Unsupervised multicomponent image segmentation combining a vectorial HMC model and ICA

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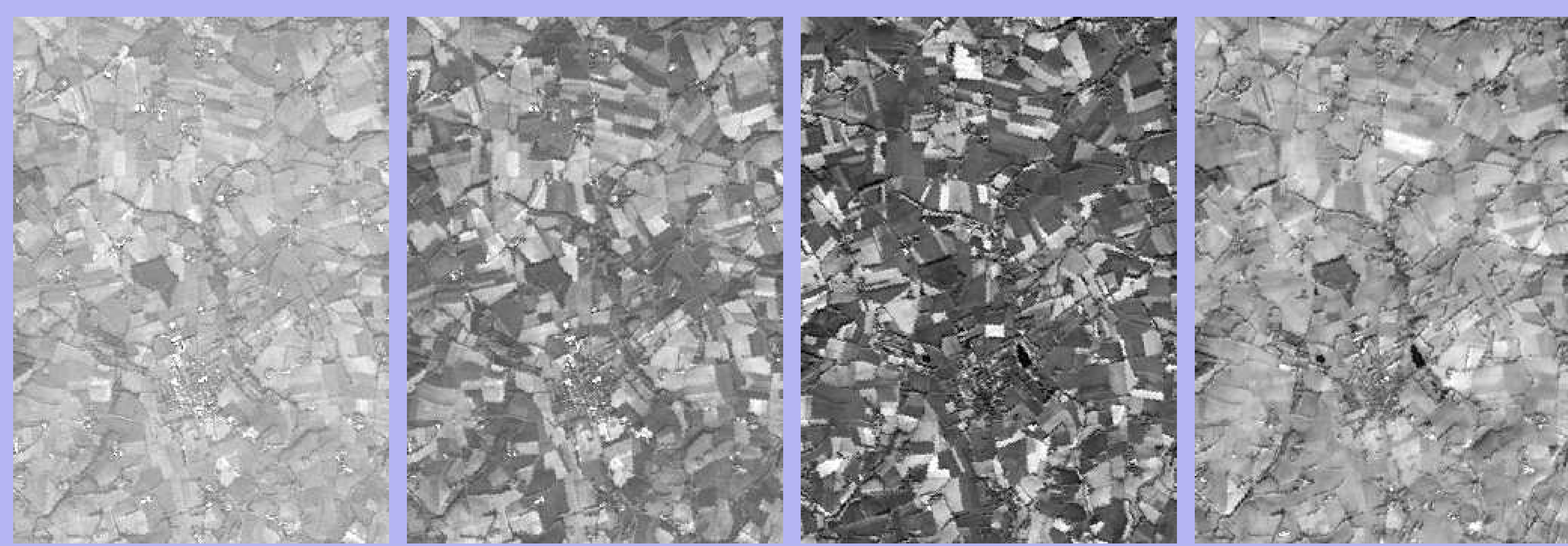
