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7 – Morphological Operations Part 2

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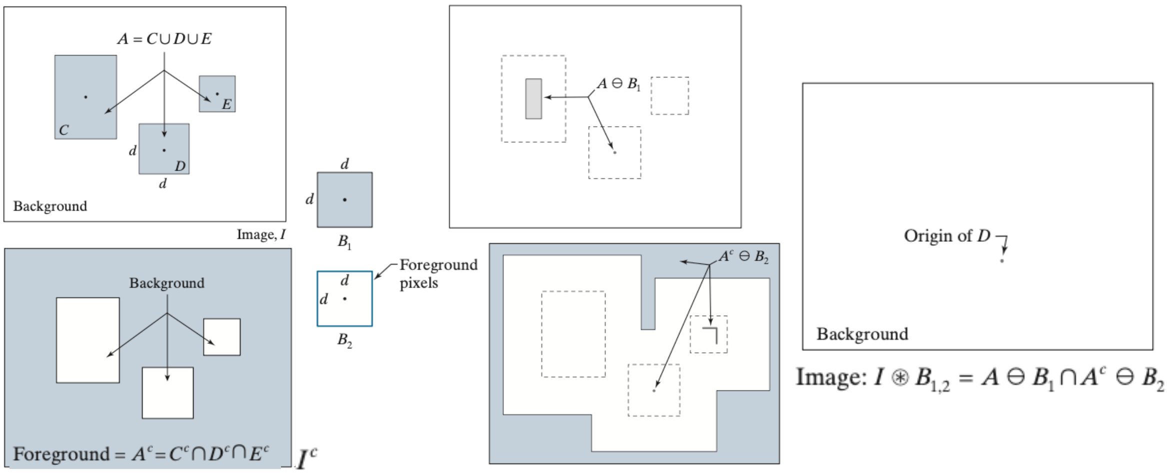
This lecture is based on materials found in the second half of Chapter 9 of the textbook, "Digital Image Processing", 4th Edition, by RC Gonzalez and RE Woods.

Hit-or-Miss Transform (HMT)

- The ***Hit-or-Miss transform*** (**HMT**) is a basic tool for shape detection.
- HMT utilizes two structuring elements: B_1, for detecting shapes in the foreground A, and B_2, for detecting shapes in the background A^c.

$$I \circledast B_{1,2} = \{z|(B_1)_z \subseteq A \text{ and } (B_2)_z \subseteq A^c\} \quad = (A \ominus B_1) \cap (A^c \ominus B_2)$$



Let I be a binary image composed of foreground (A) and background pixels, respectively. Unlike the morphological methods discussed thus far, the HMT utilizes two structuring elements: B_1 for detecting shapes in the foreground, and B_2 for detecting shapes in the background. The HMT of image I is defined as:

$$\begin{aligned} I \circledast B_{1,2} &= \{z|(B_1)_z \subseteq A \text{ and } (B_2)_z \subseteq A^c\} \\ &= (A \ominus B_1) \cap (A^c \ominus B_2) \end{aligned}$$

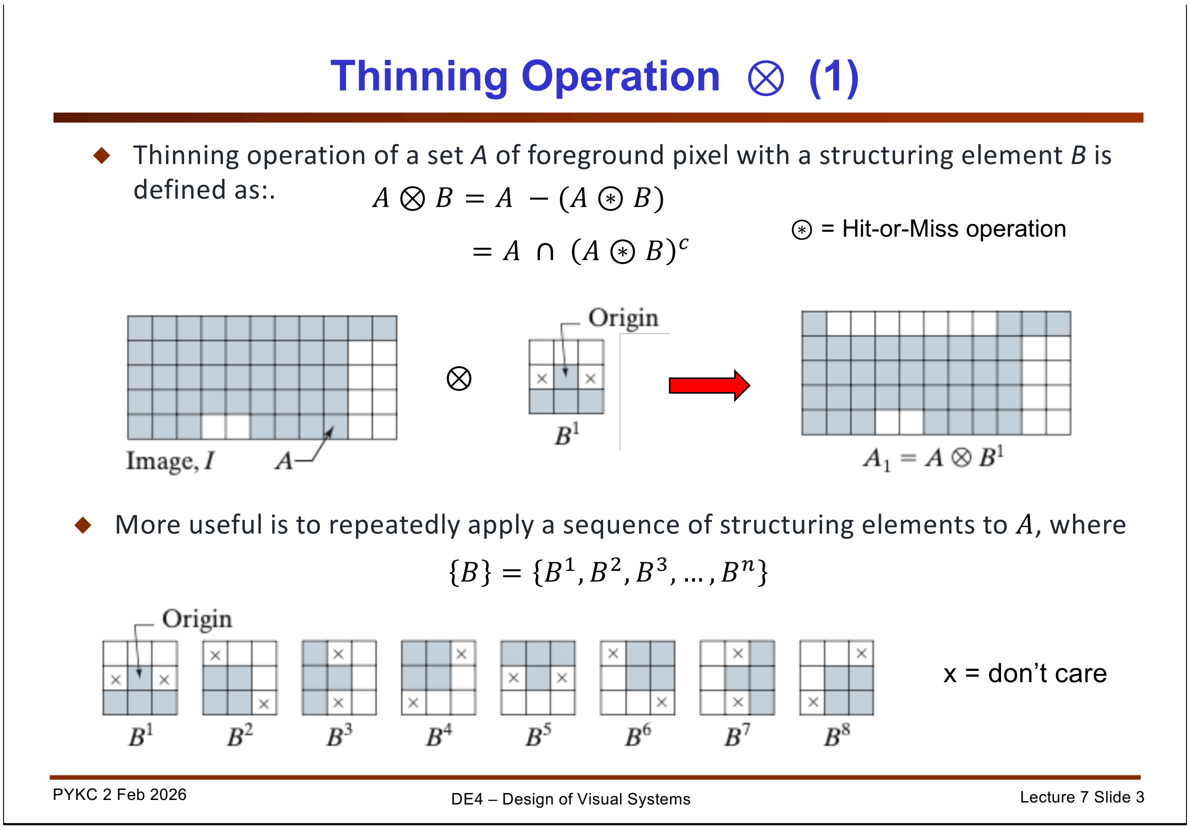
where the second line follows from the definition of erosion.

In words, this equation says that the morphological HMT is the set of translations, z, of structuring elements B_1 and B_2 such that, simultaneously, B_1 found a match in the foreground (i.e., B_1 is contained in A) and B_2 found a match in the background (i.e., B_2 is contained in A^c).

The word "simultaneous" implies that z is the same translation of both structuring elements.

The word "miss" in the HMT arises from the fact that B_2 finding a match in A^c is the same as B_2 not finding (missing) a match in A.

Note that structuring element B_1 is equal to object D itself. The erosion of A by B_1 contains a single point: the origin of D, as desired, but it also contains parts of object C. Structuring element B_2 is designed to detect D in I^c. It resulted in the middle bottom image. The intersection operation ∩ remove everything except the single point of the origin of object D – hence extracting D from I.



