



University of Murcia (Spain)

Artificial Perception and Pattern Recognition Research Group (PARP)

Component trees: yet another
promising way to represent
and process gray images

Author:

Pedro E. López-de-Teruel

pedroe@ditec.um.es



Introduction

- The component (or confinement, or max) tree is a hierarchical representation of the *level sets* of an image.
 - *Level sets*: Sets of points in an image with gray level above a given threshold (islands covered by water analogy).
 - The **connected components of those sets**, thanks to the inclusion relation, can be organized in a **tree structure**.
 - Being careful, it can be computed in **quasi-linear time** $O(n \alpha(n))$, with $\alpha(n)$ growing very slowly: $\alpha(10^{80}) \cong 4$
- Application domains
 - Image **filtering** (*preservation of shapes*) and **segmentation**.
 - Image **registration** (matching) and **feature detection** (MSER).
 - Image **compression**.
 - Data **visualization**.
 - Also as a help for efficient implementation of other interesting algorithms (**topological watershed**, etc.).



PARP

Definitions (I)

- Basic notions (graph theory related):
 - *Nodes* (pixels), *edges* (neighborhood, 4-connection), *path*, *connected component*, *vertex weighting*, ...

1	1	1	1	1	1	1
1	3	3	2	3	4	1
1	3	3	2	3	4	1
1	1	1	1	1	3	1
1	3	3	2	1	1	1
1	4	3	2	2	2	1
1	1	1	1	1	1	1

F

1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1

F_1

0	0	0	0	0	0	0
0	1	1	1	1	1	0
0	1	1	1	1	1	0
0	0	0	0	0	1	0
0	1	1	1	0	0	0
0	1	1	1	1	1	0
0	0	0	0	0	0	0

F_2

0	0	0	0	0	0	0
0	1	1	0	1	1	0
0	1	1	0	1	1	0
0	0	0	0	0	1	0
0	1	1	0	0	0	0
0	1	1	0	0	0	0
0	0	0	0	0	0	0

F_3

0	0	0	0	0	0	0
0	0	0	0	0	1	0
0	0	0	0	0	1	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0

F_4

Cross
sections

Regional
maximums

Definitions (II)

1	1	1	1	1	1	1
1	3	3	2	3	4	1
1	3	3	2	3	4	1
1	1	1	1	1	3	1
1	3	3	2	1	1	1
1	4	3	2	2	2	1
1	1	1	1	1	1	1

F

1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1

F_1

0	0	0	0	0	0	0
0	1	1	1	1	1	0
0	1	1	1	1	1	0
0	0	0	0	0	1	0
0	1	1	1	0	0	0
0	1	1	1	1	1	0
0	0	0	0	0	0	0

F_2

0	0	0	0	0	0	0
0	1	1	0	0	1	0
0	1	1	0	0	1	0
0	0	0	0	0	1	0
0	1	1	0	0	0	0
0	1	1	0	0	0	0
0	0	0	0	0	0	0

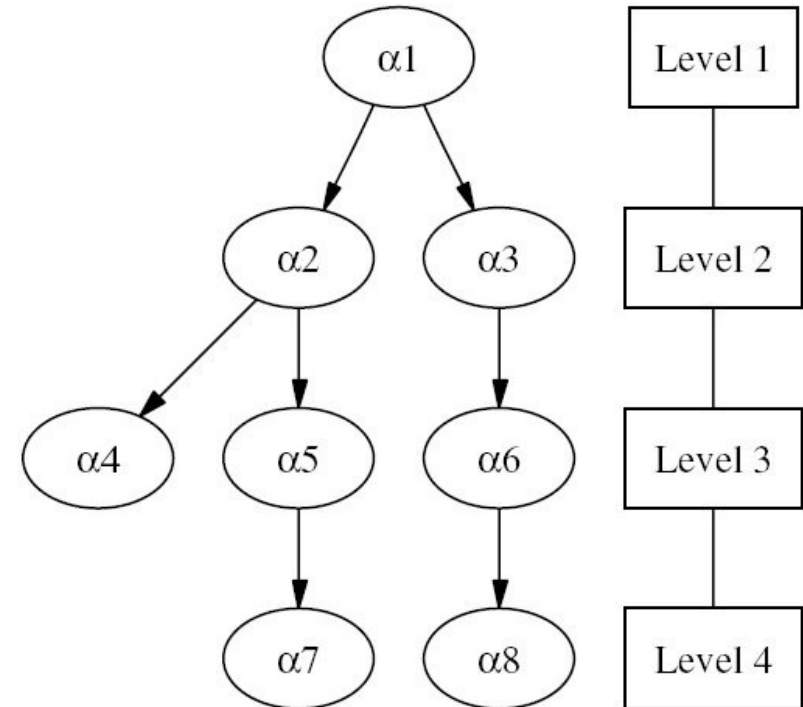
F_3

0	0	0	0	0	0	0
0	0	0	0	0	1	0
0	0	0	0	0	1	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0

F_4

Original image and cross-sections

α_1	α_1	α_1	α_1	α_1	α_1	α_1
α_1	α_4	α_4	α_2	α_5	α_7	α_1
α_1	α_4	α_4	α_2	α_5	α_7	α_1
α_1	α_1	α_1	α_1	α_1	α_5	α_1
α_1	α_6	α_6	α_3	α_1	α_1	α_1
α_1	α_8	α_6	α_3	α_3	α_3	α_1
α_1	α_1	α_1	α_1	α_1	α_1	α_1



Component tree

Component mapping

(associates each pixel to its corresponding node in the tree, at its corresponding level)

Union-find algorithm for disjoint sets

- Disjoint set problem: maintaining a collection of disjoint subsets of a set under the operation of union.
 - Quasi-linear complexity, using three operations: *MakeSet*, *Find* & *Link*.

