Discrete deformable boundaries for the segmentation of multi-dimensional images

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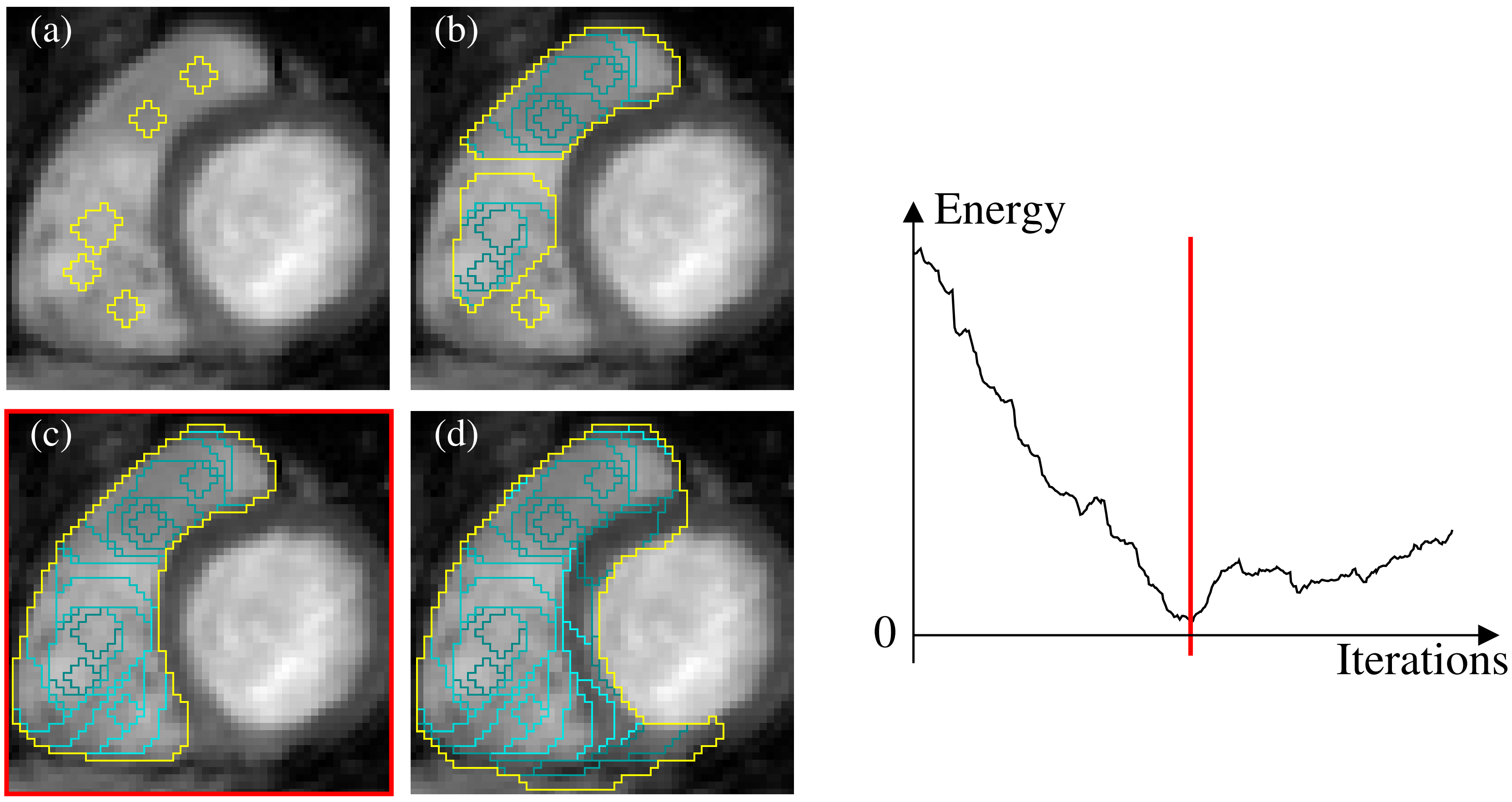
Introduction

Context

- Energy-minimizing techniques in image segmentation
- Classical framework: deformable models
  - ❶ Space of all possible shapes
  - ❷ An energy is associated to each shape
  - ❸ Segmentation = find shape of minimal energy
  - ⇒ Optimization problem
  - ⇒ Minimum extraction through progressive shape deformation

