Saliency and hierarchies

Laurent Najman

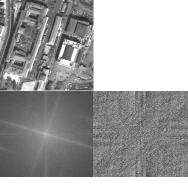
Master Course - 14 mars 2012

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- 1 Introduction
- 2 Hierarchical clustering
- 3 Hierarchical image segmentation schemes
- 4 Watershed-based hierarchical segmentation schemes
- 5 Hierarchical segmentation as a watershed-based scheme
- 6 Illustrations and applications

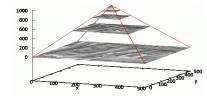
- Functional decomposition;
- Multiresolution decomposition;
- Multi-scale representation;
- Skeleton representation;
- Threshold decomposition;
- Hierarchical representations.



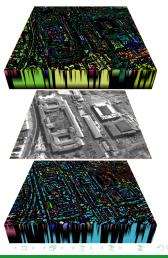
Amplitude

Phase

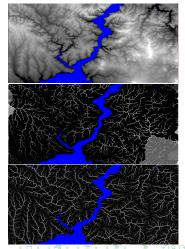
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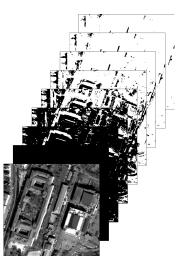
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Decomposition into primitive or fundamental elements that can be more easily interpreted:

- Functional decomposition;
- Multiresolution decomposition;
- Multi-scale representation;
- Skeleton representation;
- Threshold decomposition;
- Hierarchical representations.

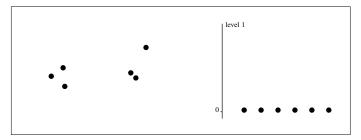
Not mutually exclusive.

Properties inherited from those of underlying operations.

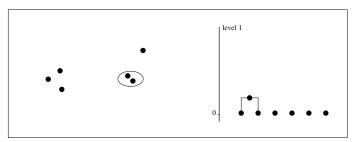
Choice driven by the application needs.



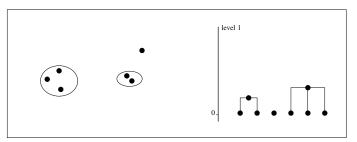
- Sequence of nested clusters such that a cluster at a given level is formed by unioning clusters existing at the previous level;
- The level, denoted by λ , is a non-negative real number controlling the coarseness degree of the clustering;
- Dendrograms (sometimes called taxonomic trees) are commonly used to represent hierarchies [Sokal & Sneath, 1963]:



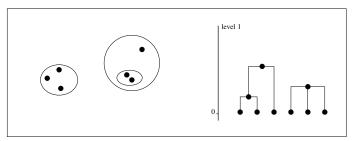
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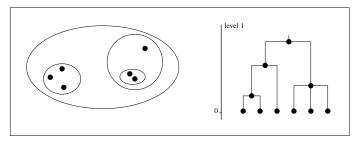
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Dissimilarity

A dissimilarity measurement between the elements of a set X is a function d^* from $X \times X$ to the set of nonnegative real numbers satisfying the three following conditions:

- 1 $d^*(x,y) \ge 0$ for all $x,y \in X$ (i.e., positivity);
- 2 $d^*(x,x) = 0$ for all $x \in X$ (i.e., nullity);
- $d^*(x,y) = d^*(y,x)$ for all $x,y \in X$ (i.e., symmetry).

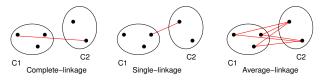
Let C_i and C_j denote two clusters obtained at a given level. The dissimilarity between between these two clusters is naturally defined as a function f of the dissimilarities between the objects belonging to these clusters:

$$d^{\star}(C_i,C_j)=f\{d^{\star}(x,y))\mid x\in C_i \text{ and } y\in C_j\}.$$



$$d^{\star}(C_i, C_j) = f\{d^{\star}(x, y)) \mid x \in C_i \text{ and } y \in C_j\}$$

- f = max: complete-linkage clustering [Sørensen 1948];
- f = min: single-linkage clustering [Sneath 1957];
- f = mean: average-linkage clustering [Sokal & Michener 1958].



	unicity	shape	'chaining effect'	graph setting
complete-linkage	no	compact	no	maximal cliques
single-linkage	yes	arbitrary	yes	connected comp. & MST
average-linkage	no	compact	no	-



Ultrametric [Jardine-Johnson, 1967]

■ The distance between two objects is defined as the minimum level from which these two objects belong to the same cluster:

$$d(x, y) = \min\{\lambda \mid x \text{ and } y \text{ belong to the same cluster}\}.$$

■ This distance is an ultrametric, i.e., a metric satisfying the ultrametric inequality:

$$d(x,y) \le \max\{d(x,z),d(z,y)\}.$$

In an ultrametric space, all triangles are either isosceles with small base or equilateral;

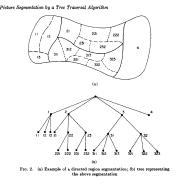
There is a one-to-one correspondence between the set of hierarchical clusterings and ultrametric distances.