Procedure MakeSet (*element* x)

Par(x) := x ; Rnk(x) := 0;

Function element Find(*element* x)

if (Par(x) $\neq x$) then Par(x) := Find(Par(x));
return Par(x);

Function element Link(*element* x , *element* y)

if (Rnk(x) > Rnk(y)) then exchange(x , y);
if (Rnk(x) == Rnk(y)) then Rnk(y) := Rnk(y) + 1;
Par(x) := y ;
return y ;

- Try to **keep each “tree” as flat as possible**, by (1) using always the deepest tree as parent, and (2) linking directly to parent each time we visit a node (while finding a *canonical element*).



Example: connected components

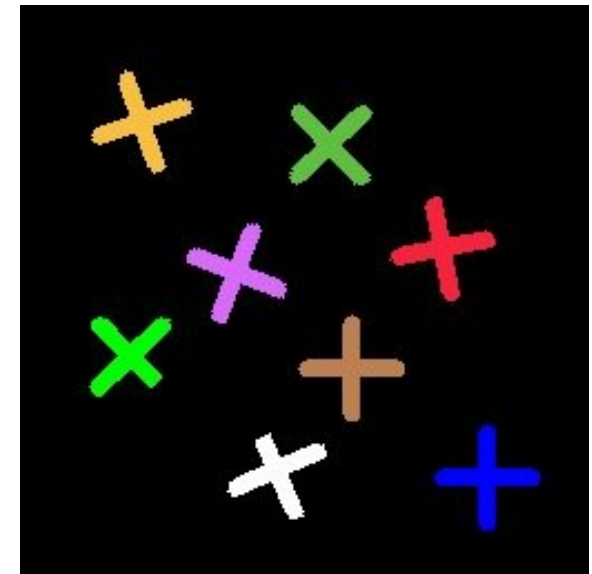
Algorithm 1: ConnectedComponents

Data: (V, E) - graph

Data: A set $X \subseteq V$

Result: M - map from X to V

```
1 foreach  $p \in X$  do MakeSet( $p$ );
2 foreach  $p \in X$  do
3    $comp_p := \text{Find}(p)$ ;
4   foreach  $q \in \Gamma(p) \cap X$  do
5      $comp_q := \text{Find}(q)$ ;
6     if ( $comp_p \neq comp_q$ ) then
7        $comp_p := \text{Link}(comp_q, comp_p)$ ;
8 foreach  $p \in X$  do  $M(p) := \text{Find}(p)$ ;
```



Output

Component tree algorithm (I)

- Simulation of an *emergence process* (islands uncovered by progressively decreasing level of water):
 - Two disjoint sets:
 - Q_{node} , for vertices belonging to the same component and with the same gray level (*flat zones*, each component has its corresponding *canonical node*), and
 - Q_{tree} , with each tree corresponding to an *emerged island*; nodes are progressively linked together to form partial trees (= *islands*)
 - An auxiliary map called ***LowestNode***, that associates the root of the corresponding partial tree to each canonical element of Q_{tree} (needed because, by construction, this canonical element is not guaranteed to be the root of the corresponding partial tree).



PARP

Component tree algorithm (II)

- Example:

110	90	100
50	50	50
40	20	50
50	50	50
120	70	80

Gray level image

0	1	2
3	4	5
6	7	8
9	10	11
12	13	14

Lexicographic order

Processing order: 12, 0, 2, 1, 14, 13, 3, 4, 5, 8, 9, 10, 11, 6, 7

└─┘
└─┘
└─┘
└─┘
└─┘
└─┘
└────────────────┘
└─┘
└─┘

120 110 100 90 80 70 50 40 20

Component tree algorithm (III)

- Beginning of 7th step (going to process level 50):

1	1	1
3	4	5
6	7	8
9	10	11
13	13	13

Par_{tree}

0	1	2
3	4	5
6	7	8
9	10	11
12	13	14

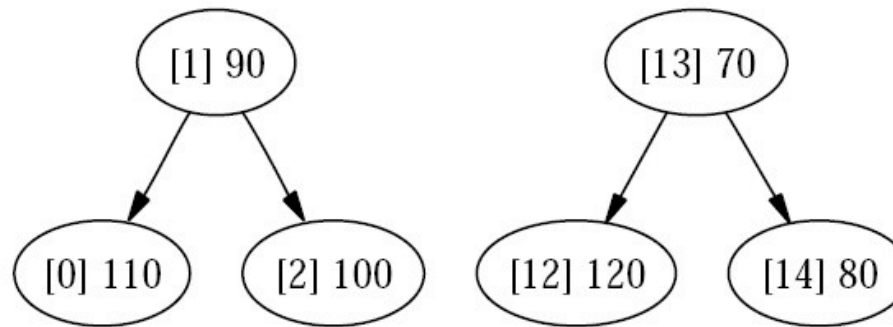
Par_{node}

0	1	2
3	4	5
6	7	8
9	10	11
12	13	14

lowestNode

Gray: updated values

Gray: values that will not get updated



(b)

