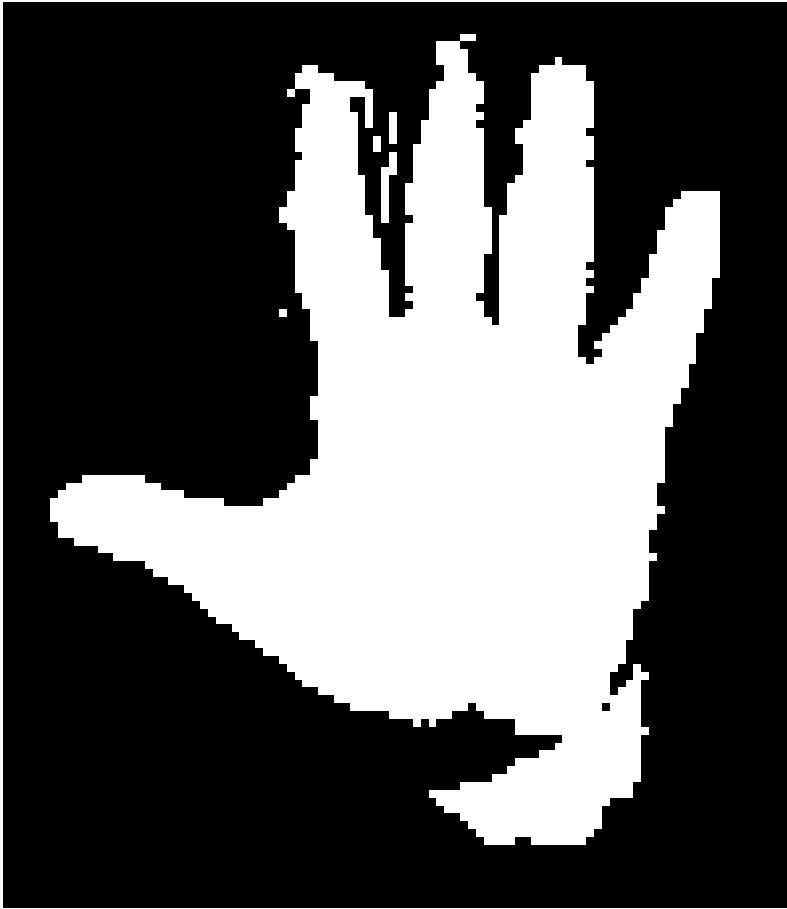


Mathematical morphology

<http://www.imagemagick.org/Usage/morphology/>



Introduction

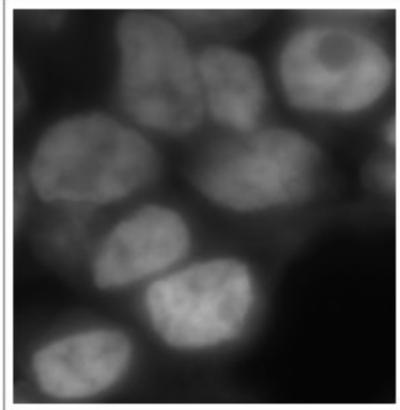
- Morphology: study of the shape (from Greek μορφή e λογία)
- Mathematical morphology is a **non-linear** theory of image analysis $(au(x) + v(x)) \otimes g(x) \neq a(u(x) \otimes g(x)) + (v(x) \otimes g(x))$
- It is not based on convolution (at least not on the type of convolution you are probably familiar with)
- It is based on the idea of **probing** an image with a smaller one to see how the image responds to it
 - By changing the shape and size of the probe, more information can be extracted

Introduction

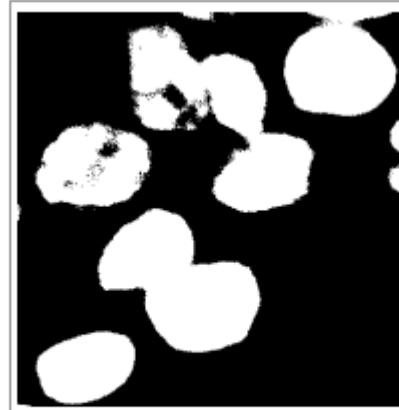
- The original theory, introduced in the late 1960,
applies to **binary images**
 - Operators are applied after image thresholding
- The theory can be extended to **grayscale images**
 - In this case operators can be used before thresholding
- It is a very popular framework (effective and efficient) for image processing with several applications:
 - noise removal,
 - feature extraction,
 - shape enhancement (skeletonization, thinning, thickening)
 - image segmentation...

Preliminaries

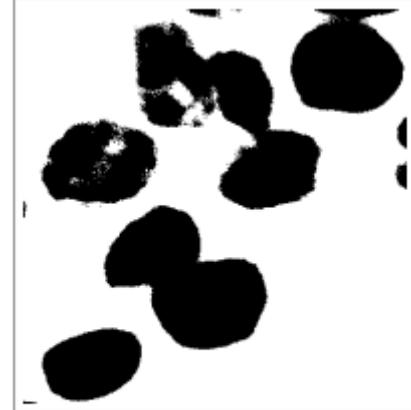
- The language of MM is set theory
 - Sets are used to represent objects in the image
- White pixels are considered the **foreground** and black pixels the **background**
 - Binary images are sets of foreground pixels



u



$I = \{x \in I | u(x) > t\}$



I^c

Preliminaries

- Basic definitions. Let A be a set of points of a linear space X

$$A^c = \{x|x \notin A\} \quad \text{Complement}$$

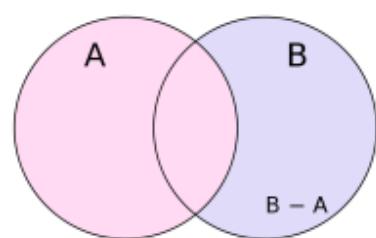
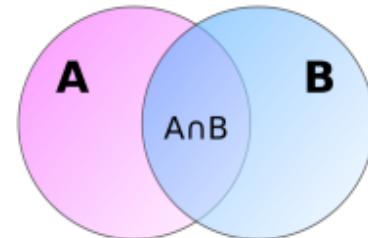
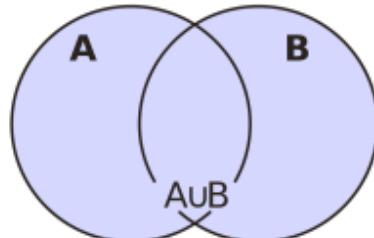
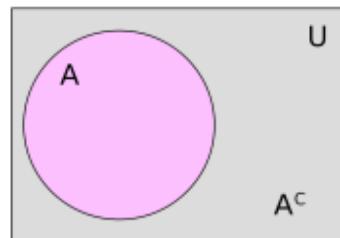
$$A \cup B = \{x|x \in A \text{ or } x \in B\} \quad \text{Union}$$

$$A \cap B = \{x|x \in A \text{ and } x \in B\} \quad \text{Intersection}$$

$$A - B = A \cap B^c \quad \text{Difference}$$

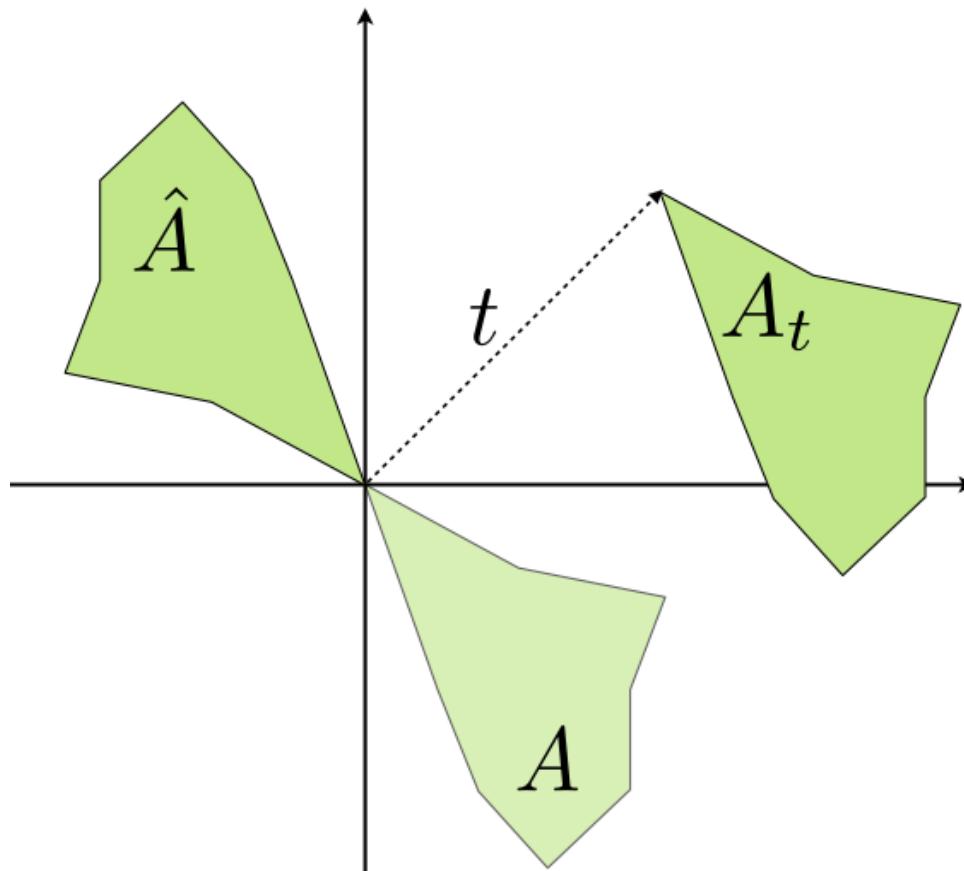
$$A_t = \{x|x = y + t \text{ for } y \in A\} \quad \text{Translation}$$

$$\hat{A} = \{x|x = -y \text{ for } y \in A\} \quad \text{Reflection}$$



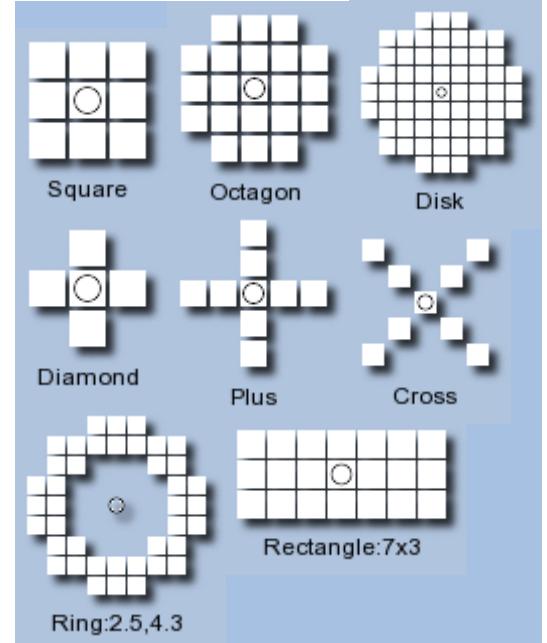
Preliminaries

- Translation and reflection are extensively used in MM



Preliminaries

- Translation and reflection are used to define operations based on **structuring elements**:
 - Small sets (objects) used to probe the image under analysis
- The SE consists of a set of points specified by their coordinates relative to an origin
 - If not specified, the origin is assumed to match the center of gravity of the SE
 - If a SE, say C , is symmetric about its origin, then $C = \hat{C}$



Basic operators

- Binary MM is based on two primitive operators: erosion and dilation

- **Erosion** of A by B:

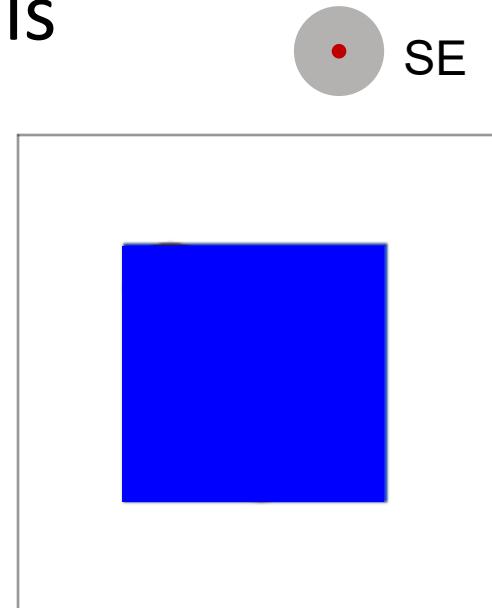
$$E(A, B) = \{z \mid B_z \subseteq A\}$$

- **Dilation** of A by B:

$$D(A, B) = \left\{ z \mid \hat{B}_z \cap A \neq \emptyset \right\}$$

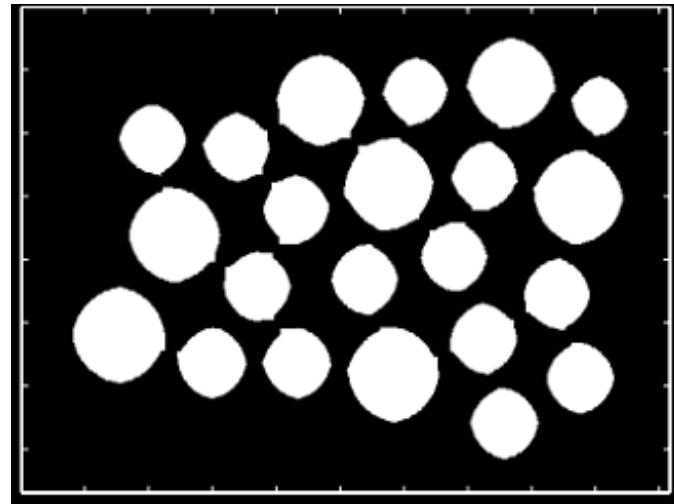
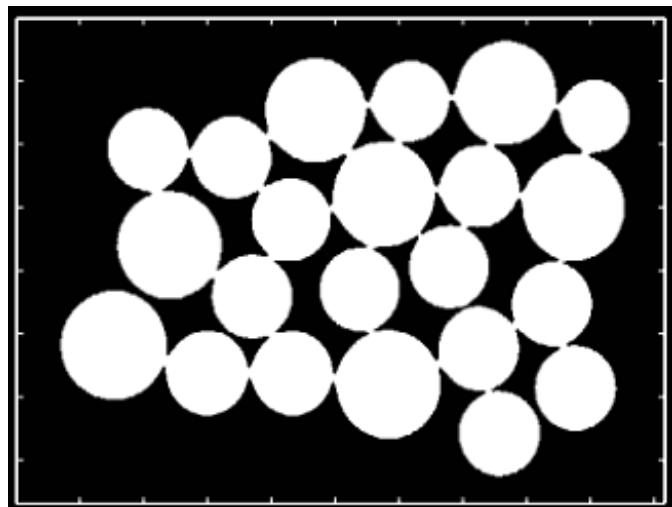
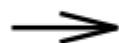
Erosion

- Erosion **thins** the image by removing FG pixels in the image where a translated version of the structuring element is not completely contained in the set of FG pixels
- The extent of thinning depends on the shape of the structuring element



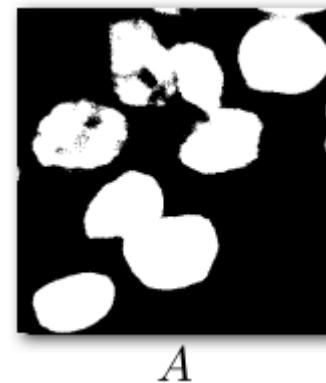
Erosion

SE



Erosion

- Erosion is typically used to **remove protrusions and thin lines** that connect image regions
- The result depends on the size of the SE



$A \ominus D_3$



$A \ominus D_5$

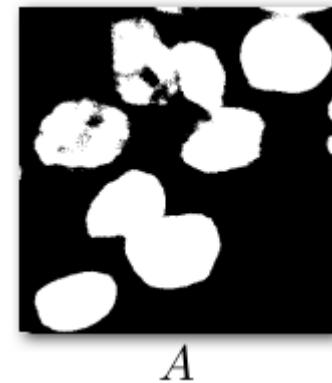


$A \ominus D_{10}$



Erosion

- Instead of eroding an image by a large SE, the image can be iteratively eroded by a small SE



$$A \ominus D_3$$



$$(A \ominus D_3) \ominus D_3$$

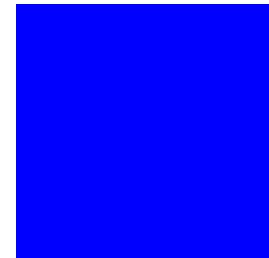


$$((A \ominus D_3) \ominus D_3) \dots \ominus D_3$$



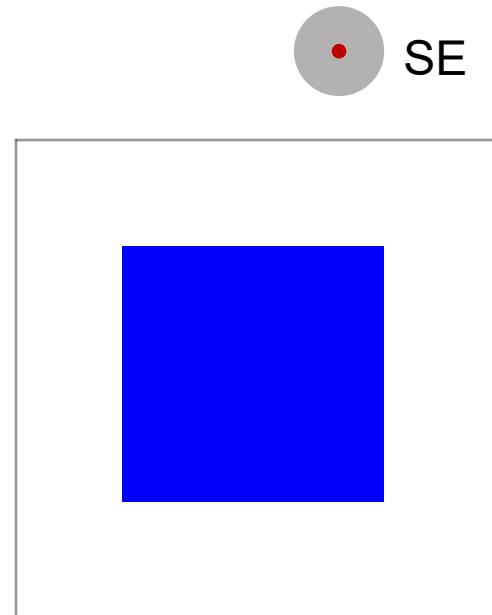
Dilation

- Dilation **thickens** the image by adding pixels where a reflected and translated version of the structuring element intersects the original set of FG pixels
- The extent of thickening depends on the shape of the structuring element
- For symmetric SE, a different geometric interpretation is usually adopted...



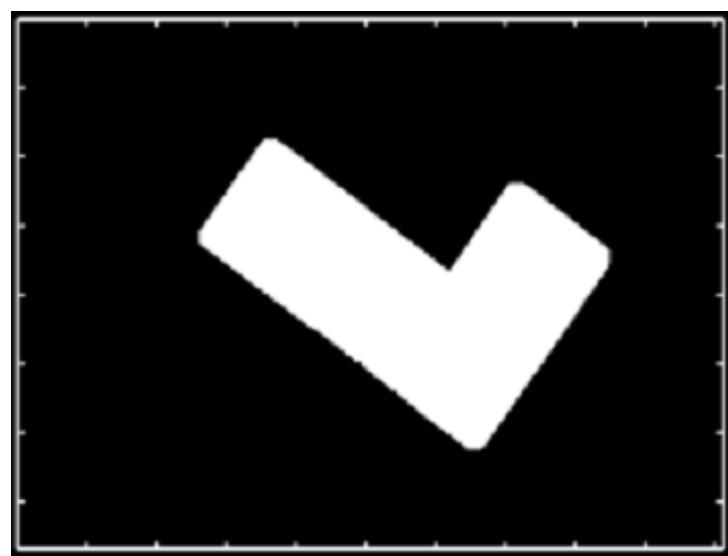
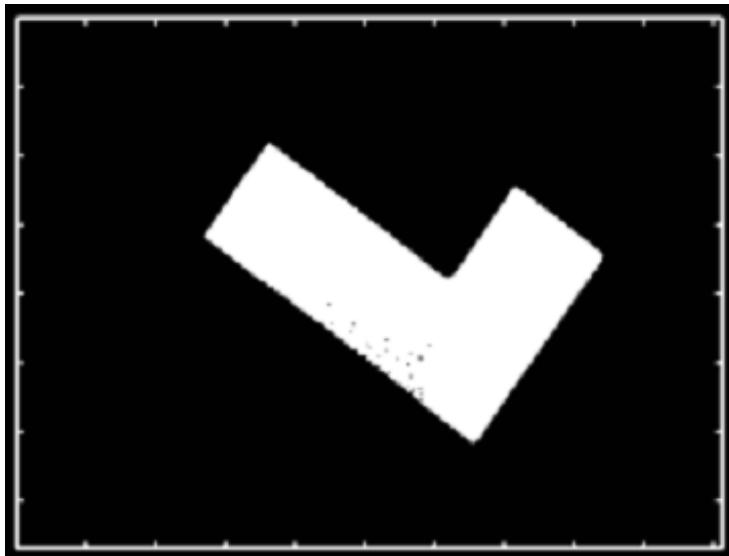
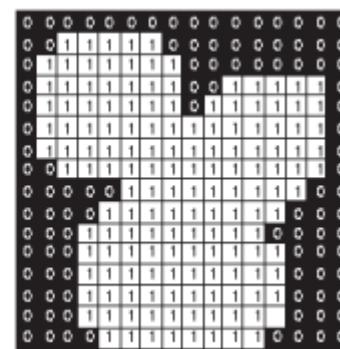
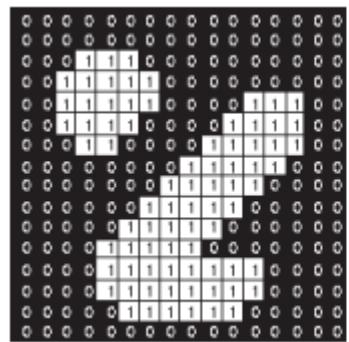
Dilation

- Dilation **thickens** the image by reproducing the structuring element at every pixel present in the original image
- The extent of thickening depends on the shape of the structuring element



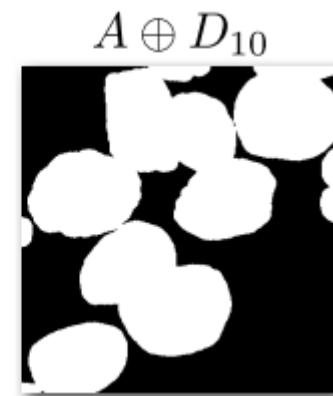
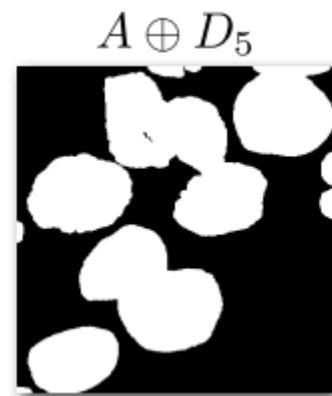
Dilation

SE



Dilation

- Dilation is typically used to **remove holes** and **thin gaps** so as to connect image regions
- The result depends on the size of the SE



Dilation

- Instead of dilating an image by a large SE, the image can be iteratively dilated by a small SE



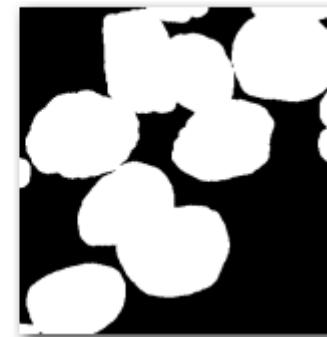
$A \oplus D_3$



$(A \oplus D_3) \oplus D_3$



$((A \oplus D_3) \oplus D_3) \dots \oplus D_3$



Duality

- Erosion and dilation are duals of each other wrt complementation and reflection

$$E(A, B)^C = D(A^C, \hat{B})$$

$$D(A, B)^C = E(A^C, \hat{B})$$

Duality

- Proof

$$\begin{aligned} E(A, B)^C &= \{z \mid B_z \subseteq A\}^C \\ &= \{z \mid B_z \cap A^C = \emptyset\}^C \\ &= \{z \mid B_z \cap A^C \neq \emptyset\} \\ &= D(A^C, \hat{B}) \end{aligned}$$

Duality

- Proof

$$\begin{aligned} D(A, B)^C &= \left\{ z \mid \hat{B}_z \cap A \neq \emptyset \right\}^C \\ &= \left\{ z \mid \hat{B}_z \cap A = \emptyset \right\} \\ &= \left\{ z \mid \hat{B}_z \subseteq A^C \right\} \\ &= E(A^C, \hat{B}) \end{aligned}$$

Duality

- In case of symmetric SE (which is usually the case), the duality principle states that we can perform any operation on A by performing the dual operation on A^c and taking the complement of the result

Hello!

A

Hello!

A^c

Hello!

$A \ominus D_5$

Hello!

$A^c \oplus D_5$

Hello!

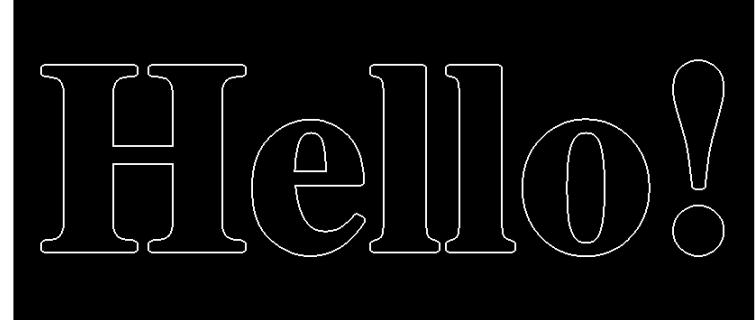
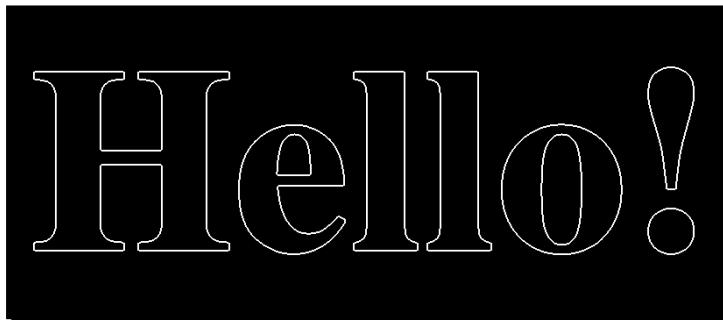
$A \oplus D_5$

Hello!

