How to mix spatial and spectral information when processing hyperspectral images

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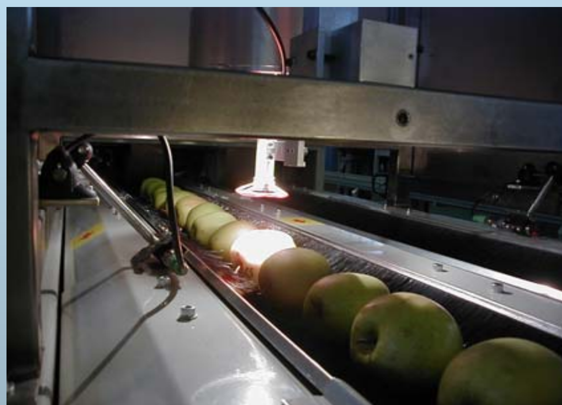
Presentation summary

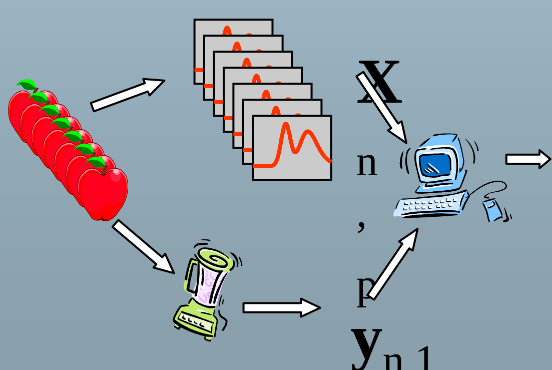
- Introduction: Hyperspectral images and spatial information
- Markov Random Fields
- Split-and-merge and Unin-Find strategies
- Anisotropic diffusion
- Conclusion

Hyperspectral imaging at Cemagref

Cemagref

Spectrometry & chemometrics (J-M Roger et al)

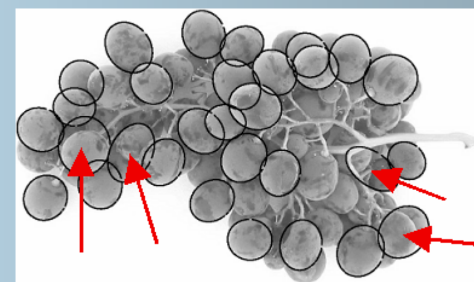


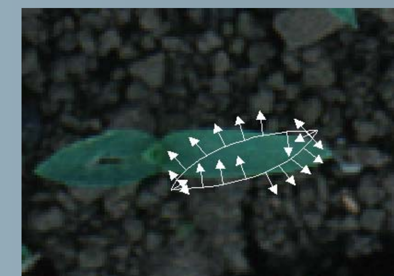


modèle

y=f(x)

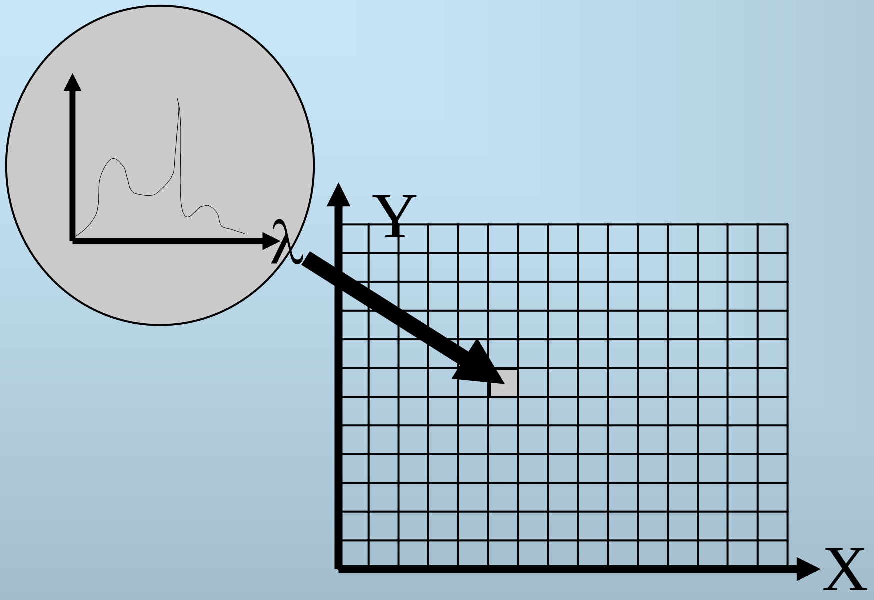
Image processing (G. Rabatel et al)