Component tree algorithm (IV)

- Beginning of 13th step (going to process node 11):

1	3	3
3	3	3
6	7	3
9	9	11
13	9	13

Par_{tree}

0	1	2
3	3	3
6	7	3
9	9	11
12	13	14

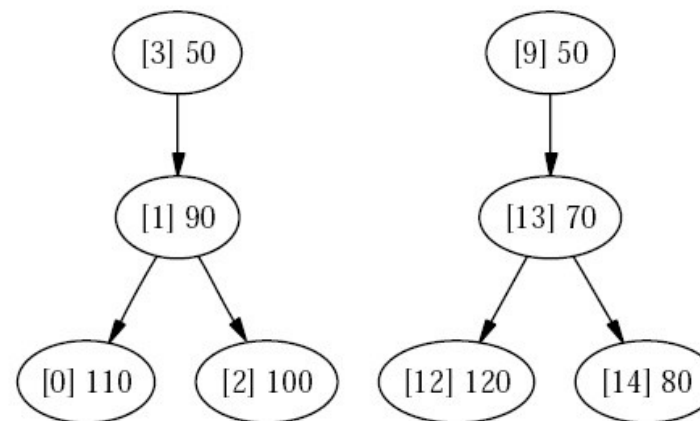
Par_{node}

0	1	2
3	4	5
6	7	8
9	10	11
12	13	14

lowestNode

(a)

110	90	100
50	50	50
40	20	50
50	50	50
120	70	80



(b)

Component tree algorithm (V)

- End of 13th step (after processing node 11 & merging level 50 components):

1	3	3
9	3	3
6	7	3
9	9	3
13	9	13

Par_{tree}

0	1	2
9	3	3
6	7	3
9	9	3
12	13	14

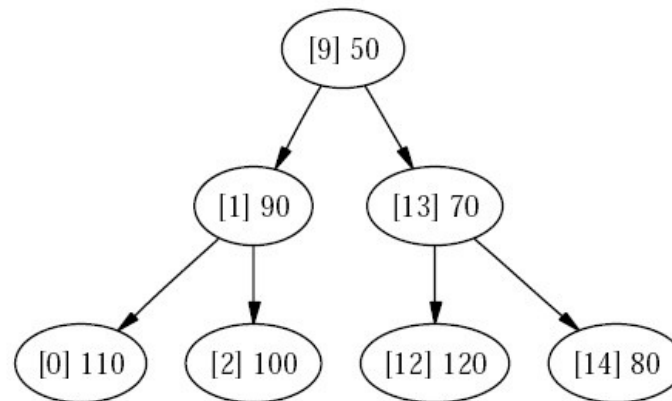
Par_{node}

0	1	2
3	4	5
6	7	8
9	10	11
12	13	14

lowestNode

(a)

110	90	100
50	50	50
40	20	50
50	50	50
120	70	80



(b)



PARP

Component tree algorithm (VI)

- Final result:

1	3	3
9	9	3
9	9	9
9	9	9
13	9	9

Par_{tree}

Not useful anymore
(just one component)

0	1	2
9	3	3
6	7	3
9	9	3
12	13	14

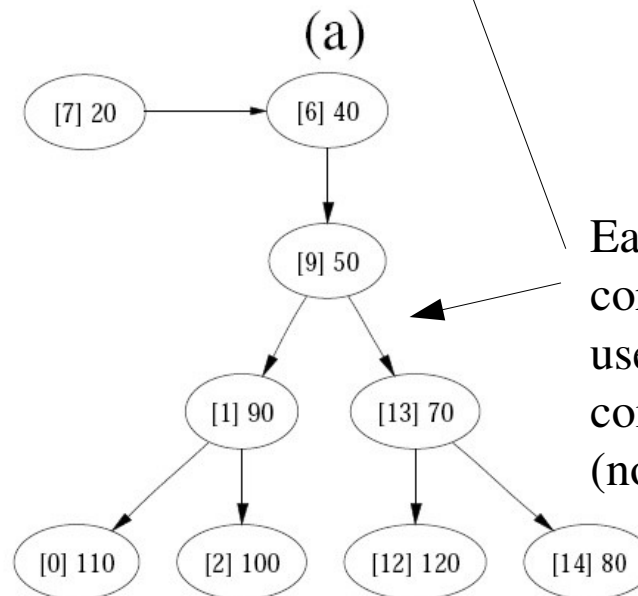
Par_{node}

0	1	2
3	4	5
6	7	8
7	10	11
12	13	14

lowestNode

Used to find the
root of the tree

110	90	100
50	50	50
40	20	50
50	50	50
120	70	80



Each canonical element
corresponds to a node;
used to finally compute
component mapping
(not shown).