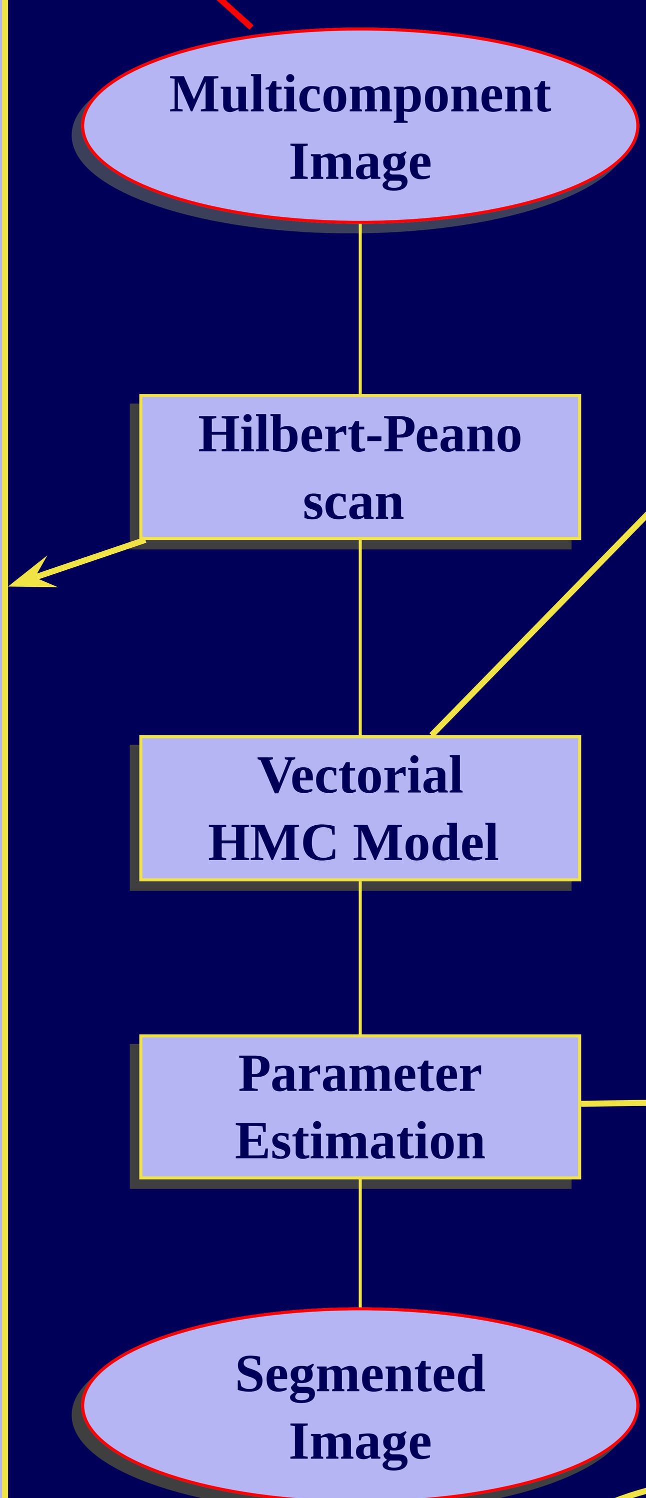
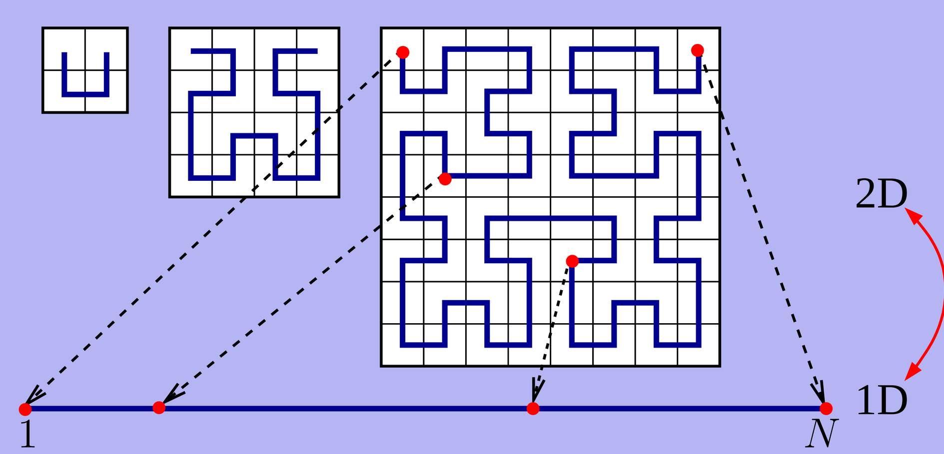
Original images: Spot IV images of Brittany, France.

