Image Processing using Graphs (lecture 2 - connected filters)

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Introduction

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- The adjacency relation $\mathcal{A}$ plays the role of a planar structuring element. For example, the ball shape defined by

$$\mathcal{A}_r : \forall t \in \mathcal{N} = \mathcal{D}_I, t \in \mathcal{A}_r(s) \quad \text{when} \quad \|t - s\|^2 \leq r^2, r \geq 1,$$

is very useful in several cases.

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- They create filtered images $\mathbf{V}_0 = (\mathcal{D}_I, V_0)$, whose values $V_0(t)$ will constitute our initial connectivity map.
- Dilation and erosion are defined by

$$
\begin{aligned}
V_0(s) &= \max_{\forall t \in \mathcal{A}_r(s)} \{I(t)\} \\
V_0(s) &= \min_{\forall t \in \mathcal{A}_r(s)} \{I(t)\}
\end{aligned}
$$

respectively.

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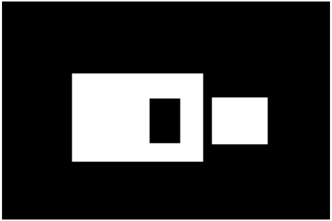
However, they may create undesirable “side effects”.



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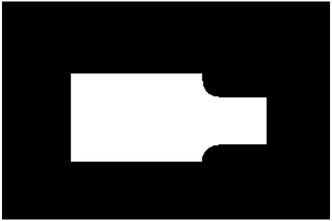

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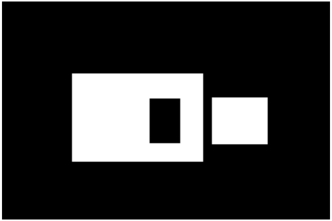

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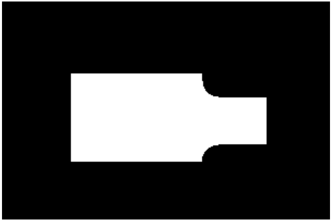

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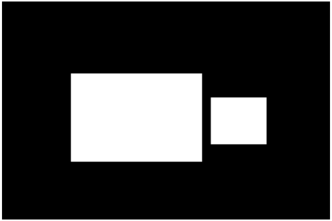

- Image $\mathbf{I}$ (mask).
- Image $\mathbf{V}_0 = \Psi_C(\mathbf{I}, \mathcal{A}_{15})$ (marker).
- Image $\mathbf{V}$ (our optimum connectivity map) after reconstruction of $\mathbf{I}$ from $\mathbf{V}_0$.

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- Superior and inferior reconstructions [1, 2].

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- Their relation with watershed-based segmentation [2, 3, 4].
- Fast binary filtering [5].

Flat zones

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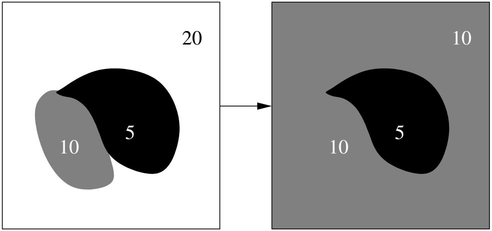
- This surface contains
  - domes — bright regions,
  - basins — dark regions, and
  - flat zones or plateaus — connected components with the same value and maximum area.

Flat zones and connected filters

Connected filters essentially remove domes and/or basins, increasing the flat zones, such that any pair of spels in a given flat zone of the input image must belong to a same flat zone of the filtered image.



Regional minima and maxima

Regional minima (maxima) are flat zones whose values are strictly lower (higher) than the values of the adjacent spels. Considering a 4-neighborhood relation in the image below,

7	6	7	4	1	5	5
8	4	4	5	1	2	5
4	6	7	2	1	5	5
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can you find minima and maxima?

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$$V_0(t) \quad \geq \quad I(t)$$

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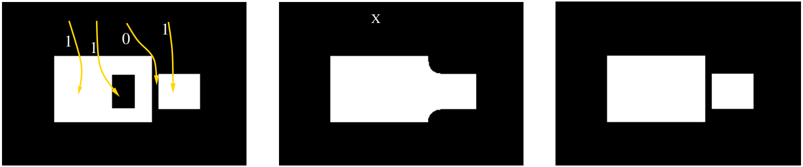
  for all $t \in \mathcal{D}_I$.
- It repeats $\Psi_E(\mathbf{V}_0, \mathcal{A}_1) \cup \mathbf{I}$ multiple times up to the idempotence:

$$\Psi_E(\Psi_E(\mathbf{V}_0, \mathcal{A}_1) \cup \mathbf{I}, \mathcal{A}_1) \cup \mathbf{I} \ldots)$$

Superior reconstruction by IFT

Instead of that, for every point t, the IFT finds a path from a regional minimum in $\mathbf{V}_0$ (component X) whose maximum altitude to reach t along that path is minimum.