(b)



Component tree algorithm (VII)

Algorithm 2: BuildComponentTree

Data: (V, E, F) - vertex-weighted graph with N points.

Result: *nodes* - array $[0 \dots N - 1]$ of nodes.

Result: *Root* - Root of the component tree

Result: *M* - map from V to $[0 \dots N - 1]$ (component mapping).

Local: *lowestNode* - map from $[0 \dots N - 1]$ to $[0 \dots N - 1]$.

Data structures

```

1 Sort the points in decreasing order of level for  $F$ ;
2 foreach  $p \in V$  do { $\text{MakeSet}_{\text{tree}}(p)$ ;  $\text{MakeSet}_{\text{node}}(p)$ ;  $\text{nodes}[p] := \text{MakeNode}(F(p))$ ;  $\text{lowestNode}[p] := p$ ;};
3 foreach  $p \in V$  in decreasing order of level for  $F$  do
4    $\text{curTree} := \text{Find}_{\text{tree}}(p)$ ;
5    $\text{curNode} := \text{Find}_{\text{node}}(\text{lowestNode}[\text{curTree}])$ ;
6   foreach already processed neighbor  $q$  of  $p$  with  $F(q) \geq F(p)$  do
7      $\text{adjTree} := \text{Find}_{\text{tree}}(q)$ ;
8      $\text{adjNode} := \text{Find}_{\text{node}}(\text{lowestNode}[\text{adjTree}])$ ;
9     if ( $\text{curNode} \neq \text{adjNode}$ ) then
10       if ( $\text{nodes}[\text{curNode}] \rightarrow \text{level} == \text{nodes}[\text{adjNode}] \rightarrow \text{level}$ ) then
11          $\text{curNode} := \text{MergeNodes}(\text{adjNode}, \text{curNode})$ ;
12       else
13         // We have  $\text{nodes}[\text{curNode}] \rightarrow \text{level} < \text{nodes}[\text{adjNode}] \rightarrow \text{level}$ 
14          $\text{nodes}[\text{curNode}] \rightarrow \text{addChild}(\text{nodes}[\text{adjNode}])$ ;
15          $\text{nodes}[\text{curNode}] \rightarrow \text{area} := \text{nodes}[\text{curNode}] \rightarrow \text{area} + \text{nodes}[\text{adjNode}] \rightarrow \text{area}$ ;
16          $\text{nodes}[\text{curNode}] \rightarrow \text{highest} := \max(\text{nodes}[\text{curNode}] \rightarrow \text{highest}, \text{nodes}[\text{adjNode}] \rightarrow \text{highest})$ ;
17        $\text{curTree} := \text{Link}_{\text{tree}}(\text{adjTree}, \text{curTree})$ ;
18        $\text{lowestNode}[\text{curTree}] := \text{curNode}$ ;
19
20  $\text{Root} := \text{lowestNode}[\text{Find}_{\text{tree}}(\text{Find}_{\text{node}}(0))]$ ;
21 foreach  $p \in V$  do  $M(p) := \text{Find}_{\text{node}}(p)$ ;
  
```

Root of the tree

Component mapping



Component tree algorithm (VIII)

- Auxiliary procedures:

Function node MakeNode (*int level*)

Allocate a new node *n* with an empty list of children;
n → *level* := *level*; *n* → *area* := 1; *n* → *highest* := *level*;
return *n*;

Function int MergeNodes (*int node1*, *int node2*)

tmpNode := Link_{node}(*node1*, *node2*);
if (*tmpNode* == *node2*) **then**
 Add the list of children of *nodes*[*node1*]
 to the list of children of *nodes*[*node2*];
 tmpNode2 := *node1*;
else
 Add the list of children of *nodes*[*node2*]
 to the list of children of *nodes*[*node1*];
 tmpNode2 := *node2*;
nodes[*tmpNode*] → *area* :=
 nodes[*tmpNode*] → *area* + *nodes*[*tmpNode2*] → *area*;
nodes[*tmpNode*] → *highest* :=
 max(*nodes*[*tmpNode*] → *highest*,
 nodes[*tmpNode2*] → *highest*);
return *tmpNode*;



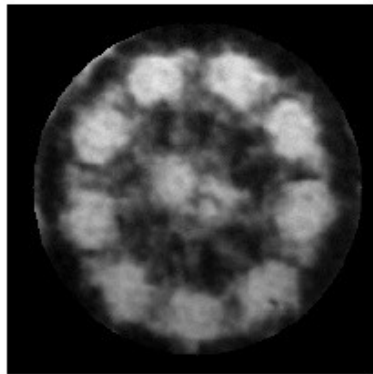
Component tree algorithm (IX)

- Some comments:
 - The *LowestNode* array is not necessary: we can modify the code so that we store its contents as negative values in Par_{tree} .
 - Another algorithm [Salembier et al.] could be teoretically faster in “normal” images, but it also has a quadratic *worst case* cost (in noisy images, with many local peaks). See also [Meijster et al.].
 - Nodes can be augmented with several **interesting attributes**. For example:
 - $\text{height}([k,c]) = \max\{F(x)-k+1, x \in c\}$
 - $\text{area}([k,c]) = |c|$
 - $\text{volume}([k,c]) = \sum_{x \in c} (F(x)-k+1)$
- } Computable while building the tree
- } Easily computable (using area) with recursive function