Thinning of a set A of foreground pixels by a structuring element B, denoted $A \otimes B$, can be defined in terms of the hit-or-miss transform $\circledast$ (Lecture 6, slide 15):

$$A \otimes B = A - (A \circledast B) \quad = A \cap (A \circledast B)^c$$

A more useful expression for thinning A symmetrically is based on a sequence of structuring elements:

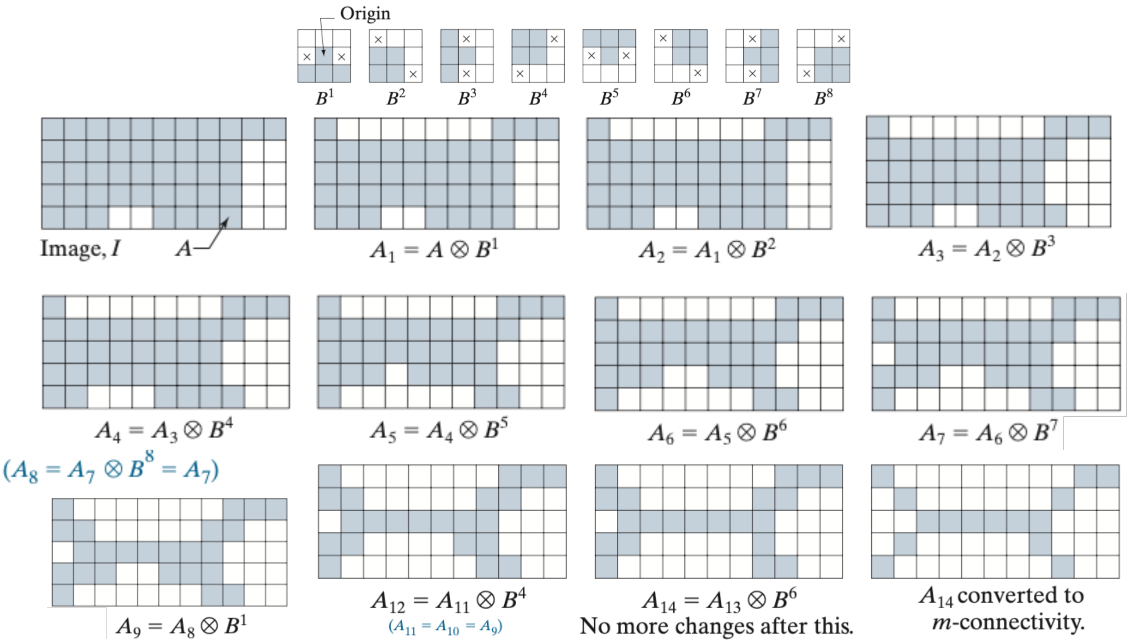
$$\{B\} = \{B^1, B^2, B^3, \ldots, B^n\}$$

Using this concept, we now define thinning by a sequence of structuring elements as:

$$A \otimes \{B^1, B^2, B^3, \ldots, B^n\} = ((\ldots((A \otimes B^1) \otimes B^2) \ldots.) \otimes B^n)$$

The entire process is repeated until no further change occurs after one complete pass through all structuring elements. See next slide.

Thinning Operation (2)



This slide shows a set of structuring elements used routinely for thinning (note that B^i is equal to B^{i-1} rotated clockwise by 45°), and set A to be thinned, using procedure stated in the previous slide.

The second image shows the A with one pass of B^1 to obtain A_1. The rest shows how the algorithm progresses until A_8 which turns out to be the same as A_7. We do not stop here. Instead we computer A_9 by computing $A_9 = A_8 \otimes B^1$. That is we go back to the first structuring element of the set! Now, A_9 turns out to be different. So we continue. Until eventually the image no longer changes.

Here the last iteration is A_{14} and the algorithm terminates. (Could have terminated earlier.). Finally, A_{14} is converted to m-connectivity. We now have a completed the thinning process!

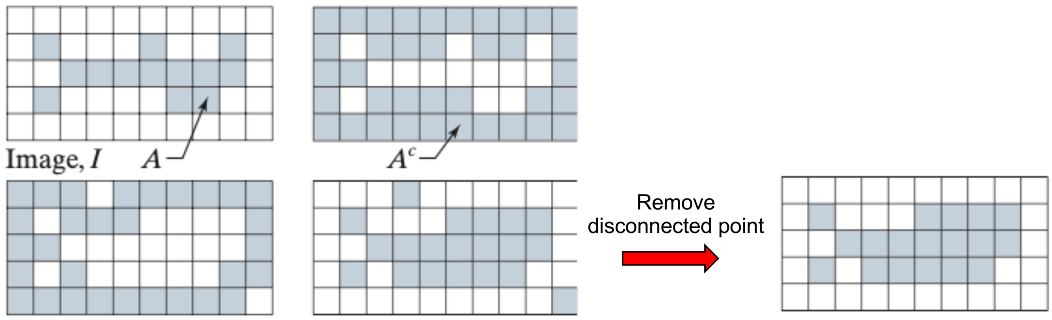
Thickening Operation $\odot$

- Thickening is the morphological dual of thinning and is defined by:

$$A \odot B = A \cup (A \circledast B)$$

$\circledast$ = Hit-or-Miss operation

- We can achieve thickening by:
  1. Obtaining A^c the complement of A.
  2. Applying thinning procedure as stated in the previous slides.
  3. Take the complement of that result.



Thickening is the dual (opposite) of thinning. The thickening operation is:

$$A \odot B = A \cup (A \circledast B)$$

Just as before, we repeatedly apply thickening to A with a set of structuring element:

$$\{B\} = \{B^1, B^2, B^3, \dots, B^n\}$$

So that:

$$A \odot \{B^1, B^2, B^3, \dots, B^n\} = ((\dots((A \odot B^1) \odot B^2) \dots.) \odot B^n)$$

However, a separate algorithm for thickening is seldom used in practice.

Instead, the usual procedure is to thin the background of the set in question, then complement the result. In other words, to thicken a set A we form A^c , thin A^c , and then complement the thinned set to obtain the thickening of A. This is illustrated here.

Morphological Reconstruction

- Morphological reconstruction has two basic operations: **geodesic dilation** and **erosion**, which involves two images: the **marker** and the **mask**.
- F denote the **marker** and G the **mask**, both are binary and $F \subseteq G$.
- The **geodesic dilation** of size 1 of the marker F with respect to the mask G is:

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

- The geodesic dilation of size 2 of F with respect to G is:

$$D_G^{(2)}(F) = D_G^{(1)}\left(D_G^{(1)}(F)\right)$$

dilate F with B, and intersect results with mask G

- This can be generalized to a recursive relationship as:

$$D_G^{(n)}(F) = D_G^{(1)}\left(D_G^{(n-1)}(F)\right), \text{ where } n \geq 1 \text{ and } D_G^{(0)}(F) = F.$$

- Similarly, geodesic erosion of size *1* is defined by:

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

- In general:

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

Morphological reconstruction is a useful method for extracting meaningful information about shapes in an image. The shapes could be just about anything: letters in a scanned text document, fluorescently stained cell nuclei, or galaxies in a far-infrared telescope image. You can use morphological reconstruction to extract marked objects, find bright regions surrounded by dark pixels, detect or remove objects touching the image border, detect or fill in object holes, filter out spurious high or low points, and perform many other operations.

