



Inverse problems in  
earth observation  
and cartography



# Shape modelling via higher-order active contours and phase fields

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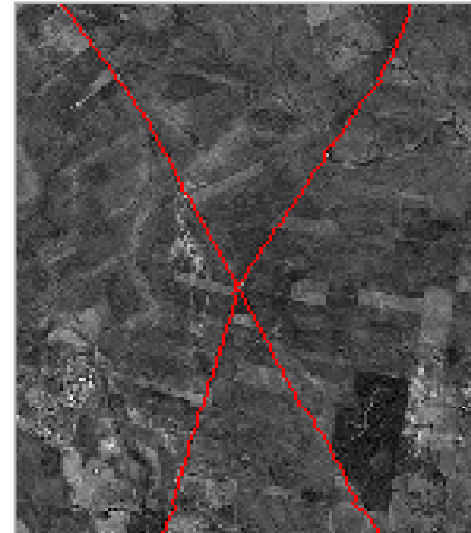


# Overview

- ◆ Problem: **entity extraction** from (remote sensing) images.
  - Need for **prior 'shape' knowledge**.
- ◆ Modelling **prior shape knowledge**: **higher-order active contours** (HOACs).
  - Two examples: networks (roads) and circles (tree crowns).
  - **Difficulties**.
- ◆ **Phase fields**:
  - What are they and why use them?
  - **Phase field HOACs**.
  - Two examples: networks (roads) and circles (tree crowns).
- ◆ Future.

# Problem: entity extraction

- ◆ Ubiquitous in image processing and computer vision:
  - Find in the image the **region** occupied by **particular entities**.
    - ◆ E.g. for remote sensing: road network, tree crowns,...



# Problem formulation

- ◆ Calculate a **MAP estimate** of the region:

$$\hat{R} = \underset{R}{\operatorname{arg\,max}} P(R|I; K)$$
$$P(R|I; K) / P(I|R; K)P(R|K)$$

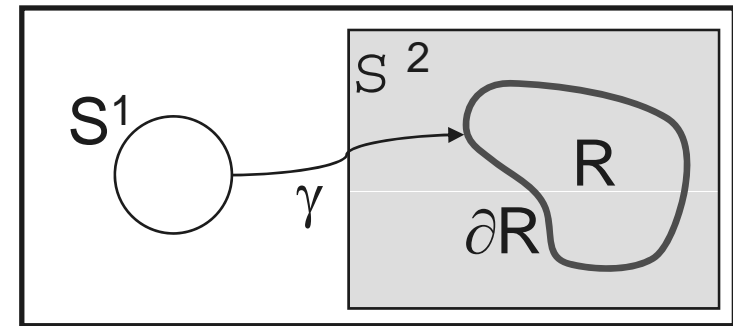
- ◆ In practice, **minimize an energy**:

$$E(R; I) = \sum_i \ln P(I_i|R; K) - \sum_i \ln P(R_i|K)$$
$$= E_I(I; R) + E_G(R) + \text{const}$$

$$\hat{R} = \underset{R}{\operatorname{arg\,min}} E(R; I)$$

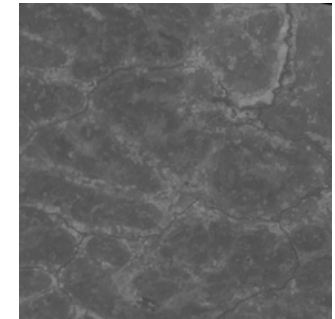
# Building $E_G$ : active contours

- ◆ A region is represented by its **boundary**,  $\partial R = [\gamma]$ , the '**contour**'.
- ◆ Standard prior energies:
  - **Length** of  $\partial R$  and **area** of  $R$ .
  - **Single** integrals over the region boundary:
    - ◆ **Short range dependencies**.
    - ◆ **Boundary smoothness**.
  - **Insufficient prior knowledge**.



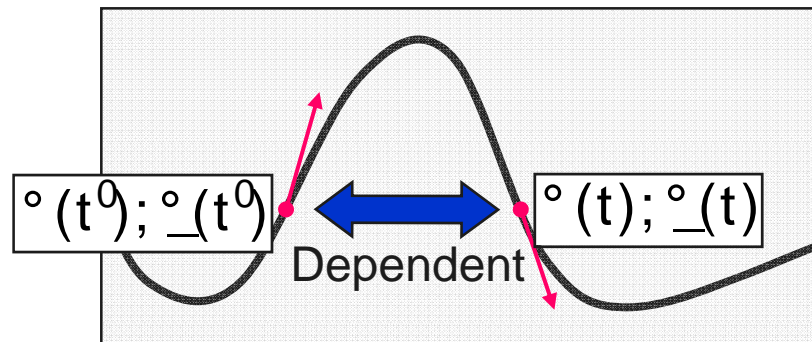
# Difficulties

- ◆ (Remote sensing) images are **complex**.
- ◆ Regions of interest distinguished by their **shape**.
  - But **topology** can be **non-trivial**, and **unknown a priori**.
- ◆ **Strong prior information** about the region needed, **without constraining the topology**.



# Building a better $E_G$ : higher-order active contours

- ◆ Introduce **prior knowledge** via **long-range dependencies** between tuples of points.