Our approach

- Shape geometry is a digital surface
  - ⇒ Multi-dimensional segmentation framework
  - ⇒ Highly deformable shape: complex topology modeling, natural topology changes
- Optimization by expansion strategy: *a posteriori* extraction of shape of minimal energy
  - ⇒ Avoid non significant local minima
  - ⇒ Provide knowledge of image/model adequation



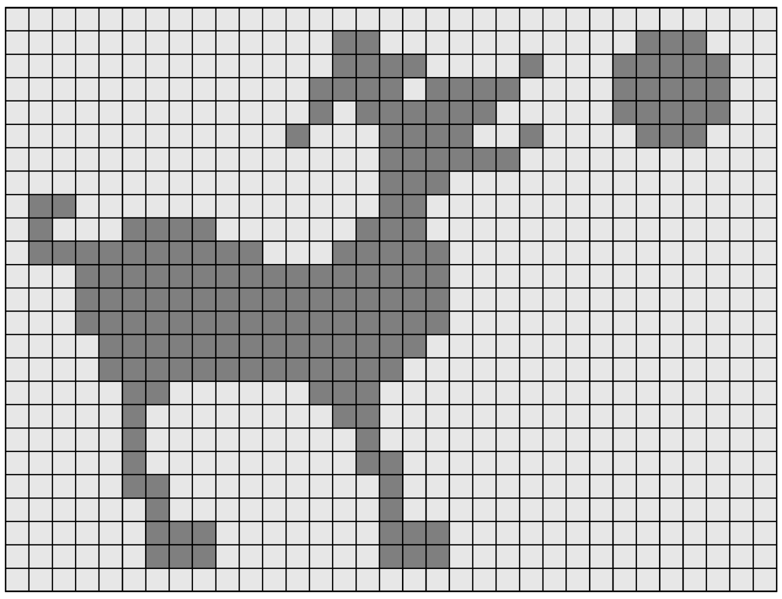
Discrete deformable model

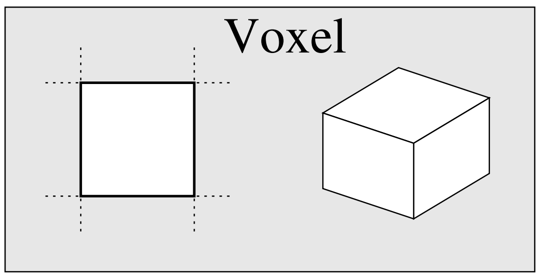
Model = ❶ discrete shape + energy

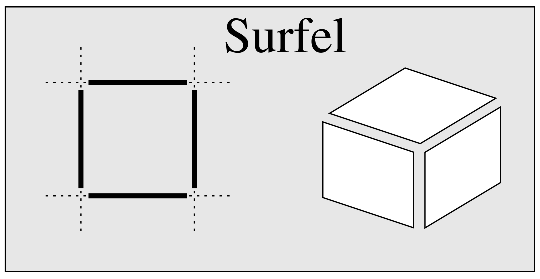
- The model has a discrete geometry:
  Possible shapes = subsets of the discrete image space

  ⇒ A shape is a set of voxels in the image

- Equivalent definition with a digital surface, i.e.
  a set of voxels O ⇔ its boundary ∂O (surfels between O and O^c)