Essentially a generalization of flood-filling, morphological reconstruction processes one image, called the **marker**, based on the characteristics of another image, called the **mask**. The **high points**, or **peaks**, in the marker image specify where processing begins. The peaks **spread out**, or **dilate**, while being forced to fit within the mask image. The spreading processing continues until the image values stop changing

Central to morphological reconstruction are the concepts of **geodesic dilation** and **geodesic erosion**.

As shown above, geodesic dilation of the marker F with respect to the mask G is defined recursively as (B is the SE):

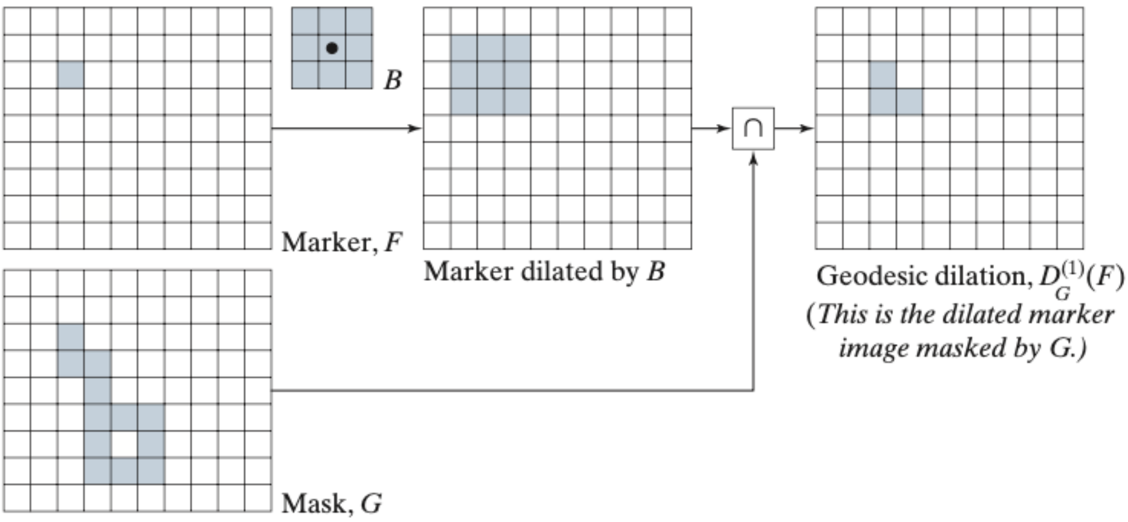
$$D_G^{(n)}(F) = D_G^{(1)}\left(D_G^{(n-1)}(F)\right), \text{ where } n \geq 1 \text{ and } D_G^{(0)}(F) = F.$$

In plain words, this is no more than "**dilate F with B, and intersect results with mask G**."

Similarly geodesic erosion is defined as:

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

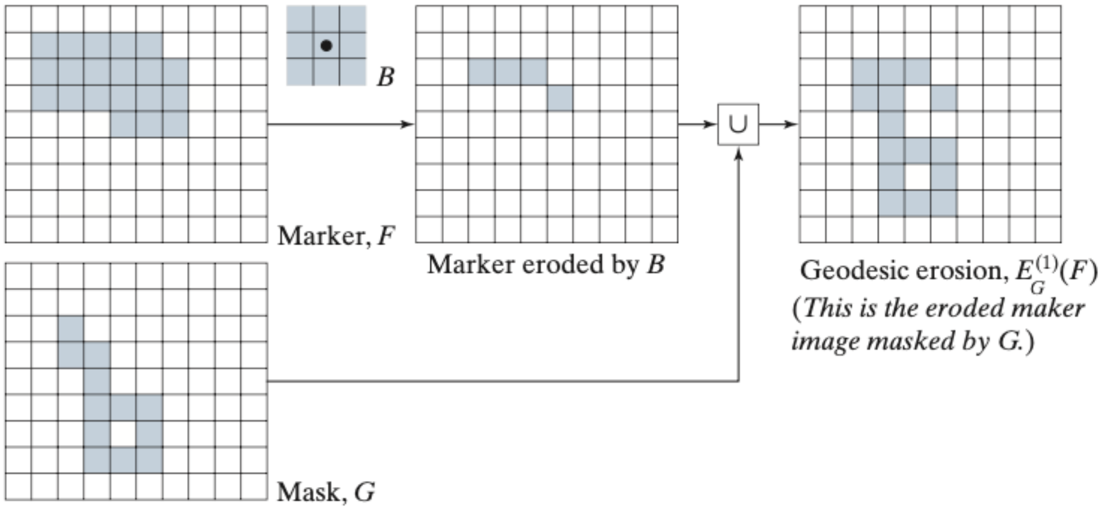
Geodesic Dilation



Here is a diagram illustrating the mechanism of geodesic dilation of F with respect to G using the SE B.

This is really a fancy name for performing a dilation on the marker F with the structuring element B, then intersect (AND for binary images) it with the mask G.

Geodesic Erosion



Here is a diagram illustrating the mechanism of geodesic erosion of F with respect to G using the SE B.

This is really a fancy name for performing an erosion on the marker F with the structuring element B, then merge it (OR for binary images) with the mask G.

Morphological Reconstruction by Dilation

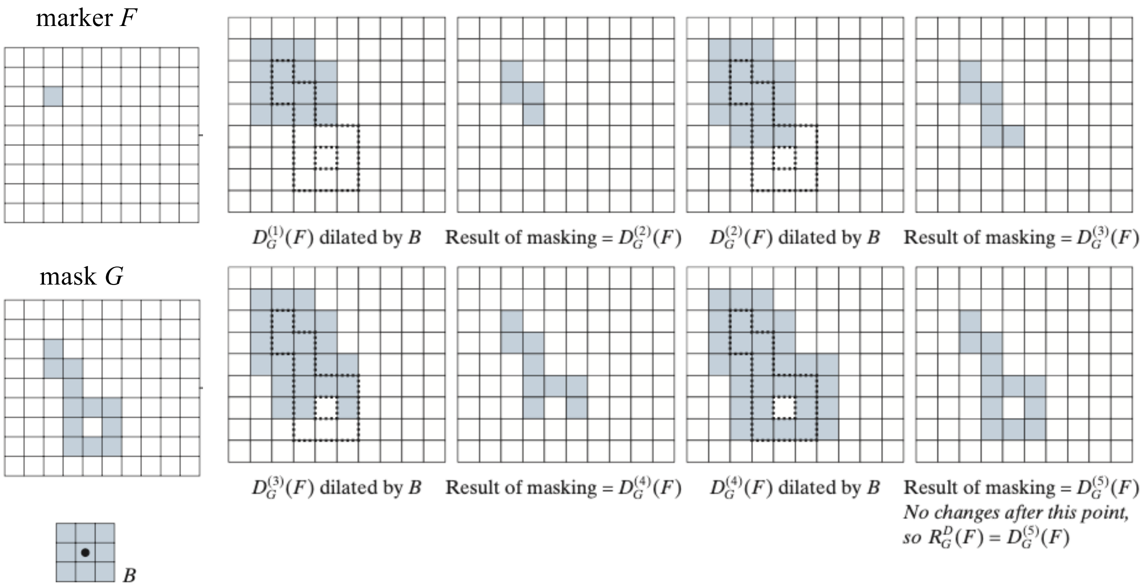
- Morphological reconstruction by dilation of a **marker** F with respect to a mask G is simply defined as the geodesic dilation of F, iterated until there are no change (i.e. achieved stability).
- Mathematically, it is formulated as:

$$R_G^D(F) = D_G^{(k)}(F), \text{ for } k \text{ iterations until } D_G^{(k)}(F) = D_G^{(k-1)}(F).$$

Equipped with geodesic dilation and erosion, we can now perform morphological reconstruction.

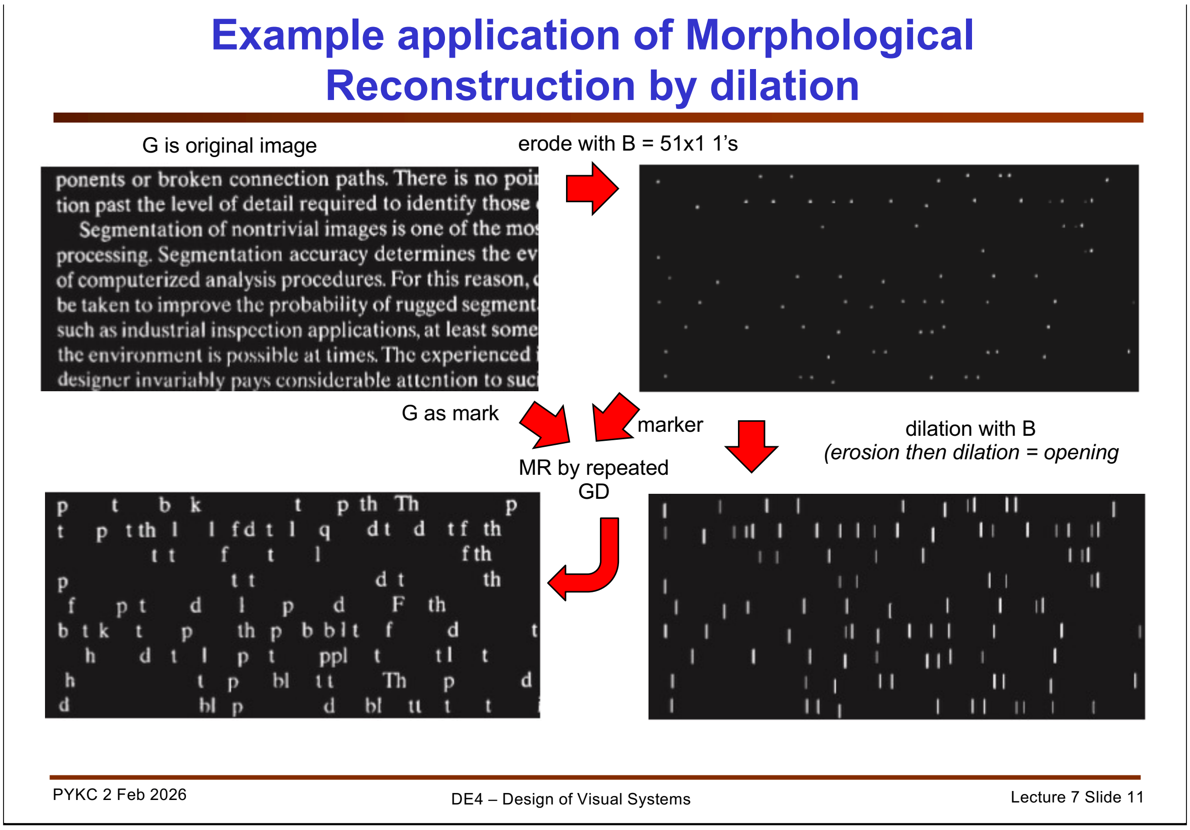
Given marker F and mnask G, we can reconstruct our image by repeatedly apply geodesic dilation to F until the output is stable – i.e. not changing.

Demonstrate how MR by dilation works



Here is what happens with F and G as shown in the slide, and used previously in slide 6.

Effectively, the marker F shows where reconstruction should happen, and after 5 iterations, the mask image is reproduced. You may wonder why this is useful. The next example will demonstrate the power of morphological reconstruction.



This slide shows an example of morphologic reconstruction by dilation.

We are interested in extracting the original image the characters that contain long, vertical strokes. This objective determines the nature of B, the SE we should use.

The average height of the tall characters in the text image is 51 pixels. By eroding the image with a thin structuring element of size 51 × 1, we should be able to isolate these characters.

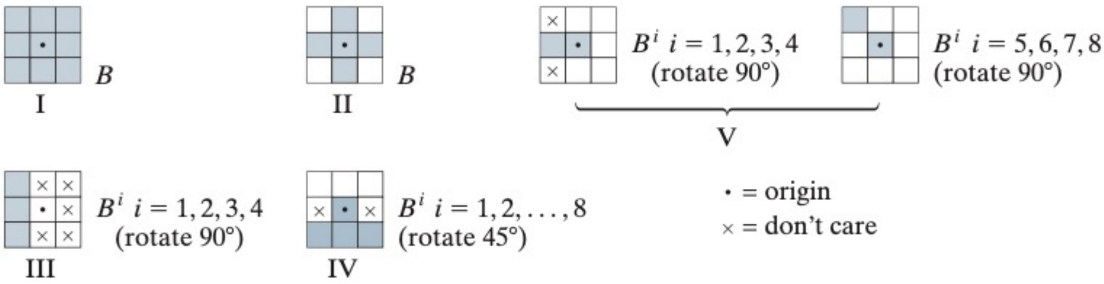
The top-right image shows one erosion with the structuring element B. The locations of the tall characters are extracted successively.

For the purpose of comparison, we computed the opening (remember this is erosion followed by the dilation) of the image using the same structuring element. The bottom-right image shows the result.

This shows that simply dilating an eroded image does not always restore the original.

Finally, the bottom-left image is the reconstruction by dilation of the original image using that image as the mask and the eroded image as the marker. The dilation in the reconstruction was done using a 3 × 3 SE of 1's.

Five basic types of structuring elements in Binary Morphology



The Roman numerals in the third column of the table in the next few slides refer to the structuring elements used in the operation.

Here is a summary of the morphological operators that we have considered so far.