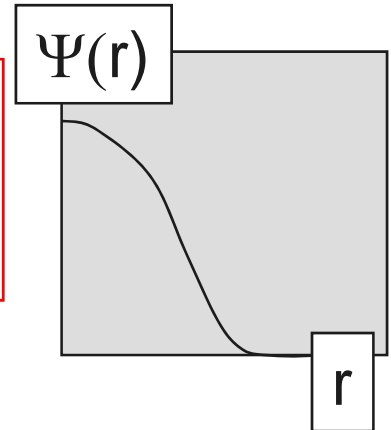


- ◆ How? **Multiple integrals** over the contour.
  - E.g. **Euclidean invariant** two-point term:

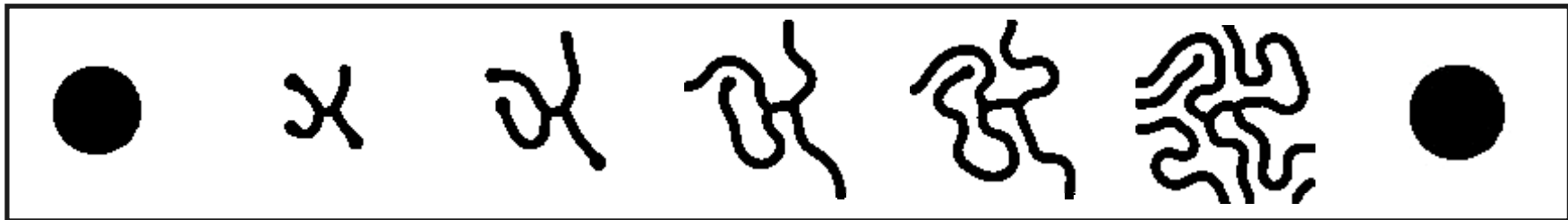
$$E(\phi) = \int \int dt dt^0 \phi(x(t), y(t), x(t^0), y(t^0)) \sum_i (j^i(t) - j^i(t^0))^2$$

# Prior for networks

$$E_G(R) = \sum_i \int_{\mathbb{R}^2} \left( \frac{1}{2} \left( \frac{d\phi_i}{dt} \right)^2 + \phi_i^2 \right) dt + \sum_j \int_{\mathbb{R}^2} \left( \frac{1}{2} \left( \frac{d\psi_j}{dt} \right)^2 + \psi_j^2 \right) dt$$



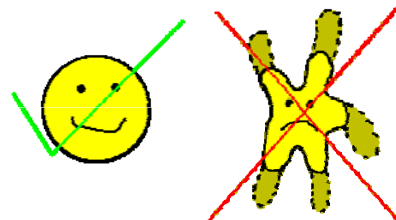
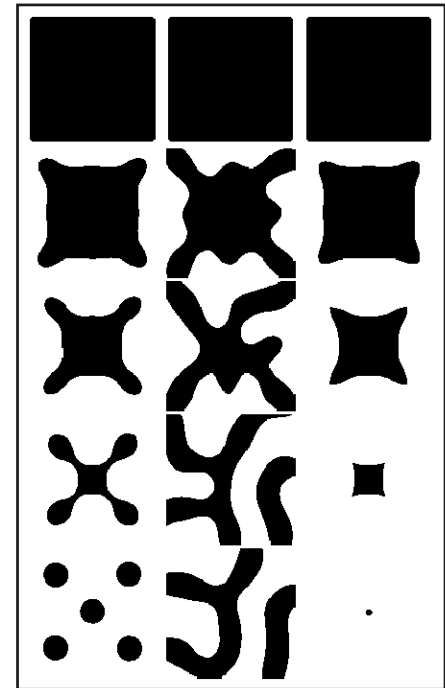
- ◆ Gradient descent with this energy.
  - A perturbed circle evolves towards a structure composed of arms joining at junctions.



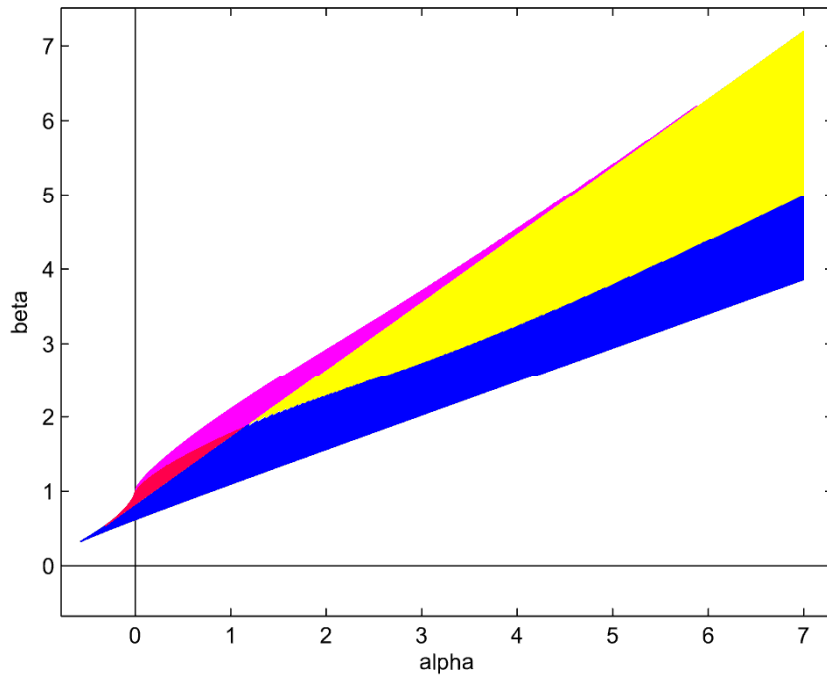


# Prior for a gas of circles

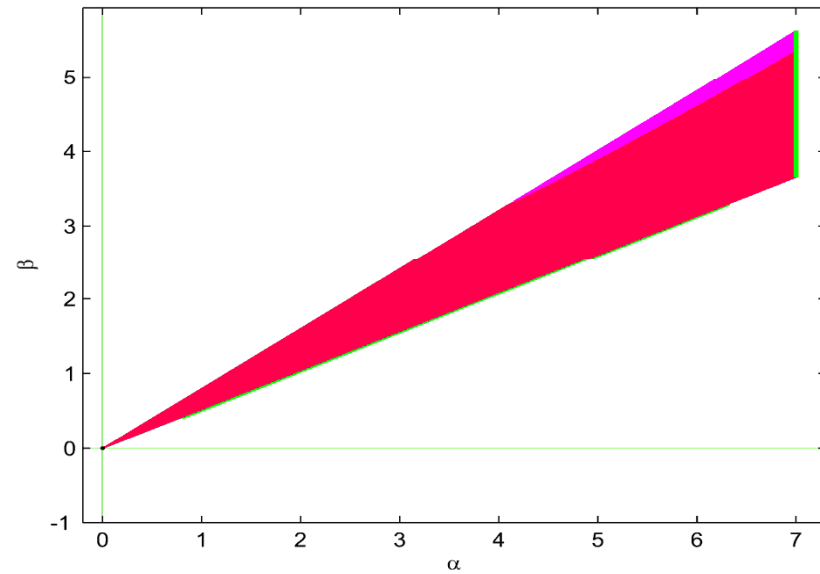
- ◆ The **same** energy  $E_G$  can model a 'gas of circles' for certain **parameter ranges**.
  - Which ranges?
- ◆ A **circle** should be a **stable configuration** of the energy (local minimum).
  - **Stability analysis.**