$\mathbf{I} = (\mathcal{D}_I, I)$ $\mathbf{V}_0 = (\mathcal{D}_I, V_0)$ $\mathbf{V} = (\mathcal{D}_I, V)$

Superior reconstruction by IFT

The IFT minimizes

$$V(t) = \min_{\forall \pi_t \in \Pi(\mathcal{D}_I, \mathcal{A}_1, t)} \{f_{srec}(\pi_t)\}$$

where f_{srec} is defined by

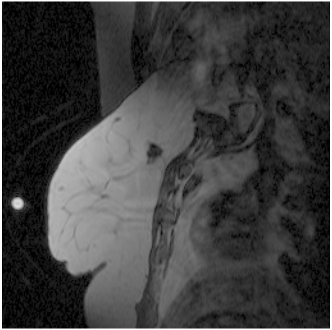
$$\begin{aligned} f_{srec}(\langle t \rangle) &= V_0(t) \\ f_{srec}(\pi_s \cdot \langle s, t \rangle) &= \max\{f_{srec}(\pi_s), I(t)\}. \end{aligned}$$

Superior reconstruction by IFT

Indeed, the problem could also be easily solved without the closing operation, by marker imposition

$$V_0(t) = \begin{cases} I(t) & \text{if } t \in \mathcal{S}, \\ +\infty & \text{otherwise,} \end{cases}$$

where $\mathcal{S}$ represents seed spels (e.g., the border of $\mathbf{I}$).



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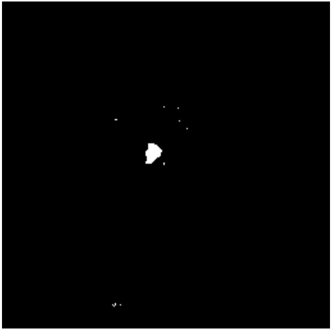

- Original image of a carcinoma.
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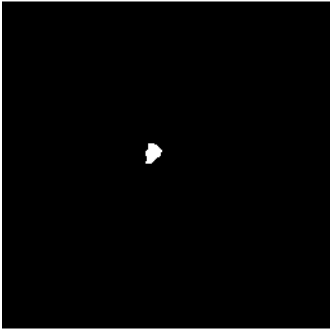

- Original image of a carcinoma.
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- An opening by reconstruction.

Inferior reconstruction by IFT

- Similarly, the inferior reconstruction of $\mathbf{I}$ from $\mathbf{V}_0$ requires

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for all $t \in \mathcal{D}_I$ in order to eliminate domes rather than basins.

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- In this case, for every point t, the IFT finds a path from a regional maxima in $\mathbf{V}_0$ whose minimum altitude to reach t along that path is maximum.

Inferior reconstruction by IFT

The IFT maximizes

$$V(t) = \max_{\forall \pi_t \in \Pi(\mathcal{D}_I, \mathcal{A}_1, t)} \{f_{irec}(\pi_t)\}$$

for path function f_{irec} defined by

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Marker imposition using a set $\mathcal{S}$ of seed spels is also valid.

$$V_0(t) = \begin{cases} I(t) & \text{if } t \in \mathcal{S}, \\ -\infty & \text{otherwise.} \end{cases}$$

Superior and inferior reconstructions

Therefore, we define

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- The way $\mathbf{V}_0$ is created gives other specific names to them.

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- h-Basins: residue $\Psi_{srec}(\mathbf{I}, \mathbf{V}_0) - \mathbf{I}$, $\mathbf{V}_0 = \mathbf{I} + h$, and $h \geq 1$.

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- h-domes: residue $\mathbf{I} - \Psi_{irec}(\mathbf{I}, \mathbf{V}_0)$, $\mathbf{V}_0 = \mathbf{I} - h$, and $h \geq 1$.

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- h-domes: residue $\mathbf{I} - \Psi_{irec}(\mathbf{I}, \mathbf{V}_0)$, $\mathbf{V}_0 = \mathbf{I} - h$, and $h \geq 1$.
- Closing of basins or opening of domes: $\mathbf{V}_0$ is created by marker imposition.

