

Some Tree-Based Representations in Mathematical Morphology

T. Géraud

EPITA Research and Development Laboratory (LRDE), France

`thierry.geraud@lrde.epita.fr`



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Forewords



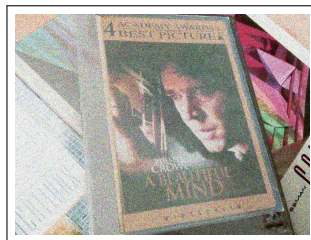
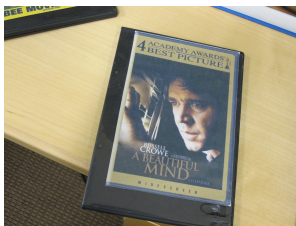
Which animal is it?

Forewords



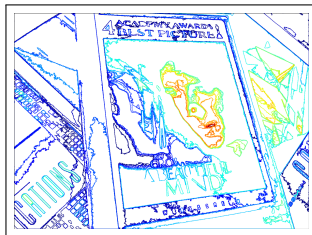
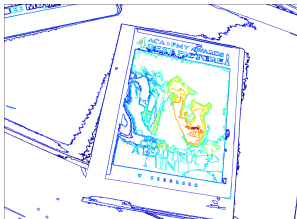
How many signs are there?

Forewords



How to be robust to variations of the image contents?

Forewords



“stable” contours \Leftrightarrow nice invariants

Forewords

Key ideas:

- we have to deal with
 - poor contrast
 - illumination changes
 - ...
- shapes matter a lot (colors are sometimes *not so* important)
- we want to ensure some strong “invariance” properties

⇒ mathematical morphology!

A Short History of Mathematical Morphology (MM)

- *Mid 60's*
Invention of MM by Georges Matheron and Jean Serra in CMM, France.
- *From 70's to 80's*
Extension to sets (binary images) to functions (gray-level images).
- *End of the 80's*
MM on graphs is defined (structural elements neighborhood).
- *1995*
Connected operators appear...
- *Beginning 2YK's*
First attempts to get MM works on color images.
- *Since then*
Adaptive filtering, optimization-related MM, etc. but remaining very confidential...

Mathematical Morphology (MM)

Mathematical Morphology is:

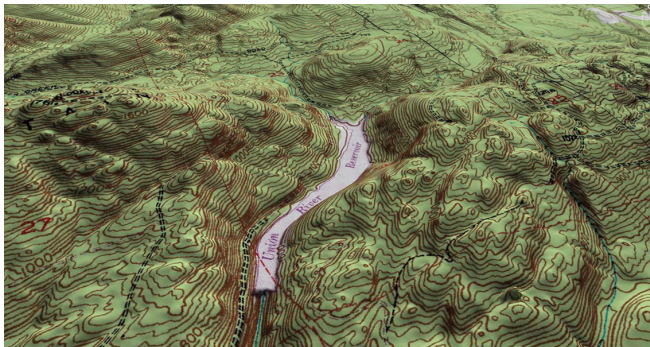
- a mathematical framework
 \rightsquigarrow some common properties are expected
- a large toolkit
 \rightsquigarrow some tools are very simple and powerful
- a way of thinking...

Main idea

an image $f \equiv$ a landscape where $f(x, y)$ is the elevation at (x, y)
processing an image \equiv modifying the landscape / function f

Mathematical Morphology (MM)

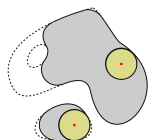
This is a landscape:



so we have paths, mountains, peaks, valleys, flat zones, level lines,
crest lines, passes, catchment basins...

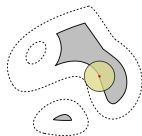
Basic operators

Opening

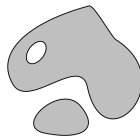


$$\gamma_B(X) = \delta_B \circ \varepsilon_B(X)$$

Erosion

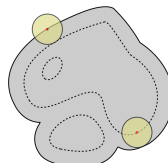


$$\varepsilon_B(X)$$



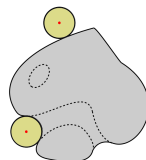
$$X$$

Dilation



$$\delta_B(X)$$

Closing



$$\phi_B(X) = \varepsilon_B \circ \delta_B(X)$$

with B a structuring element / parameter

we have dual operators: $\delta_B(X) = \mathbb{C} \varepsilon_B(\mathbb{C} X)$ and $\phi_B(X) = \mathbb{C} \gamma_B(\mathbb{C} X)$

From sets to functions

From Mathematical Morphology on **sets**...

...we want to have Mathematical Morphology on **functions**

Threshold Decomposition Principle

Given a gray-level image / scalar function f .