« Proximity » hyperspectral imaging

Hyperspectral imaging in a few words



- Compared to standard imagery:
  - More pixel information → better classification potential
- Compared to spectrometry:
  - Spatial mapping of the data
- Some applications:
  - Image segmentation (urban areas, forests, etc.)
  - Object detection (e.g. military applications)
  - Mapping of chemical components (pharmacy, biology, geology…)

The basics of hyperspectral processing

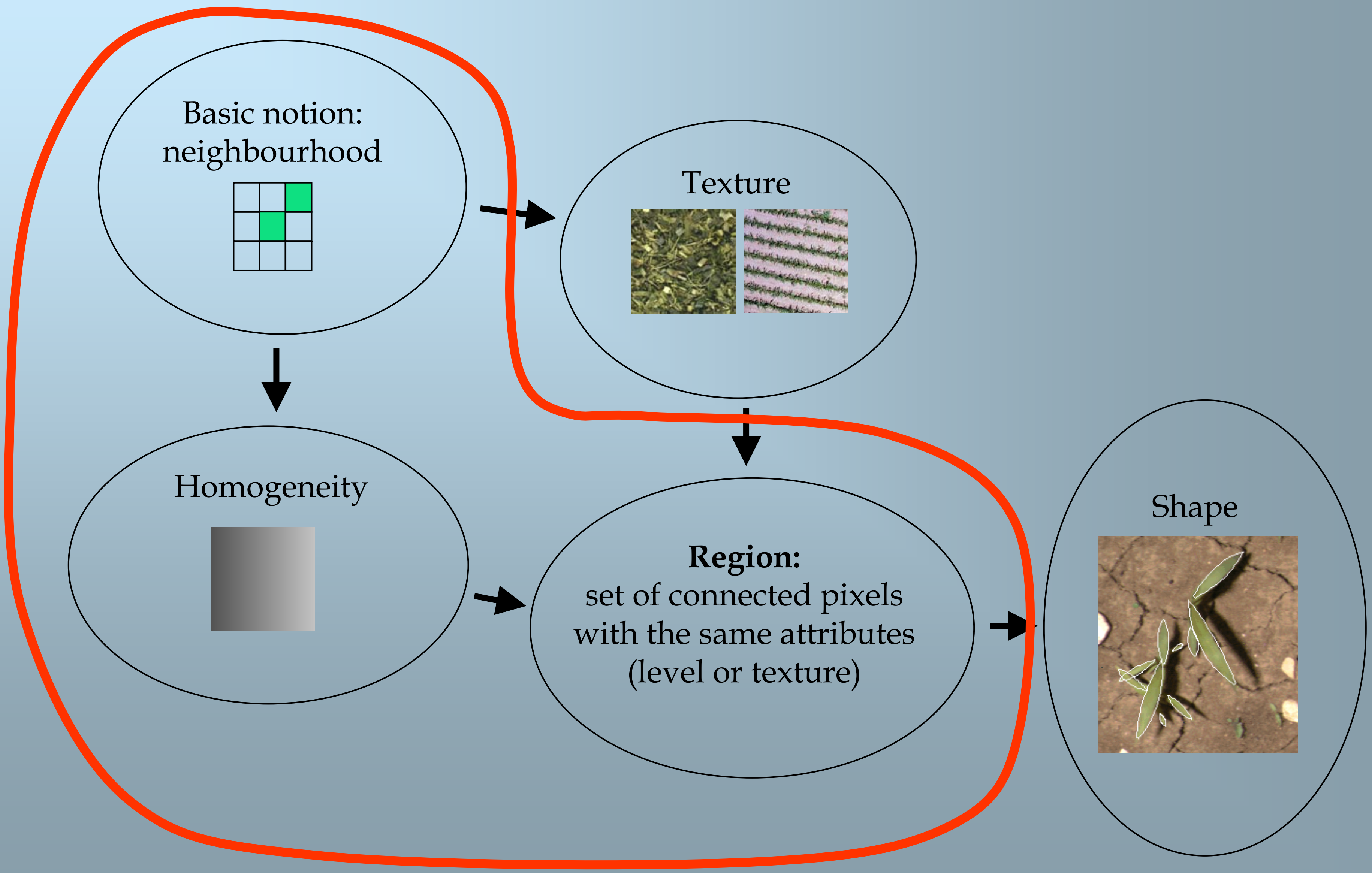
- Two main approaches
  - Supervised learning:
    output/spectra relationship learned from examples
  - Unsupervised processing:
    clusterisation, pure spectra extraction…
- A common requirement: model parcimony
  - Looking for a data subspace that keeps class separability
    PLS (supervised) ; PCA, projection pursuit (unsupervised)