Segmentation tree

[Horowitz & Pavlidis, JACM 1976];

- Hierarchical stepwise optimisation
 [Beaulieu & Goldberg, PAMI 1986];
- Shortest spanning tree segmentation
 [Morris et al., IEE Proc. 1986];
- Pyramid of region adjacency graphs
 [Montanvert et al. 1991];
- Graph weighted hierarchy [Kropatsch & Haximusa, SPIE-5299 2004];
- Scale-sets: cuts minimising an energy based on complexity and distortion measures [Guigues et al, IJCV 2006];
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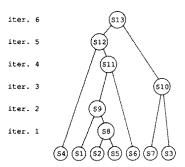


Fig. 3. Sequence of segment merges.

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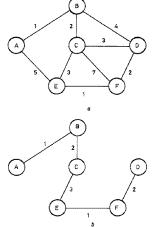


Fig. 1 Example of a graph and its SST a Example graph

IEE PROCEEDINGS, Vol. 133, Pt. F, No. 2, APRIL 1986

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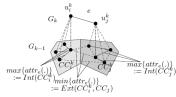
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e) Internal and External contrast.

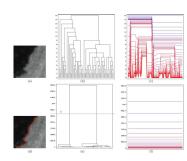
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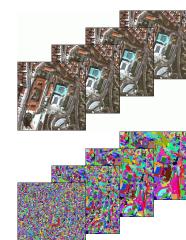
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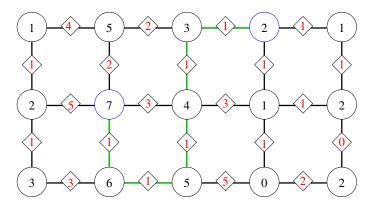
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α -connectivity (introduction)

Graph G = (V, E), f for the node weights, F for the edge weights.

Example with $F(\{p,q\} \in E) = |f(p) - f(q)|$:



α -connectivity

example with
$$F(\lbrace p,q\rbrace \in E) = \mid f(p) - f(q) \mid$$

$$\alpha = 0$$
 $\alpha = 1$ $\alpha = 2$
 $\alpha\text{-CC}(p) = \{p\} \cup \{q \mid \text{ there exists a path } \langle p = p_1, \dots, p_n = q \rangle, \text{ such that } F(\{p_i, p_{i+1}\}) \le \alpha \text{ for all } 1 \le i < n\}.$
 $d_{\alpha}(p, q) = \min\{\alpha \mid p \text{ and } q \text{ belong to the same } \alpha\text{-CC}\} \text{ is an } q$

 $d_A(p,q) = \min\{\alpha \mid p \text{ and } q \text{ belong to the same } \alpha\text{-CC}\}\$ is an **ultrametric**.

Constrained connectivity with global range constraint: (α, ω) -connectivity [Soille, PAMI 2008]

$$(\alpha, \omega)\text{-}\mathrm{CC}(p) = \max \left\{ \alpha_i\text{-}\mathrm{CC}(p) \mid \alpha_i \leq \alpha \text{ and } \mathrm{R}\Big(\alpha_i\text{-}\mathrm{CC}(p)\Big) \leq \omega \right\}$$

$$\alpha = \omega = 1$$

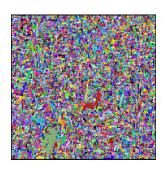
$$\alpha = \omega = 2$$

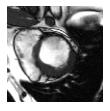
$$\alpha = \omega = 3$$

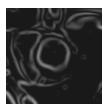
 $d_{\Omega}(p,q) = \min\{R(\alpha - CC(p)) \mid q \in \alpha - CC(p)\}\$ is an ultrametric.

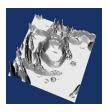
(α,ω) -CC















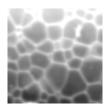
■ 1978: introduction of "the" watershed as a segmentation tool.



Hypothesis

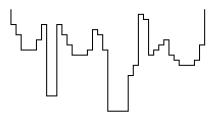
- There exists numerous watershed definitions and algorithms.
- The image is seen as a graph with values on nodes.