Summary of Binary Morphological Operators (1)

Operation	Equation	Comments
Translation	$(B)_z = \{c \mid c = b + z, \text{ for } b \in B\}$	Translates the origin of B to point z.
Reflection	$\hat{B} = \{w \mid w = -b, \text{ for } b \in B\}$	Reflects B about its origin.
Complement	$A^c = \{w \mid w \notin A\}$	Set of points not in A.
Difference	$A - B = \{w \mid w \in A, w \notin B\} = A \cap B^c$	Set of points in A, but not in B.
Erosion	$A \ominus B = \{z \mid (B)_z \subseteq A\}$	Erodes the boundary of A. (I)
Dilation	$A \oplus B = \{z \mid (\hat{B})_z \cap A \neq \varnothing\}$	Dilates the boundary of A. (I)

Here is a summary of the morphological operators that we have considered so far.

Summary of Binary Morphological Operators (2)

Operation	Equation	Comments
Opening	$A \circ B = (A \ominus B) \oplus B$	Smoothes contours, breaks narrow isthmuses, and eliminates small islands and sharp peaks. (I)
Closing	$A \bullet B = (A \oplus B) \ominus B$	Smoothes contours, fuses narrow breaks and long thin gulfs, and eliminates small holes. (I)
Hit-or-miss transform	$I \circledast B = \{z \mid (B)_z \subseteq I\}$	Finds instances of B in image I. B contains *both* foreground and background elements.
Boundary extraction	$\beta(A) = A - (A \ominus B)$	Set of points on the boundary of set A. (I)
Hole filling	$X_k = (X_{k-1} \oplus B) \cap I^c$ $k = 1, 2, 3, \ldots$	Fills holes in A. X_0 is of same size as I, with a 1 in each hole and 0's elsewhere. (II)

Here is a summary of the morphological operators that we have considered so far.

Summary of Binary Morphological Operators (3)

Operation	Equation	Comments
Connected components	$X_k = (X_{k-1} \oplus B) \cap I \quad k = 1, 2, 3, \ldots$	Finds connected components in I. X_0 is a set, the same size as I, with a 1 in each connected component and 0's elsewhere. (I)
Thinning	$A \otimes B = A - (A \circledast B) = A \cap (A \circledast B)^c$ $A \otimes \{B\} = ((\ldots((A \otimes B^1) \otimes B^2)\ldots) \otimes B^n)$ $\{B\} = \{B^1, B^2, B^3, \ldots, B^n\}$	Thins set A. The first two equations give the basic definition of thinning. The last two equations denote thinning by a sequence of structuring elements. This method is normally used in practice. (IV)
Thickening	$A \odot B = A \cup (A \circledast B)$ $A \odot \{B\} = ((\ldots((A \odot B^1) \odot B^2)\ldots) \odot B^n)$	Thickens set A using a sequence of structuring elements, as above. Uses (IV) with 0's and 1's reversed.

Here is a summary of the morphological operators that we have considered so far.

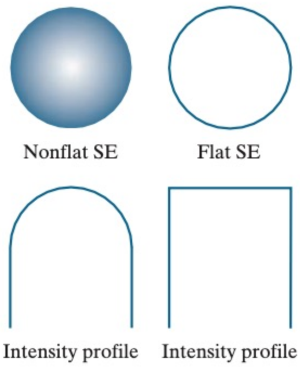
Summary of Binary Morphological Operators (4)

Operation	Equation	Comments
Geodesic dilation–size 1	$D_G^{(1)}(F) = (F \oplus B) \cap G$	F and G are called the *marker* and the *mask* images, respectively. (I)
Geodesic dilation–size n	$D_G^{(n)}(F) = D_G^{(1)}\left(D_G^{(n-1)}(F)\right)$	Same comment as above.
Geodesic erosion–size 1	$E_G^{(1)}(F) = (F \ominus B) \cup G$	Same comment as above.
Geodesic erosion–size n	$E_G^{(n)}(F) = E_G^{(1)}\left(E_G^{(n-1)}(F)\right)$	Same comment as above.
Morphological reconstruction by dilation	$R_G^D(F) = D_G^{(k)}(F)$	With k is such that $D_G^{(k)}(F) = D_G^{(k+1)}(F)$.

Here is a summary of the morphological operators that we have considered so far.

Grayscale Morphology

- Let us apply basic operation of dilation, erosion, opening and closing tp grayscale instead of just binary images.
- For this discussion, $f(x, y)$ is a grayscale image and $b(x, y)$ is a structuring element. These are functions that assign an intensity value to each distinct pair of coordinate (x, y).
- The structuring elements may take various forms:



So far, we have only considered morphological operators on binary images. Same operations can be applied to grayscale images, but logic operations are replaced by minimum and maximum operators.

Further, the image has intensity values, and so may the structuring element.

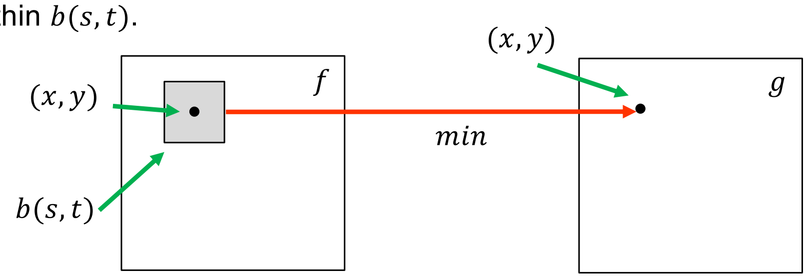
Show here are nonflat and flat structuring elements, and corresponding horizontal intensity profiles through their centers. All examples in this section are based on flat SEs.

Grayscale Erosion

- **Erosion** of $f(x, y)$ by the **flat** structuring element $b(x, y)$ is defined by:

$$[f \ominus b](x, y) = \min_{(s,t)\in b} \{f(x+s, y+t)\}$$

- This implies that the output intensity $g(x, y)$ is found by the **minimum** values within $b(s, t)$.



- **Erosion** of $f(x, y)$ by the **nonflat** structuring element $b(x, y)$ is defined by:

$$[f \ominus b_N](x, y) = \min_{(s,t)\in b_N} \{f(x+s, y+t) - b_N(s, t)\}$$

The grayscale erosion of f by a flat structuring element b at location (x, y) is defined as the **minimum value** of the image in the region coincident with $b(x, y)$ when the origin of b is at (x, y).

In equation form, the erosion at (x, y) of an image f by a structuring element b is given as:

$$[f \ominus b](x, y) = \min_{(s,t)\in b} \{f(x+s, y+t)\}$$

Put in words, to find the erosion of f by b, we place the origin of the structuring element b at every pixel location in the image. The erosion at any location is determined by selecting the **minimum value** of f in the region coincident with b. For example, if b is a square structuring element of size 3 × 3 with flat intensity profile, obtaining the erosion at a point requires finding the minimum of the nine values of f contained in the 3 × 3 region spanned by b when its origin is at that point.