Levelings

Superior and inferior reconstructions can also be combined into a leveling transformation to correct edge blurring created by linear smoothing [6].

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- Original image.
- Regular Gaussian filtering.
- Leveling transformation.

This leveling operator uses the following sequence of transformations from $\mathbf{I}$ and the impaired image $\mathbf{V}_0$.

Algorithm

– LEVELING ALGORITHM

1. $\mathbf{X} \leftarrow \Psi_D(\mathbf{V}_0, \mathcal{A}_1) \cap \mathbf{I}$.
2. $\mathbf{I_R} \leftarrow \Psi_{iref}(\mathbf{I}, \mathbf{X}, \mathcal{A}_1)$.
3. $\mathbf{Y} \leftarrow \Psi_E(\mathbf{I}, \mathcal{A}_1) \cup \mathbf{I_R}$.
4. $\mathbf{S_R} \leftarrow \Psi_{srec}(\mathbf{I_R}, \mathbf{Y}, \mathcal{A}_1)$.

Superior reconstruction computation

For superior reconstruction:

- First, all nodes $t \in \mathcal{D}_I$ are trivial paths with initial connectivity values $V_0(t)$.

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- The process continues from the adjacent nodes in a non-decreasing order of path values.

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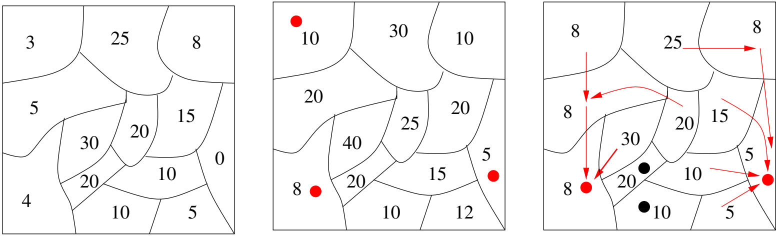
- Essentially the regional minima in $V_0(t)$ compete among themselves and some of them become roots (i.e., minima in $V(t)$).

Superior reconstruction computation

The optimum-path forest with filtered values $V(t)$ (right) resulting from the superior reconstruction of $\mathbf{I} = (\mathcal{D}_I, I)$ (left) from marker $\mathbf{V}_0 = (\mathcal{D}_I, V_0)$ (center) contains unconquered regions (black dots) and the winner regional minima (red dots) as roots.



Images $\mathbf{I}$ (left), $\mathbf{V}_0$ (center), and $\mathbf{V}$ (right).

Algorithm

– SUPERIOR RECONSTRUCTION ALGORITHM

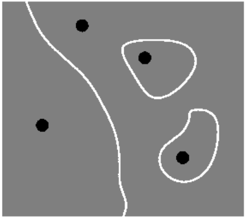
For each $t \in \mathcal{D}_I$, *do*
    Set $V(t) \leftarrow V_0(t)$.
    If $V(t) \neq +\infty$, *then insert* t *in* Q.
While Q *is not empty, do*
    Remove from Q *a spel* s *such that* $V(s)$ *is minimum.*
    For each $t \in \mathcal{A}_1(s)$ *such that* $V(t) > V(s)$, *do*
        Compute $tmp \leftarrow \max\{V(s), I(t)\}$.
        If $tmp < V(t)$, *then*
            If $V(t) \neq +\infty$, *remove* t *from* Q.
            Set $V(t) \leftarrow tmp$.
            Insert t *in* Q.

Organization of this lecture

- Basic definitions.
- Superior and inferior reconstructions.
- Their relation with watershed-based segmentation.
- Fast binary filtering.

Superior reconstruction and watershed transform

Suppose we make a hole in each minimum of an image **I** and submerge its surface in a lake, such that each hole starts a flooding with water of different color. A watershed segmentation is obtained by preventing the mix of water from different colors.



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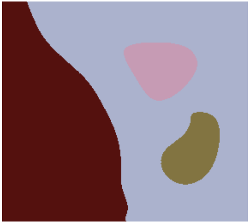

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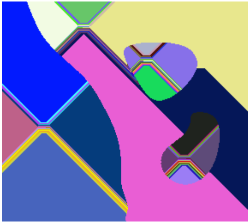

- Original image **I**.
- IFT-watershed segmentation.
- Classical watershed segmentation requires to detect and label each minimum before the flooding process.

