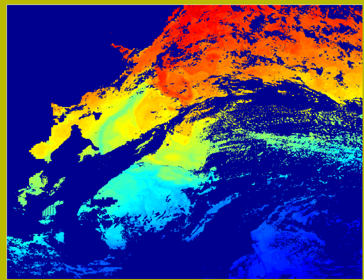
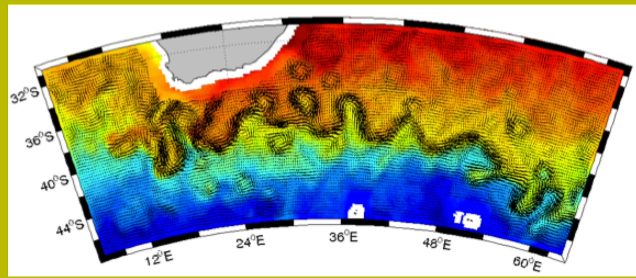
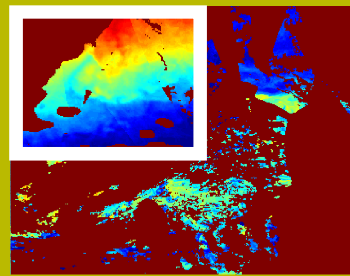
Stochastic models for texture geometry: application to texture recognition and super-resolution







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INSTITUT Mines-Télécom

06/03/2013

Telecom Bretagne

- Yearly budget: 38 M€ - 70 % from State grant (Ministry of Industry)
- Staff: 354
  - 154 Professors
  - 20 full-time researchers
- > 1000 Students (MSc, PhD)
- UMR LabSTICC, équipe TOMS (~50 pers.)

3 scho
engine

1 busi
school

4 assoc
schools
EURECOM and
Telecom Lille 1,
Telecom Saint
Étienne and ENSPS

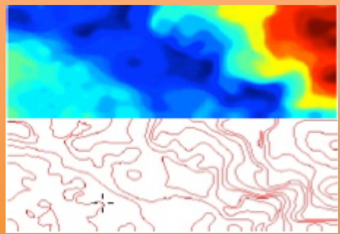
TELECOM SudParis

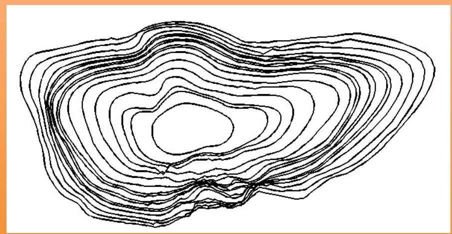
TELECOM Bretagne

Remote sensing group: research interests

Image and shape geometry, stochastic geometry

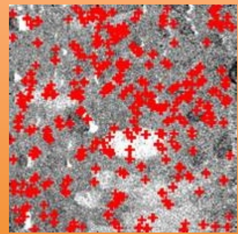
Extraction of geometric information
Multiscale geometric pattern

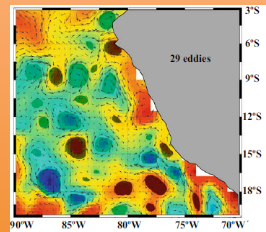


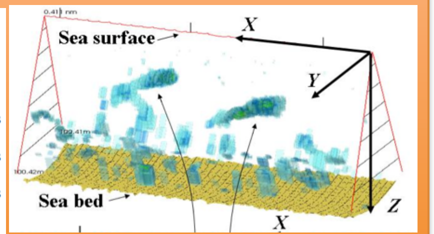


[e.g., CVIU’2008, GRSL’2011]

Distribution of local signatures
Random point process



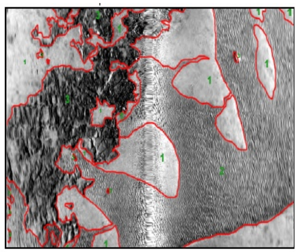


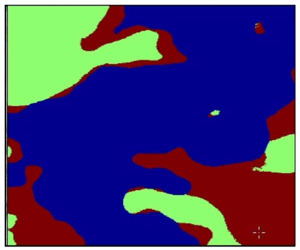


[e.g., IEEE GRS 2011, CVPR’2011]

Learning and classification

Weakly supervised learning
Texture recognition and classification
Statistical downscaling/super-resolution

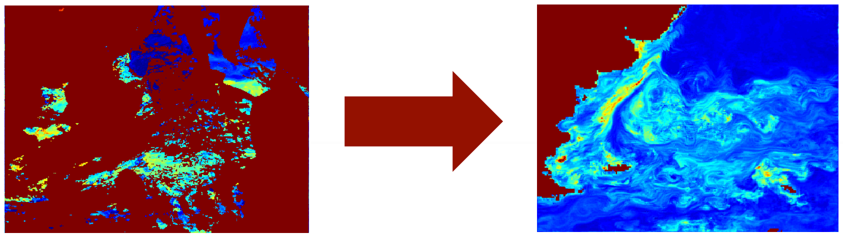




[e.g., IEEE IP 2010, ECCV’2010]

Variational methods

Detection and tracking
Missing data interpolation
Multiscale assimilation



[e.g., IEEE IP 2010, ECCV’2006]

Remote sensing group: application to marine ecology and oceanography

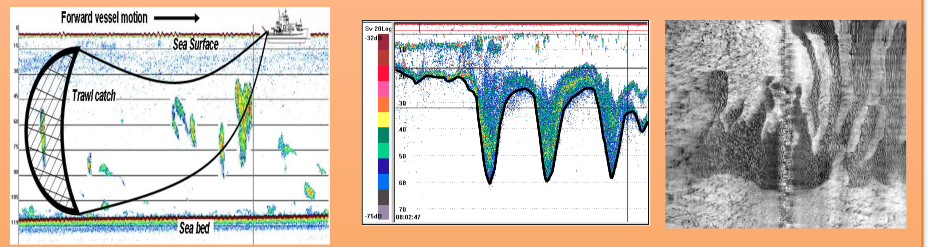
Biocalcified archives

Morphogenesis
Bio-energetic biomineralization models

[e.g., CVIU'2008, PLOS One'2011]

Sonar ocean sensing

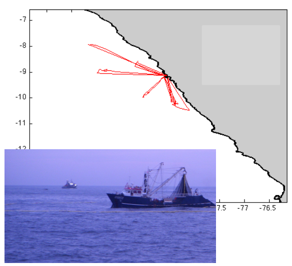
Seabed mapping
Sonar imaging of the pelagic system

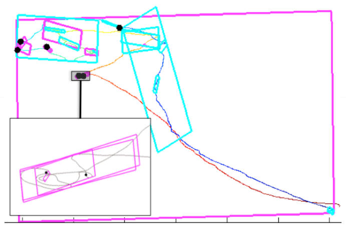


[e.g., GRSL 2011, IEEE GRS 2011, IEEE IP 2011]

Movement ecology

Random walk models
Multiscale pattern detection
State-space models

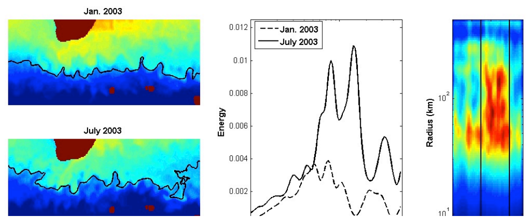




[e.g., RFIA'2012]

