

ĐẠI HỌC TÔN ĐỰC THẮNG Ton Duc Thang University (TDTU)

Digital Image Processing

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Lecture 03

Morphological Operations

- 1. Image thresholding (binarization *Example*: Foreground extraction
- 2. Connected-components
 - Pixel neighborhoods
 - Region labeling
 - Region properties

Application: Blob-based motion detection

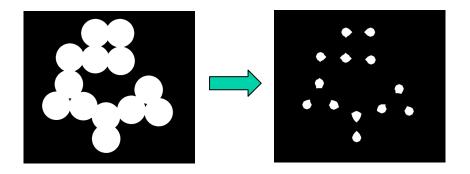
- 3. Morphological operations
 - Erosion/dilation/opening/closing Applications



Morphological Image Processing



- Binary dilation and erosion
- Set-theoretic interpretation
- Opening, closing, morphological edge detectors
- Hit-miss filter
- Morphological filters for gray-level images
- Cascading dilations and erosions
- Rank filters, median filters, majority filters



INTEREST-POINT DETECTION

Feature extraction typically starts by finding the salient interest points in the image. For robust image matching, we desire interest points to be repeatable under perspective transformations (or, at least, scale changes, rotation, and translation) and real-world lighting variations. An example of feature extraction is illustrated in Figure 3. To achieve scale invariance, interest points are typically computed at multiple scales using an image pyramid [15]. To achieve rotation invariance, the patch around each interest point is canonically oriented in the direction of the dominant gradient. Illumination changes are compensated by normalizing the mean and standard deviation of the pixels of the gray values within each patch [16].

Morphological operations

Structuring element

Neighborhood "window" operator

$$W\left\{f\left[x,y\right]\right\} = \left\{f\left[x-x',y-y'\right] : \left[x',y'\right] \in \Pi_{xy}\right\}$$

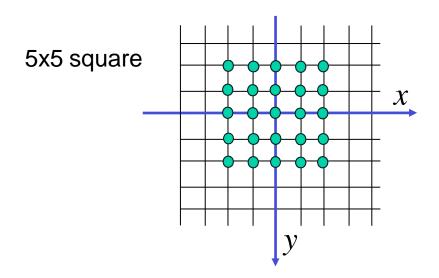
$$\hat{W}\{f[x,y]\} = \{f[x+x',y+y']:[x',y'] \in \Pi_{xy}\}$$

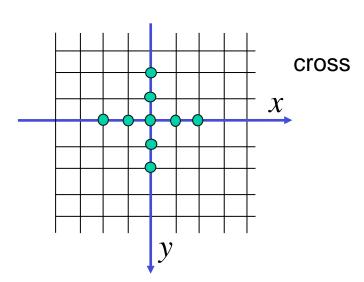
The "hat" notation indicates

"structuring element"

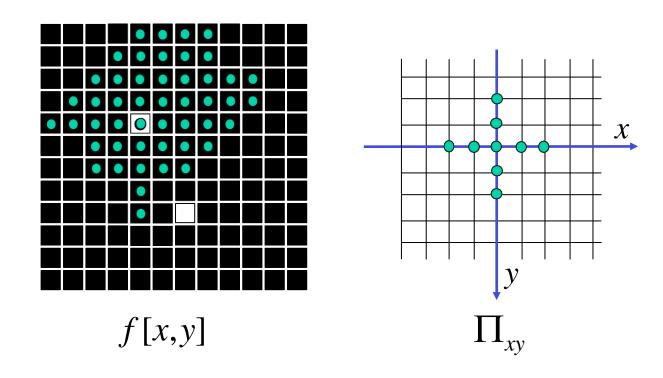
upright structuring element (i.e., <u>not</u> rotated!)