# Phase diagrams



Circle

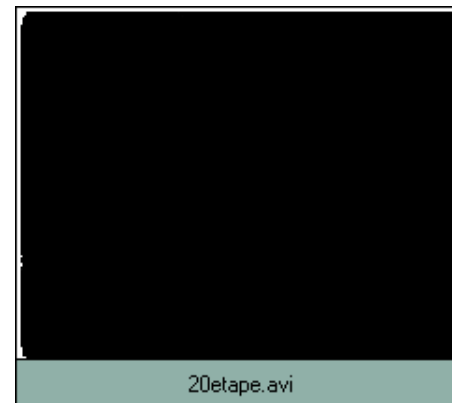
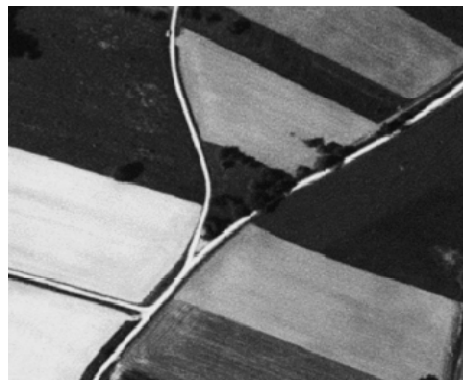


Bar

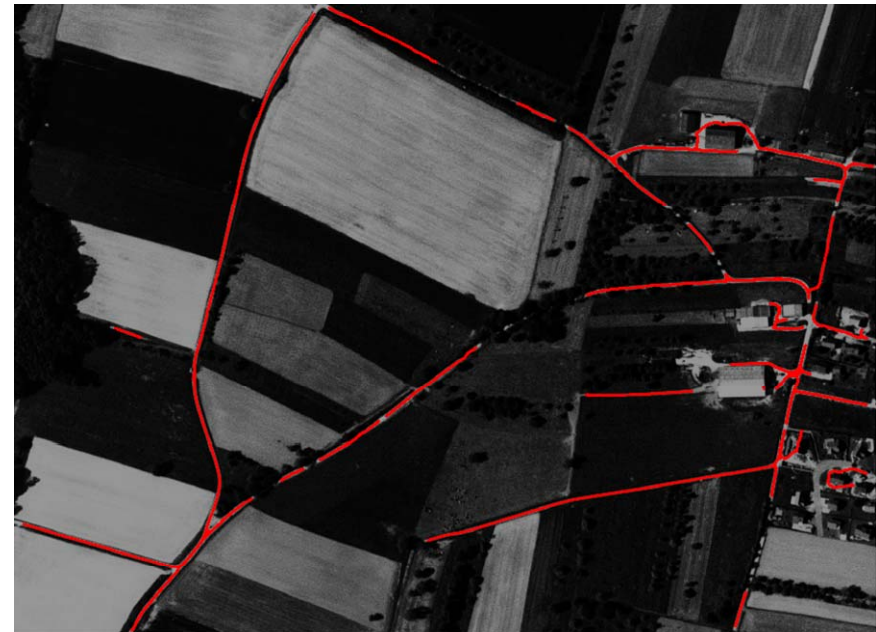
# Optimization problem

- ◆ **Minimize**  $E(R, I) = E_I(I, R) + E_G(R)$ .
- ◆ **Algorithm**: gradient descent using **distance function level sets**.
- ◆ **But** the gradient of the HOAC term is **non-local**, and requires:
  - **The extraction** of the contour;
  - Many **integrations** around the contour;
  - Velocity **extension**.