$A^c \ominus D_5$

MM and spatial filtering

- Erosion and dilation can be used to define a **morphological** analogue to the image **gradient**:



$$A - (A \ominus B_2)$$

inner

$$(A \oplus B_2) - A$$

outer



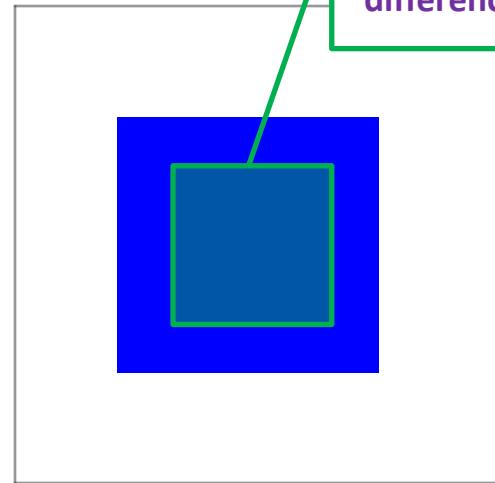
Beyond erosion and dilation

- Dilation expands the objects in the image whereas erosion shrinks them
- However, limiting ourselves to erosion and dilation wouldn't leave us with a very interesting theory
- The combination of erosion and dilation yields two important operators: Opening and Closing
 - **Opening** smoothes the object contour by removing thin protrusions and thin bridges
 - **Closing** smoothes the object contour by filling gaps and narrow breaks

Opening and closing

- Opening

$$A \circ B = D(E(A, B), B)$$



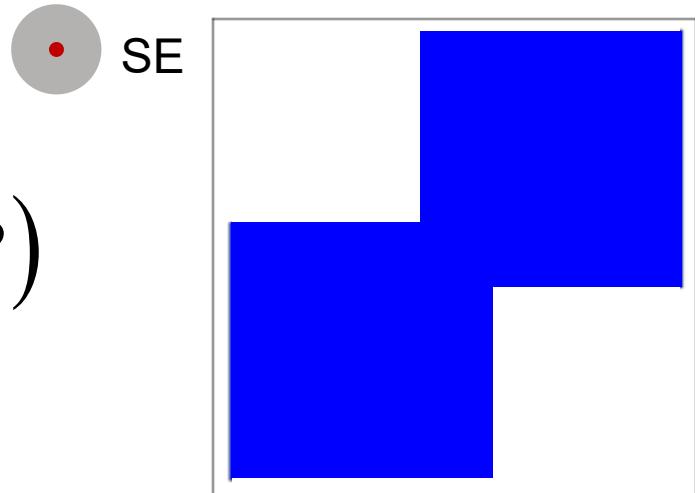
This would be
the erosion:
notice the
difference!!!

- Geometric interpretation:
 - A opened by B is the union of all translates of B that fit into A

Opening and closing

- Closing

$$A \bullet B = E(D(A, B), B)$$



- Geometric interpretation:
 - A closed by B is the complement of the union of all translates of B that do not intersect A

Duality of Open and Close

- Similarly to erode and dilate, also open and close are dual of each other with respect to set complementation and reflection

$$(A \circ B)^C = A^C \bullet \hat{B}$$

$$(A \bullet B)^C = A^C \circ \hat{B}$$

Opening and closing

Hello!

A

Hello!

$A \circ D_5$

Hello!

$A \circ D_{15}$

ll. ...

$A \circ D_{21}$

Hello!

$A \bullet D_5$

Hello!

$A \bullet D_{15}$

Hello!

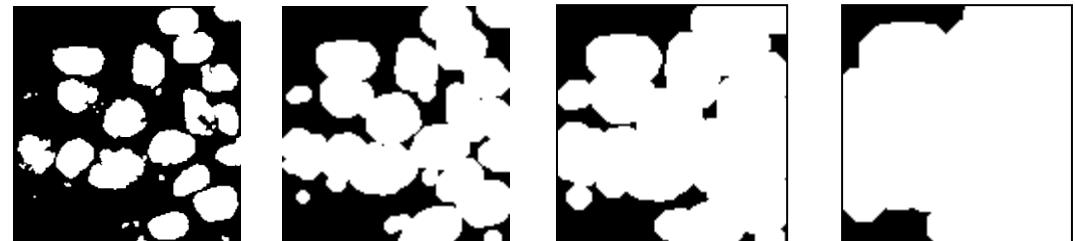
$A \bullet D_{21}$

Idempotence

- Iterated application of the erosion operator leads to the empty set



- Iterated application of the dilation operator leads to the entire image



- Does this hold also for opening and closing?

Idempotence

- A set A is said to be **B-open** if opening A with B has no effect:

$$(A \circ B) = A$$

- A set A is said to be **B-closed** if closing A with B has no effect:

$$(A \bullet B) = A$$

- **Idempotence** of opening and closing:

- $(A \circ B)$ is B-open: $(A \circ B) \circ B = (A \circ B)$

- $(A \bullet B)$ is B-closed: $(A \bullet B) \bullet B = (A \bullet B)$

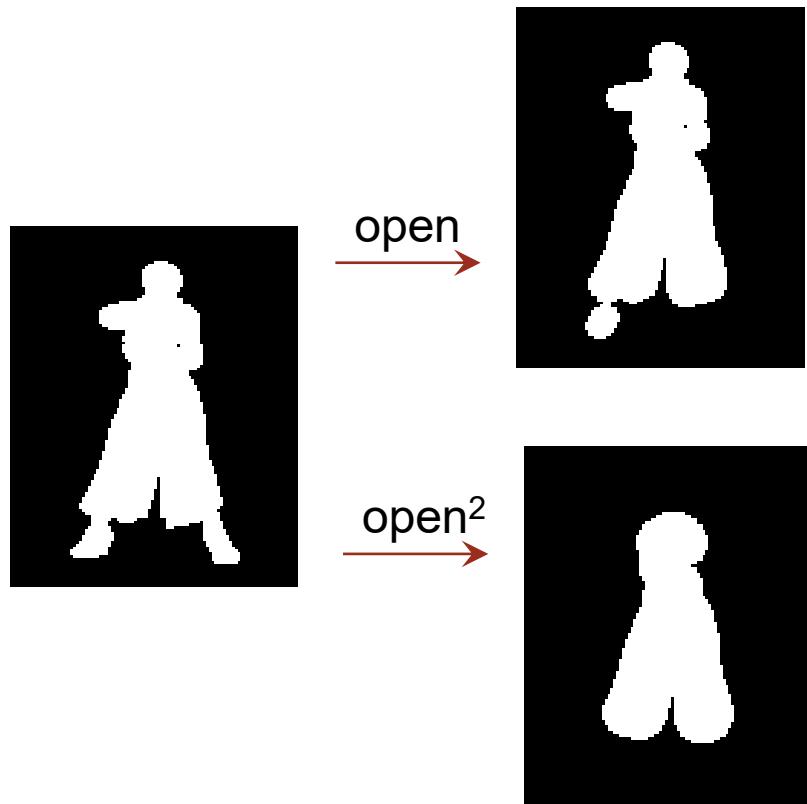
Idempotence

- Notice:
 - $(A \circ B)$ is B-open but it is not B-closed
 - $(A \bullet B)$ is B-closed but it is not B-open
- Since the iterated application of open (or close) is useless, to increase their effect the individual dilate and erode sub-methods are iterated:

$$A^{\circ 2} = D(D(E(E(A, B), B), B), B)$$

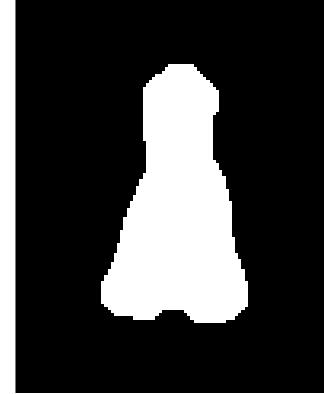
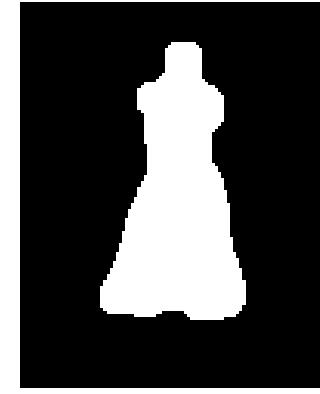
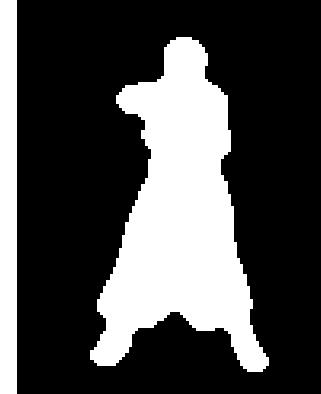
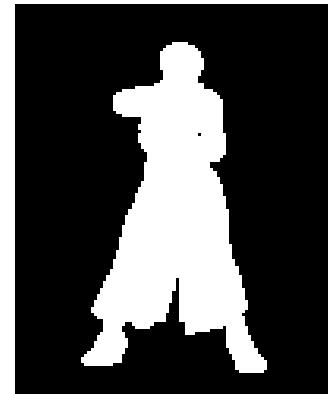
$$A^{\bullet 2} = E(E(D(D(A, B), B), B), B)$$

Morphological Open/Close



Morphological Smooth

- The **smooth** operator is obtained by applying a **open followed by a close**
 - This first removes any small objects then fills in and 'holes' or 'gaps' about the size of the SE
- The smooth operator is often repeated with slowly increasing sized SE, so as to slowly remove noise from images
- Iterated smoothing with the same SE is useless



`smooth(disk(2))`

`smooth(disk(4))`

`smooth(disk(6))`

`smooth(disk(8))`

Smooth vs Open vs Close

Close disk 2



Close disk 4



Close disk 6



Close disk 8



Smooth disk 2



Smooth disk 4



Smooth disk 6



Smooth disk 8



Open disk 2



Open disk 4



Open disk 6



Open disk 8

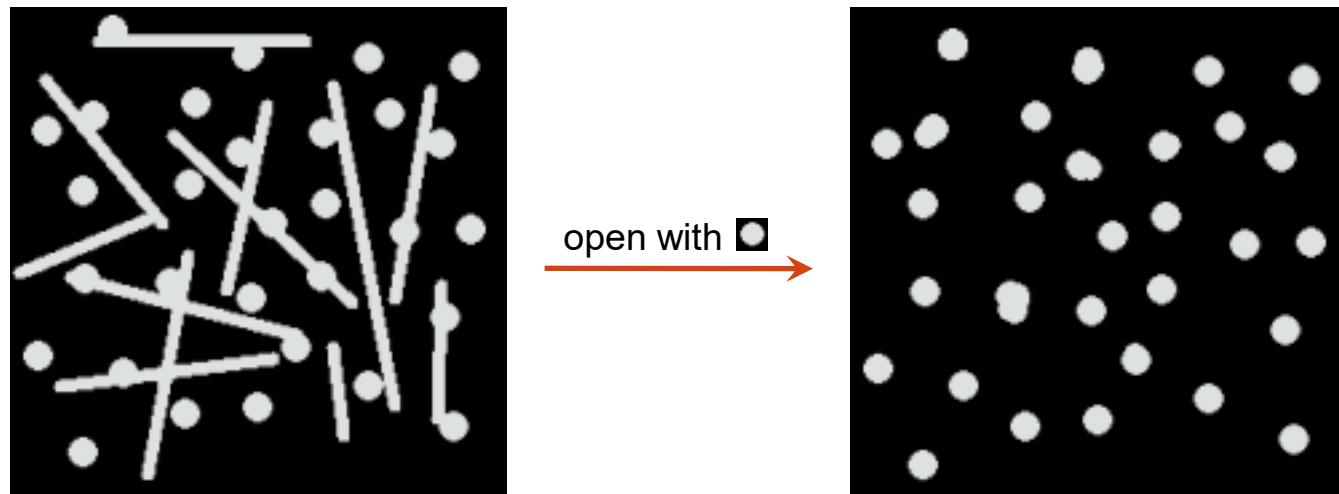


Other properties

- Opening:
 - $(A \circ B)$ is a subset of A
 - If C is a subset of D, then $(C \circ B)$ is a subset of $(D \circ B)$
- Closing:
 - A is a subset of $(A \bullet B)$
 - If C is a subset of D, then $(C \bullet B)$ is a subset of $(D \bullet B)$

More about opening

- The result of the opening operator is the union of all the parts of the image that match the SE
- This suggests a template matching analogy to highlight the parts of the image where a pattern corresponding to the template is represented



- However, there is a remarkable difference: In fact ...

More about opening

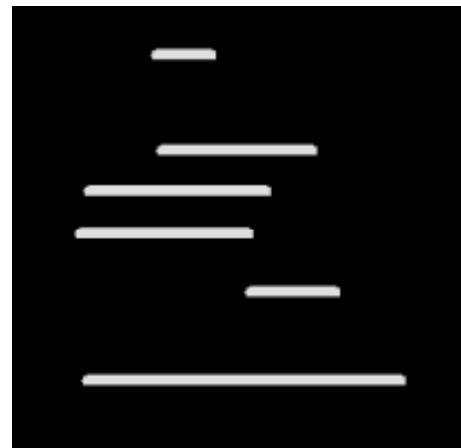
- The result of the opening operator can be regarded as the union of all the parts of the image that match the SE



open with
→



open with
→



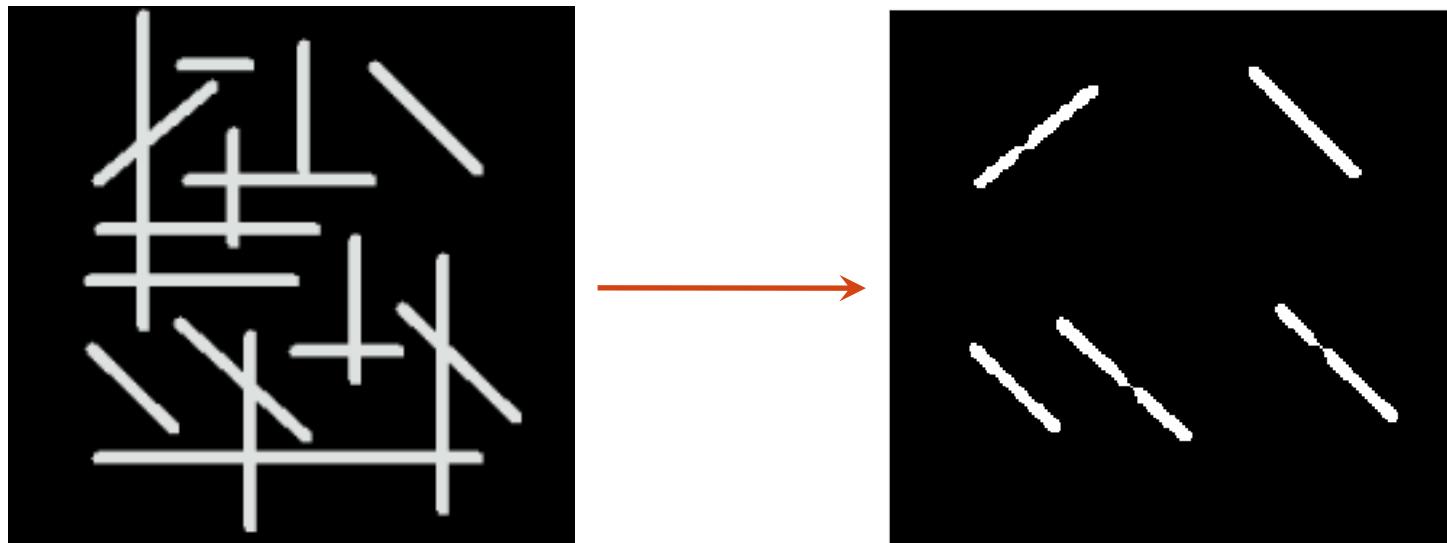
More about opening

- How to select the slanted lines?



More about opening

- How to select the slanted lines?
 - Select the horizontal lines, select the vertical ones and remove both from the original, then close with a disk



MM and spatial filtering

- Opening and closing are extremely good at removing shot (salt and pepper) noise



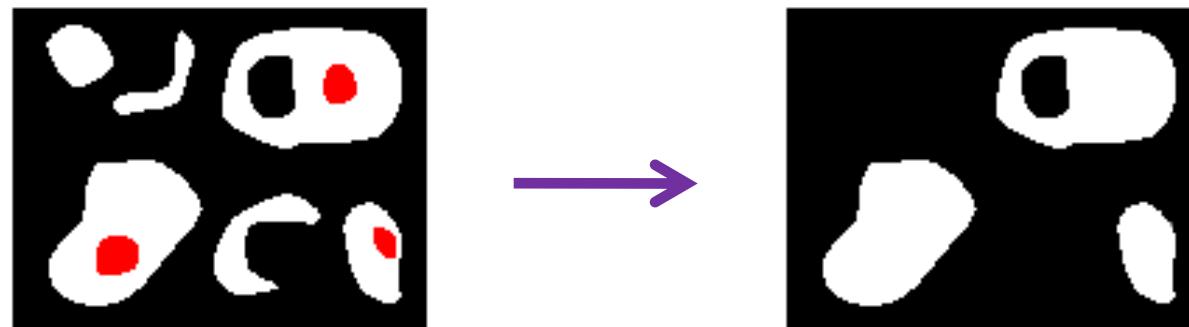
$$(I \bullet D) \circ D$$



$$(I \circ D) \bullet D$$

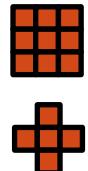
Morphological reconstruction

- In many cases it is necessary to process an image so as to **remove irrelevant regions**:
 - Retain only a subset of FG pixels, corresponding to some regions of interest
- The **morphological reconstruction** operator makes this possible under the assumption that a seed pixel (or patch) is available inside each region of interest



Morphological reconstruction

- The morphological reconstruction is used to **retain some connected components** of an image
- It is a process that involves two images and one SE
 - The first image is the **marker**: it contains the seeds for the reconstruction
 - The second image is the **mask**: it constrains the reconstruction
 - The SE implicitly defines the connectivity (4/8 neigh.)
- The process relies on the **geodesic dilation** and **geodesic erosion** operators



Geodesic dilation

- Let F and G denote the marker and mask images (both binary, $F \subseteq G$)
- The **geodesic dilation of size 1** of the marker F wrt the mask G is:

guarantees that the mask G will limit the growth of the marker F

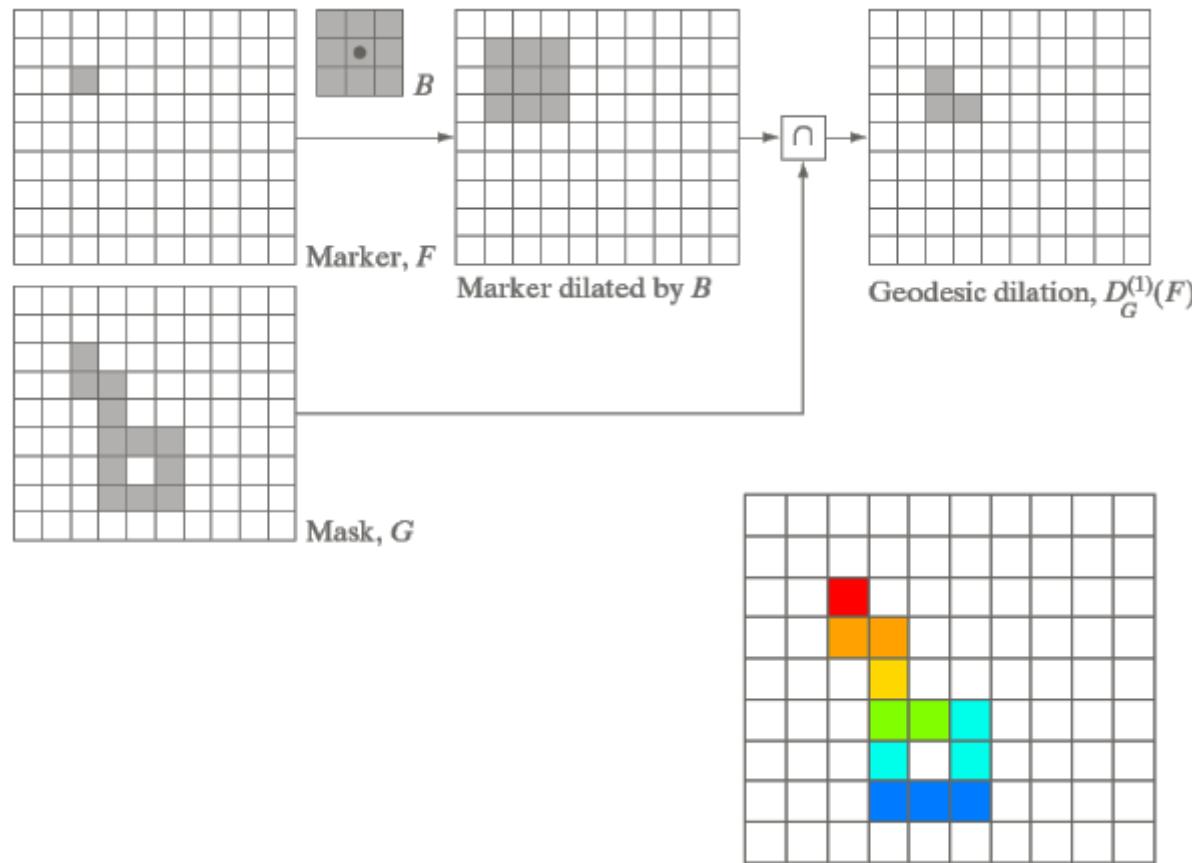
$$D_G^{(1)}(F) = (F \oplus B) \cap G$$

- The **geodesic dilation of size n** of the marker F wrt the mask G is:

$$D_G^{(n)}(F) = D_G^{(1)}\left(D_G^{(n-1)}(F)\right)$$

with $D_G^{(0)}(F) = F$

Geodesic dilation



Geodesic erosion

- Let F and G denote the marker and mask images (both binary)
- The **geodesic erosion of size 1** of the marker F wrt the mask G is:

guarantees that the mask G will limit the collapse of the marker F

$$E_G^{(1)}(F) = E(F, B) \cup G$$

- The **geodesic erosion of size n** of the marker F wrt the mask G is:

$$E_G^{(n)}(F) = E_G^{(1)}(E_G^{(n-1)}(F))$$

with $E_G^{(0)}(F) = F$

Morphological reconstruction

- The **MREC by dilation** of a mask G by a marker F is the geodesic dilation of F wrt G iterated until stability

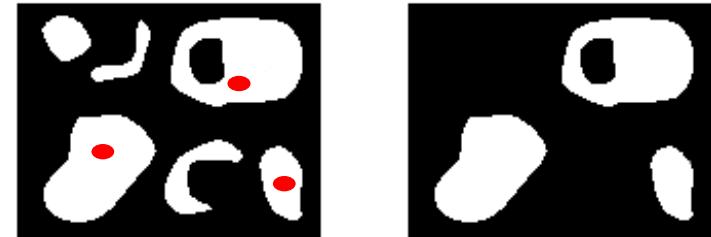
$$REC_G^D(F) = D_G^{(n)}(F) \quad \text{such that} \quad D_G^{(n)}(F) = D_G^{(n+1)}(F)$$

- The **MREC by erosion** of a mask G by a marker F is the geodesic erosion of F wrt G iterated until stability

$$REC_G^E(F) = E_G^{(n)}(F) \quad \text{such that} \quad E_G^{(n)}(F) = E_G^{(n+1)}(F)$$

Morphological reconstruction

- Sometimes it is necessary to retain only a subset of the connected components of the foreground data:
 - Retain only the regions of X that include the red marker Y
- This is obtained by the morphological reconstruction by dilation of the set X by the marker Y:
$$REC_X^D(Y)$$



Morphological reconstruction

- The morphological reconstruction can be used for different purposes
- The result of its application depends on the marker, the mask and the SE (to encode the connectivity)
- If the marker is obtained by iteratively eroding the mask, the **open by reconstruction of size n** operator is defined:
 - This restores only those parts of the mask that remain after iterating the erosion by B

$$O_R^n(F) = REC_F^D(E(F, nB))$$

where $E(F, nB)$ is the iterated (n times) erosion of F by B

Morphological reconstruction

- Can we define a fully automatic procedure for filling all the holes that are present in image regions?
- Let I be the image that we want to process for hole filling



Morphological reconstruction

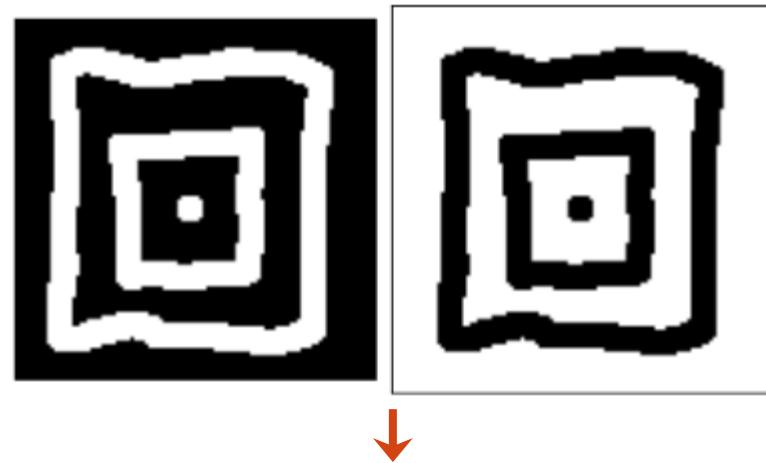
- Can we define a fully automatic procedure for filling all the holes that are present in image regions?
- Let I be the image that we want to process for hole filling
- Let the marker F be defined as 0 everywhere except at the image border where it is set to $1 - I$

$$F(x, y) = \begin{cases} 1 - I(x, y) & \text{if } (x, y) \text{ is on the border} \\ 0 & \text{otherwise} \end{cases}$$

- The result of $[REC_{I^c}^D(F)]^c$ is a binary image equal to I with all holes filled

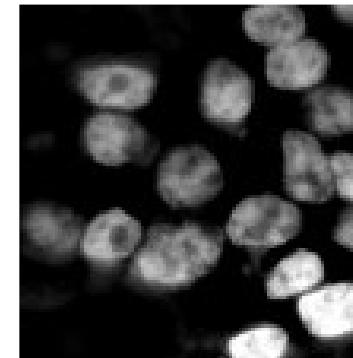
Morphological reconstruction

- How this procedure expected to operate on the following two images?

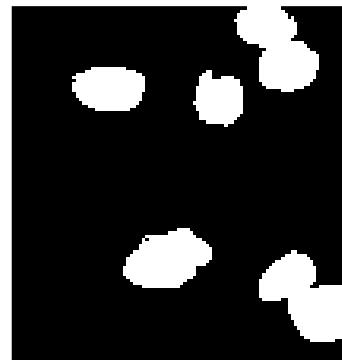
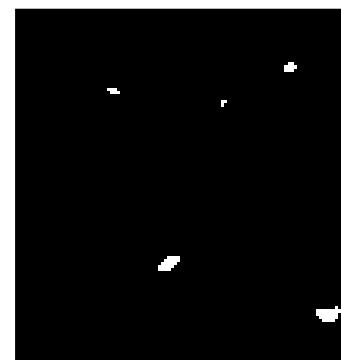
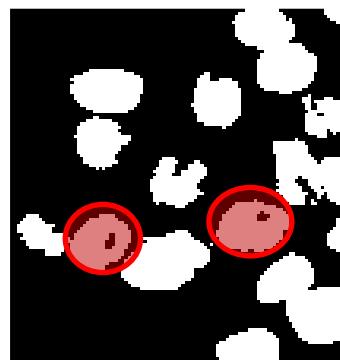


Morphological reconstruction

- How could we process the image so as to retain all the cells that are larger than a disk of radius 7 ?
 - `img_bw = im2bw(img, graythresh(img));`
 - `se = strel('disk',7);`
 - `img_eroded = imerode(img_bw,se);`
 - `img_reco = imreconstruct(img_eroded, img_bw);`



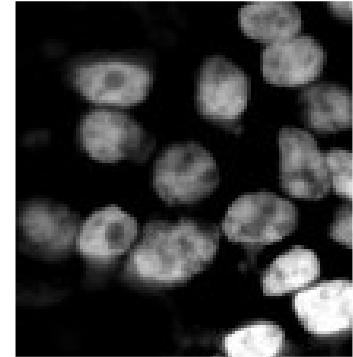
Notice that regions with one or more holes have been discarded: perform hole filling before open by reconstruction...