Example structuring elements Π_{xy} :



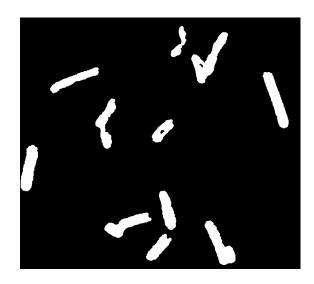


Binary dilation (expanding foreground)

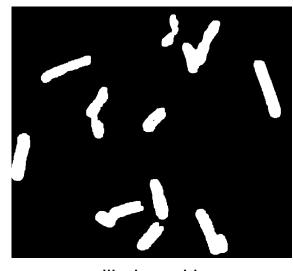


Binary dilation with square structuring element

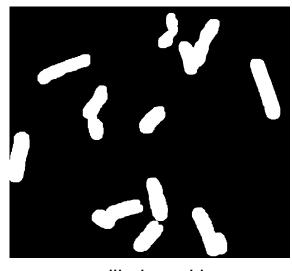
$$g[x,y] = OR[W\{f[x,y]\}] := dilate(f,W)$$



Original (701x781)



dilation with 3x3 structuring element



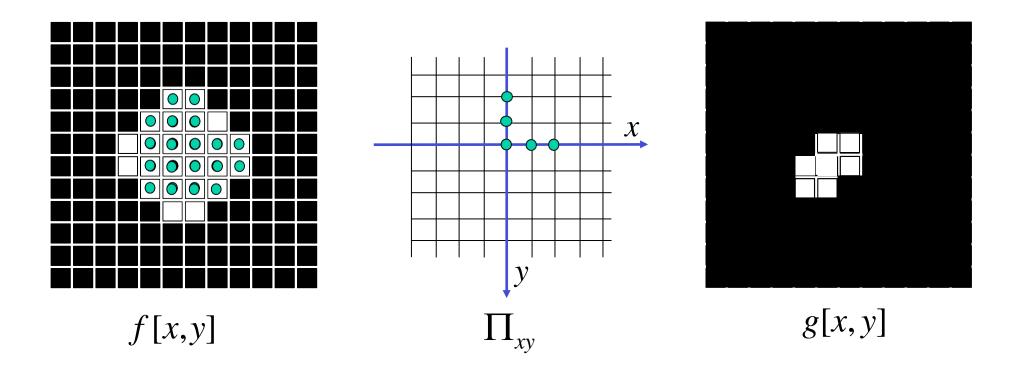
dilation with 7x7 structuring element

- Expands the size of 1-valued objects
- Smoothes object boundaries
- Closes holes and gaps



Binary erosion (shrinking foreground)

$$g[x,y] = AND[\hat{W}\{f[x,y]\}] := erode(f,W)$$



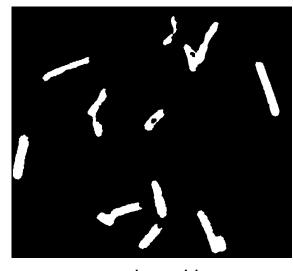
<u>Caveat:</u> There is another definition of erosion in the literature, which flips the structuring element, as for dilation. The Lagunita online videos use that alternative definition. Matlab function *imerode* uses the definition on this slide. To the best of our knowledge, there is no such discrepancy defining dilation.

Binary erosion with square structuring element

$$g[x,y] = AND[\hat{W}\{f[x,y]\}] := erode(f,W)$$



Original (701x781)



erosion with 3x3 structuring element



erosion with 7x7 structuring element

- Shrinks the size of 1-valued objects
- Smoothes object boundaries
- Removes peninsulas, fingers, and small objects



Relationship between dilation and erosion

Duality: erosion is dilation of the background

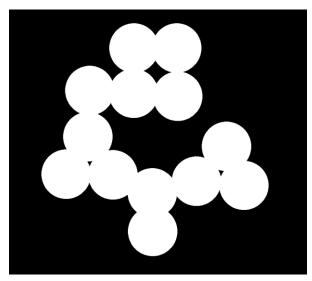
$$\begin{aligned} & dilate(f,W) = NOT \Big[erode(NOT[f], \hat{W}) \Big] \\ & erode(f,W) = NOT \Big[dilate(NOT[f], \hat{W}) \Big] \end{aligned}$$

But: erosion is not the inverse of dilation

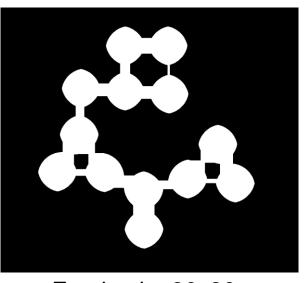
$$f[x,y] \neq erode(dilate(f,W),W)$$

 $\neq dilate(erode(f,W),W)$

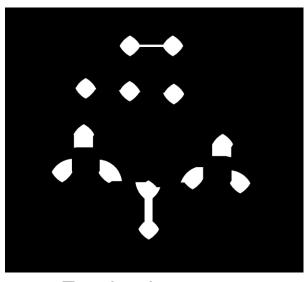
Example: blob separation/detection by erosion