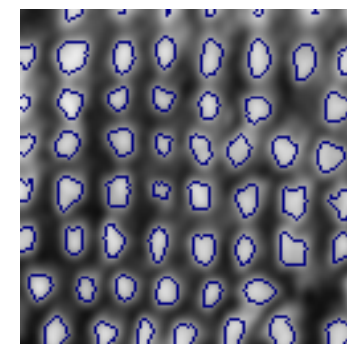
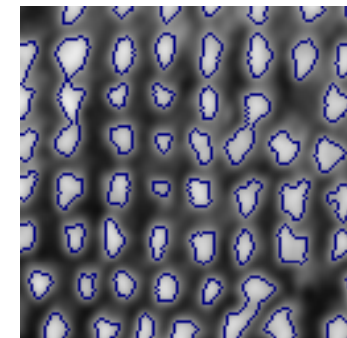
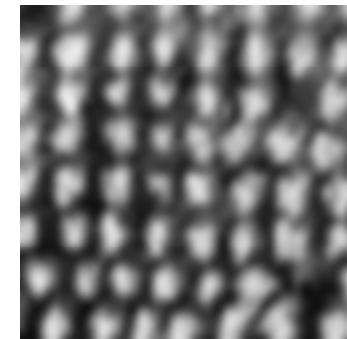
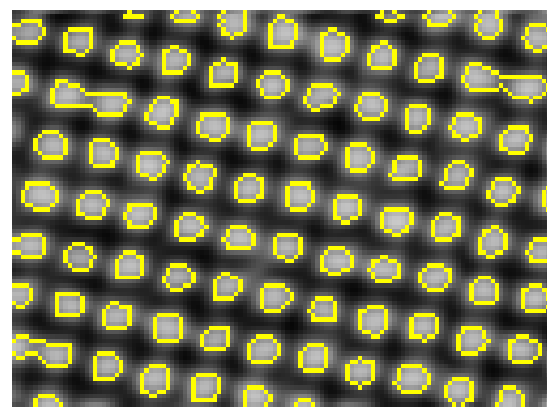
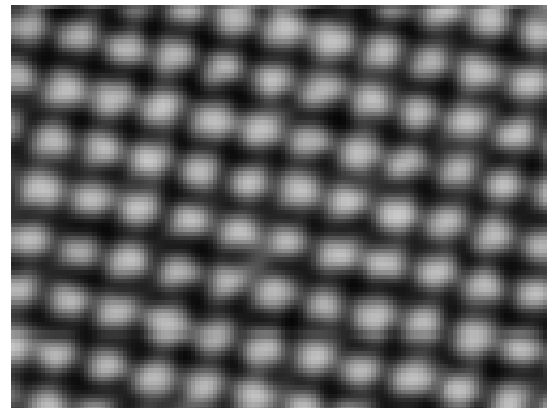
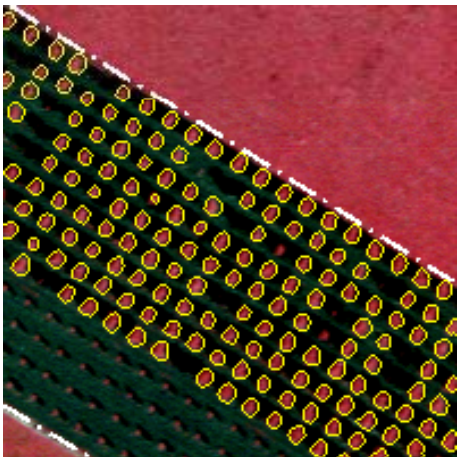
# Example I: HOAC results



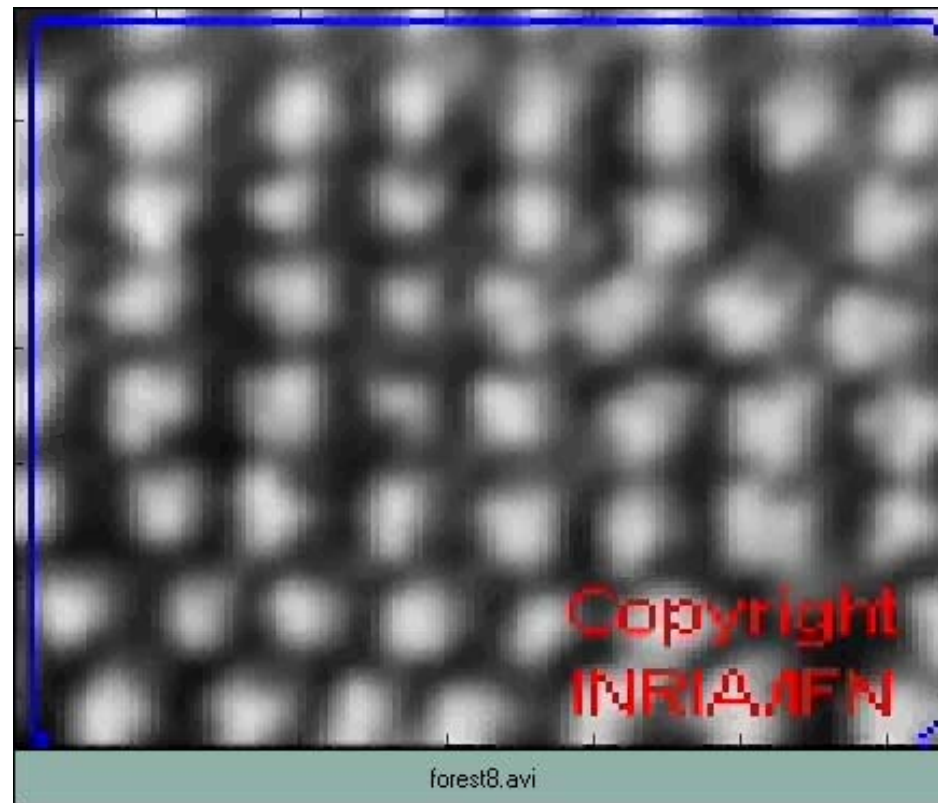
# Example I: HOAC results



# Example II: HOAC results



# Example II: HOAC results



# Problems with HOACs

- ◆ Modelling:
  - Space of regions is **complicated** to express in the **contour representation**.
  - **Probabilistic** formulation is **difficult**.
    - ◆ Parameter and model **learning** are **hampered**.
- ◆ Algorithm:
  - **Not enough** topological freedom.
  - Gradient descent is **complex** to implement for **higher-order terms**.
  - **Slow**.
- ◆ **Solution**: ‘**phase fields**’.

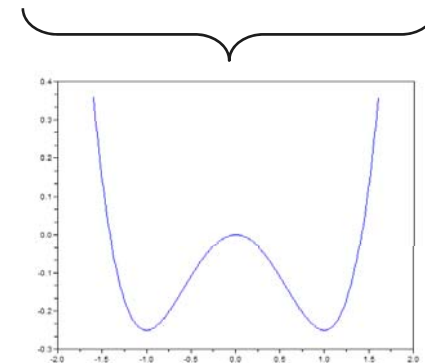
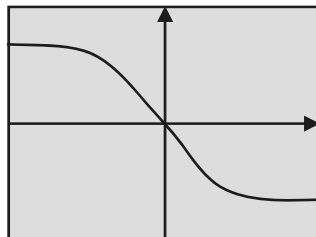
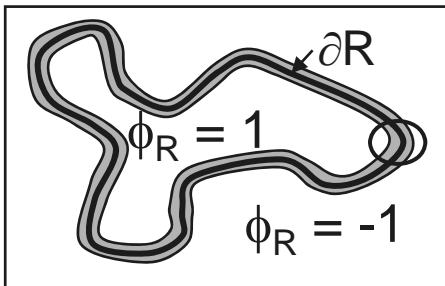