Upper threshold set at level λ = binary image:

$$[f \geq \lambda] = \{x \in \Omega; f(x) \geq \lambda\} \in \mathcal{P}(\Omega)$$

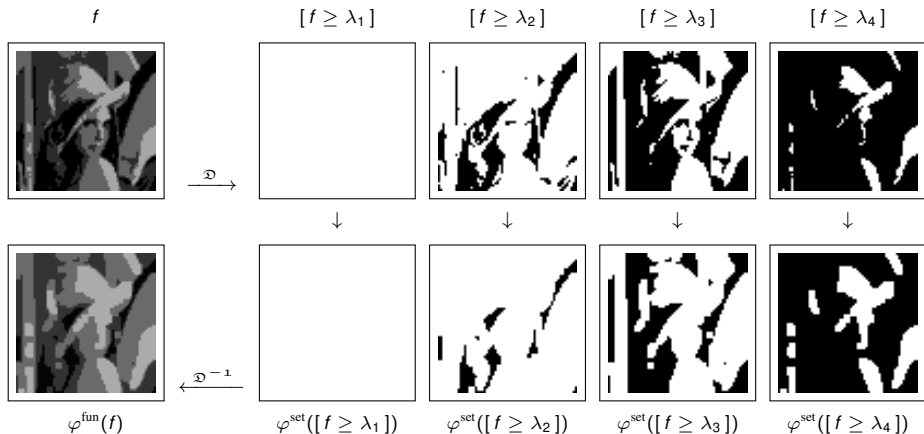
Decomposition:

$$f \xrightarrow{\mathfrak{D}} \{ [f \geq \lambda] \}_\lambda$$

Extension from φ^{set} to φ^{fun} :

$$\{ \varphi^{\text{set}}([f \geq \lambda]) \}_\lambda \xrightarrow{\mathfrak{D}^{-1}} \varphi^{\text{fun}}(f)$$

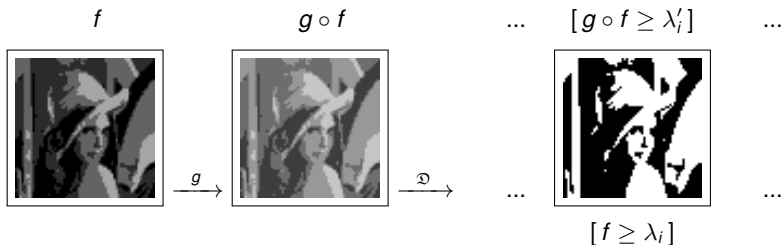
Applying an Operator (the theoretical way)



with $\varphi = \delta_B$ in this example.

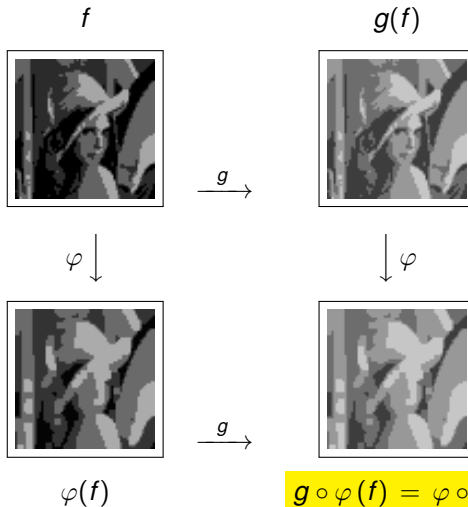
Contrast Change Invariance

With any contrast change g (non-decreasing function):



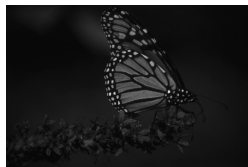
$\lambda'_i = g(\lambda_i) \Rightarrow g \circ f$ and f have the same family of threshold sets!

Contrast Change Invariance



Contrast Change Invariance

Applying a morphological operator on these 3 images:



is equivalent (subject to g).

The right-most images are not more difficult to process than the left one!

Contrast does not matter for MM, meaning that:

- values does not matter but...
- ...only the ordering of values matters!

Contrast Inversion Invariance

If in addition φ is self-dual, that is $\varphi(f) = -\varphi(-f)$, we have:

$$\varphi \circ h = h \circ \varphi$$

with any *monotonic* change h .

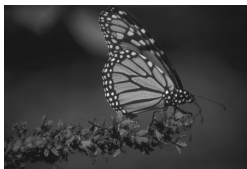
Applying a *self-dual* morphological operator on these 3 images:



is equivalent (subject to h).

