Medical Image Processing: Some Tools

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M2 MIA / GICAO (P+R)

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Overview

Negative of an image

- Transformation T on an image such that each pixel is modified independently of its neighbors.
- Also called LUT (*Look Up Table*)

$$\forall p_{i,j} \in I p'_{i,j} = T(p_{i,j})$$

Negative of an image

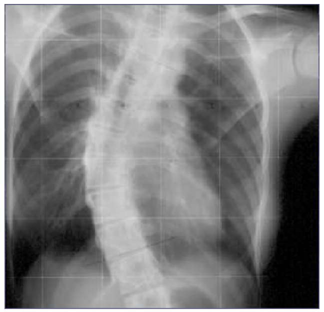
For grey levels between V_{min} and V_{max}

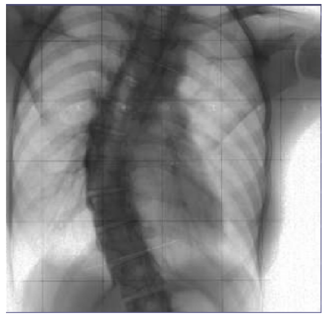
$$p'_{i,j} = T(p_{i,j}) = V_{max} - pV_{min}$$

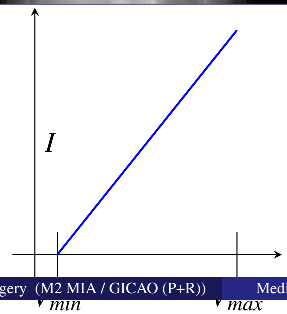
The transformation is linear so that:

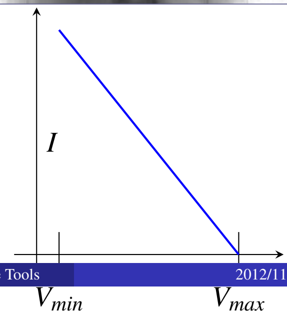
$$T(V_{min}) = V_{max} \text{ et } T(V_{max}) = V_{min}.$$

Negative of an image









Contrast Enhancement

- Transformation T on an image such that each pixel is modified independently of its neighbors.
- Also called LUT (*Look Up Table*)

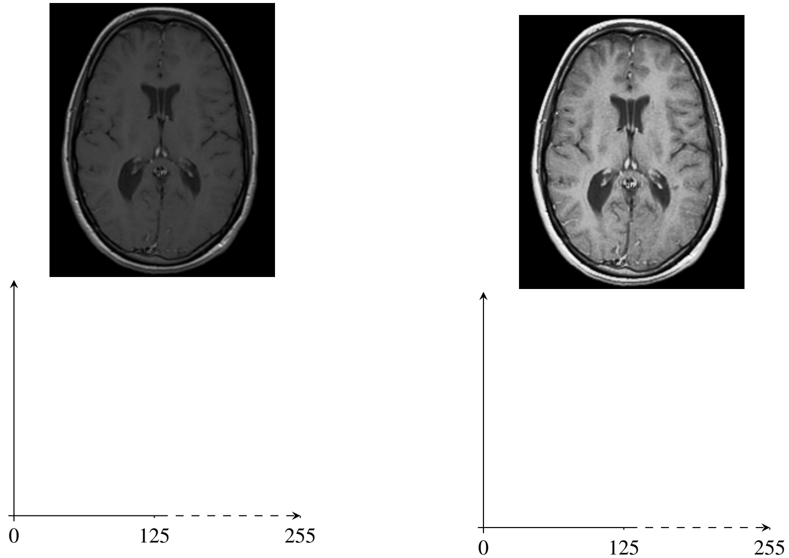
$$\forall p_{i,j} \in I p'_{i,j} = T(p_{i,j})$$