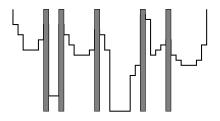
Illustration: topological watershed [Bertrand 2005, Couprie et al 2005, JMIV]

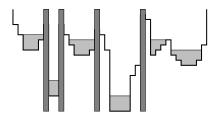


Topological

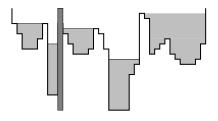


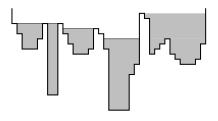


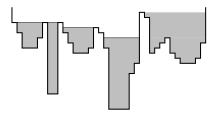






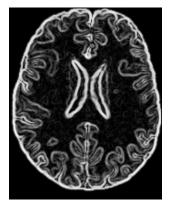




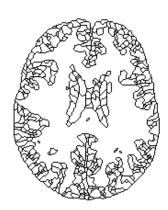


Important idea

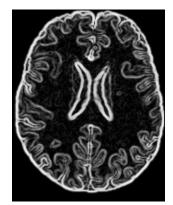
- There exists numerous criterions for flooding a surface.
- Flooding can be done through the min-(component-)tree.
- Among those criterions, notably: depth, surface, volume.
- [Beucher, ISMM, 1994 Najman & Schmitt, PAMI, 1996 Meyer et al., An. Telecom, 1997]



(a) Original image



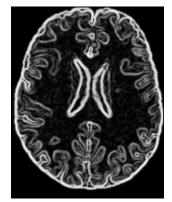
(b) Some contours



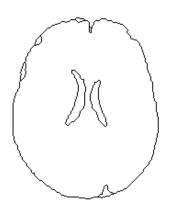
(a) Original image



(b) Some contours

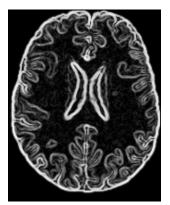


(a) Original image



(b) Some contours

Stacking the contours gives a saliency map [Najman & Schmitt, PAMI, 1996]



(a) Original image



(b) A saliency map

Some examples



Depth driven hierarchy



One of the segmentations

Some examples

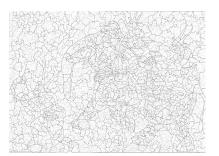


Area driven hierarchy



One of the segmentations

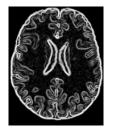
Some examples

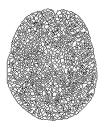


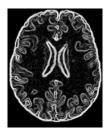
Volume driven hierarchy

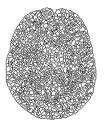


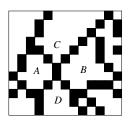
One of the segmentations

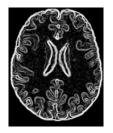


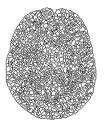


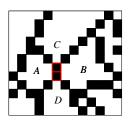


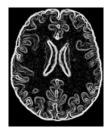


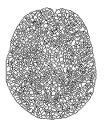


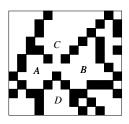


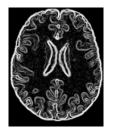


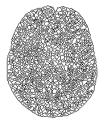


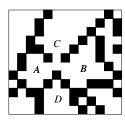












Important idea

- On the nodes: Fusion graphs [Cousty et al. JMIV 2008, Cousty et al. DAM 2008]
- There is no problem on edge-weighted graphs

Main claim

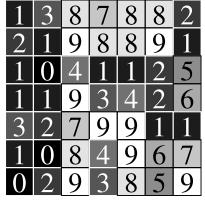
Important idea

Any hierarchical segmentation scheme can be seen as a watershed-based hierarchical scheme.

Main claim

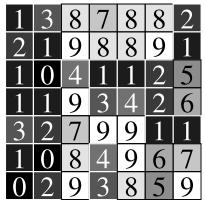
Important idea

- Any hierarchical segmentation scheme can be seen as a watershed-based hierarchical scheme.
- The trick is to consider edge-weighted graphs instead of node-weighted graphs.