Satellite ocean sensing

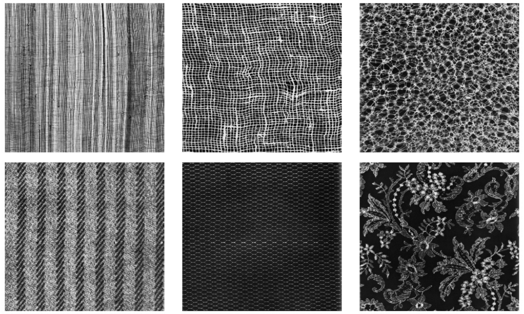
Statistical models of ocean turbulence
Multisscale interpolation
Geophysical field assimilation

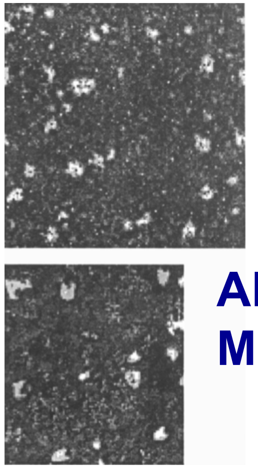


[e.g., GRSL'2011, TGRS'2013, ICASSP'2013]

Texture modelling and recognition: a long story

Haralick features (70's)
Cooccurrence matrices
Brodatz textures

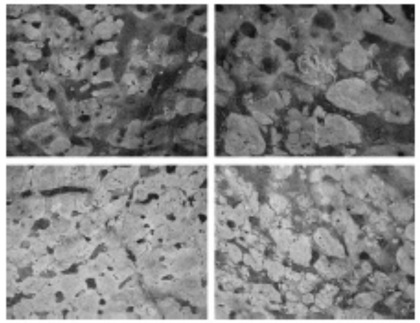




Gabor filters
Oriented filters (80's)

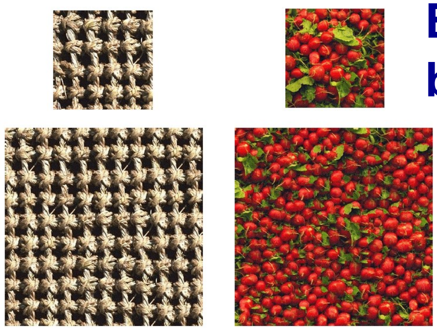
AR models,
MRFs 80's, 90's

Invariance to geometric transforms (rotation) (90's)



Pyramid-based moldes (90's)
FRAME (1998)

Local signatures (2004-)
Invariances: contrast & geometry
New texture databases



Exemplar-based and patch-based models (2000-)

Gaussian random fields(2012),
Multiplicative cascades (2007)

Texture modelling and recognition: texture geometry

- «Independence» of contrast and geometry component in images

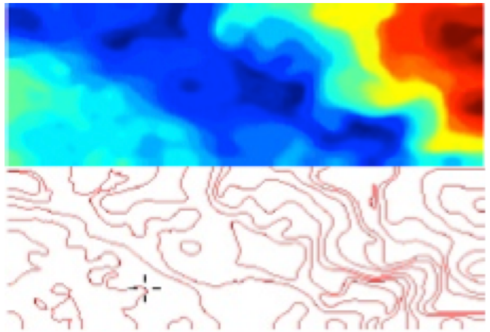
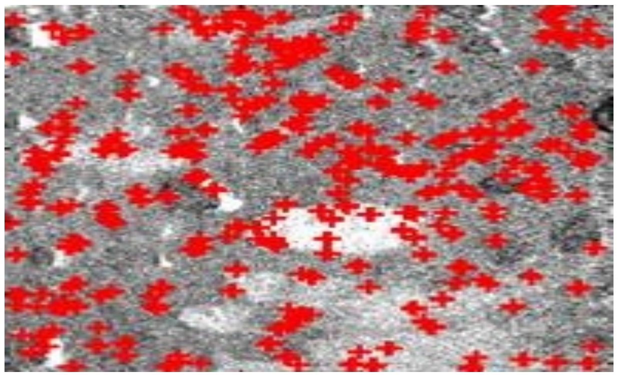
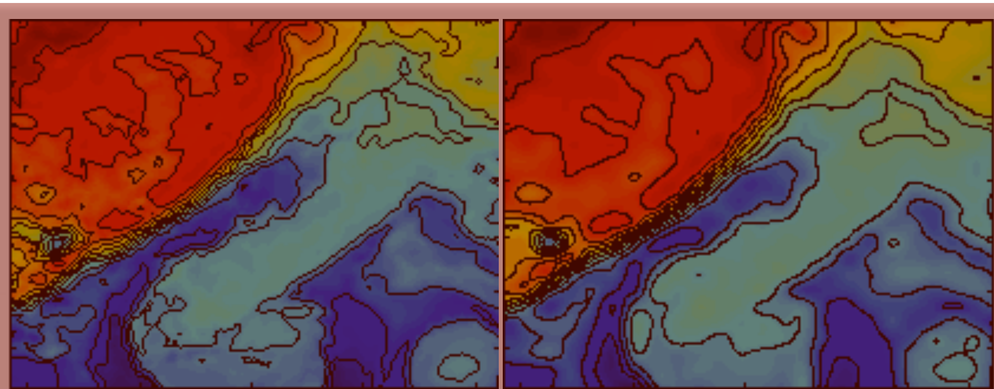


Image representation based on their level-lines [Monasse, 2000]

- Which representations for texture geometry?



Spatial distribution of local features for texture recognition



Geometry-driven texture super-resolution

Oceanic regimes from SST observations: context and objectives

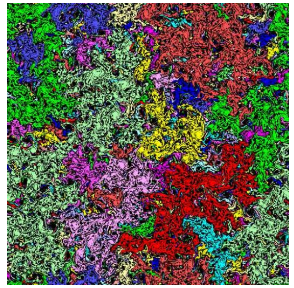
Scalar tracers as markers of turbulence regimes

- Passive transport (advection-diffusion)

$$\frac{\partial T}{\partial t} + v \cdot \nabla T = \nu \Delta T$$

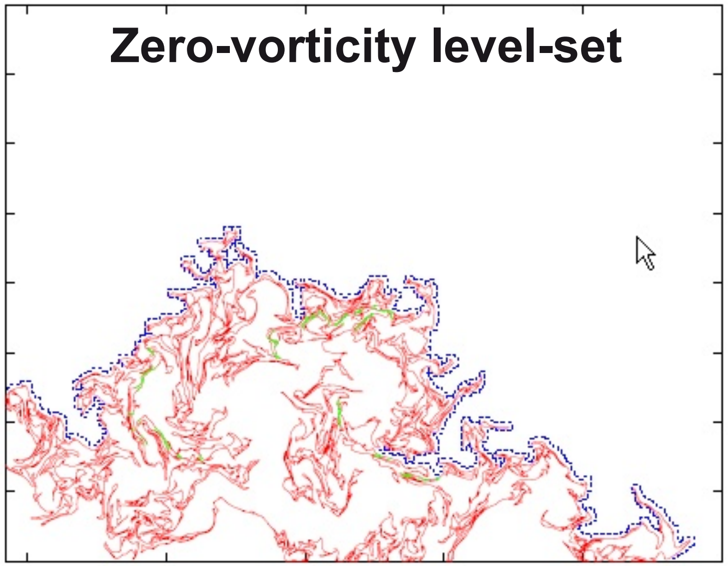
- Coupled 3D dynamics of flow velocities and temperatures, SQG model [Klein et al.]
  - **Temperature becomes an active tracer**
  - 3D dynamics determined by surface dynamics
  - Alpha-turbulence model