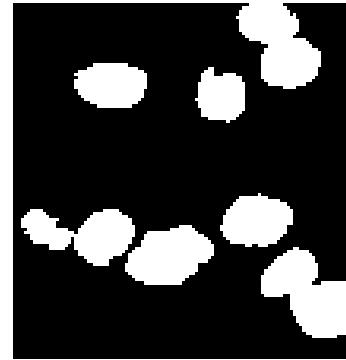
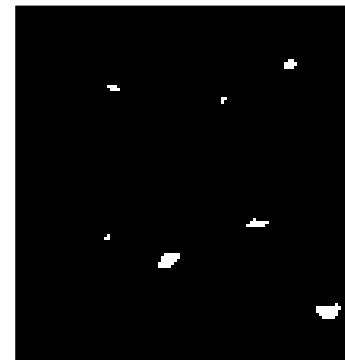
Morphological reconstruction

- How could we process the image so as to retain all the cells that are larger than a disk of radius 7 ?

```
➤ img_bw = im2bw(img, graythresh(img));  
➤ se = strel('disk',7);  
➤ img_noholes = imfill(img_bw, 'holes');  
➤ img_eroded = imerode(img_noholes,se);  
➤ img_reco = imreconstruct(img_eroded, img_noholes);
```



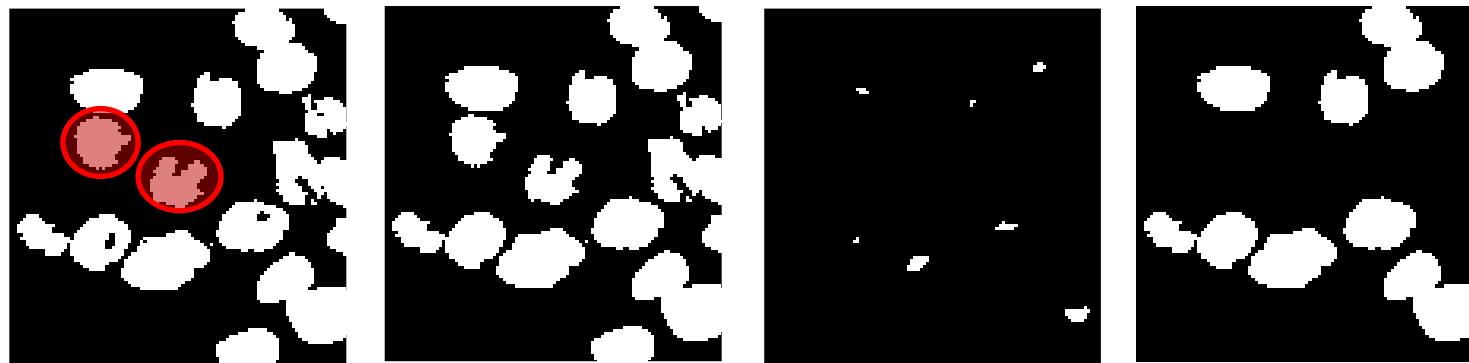
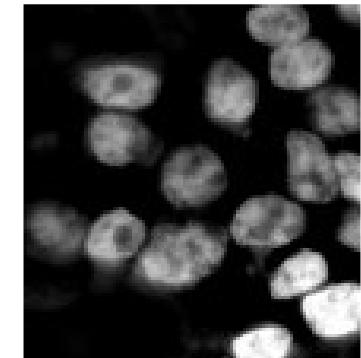
If img_bw is used as mask, regions are reconstructed with their holes inside



Morphological reconstruction

- How could we process the image so as to retain all the cells that are larger than a disk of radius 7 ?

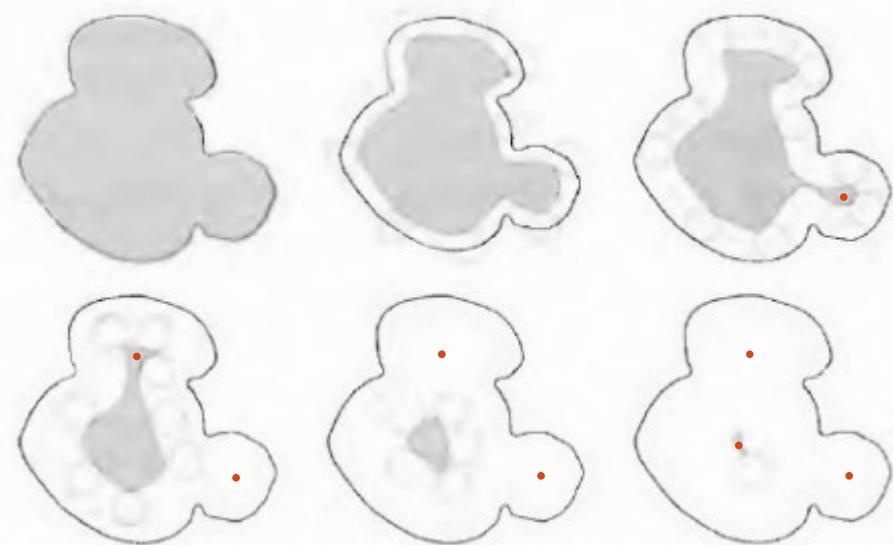
Notice that due to the results of thresholding (that removes some dark parts of the cells) some blobs are discarded although they are larger than a disk of radius 7



Ultimate erosion

- The **ultimate erosion** operator identifies a reduced set of seed points that support the reconstruction of region R (useful for robust marker selection)
- Consider the case of a region R that is iteratively eroded:

- At some steps, one connected component may originate disconnected parts
 - The **union of residuals** of all connected components (just before they disappear) identifies the ultimate erosion of the original region R

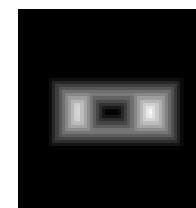
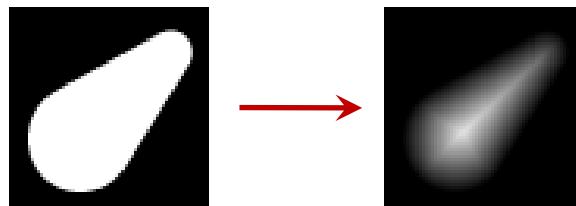
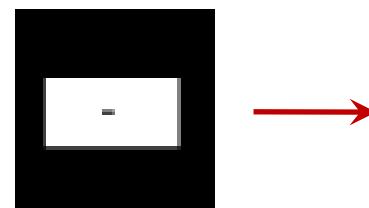
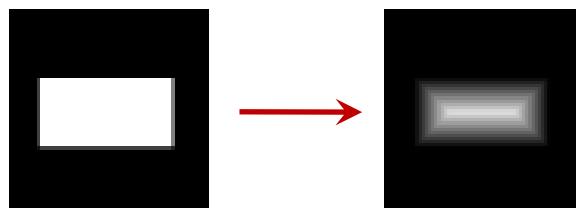


Distance transform

- In many cases it is necessary to apply the erosion operator iteratively (i.e. open by reconstruction of size n)
- A convenient way to perform this computation efficiently is through the **distance transform** operator

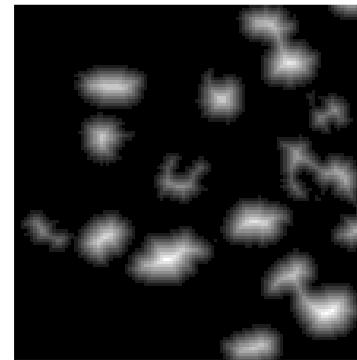
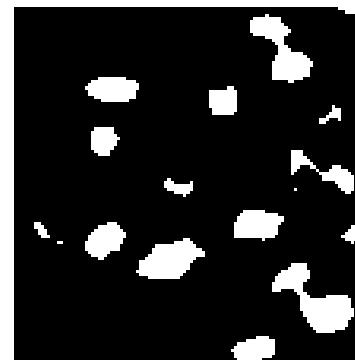
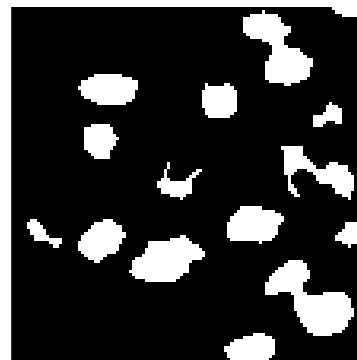
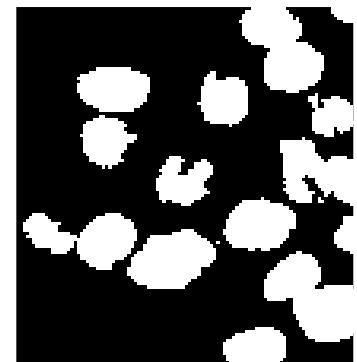
$$DT(A)[x] = \min_{y \in A^C} \|x - y\|$$

- The distance transform is a function that returns for each point $x \in A$ the distance to the nearest point in A^C



Distance transform

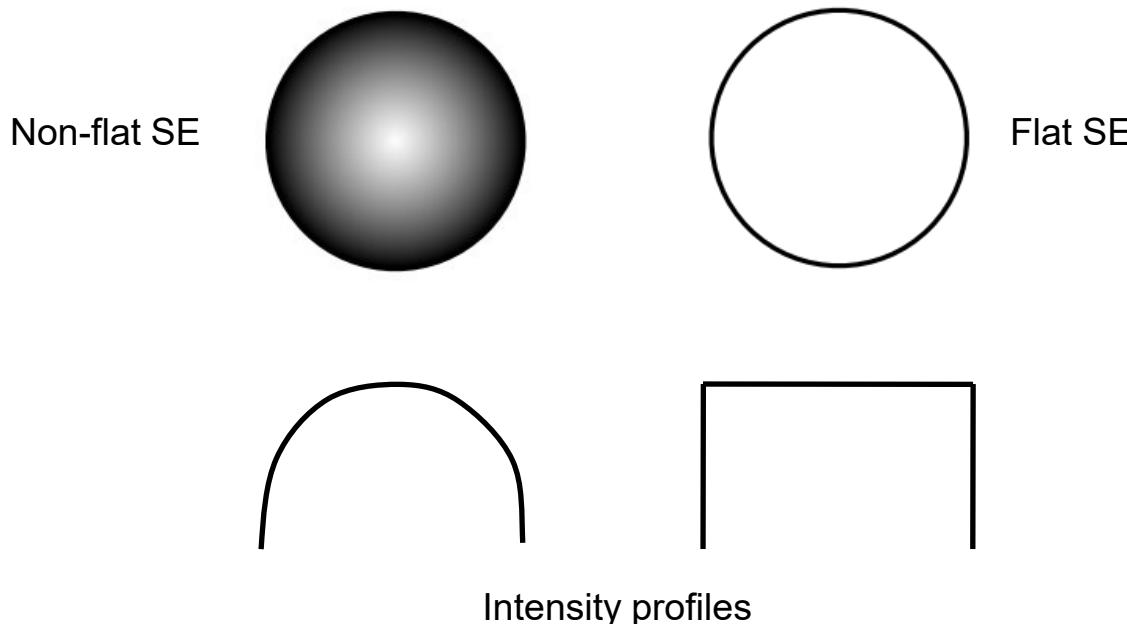
- Using the distance transform, the iterated application of erosion can be computed by simple thresholding
- Local maxima of the distance transform of a region R represent the ultimate erosion of R



LATTICE MORPHOLOGY

Introduction

- Morphological operators defined for binary images can be extended to operate on graylevel images
- Although in its most general form the framework allows also the structuring element to have graylevel values, we will focus on the case of **flat** (binary) SE



Erosion and dilation

- Let b a SE and $S(b)$, its support, the set of points (u,v) such that $b(u,v)=1$
- **Erosion** of $f(x,y)$ by b :

$$E(f,b)[x,y] = \min_{(u,v) \in S(b)} \{f(x+u, y+v)\}$$

- **Dilation** of $f(x,y)$ by b :

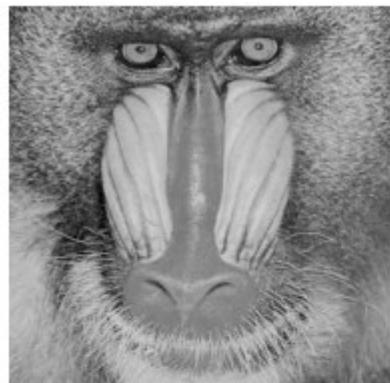
The minus sign accounts for the reflection of $b = b(-x,-y)$

$$D(f,b)[x,y] = \max_{(u,v) \in S(b)} \{f(x-u, y-v)\}$$

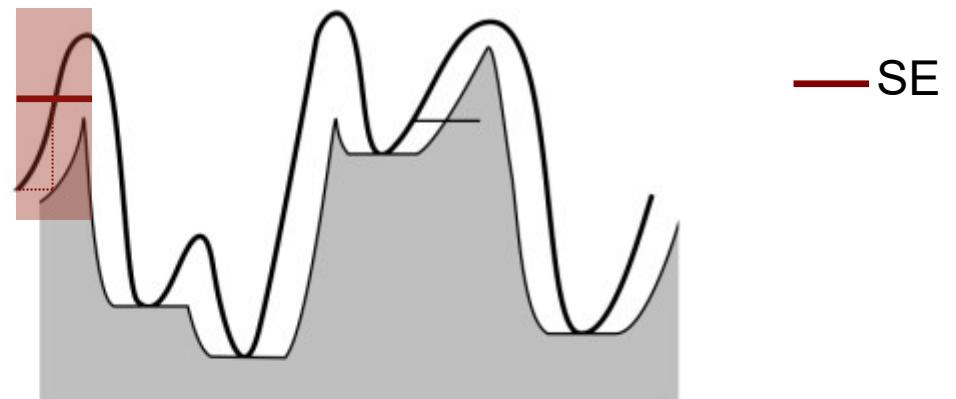
In case F is a binary image these definitions are consistent with binary operators

Erosion and dilation

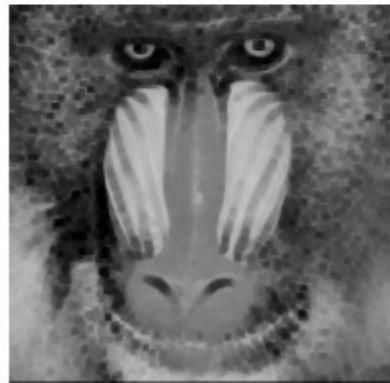
- The eroded image is darker than the original



f



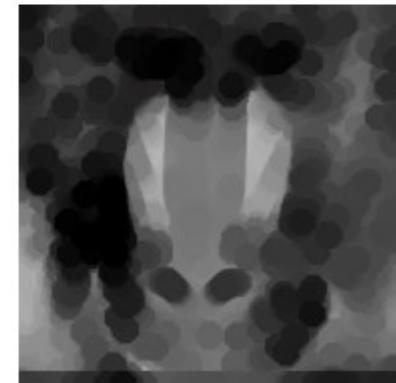
— SE



$f \ominus g_{D_3}$



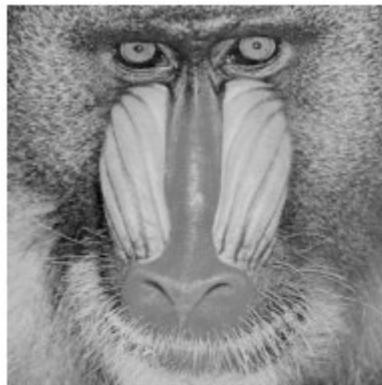
$f \ominus g_{D_5}$



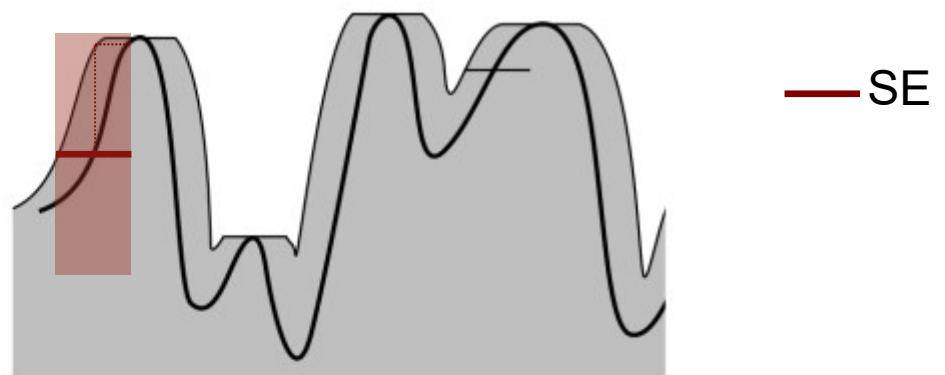
$f \ominus g_{D_{11}}$

Erosion and dilation

- The dilated image is lighter than the original



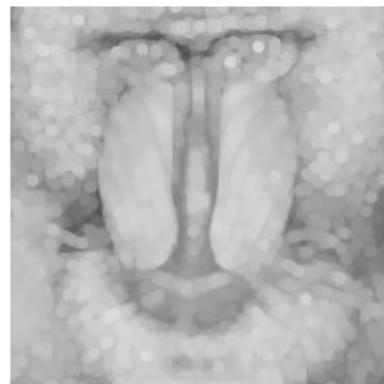
f



— SE



$f \oplus g_{D_3}$



$f \oplus g_{D_5}$



$f \oplus g_{D_{11}}$

Morphological gradient

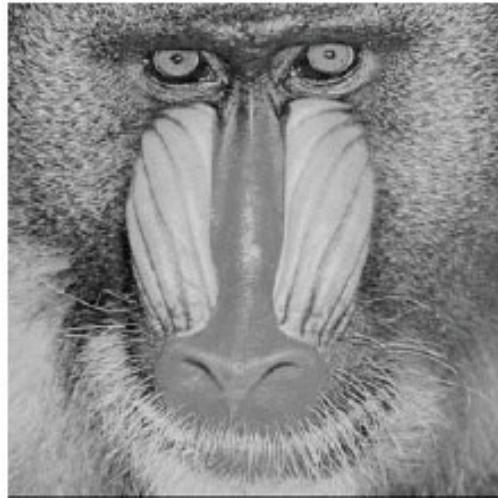
- Dilation and erosion can be combined to obtain the morphological gradient of an image

$$Gr(f,b) = D(f,b) - E(f,b)$$

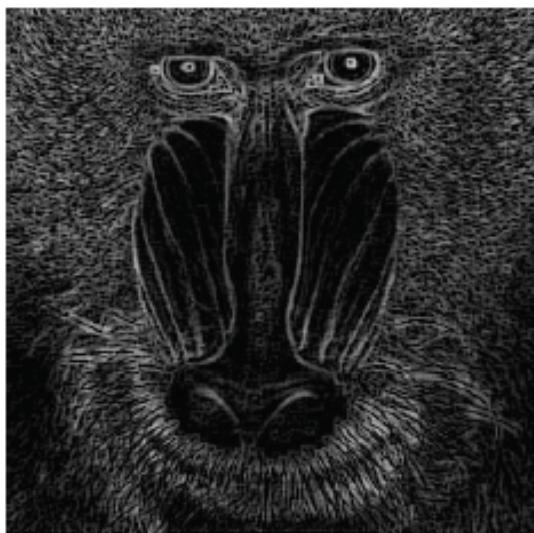
- The dilation thickens image regions whereas the erosion shrinks them
 - Homogeneous regions are not affected, hence they are removed by the difference
 - As a result, edges are enhanced and homogeneous regions suppressed

Compared to the binary operator,
the result is a grayscale image

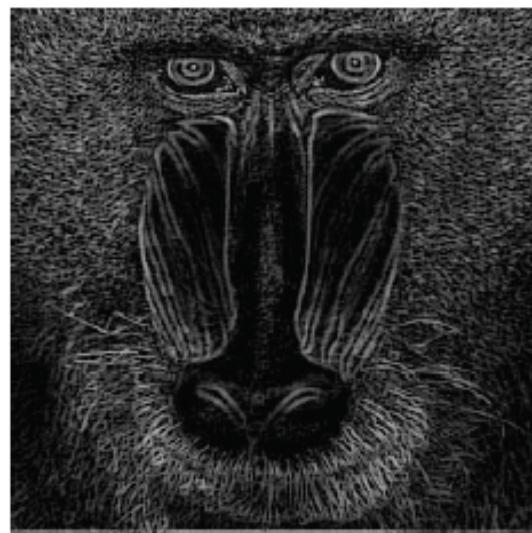
Morphological gradient



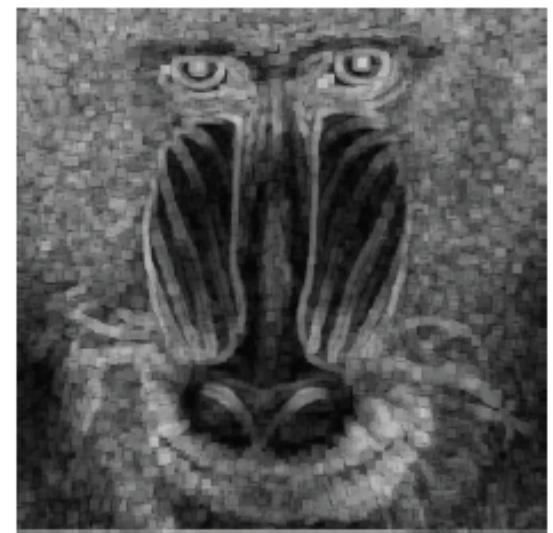
f



$(f \oplus g_{D_3}) - f$



$f - (f \ominus g_{D_3})$



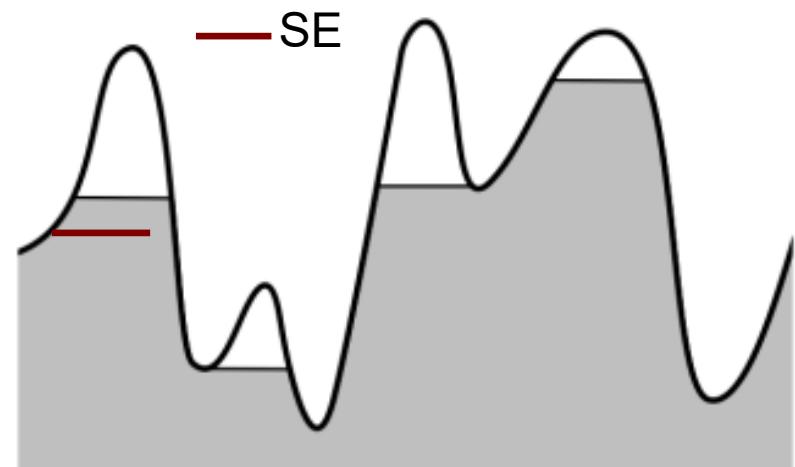
$(f \oplus g_{D_3}) - (f \ominus g_{D_3})$

Beyond erosion and dilation

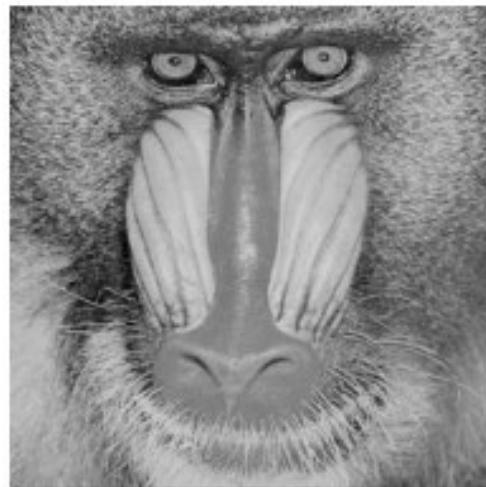
- Erosion and dilation can be used in combination to yield the opening and closing operators
- **Opening** of f by b : $f \circ b = D(E(f,b),b)$
- **Closing** of f by b : $f \bullet b = E(D(f,b),b)$

Opening

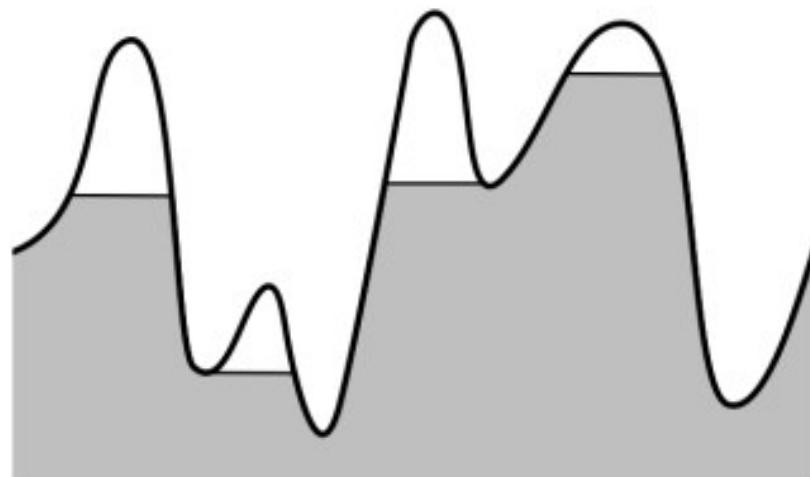
- Suppose that $f(x,y)$ is viewed as a surface in 3D
- Opening of f by b can be viewed as pushing b up from below against the undersurface of f
- Opening removes small (smaller than b) bright details leaving the overall intensity and larger bright areas unaltered