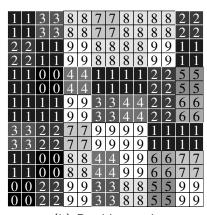


(a) Original image

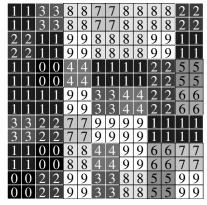
Doubling the graph (I like to split hairs ... and pixels)



(a) Original image

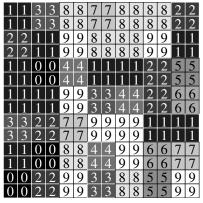


(b) Double graph
Flat zones == null gradient

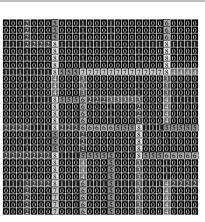


(b) Double graph

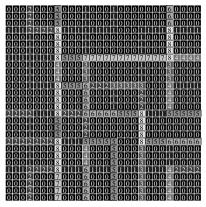
Doubling the graph again (to visualize the gradient)



(b) Double graph

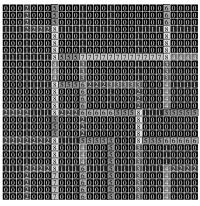


(c) Gradient

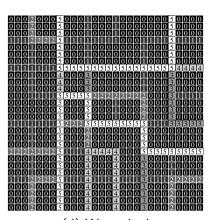


(c) Gradient

Watershed: propagate the pass altitude

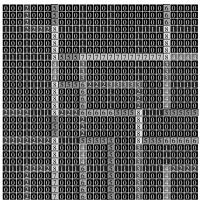


(c) Gradient

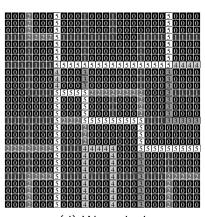


(d) Watershed

the watershed is the saliency map of the α -connectivity



(c) Gradient



(d) Watershed

Application



Original image



lpha-connectivity saliency map

Main result - a new class of watersheds: ultrametric watersheds

Theorem

- Saliency maps can be characterized as ultrametric watersheds
- Ultrametric watersheds have a computable definition
- There exists a bijection between the set of ultrametric watersheds and the set of hierarchical segmentations.
- [Najman, ISMM 2009]

Ultrametric watersheds: formal definitions

- If $S \subset E$, $\overline{S} = E \setminus S$.
- $F[\lambda] = \{ v \in E \mid F(v) \le \lambda \}.$
- An edge $u \in \overline{E(X)}$ is said to be *W-simple* (for X) if X has the same number of connected components as X + u.
- An edge u such that $F(u) = \lambda$ is said to be W-destructible (for F) with lowest value λ_0 if there exists λ_0 such that, for all λ_1 , $\lambda_0 < \lambda_1 \le \lambda$, u is W-simple for $F[\lambda_1]$ and if u is not W-simple for $F[\lambda_0]$.
- A topological watershed (on G) is a map that contains no W-destructible edges.
- A map F is an *ultrametric watershed* if F is a topological watershed, and if furthemore, for any minimum X of F, F(X) = 0.

Ultrametric watersheds: some properties

The *connection value* is the number

 $F(x,y) = \min_{\pi \in \Pi(x,y)} \max\{F(u) | u \in \pi\}$, where $\Pi(x,y)$ is the set of all paths linking x to y in G. If X and Y are two subgraphs of G, we set $F(X,Y) = \min\{F(x,y) \mid x \in X, y \in Y\}$.

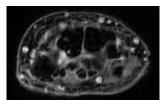
Theorem

A map F is a topological watershed if and only if:

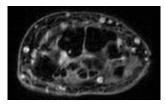
- (i) Its minima form a segmentation of G;
- (ii) for any edge $v = \{x, y\}$, if there exist X and Y in $\mathcal{M}(F)$, $X \neq Y$, such that $x \in V(X)$ and $y \in V(Y)$, then F(v) = F(X, Y).

Property

A map F is an ultrametric watershed if and only if for all $\lambda \geq 0$, $F[\lambda]$ is a segmentation of G.



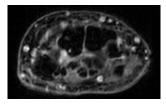
(a) Original image



(a) Original image



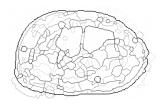
(b) Ultrametric watershed



(a) Original image



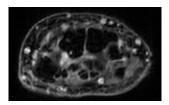
(c) One of the segmentations



(b) Ultrametric watershed

Illustration of main theorem

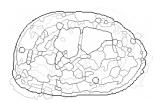
Novel potential methodology



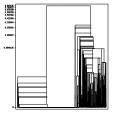
(a) Original image



(c) One of the segmentations



(b) Ultrametric watershed



(d) Dendrogram

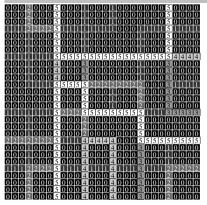
Illustration of main theorem

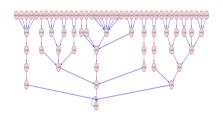
Result

Main theorem: the dendrogram can be replaced by an ultrametric watershed

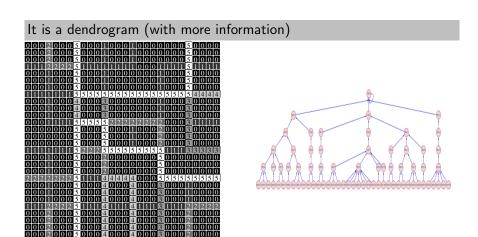
Looking at min-tree of edge-maps

The min-tree of a saliency map : the connected components of all the thresholds of a saliency map