SST-based Markers of oceanic regimes

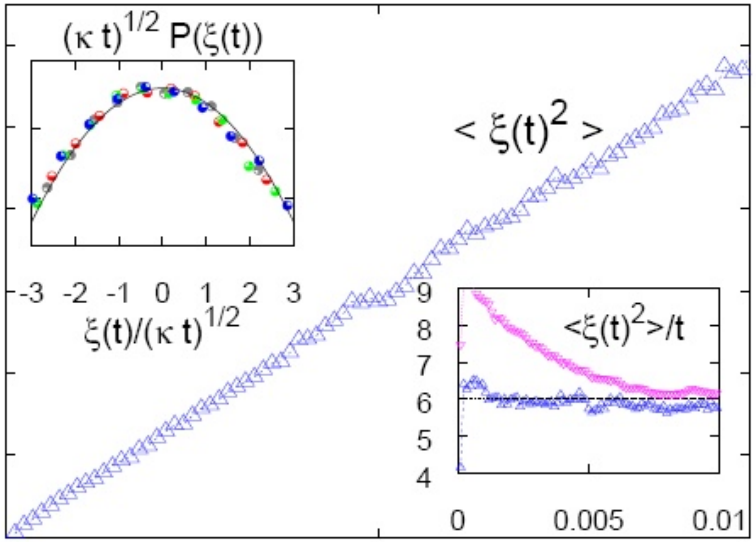


Background and motivations

- Turbulence involves fractal « textural » features
- Statistical geometric properties of 2D turbulence [e.g., Bernard et al., 2006] (***SLE process, conformal invariance***)

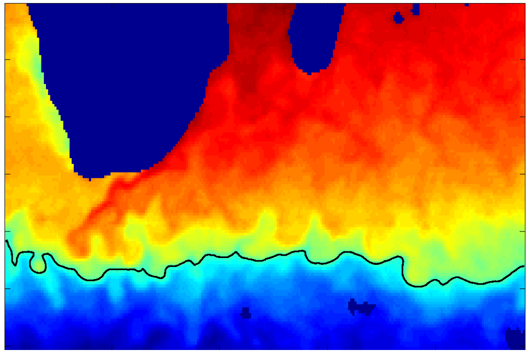


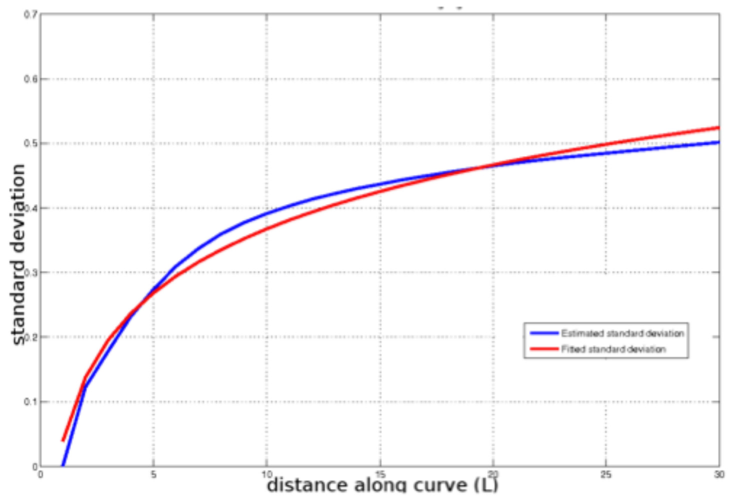
Winding angle statistics



Fractal Geometry of Ocean Dynamics?

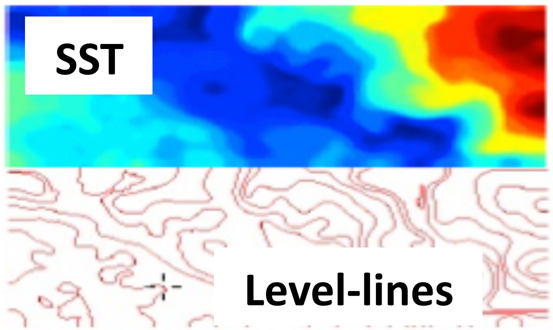
Winding angle statistics of SST level-lines