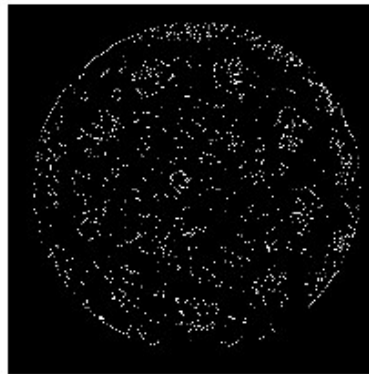


N most significant lobes (I)

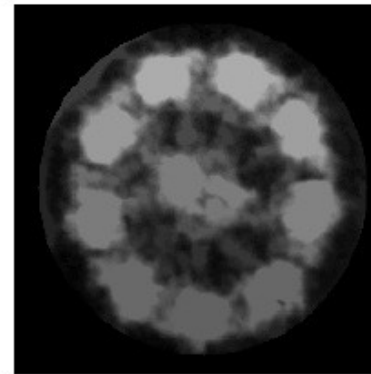
- We want to find the N most significant components with respect some attribute (for example, height, area or volume).
- Of course, components **should not be bounded with each other** by the inclusion relation.
- Example of application (10 most significant lobes, using volume):



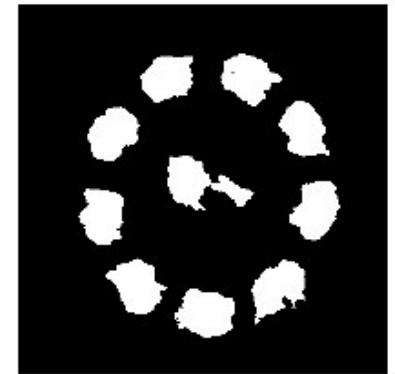
Original
gray image



Maxima of
gray image



Filtered
image



Maxima of filtered
image (corresponds to
10 most significant lobes)

N most significant lobes (II)

- Algorithm to filter the tree (pruning until only N leaves remain):

Algorithm 3: Keep_N_Lobes

Data: A vertex-weighted graph (V, E, F) , its component tree T with attribute value for each node, and the associated component mapping M

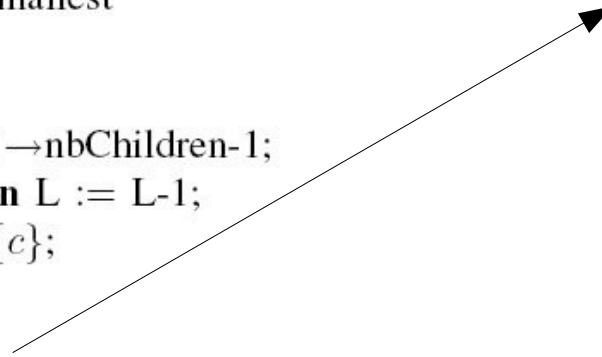
Data: The number N of wanted lobes.

Result: The filtered map F

```
1 Sort the nodes of  $T$  by increasing order of
  attribute value;
2  $Q := \emptyset$ ;  $L :=$  number of leaves in  $T$ ;
3 forall  $n$  do  $nodes[n] \rightarrow mark := 0$ ;
4 while  $L > N$  do
5   Choose a (leaf) node  $c$  in  $T$  with smallest
     attribute value;
6    $p := nodes[c] \rightarrow parent$  ;
7    $nodes[p] \rightarrow nbChildren := nodes[p] \rightarrow nbChildren - 1$ ;
8   if  $(nodes[p] \rightarrow nbChildren > 0)$  then  $L := L - 1$ ;
9    $nodes[c] \rightarrow mark := 1$  ;  $Q := Q \cup \{c\}$ ;
10 while  $\exists c \in Q$  do
11    $Q := Q \setminus \{c\}$ ; RemoveLobe( $c$ );
12 foreach  $x \in V$  do  $F(x) := nodes[M[x]] \rightarrow level$ ;
```

Function int RemoveLobe (int n)