Local Illumination Change Invariance

Some operators φ behave the *same way* on:



and



they are invariant by any *local illumination* change ℓ :

$$\varphi \circ \ell = \ell \circ \varphi$$

Temporary conclusion

About Mathematical Morphology:

- many tools [...]
- sound mathematical foundations

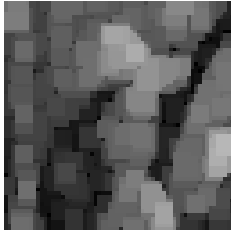
so we can understand what we have to do, and we can interpret the results we obtain

- important invariants for PR + CV

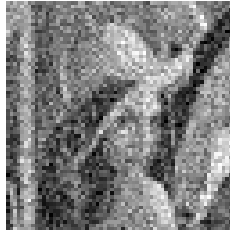
Operators deal with (*connected components of*) *threshold sets*:

- so IP operators can do some PR tasks
- but MM with structuring elements shift contours :- (

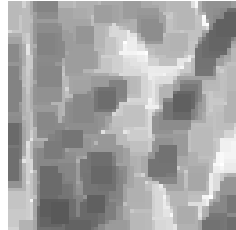
An illustration



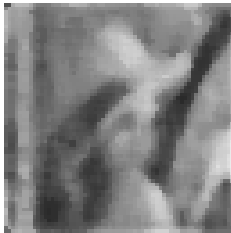
$\gamma_B(f)$



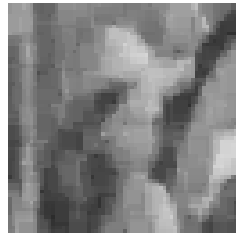
f



$\phi_B(f)$



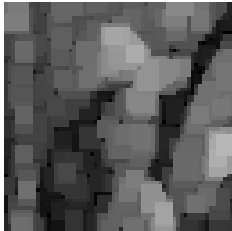
$\varphi_B^{\text{median}}(f)$



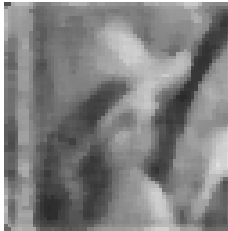
← self-dual →

$$(\gamma_B + \phi_B)/2$$

Pick your favorites...



$$\gamma_B(f)$$



$$\varphi_B^{\text{median}}(f)$$



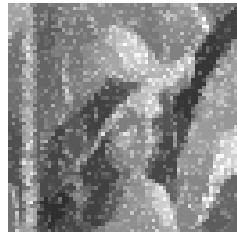
$$\phi_B(f)$$



$$\gamma_{(\mathcal{A}, \alpha)}(f)$$



$$\nu_{(\mathcal{A}, \alpha)}(f)$$



$$\phi_{(\mathcal{A}, \alpha)}(f)$$

Morphological dual trees

When thresholding f at level λ , we get:

- an upper level set: $[f \geq \lambda] = \{x \in \Omega; f(x) \geq \lambda\}$
- a lower level set: $[f < \lambda] = \{x \in \Omega; f(x) < \lambda\}$

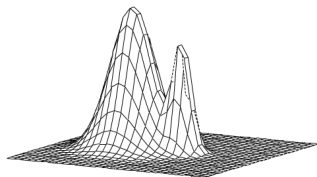
Considering the connected components (\mathcal{CC}) of threshold sets:

- **max-tree:** $\mathcal{T}_{\max}(f) = \{ \Gamma \in \mathcal{CC}([f \geq \lambda]) \}_\lambda$
- **min-tree:** $\mathcal{T}_{\min}(f) = \{ \Gamma \in \mathcal{CC}([f < \lambda]) \}_\lambda$

We have the duality: $\mathcal{T}_{\min}(-f) = \mathcal{T}_{\max}(f)$

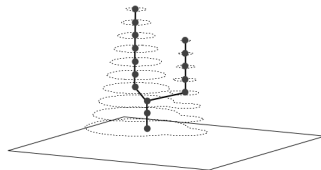
Morphological dual trees

Example with the max-tree:



f

\equiv

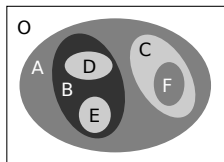


$\{ [f \geq \lambda] \}_\lambda$

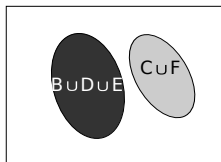
The morphological tree of shapes (ToS)

Using the cavity-fill-in operator (Sat):

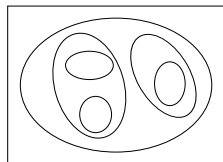
- **tree of shapes:** $\mathfrak{S}(f) = \{ \text{Sat}(\Gamma); \Gamma \in \mathcal{T}_{\max}(f) \cup \mathcal{T}_{\min}(f) \}$
- it is also the inclusion tree of level lines



f



two shapes of f



level lines of f

We have the self-duality: $\mathfrak{S}(-f) = \mathfrak{S}(f)$

Invariances

With g strictly increasing:

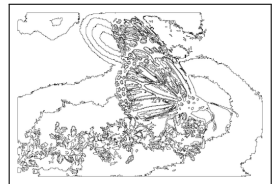
$$\mathcal{T}_{\max}(g \circ f) = \mathcal{T}_{\max}(f) \quad \text{and} \quad \mathcal{T}_{\min}(g \circ f) = \mathcal{T}_{\min}(f)$$