Looking at min-tree of edge-maps

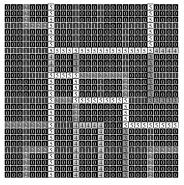


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- By flooding a watershed of the gradient with the range constraint, we obtain the constrained connectivity saliency map

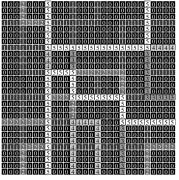
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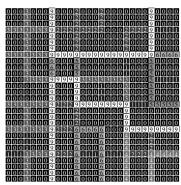
 α -connectivity



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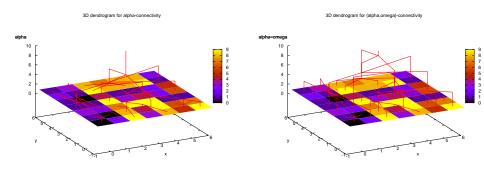


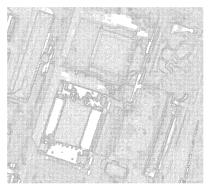
 α -connectivity



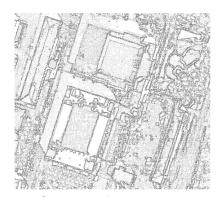
Constrained connectivity

Spatially rooted dendrogram (3D dendrograms)





 α -connectivity



Constrained connectivity

Important idea

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Choose what is best adapted to the problem at hand

Component tree / dendrogram == to know when regions are merging

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- Component tree / dendrogram == to know when regions are merging
- Minimum spanning tree / Binary partition tree == to give an order in the merging of regions
- Ultrametric watersheds / saliency maps == to visualize the hierarchy and to know the neighborhood graph of the regions
- Ultrametric watersheds / saliency maps == to see any hierarchy as an image

The problem of transition pixels

Difficulty

Transition pixels are present in any hierarchical scheme

0	1	0	7	8	7	8
1	0	1	6	7	8	7
0	1	0	5	8	7	8
1	0	1	4	7	8	7
0	1	0	3	8	7	8
1	0	1	2	7	8	7
0	1	0	1	8	7	8

An image

0	1	0	7	8	7	8
1	0	1	6	7	8	7
0	1	0	5	8	7	8
1	0	1	4	7	8	7
0	1	0	3	8	7	8
1	0	1	2	7	8	7
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Constrained connectivity saliency map

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An image

The ramp (of gradient == 1)

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Seing a hierarchy as an image allows to apply any operator to solve a difficulty

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Constrained connectivity

Important idea

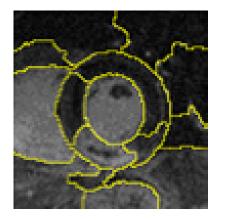
Seing a hierarchy as an image allows to apply any operator to solve a difficulty

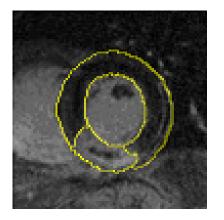


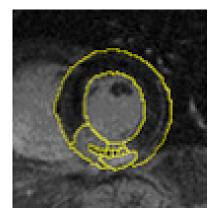
Constrained connectivity

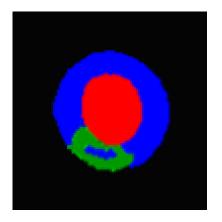


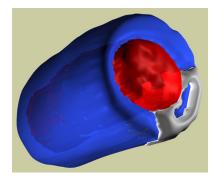
area-filtering











Example: magic-wand driven hierarchy



Example: magic-wand driven hierarchy



Example: magic-wand driven hierarchy



Example: hierarchical lasso



Example: hierarchical lasso



Example: hierarchical lasso



Example: hierarchical brush



Example: hierarchical brush



Example: hierarchical brush



Conclusion

- Limitations of hierarchical schemes: need for overlapping clusters?
- Further benefit from huge litterature on data clustering expected.