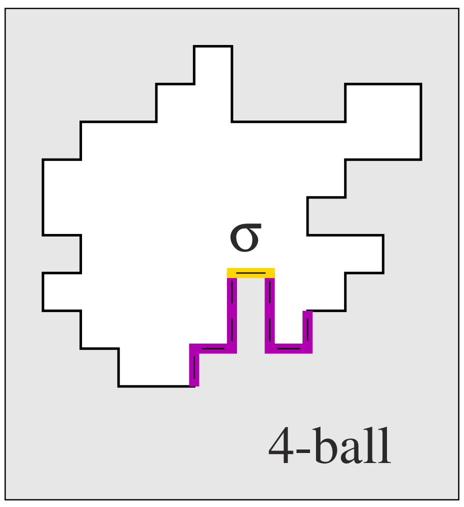


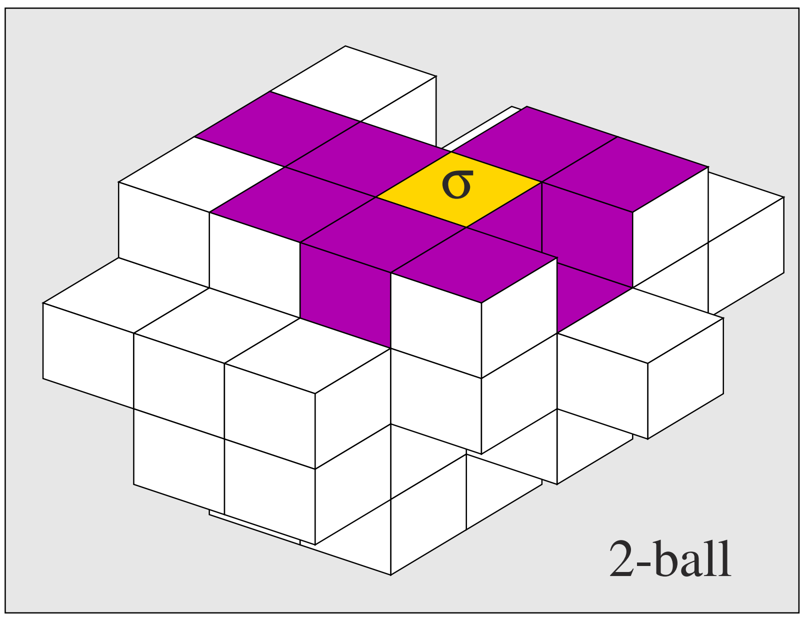


Discrete geometry terminology

- An adjacency between surfels on a boundary can always be defined

  ⇒ Definition of a k-ball around a surfel σ on ∂O



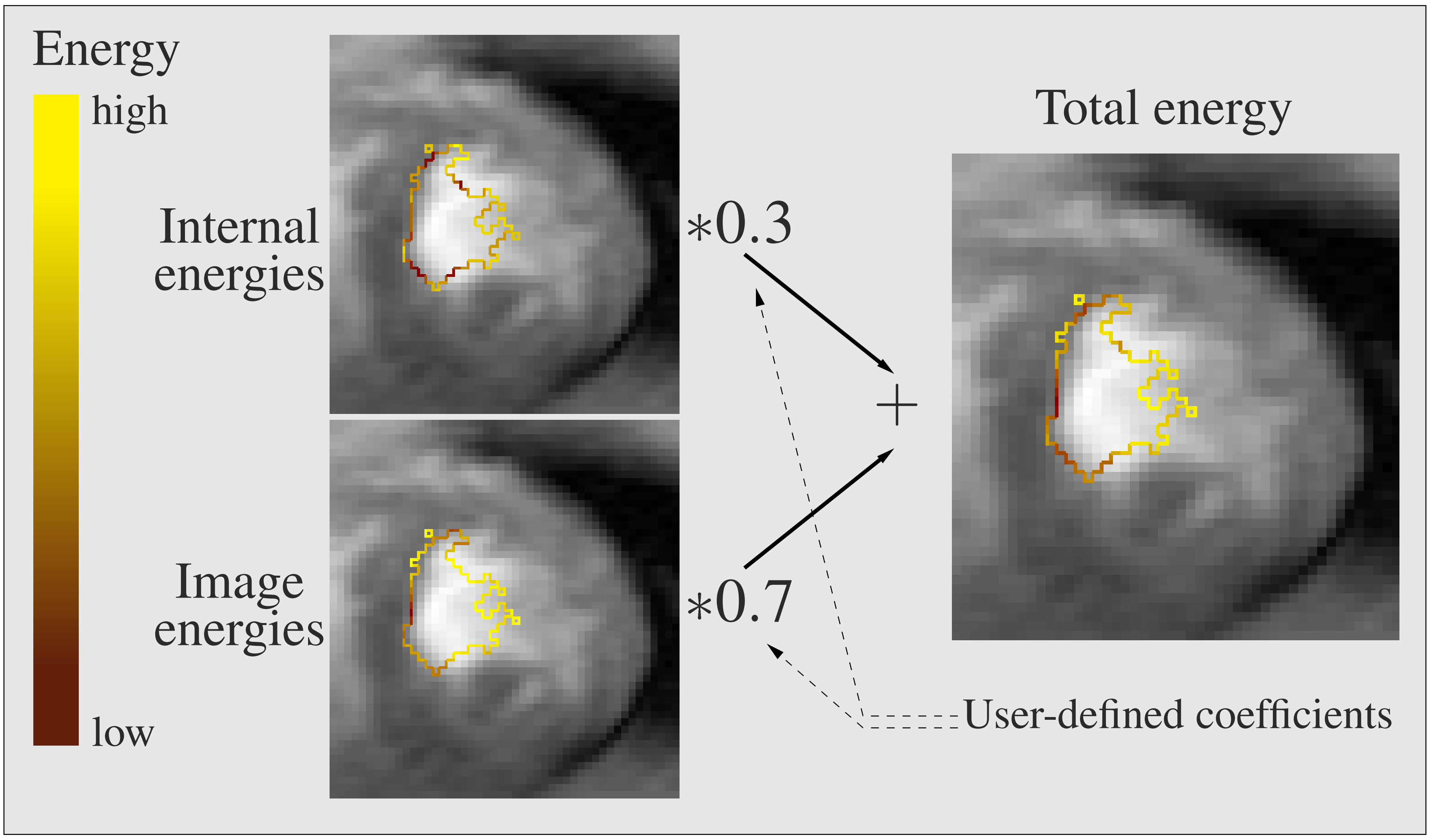


Discrete deformable model

Model = discrete shape + ❷ energy

- The energy is tailored for the segmentation problem:
  Low energy $\Leftrightarrow$ model close to image component
- Local formulation: $E(O) = E(\partial O) = \sum_{\sigma \in \partial O} E(\sigma)$
  $E(\sigma)$ depends on a neighborhood of σ over ∂O

  $\Rightarrow$ Efficient energy computation
- The energy measures the shape smoothness (internal energy) and the image/shape adequation (image energy)
  $E(\sigma) = \alpha_{\text{int}} E_{\text{int}}(\sigma) + \alpha_{\text{img}} E_{\text{img}}(\sigma)$
- Example of 2D energy definitions
  - Internal energy $E_{\text{int}}(\sigma) =$ stretching energy $+$ bending energy (Computed with discrete perimeter and curvature estimators)
  - Image energy $E_{\text{img}}(\sigma) = \|I(u) - I(v)\|$, where $\sigma = (u, v)$



Expansion Strategy For Segmentation

❸ Segmentation: progressive growth in the minimal energy direction

At each step, a voxel patch is added to the model. Among the possible resulting shapes, the one with the smallest energy is chosen.