Opening



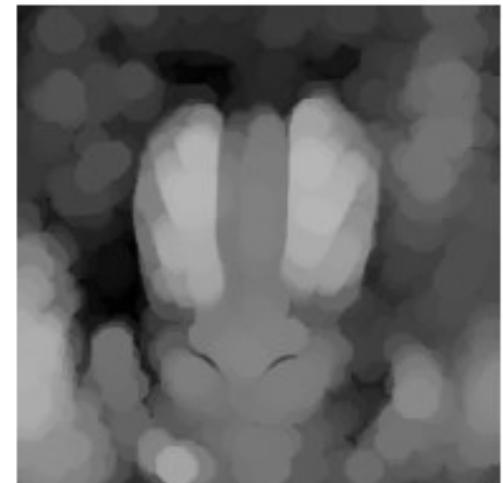
f



$f \circ g_{D_3}$

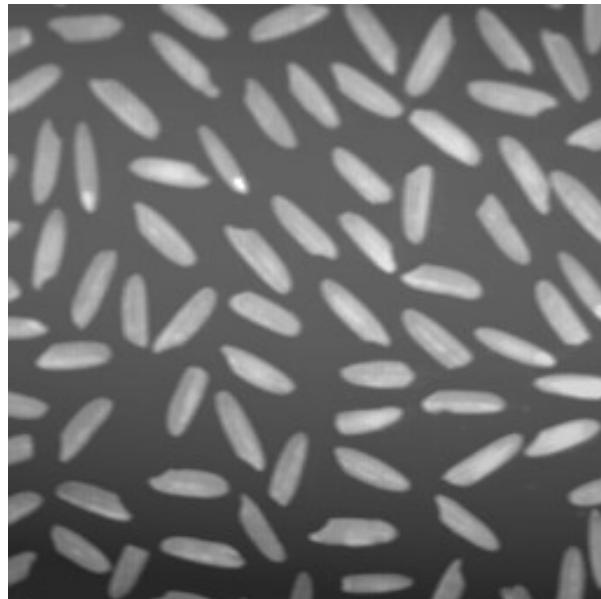


$f \circ g_{D_5}$

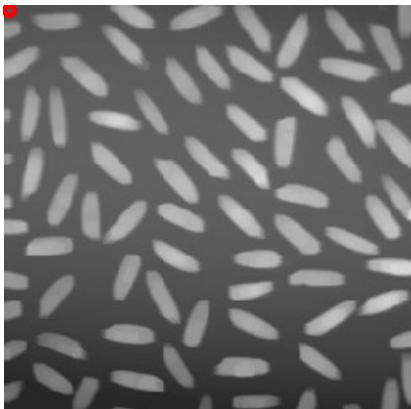


$f \circ g_{D_{11}}$

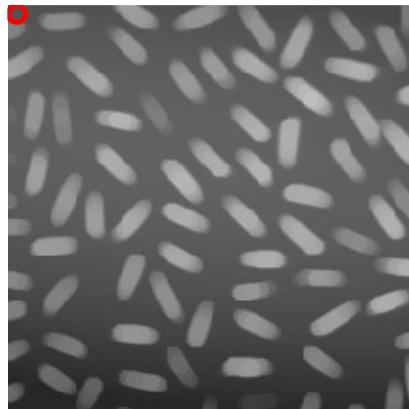
Opening



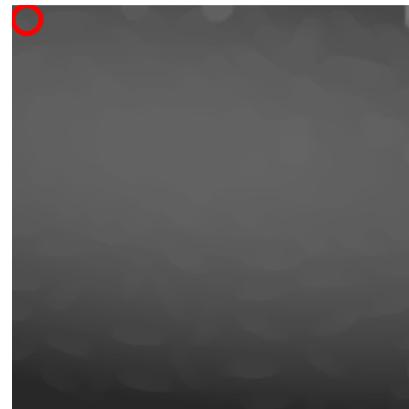
Radius 3



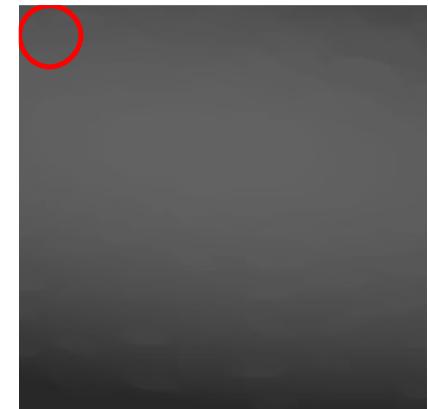
Radius 5



Radius 9

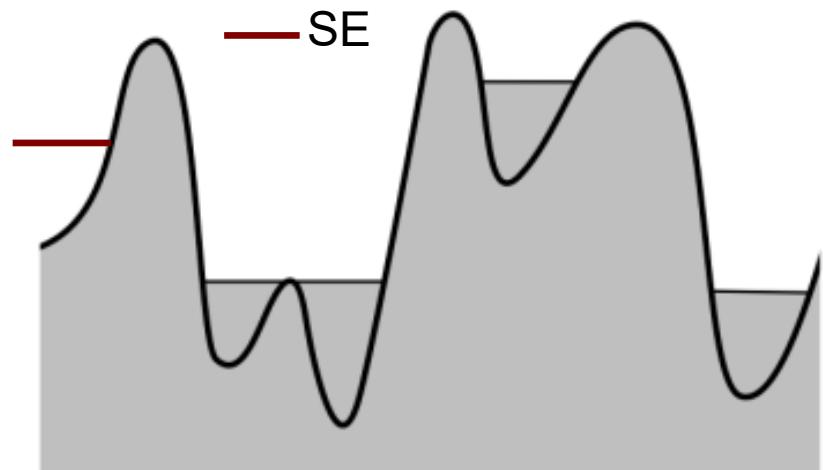


Radius 19

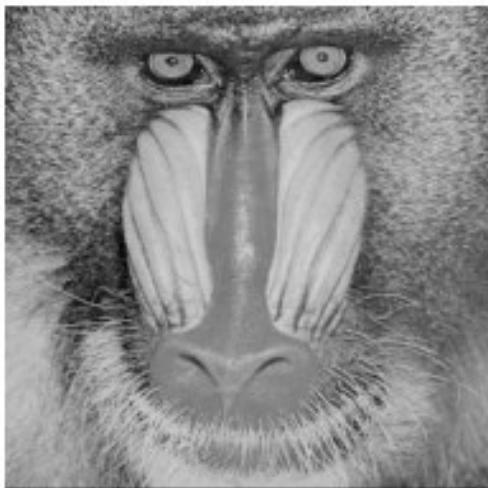


Closing

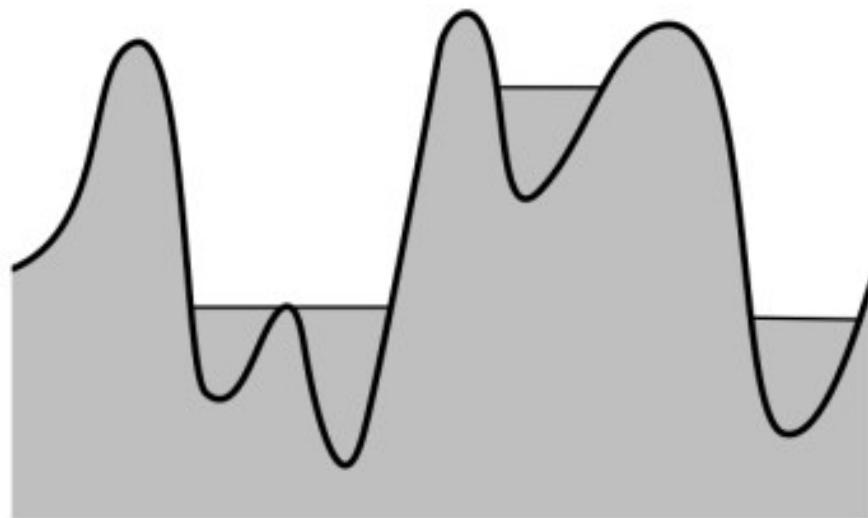
- Closing of f by b can be viewed as pushing b down over the surface of f
- Closing removes small (smaller than b) dark details leaving the overall intensity and larger dark areas unaltered



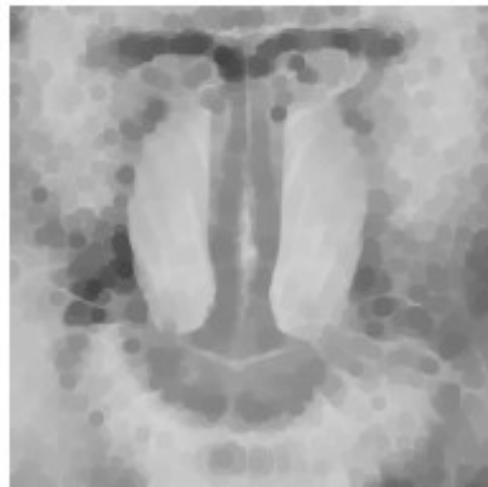
Closing



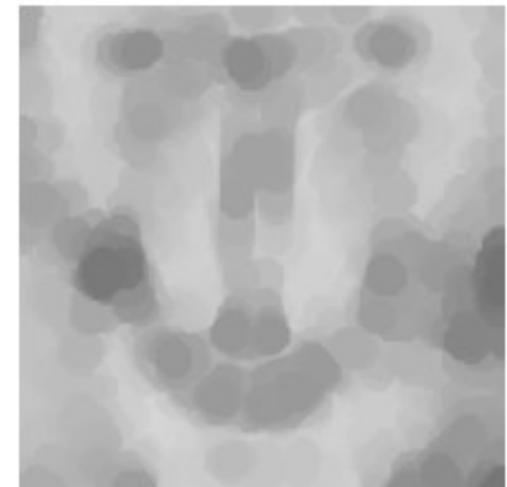
f



$f \bullet g_{D_3}$

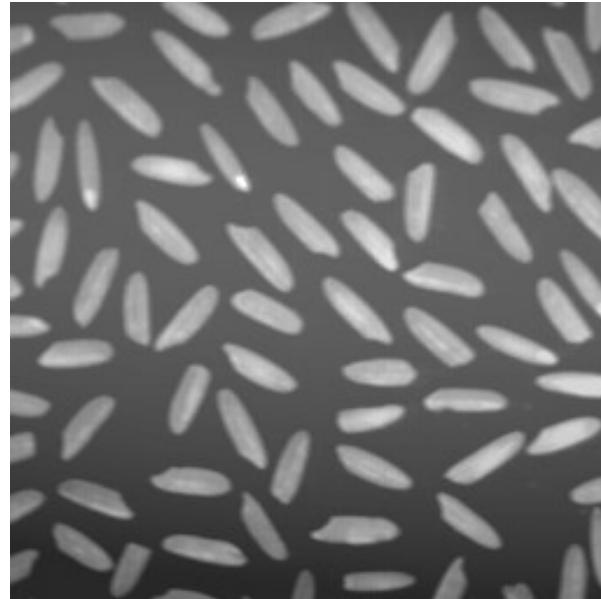


$f \bullet g_{D_5}$



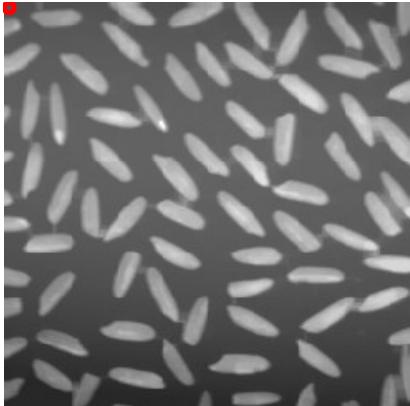
$f \bullet g_{D_{11}}$

Closing

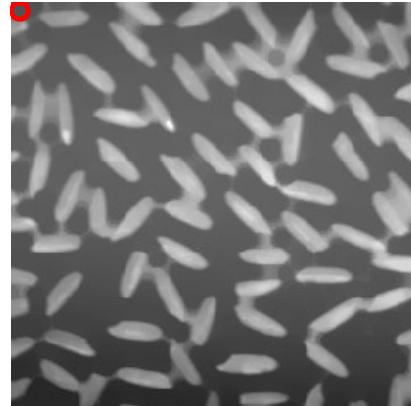


Does not seem to
be really useful...
However, for
images with dark
FG over light BG...

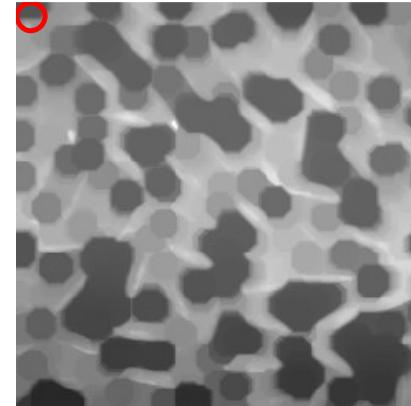
Radius 3



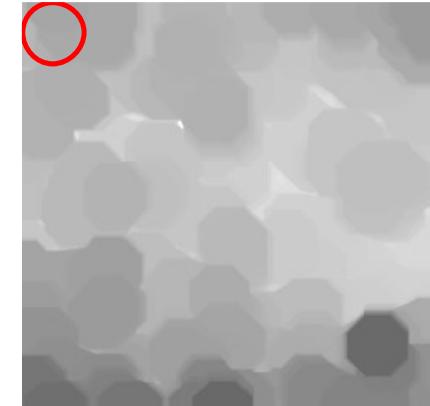
Radius 5



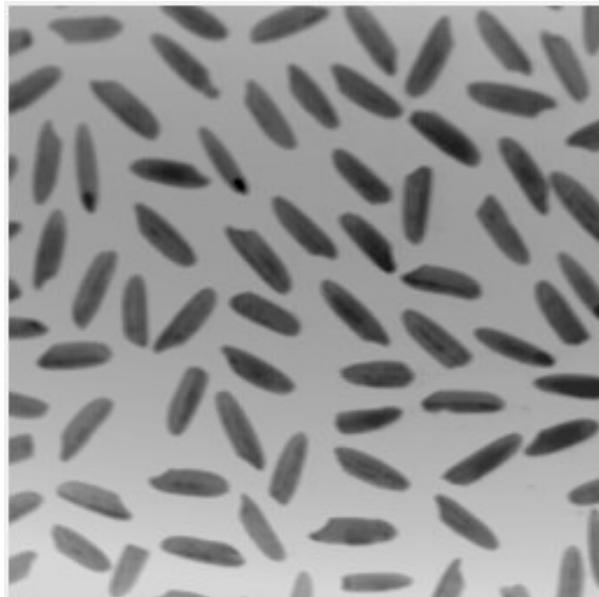
Radius 9



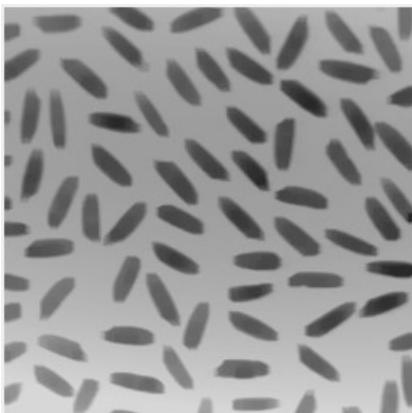
Radius 19



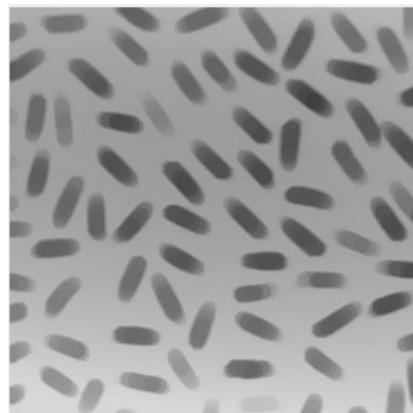
Closing



Radius 3



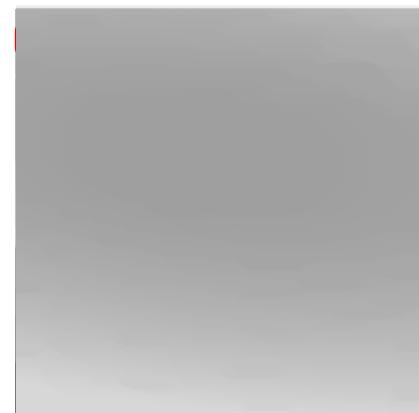
Radius 5



Radius 9



Radius 19



Duality

- Erosion and dilation for grayscale images are dual wrt function complementation and reflection of the SE

$$E(f, b)^C = D(f^C, \hat{b})$$

$$D(f, b)^C = E(f^C, \hat{b})$$

- The same holds for opening and closing

$$(f \circ b)^C = f^C \bullet \hat{b}$$

$$(f \bullet b)^C = f^C \circ \hat{b}$$

Top hat and bottom hat

- The residual of opening compared to the original image represents the **top hat** operator:

$$TH(f) = f - f \circ b$$

- Its dual, the **bottom hat** operator, is defined as the residual of the image after the closing is removed:

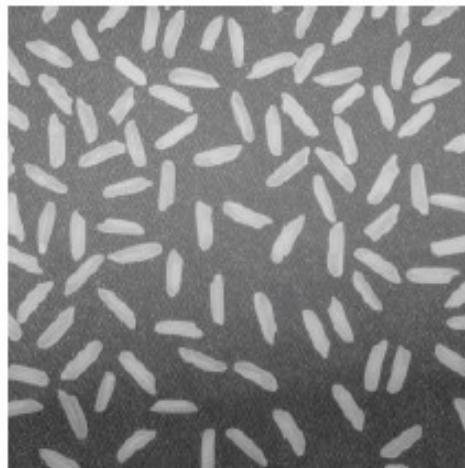
$$BH(f) = f \bullet b - f$$

- TopHat and BottomHat are sometimes referred to as **White TopHat** and **Black TopHat**, respectively

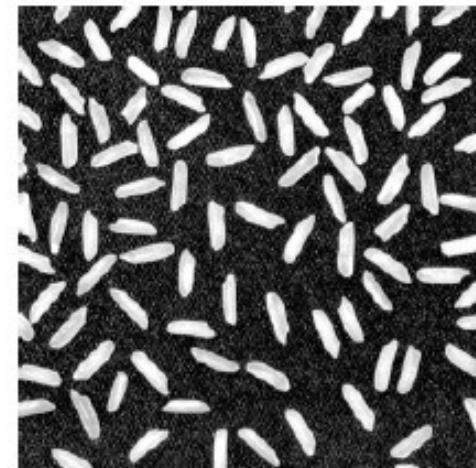
Top hat and bottom hat

- Top hat and bottom hat are used to **enhance the objects** in the image **that do not fit the SE**
 - Top hat enhances bright objects on dark background
 - Bottom hat enhances dark objects on bright background
- The size of the SE should be large enough so as **not to fit** the objects to be retained