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- During superior reconstruction, we may force each regional minimum in $\mathbf{I}$ to produce a single optimum-path tree in P with a distinct label in L.

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- Moreover, by choice of $\mathbf{V}_0$, we may also eliminate the influence zones of "irrelevant" minima and considerably reduce the over-segmentation problem.
- A change of topology in $\Psi_{srec}(\mathbf{I}, \mathbf{V}_0, \mathcal{A}_r)$ for $r > 1$ also helps on that.

This requires a simple modification in f_{srec}.

$$
\begin{aligned}
f_{srec}(\langle t \rangle) &= \begin{cases} I(t) & \text{if } t \in \mathcal{R}, \\ V_0(t) + 1 & \text{otherwise}, \end{cases} \\
f_{srec}(\pi_s \cdot \langle s, t \rangle) &= \max\{f_{srec}(\pi_s), I(t)\},
\end{aligned}
$$

where $\mathcal{R}$ is found on-the-fly with a single root for each regional minimum of the filtered image **V**. The condition $V_0(t) + 1 > I(t)$ guarantees that all spels in $\mathcal{D}_I$ will be conquered.

The choice of $V_0(t) = I(t) + h$, $h \geq 0$ will preserve all minima of $\mathbf{I}$ whose basins have depth greater than h. For $h = 0$, all minima will be preserved.

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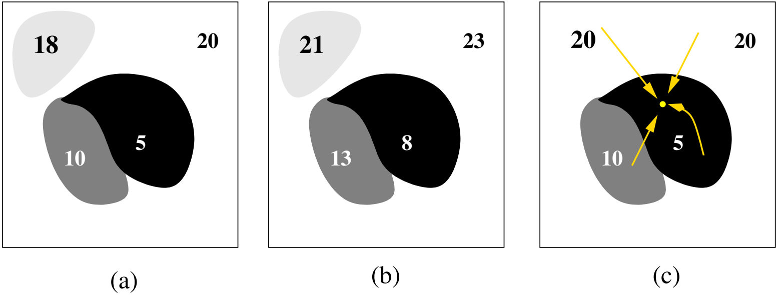

(a) Image $\mathbf{I}$. (b) Image $\mathbf{V}_0 + 1$ for $h = 2$. (c) Image $\mathbf{V} = \Psi_{srec}(\mathbf{I}, \mathbf{V}_0, \mathcal{A}_1)$ with indication of optimum paths in P.

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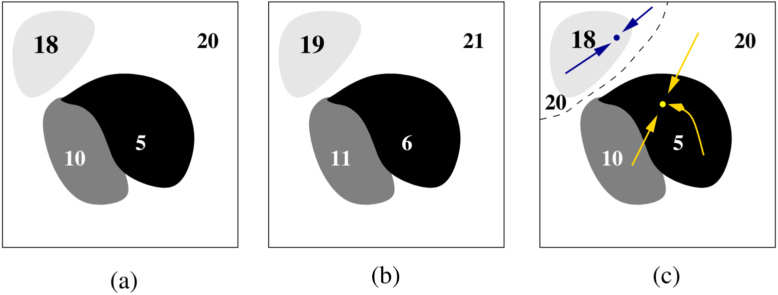

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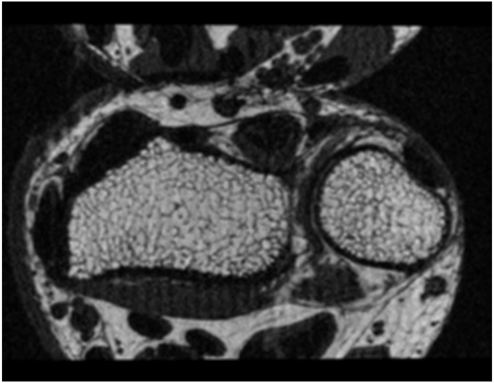
Watershed from grayscale marker

For grayscale images $\mathbf{V}_0$, the simultaneous computation of a superior reconstruction in $\mathbf{V}$ and a watershed segmentation in L is called watershed from grayscale marker [4].



- MR-image of a wrist.