Algorithm

(i) Initialization by user inside the component $\Rightarrow$ object O_0

(ii) $\forall \sigma \in \partial O_i$

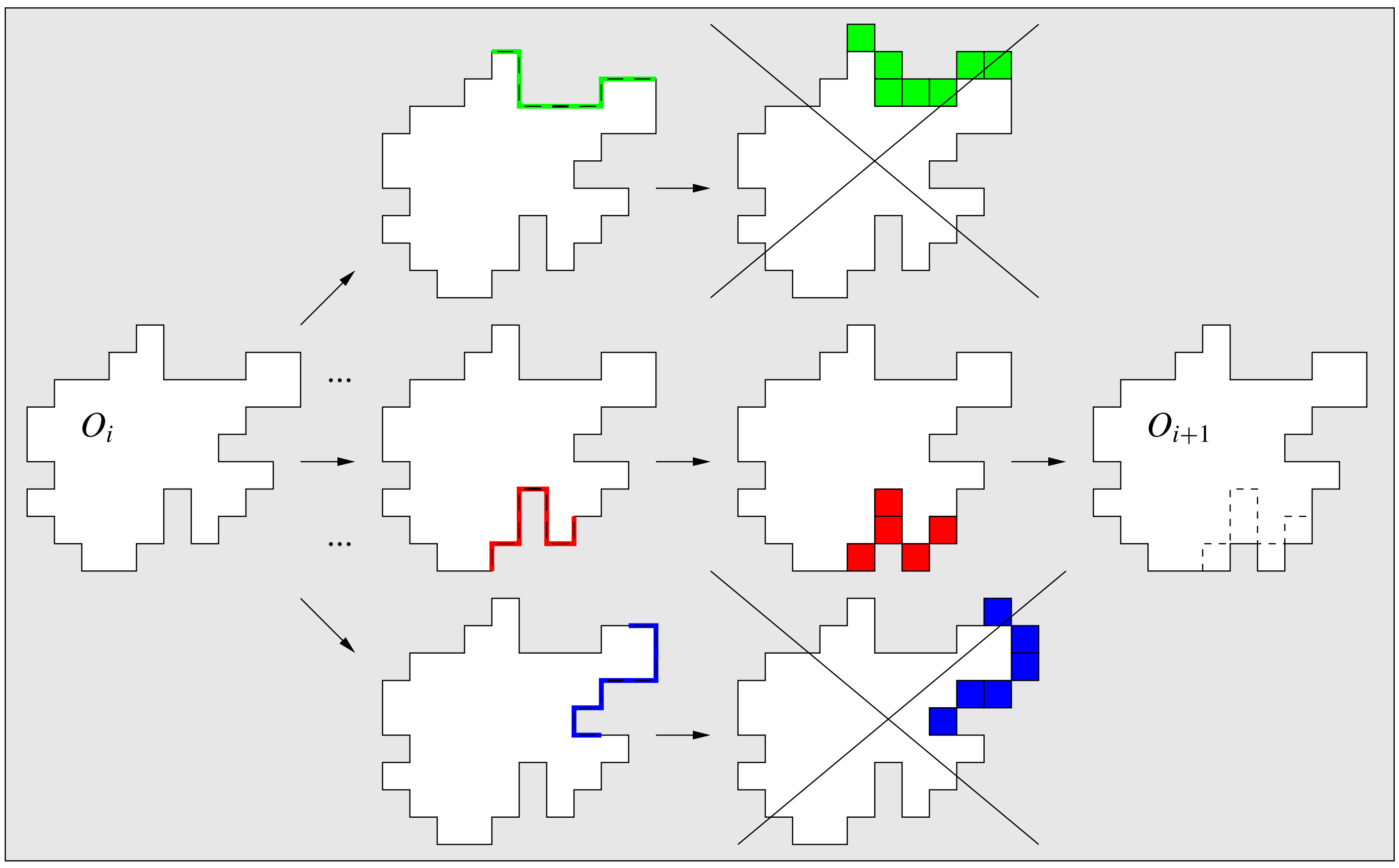
(a) Extract V_σ the k-ball around σ

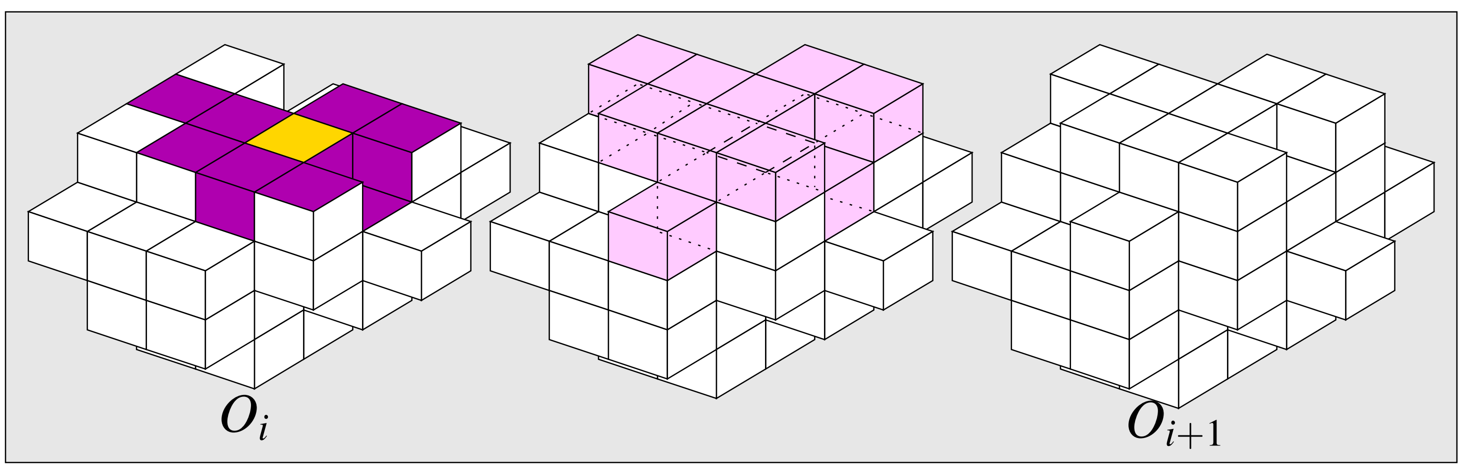
(b) $Voxelpatch(\sigma) =$ immediate exterior of V_σ