With h strictly monotonic:

$$\mathfrak{S}(h \circ f) = \mathfrak{S}(f)$$

With ℓ some local illumination changes:

$$\mathfrak{S}(\ell \circ f) = \mathfrak{S}(f)$$



Advertising

Having a tree structure is great:

- simple structure
- easy to browse and do some iterative / recursive computations
- easy to transform
- and very versatile

A **node** represents a **component** of the image

⇒ we are at **Pattern Recognition level!**

Connected Operators

Definition

A morphological operator φ is a *connected operator* iff:

$$\forall f, \forall x \mathcal{N} x', \varphi(f)(x) \neq \varphi(f)(x') \Rightarrow f(x) \neq f(x').$$

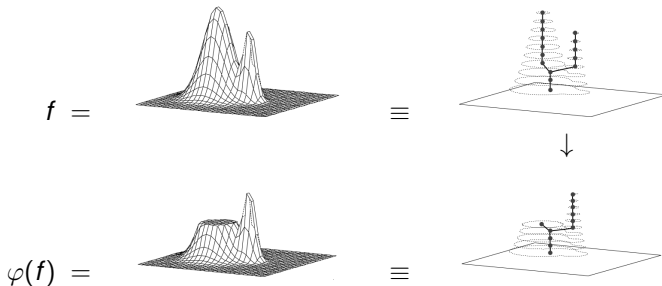
A very interesting class of operators:

- do not create new contours \Rightarrow do not shift contours
- not based on structuring elements
- intuitive, powerfull, and efficient
- can be implemented as tree filtering

Connected Operators

A well-known family:

- remember that “MM operating = landscape modifying”
- tree-pruning \rightsquigarrow connected operators



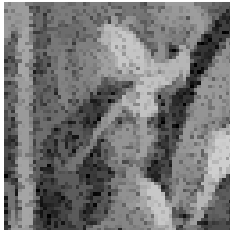
Connected Operators

Pruning is based on:

- an increasing attribute $\mathcal{A} = \text{effect}$ of the filtering
- and a threshold $\alpha = \text{strength}$ of the filtering
- nodes n such as $\mathcal{A}(n) < \alpha$ are removed

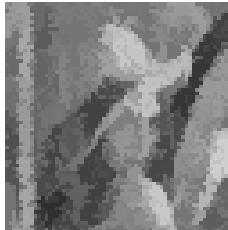
The *type* of filtering depends of the tree:

on $\mathcal{T}_{\max}(f)$



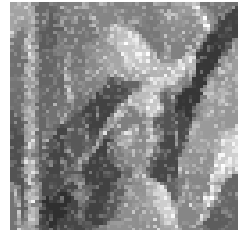
openings $\gamma_{(\mathcal{A}, \alpha)}(f)$

on $\mathcal{G}(f)$



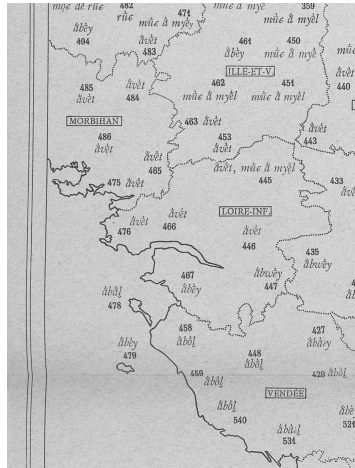
grain filters $\nu_{(\mathcal{A}, \alpha)}(f)$

on $\mathcal{T}_{\min}(f)$



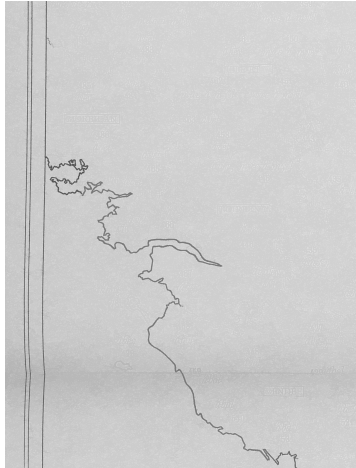
closings $\phi_{(\mathcal{A}, \alpha)}(f)$