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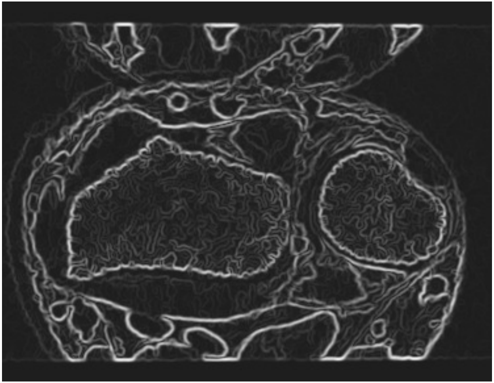

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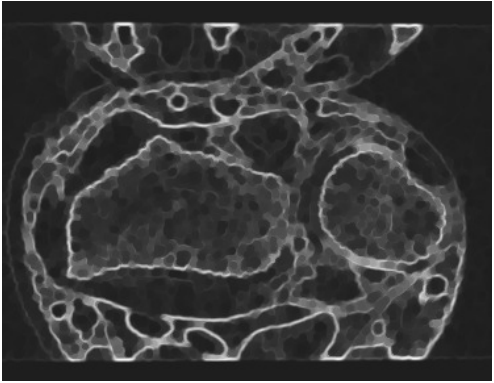

- MR-image of a wrist.
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- The closing $\mathbf{V}_0 = \Psi_C(\mathbf{I}, \mathcal{A}_{2.5})$.

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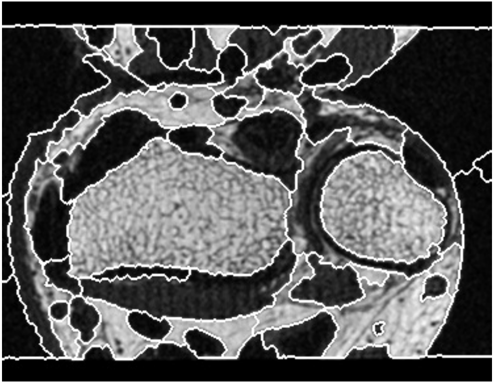

- MR-image of a wrist.
- A gradient image $\mathbf{I}$.
- The closing $\mathbf{V}_0 = \Psi_C(\mathbf{I}, \mathcal{A}_{2.5})$.
- Segmentation in L for $\Psi_{srec}(\mathbf{I}, \mathbf{V}_0, \mathcal{A}_{3.5})$.

Watershed from grayscale marker

Algorithm

– WATERSHED FROM GRAYSCALE MARKER

For each $t \in \mathcal{D}_I$, *do*
    Set $P(t) \leftarrow nil$, $\lambda \leftarrow 1$, *and* $V(t) \leftarrow V_0(t) + 1$.
    Insert t *in* Q.
While Q *is not empty, do*
    Remove from Q *a spel* s *such that* $V(s)$ *is minimum.*
    If $P(s) = nil$ *then set* $V(s) \leftarrow I(s)$, $L(s) \leftarrow \lambda$, *and* $\lambda \leftarrow \lambda + 1$.
    For each $t \in \mathcal{A}(s)$ *such that* $V(t) > V(s)$, *do*
        Compute $tmp \leftarrow \max\{V(s), I(t)\}$.
        If $tmp < V(t)$, *then*
            Set $P(t) \leftarrow s$, $V(t) \leftarrow tmp$, $L(t) \leftarrow L(s)$.
            Update position of t *in* Q.

Organization of this lecture

- Basic definitions.
- Superior and inferior reconstructions.
- Their relation with watershed-based segmentation.
- Fast binary filtering.

Fast binary filtering via IFT

For binary images $\mathbf{I}$ and Euclidean relations $\mathcal{A}_r$, it is also possible to exploit the IFT for fast computation of morphological operators, which can be decomposed into alternate sequences of erosions and dilations (or vice-versa). For instance,

$$\begin{aligned}
\Psi_C(\mathbf{I}, \mathcal{A}_r) &= \Psi_E(\Psi_D(\mathbf{I}, \mathcal{A}_r), \mathcal{A}_r). \\
\Psi_{CO}(\mathbf{I}, \mathcal{A}_r) &= \Psi_D(\Psi_E(\Psi_E(\Psi_D(\mathbf{I}, \mathcal{A}_r), \mathcal{A}_r), \mathcal{A}_r), \mathcal{A}_r) \\
&= \Psi_D(\Psi_E(\Psi_D(\mathbf{I}, \mathcal{A}_r), \mathcal{A}_{2r}), \mathcal{A}_r). \\
\Psi_{CO}(\Psi_{CO}(\mathbf{I}, \mathcal{A}_r), \mathcal{A}_{2r}) &= \Psi_D(\Psi_E(\Psi_D(\Psi_E(\Psi_D(\mathbf{I}, \mathcal{A}_r), \mathcal{A}_{2r}), \\
&\quad \mathcal{A}_{3r}), \mathcal{A}_{4r}), \mathcal{A}_{2r}).
\end{aligned}$$

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- to extract the object's (background's) border $\mathcal{S}$,
- compute their propagation in sub-linear time outward (inward) the object for dilation (erosion), alternately.
- Each border propagation stops at the adjacency radius specified for dilation (erosion).