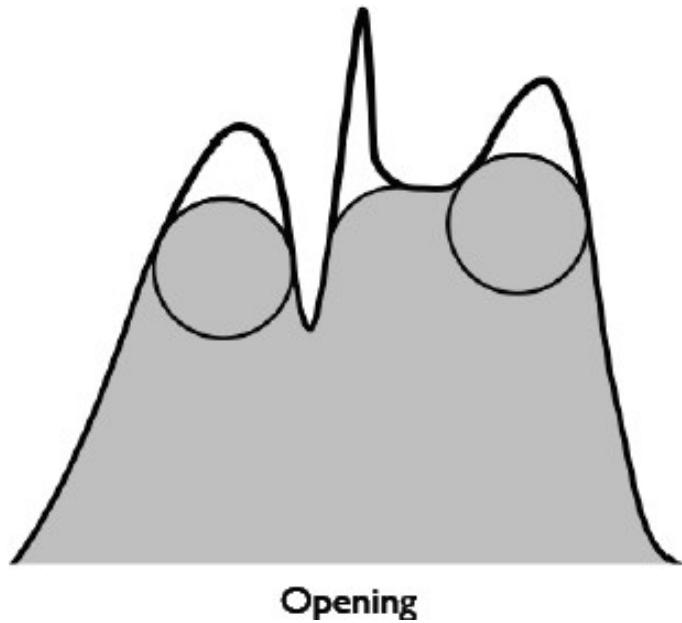
Top hat



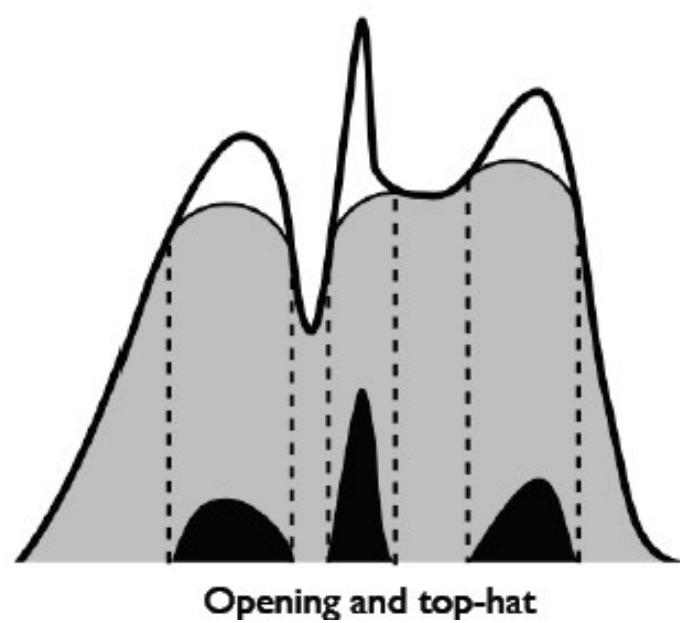
Original image



Top-hat $g_{D_{12}}$



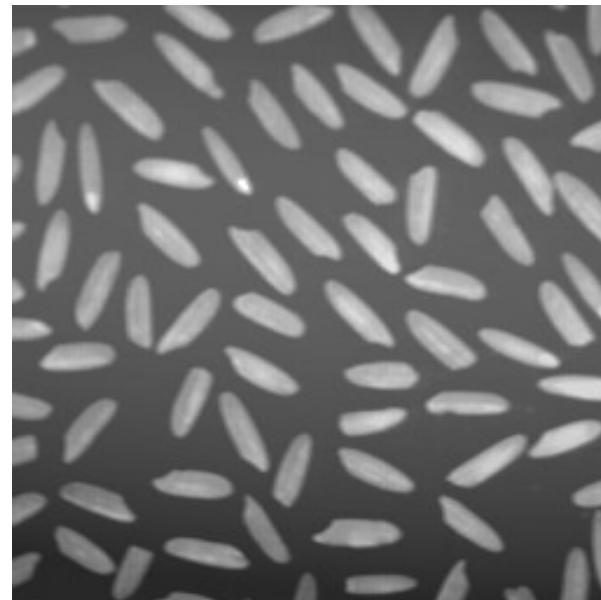
Opening



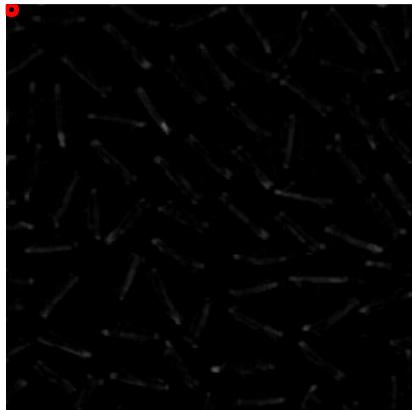
Opening and top-hat

Top hat

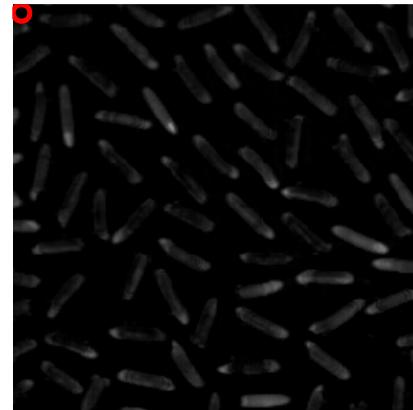
Original



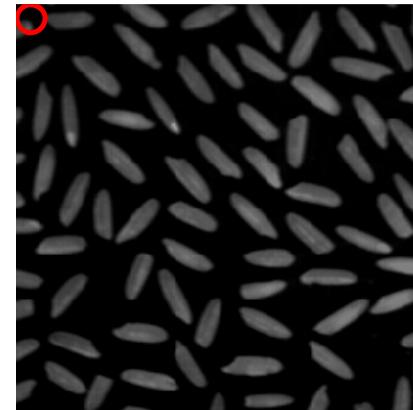
Radius 3



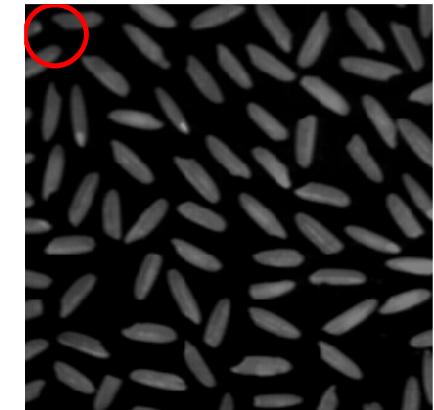
Radius 5



Radius 9

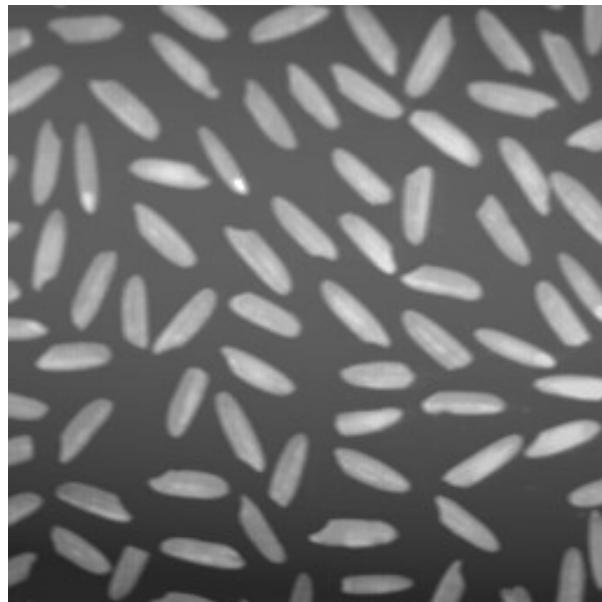


Radius 19

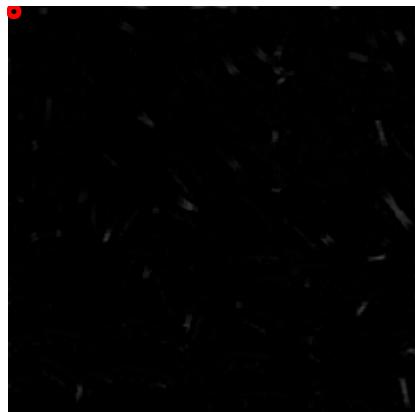


Bottom hat

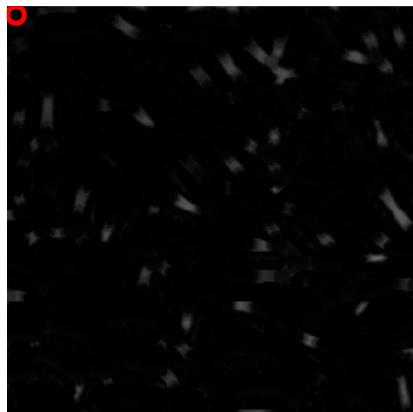
Original



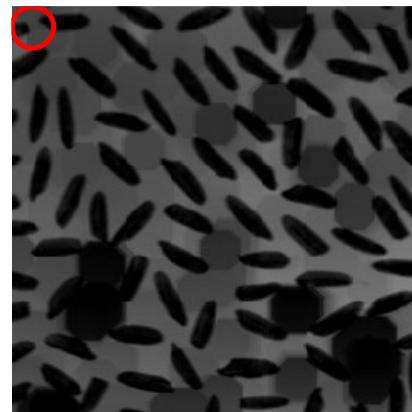
Radius 3



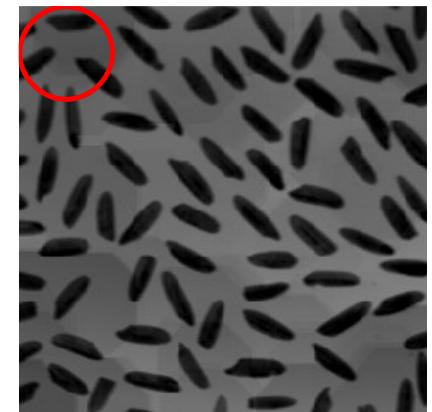
Radius 5



Radius 13

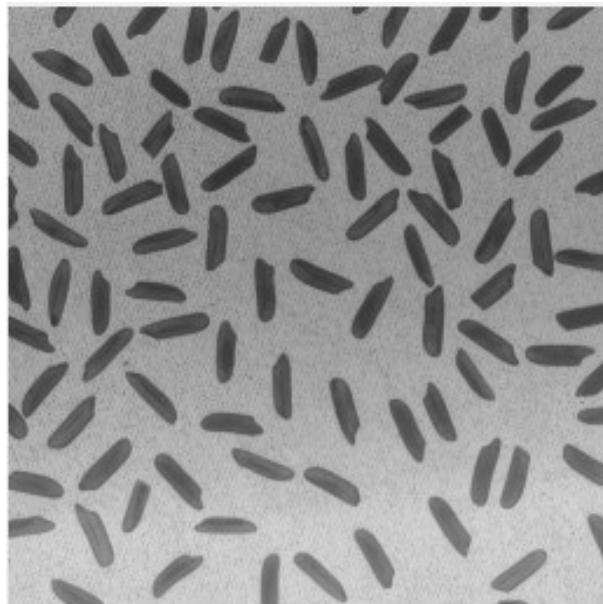


Radius 29

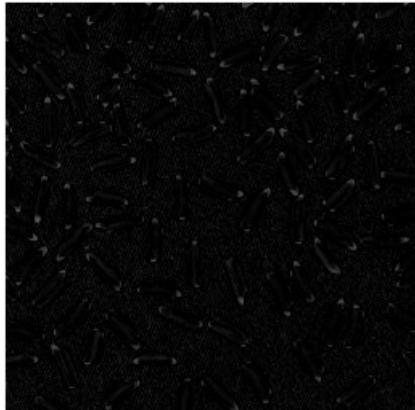


Bottom hat

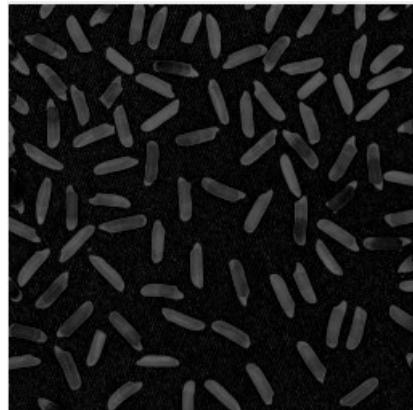
Original



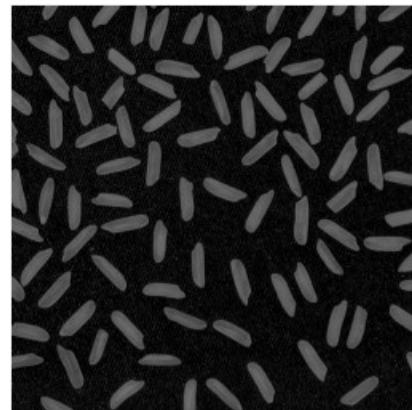
Radius 3



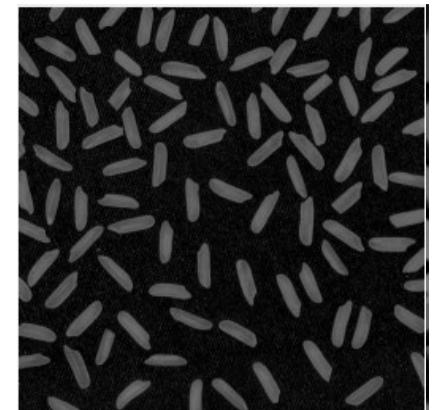
Radius 5



Radius 13



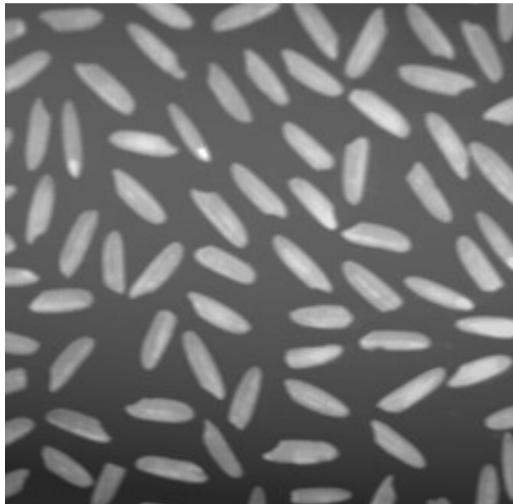
Radius 29



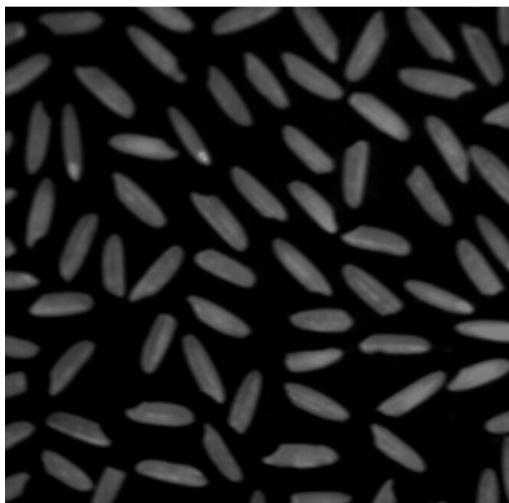
Top hat and bottom hat

- Top hat is frequently used to correct the effects of non uniform illumination
 - This is particularly convenient before applying a threshold

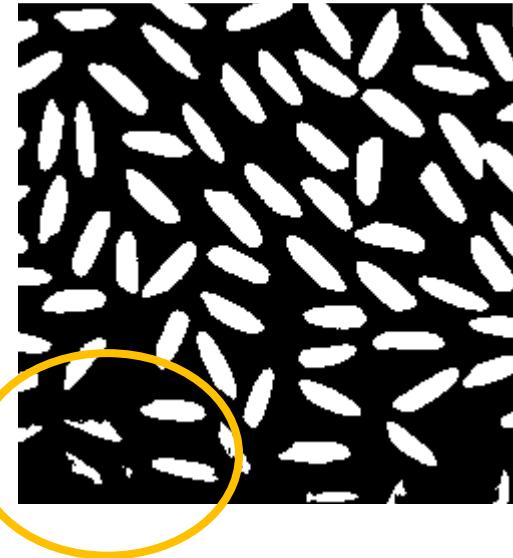
Top-hat for thresholding



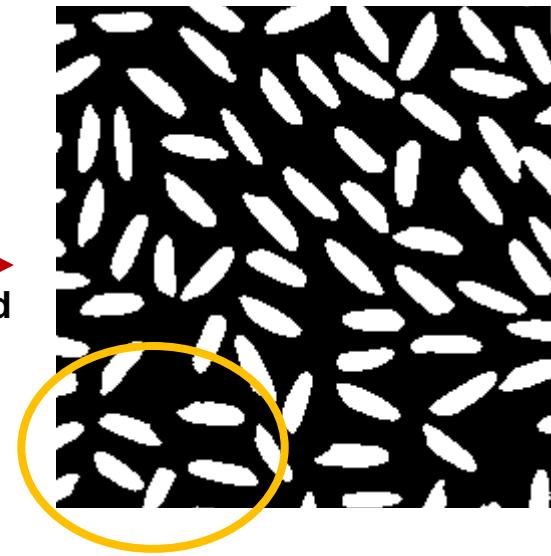
↓
Top-hat



→
Thresholded
using Otsu



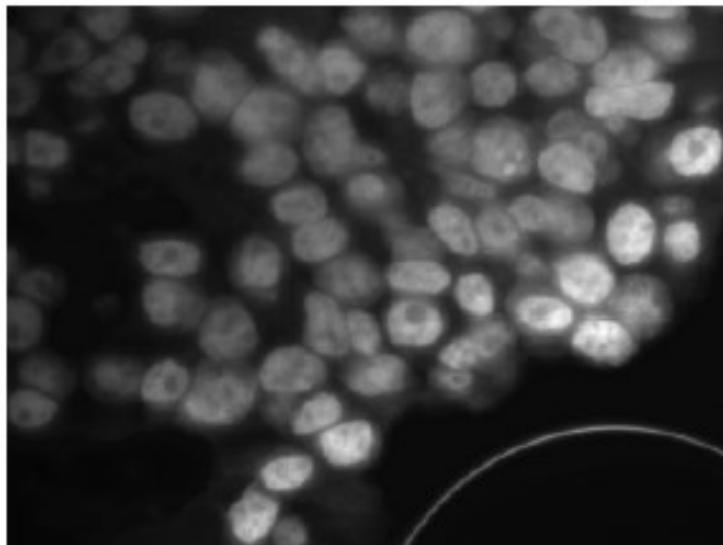
→
Thresholded
using Otsu



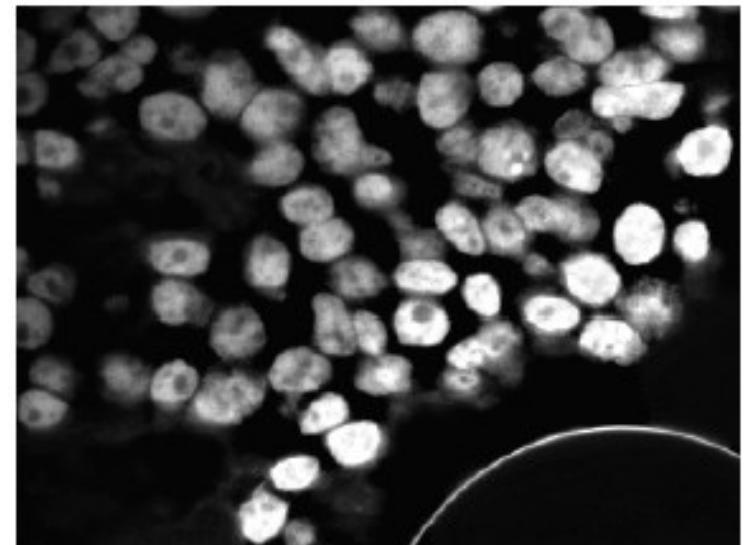
Morphological contrast enhancement

- To enhance image contrast we can add the top hat filtered image to the image and then subtract the bottom hat filtered image

$$CE(f,b) = f + TH(f,b) - BH(f,b)$$



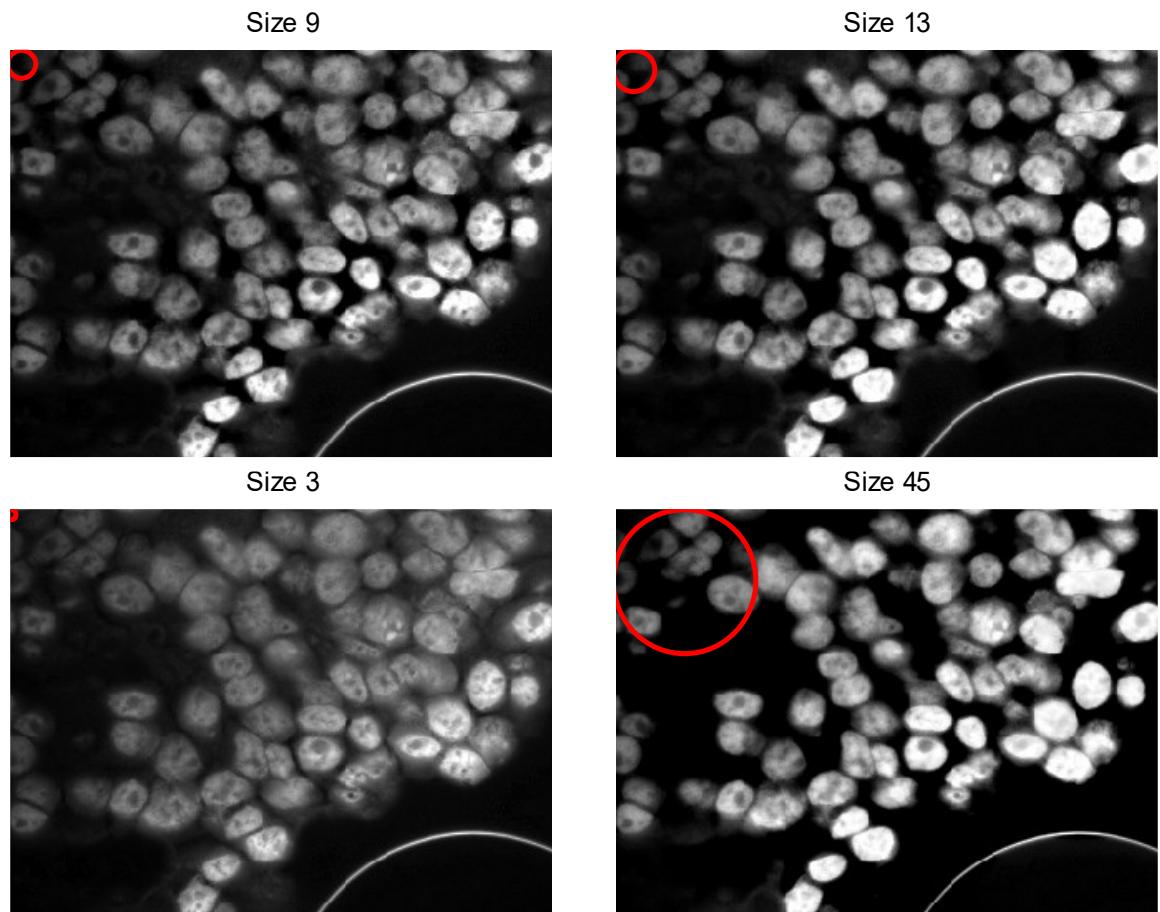
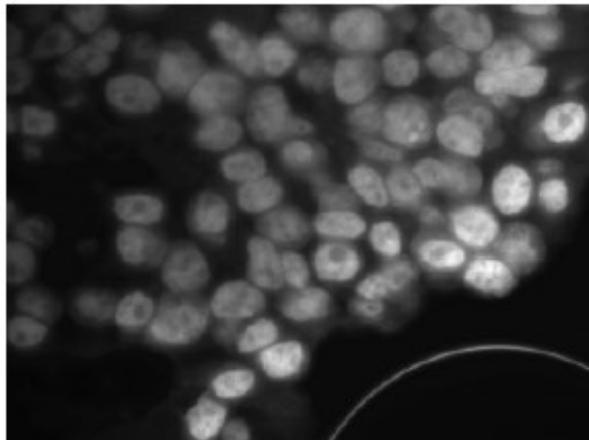
Original



Contrast enhanced

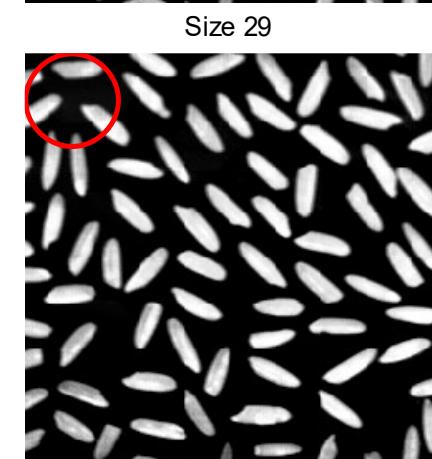
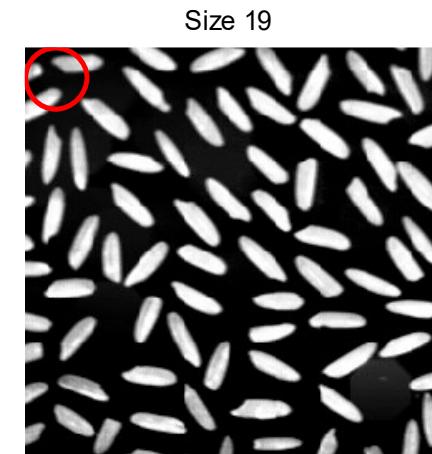
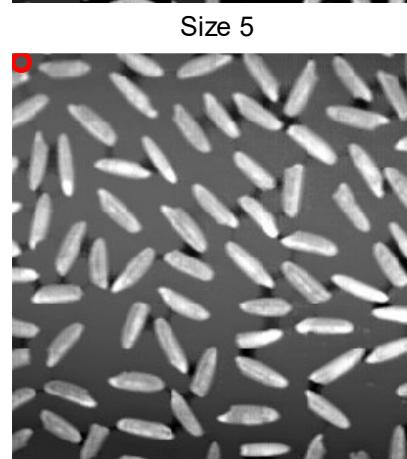
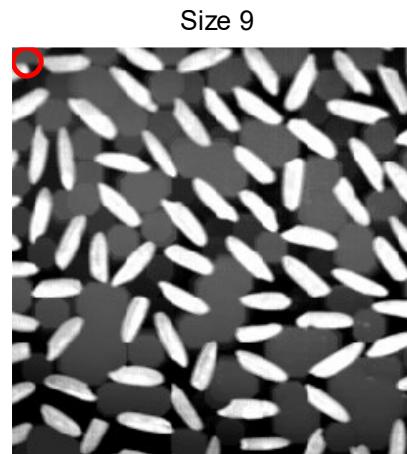
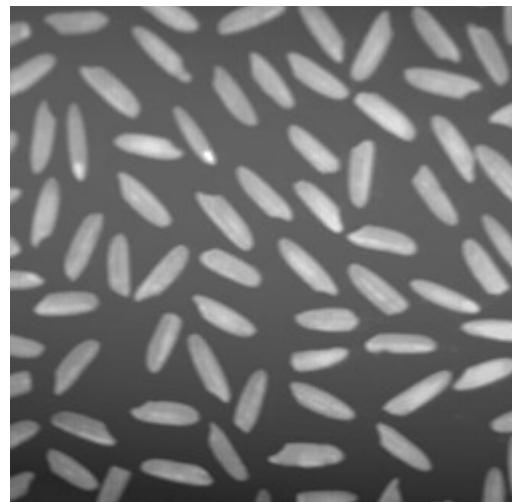
Morphological contrast enhancement

- b should be large enough not to be included in the largest image patch that we want to enhance



Morphological contrast enhancement

- b should be large enough not to be included in the largest image patch that we want to enhance



Morphological smoothing

- The combination of opening followed by closing is often effective for noise removal (particularly isolated noise)

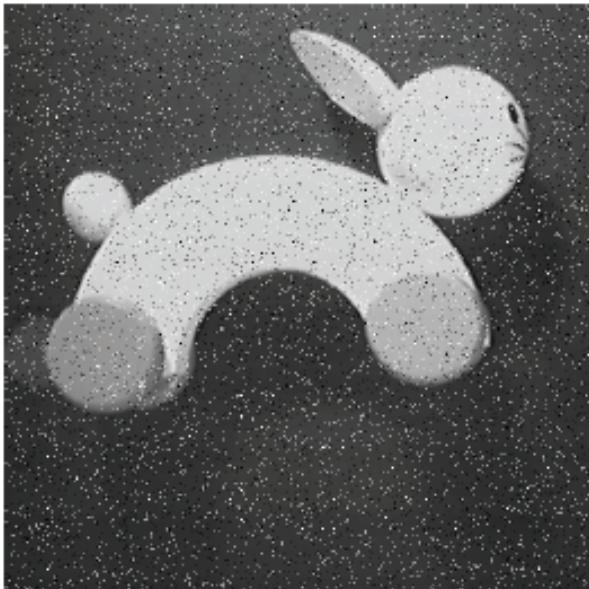
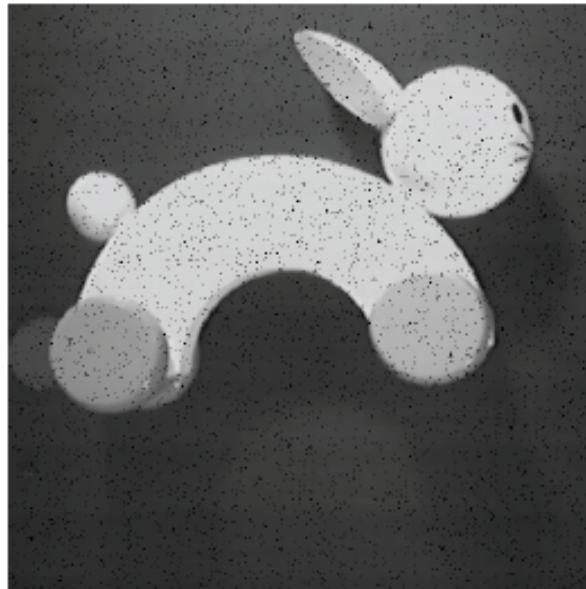
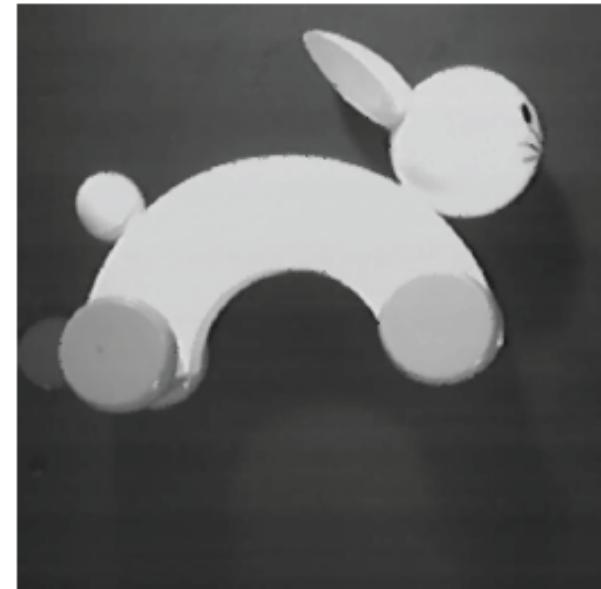


Image with salt-pepper noise



Opening



Closing

Geodesic dilation

- Grayscale morphological reconstruction extends the concepts defined for binary images
- Given a **marker** image f and a **mask** image g (same size) and such that $f \leq g$, the **geodesic dilation** of size 1 of f wrt g with SE b is

$$GD_g^1(f, b) = D(f, b) \wedge g$$

being \wedge the point-wise minimum operator (\vee the maximum)

Geodesic dilation

- Given a **marker** image f and a **mask** image g (same size) and such that $f \leq g$, the **geodesic dilation** of size n of f wrt g with SE b is

$$GD_g^n(f, b) = GD_g^1(GD_g^{n-1}(f, b), b)$$

with $GD_g^0(f, b) = f$

Geodesic erosion

- The **geodesic erosion** is defined similarly

$$GE_g^1(f, b) = E(f, b) \vee g$$

$$GE_g^n(f, b) = GE_g^1(GE_g^{n-1}(f, b), b)$$

with $GE_g^0(f, b) = f$

Morphological reconstruction

- The **morphological reconstruction by dilation** of a grayscale mask image g by a grayscale marker image f is the geodesic dilation of f wrt g iterated until stability