$M = 4$ bands: red, green, near infrared and middle infrared. Size: $250 \times 350 = 87500 = N$.



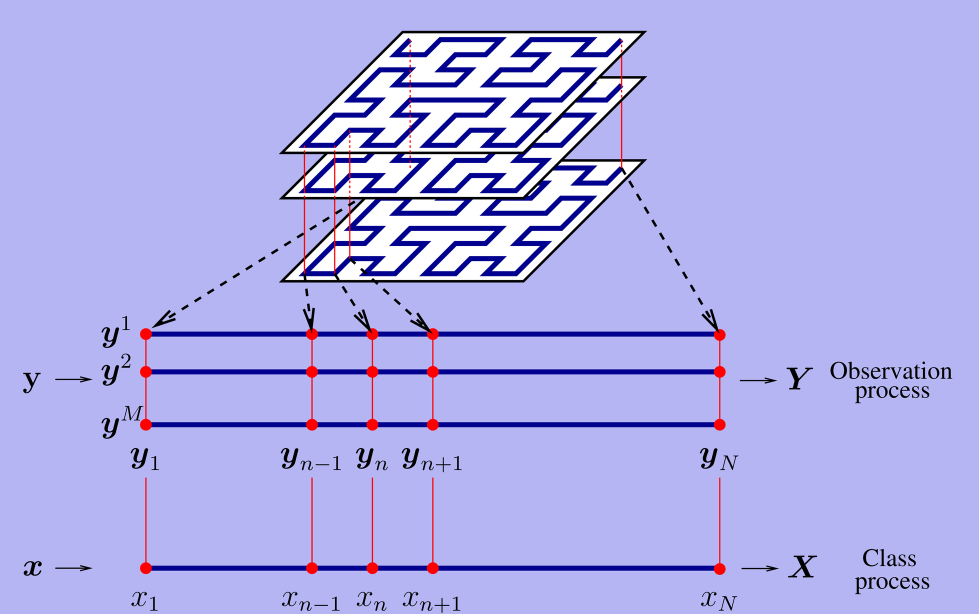


Peano scan



The Peano Scan (PS) transforms the 2D set of pixels into a 1D sequence (and conversely). The good exploitation of the 2D locality and the pseudo randomness of direction changes implies that the PS would work well (statistically) for a large family of images (especially real images).

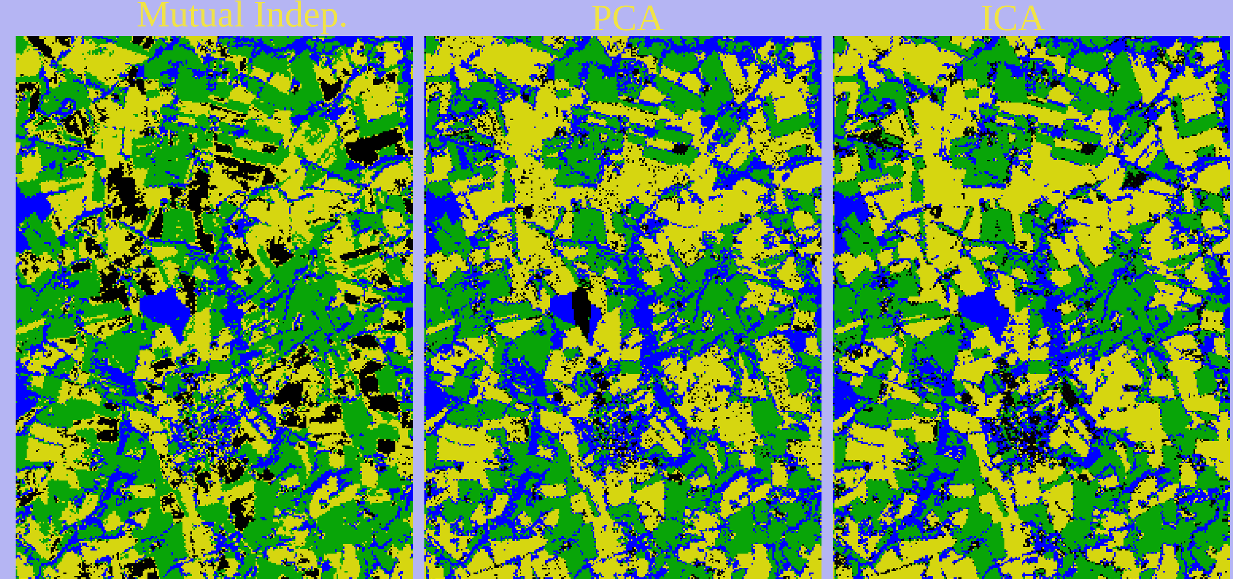
Vectorial representation of data



We want to classify each $\boldsymbol{y}_n$ in order to obtain the segmented chain $\boldsymbol{x} = (x_1, \ldots, x_N)$, $x_n \in \Omega = \{\omega_1, \ldots, \omega_K\}$. The problem is to estimate the unobserved realization $\boldsymbol{x}$ of a random process $\boldsymbol{X} = (X_1, \ldots, X_N)$ from the observed realization $\boldsymbol{y}$ of a random process $\boldsymbol{Y} = (\boldsymbol{Y}_1, \ldots, \boldsymbol{Y}_N)$.

