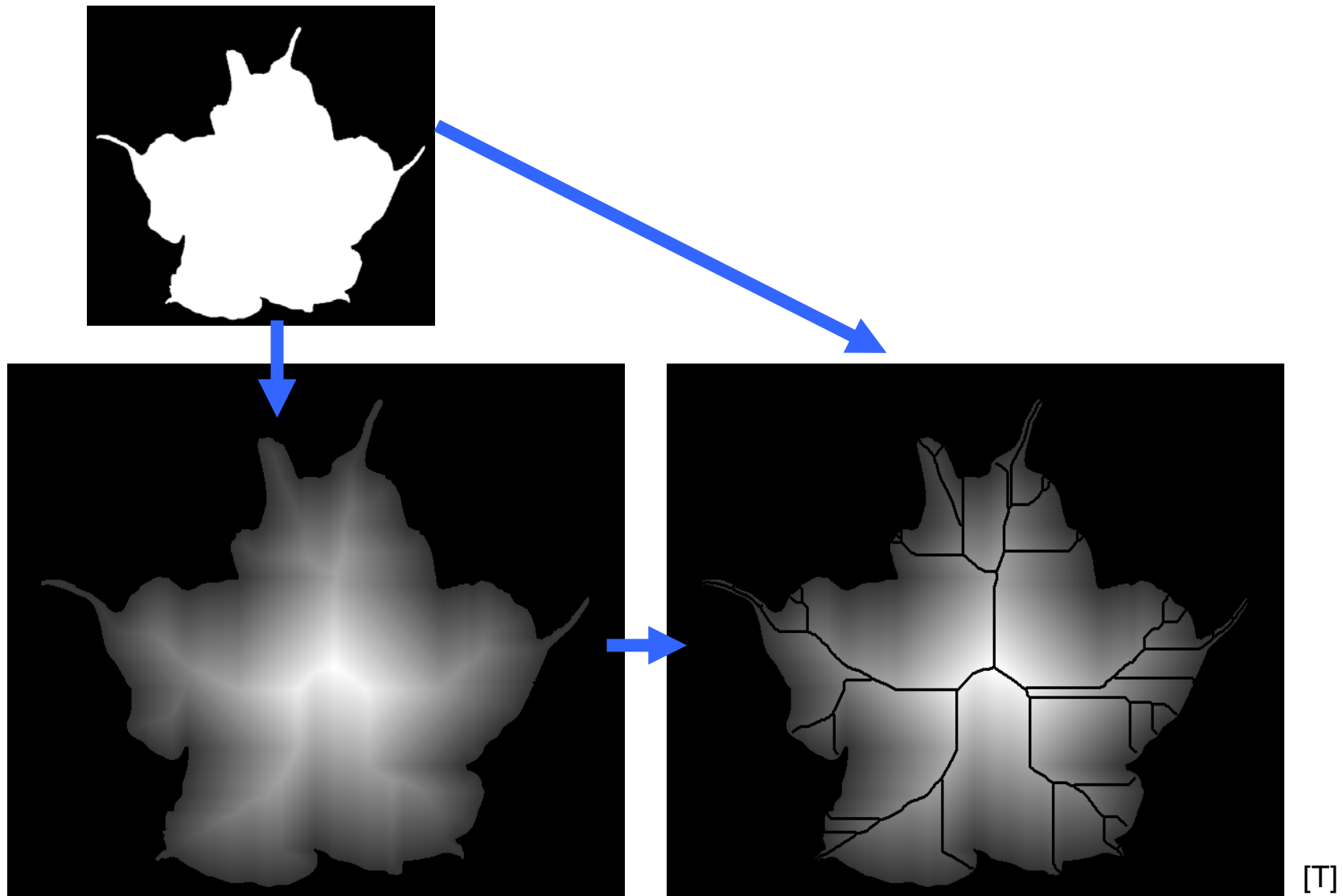
$$S_u = \begin{pmatrix} 1 & 1 & 1 \\ X & 1 & X \\ 0 & 0 & 0 \end{pmatrix}$$

$$S_{lu} = \begin{pmatrix} X & 1 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & X \end{pmatrix}$$

$$S_{lo} = \begin{pmatrix} 0 & 0 & X \\ 0 & 1 & 1 \\ X & 1 & 1 \end{pmatrix}$$

$$S_{ru} = \begin{pmatrix} 1 & 1 & X \\ 1 & 1 & 0 \\ X & 0 & 0 \end{pmatrix}$$

$$S_{ro} = \begin{pmatrix} X & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & X \end{pmatrix}$$