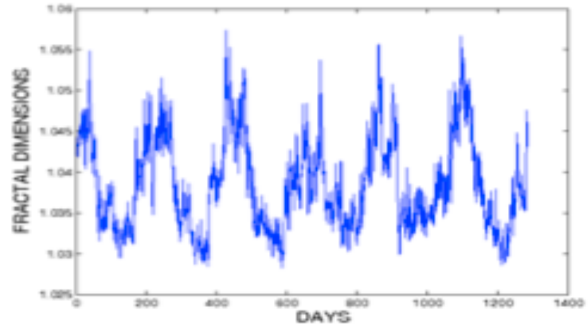




Evaluation of SQG hypothesis in front region

Estimation of **diffusivity coefficient** from winding angle statistics

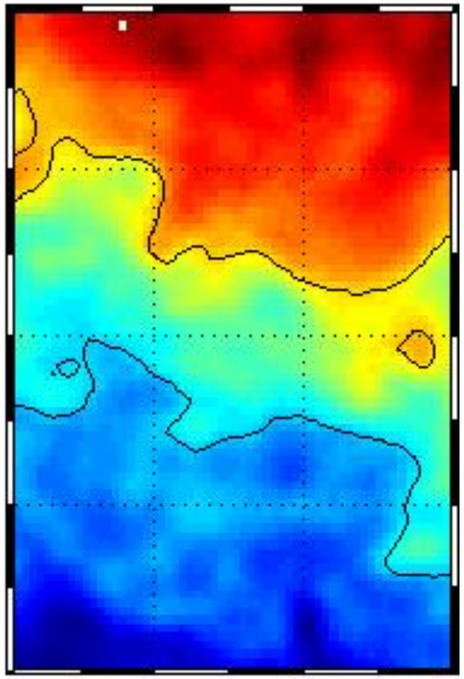




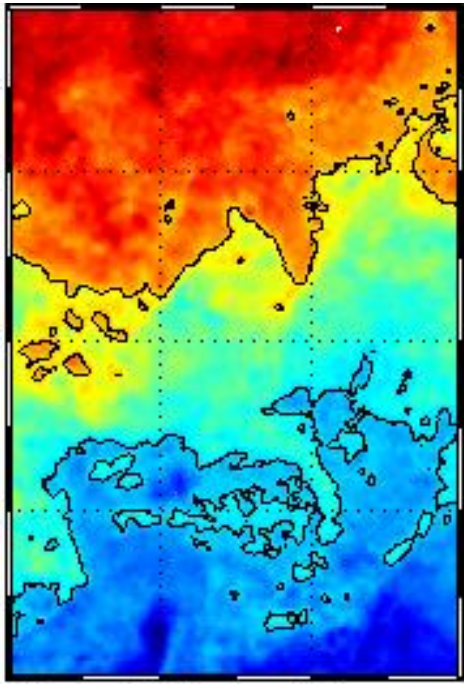
Ba et al., 2012

Beyond fractal signatures: focus on super-resolution/two-scale analysis

Low-resolution observation



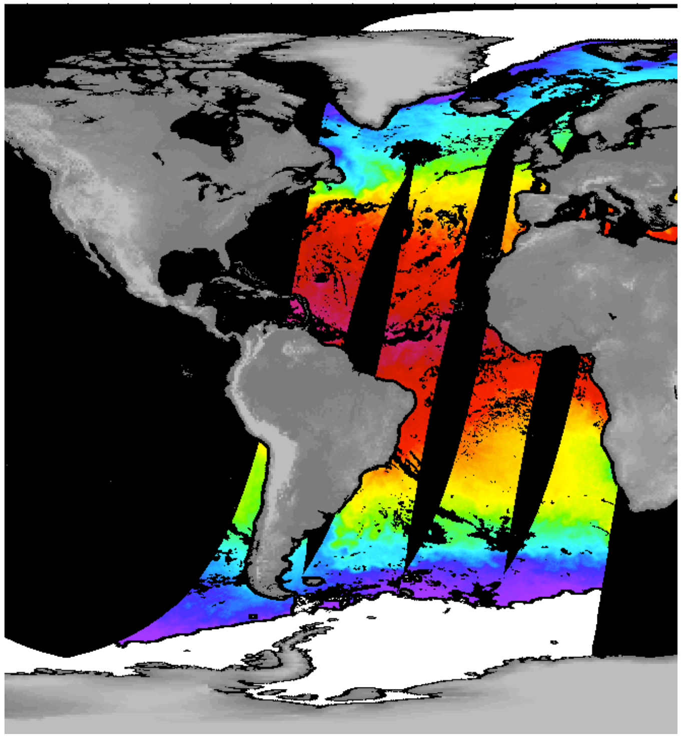
High-resolution observation



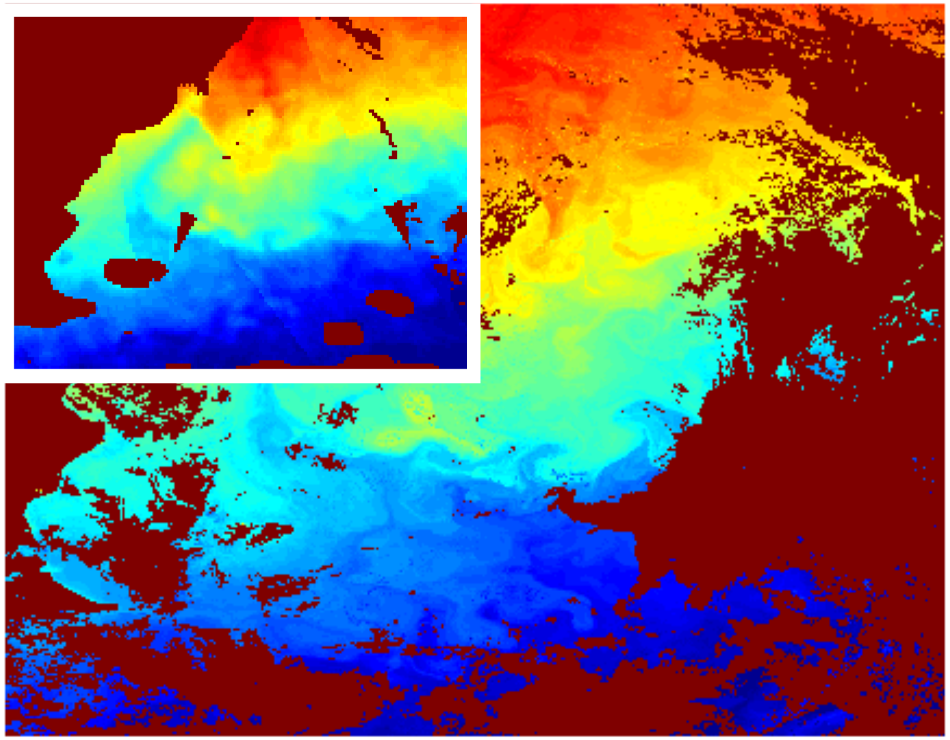
S'il vous plaît, ……
dessine-moi des détails

Which model to drive the emulation of high-resolution details from a low-resolution observation?

Why super-resolution issues in the remote sensing of the ocean?



Space-time satellite sampling



Missing data issues with multi-sensor/multiscale sources

Geometry/deformations in SST fields

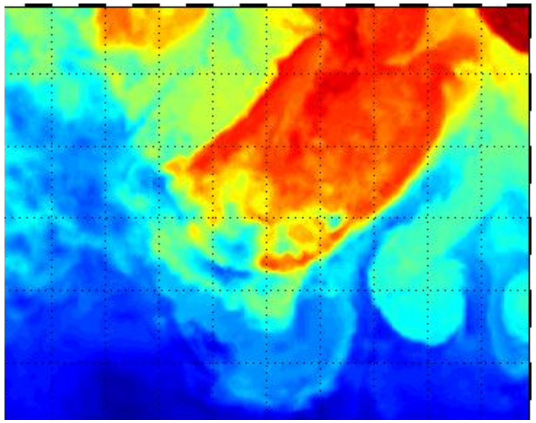
$$\vec{\nabla} I_0 = \left(\frac{\partial I_0}{\partial x}, \frac{\partial I_0}{\partial y}\right)$$

Gradient module

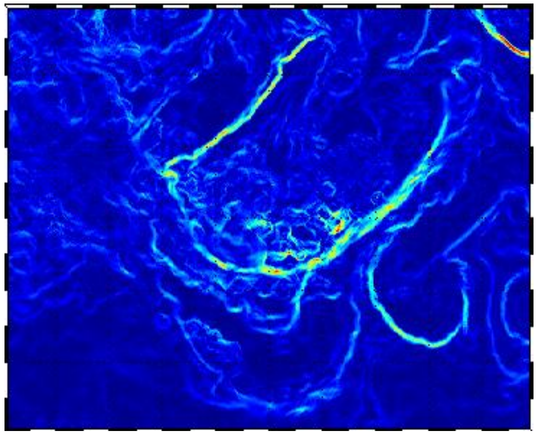
$$|\vec{\nabla} I_0| = \sqrt{[\frac{\partial I_0}{\partial x}]^2 + [\frac{\partial I_0}{\partial y}]^2}$$

Gradient orientation

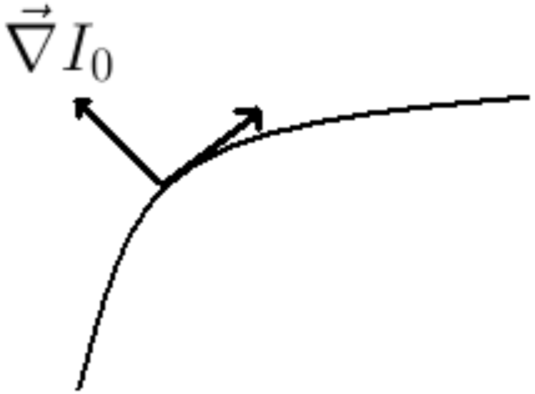
$$\Theta_0 = arg(\vec{\nabla} I_0) = \arctan(\frac{\partial I_0}{\partial y} / \frac{\partial I_0}{\partial x})$$