Contrast Enhancement

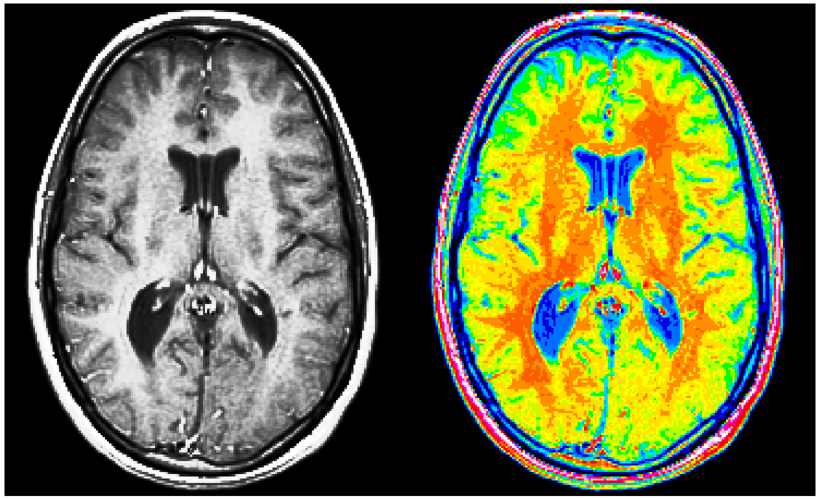
- Range of grey level values between V_{min} and V_{max}
- Effective dynamic range between I_{min} and I_{max}

$$p'_{i,j} = T(p_{i,j}) = (p_{i,j} - I_{min}) \frac{(V_{max} - V_{min})}{(I_{max} - I_{min})}$$

Contrast Enhancement



Color map



Segmentation : definition

Goal: define objects in the image

Object

Semantically coherent parts of the image

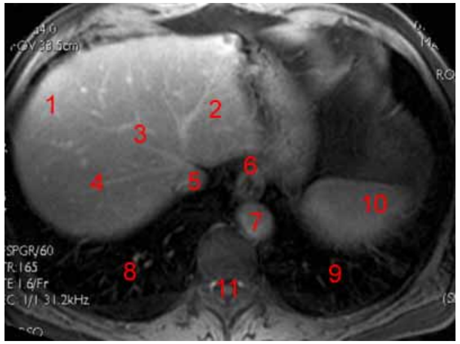
Segmentation

Partition of an image in a finite number of regions $R_1, ...R_S$ such that:

$$\forall i, j, i \neq j, R_i \bigcap R_j = \emptyset$$

$$I = \bigcup_{i=1}^{S} R_i$$

Segmentation : definition

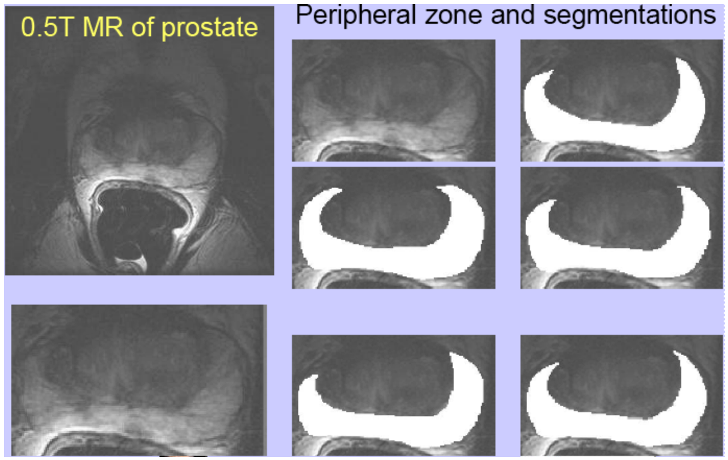


1. liver
2. left hepatic vein,
3. medial hepatic vein,
4. right hepatic vein,
5. lower vena cava,
6. oesophagus,
7. abdominal aorta,
8. lower right pulmonary lobe,
9. lower left pulmonary lobe,
10. spleen,
11. spinal canal,
12. costal arc.