Segmentation results: 4 classes, $g(x;\alpha,\beta) = \frac{\beta}{2\alpha\Gamma(1/\beta)} e^{-\left(\frac{|x|}{\alpha}\right)^\beta}$

Mutual Indep. | PCA | ICA



Vectorial HMC model

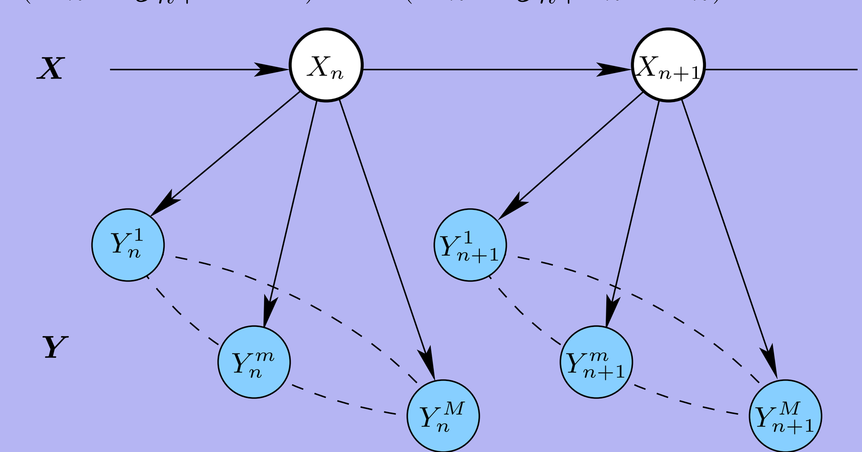
The distribution $P(\boldsymbol{X} = \boldsymbol{x}, \boldsymbol{Y} = \boldsymbol{y})$ is unknown and must be estimated in order to apply the Bayesian Maximum Posteriori Mode (MPM) criterion:

$$\hat{\boldsymbol{x}} = \hat{s}_{MPM}(\boldsymbol{y}) \Leftrightarrow \hat{x}_n = \arg \underbrace{\max}_{x_n \in \Omega} P(X_n = x_n | \boldsymbol{Y} = \boldsymbol{y}).$$

The process $\boldsymbol{X}$ is supposed to be Markovian and stationary. We also consider the usual two following assumptions:

① $P(\boldsymbol{Y} = \boldsymbol{y} | \boldsymbol{X} = \boldsymbol{x}) = P(\boldsymbol{Y}_n = \boldsymbol{y}_n | \boldsymbol{X} = \boldsymbol{x})$,

② $P(\boldsymbol{Y}_n = \boldsymbol{y}_n | \boldsymbol{X} = \boldsymbol{x}) = P(\boldsymbol{Y}_n = \boldsymbol{y}_n | X_n = x_n)$.



Model parameters

- Stationary Markov chain: $\widehat{\Pi}(\boldsymbol{X})$ set
  - Transition matrix $a_{\omega_k,\omega_l} = P(X_n = \omega_l \mid X_{n-1} = \omega_k)$
  - Initial probabilities $\pi_{\omega_k} = P(X_n = \omega_k)$
- Class parametrization: $\widehat{\Delta}(\boldsymbol{X}, \boldsymbol{Y})$ set
  - Distributions $f_{\omega_k}(\boldsymbol{y}) = P(\boldsymbol{Y} = \boldsymbol{y} \mid X_n = \omega_k)$

Parameters estimation

The estimation of parameters can be achieved using the Iterative Conditional Estimation (ICE) algorithm[a]. ICE produces a sequence of estimations θ^q of parameter θ as follows :

① initialize θ^0;

② compute $\theta^{q+1} = \mathrm{E}\left[\hat{\theta}(\boldsymbol{X}, \boldsymbol{Y}) | \boldsymbol{Y} = \boldsymbol{y}\right]$, where $\hat{\theta}$ is an estimator of θ;

③ stop if $\theta^{q-1} \approx \theta^q$.