Fast binary filtering via IFT

This requires to constrain the computation of an Euclidean distance transform (EDT) either outside (dilation) or inside (erosion) the object up to a distance r from it.

The EDT assigns to every spel in $\mathcal{D}_I$ its distance to the closest spel in a given set $\mathcal{S} \subset \mathcal{D}_I$ (e.g., the object's or background's border).

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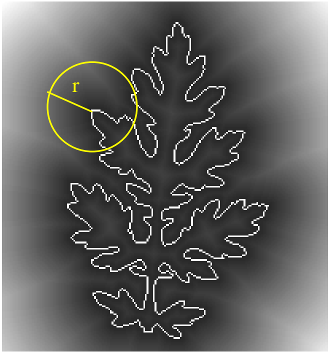

The EDT assigns to every spel in $\mathcal{D}_I$ its distance to the closest spel in a given set $\mathcal{S} \subset \mathcal{D}_I$ (e.g., the object's or background's border).

- A spel $s \in \mathcal{D}_I$ belongs to an object's border $\mathcal{S}$, when $I(s) = 1$ and $\exists t \in \mathcal{A}_1(s)$, such that $I(t) = 0$. Similar definition applies to backgroud's border.

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- For dilation, the value 1 is propagated to every spel t with value $I(t) = 0$ and distance $\|t - R(\pi_t)\|^2 \leq r^2$, $R(\pi_t) \in \mathcal{S}$.

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- For erosion, the value 0 is propagated to every spel t with value $I(t) = 1$ and distance $\|t - R(\pi_t)\|^2 \leq r^2$, $R(\pi_t) \in \mathcal{S}$.
- During dilation (erosion), spels t whose distance $\|t - R(\pi_t)\|^2 > r^2$ but $\|P(t) - R(\pi_t)\|^2 \leq r^2$ are stored in a new set $\mathcal{S}'$ for a subsequent erosion (dilation) operation.

The EDT is propagated in V from a set $\mathcal{S} \subset \mathcal{D}_I$ to every spel $t \in \mathcal{D}_I$ in a non-decreasing order of squared distance using $\mathcal{A}_{\sqrt{2}}$ in 2D (8-neighbors) [7]. For fast dilation, it uses path function

$$
\begin{aligned}
f_{euc}(\langle t \rangle) &= \begin{cases} 0 & \text{if } t \in \mathcal{S}, \\ +\infty & \text{if } I(t) = 0, \\ -\infty & \text{otherwise.} \end{cases} \\
f_{euc}(\pi_s \cdot \langle s, t \rangle) &= \| t - R(\pi_s) \|^2.
\end{aligned}
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Fast binary filtering via IFT

For fast erosion, it uses path function

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f_{euc}(\pi_s \cdot \langle s, t\rangle) &= \|t - R(\pi_s)\|^2.
\end{aligned}
$$

A dilated (eroded) binary image $\mathbf{J} = (\mathcal{D}_I, J)$ is created during the distance propagation process.

Algorithm

– FAST DILATION IN 2D UP TO DISTANCE r FROM $\mathcal{S}$

1. For each $t \in \mathcal{D}_I$, set $J(t) \leftarrow I(t)$, $R(\pi_t) \leftarrow t$ and $V(t) \leftarrow f_{euc}(\langle t \rangle)$.
2. While $\mathcal{S} \neq \emptyset$, remove t from $\mathcal{S}$ and insert t in Q.
3. While Q is not empty, do
4. Remove from Q a spel s such that $V(s)$ is minimum.
5. if $V(s) \leq r^2$, then
6. Set $J(t) \leftarrow 1$.
7. For each $t \in \mathcal{A}_{\sqrt{2}}(s)$ such that $V(t) > V(s)$, do
8. Compute $tmp \leftarrow \|t - R(\pi_s)\|^2$.
9. If $tmp < V(t)$, then
10. If $V(t) \neq +\infty$, remove t from Q.
11. Set $V(t) \leftarrow tmp$ and $R(\pi_t) \leftarrow R(\pi_s)$.
12. Insert t in Q.
13. **Else** insert s in $\mathcal{S}$.