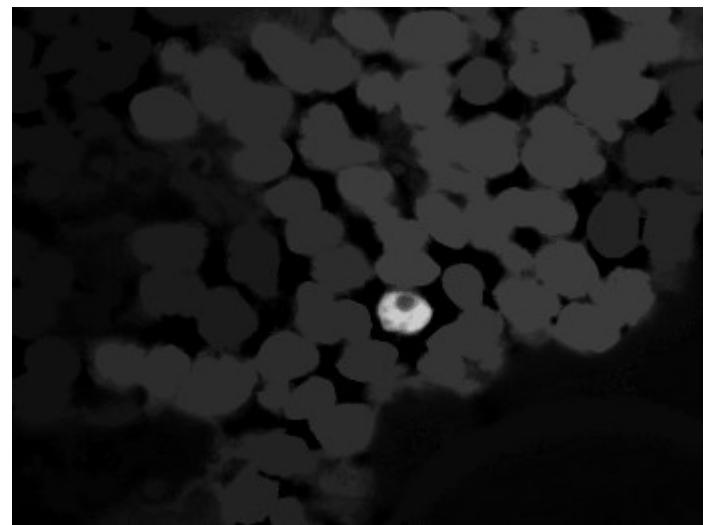
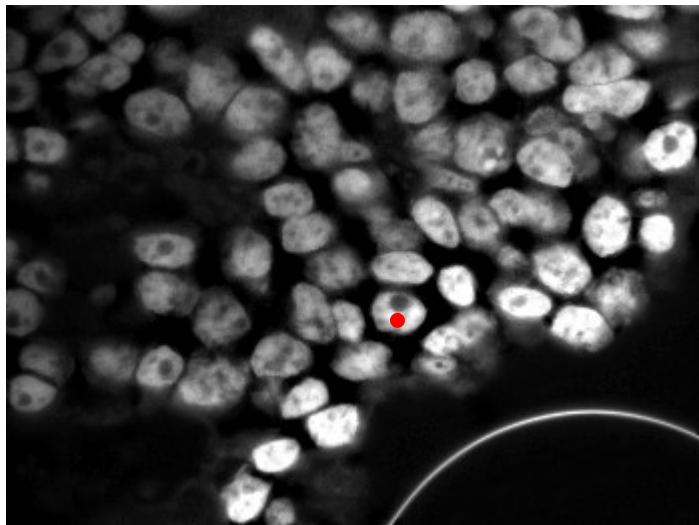
$$R_g^D(f, b) = GD_g^n(f, b)$$

such that $GD_g^n(f, b) = GD_g^{n+1}(f, b)$

- The **morphological reconstruction by erosion** is defined similarly

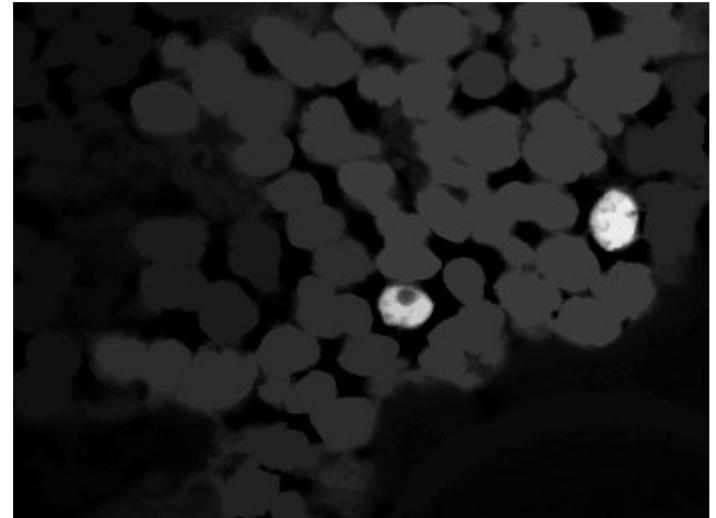
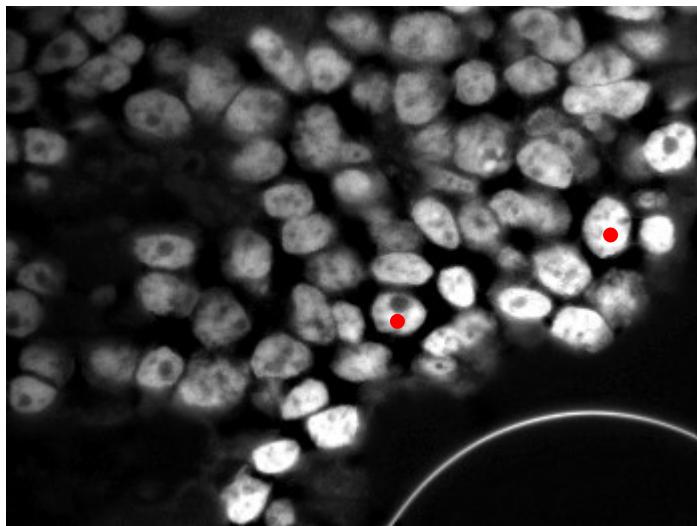
Morphological reconstruction

- Morphological reconstruction by dilation of the mask image shown below using as marker the red point



Morphological reconstruction

- Morphological reconstruction by dilation of the mask image shown below using as marker the two red points



Opening by reconstruction

- **Opening by reconstruction** of size n of a grayscale image f is the reconstruction by dilation of f from the erosion of size n of f

$$O_R^n(f, b) = R_f^D(E(f, nb), b)$$

being $E(f, nb)$ the result of n erosions of f by b

- As in the case of binary images, the goal of opening by reconstruction is to retain the image components that remain after erosion

Opening by reconstruction

- A useful technique is the **top-hat by reconstruction** consisting of subtracting from an image its opening by reconstruction

$$THbR^n(f, b) = f - O_R^n(f, b)$$

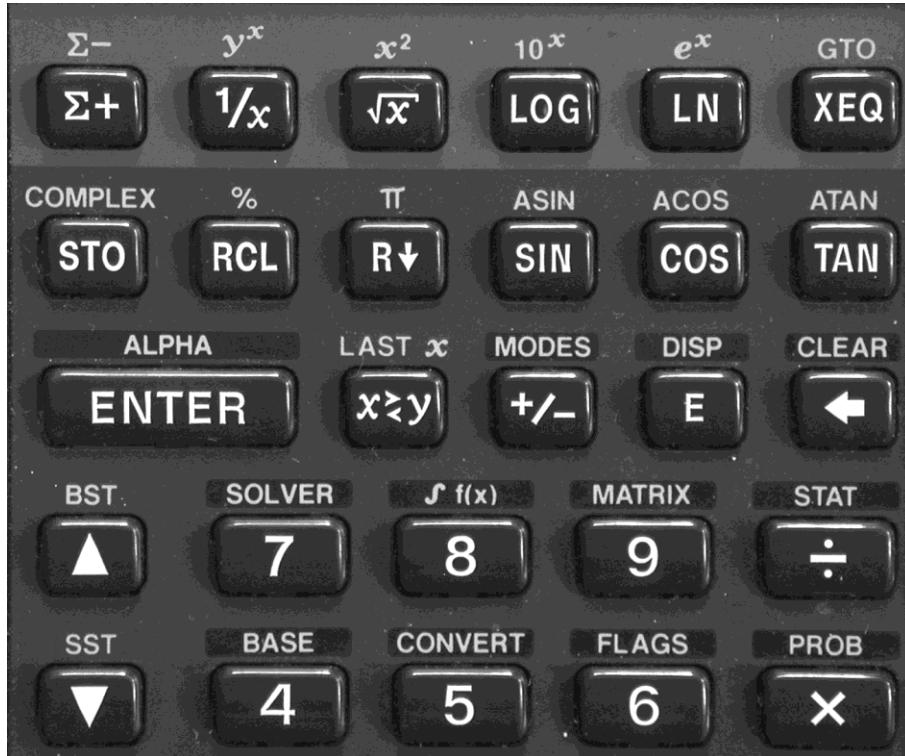
- This can be used to **remove noise of known form** from an image
 - Define a SE that fits the noise
 - Open by reconstruction using the SE so as to retain only the noise
 - Top-hat by subtracting the ObR to the original image

Opening by reconstruction

- **Open by reconstruction** and **top-hat by reconstruction** are adopted for two opposite goals:
 - There is a SE that fits the noise and does not fit the “interesting parts” of the image: apply THbR to the image with the SE
 - There is a SE that fits the “interesting parts” of the image and does not fit the noise: apply ObR to the image with the SE

An example

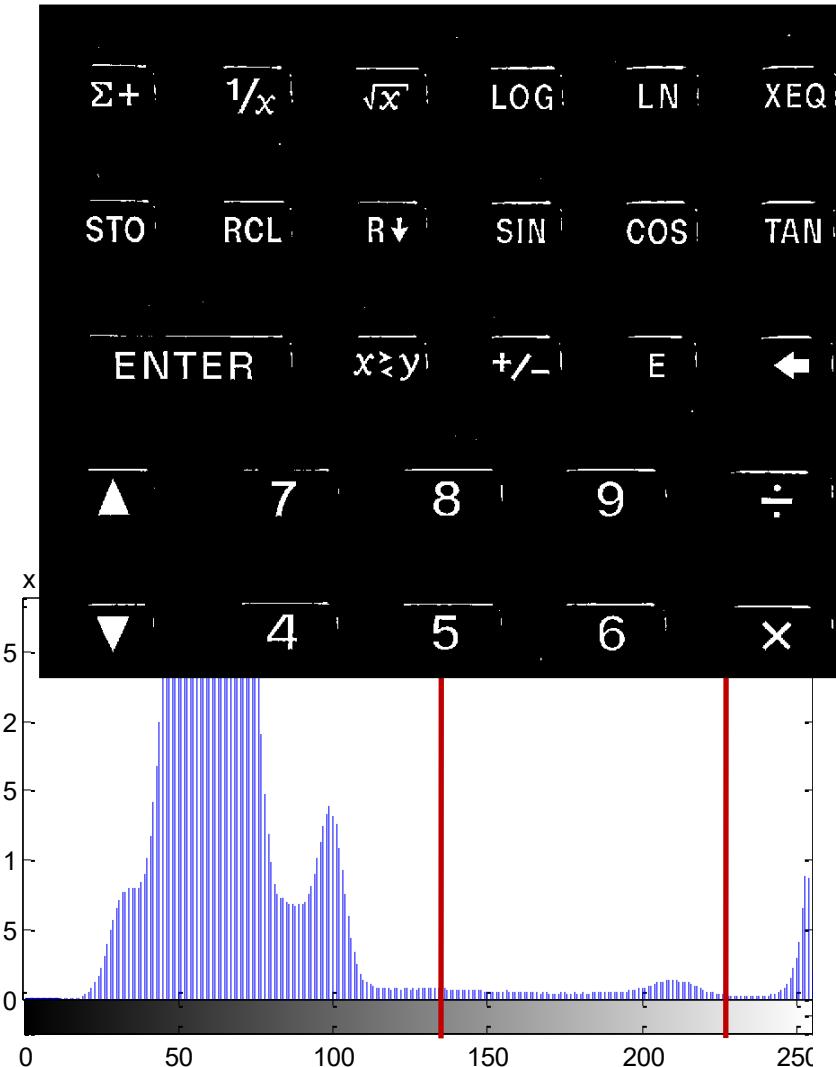
- We want to remove shading and reflection effects so as to retain only text/symbols useful to feed an OCR module



Noise: vertical
and horizontal
bright bars

An example

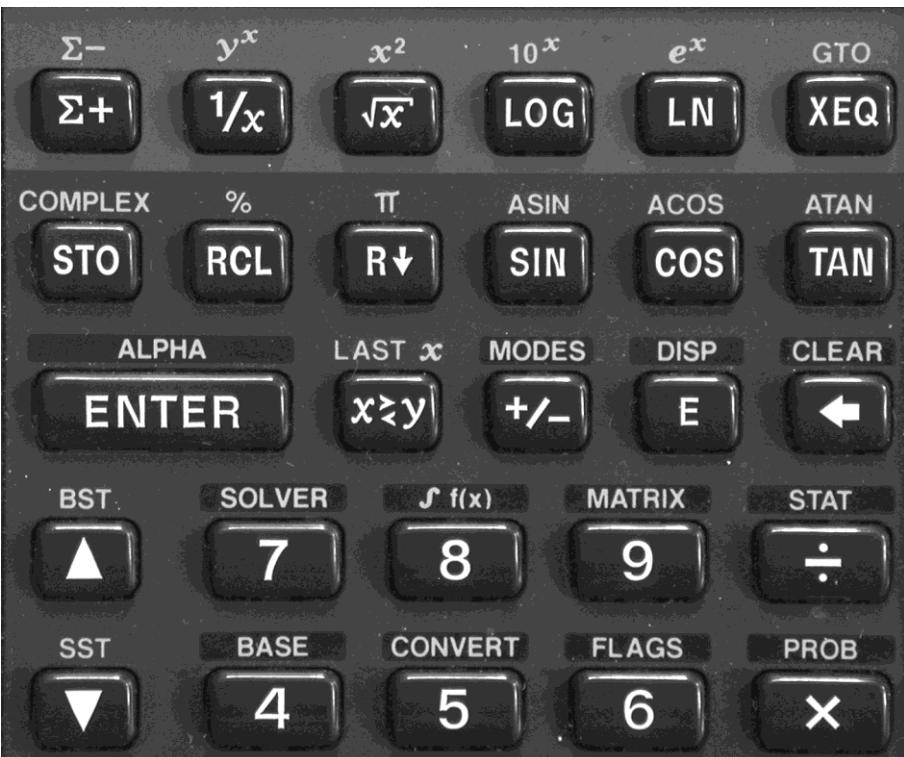
- Thresholding would not remove reflection effects ...



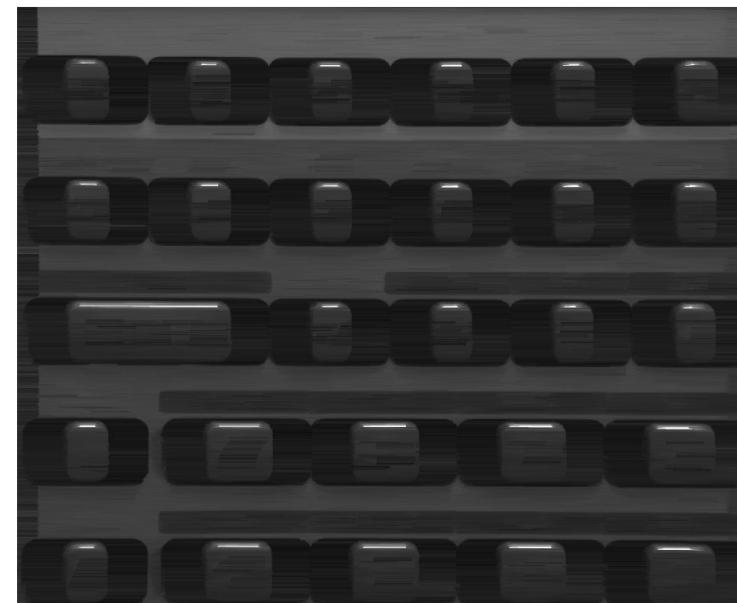
An example

- The first step is to remove horizontal reflections along the top of each key. These can be isolated through the open by reconstruction with a horizontal bar structuring element:

```
imreconstruct( imerode (img, ones(1,71) ), img));
```



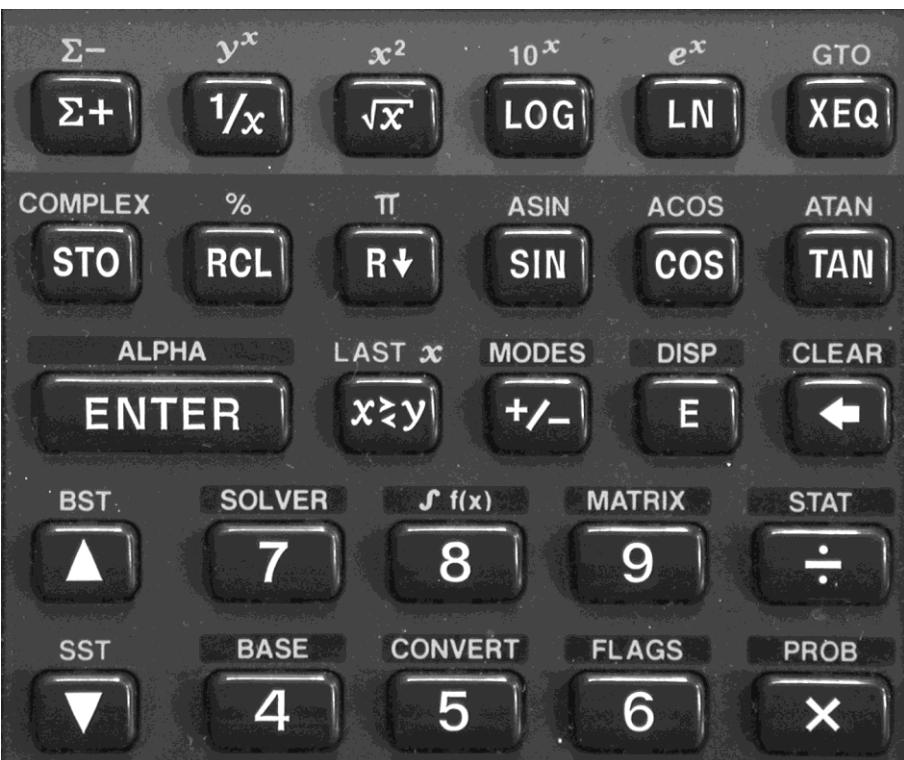
Slide one horizontal bar and replace the central pixel with the minimum



An example

- The first step is to remove horizontal reflections along the top of each key. These can be isolated through the open by reconstruction with a horizontal bar structuring element:

```
imreconstruct( imerode (img, ones(1,71) ), img));
```

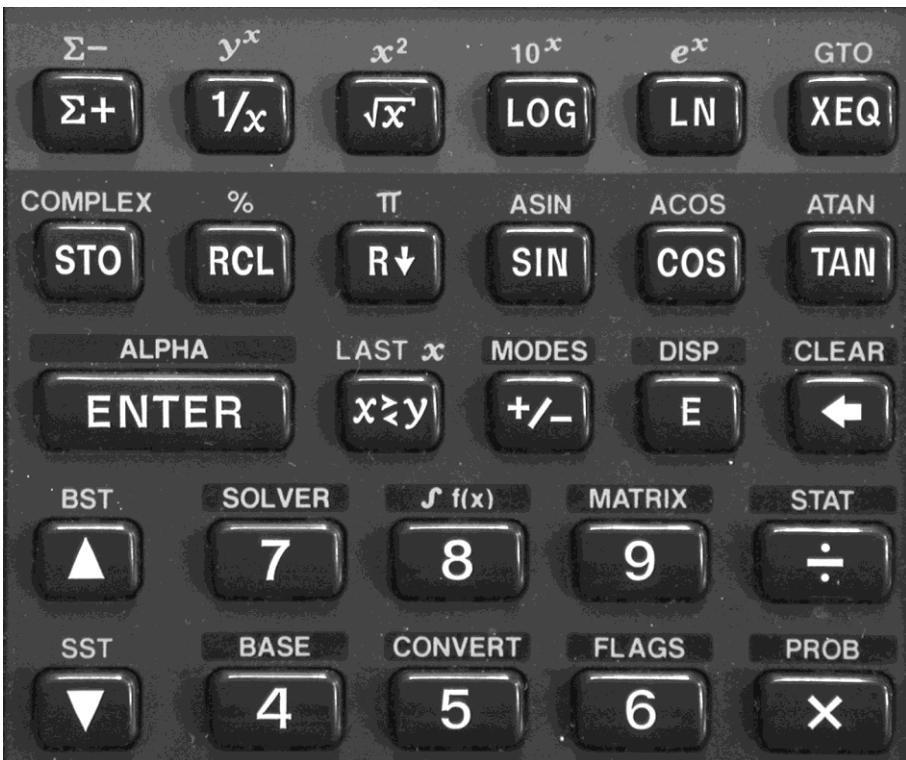


Reconstruction by dilation is performed using a 3x3 square SE



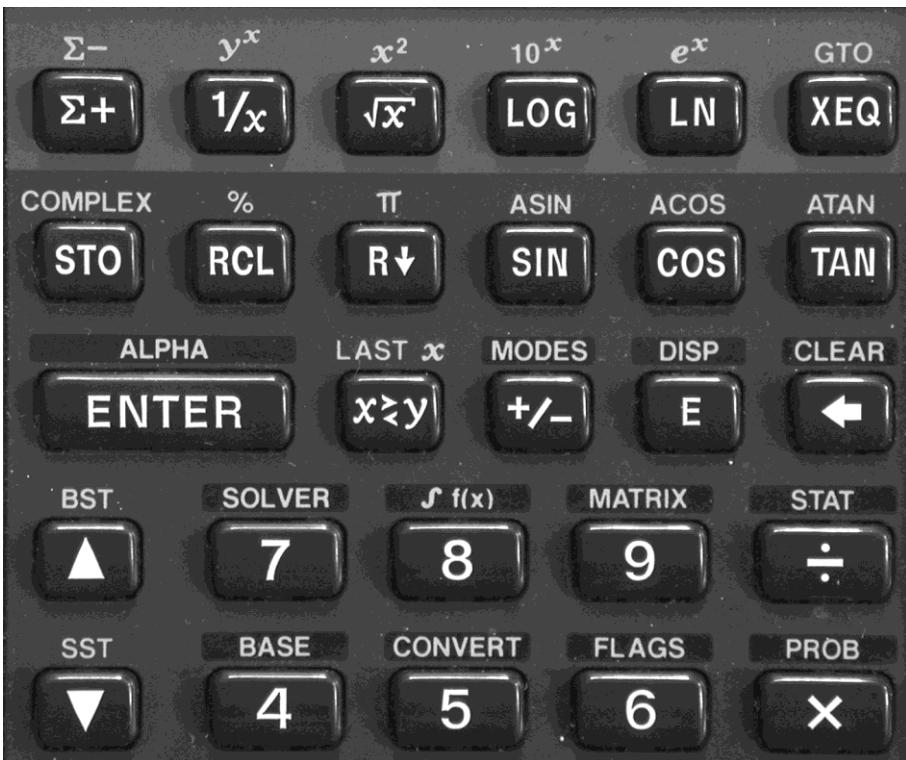
An example

- Some bright regions are not reconstructed: all bright regions that do not fit a horizontal bar 71 pixel wide. These are exactly the characters that we want to extract from the original image ...



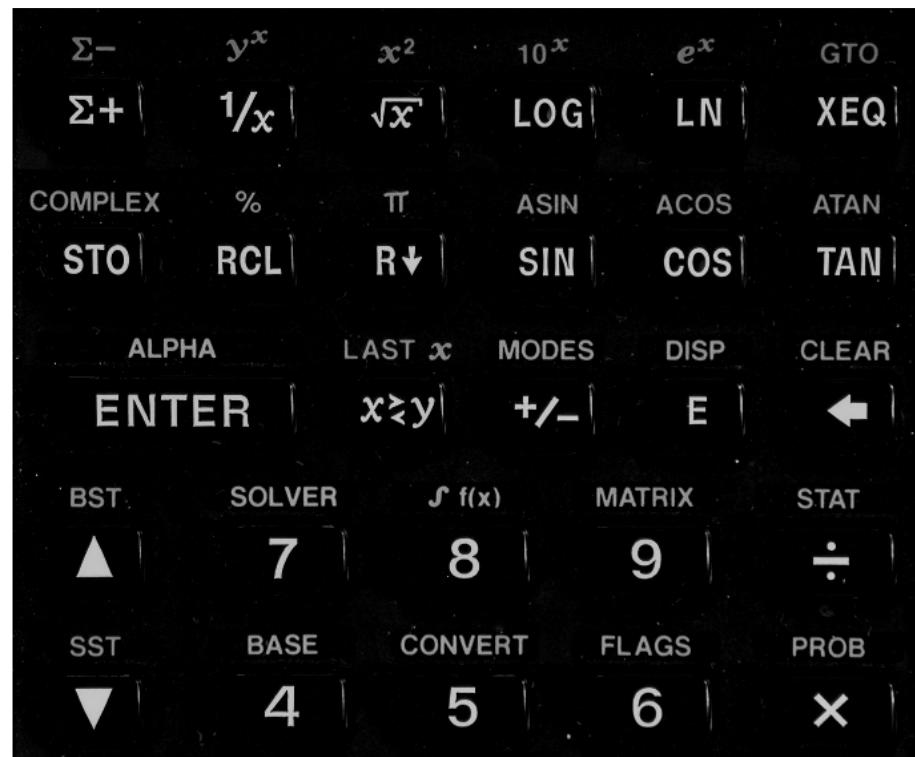
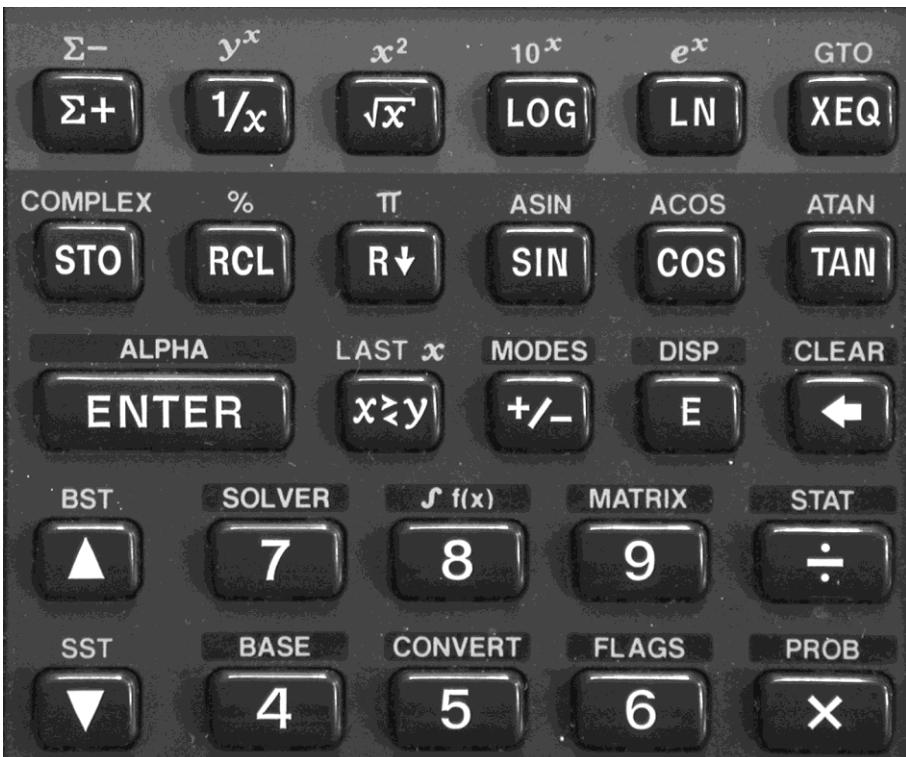
An example

- The open by reconstruction should be subtracted to the original image yielding the top hat by reconstruction operator