This procedure leads to two different situations:

- For parameters in $\boldsymbol{\Pi}$, the expectation can be calculated analytically, by using the normalized Baum's Forward and Backward probabilities;
- For parameters in $\boldsymbol{\Delta}$, θ^{q+1} is not tractable. However, it can be estimated by computing the empirical mean of several estimates according to $\theta^{q+1} = \frac{1}{L}\sum_{l=1}^{L} \hat{\theta}\left(\boldsymbol{x}^l, \boldsymbol{y}\right)$, where $\boldsymbol{x}^l$ is a realization of of $\boldsymbol{X} | \boldsymbol{Y}^b$.

Let $\boldsymbol{x}$ be a realization of $\boldsymbol{X} | \boldsymbol{Y}$ and let $\boldsymbol{z}$ denotes the data of $\boldsymbol{y}$ corresponding to a given class ω_k in $\boldsymbol{x}$.

[a] W. Pieczynski, *Statistical image segmentation*, Mach. Graph. and Vis., Vol. 1, pp. 261-268, 1992.
[b] $\boldsymbol{X} | \boldsymbol{Y}$ is a non stationary Markov chain whose transition matrix is tractable analytically.

Multidimensional density estimation $f_{\omega_k}(\boldsymbol{y})$

Non-Gaussian multidimensional densities can be difficult to estimate. One solution is to decompose the problem into M 1D Pdf estimations. Several strategies are possible:

Mutual Independence

f_{ω_k} is the product of M densities $g^1_{\omega_k}$, $\ldots$, $g^M_{\omega_k}$ defined on $\mathbb{R}$:

$$f_{\omega_k}(\boldsymbol{z}_n) = \prod_{m=1}^{M} g^m_{\omega_k}(z^m_n).$$

Principal Component Analysis

A PCA algorithm can be done by projecting $\boldsymbol{z}$ onto an orthonormal system $\boldsymbol{W}$ so that $\boldsymbol{t}_n = \boldsymbol{W}\,\boldsymbol{z}_n$ are decorrelated:

$$f_{\omega_k}(\boldsymbol{z}_n) = |\det(\boldsymbol{W})| \prod_{m=1}^{M} g^m_{\omega_k}(t^m_n).$$

Independent Component Analysis

The objective of ICA is to find a linear transformation $\boldsymbol{W'}$ so that $\boldsymbol{s}_n = \boldsymbol{W'}\,\mathbf{z}_n$ are mutually independent. This is an optimization problem that has no analytical solution. The computation of $\boldsymbol{W'}$ requires the optimisation of a 'non-gaussianity' criterion (kurtosis or neguentropy). We adapted the one proposed by Hyvärinen[a] and f_{ω_k} can then be reconstructed using:

$$f_{\omega_k}(\boldsymbol{z}_n) = |\det(\boldsymbol{W'})| \prod_{m=1}^{M} g^m_{\omega_k}(s^m_n).$$

[a] A. Hyvärinen et al, *ICA: algorithms and applications*, Neural Networks, Vol. 13, pp. 411-430, 2000.

Conclusion

- Vectorial extension of the HMC model;
- Parameters estimation is performed from the general *Iterative Conditional Estimation* (ICE) procedure;
- Multi-dimensional densities are estimated by a set of 1D densities through a projection step that makes components independent. This allows to perform multidimensional *generalized* (i.e. non-gaussian) mixture estimation;
- The number of pixels on each band should remain significative relatively to the number of spectral bands.

Applications

- *Multiscale* segmentation of oil slicks in SAR images:
  G. Mercier, S. Derrode, W. Pieczynski, JM. Lecaillec and R. Garello, *Multiscale oil slick segmentation with Markov chain model*, IGARSS'03, Toulouse (Fr.), 21-25 July 2003.
- *Hyperspectral* segmentation of CASI images with dimension reduction:
  G. Mercier, S. Derrode and M. Lennon, *Hyperspectral image segmentation with Markov chain model*, IGARSS'03, Toulouse (Fr.), 21-25 July 2003.
- *Multitemporal* segmentation and change detection in SAR images:
  S. Derrode, G. Mercier and W. Pieczynski, *Unsupervised change detection in SAR images using a multicomponent HMC model*, MultiTemp'03, Ispra (It.), 16-18 July 2003.

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