# Phase fields

- ◆ Phase fields are a **level set representation** ( $\zeta_z(\phi) = \{x : \phi(x) > z\}$ ), but the functions,  $\phi$ , are **unconstrained**.
- ◆ How do we know we are modelling **regions**?

$$E_0(\dot{A}) = \int_{\dot{A}} d^2x \left[ \frac{D}{2} |\nabla \phi|^2 + \left( \frac{1}{4} \dot{A}^4 + \frac{1}{2} \dot{A}^2 \right)^{3/4} \right]$$

$$R = \arg \min_{\dot{A}: \mathcal{A}(\dot{A})=R} E_0(\dot{A})$$



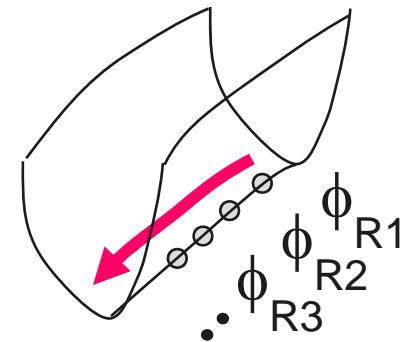
# Relation to active contours

- ◆ One can show that

$$E_0(\Gamma_R) = \int_C L(\phi, R)$$

- ◆  $\phi_R$  is a **minimum** for **fixed**  $R$ .
  - Thus gradient descent with  $E_0$  **mimics** gradient descent with  $L$ : ‘**valley following**’.
- ◆ Can also add **odd** potential term to mimic:

$$E_0(\Gamma_R) = \int_C L(\phi, R) + \int_C A(R)$$

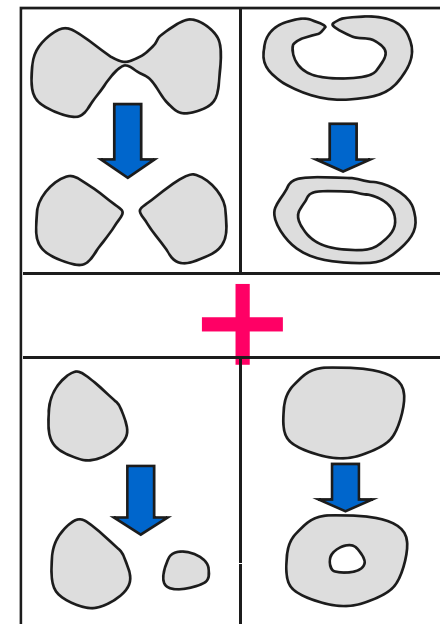
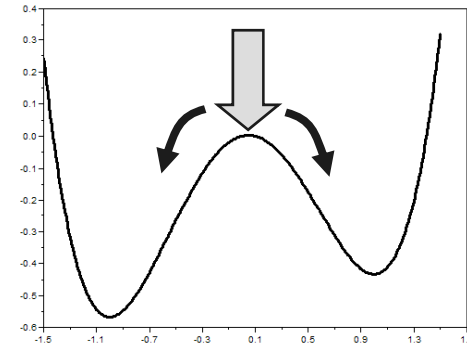


# Why use them?

- ◆ Complex topologies are easily represented.
- ◆ Representation space is linear:
  - $\phi$  can be expressed, e.g., in wavelet basis for multiscale analysis of shape.
  - Probabilistic formulation (relatively) simple.
- ◆ Gradient descent is based solely on the PDE arising from the energy functional:
  - No reinitialization or ad hoc regularization.
  - Implementation is simple and the algorithm is fast.

# Why use them?

- ◆ Neutral initialization:
  - No initial region.
  - No bias towards “interior” or “exterior”.
- ◆ Greater topological freedom:
  - Can change number of connected components and number of handles without splitting or wrapping.



# How to write HOACs as phase fields?

- ◆ Use that  $\delta \phi_R$  is **zero** except near  $\partial R$ , where it is **proportional to the normal vector**.

$$E_Q(R) = i \frac{c}{2} \int dt dt^0 \phi(t) \phi G_c(\phi(t); \phi(t^0)) \phi^*(t^0)$$

$$E_{NL}(\dot{A}) = i \frac{c}{2} \int d^2x d^2x^0 \dot{A}(x) \phi G(x; x^0) \phi^* \dot{A}(x^0)$$

- ◆ One can show that

$$E_{NL}(\dot{A}_R; \dot{\phi}; G) \approx E_Q(R; \phi; G)$$



# Phase fields : likelihood energies $E_l$

- ◆  $\nabla \phi$  : **normal vector** to the contour.
- ◆  $\delta \phi / |\nabla \phi|$  : **boundary indicator**.
- ◆  $(1 \pm \phi)/2$  : **characteristic function** of the region (+) or its complement (-).
- ◆ Using these elements, one can construct the **equivalents** of active contour and HOAC likelihoods.

# Optimization problem

- ◆ Minimize

$$\begin{aligned} E(R; I) &= E_I(I; R) + E_G(R) \\ &= E_I(I; R) + E_0(R) + E_{NL}(R) \end{aligned}$$

- ◆ Algorithm: gradient descent, but...