The present situation

- In almost cases, **pixel-based** processing
  - Pixels are just considered as a large set of samples
  - Their neighbourhood relations are not taken into account:
    - neither in the calibration step
    - nor in the classification step
  - A spatial mixing of the pixels would lead to the same processing and the same results

- **A simple question: can we do better by considering pixels as « picture elements », not only as samples ?**

Spatial relationships



Homogeneity constraint

- Every pixel in the image have a high *a priori* probability to have spectral attributes close to its' neighbour ones

- Can be used to:
  - overcome classification ambiguities
  - remove erroneous pixels (outsiders)
  - Improve pixel clusterisation

Example 1: Markov Random Fields (MRF)

Markov Random Field: definition

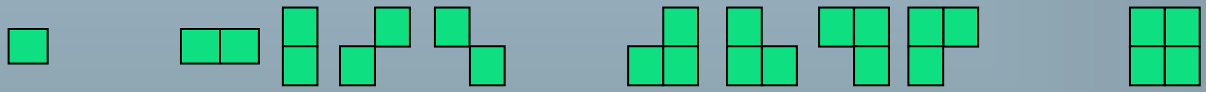
- Let us consider a 2D image I(x,y)
  (I: attribute vector, attribute scalar, or label)
- Let us consider p(I(i,j) = xs / I(k,l) {k≠i, l≠j})
  Probability for the pixel (i,j) to have a value xs, knowing every other values in the image

If I(x,y) is a Markov Random Field, this probability only depends on (i,j) neighbourhood, and can be written as:

$$p(xs) = \frac{1}{Z}\exp\left(-\sum_{C} V(C)\right)$$

- Z: normalisation constant
- V(C): potential of the clique C
- C: clique or neighbourhood configuration

Cliques:



1st order *2^{nd} order* *3rd order* *4th order*

Can be used for texture modelisation

MRF for homogeneity regularisation

The Potts model: *limited to cliques of 1st and 2nd orders*

⇨ First order potential:

V(C1) = Log [Pr(xs / S)]

Pr(xs / S): probability to have a label xs for a spectrum S

Gaussienne hypothesis: $V(C1) = (S - \mu_{xs})^T . COV^{-1} . (S - \mu_{xs})$

⇨ Second order potential:

V(C2) = V(xs, xt) = - β if xs = xt

= + β if xs ≠ xt

β parameter: tuning of the regularisation effect

MRF implementation

- The problem: to find the output image corresponding to the maximal probability pr(xs) for every pixel

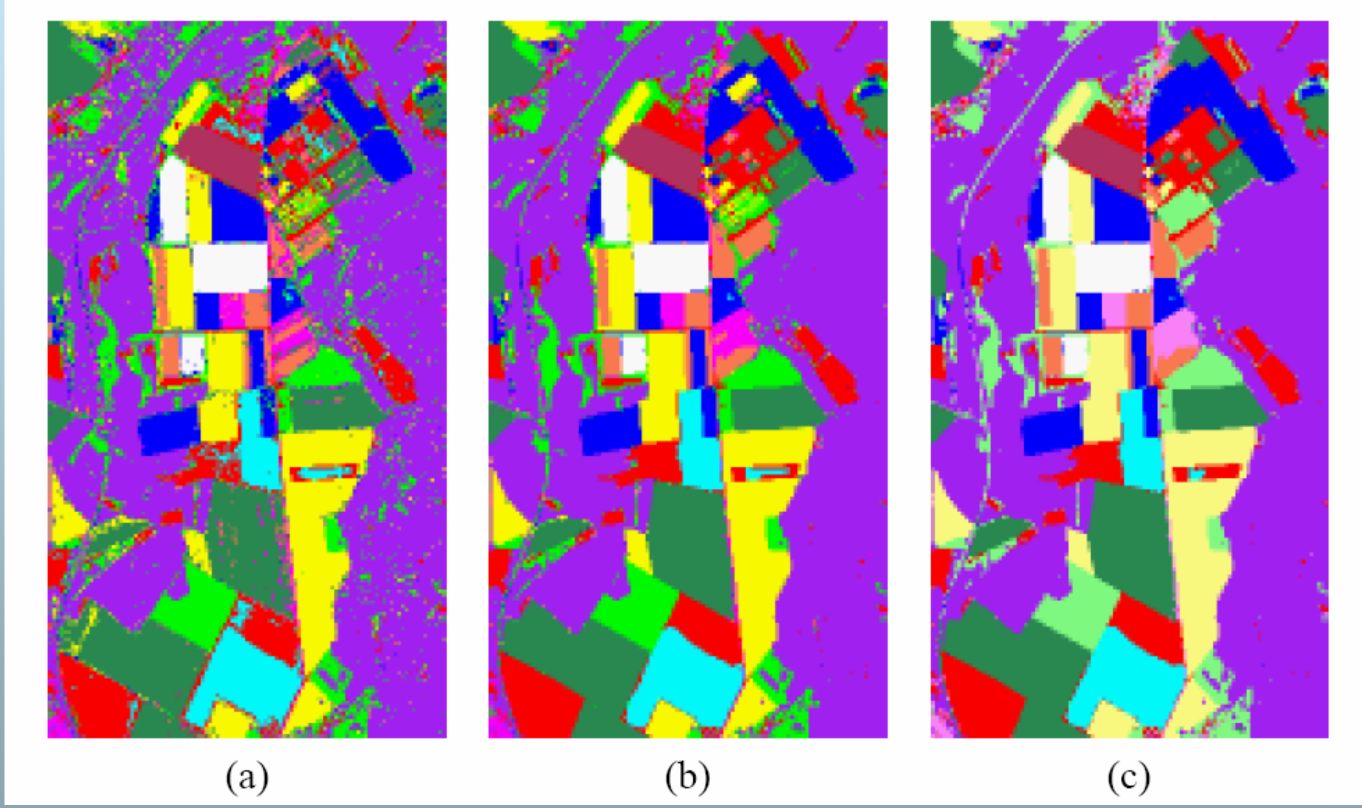
  - Simulated annealing (optimal, heavy computation)
    - Introduction of a temperature parameter
    - Slow decreasing of T to zero.