Nonflat SEs have grayscale values that vary over their domain of definition. The erosion of image f by nonflat structuring element, b_N , is defined as:

$$[f \ominus b_N](x, y) = \min_{(s,t)\in b_N} \{f(x+s, y+t) - b_N(s, t)\}$$

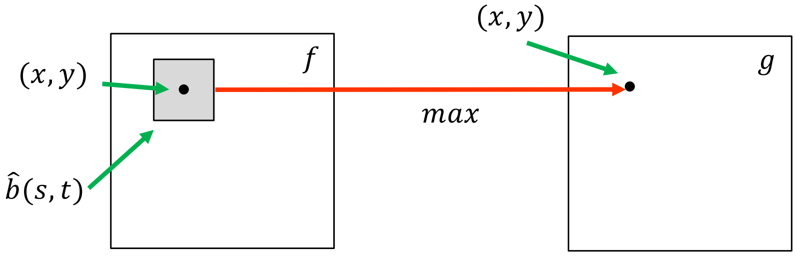
Here, we subtract values from f to determine the erosion at any point.

Grayscale Dilation

- **Dilation** of $f(x,y)$ by the **flat** structuring element $b(x,y)$ is defined by:

$$[f \oplus b]\,(x,y) = \max_{(s,t)\in\hat{b}} \{f(x-s, y-t)\}$$

- This implies that the output intensity $g(x,y)$ is found by the **maximum** values within $\hat{b}(s,t)$ which is $b(s,t)$ reflect at the origin.



- **Dilation** of $f(x,y)$ by the **nonflat** structuring element $b(x,y)$ is defined by:

$$[f \oplus b_N]\,(x,y) = \max_{(s,t)\in\hat{b}_N} \{f(x-s, y-t) + \hat{b}_N\,(s,t)\}$$

The grayscale **dilation** of f by a flat structuring element b at location (x,y) is defined as the **maximum value** of the image in the region coincident with $b(x,y)$ when the origin of b is at (x,y). However, we must use the reflected SE about the origin:

$$\hat{b}(s,t) = b(-s,-t) = b(s,t)$$

In equation form, the dilation at (x,y) of an image f by a structuring element b is given as:

$$[f \oplus b]\,(x,y) = \max_{(s,t)\in\hat{b}} \{f(x-s, y-t)\}$$

This is very similar to that of erosion except that we choose the maximum instead of minimum value.

Nonflat SEs have grayscale values that vary over their domain of definition. The dilation of image f by nonflat structuring element, b_N , is defined as:

$$[f \oplus b_N]\,(x,y) = \max_{(s,t)\in\hat{b}_N} \{f(x-s, y-t) + \hat{b}_N\,(s,t)\}$$

Here, we ADD values from f to determine the dilation at any point.

Grayscale Opening and Closing

- **Opening** of $f(x, y)$ by the structuring element $b(x, y)$ is defined in a similar way to for binary images:

$$f \circ b = (f \ominus b) \oplus b$$

- For **Closing**:

$$f \cdot b = (f \oplus b) \ominus b$$

- Opening and closing for grayscale images are duals with respect to complementation and SE reflection:

$$(f \cdot b)^c = f^c \circ \hat{b}$$

and

$$(f \circ b)^c = f^c \cdot \hat{b}$$

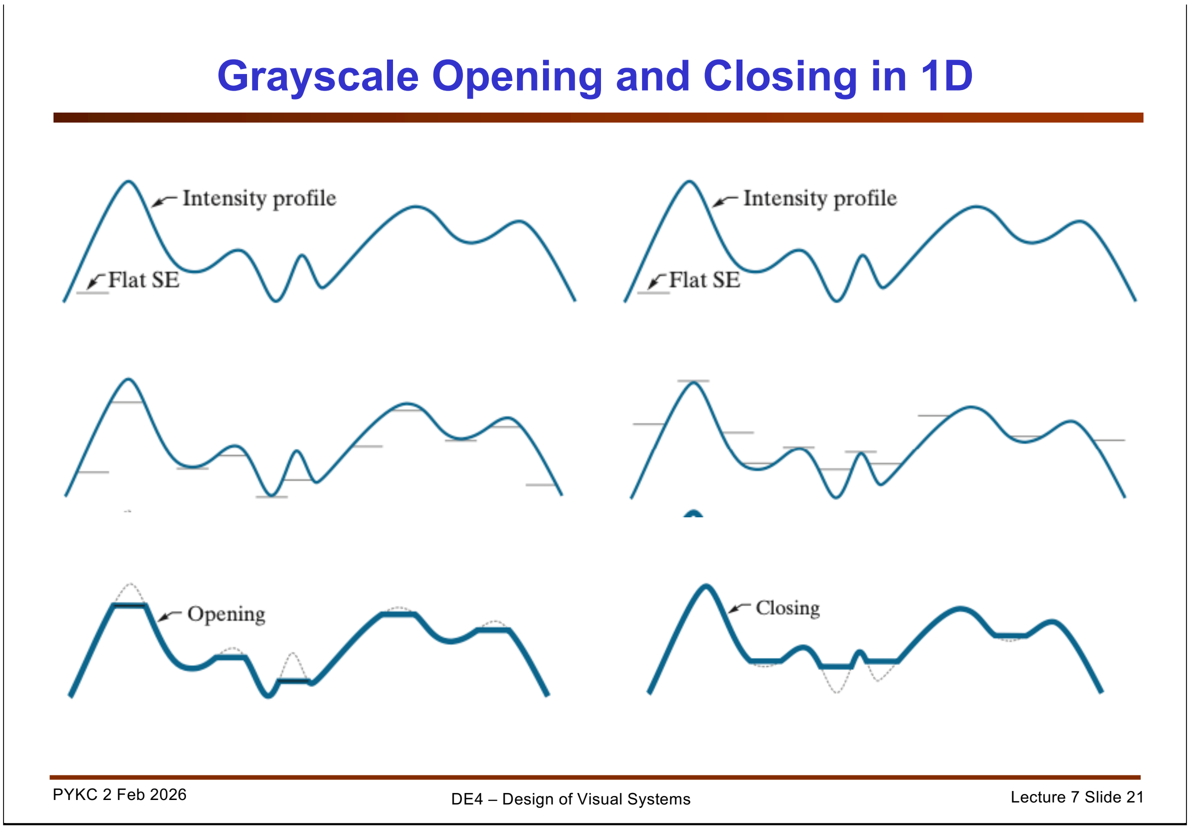
- Because $f^c = -f$,

$$(f \cdot b)^c = -(f \cdot b) = (-f \circ b)$$

Opening and closing of grayscale images have a simple geometric interpretation.

Suppose that an image function $f(x, y)$ is viewed as a 3-D surface; that is, its intensity values are interpreted as height values over the *xy*-plane. Then the opening of f by b can be interpreted geometrically as **pushing the structuring element up from below** against the undersurface of f.

At each location of the origin of b, the opening is the highest value reached by any part of b as it pushes up against the undersurface of f. The complete opening is then the set of all such values obtained by the origin of b visiting every (x, y) coordinate of f.