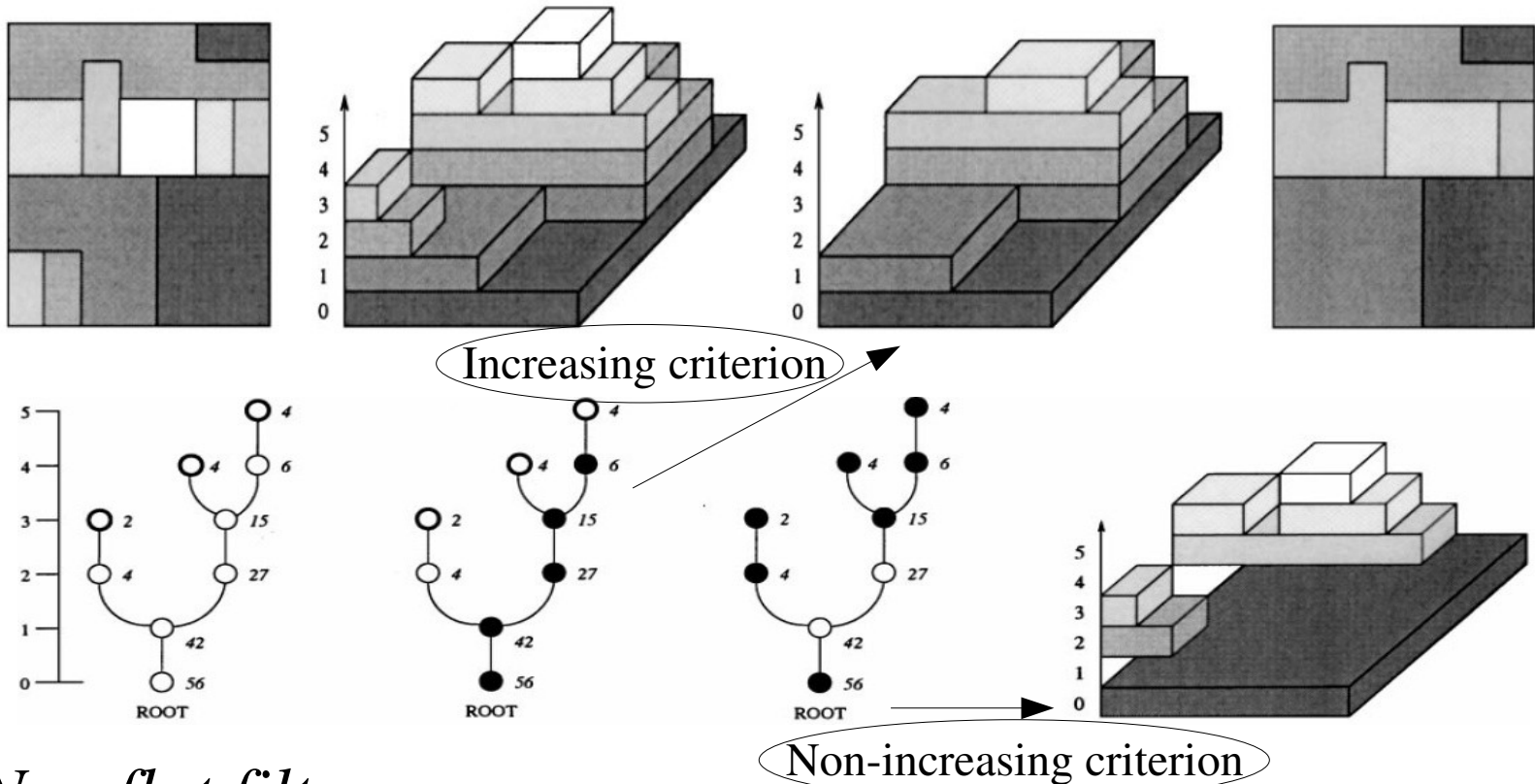
```
if  $(nodes[n] \rightarrow mark == 1)$  then
   $nodes[n] := nodes[RemoveLobe(nodes[n] \rightarrow parent)]$ ;
return  $n$ ;
```



Filtering using the component tree (I)

- Flat filters

- Cannot use links between components (applied on the binary image as result of thresholding; for example, using *area*):

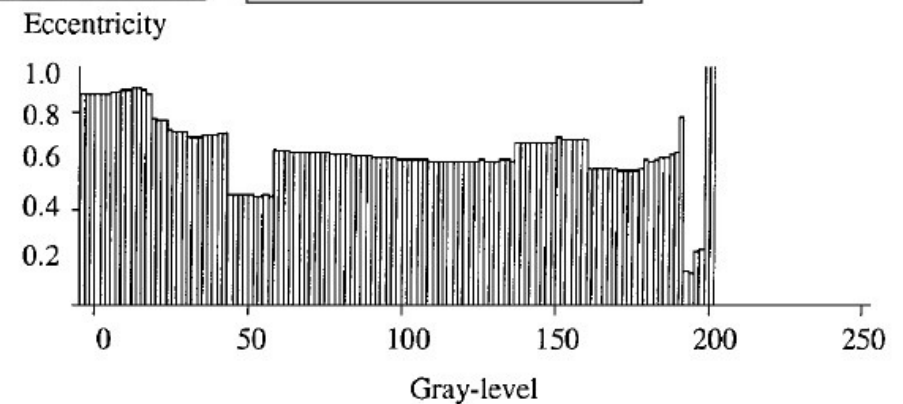
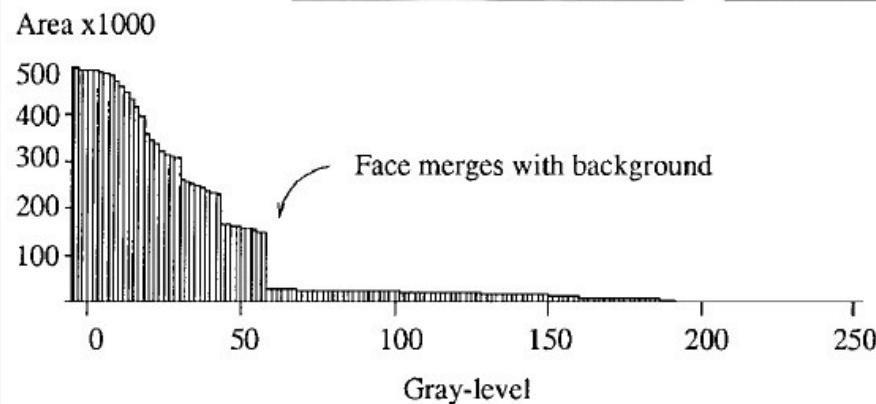
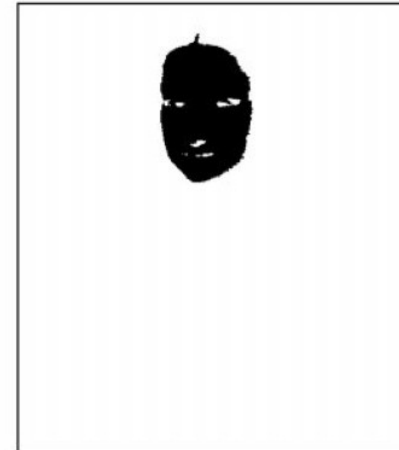