$$p(xs,T) = \frac{1}{Z(T)}\exp\left(-\frac{\sum_C V(C))}{T}\right)$$

  - Algorithm ICM (sub-optimal, faster)
    - Image scanning
    - For each pixel, setting of the xs value with the higher probability pr(xs)
    - Re-iteration until a stationary state is reached

Hyperspectral example (Prony et al, 2000)

ICM regularisation



a) No regulation b) $\beta = 3$ c) $\beta = 5$

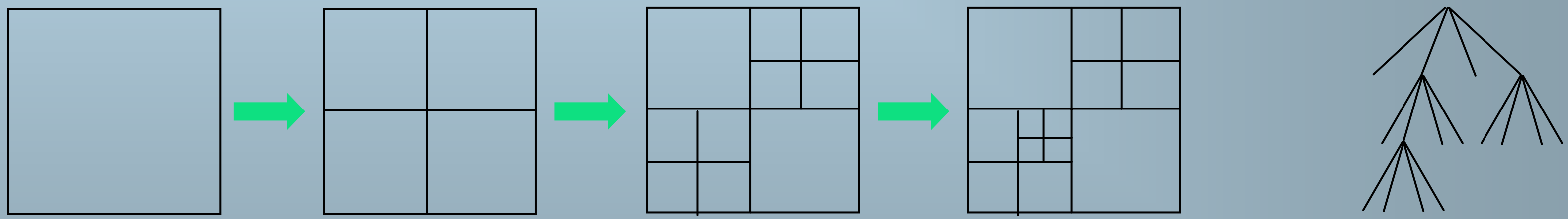
Unsupervised segmentation based on split-and-merge

N. Gorretta, Cemagref

(under development)

Basic principles

- Objective: to partition the hyperspectral image in a set of homogeneous regions
- Splitting process:
  Building of a quad-tree
  - Root = initial image
  - For each tree node: children nodes are created as long as the subimage variance is too high



- Merging process:
  Adjacent regions are merged if the distance between their average pixel values is below a threshold