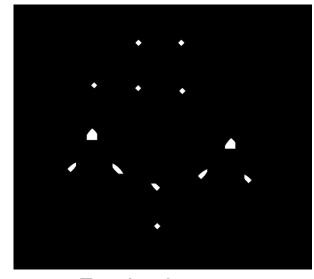
Original binary image *Circles* (792x892)



Erosion by 30x30 structuring element



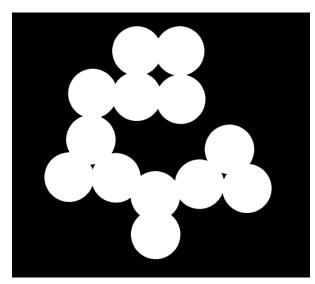
Erosion by 70x70 structuring element



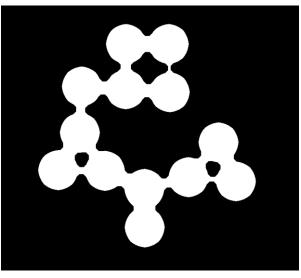
Erosion by 96x96 structuring element



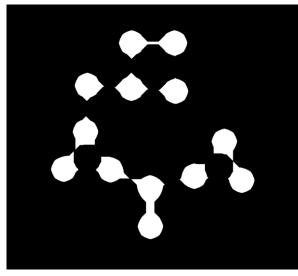
Example: blob separation/detection by erosion



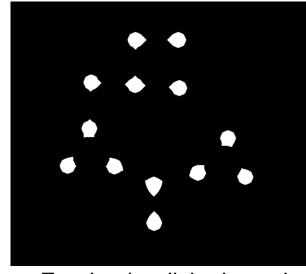
Original binary image *Circles* (792x892)



Erosion by disk-shaped structuring element Diameter=15



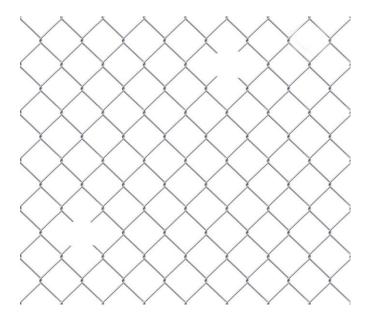
Erosion by disk-shaped structuring element Diameter=35



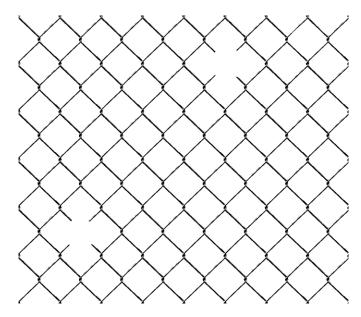
Erosion by disk-shaped structuring element Diameter=48



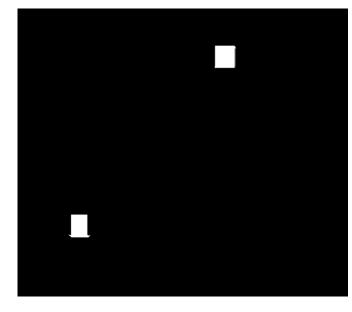
Example: chain link fence hole detection



Original grayscale image Fence (1023 x 1173)



Fence thresholded using Otsu's method



Erosion with 151x151 "cross" structuring element



Opening and closing

- Goal: smoothing without size change
- Open filter

$$open(f,W) = dilate(erode(f,W),W)$$

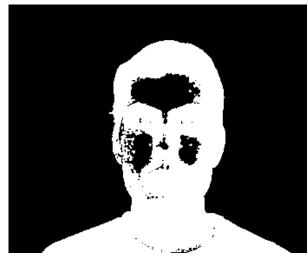
- Close filter close(f,W) = erode(dilate(f,W),W)Open filter and close filter are biased Close filter
- - Open filter removes small 1-regions
 - Close filter removes small 0-regions
 - Bias is often desired for enhancement or detection!
- Unbiased size-preserving smoothers

$$close - open(f, W) = close(open(f, W), W)$$

 $open - close(f, W) = open(close(f, W), W)$

close-open and open-close are duals, but not inverses of each other.