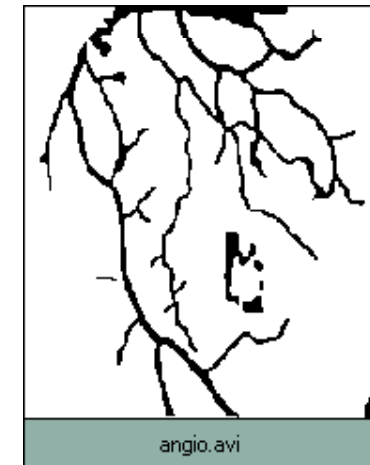
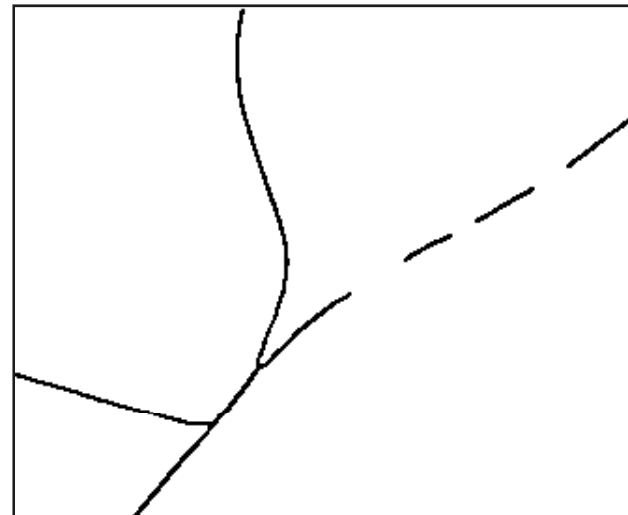
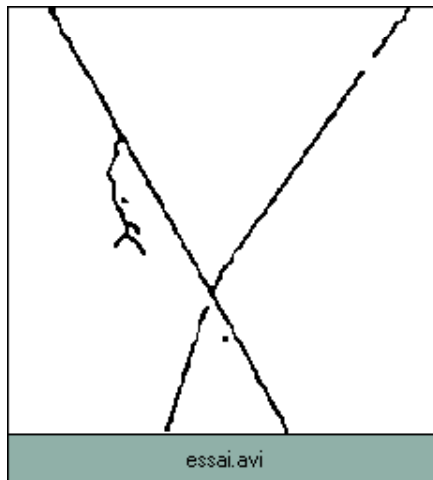
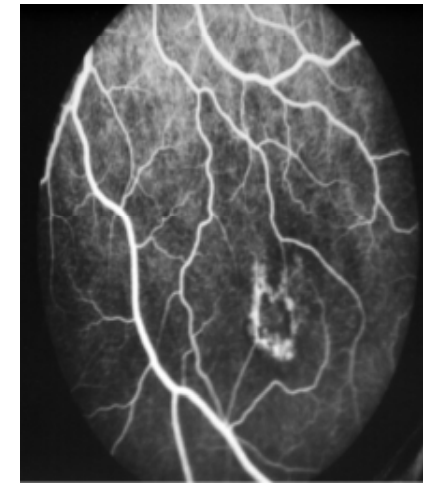
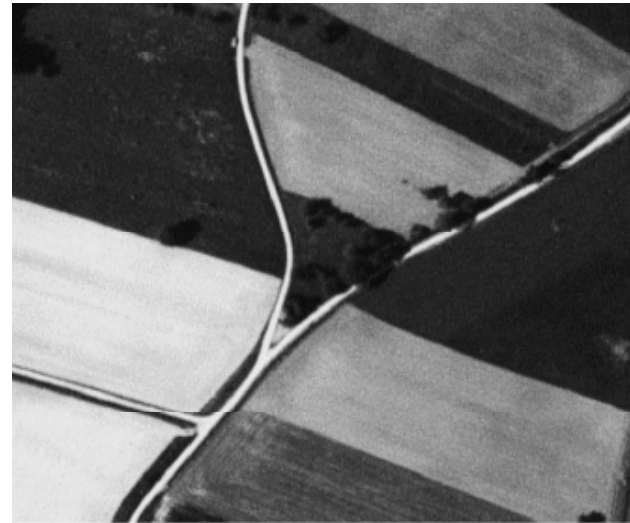
# Major advantage of phase fields for HOAC energies

- ◆ Whereas, due to the **multiple integrals**, HOAC terms require
  - Contour **extraction**, contour **integrations**, and force **extension**,
- ◆ **Phase field HOACs** require only a **convolution**:

$$\frac{\pm E_{NL}}{\pm \dot{A}(x)} = - \int_{-Z}^Z d^2x \, \delta r^2 G(x; x^0) \dot{A}(x^0)$$