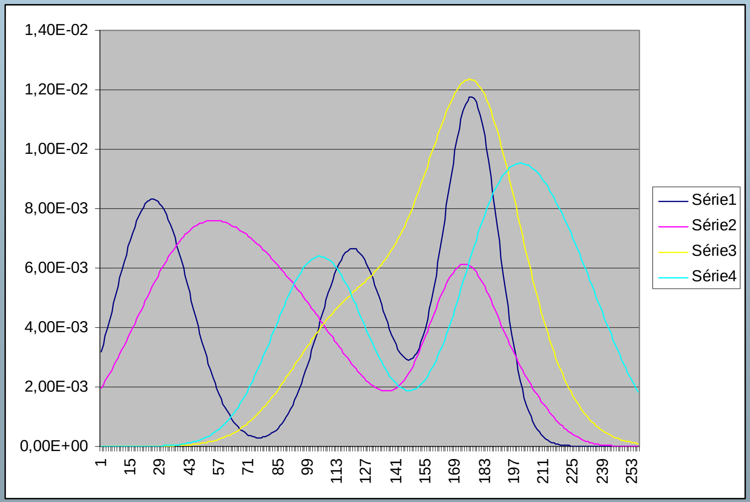
Implementation

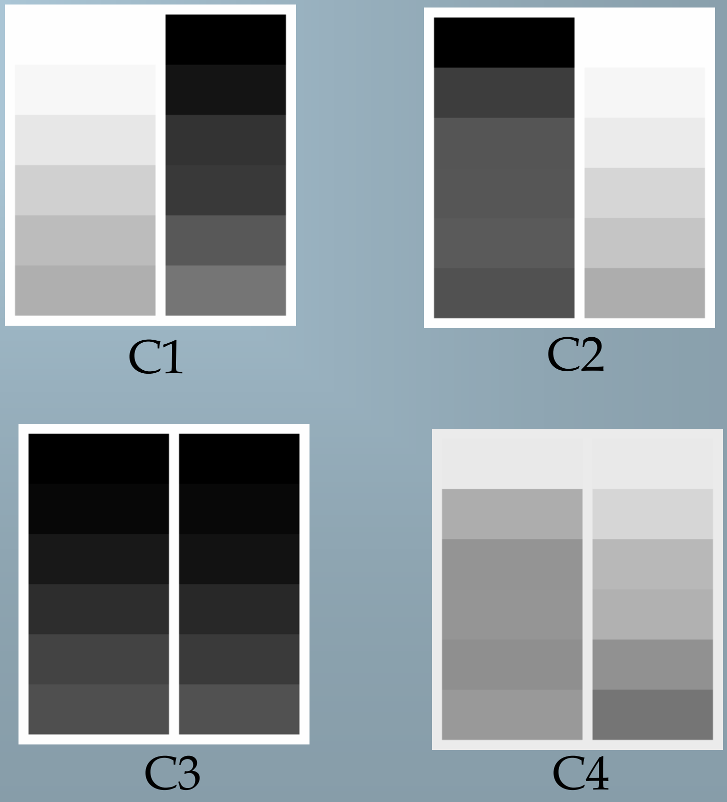
- Before the split-and-merge segmentation
  - a PCA is made on the spectral data of the subregion
  - Score images are builded using a grey-level renormalisation
  - Subregion variances (split) and Euclidian distances (merge) are computed using the multi-dimensional set of scores

- Local segmentation refinement
  - For each resulting sub-region, the entire process is launched again (PCA computation + split-and-merge process)
  - Refinement is stopped when no more subregions are created
  - This allows a hierachical image segmentation, where the user can tune the level of segmentation detail required.