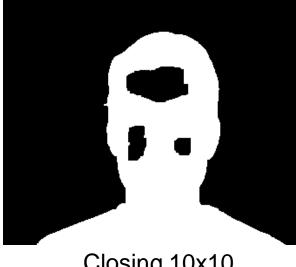
Small hole removal by closing







Dilation 10x10



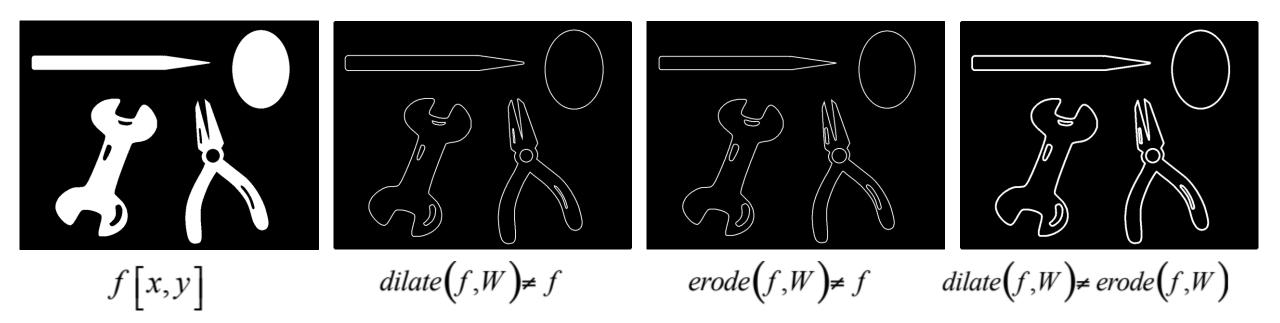
Closing 10x10



Difference to original mask



Morphological edge detectors

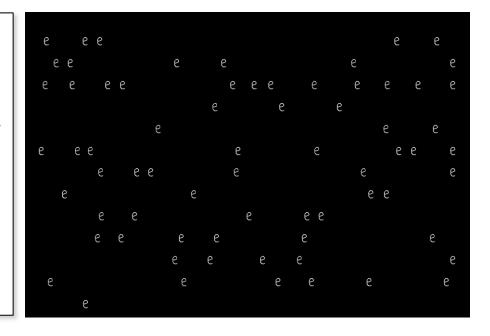




Binary image f

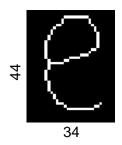
INTEREST-POINT DETECTION

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2000

Structuring element W



9

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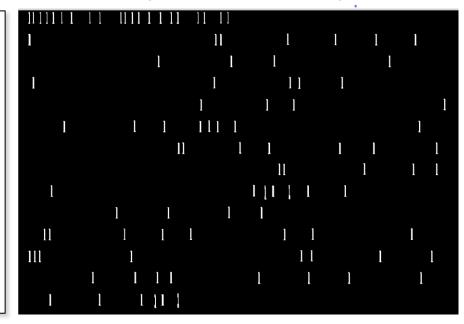


Binary image f

INTEREST-POINT DETECTION

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dilate(erode(NOT[f],W),W)



2000

Structuring element W



INTEREST-POINT DETECTION

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Structuring element W

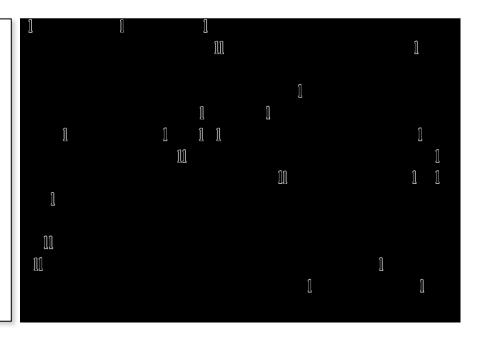
Hit-miss filter

dilate(erode(NOT[f],V)&erode(f,W),W)