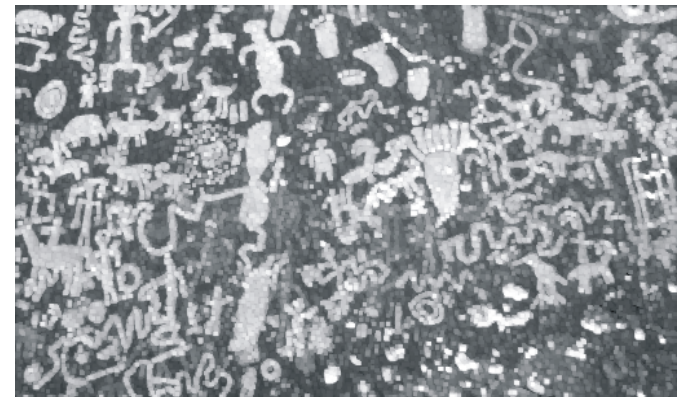
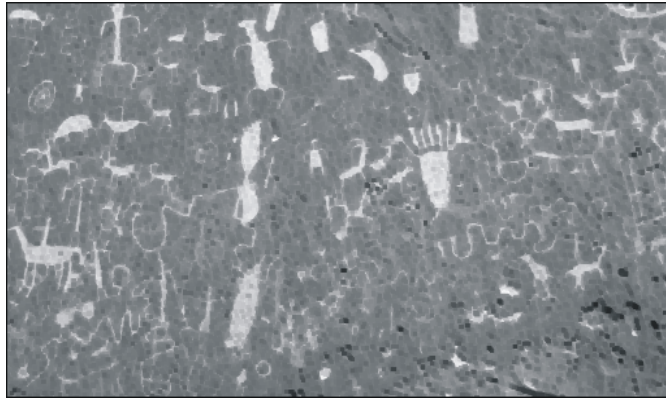
[T]

- Now: Images with many (e.g., 8 bit) gray values
 - Binary structuring element
1. Erosion: Result value is the **minimum** of the gray values of g which are covered by **1-elements** of S :

$$g'(x,y) = \min_{k \in [-m,m], l \in [-n,n]} (S(k+m, l+n) \cdot g(x+k, y+l))$$

2. Dilation: **Maximum**

Generalization to gray value images



Erosion

Input

Dilation

- Morphological operations for recognition of simple patterns, specified by structuring element.
- Basic operations: Erosion, dilation.
- Composed operations: Opening, closing.
- Applications are, e.g., removal of artifacts such as disrupted pixels, unwanted connection of segments, holes in segments or uneven boundaries.
- Specialized structuring elements, e.g., for the removal of special disruptions such as stripes in a particular direction.
- Exact search for pre-defined patterns using hit-or-miss operation.
- Distance transform yields the distance between arbitrary pixels and the boundary of an object.
- Skeletonization yields compact shape description of objects.

- [T] Klaus D. Tönnies, *Grundlagen der Bildverarbeitung*, Pearson Studium, 2005.
- [J] Bernd Jähne, *Digitale Bildverarbeitung*, Springer, 2005.
- [FP] David Forsyth, Jean Ponce, *Computer Vision: A Modern Approach*, Prentice Hall, 2002.
- [SS] Linda G. Shapiro, George C. Stockman, *Computer Vision*, Prentice Hall, 2001.
- [BK] Henning Bässmann, Jutta Kreyss, *Bildverarbeitung Ad Oculos*, Springer, 2004.
- [He] Hecht, *Optics*, Addison-Wesley, 1987.
- [L] David Lowe, Slides, <http://www.cs.ubc.ca/~lowe/425/>.
- [A] *Artexplosion Explosion® Photo Gallery*, Nova Development Corporation, 23801 Calabasas Road, Suite 2005 Calabasas, California 91302-1547, USA.
- [C] Corel GALLERY™ Magic 65000, Corel Corporation, 1600 Carling Ave., Ottawa, Ontario, Canada K1Z 8R7.
- [V] Vision Texture Database (VisTex). R. Picard, C. Graczyk, S. Mann, J. Wachman, L. Picard and L. Campbell. Media Laboratory, MIT. Copyright 1995 by the Massachusetts Institute of Technology.
<http://vismod.media.mit.edu/vismod/imagery/VisionTexture/vistex.html>
- [COIL] S.A. Nene, S.K. Nayar, H. Murase: Columbia Object Image Library: COIL-100, Technical Report, *Dept. of Computer Science, Columbia Univ.*, CUCS-006-96, 1996.
- [H] Copyright Gunther Heidemann, 2008.

- [MQ] J. MacQueen. Some Methods for Classification and Analysis of Multivariate Observations. In *Proc. 5th Berkeley Symp. Math. Stat. Probab.*, volume 1, pp. 281-297, 1965.
- [CM] D. Comaniciu, P. Meer. Mean Shift: A Robust Approach Toward Feature Space Analysis. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 24(5): 603-619, 2002.
- [HIm] G. Heidemann. Region Saliency as a Measure for Colour Segmentation Stability. *Image and Vision Computing*, Vol. 23, p. 861-876, 2005.
- [TP] M. Turk, A. Pentland: Eigenfaces for Recognition, *J. Cognitive Neuroscience*, Vol. 3, p. 71-86, 1991.
- [MN] H. Murase, S.K. Nayar: Visual Learning and Recognition of 3-D Objects from Appearance, *Int. J. of Computer Vision*, Vol. 14, p. 5-24, 1995.
- [DL] D. Lowe: Distinctive image features from scale-invariant keypoints, *Int. J. of Computer Vision*, Vol. 60(2), p. 91-110, 2004.
- [HCv] G. Heidemann: Combining spatial and colour information for content based image retrieval, *Computer Vision and Image Understanding*, Vol. 94(1-3), p. 234-270, 2004.
- [IKH] J. Imo, S. Klenk, G. Heidemann: Interactive Feature Visualization for Image Retrieval. *Proc. 19th Int. Conf. on Pattern Recognition ICPR 2008*, 2008.