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- Multiple borders,

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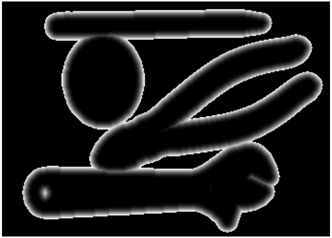

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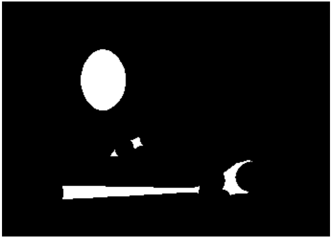

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Sets $\mathcal{S}$ and $\mathcal{S}'$ may contain spels from multiple borders.

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Sets $\mathcal{S}$ and $\mathcal{S}'$ may contain spels from multiple borders.

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3D visualization of cortical dysplastic lesions

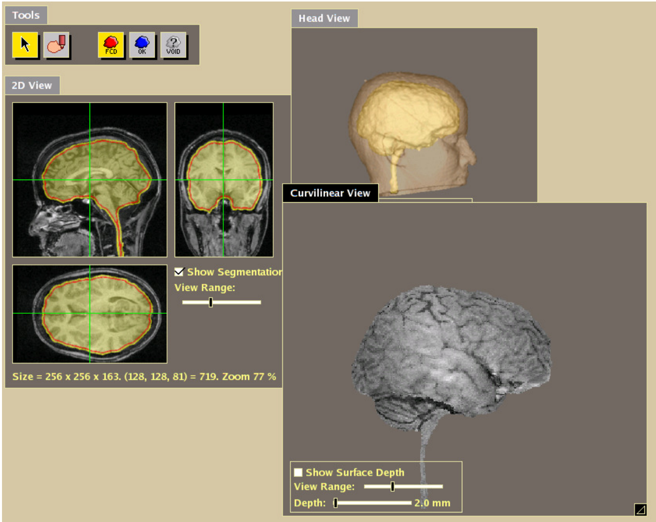
Fast 3D closing with $r = 20$ has been succesfully used in the visual inspection of focal cortical dysplastic (FCD) lesions — one of the major causes of refractory epilepsy [8].

(a) (b) (c)

(a) 3D image $\mathbf{I}$. (b) Brain after closing. (c) FCD lesion.

3D visualization of cortical dysplastic lesions

After closing with $r = 20$, the texture of the 3D brain surface is presented in curvilinear cuts.



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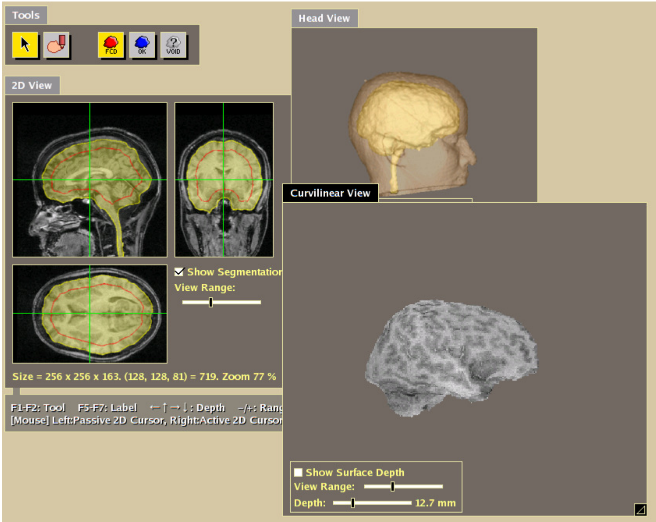

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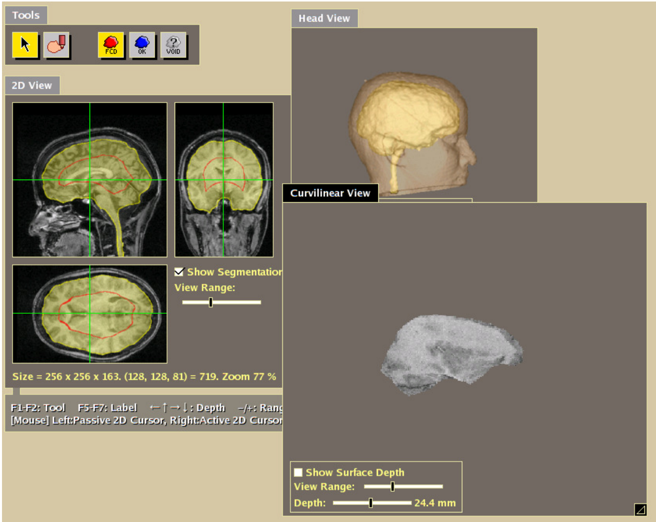