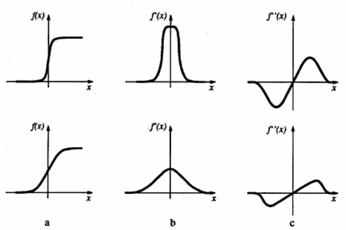
Medical images $\longrightarrow$ organs
Ideally, parts of the image that are:

- connected
- with similar grey levels
- delimited by sharp contours

Difficulties of segmentation



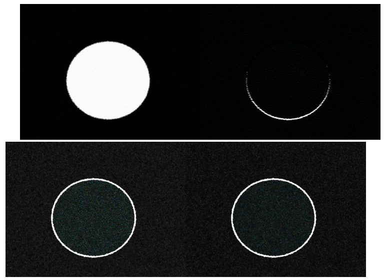
Contour based methds



Location of the contours on the image:

- where grey levels change brutally
- where the intensity profile makes a step
- i.e. the profile's first derivative is maximum
- i.e. the profile's second derivative is null

Example of contour detection: maximum of the first derivative



- Prewitt detector

$$h_1 = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

$$h_2 = \begin{bmatrix} 0 & 1 & 1 \\ -1 & 0 & 1 \\ -1 & -1 & 0 \end{bmatrix}$$

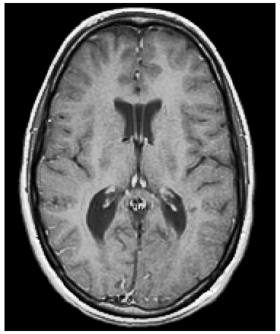
$$h_3 = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

- Canny detector

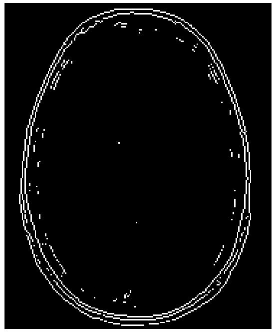
$$h_1 = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

$$h_2 = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

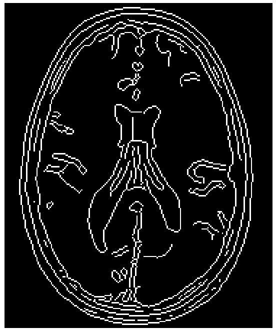
Example of contour detection: maximum of the first derivative



Original image

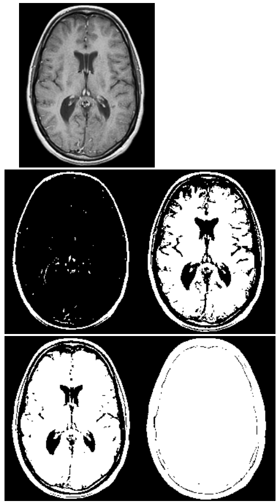


Sobel filter



Canny filter

Region Based Segmentation: Threshold



Separates the image into regions with one ore several thresholds on grey levels.

- $g(x, y) = 1$ si $f(x, y) \geq T$
- $g(x, y) = 0$ sinon

Problem: Which value for the threshold ?

Automatic optimal threshold determination

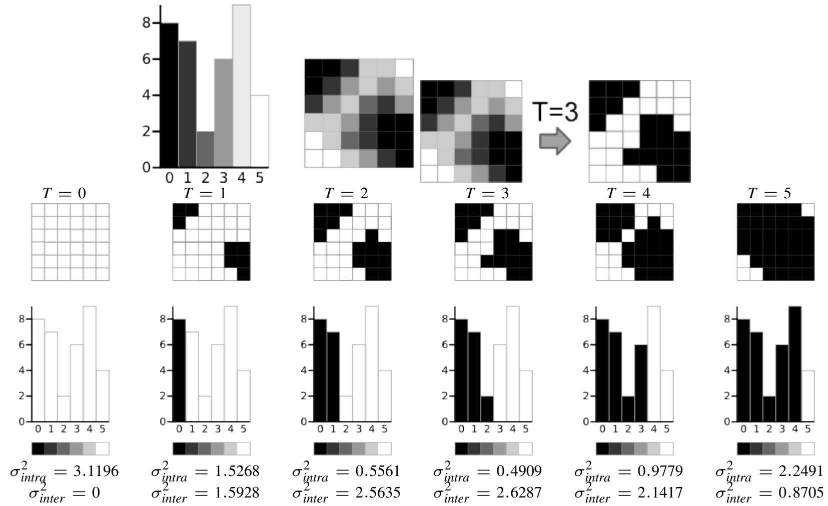
Non parametric methods

- Maximisation / minimisation between class variances (Otsu)