(c) Compute the energy of $O_i \cup Voxelpatch(\sigma)$

(iii) Select the surfel τ inducing the shape of minimal energy

(iv) $O_{i+1} = O_i \cup Voxelpatch(\tau)$. Go back to (ii)



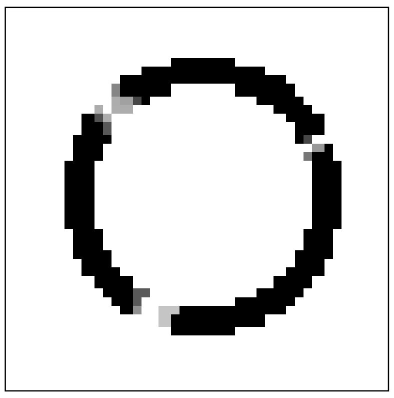


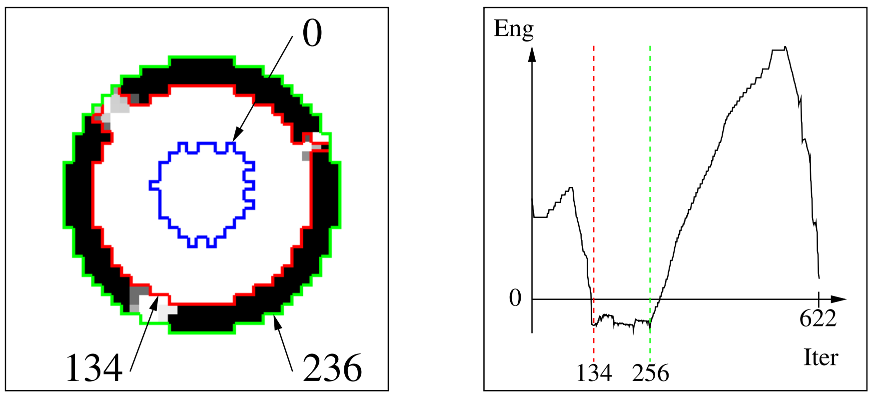
Validation on synthetic images

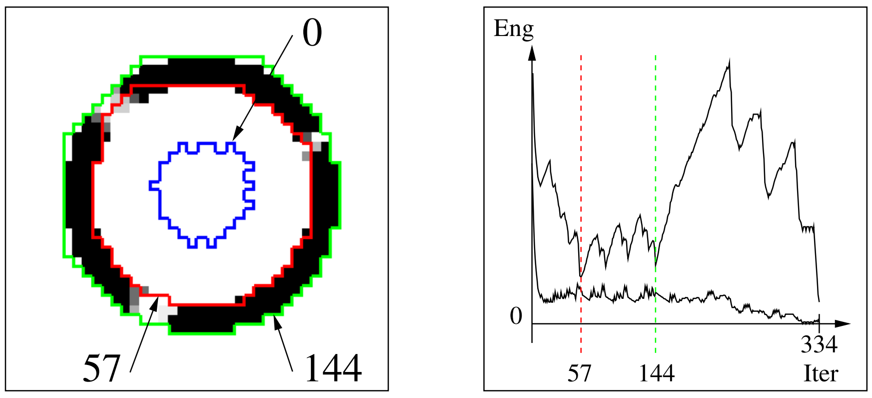
1. Recovering fragmented contours

   $\Rightarrow$ by increasing internal energy ($\alpha_{int} \nearrow$)

Evolution without internal energy ($\alpha_{int} = 0$, $\alpha_{img} = 1$)