SST field

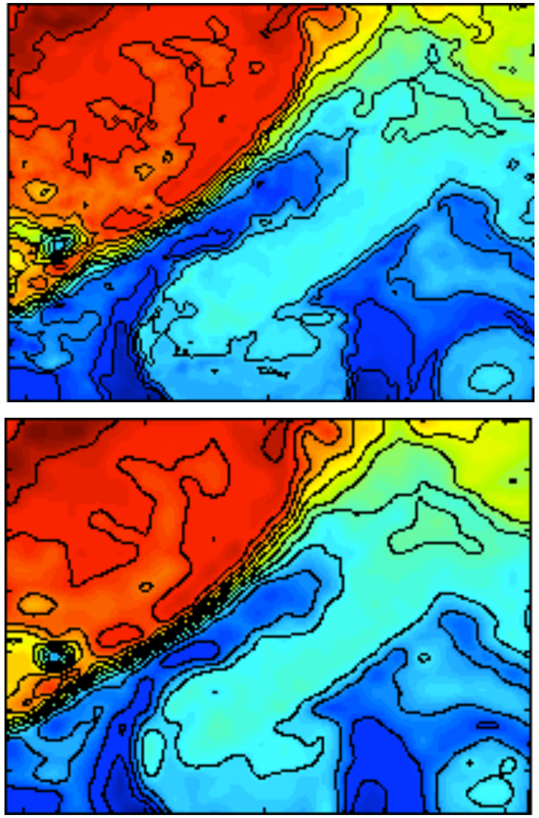


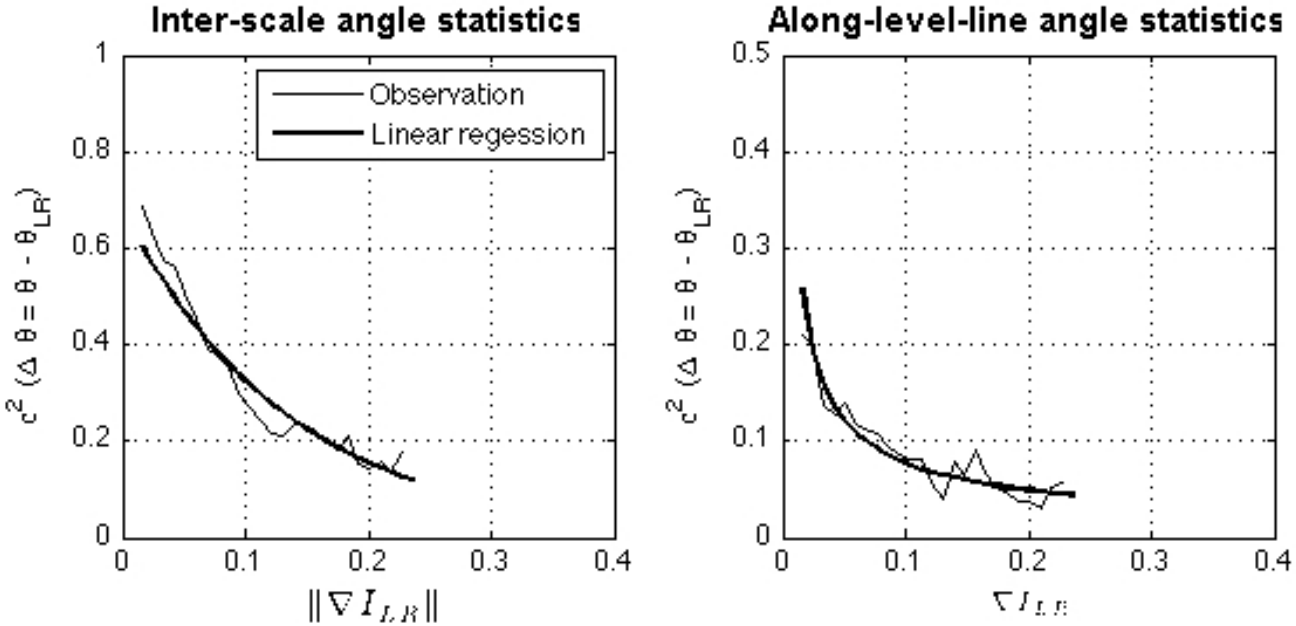
Gradient module



Gradient vs. Level-line

Empirical cues: geometrical regularity of the level-lines

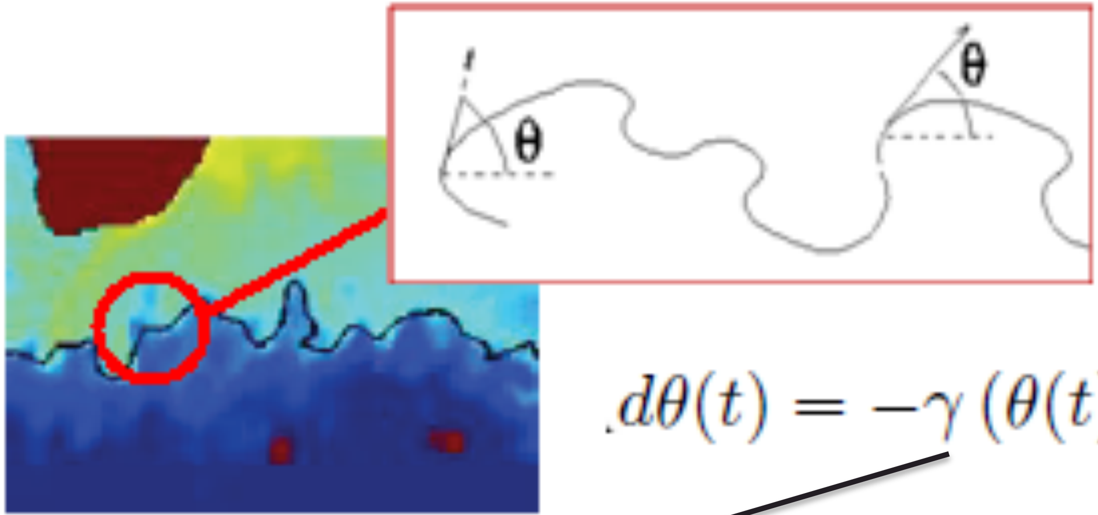




The low-resolution gradient drives the local regularity at high-resolution: THE GREATER THE GRADIENT, THE MORE REGULAR

From empirical orientation statistics to a probabilistic model

- **Image level-lines as 2D random walks**
  - Correlated random walks/Orstein-Uhlenbeck process
  - « Geometrical random walk »: parameterization according to the turning angle (constant-speed walk)