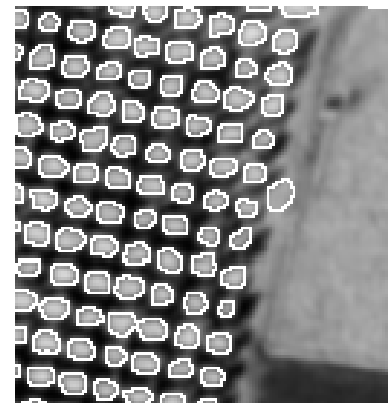
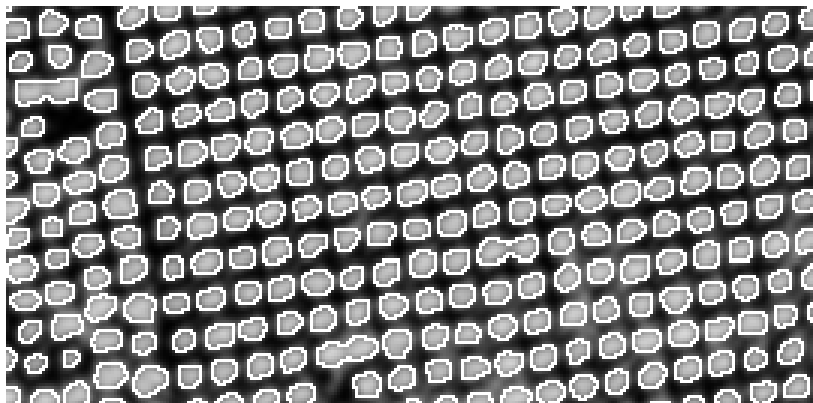
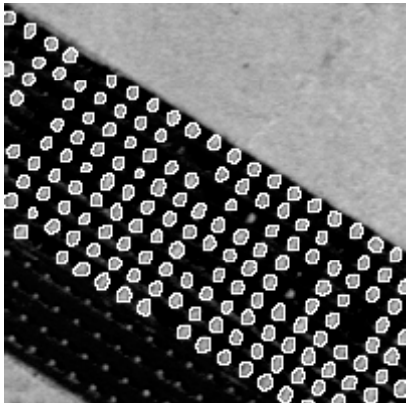
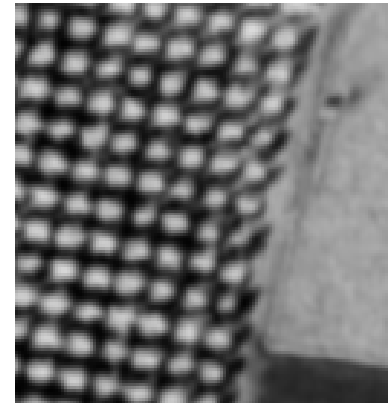
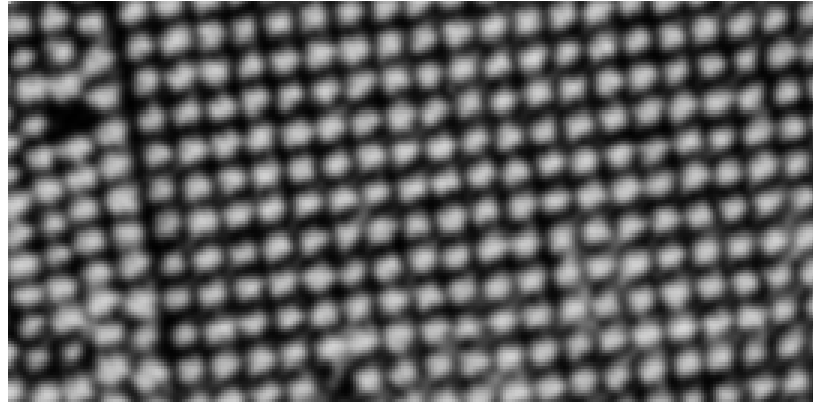
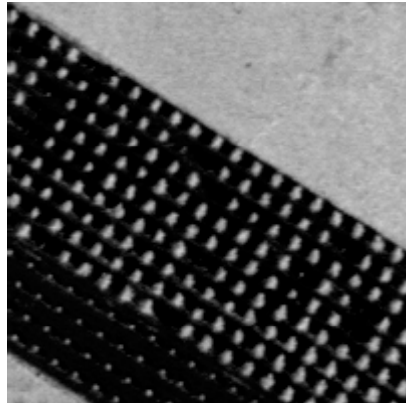
# Phase field HOACs: results



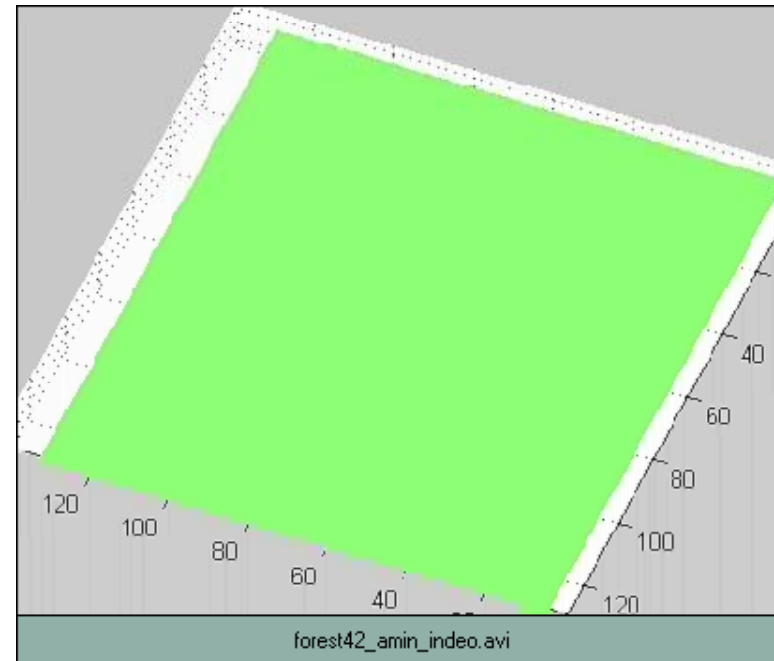
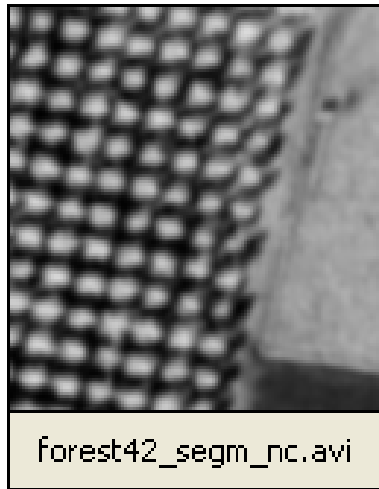
# Phase field HOACs: VHR image results