Binary image f

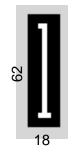
INTEREST-POINT DETECTION

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2000

Structuring element V





Structuring element *W*

140

Hit-miss filter

INTEREST-POINT DETECTION

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Structuring element V



Structuring element *W*



Dilation/erosion for gray-level images

- Explicit decomposition into threshold sets not required in practice
- Flat dilation operator: local maximum over window W

$$g[x,y] = \max\{W\{f[x,y]\}\} := dilate(f,W)$$

Flat erosion operator: local minimum over window W

$$g[x,y] = \min\{\hat{W}\{f[x,y]\}\} := erode(f,W)$$

Binary dilation/erosion operators contained as special case

1-d illustration of erosion and

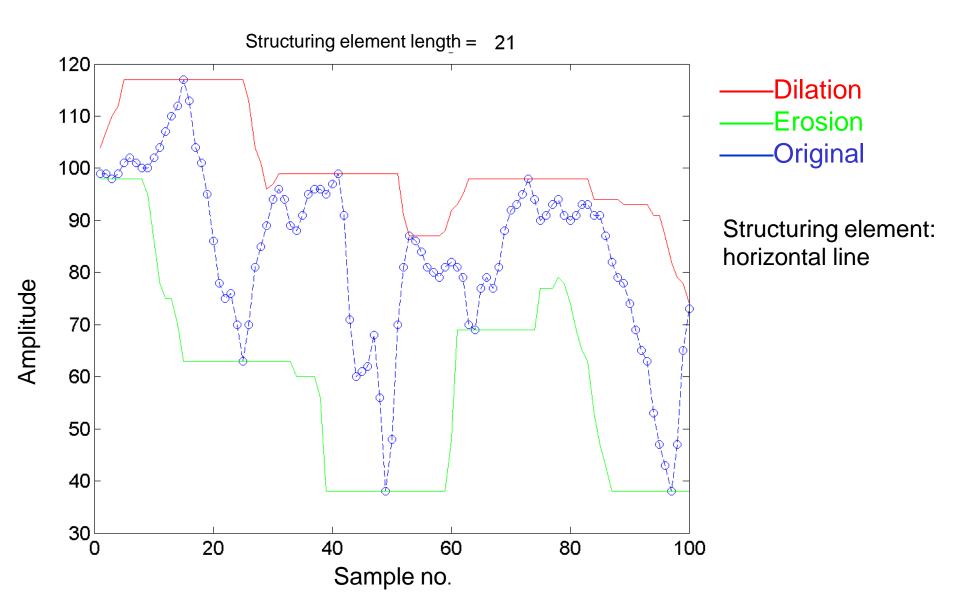
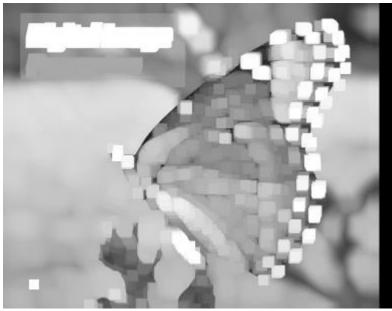