Illustrations



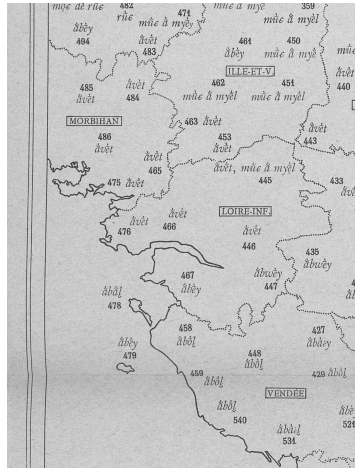
input

Illustrations



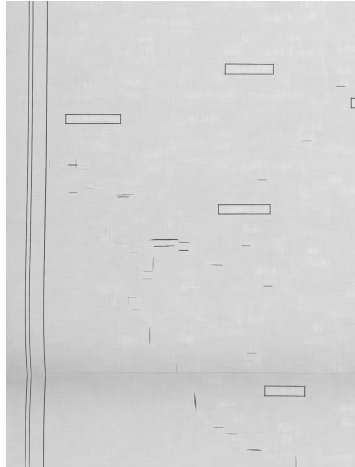
coast and frames

Illustrations



input

Illustrations



we apply $\min(\phi_{B_{\text{horizontal}}}, \phi_{B_{\text{vertical}}}) \dots$

Illustrations



...and some connected operators

A glitch

For morphological operators to work:

getting threshold sets (and trees) means ordering pixel values.

A lot of data are **not** scalar, but multi-variate data:

- color images
- multi-modal medical images
- multi-spectral and hyper-spectral satellite images
- ...

A major issue is: how to get a *sensible* ordering for vectors?

Hum... red is greater than green, or is it the contrary?

ToS for multi-variate data

Consider

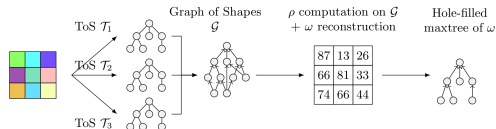
- a function having n scalar components: $\mathbf{f} = (f_1, \dots, f_n)$
- several monotonic transforms ℓ_i to form: $\ell = (\ell_1, \dots, \ell_n)$
- the marginal composition: $\ell \circ \mathbf{f} = (\ell_1 \circ f_1, \dots, \ell_n \circ f_n)$

If we can compute a tree \mathfrak{S} from multi-variate functions such that:

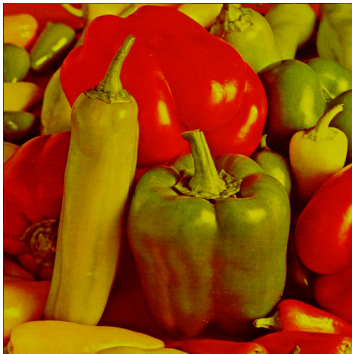
$$\mathfrak{S}(\ell \circ \mathbf{f}) = \mathfrak{S}(\mathbf{f})$$

we have a “tree of shapes” for multi-variate data.

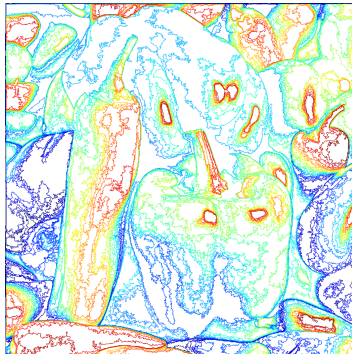
Actually we did it:



ToS for multi-variate data



f



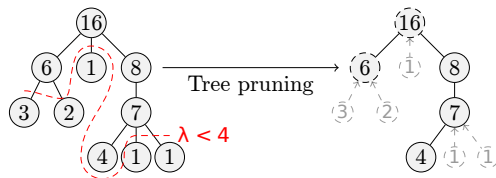
Level lines from $\mathfrak{G}(f)$

No ordering of colors is required! :-)

Transition

There are many morphological tools
among them we have trees
so let's see some applications...

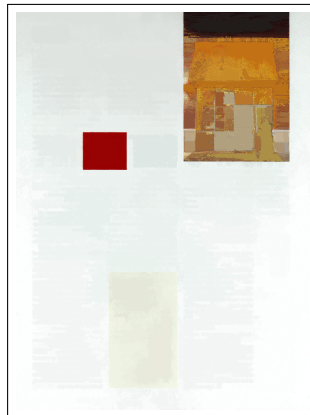
App: Grain filter



1. Compute an increasing attribute \mathcal{A} over the tree.
2. Threshold to prune, and reconstruct.

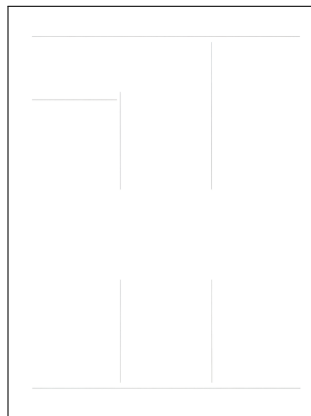
\mathcal{A} can be: area, diameter, width and/or height...