# Phase field HOACs: tree crown results



# Phase field HOACs: results



# Future

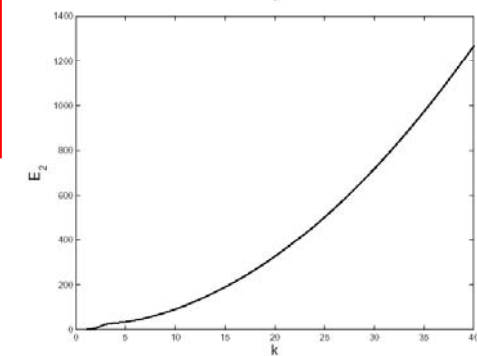
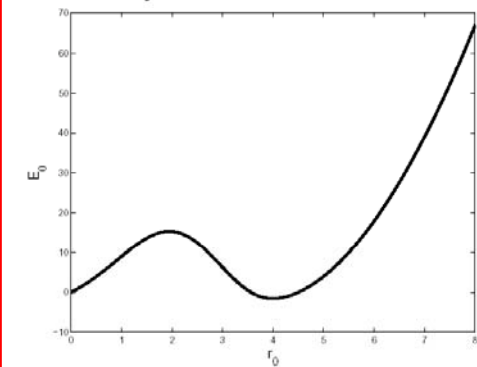
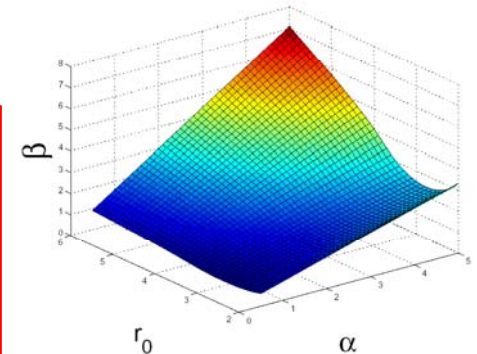
- ◆ **New** prior models
  - **Directed** and **rectilinear** networks (rivers, big cities...).
  - 'Gas of **rectangles**';
  - **Controlled** perturbed circle.
- ◆ **Multiscale** models;
- ◆ New **algorithms** (**multiscale**, stochastic,...);
- ◆ **Parameter** estimation;
- ◆ **Higher-dimensions**;
- ◆ ...

*Ariana*

Thank you

# Stability analysis

$$\begin{aligned}
 E_{C;g}(\omega_0 + \pm\omega) = & \left[ \frac{C}{2} r_0 + \mathbb{R} \frac{C}{2} r_0^2 \right] i \int_0^{Z/2} F_{00} dp \\
 & + a_0 \left[ \frac{C}{2} r_0 + \mathbb{R} \frac{C}{2} r_0^2 \right] i \int_0^{Z/4} F_{10} dp \\
 & + \sum_k j a_k k^2 \left[ \frac{C}{2} r_0 k^2 + \mathbb{R} \frac{C}{2} \right. \\
 & \quad \left. i \int_0^{Z/2} \tilde{A} \int_0^{Z/2} F_{20} dp + \int_0^{Z/2} F_{21} e^{i r_0 k p} dp \right. \\
 & \quad \left. + k \int_0^{Z/2} \tilde{A} \int_0^{Z/2} F_{23} e^{i r_0 k p} dp \right. \\
 & \quad \left. + k^2 \int_0^{Z/2} \tilde{A} \int_0^{Z/2} F_{24} e^{i r_0 k p} dp \right]
 \end{aligned}$$



# HOACs: $E_1$

- ◆ Linear term that favours large gradients normal to contour.

$$E_{1;1}(\theta) = \int_{S^1} dt \dot{\theta}(t) \otimes r \perp I(\theta(t))$$

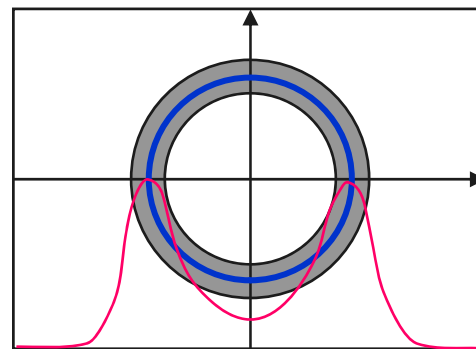
- ◆ Quadratic term that favours pairs of points with tangents and image gradients parallel or anti-parallel.

$$E_{1;2}(\theta) = \int_i \int_j dt dt^0 \underbrace{\dot{\theta}_i \otimes \dot{\theta}_j}_{\text{gradients}} \underbrace{(r \perp I \otimes r \perp I^0)}_{\text{tangent vectors}} \underbrace{a(j(\theta(t)) \otimes \theta(t^0)j)}_{\text{weighting function}}$$



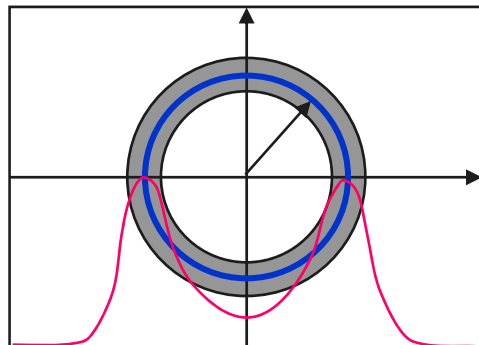
# Nonlinearity in the model, not the representation

- ◆ Space of regions  $S$  is not a linear space.
- ◆ Possibility 1: use representation space **isomorphic to  $S$**  and put energy/probability on this space.
- ◆ Possibility 2: use **larger linear space** with probability **peaked on nonlinear subset** isomorphic to  $S$ .



# Nonlinearity in the model, not the representation: example

- ◆ Probability distribution  $P$  on  $S^2$ .
  - $P$  pushes forward to  $Q$  on  $S^1$ .
  - If  $P$  is strongly peaked at  $r_0$  then  $Q(\theta) \propto P(r_0, \theta)$ .
  - Gradient descent with  $-\ln(P)$  on  $S^2$  mimics gradient descent with  $-\ln(Q)$  on  $S^1$  ('valley following').



$$P(r; \mu) = \int d^2x e^{i E(r; \mu)}$$

$$\propto \exp \left( i \left( \frac{r^4}{4} - \frac{r^2}{2} \right) \right)$$

# Turing stability

- ◆ To avoid decay of interior and exterior, we require **stability** of functions  $\phi_{\pm} = \dots$  1:
  - $\delta^2 E / \delta \phi^2$  must be positive definite ( $E = E_0 + E_{NL}$ ).
- ◆ For prior terms, this is **diagonal in the Fourier basis**:

$$\frac{\delta^2 E}{\delta \hat{\phi}(k^0) \delta \hat{\phi}(k)} (\hat{\phi}_{\pm}) = \pm(k; k^0) \left[ k^2 (D_i - \hat{G}(k)) + 2(\dots) \right] \textcircled{R}$$

- ◆ Gives **condition on parameters**.
- ◆ Better result would be **existence and uniqueness** of  $\phi_R$  for 'any' R.