Image example



Original 394 x 305



Dilation 10x10 square



Erosion 10x10 square



Flat dilation with different structuring elements







Diamond



Disk



20 degree line



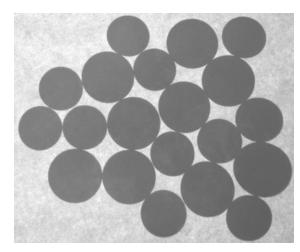
9 points



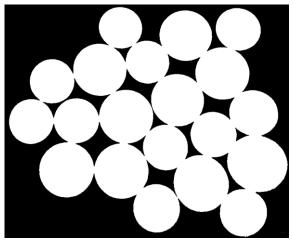
2 horizontal lines



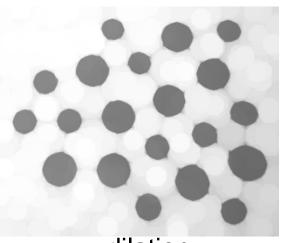
Example: counting coins



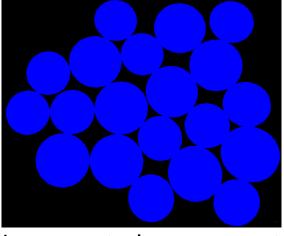
Original



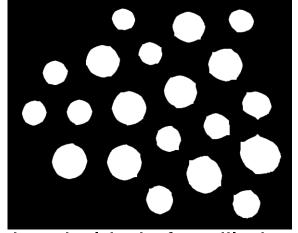
thresholded



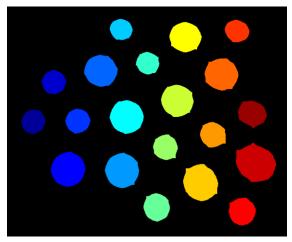
dilation



1 connected component



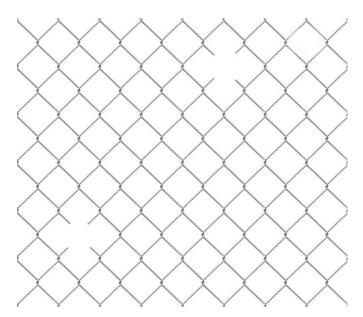
thresholded after dilation



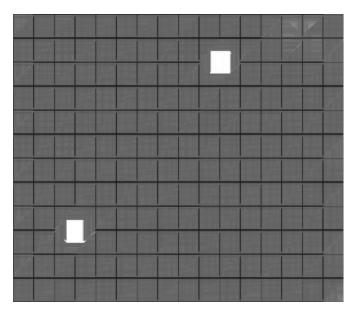
20 connected components



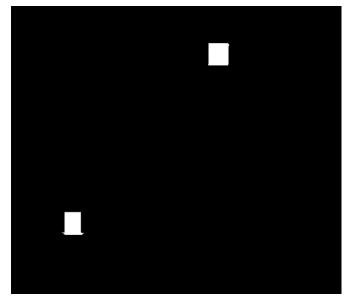
Example: chain link fence hole detection



Original grayscale image Fence (1023 x 1173)



Flat erosion with 151x151 "cross" structuring element



Binarized by Thresholding



Morphological edge detector









 $\mathsf{original} f$

dilation g

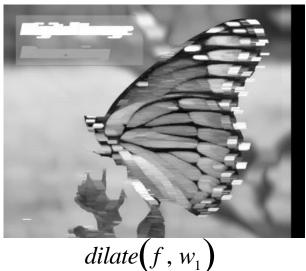
g-f

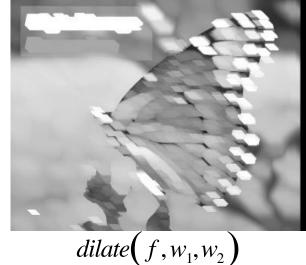
g-f thresholded

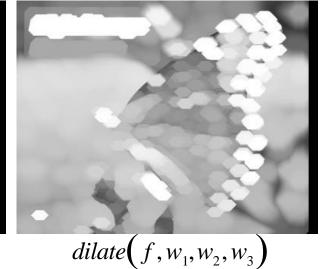


Cascaded dilations









(3,11,112)

$$dilate[dilate(f, w_1), w_2] = dilate(f, w)$$

where
$$w = dilate(w_1, w_2)$$



Cascaded erosions

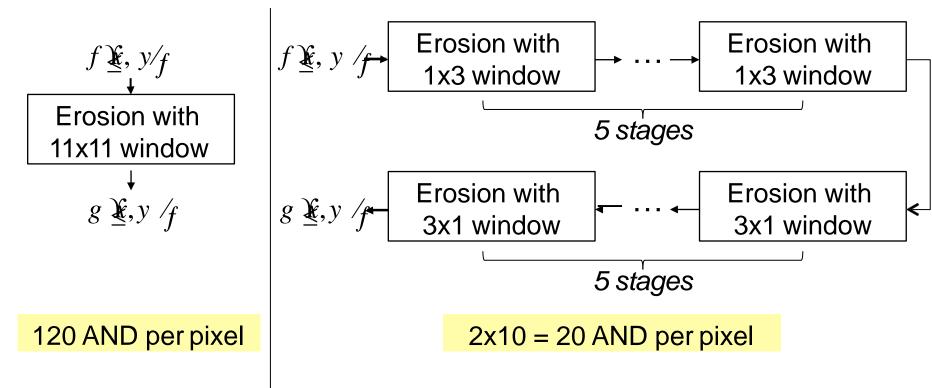
Cascaded erosions can be lumped into single erosion

$$\begin{split} erode\Big[erode\big(f,w_1\big),w_2\Big] &= erode\Big[-dilate\big(-f,\hat{w}_1\big),w_2\Big] \\ &= -dilate\Big[dilate\big(-f,\hat{w}_1\big),\hat{w}_2\Big] \\ &= -dilate\Big(-f,\hat{w}\Big) \\ &= erode\Big(f,w\Big) \\ \text{where } w = dilate\Big(w_1,w_2\Big) \end{split}$$

 New structuring element (SE) is <u>not</u> the erosion of one SE by the other, but dilation.