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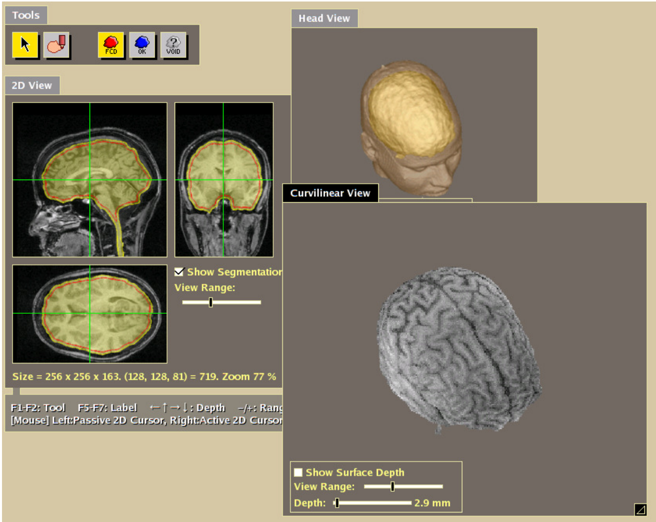

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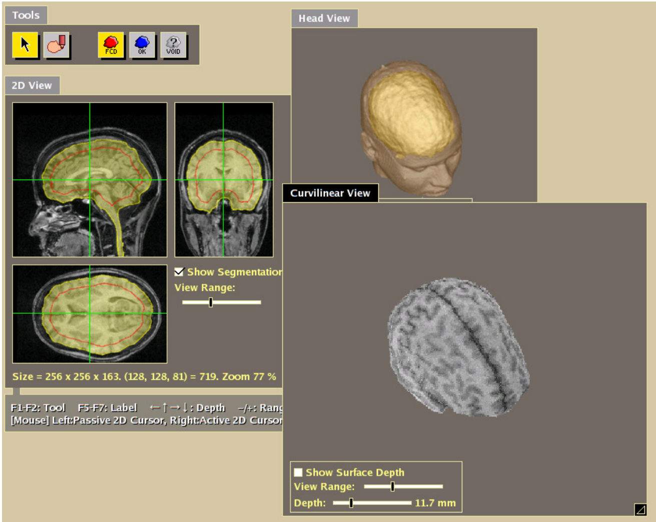

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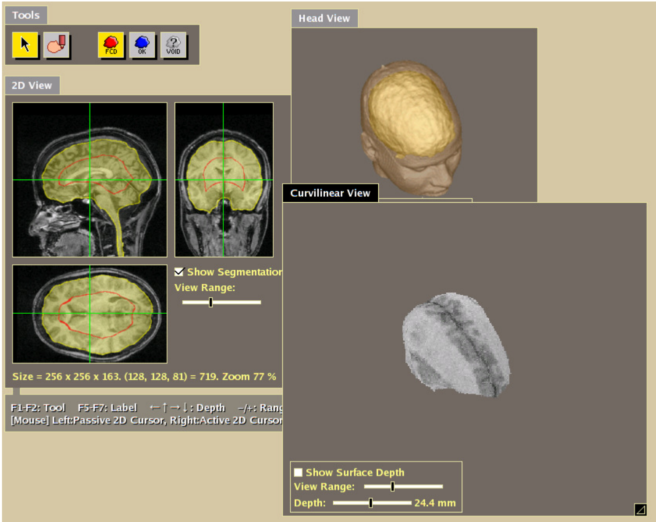

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Conclusion

- The IFT framework has been demonstrated to the design of connected filters and for understanding the relation between watershed transform and superior reconstruction.
- It should be clear the advantages of a unified framework to understand the relation between different image operations.
- We have also demonstrated the decomposition of some binary operators into alternate sequences of fast dilation and erosion by Euclidean IFT.
- Finally, we have illustrated one application for these fast binary operators in 3D medical imaging.

Next lecture

- The IFT framework.
- Connected filters.
- Interactive and automatic segmentation methods.
- Shape representation and description.
- Clustering and classification.

Thanks for your attention

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