$$v = p(classe1_t) * v(classe1_t) + p(classe2_t) * v(classe2_t)$$

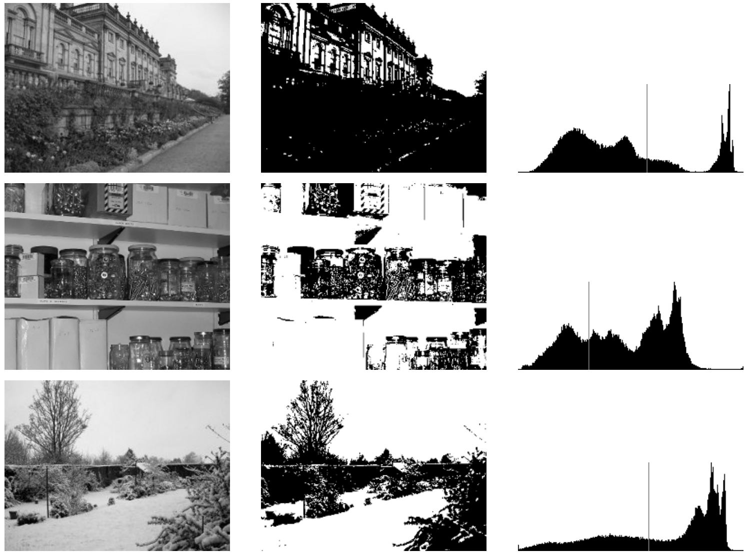
```
For (each grey level g in the histogram)
    threshold t = g
    compute v
Keep t for v minimum
```