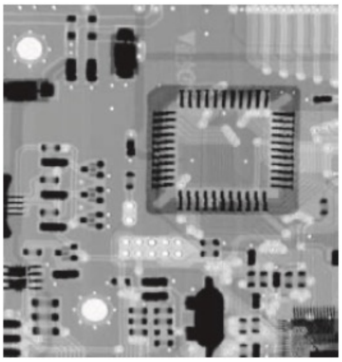


The diagram in the slide illustrates the concept of opening and closing in one dimension.

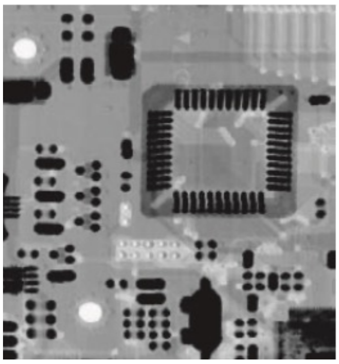
Suppose the top left curve is the intensity profile along a single row of an image. The one below shows a flat structuring element in several positions, pushed up against the bottom of the curve. The heavy curve at the bottom is the complete opening. Because the structuring element is too large to fit completely inside the upward peaks of the curve, the tops of the peaks are clipped by the opening, with the amount removed being proportional to how far the structuring element was able to reach into the peak. In general, openings are used to remove small, bright details, while leaving the overall intensity levels and larger bright features relatively undisturbed.

The right column of figures is a graphical illustration of closing. Observe that the structuring element is pushed down on top of the curve while being translated to all locations. The closing is constructed by finding the lowest points reached by any part of the structuring element as it slides against the upper side of the curve.

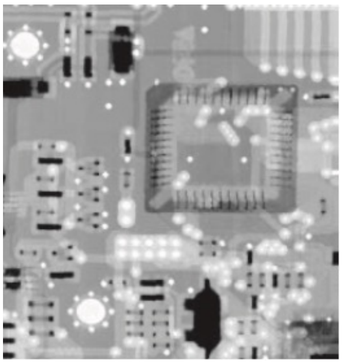
Example of Grayscale – Erosion and Dilation



448 x 425
X-ray image of a PCB



Erosion with a
flat disk SE with
radius of 2 pixels



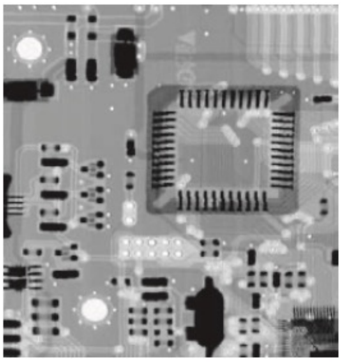
Dilation using the
same SE

Because grayscale erosion with a flat SE computes the minimum intensity value of f in every neighbuorhood of (x, y) coincident with b, we expect in general that an eroded grayscale image will be darker than the original, that the sizes (with respect to the size of the SE) of bright features will be reduced, and that the sizes of dark features will be increased.

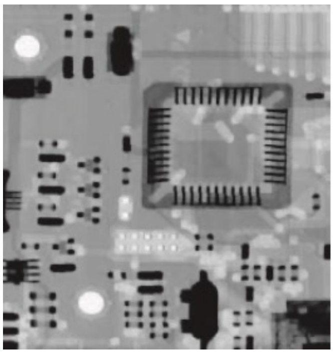
The middle image shows the erosion of the input image using a disk SE of unit height and a radius of 2 pixels. The effects mentioned in the last paragraph are clearly visible in the eroded image. For instance, note how the intensities of the small bright dots were reduced, making them barely visible, while the dark features grew in thickness. The general background of the eroded image is slightly darker than the background of the original image.

Similarly, the right image is the result of dilation with the same SE. The effects are the opposite of using erosion. The bright features were thickened and the intensities of the darker features were reduced. In particular, the thin black connecting wires in the left, middle, and right bottom the input image are barely visible. The sizes of the dark dots were reduced as a result of dilation, but, unlike the eroded small white dots in the eroded image (middle), they still are easily visible in the dilated image. The reason is that the black dots were originally larger than the white dots with respect to the size of the SE. Finally, observe that the background of the dilated image is slightly lighter than that of the orginal.

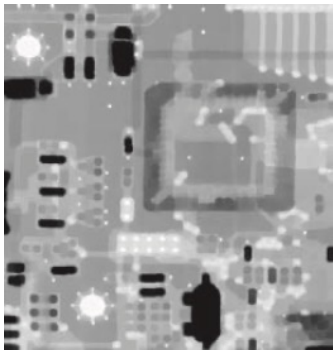
Example of Grayscale Opening and Closing



448 x 425
X-ray image of a PCB



Opening using a disk SE with radius of 3 pixels



Closing using a disk SE with radius of 5 pixels

This is an X-ray image of a PCB is the opening obtained using a disk structuring element of unit height and radius of 3 pixels. As expected, the intensity of all bright features decreased, depending on the sizes of the features relative to the size of the SE.

Comparing this result with that of the previous slide, we see that, unlike the result of erosion, opening had negligible effect on the dark features of the image, and the effect on the background was negligible.

Similarly, the right-hand image shows the closing of the image with a disk of radius 5 (the small round black dots are larger than the small white dots, so a larger disk was needed to achieve results comparable to the opening).

In this image, the bright details and background were relatively unaffected, but the dark features were attenuated, with the degree of attenuation being dependent on the relative sizes of the features with respect to the SE.

Morphological Gradient

- By subtracting an eroded image from a dilated image, we can obtain the morphological gradient:

$$g = (f \oplus b) - (f \ominus b)$$

- Let us apply basic operation of dilation, erosion, opening and closing tp grayscale instead of just binary images.
- For this discussion, $f(x, y)$ is a grayscale image and $b(x, y)$ is a structuring element. These are functions that assign an intensity value to each distinct pair of coordinate (x, y).
- The structuring elements may take various forms:

Dilation and erosion can be used in combination with image subtraction to obtain the morphological gradient, *g*, of a grayscale image *f*, as follows:

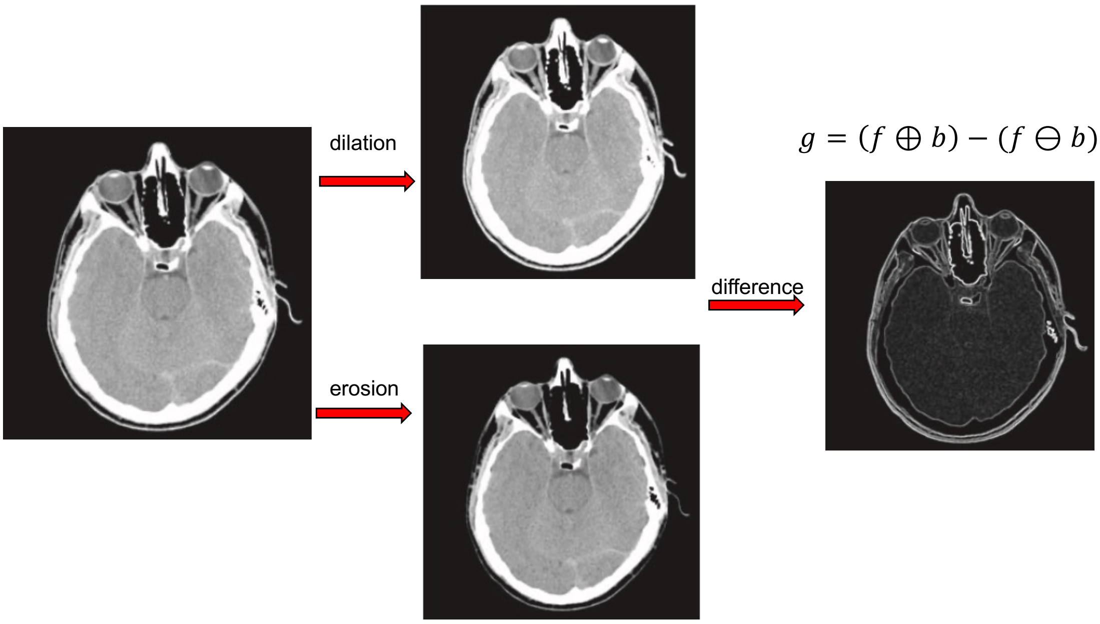
$$g = (f \oplus b) - (f \ominus b)$$

The overall effect achieved by using this equation is that dilation thickens regions in an image, and erosion shrinks them. Their difference emphasizes the boundaries between regions.

Homogenous areas are not affected (provided that the SE is not too large relative to the resolution of the image) so the subtraction operation tends to eliminate them.

The net result is an image in which the edges are enhanced and the contribution of the homogeneous areas is suppressed, thus producing a “derivative-like” (gradient) effect.

Example of using Morphological Gradient



$$g = (f \oplus b) - (f \ominus b)$$

The original image is a head CT scan. The two middle figures are the dilated and eroded images with a 3×3 flat SE of 1's. Note the thickening and shrinking. The final figure is the morphological gradient obtained using the gradient equation. As you can see, the boundaries between regions were clearly delineated, as expected of a 2-D derivative image.

Top-Hat and Bottom-Hat Transformations

- Combining image subtraction with openings and closings results in top-hat and bottom-hat transformations.
- Top-hat transformation is:

$$T_{hat}(f) = f - (f \circ b) = f - (f \ominus b) \oplus b$$

- Bottom-hat transform is:

$$T_{bot}(f) = (f \cdot b) - f = (f \oplus b) \ominus b - f$$

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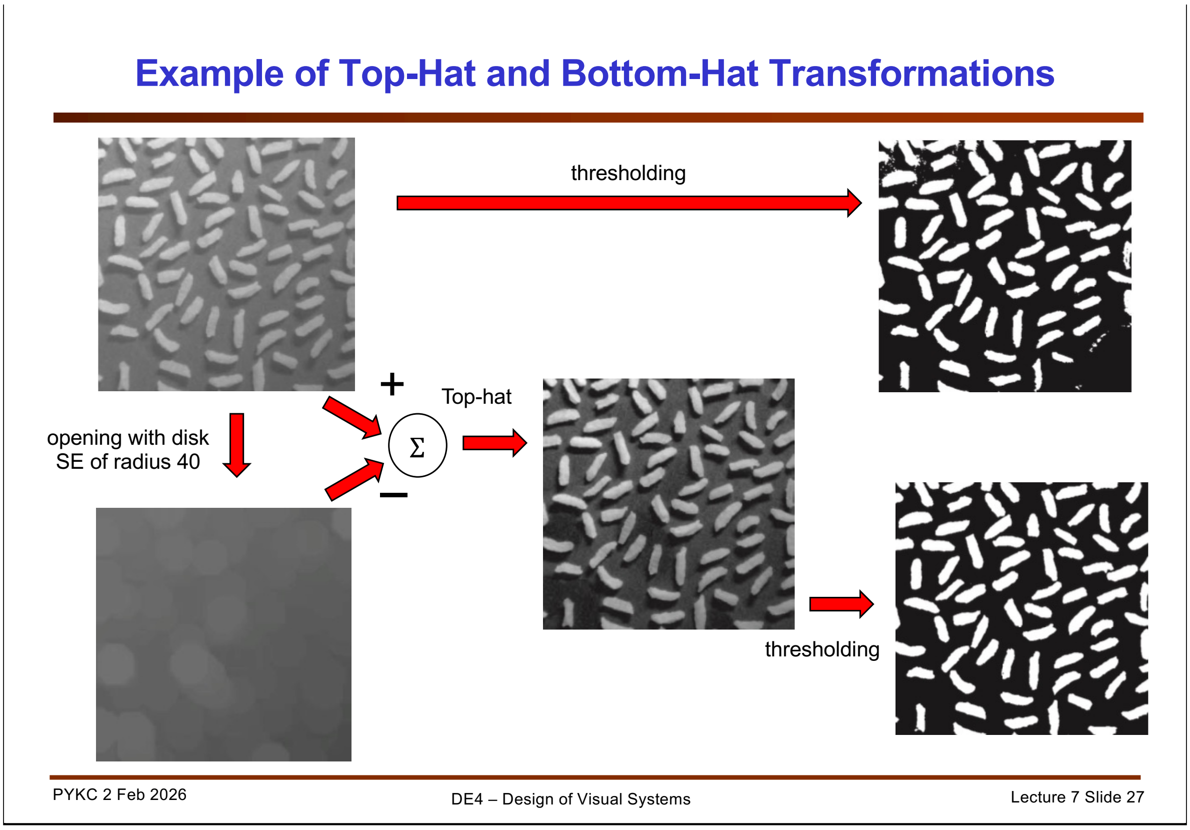
One of the principal applications of these transformations is in removing objects from an image by using a structuring element in the opening or closing operation that does not fit the objects to be removed. The difference operation then yields an image in which only the removed components remain.

The top-hat transformation is used for light objects on a dark background, and the bottom-hat transformation is used for the opposite situation. For this reason, the names *white top-hat* and *black top-hat*, respectively, are used frequently when referring to these two transformations.



This slide shows an image of grains of rice.

This image was obtained under nonuniform lighting, as evidenced by the darker area in the bottom rightmost part of the image. The top--right image shows the result of thresholding. The net result of nonuniform illumination was to cause several grains of rice were not extracted from the background. Furthermore, in the top left part of the image, parts of the background were interpreted as rice.

The bottom-left image shows the opening of the image with a disk of radius 40. This SE was large enough so that it would not fit in any of the objects. As a result, the objects were eliminated, leaving only an approximation of the background. The shading pattern is clear in this image.

By subtracting this image from the original (i.e., by applying a top-hat transformation), the background becomes more uniform as shown in the middle image. The background is not perfectly uniform, but the differences between light and dark extremes are less, and this was enough to yield a correct thresholding result, in which all the rice grains were properly extracted.

Comparing the top-right and bottom-right images, top-hat has done its job!