Fast dilation and erosion

- Idea: build larger dilation and erosion operators by cascading simple, small operators
- Example: binary erosion by 11x11 window



Rank filters

- Generalisation of flat dilation/erosion: in lieu of min or max value in window, use the p-th ranked value
- Increases robustness against noise
- Best-known example: median filter for noise reduction
- Concept useful for both gray-level and binary images
- All rank filters are commutative with thresholding

Median filter

Gray-level median filter

$$g[x,y] = median[W\{f[x,y]\}] := median(f,W)$$

Binary images: majority filter

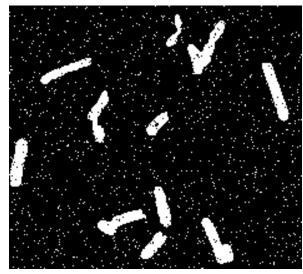
$$g[x,y] = MAJ[W\{f[x,y]\}] := majority(f,W)$$

Self-duality

$$median(f,W) = -\left[median(-f,W)\right]$$

$$majority(f,W) = NOT\left[majority(NOT[f],W)\right]$$

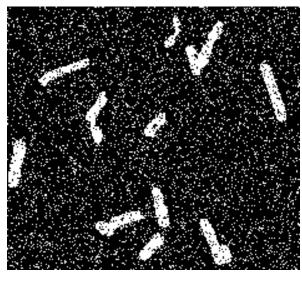
Majority filter: example



Binary image with 5% 'Salt&Pepper' noise



3x3 majority filter



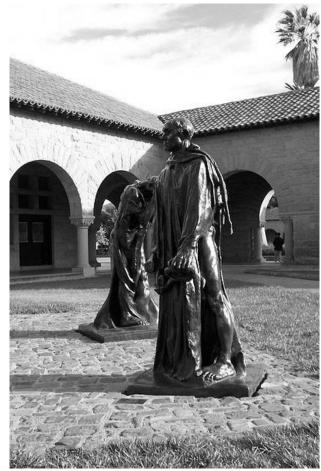
20% 'Salt&Pepper' noise

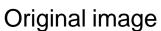


3x3 majority filter



Median filter: example







5% 'Salt&Pepper' noise



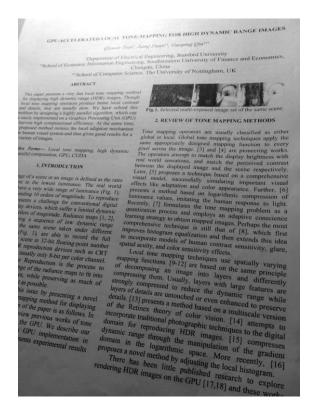
3x3 median filtering



7x7 median filtering



Example: non-uniform lighting compensation



Original image 1632x1216 pixels



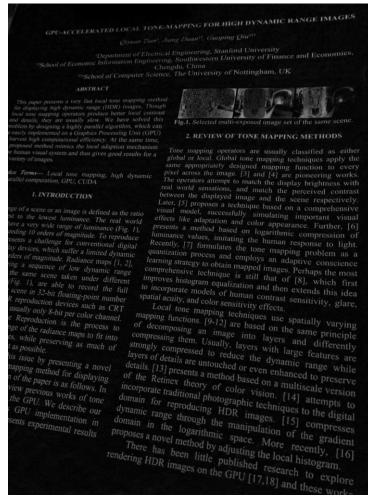
Dilation (local max) 61x61 structuring element



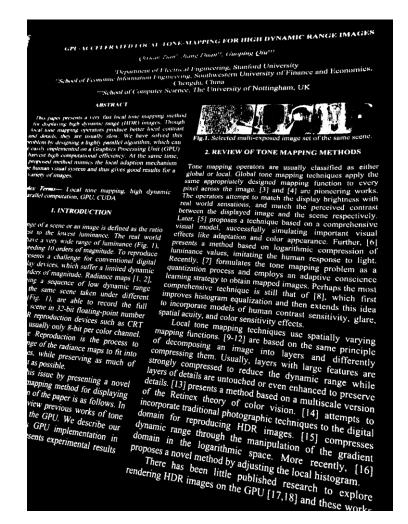
Rank filter
10st brightest pixel
61x61 structuring element



Example: non-uniform lighting compensation



Background – original image



After global thresholding