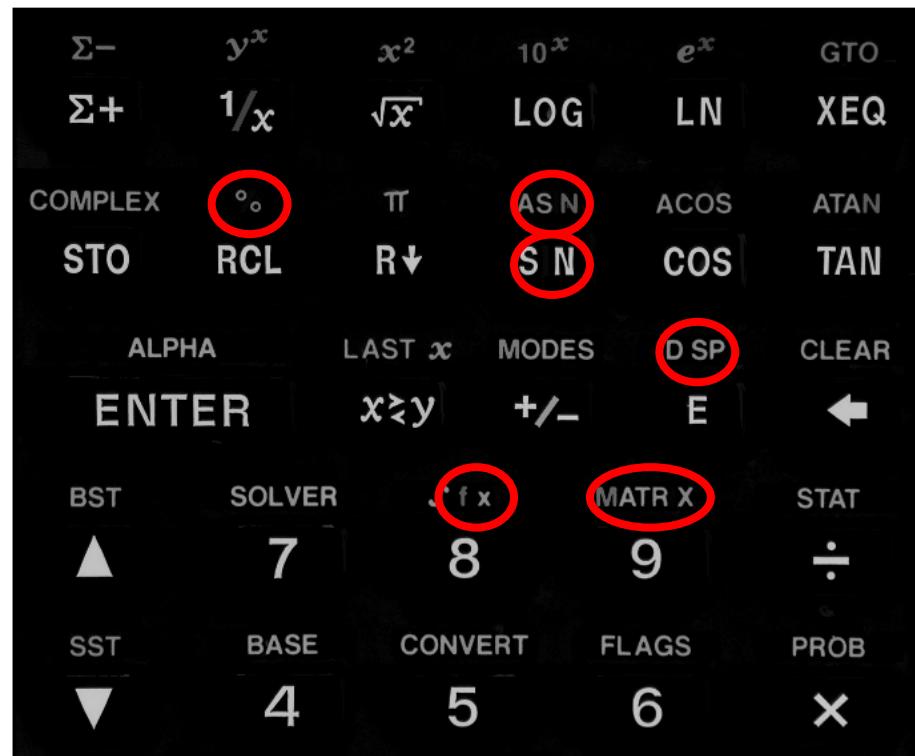
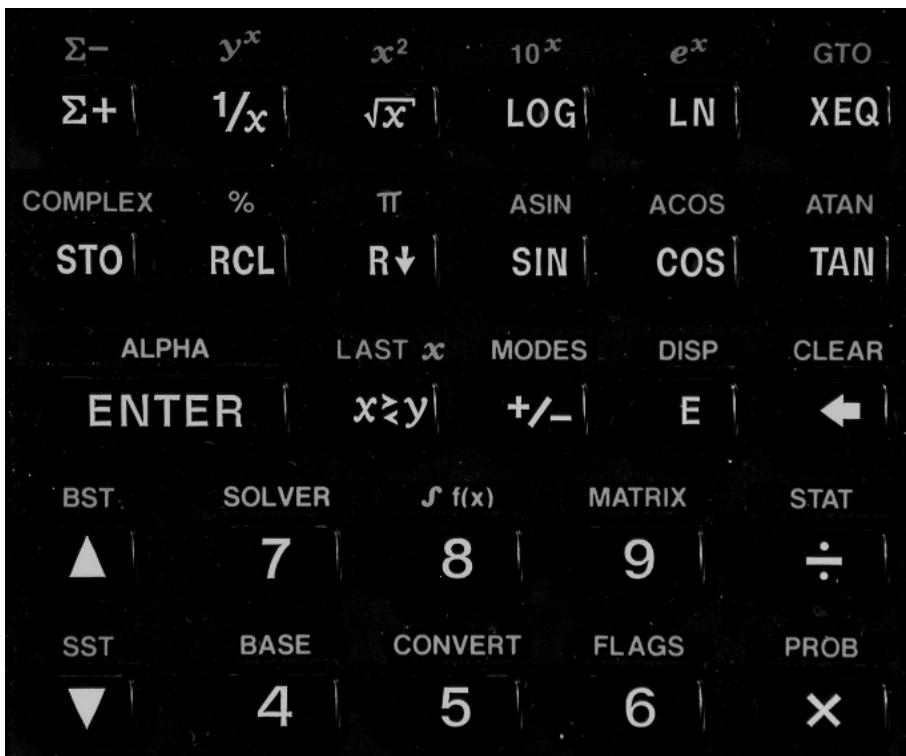
An example

- The top hat by reconstruction has successfully removed horizontal reflections and rendered a more uniform background



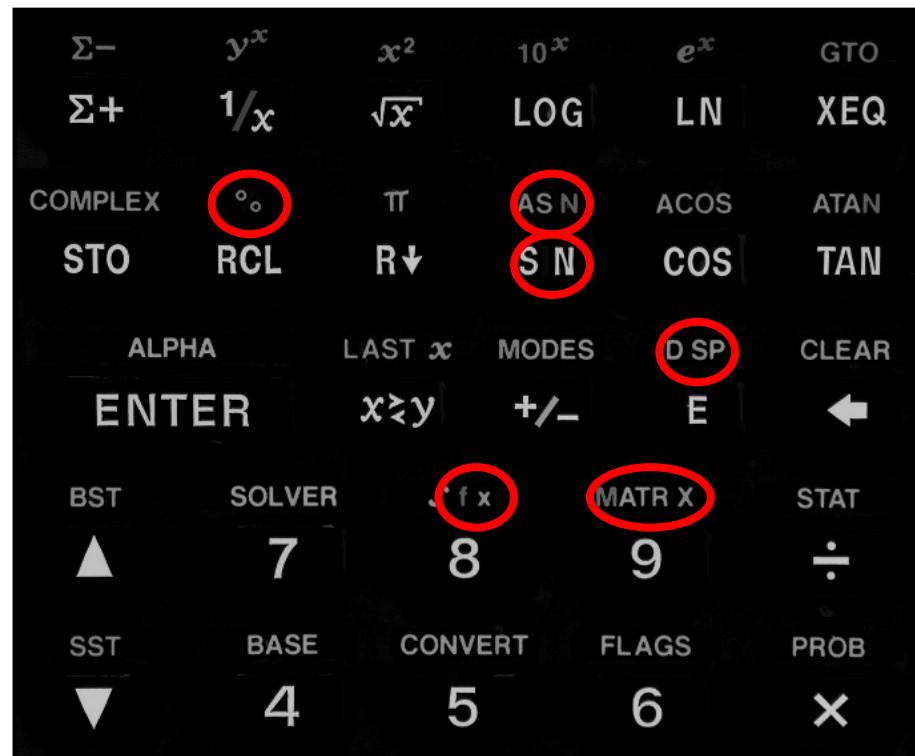
An example

- Vertical reflections can be removed through open by reconstruction with a **horizontal bar** 11 pix wide (all isolated vertical elements are completely removed)



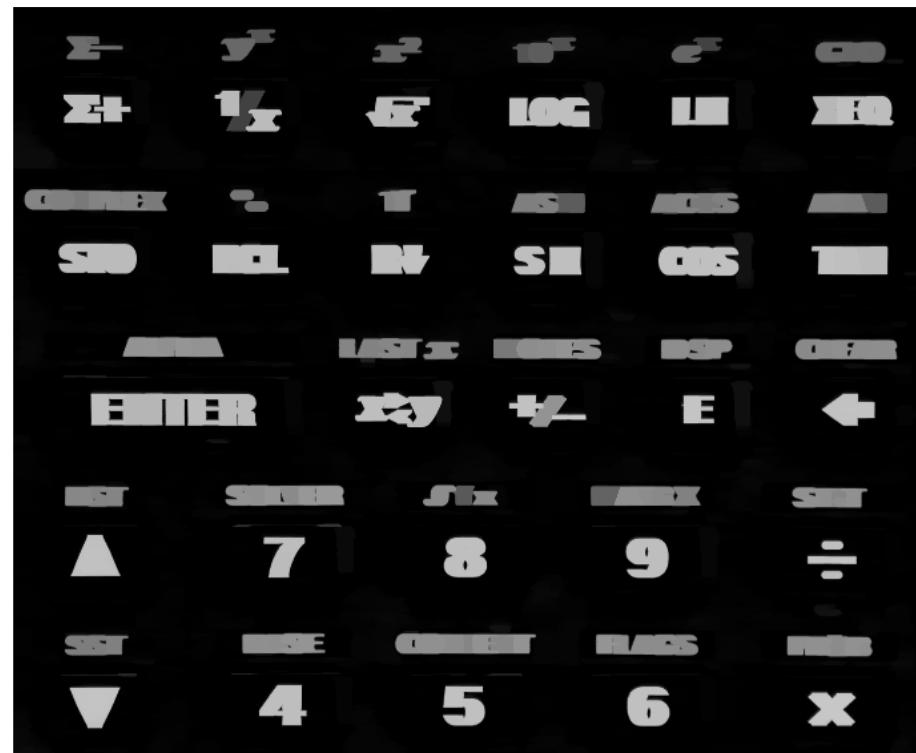
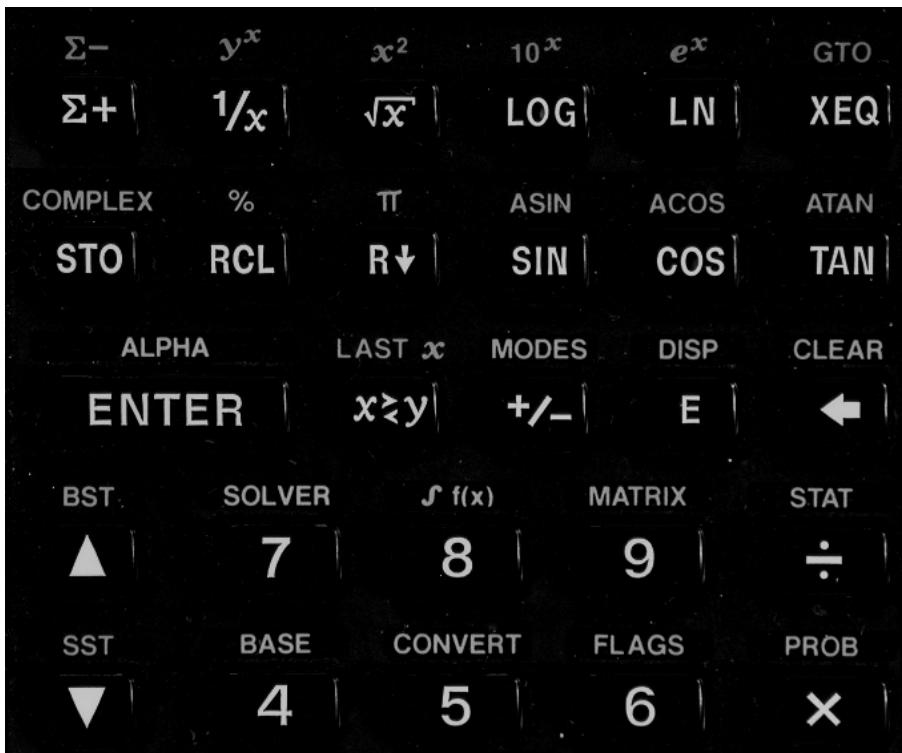
An example

- Vertical characters that have been suppressed by error are very close to other characters that have not been removed. They can be recovered by dilation with a horizontal bar 21 pix wide



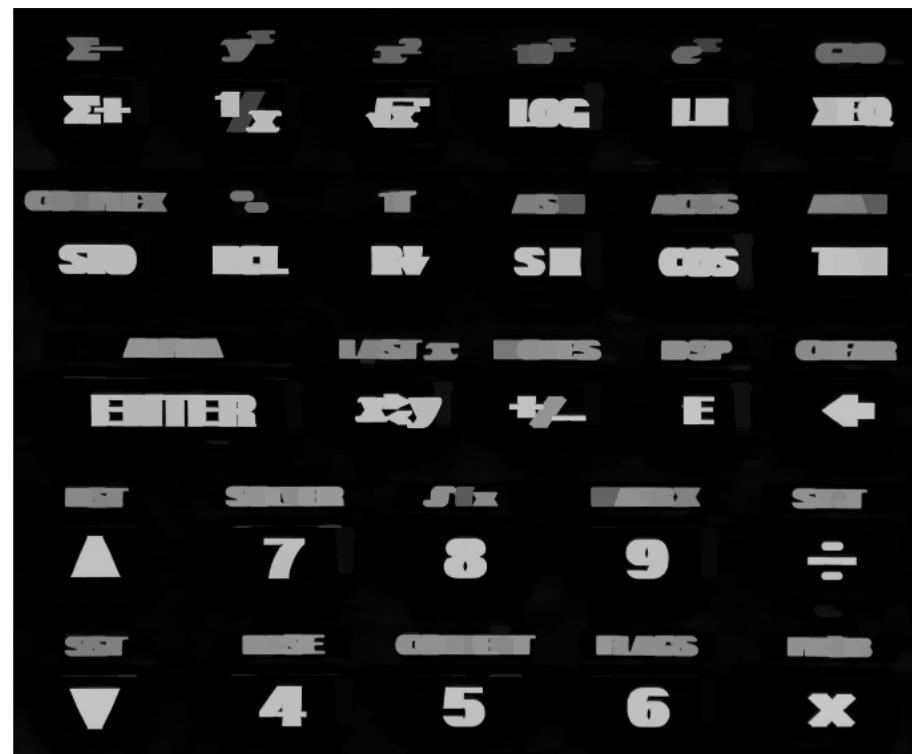
An example

- Vertical characters that have been suppressed by error are very close to other characters that have not been removed. They can be recovered by dilation with a horizontal bar 21 pix wide



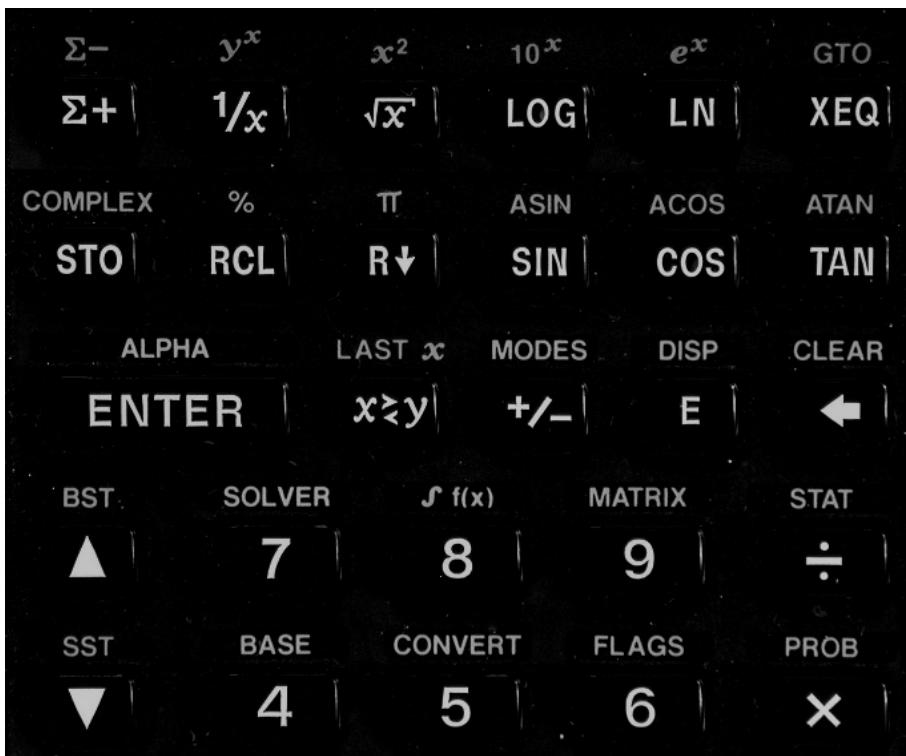
An example

- The minimum between the two images below can be used to perform reconstruction by dilation using the first image as mask



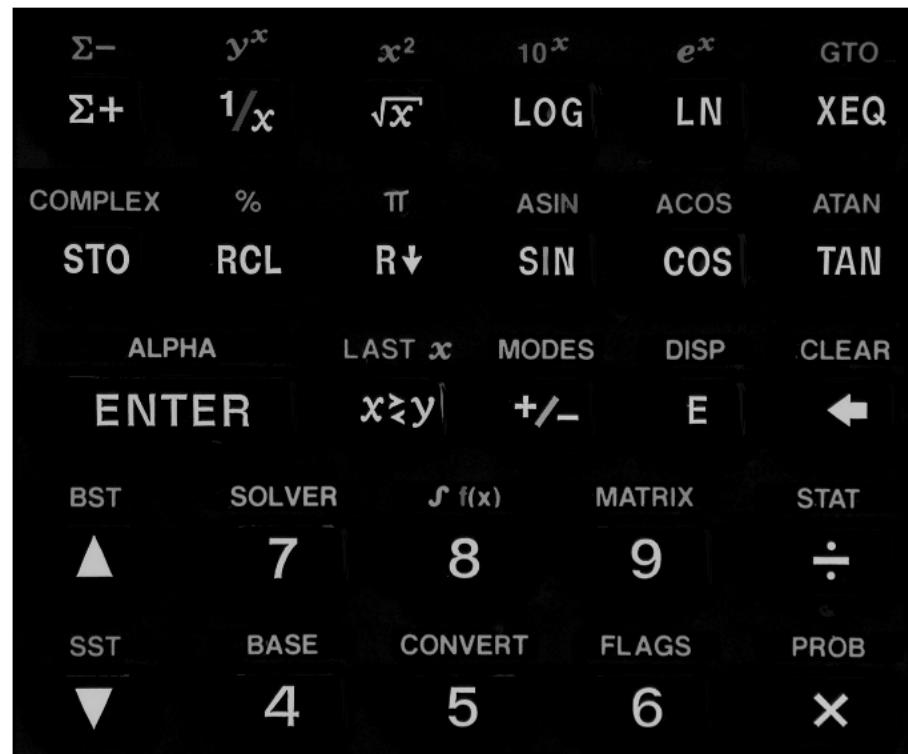
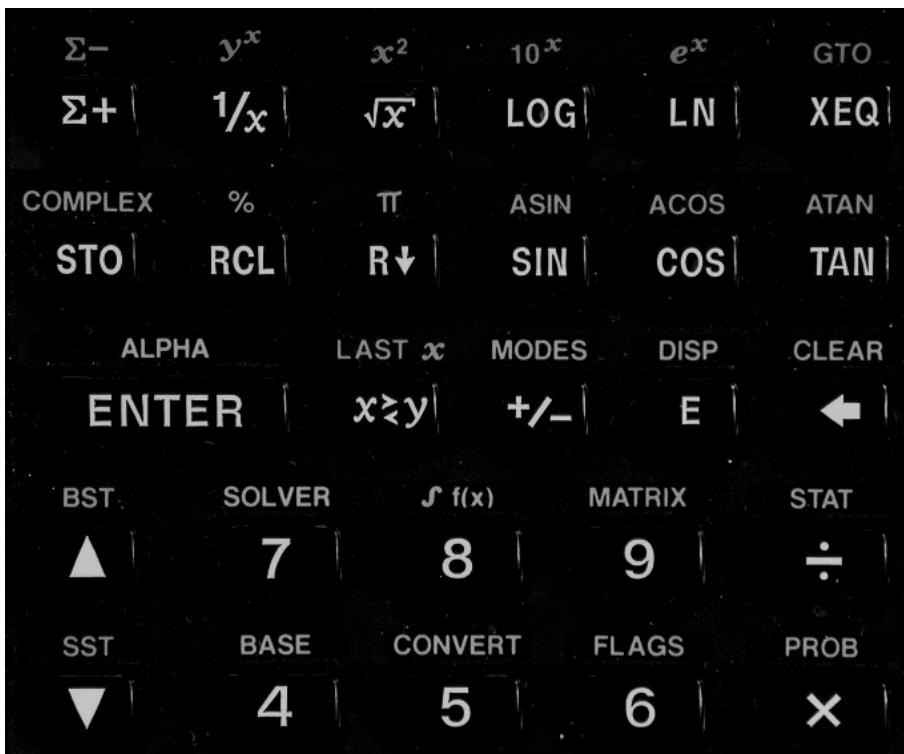
An example

- The minimum ...



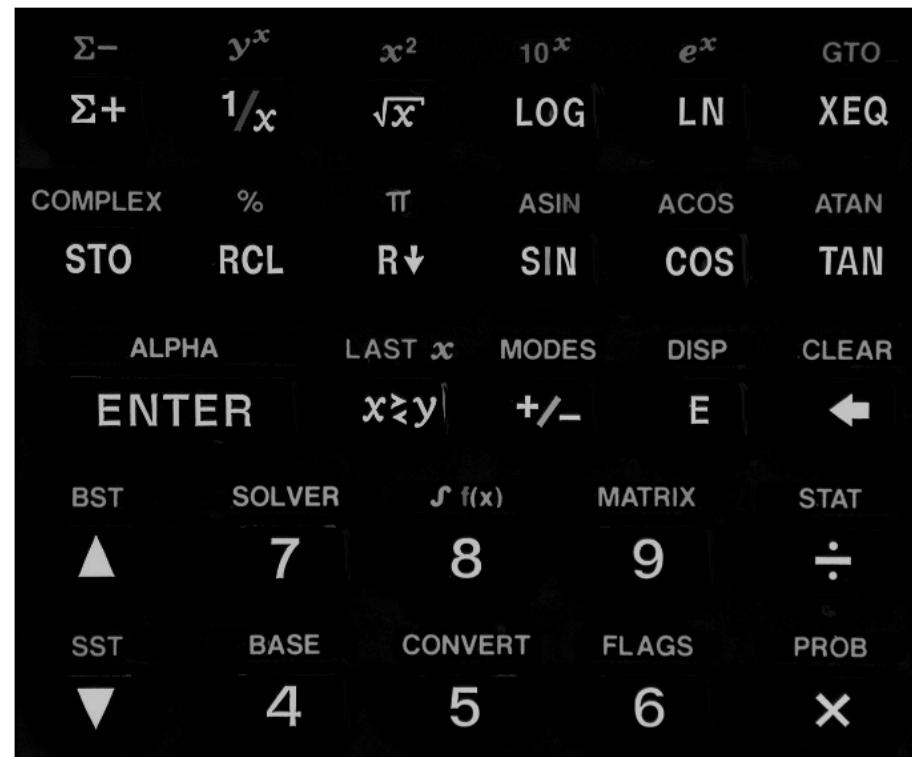
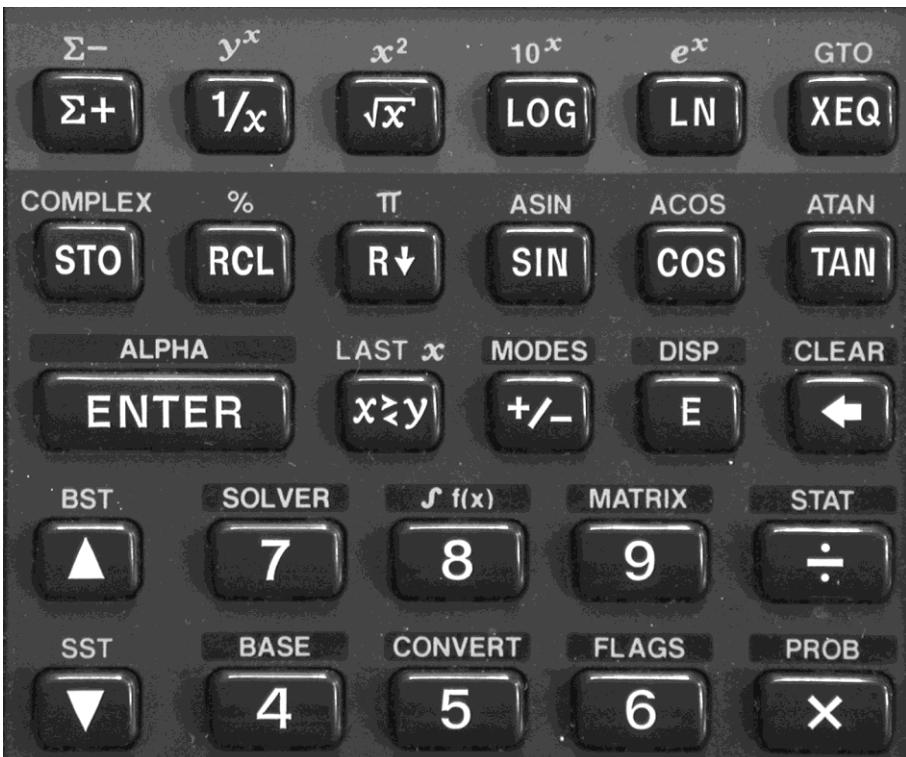
An example

- The reconstructed image



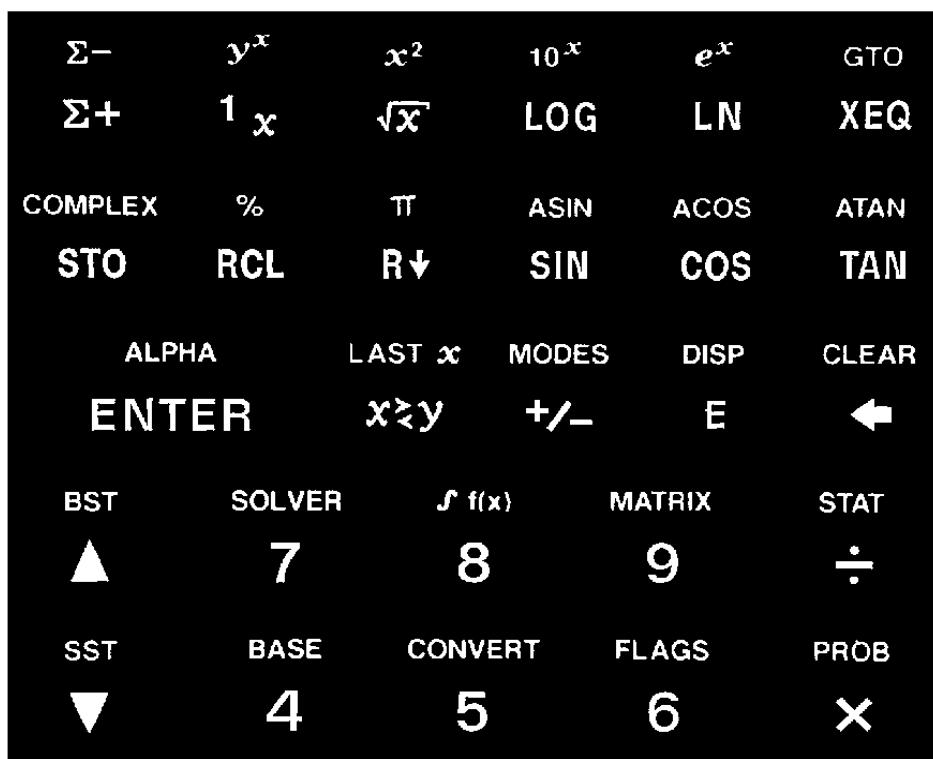
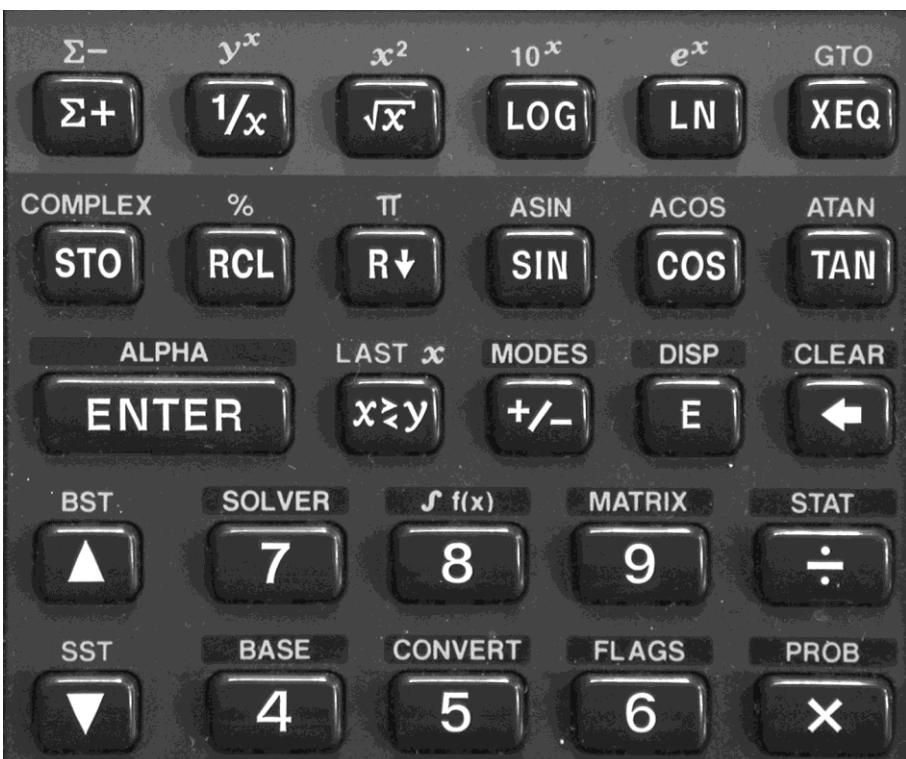
An example