- Non flat filters

- Can use link information between components (from *leave to root* → *attribute signature*; for example, using *area*):

Filtering using the component tree (II)

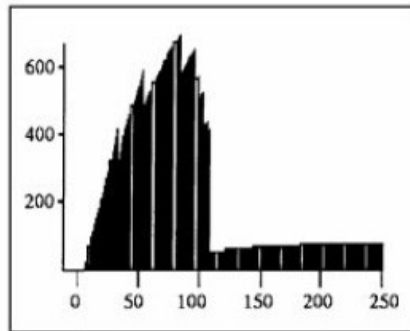
- Example
 - **Filtering & segmenting** Mona Lisa using a certain criterion on *area* and *eccentricity* (searching elliptical regions) signatures.



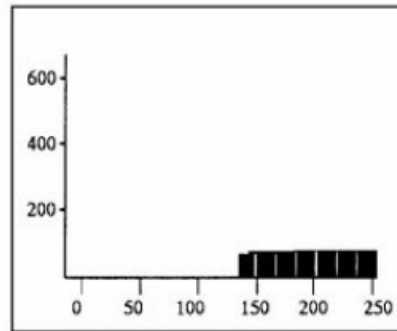
“Signature must contain a node with area between 5000-10000, and eccentricity 0.6-0.7”

Filtering using the component tree (III)

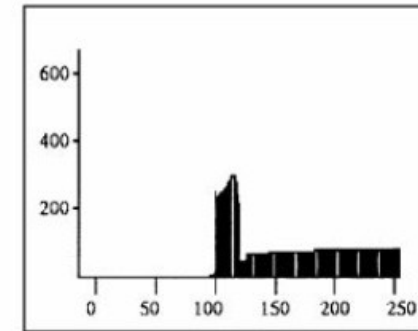
- Another example
 - Filtering *vessels in wood* texture using “area per regional minimum” signature:



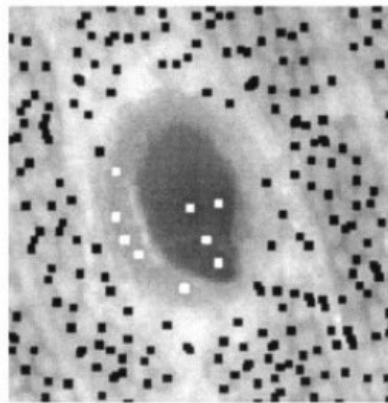
For regional minima
INSIDE the vessel



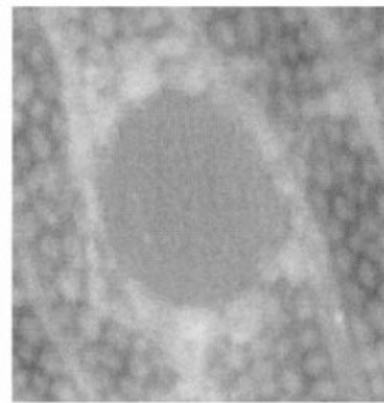
For regional minima
OUTSIDE the vessel



For regional minima in
RING around the vessel



Input image with
regional minima



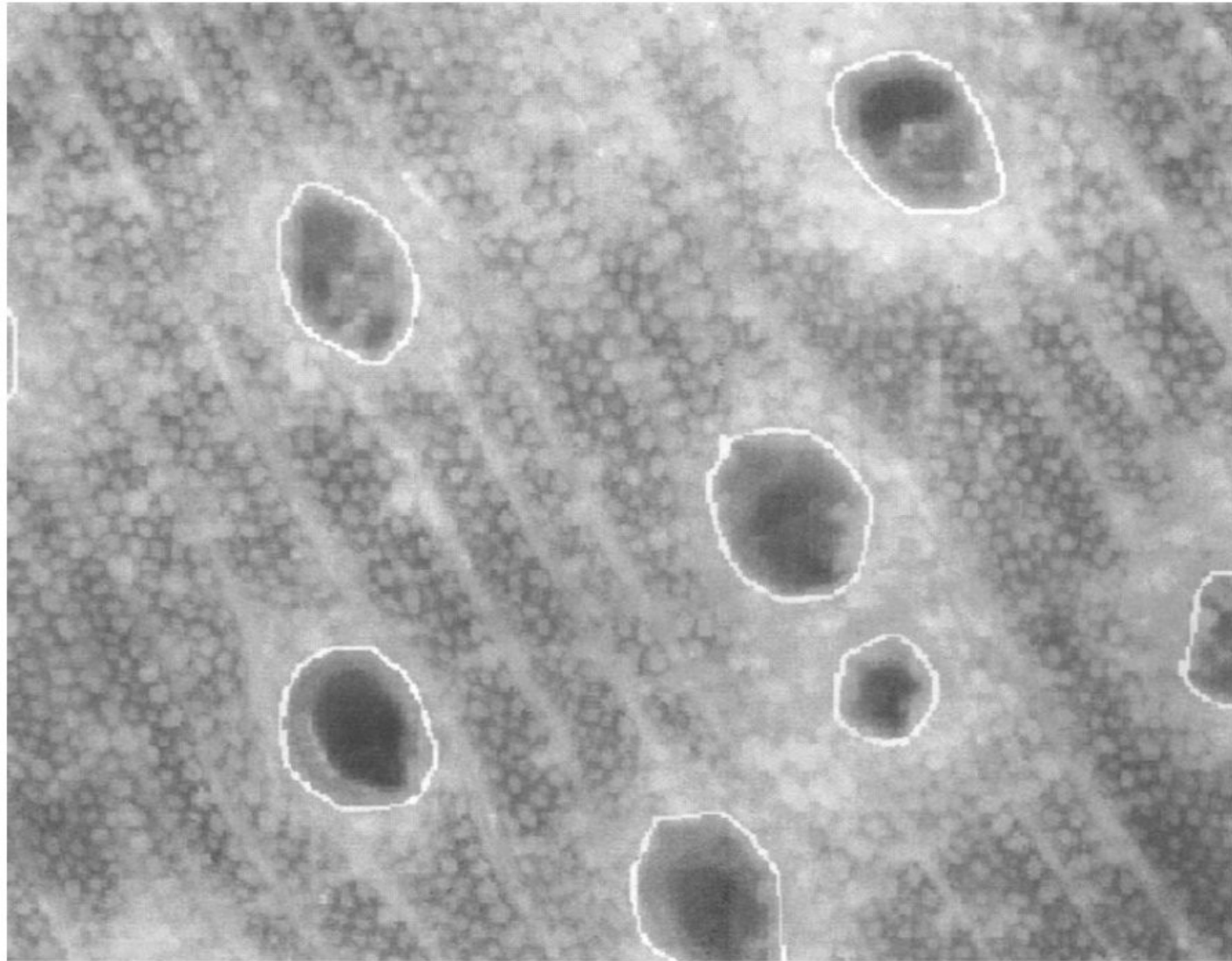
Filtered image



Segmented image

Filtering using the component tree (IV)

- Final result:



Filtering using the component tree (V)

- Some other (*flat*) criteria examples [Salembier et al.]:
 - **Geometrical:** *simplicity* (ratio perimeter^(squared or not)/area):



A) Original Image



B) Simplicity operator



C) Dual operator

- **Gray level:** contrast (λ -max), or *entropy*:



A) Original



B) Entropy operator + dual



C) Original



D) Entropy operator + dual

- **Sequences:** *motion* (using sequences of images).

Key ideas on tree filtering

- Merging of flat zones → Do **preserve contour information**
- The **definition of “flat zone”** can be relaxed (to cope with textured areas).
- **Leakage problem** (thin connections between different objects) → Could (in principle) be coped with during tree construction.
- **Restitution process**: for each image pixel, assign the gray level of the component it belongs to (but this could be changed, for example, trying to “substitute” the removed area using the gray levels “behind” the object).
- **Duality**: working on *Min-tree* as well as *Max-tree*.
- **Increasing criteria**: if region $X \subseteq Y$ (X descendant of Y), the criteria $M(.)$ should (in principle) be monotonical ($M(X) < M(Y)$) (to be “stable”).



Tree matching

- Coming soon...



References

- L. Najman and M. Couprie, “*Building the component tree in quasi-linear time*”, IEEE Trans. on Image Processing, vol. 15, n. 11, November 2006.
- R. Jones, “*Connected Filtering and Segmentation Using Component Trees*”, CVIU, vol.75, n. 3, September 1999.
- P. Salembier, A. Oliveras and L. Garrido. “*Anti-extensive connected operators for image and sequence processing*”, IEEE Trans. on Image Processing, vol. 7, n. 4, April 1998.
- H. Nattesm, M. Richard and J. Demongeot, “*Tree representation for image matching and object recognition*”, DGCI'99, LNCS 1568, pp. 298-309, 1999.
- A. Meijster and M. Wilkinson, “*A comparison of algorithms for connected sets openings and closings*”, IEEE Trans. PAMI, vol. 24, n. 4, April 2002.