App: Grain filter



getting the yellowish low-contrasted box is possible, and with very precise contours

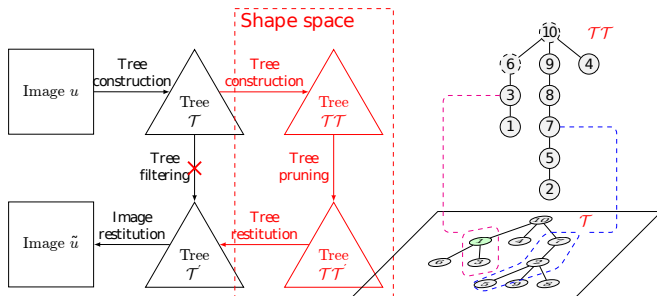
App: Grain filter



Left as an exercise so DIY... (this is filtering at PR level!)

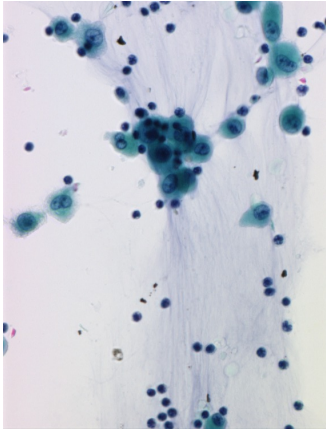
App: Shaping

When \mathcal{A} is not increasing:



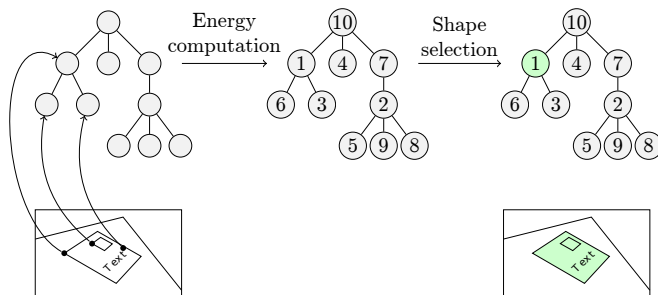
it is no more a pruning.

App: Shaping



Nodes with low circularity are filtered out.

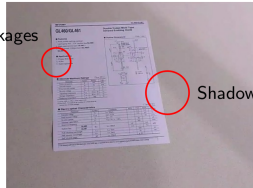
App: Object detection



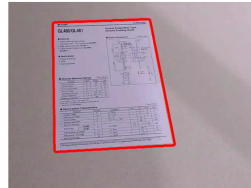
1. Valuate an energy adapted to the object(s) to detect
2. Retrieve the shape(s) with minimal energy

App: Object detection

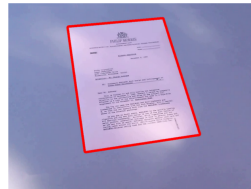
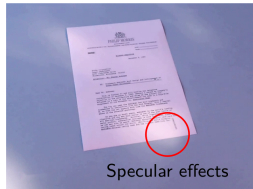
Leakages