Otsu Threshold

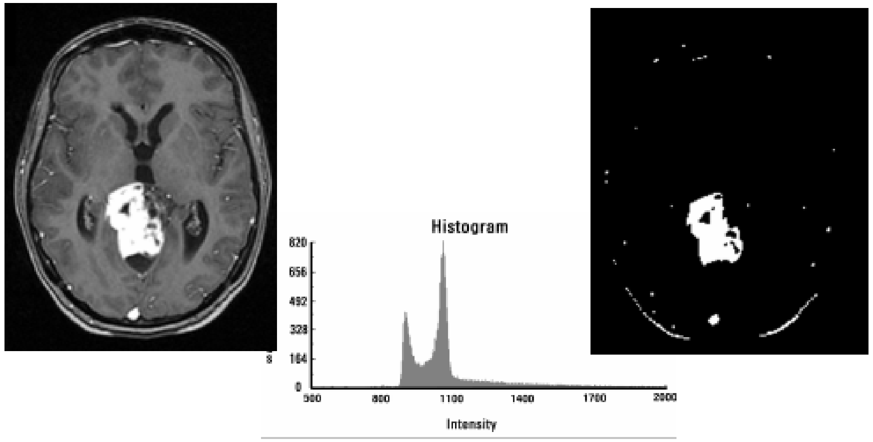


Otsu Threshold: using the histograms

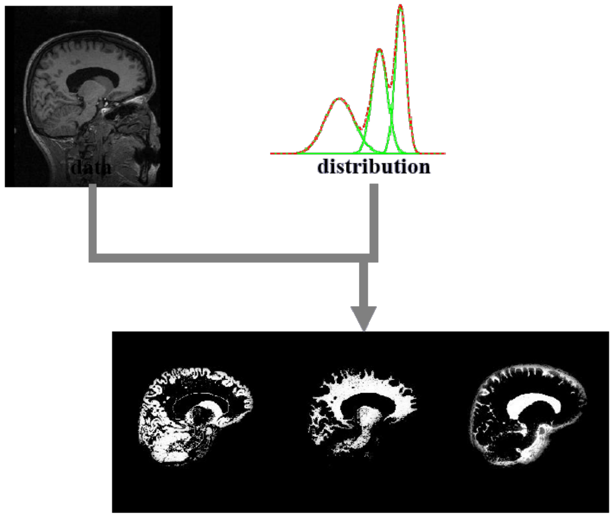
Original Image | Segmented Image | Histogram



Otsu Threshold: using the histograms



Parametric Classification



Courtesy of D. Vandermeulen & H. Delingette

Classification Methods

- Principle: to classify voxels according several labels
- Histogram: example of 1D classification
- Examples of classification algorithms: K-means, Expectation-Maximization

Threshold

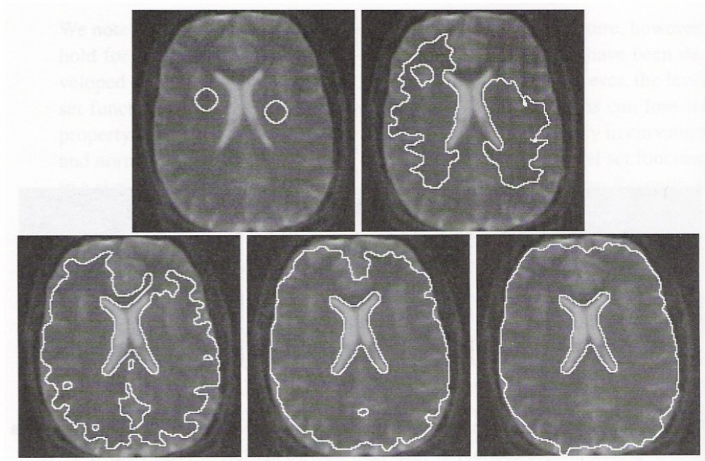
Advantages

- Fast (possible real time)
- Works well when there are good contrasts in the image
  - bones/soft tissues in scanner
  - ...
- May be used interactively
- Often: First step of operations on images

Drawbacks

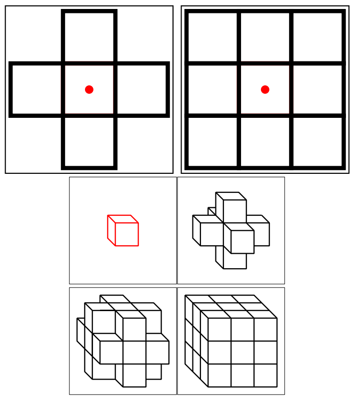
- No spatial correlation
- Several structures may have same grey levels
- Sensitive to noise

Region growing



Neighborhood

- 2D
  Given a point $p(i,j)$ of 2D discrete plane
  $N_d(p) = \{q(x,y) \in \mathbb{Z}^2 |x-i| + |y-j| \leq d\}$
  - 4-neighborhood (N_1)
  - 8-neighborhood (N_2)
- 3D
  Given a point $p(i,j,k)$ of the 3D discrete volume
  $N_d(p) = \{q(x,y,z) \in \mathbb{Z}^3 |x-i| + |y-j| + |z-k| \leq d\}$
  - 6-neighborhood (N_1)
  - 18-neighborhood (N_2)
  - 26-neighborhood (N_3)

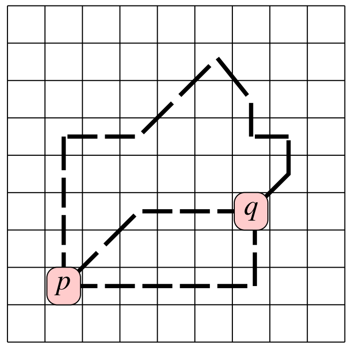


Connected Component

A discrete **path** or **curve** from a point p to a point q is a sequence of pixels (*voxels*) $s_1 s_2 \ldots s_n$ such that:

- $s_1 = p$
- $_2 = q$
- for all $i \in 1 \ldots n-1$ s_i et s_{i+1} are k-neighbours

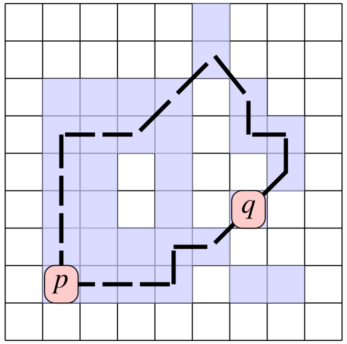
We can define 4-paths, 8-paths in 2D, and 6-paths, 18-paths, and 26-paths in 3D.



Connected Component

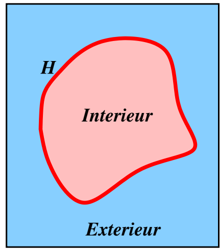
Let us give a set of pixels (*voxels*) S of an image.
Two pixels (*voxels*) p and q of S are said to be **connected** in S if there exists a path between p and q containing only pixels (*voxels*) of S/

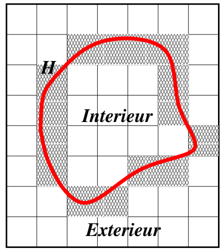
A set S is said to be k-connected if and only if for all points p and q of S, p and q are k-connected.



Jordan's Theorem

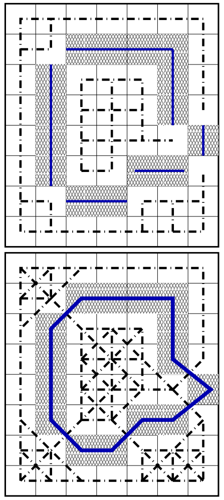
- Jordan's Theorem
  Any simple closed curve separates the space into 2 connected components defining the interior and the exterior of the curve.





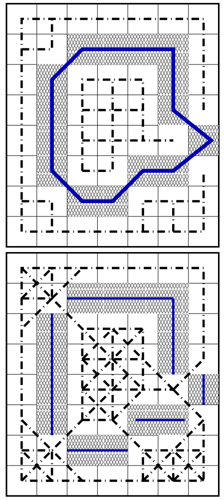
Jordan's Theorem

- 1^{st} paradox of Rosenfeld
  There exist open lines which define an interior and an exterior.
- 2^{nd} paradox of Rosenfeld
  There exist closed cured which do not define an interior and an exterior



Jordan's Theorem

- Use of 2 connexity/neighborhood
  - 4-neighborhood for the background, 8-neighborhood for the object
    - closed curve
    - 1 interior et 1 exterior
  - 8-neighborhood pour the background, 4-neighborhood for the object
    - no close curve
    - only one connected component