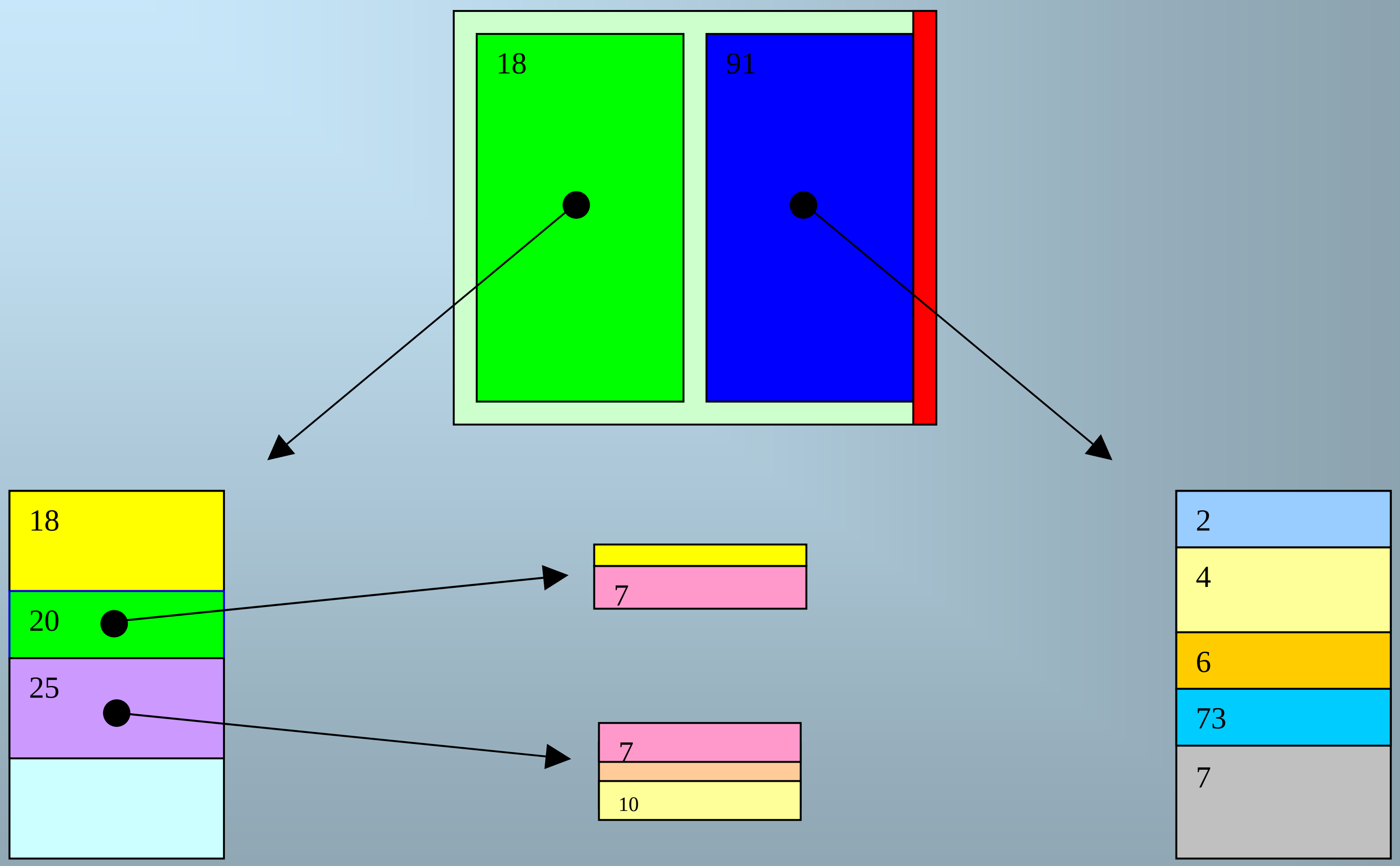
Results: synthetic test image

- The test image
  - Four different spectra have been generated using a random process
  - A synthetic image has been built, using a particular concentration pattern