Brownian motion

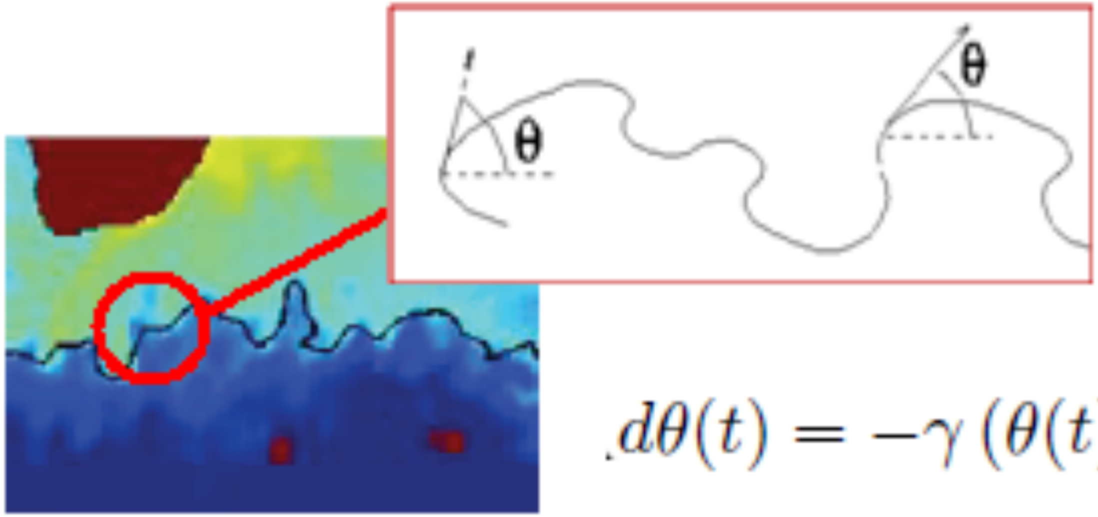
$$d\theta(t) = -\gamma\left(\theta(t) - \theta_0\right)dt + \sigma dW(t)$$

Recall

Directional drift

From empirical orientation statistics to a probabilistic model

- Image level-lines as 2D random walks



$$d\theta(t) = -\gamma\left(\theta(t) - \theta_0\right)dt + \sigma dW(t)$$

- Fokker-Plank representation

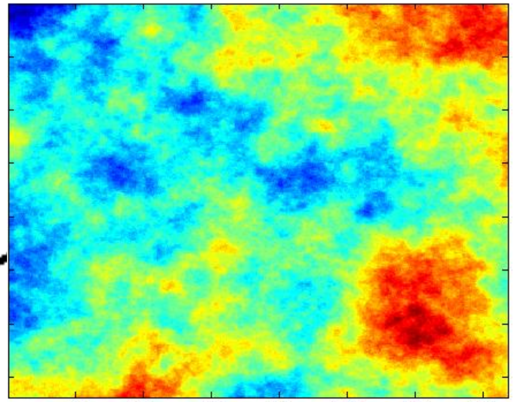
$$\frac{\partial P(\theta,s)}{\partial s} = -\frac{\partial[DP(\theta,s)]}{\partial\theta} - \frac{1}{2}\frac{\partial^2[\sigma^2 P(\theta,s)]}{\partial\theta^2}$$

Stationary distribution $P(\Theta) \sim \exp(-\lambda\Theta^2)$ $\lambda = \frac{\alpha}{\sigma^2}$

Geometry-driven 2D image model

- **Stochastic model for Image orientation**

$$d\Theta_p = \boxed{-\alpha(\Theta_p - \Theta_0)}\, dP + \sigma \boxed{dW_p}$$



Brownian surface

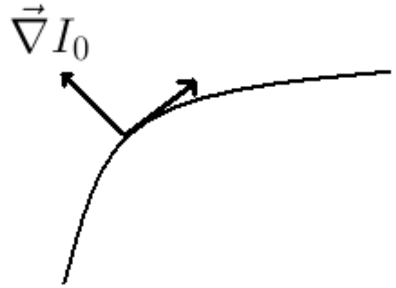
Recall to the low-resolution orientation

- **Control of the local geometrical regularity from parameters α and σ**

Geometry-driven 2D image model

- **Stochastic image model**

$$\begin{cases} d\theta(p) = -\gamma\left(\theta(p) - \theta_0(p)\right)dp + \sigma dW(p) \\ \langle n_{\tilde{I}}(p), u_\theta(p)\rangle = 0,\ \forall p \end{cases}$$