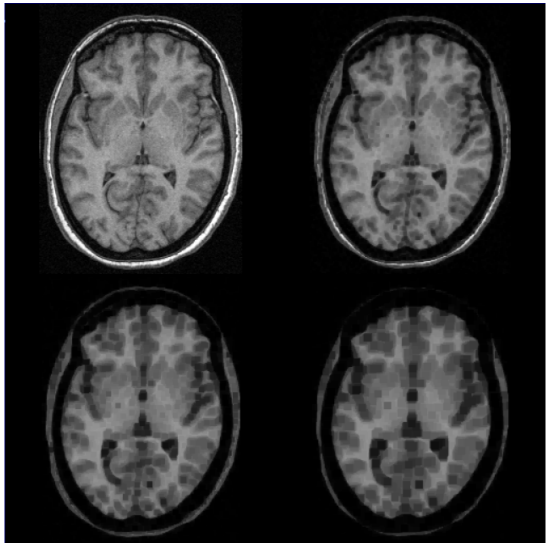
Morphological Operator: Erosion

150	55	82
32	16	65
16	122	76

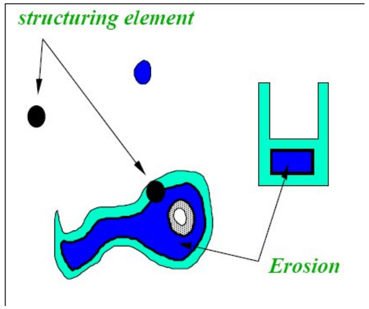
For each pixel/voxel of the image

- We consider the neighborhood of this pixel/voxel
- Replace the value of the central pixel/voxel by the **minimum** of the pixel/voxel values

Morphological Operator: Erosion



Morphological Operator: Erosion



http://cmm.ensmp.fr/ serra/cours/index.htm

Morphological Operator: Dilation

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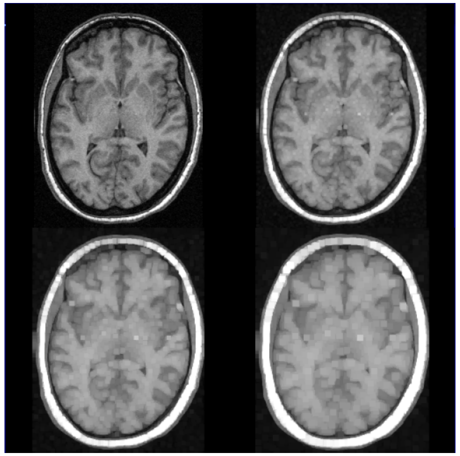
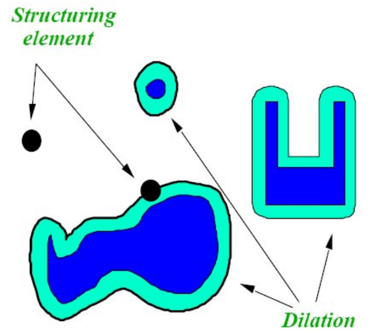
Morphological Operator: Dilation



Morphological Operator: Dilation



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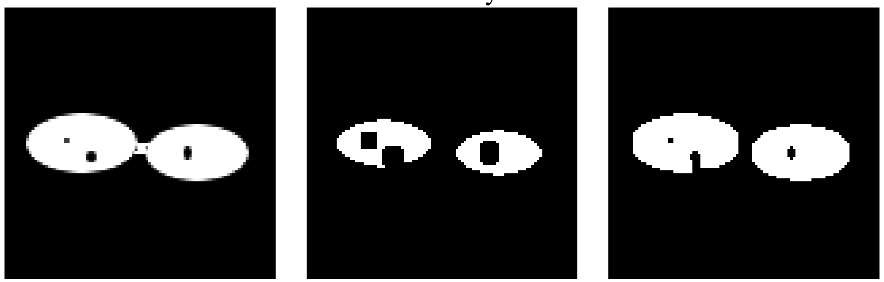
Morphological Operator: Opeining

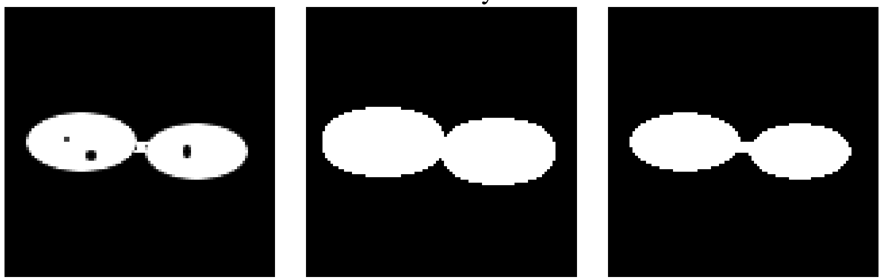
Erosion followed by a dilation



original binary image | eroded image | image after opeining

Morphological Operator: Closure

Dilation followed by an erosion



original binary image | dilated image | image after closure