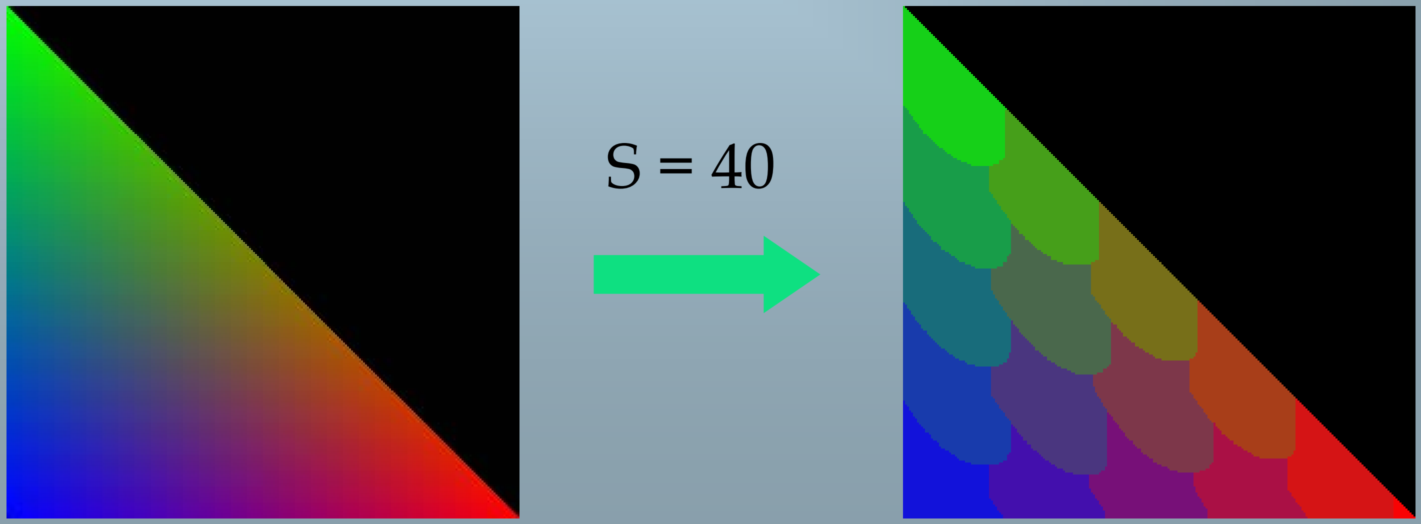


Results: image segmentation



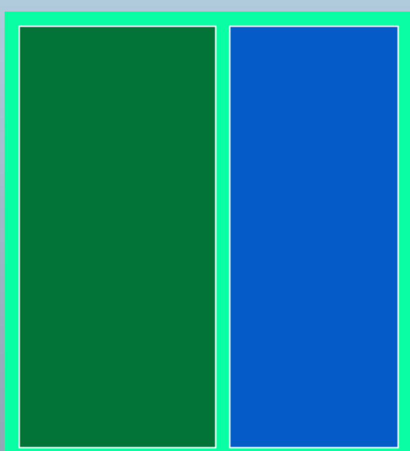
Alternative: Union-Find algorithm (Fiorio, 1996)

- Starting with a region associated to each pixel
- Image scanning, and comparison of each pixel (region) with the pixel (region) above and on the right.
- Merging condition: euclidian distance < S

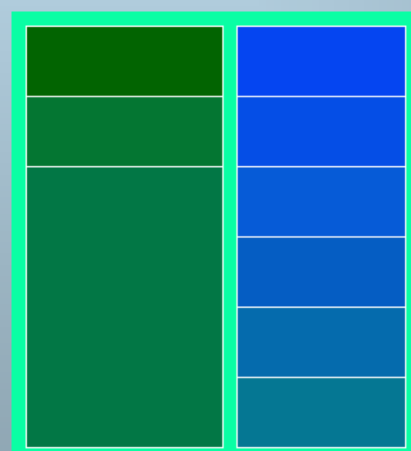


Union-Find result

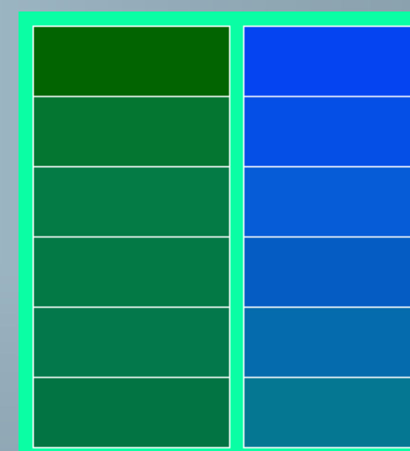
Application to the PC score vector
(after normalisation 0-255)



S = 100



S = 10



S = 2

Anisotropic diffusion

Basic principle (Perona & Malik, 1990)

- Objective: to smooth an image (noise reduction) while preserving edges
- Method:
  - Implementation of the Gaussian smoothing as an iterative process, using PDE formalism (PDE: Partial Derivative Equation)
  - Local attenuation of the iterative smoothing in high gradient areas

Isotropic diffusion

- Let us consider the temporal equation for the image I(x,y):

$$\frac{\partial I(x,y)}{\partial t} = div(\nabla I) = \Delta I$$

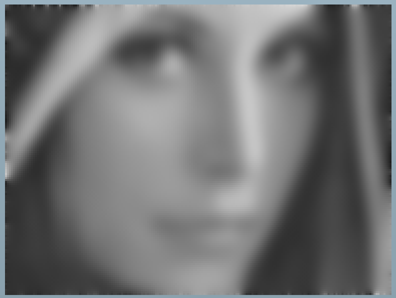
« Heat equation »

- The equation solution is a temporal gaussian filtering:

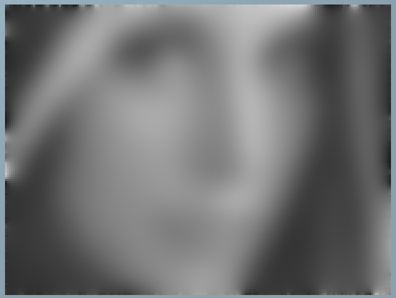
$I(x,y,t) = I(x,y,t_0) * G(x,y,t)$ where: $G(x,y,t) = \frac{1}{4\pi t}\exp(-\frac{(x^2+y^2)}{4t})$