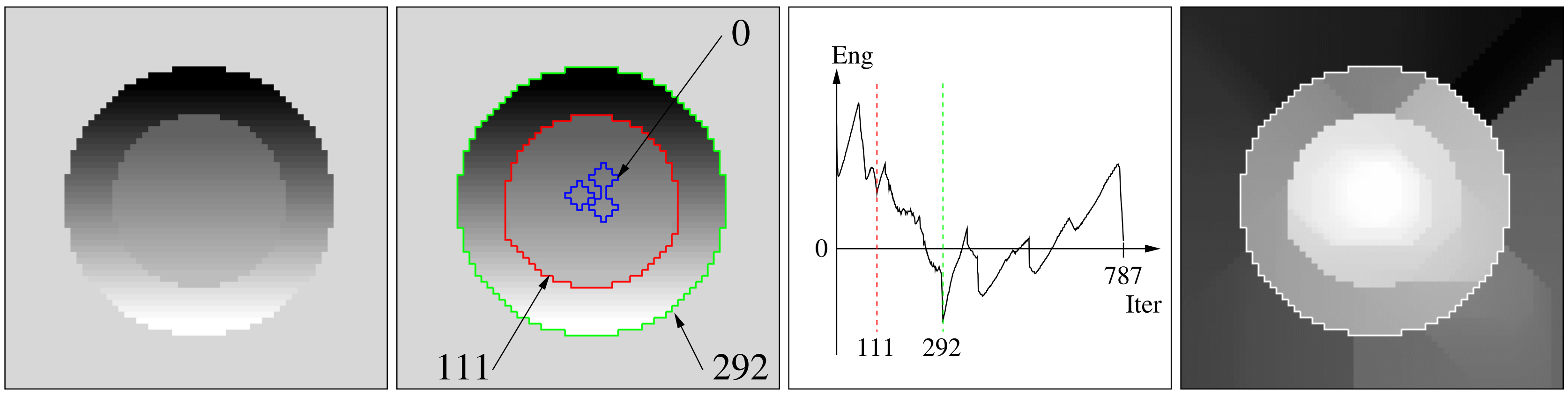




Evolution with internal energy ($\alpha_{int} = 1$, $\alpha_{img} = 1$)

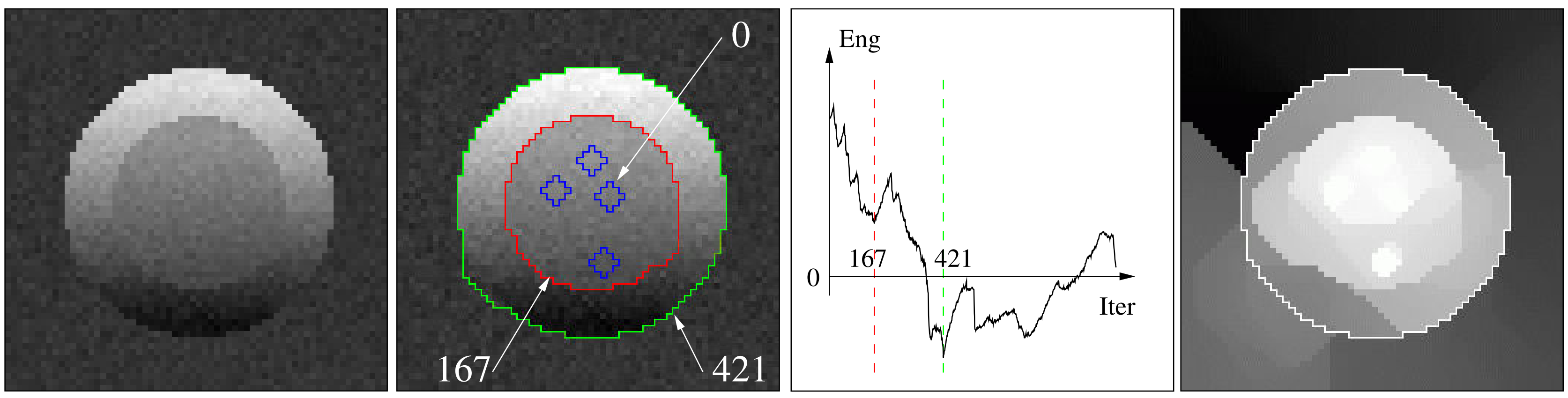
2. Segmentation of inhomogeneous components