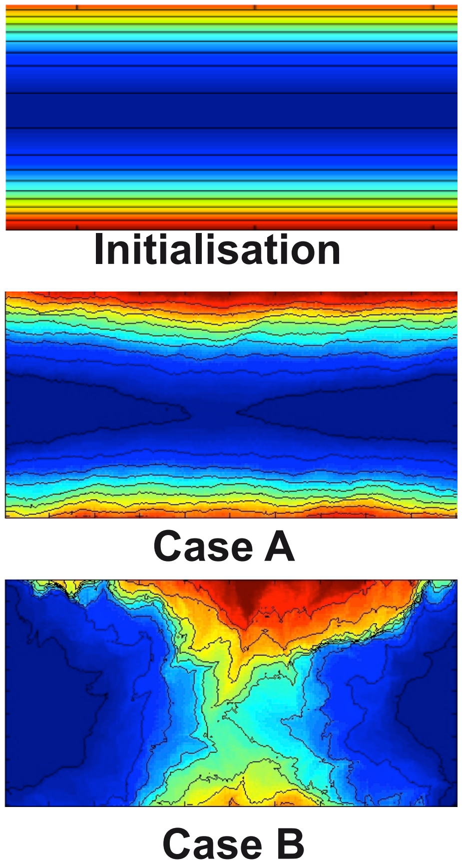


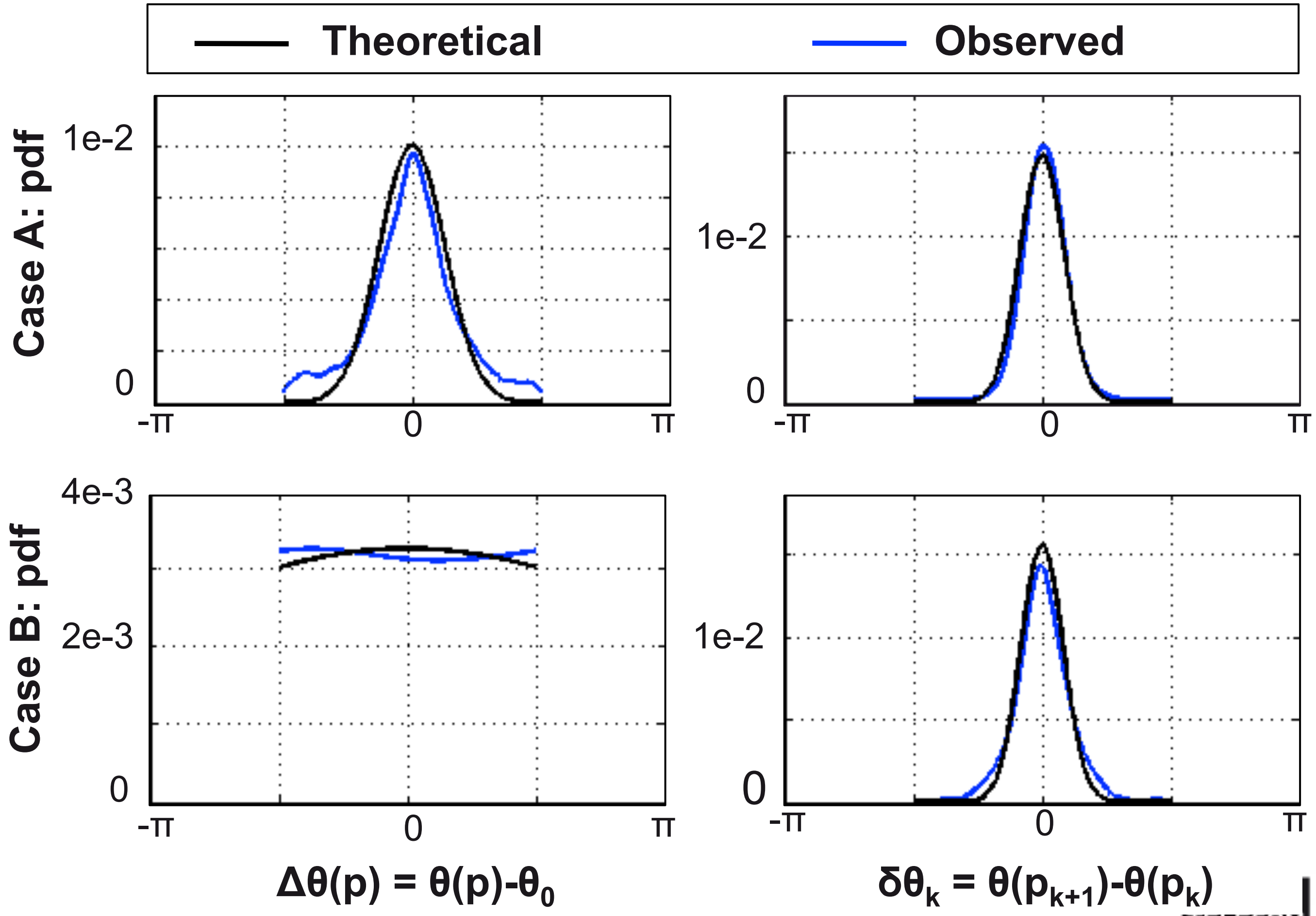
- **Implementation:**
  - 1. Sampling an orientation field **θ**
  - 2. Solving the variational minimization

$$\tilde{I} = \arg\min_I \int \| \langle \nabla I(p), u_\theta(p)\rangle \| dp$$

Geometry-driven 2D image model: simulations

- **Simulations with « simple » low-resolution orientation fields**





Application to texture super-resolution

Problem statement

I_{HR}: High-resolution image, NxM grid

I_{LR}: Low-resolution image, N/KxM/K grid

Projection constraint: $I_{LR} = \mathcal{P}\left[I_{HR}\right]$

$$I_{LR} = \mathcal{P}\left[\mathcal{P}^{-1}\left[I_{LR}\right]\right] \qquad \mathcal{P}\left[I_{HR} - \mathcal{P}\left[I_{HR}\right]\right] = 0$$

Stochastic super-resolution model:

$$\begin{cases} d\theta(p) = -\gamma(p)\left(\theta(p) - \theta_{LR}(p)\right)dp + \sigma(p)dW(p) \\ \tilde{I} = \arg\min_{I} \int \| \langle \nabla I(p), u_\theta(p) \rangle \| dp \\ \text{Subject to } I_{LR} = \mathcal{P}\left[\tilde{I}\right] \end{cases}$$

Application to texture super-resolution

Implementation

- **Projection/subsampling operator: dyadic wavelet (K=2^h)**
- **Sampling** $d\theta(p) = -\gamma(p)\left(\theta(p) - \theta_{LR}(p)\right)dp + \sigma(p)dW(p)$
- **Variational minimization**

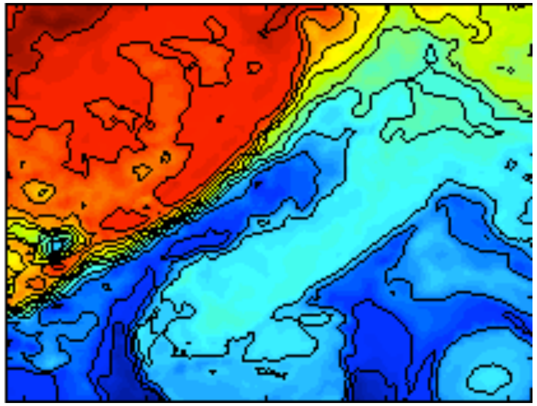
$$\tilde{I} = \arg\min_{I} \int \| \langle \nabla I(p), u_\theta(p) \rangle \| dp$$

$$\text{Subject to } I_{LR} = \mathcal{P}\left[\tilde{I}\right]$$

Iterative gradient descent $$\begin{cases} I^{(0)} = I_{LR} \\ I^{(k+1)} = I^{(k)} + \lambda\left[\delta I^{(k)} - \mathcal{P}[\delta I^{(k)}]\right] \end{cases}$$

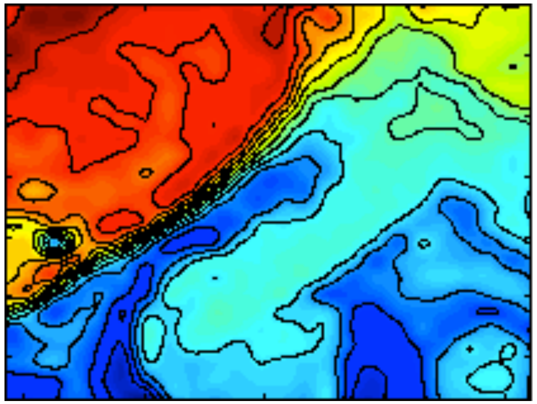
Application to texture super-resolution

- **Setting regularity parameters**



$$d\theta(p) = -\gamma(p)\left(\theta(p) - \theta_{LR}(p)\right)dp + \sigma(p)dW(p)$$

$$\begin{cases} \gamma(p) = \gamma_0 \|\nabla I_{LR}(p)\|^{\nu} \\ \sigma(p) = \sigma_0 \|\nabla I_{LR}(p)\|^{-\beta} \end{cases}$$