Gaussian with a variance $\sigma^2 = 2\,t$

Original image



30 iterations



100 iterations

Anisotropic diffusion

- Introduction of a function $g(\nabla I)$ so that:
  - $g(\nabla I) \approx 0$ if ∇I high
  - $g(\nabla I) \approx 1$ if ∇I low

e.g: $g(\nabla I) = \exp(-\nabla I^2)$

$$\frac{\partial I(x,y)}{\partial t} = div(g(\nabla I).\nabla I)$$

Original image

30 iterations

100 iterations

Extension to vectoriel data

- ⇨ The notion of gradient ∇I has to be redefined

Di Zenzo analysis (Di Zenzo, 1986)

$$\|dI\|^2 = \begin{bmatrix} dx \\ dy \end{bmatrix}^T \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \begin{bmatrix} dx \\ dy \end{bmatrix} \quad \text{where} \quad g_{ij} = \left\langle \frac{\partial I}{dx_i}, \frac{\partial I}{dx_j} \right\rangle$$

Maximum and minimum vectorial variations (eigen values of [gij]) :

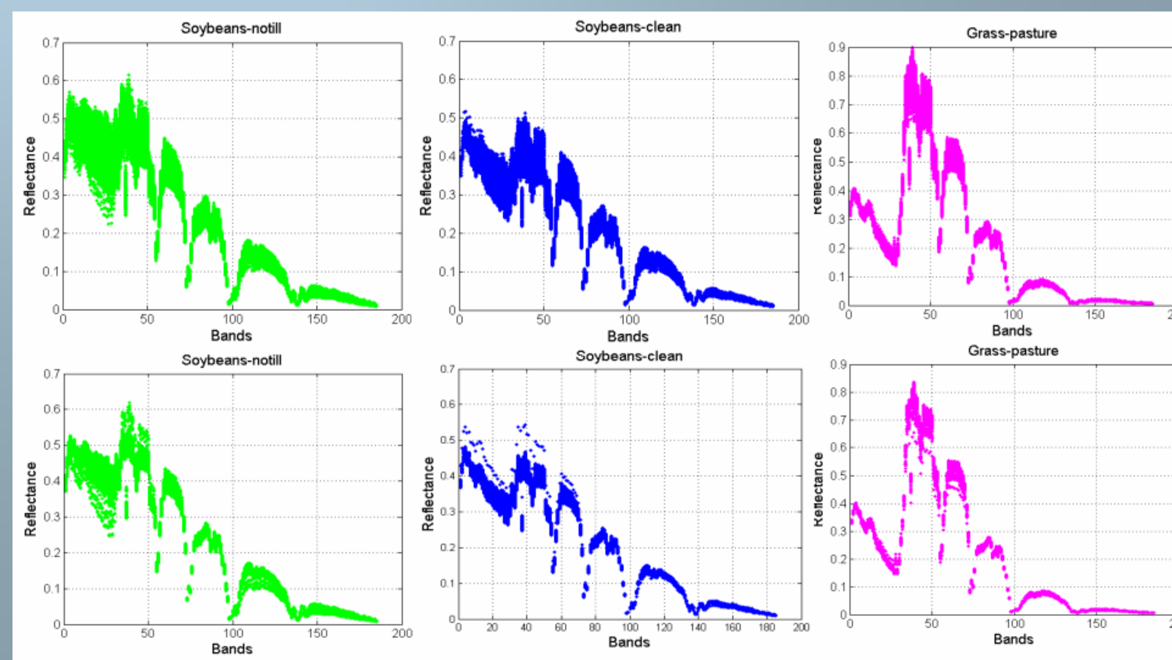
$$\begin{cases} \lambda + = g_{11} + g_{22} + \sqrt{(g_{11} - g_{22})^2 + 4 g_{12}^2} \\ \lambda - = g_{11} + g_{22} - \sqrt{(g_{11} - g_{22})^2 + 4 g_{12}^2} \end{cases}$$

- ⇨ Then:
  - ➢ | ∇I | = √λ+ (Di Zenzo)
  - ➢ ∇I | = √(λ+ - λ-) (Sapiro)

Hyperspectral example (Velez-Reyes, 2006)

Anisotropic diffusion

Reduction of the spectra deviation



Conclusion

- Taking into account the spatial relationships between hyperspectral imaging pixels can help in :
  - Reduction of classification errors
  - Unsupervised segmentation
  - Spectral noise reduction

- An apparent paradox
  - « Classical » hyperspectral processing requires a very accurate instrumental calibration
  - Image processing tools have been developed for years to overcome image signal inaccuracy (8 bits signal level, lighting variations, etc.)

Can spatial information reduce hyperspectral calibration requirements ?

- Unsupervised clusterisation merging smooth spectral variations
- Chemometric modelisation adapted to these «deviating » clusters (e.g. EPO (J-M Roger, 2003) …..

References

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- Prony, O., Descombes, X., Zerubia, J. Classification d'images satellitaires hyperspectrales en zone rurale et périurbaine. Rapport de recherche INRIA N°4008, septembre 2000.
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