   - $\alpha_{int} = 0.5$, $\alpha_{img} = 1.0$



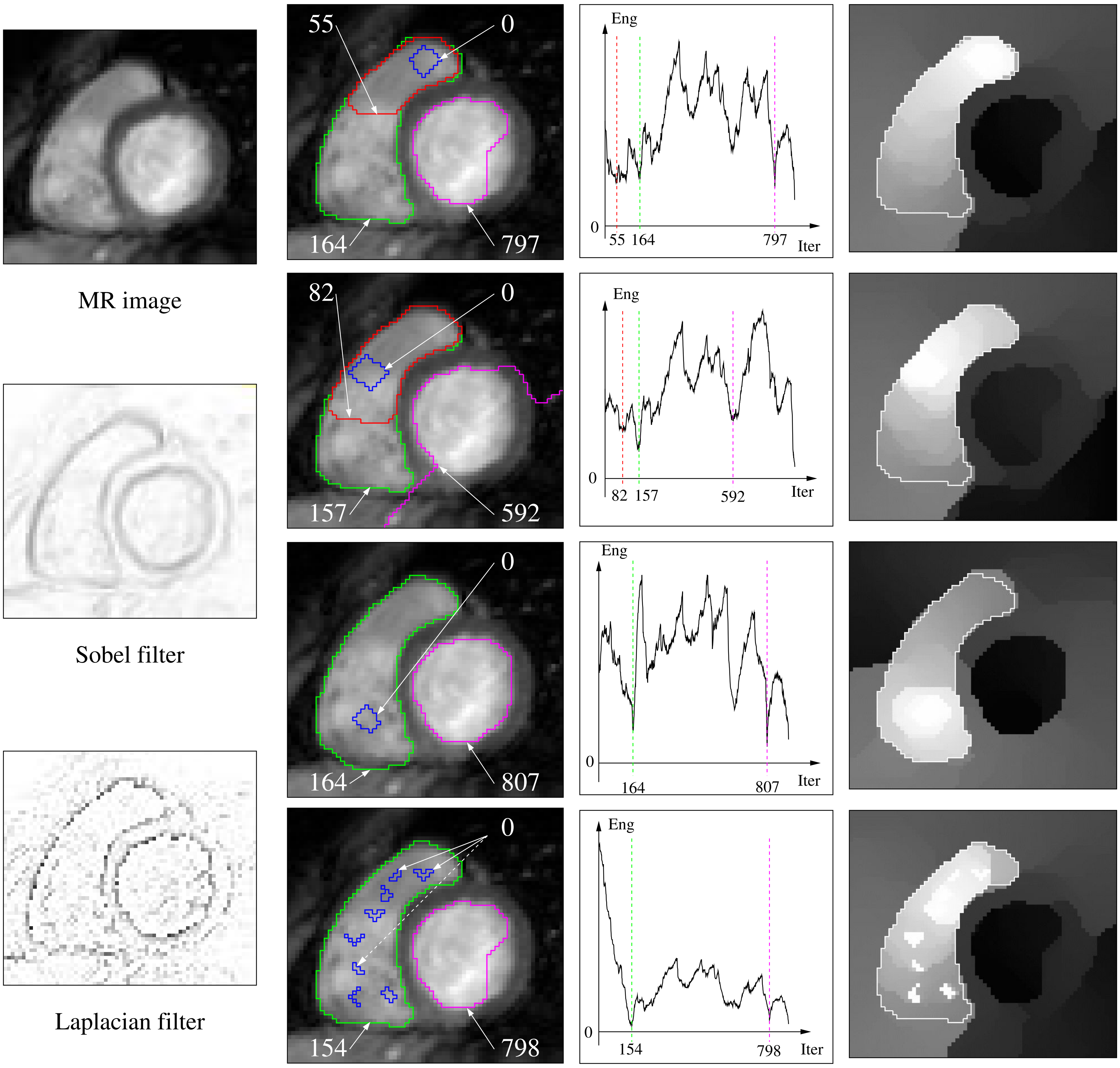
3. Robustness to Gaussian noise

   - $\alpha_{int} = 0.5$, $\alpha_{img} = 1.0$, Gaussian noise with variance 12.8



Results on medical data

- Test image: MR image of human heart at diastole
- Component to segment: right ventricle
  - ⇒ robustness to shape initialization
  - ⇒ extraction of weak contours (bottom of right ventricle)



Current works

- Development of a 3D prototype
- Multi-resolution approach
- Optimization of energy computations