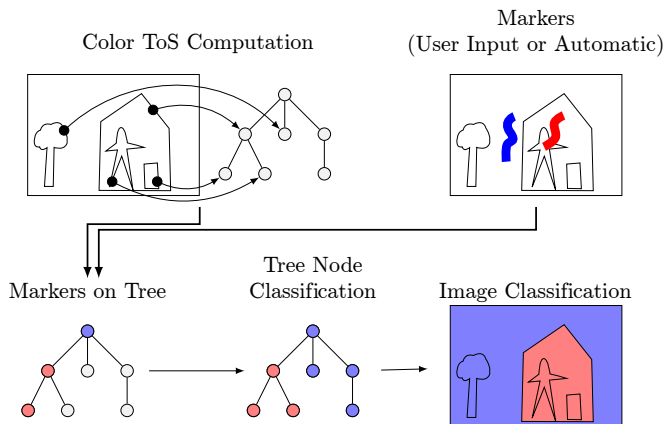
Shadows



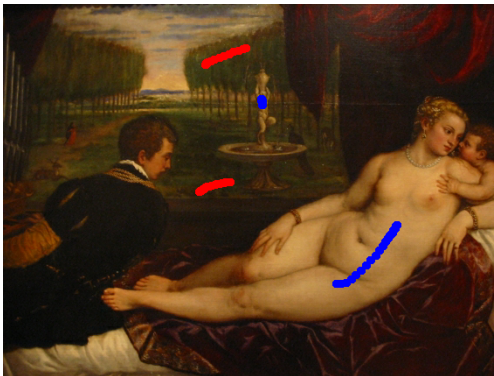
Specular effects



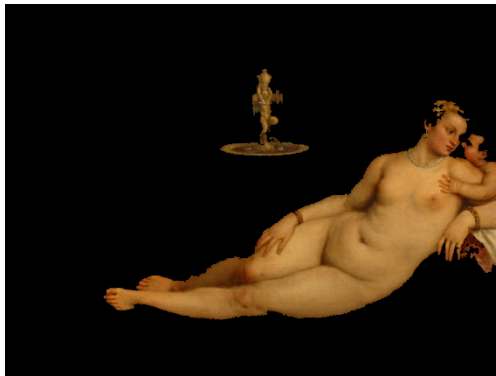
App: Object picking



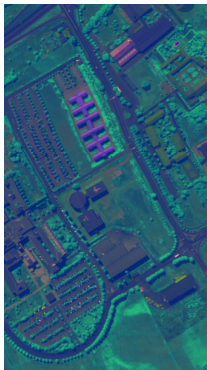
App: Object picking



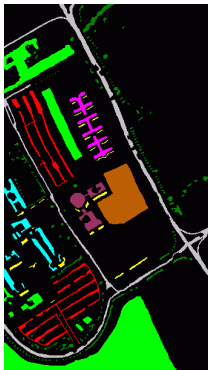
App: Object picking



App: Object picking → classification



3 PCA
components



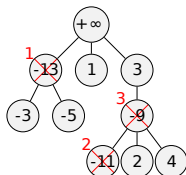
GT



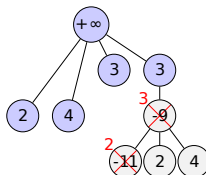
result

App: Simplification / segmentation

Δ Energy

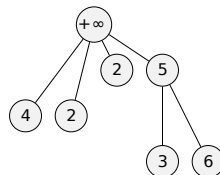


Iteration 1



...

Iteration n



1. Sort nodes by increasing meaningfulness
2. Compute ΔE on the tree
3. For each node
 - if removing it makes the energy decrease ($\Delta E < 0$)
remove it and update the local Δ energy of its relatives
 - otherwise stop

App: Simplification / segmentation



based on the cartoon model of the Mumford-Shah functional

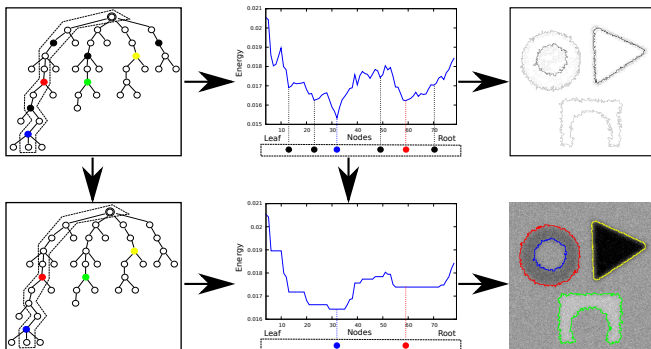
App: From a direct approach to a hierarchical one

For both filtering and segmenting \rightsquigarrow we set a strength value

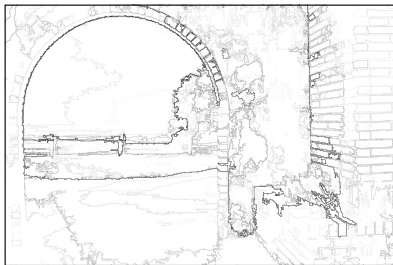
- we can analyze what happens when this strength is varying
- we are interesting in the *saliency* of components
(their persistence w.r.t. this strength)

App: From a direct approach to a hierarchical one

Illustration with ToS + contour meaningfulness energy + shaping:



App: Saliency map



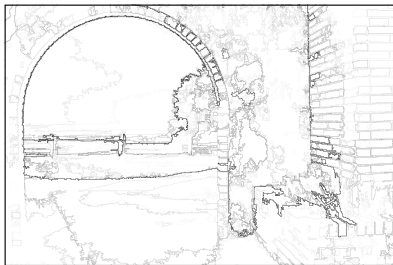
saliency map



original image

there is an underlying hierarchy of segmentations

App: Saliency map



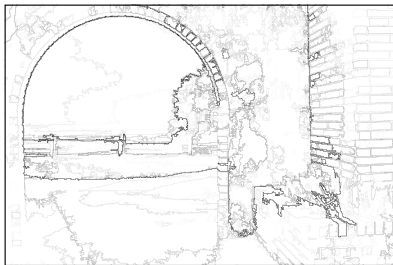
saliency map



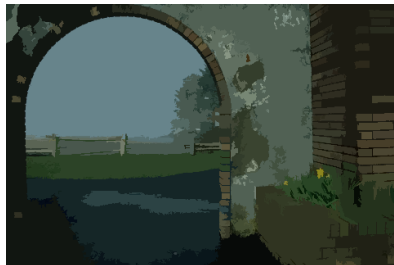
low threshold

there is an underlying hierarchy of segmentations

App: Saliency map



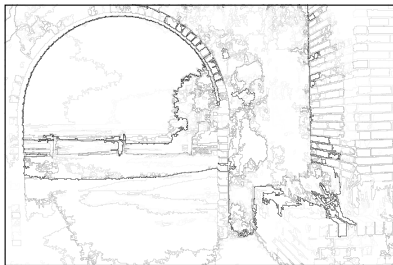
saliency map



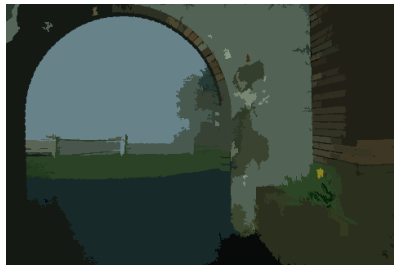
mid threshold

there is an underlying hierarchy of segmentations

App: Saliency map



saliency map



high threshold

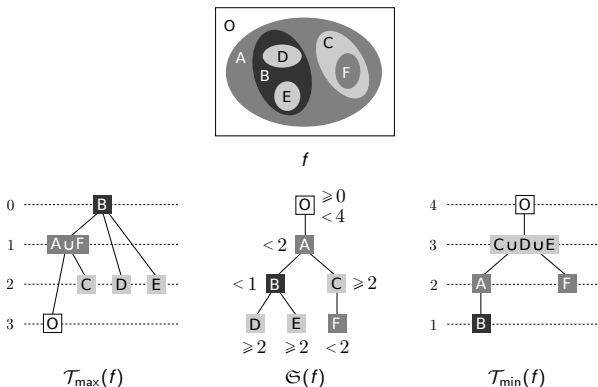
there is an underlying hierarchy of segmentations

App: Saliency map



Conclusion

three ways to represent a landscape with component inclusion



from which we can derive many simple applications

Conclusion

Pros:

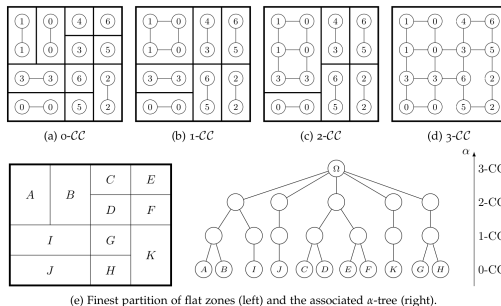
- tree = very convenient structure
- at pattern recognition level
- important invariants of MM

Cons:

- sometimes, object contours \approx only *parts* of level lines

Conclusion

Actually there exist some other morphological hierarchies...



hierarchy of quasi-flat zones

Conclusion

Actually there exist some other morphological hierarchies...

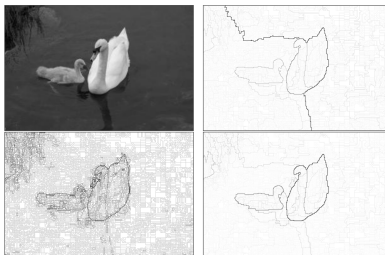


Figure 16: Hierarchies of watershed. Top left: original, top right: flooding by dynamics, bottom left: flooding by area, bottom right: flooding by volume. Hierarchies are represented through their saliency map.

hierarchy of minima dynamics / watersheds

References

- F. Cao, J.-L. Lisani, J.-M. Morel, P. Musé and F. Sur, “A Theory of Shape Identification,” *Lecture Notes in Mathematics*, vol. 1948, Springer, 2008.
- E. Carlinet and TG, “A comparative review of component tree computation algorithms,” *IEEE Transactions on Image Processing*, vol. 23, num. 9, pp. 3885–3895, 2014. [\[PDF\]](#)
- TG, E. Carlinet, S. Crozet, and L.W. Najman, “A quasi-linear algorithm to compute the tree of shapes of n -D images,” in: *Proc. of ISMM, LNCS*, vol. 7883, pp. 98–110, Springer, 2013. [\[PDF\]](#)
- S. Crozet and TG, “A first parallel algorithm to compute the morphological tree of shapes of n D images,” in: *Proc. of ICIP*, pp. 2933–2937, 2014. [\[PDF\]](#)
- E. Carlinet and TG, “MToS: A tree of shapes for multivariate images,” *IEEE Transactions on Image Processing*, vol. 24, num. 12, pp. 5330–5342, 2015. [\[PDF\]](#)
- Y. Xu, TG, and L. Najman, “Connected filtering on tree-based shape-spaces,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 38, num. 6, pp. 1126–1140, 2016. [\[PDF\]](#)
- G. Cavallaro, M. Dalla Mura, E. Carlinet, TG, N. Falcon, and J.A. Benediktsson, “Region-Based Classification of Remote Sensing Images with the Morphological Tree of Shapes,” *Proc. of the IEEE Intl. Geoscience and Remote Sensing Symposium (IGARSS)*, pp. 5087–5090, 2016. [\[PDF\]](#)
- Y. Xu, E. Carlinet, TG, and L. Najman, “Hierarchical segmentation using tree-based shape spaces,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, num. 3, pp. 457–469, 2017. [\[PDF\]](#)

The end

Thanks for your attention; any questions?