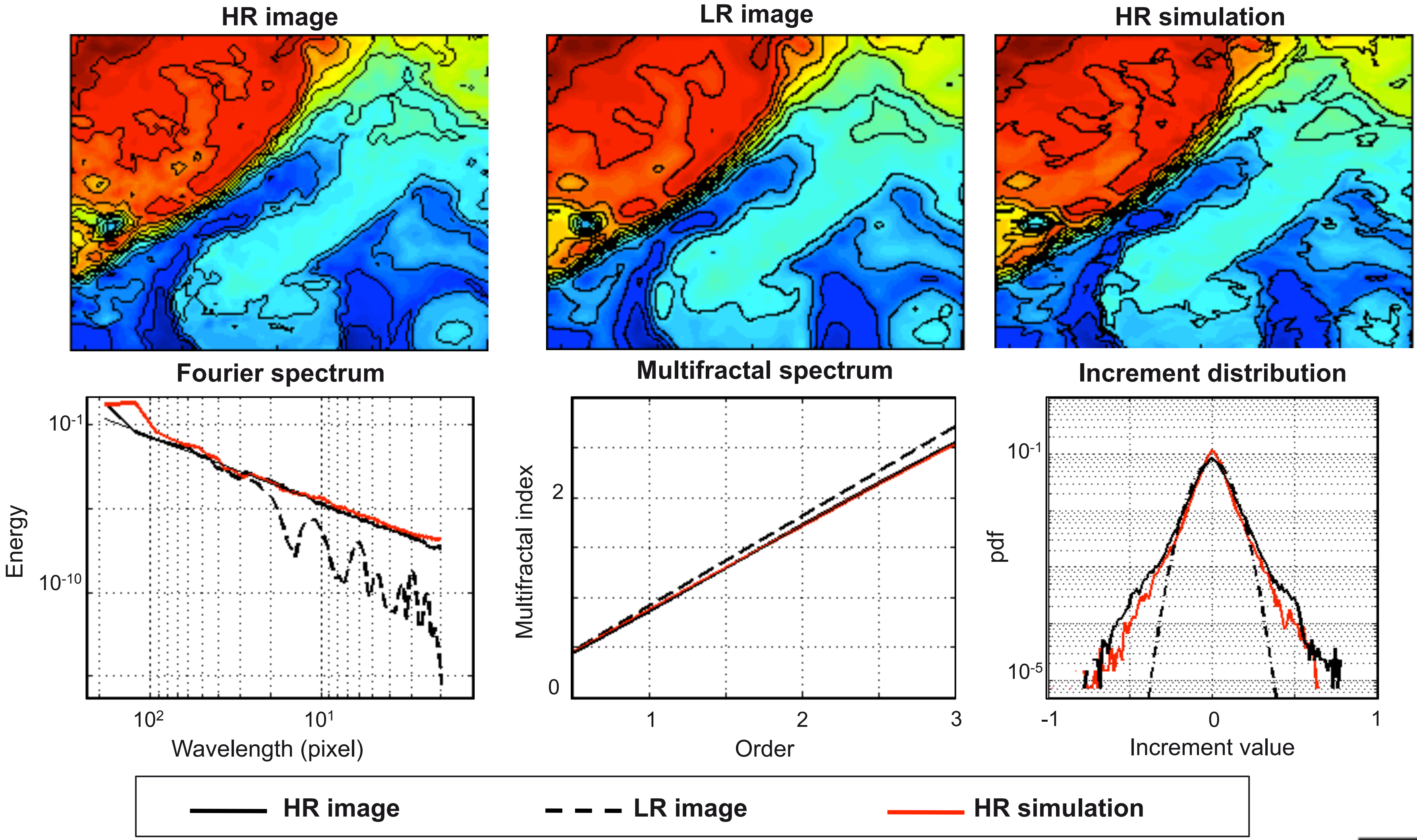


Low-gradient areas depict irrerular level-lines

Vs.

Image contours are more regular.

Results



HR image
LR image
HR simulation
Fourier spectrum
Energy
10-1
10-10
10²
10¹
Wavelength (pixel)
Multifractal spectrum
Multifractal index
2
0
1
2
3
Order
Increment distribution
pdf
10-1
10-5
-1
0
1
Increment value
HR image
LR image
HR simulation

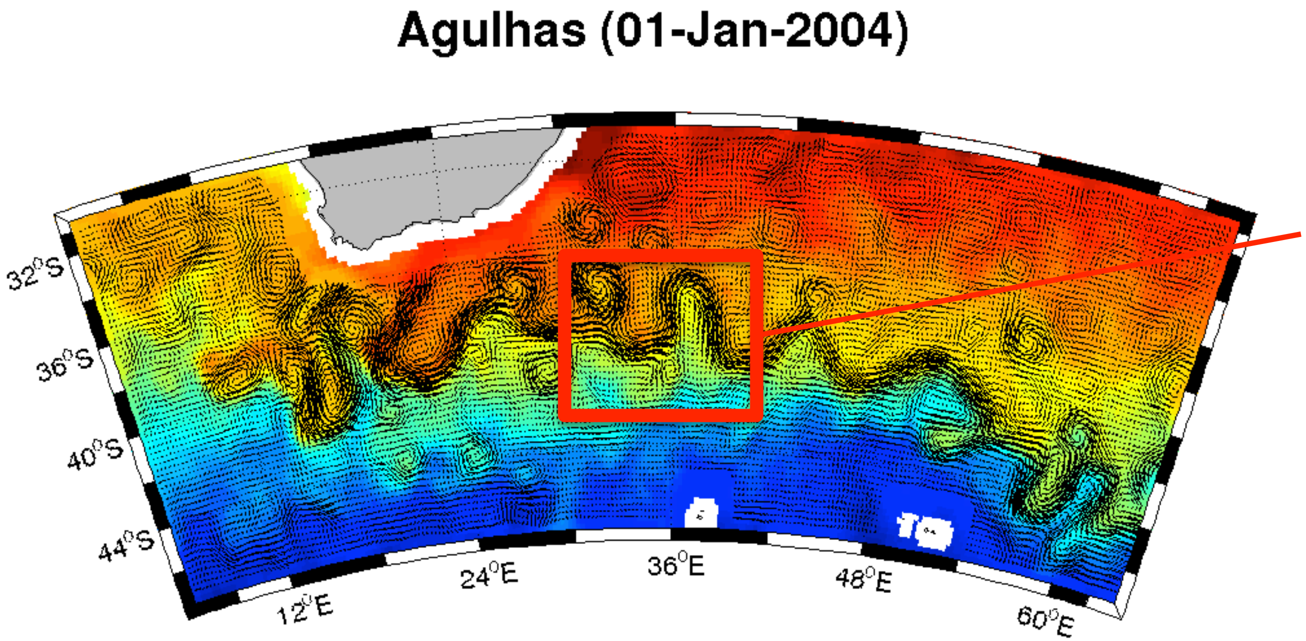
Future work

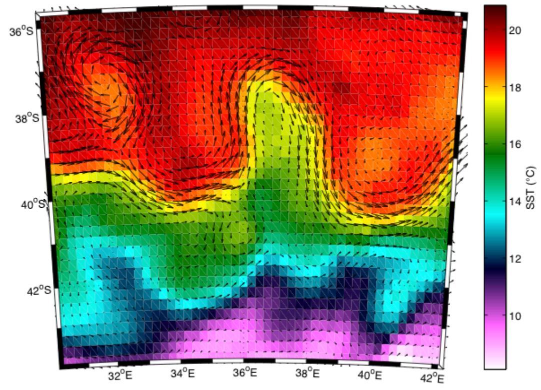
- **Model extension**
  - **Model calibration from observed geometrical features**
  - **Fractional Brownian « noise »**

$$d\theta(p) = -\gamma(p)\left(\theta(p) - \theta_{LR}(p)\right)dp + \sigma(p)\,dW(p)$$

  - **Investigate alternate formulation using Gaussian random fields and associated PDEs (e.g., advection-diffusion dynamics)**
  - **Multi-scale/spatio-temporal extension**
  - **Application to missing data interpolation**

Future work: application to the emulation of high-resolution upper ocean dynamics





Goal: Emulate daily high-resolution sea surface currents from daily HR SST images and « weekly » LR SSH images

Acknowledgements

- Joint work with B. Boussidi, H. G. Nguyen, J.M. Boucher (Telecom Bretagne), C. Scalabrin, B. Chapron, E. Autret (Ifremer)

Ifremer

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Thanks you for your attention.

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