- The reconstructed image compared to the original



An example

- The thresholded (Otsu) reconstructed image compared to the original



Python code

```
filename = 'calculator.tif'
```

```
img = cv2.imread(filename,0)
```

```
bar_hor = np.ones((1,71))
```

```
img_01 = cv2.erode(img, bar_hor)
```

```
img_02 = morpho_reconstruct(img, img_01)
```

```
img_03 = img - img_02
```

```
bar_hor = np.ones((1,11))
```

```
img_04 = cv2.erode(img_03, bar_hor)
```

```
img_05 = morpho_reconstruct(img_03, img_04)
```

```
img_06 = cv2.dilate(img_05, np.ones((1,21)))
```

```
img_07 = np.minimum(img_03, img_06)
```

```
img_08 = morpho_reconstruct(img_03, img_07)
```

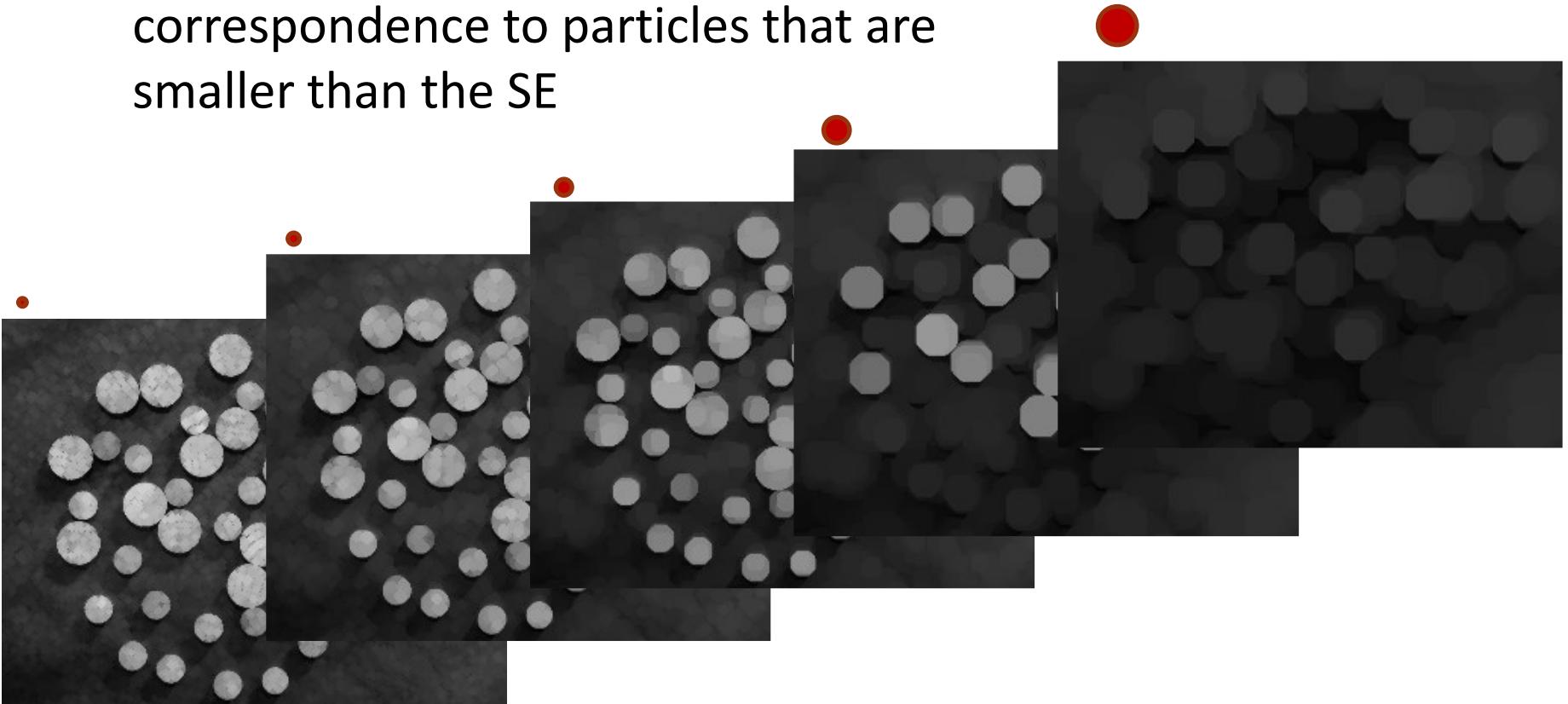
Granulometry

- Granulometry deals with determining the **size distribution** of particles in an image
- Usually, particles are not well separated
 - This makes it difficult to isolate and count them
- MM can be used to estimate the distribution of particle size indirectly, without having to identify and measure each particle in the image
- **ASSUMPTION:** all particles have the same shape and this should match the SE



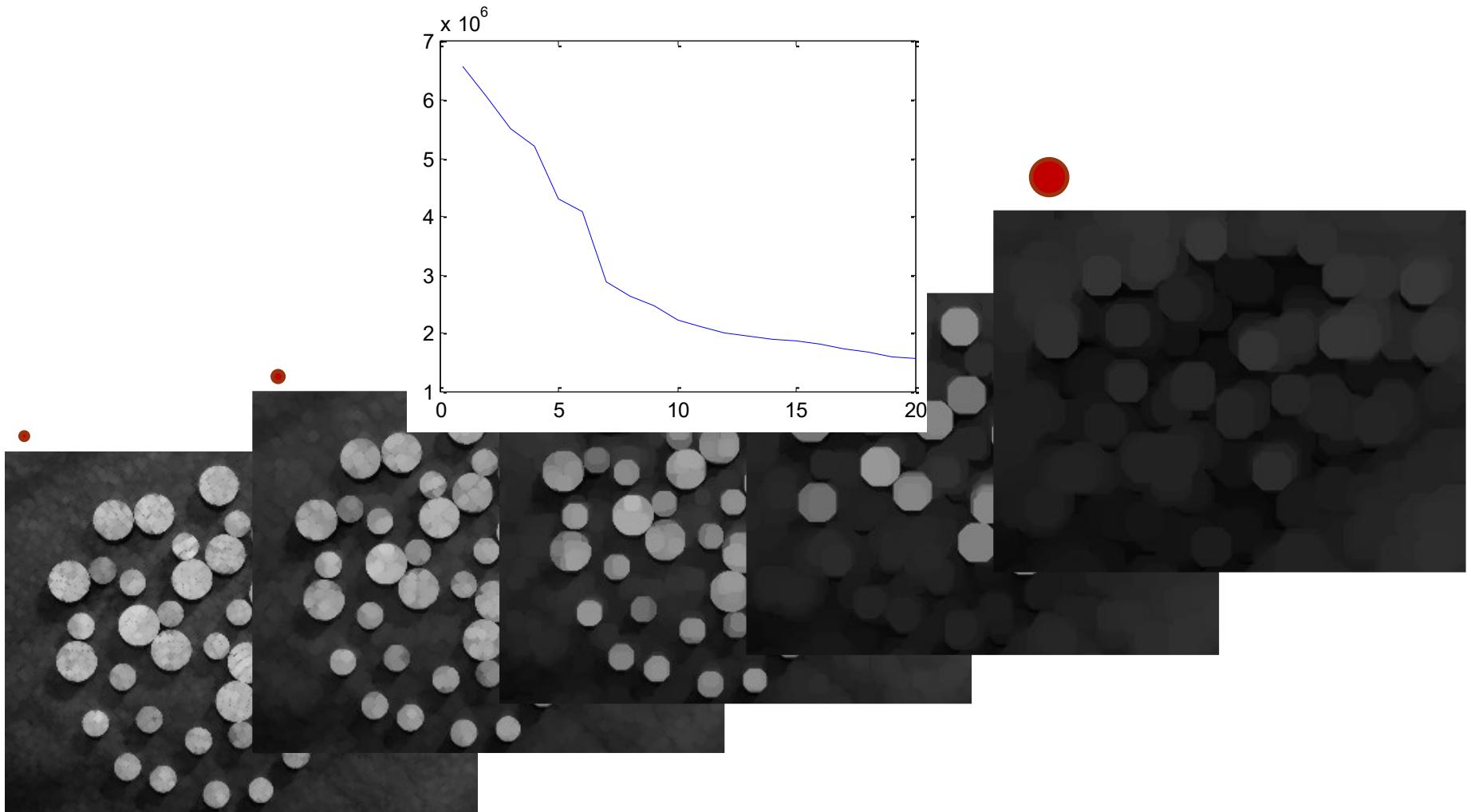
Granulometry

- Assuming that the particles are brighter than the background, the approach relies on application of the opening operator with SE of increasing size
- For a given SE size, opening supresses the output in correspondence to particles that are smaller than the SE



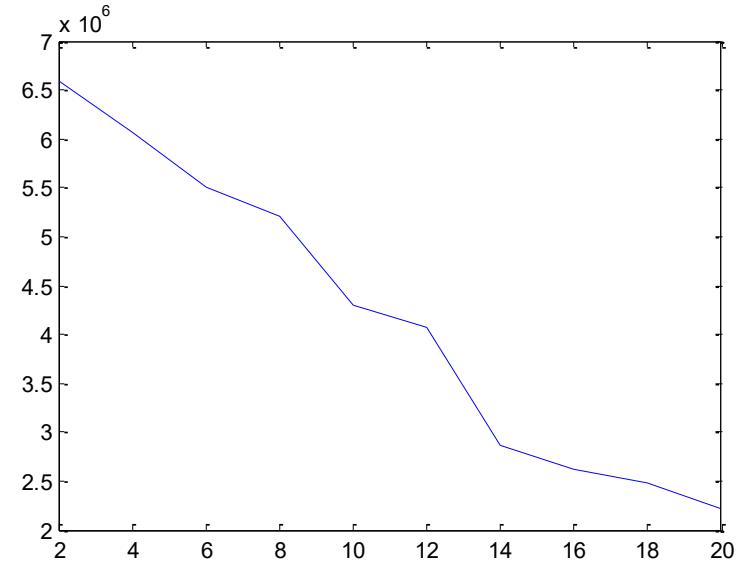
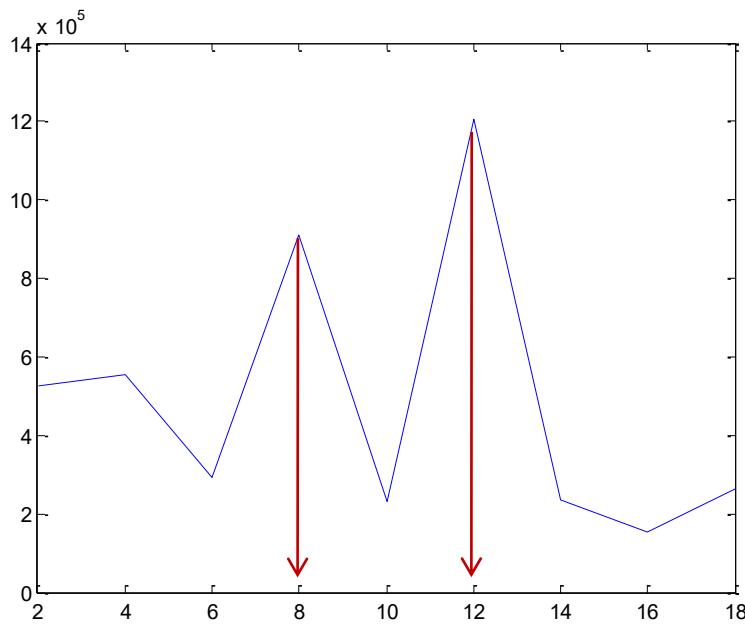
Granulometry

- At each opening step (SE size), the sum of output pixel values defines the **surface area**



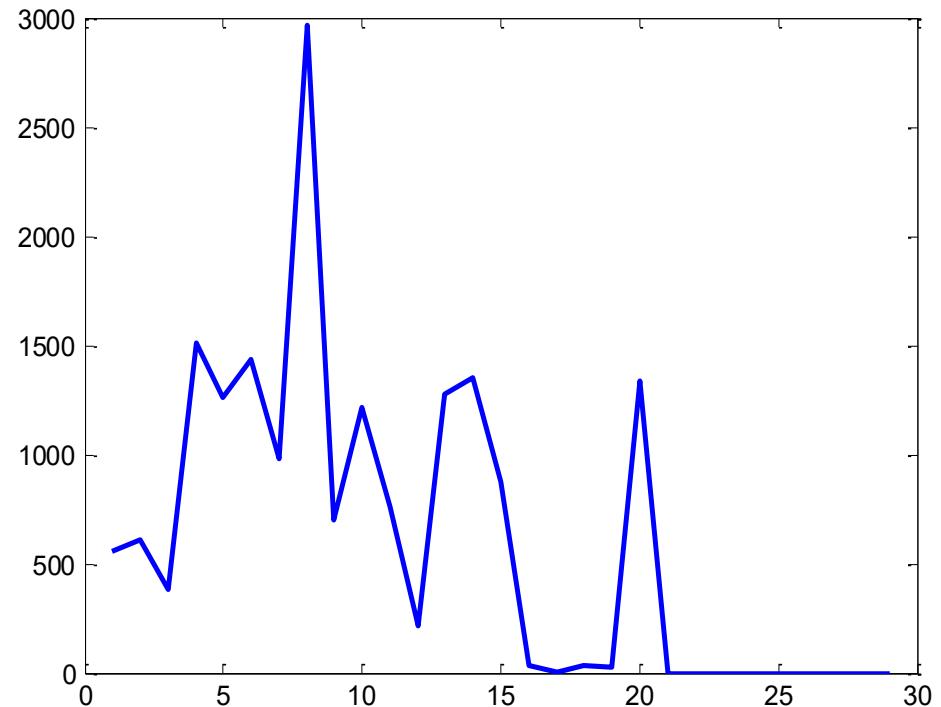
Granulometry

- Results are represented by the incremental differences of surface area values
- Peaks are expected when the size of the SE slightly exceeds the size of some particles



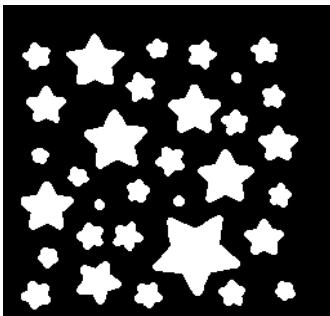
Granulometry

- Accurate results are obtained only if the shape of the objects matches the shape of the structuring element. In the case reported below the SE is a disk.

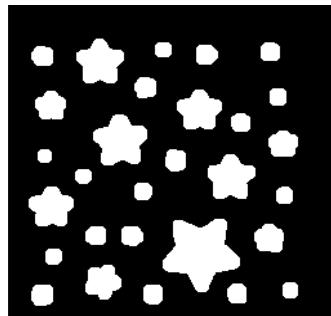


Granulometry

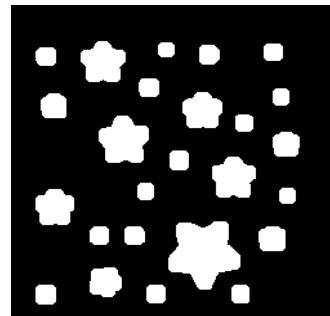
Radius 4



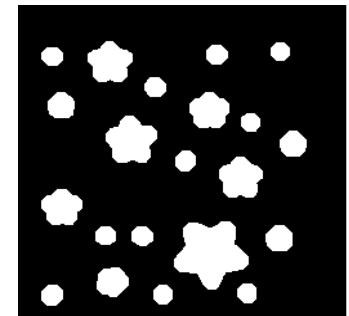
Radius 6



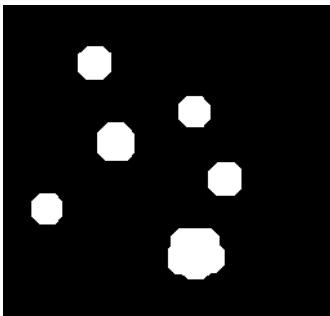
Radius 7



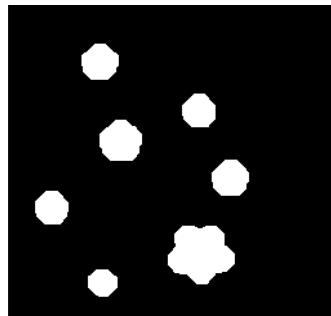
Radius 8



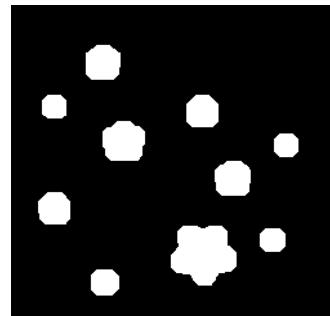
Radius 13



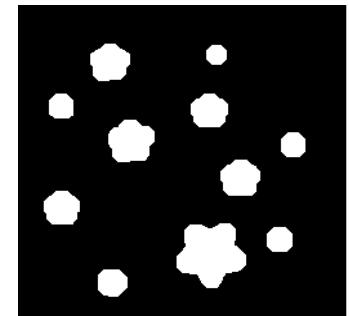
Radius 11



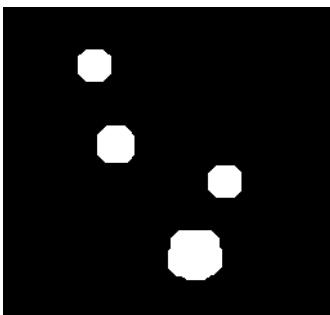
Radius 10



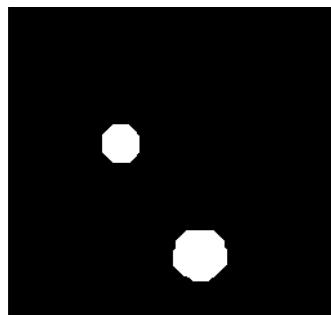
Radius 9



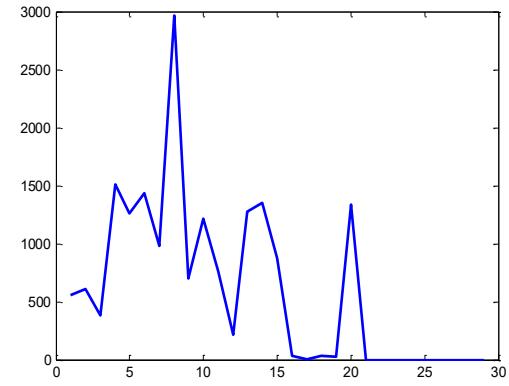
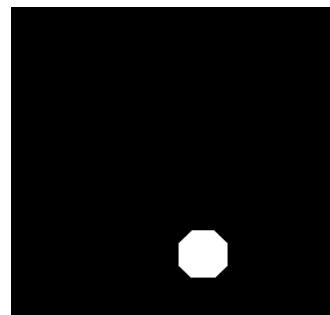
Radius 14



Radius 15

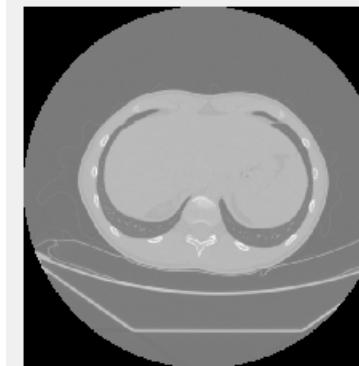
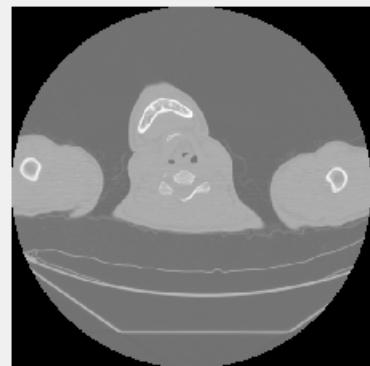
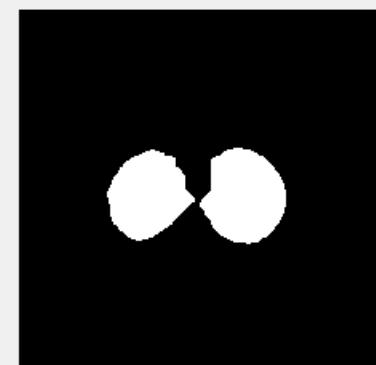
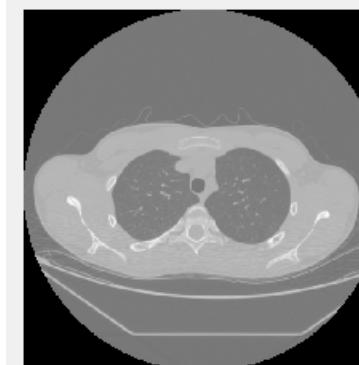
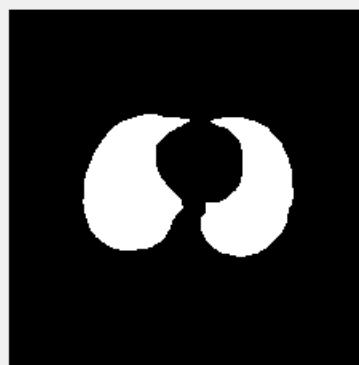


Radius 20

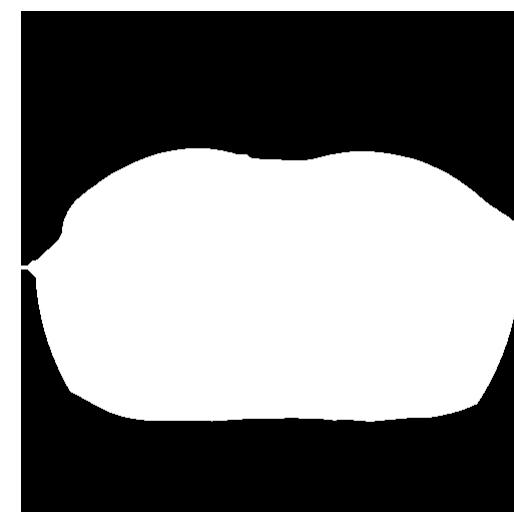
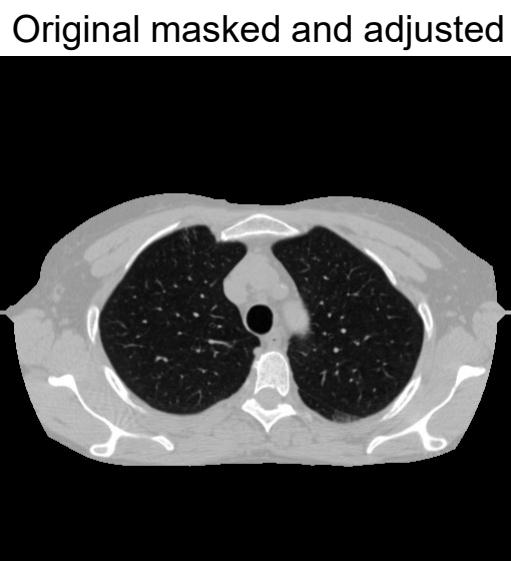
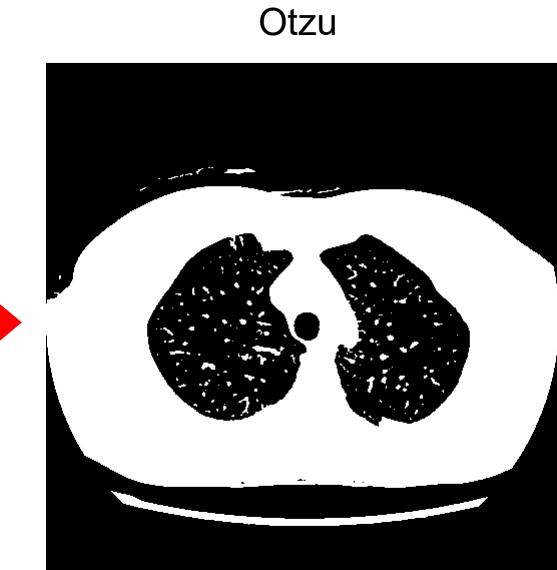
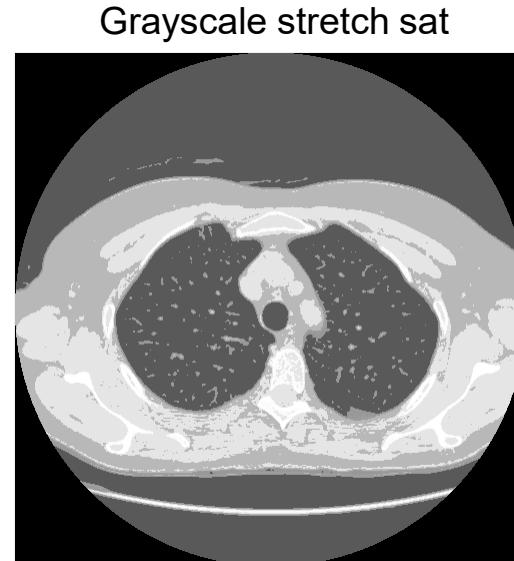
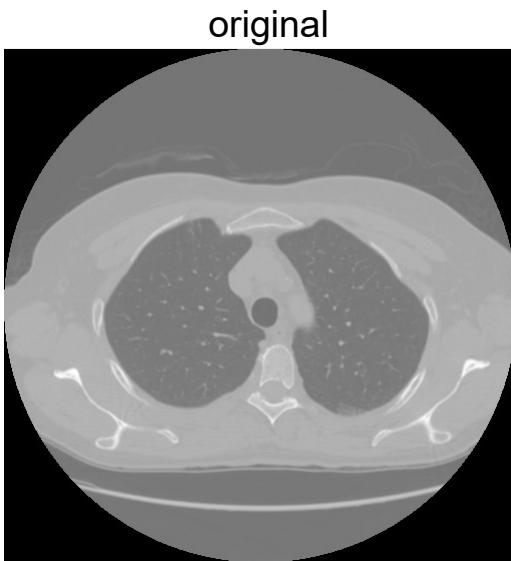


Morphological processing

- Define a processing pipeline that is able to extract a binary mask of lung regions in Computed Tomography slices of body chest



Discard regions outside the chest



Discard regions outside the chest

