Bioimage Informatics

Daniel Sage & Arne Seitz

Course

Advanced Segmentation Techniques

Engineering ▫ Model-based

Segmentation Science or Art ?

- ➡ Grouping pixels into regions (duality regions/edges)
- ➡ Segment image into objects
- ➡ Classify objects of the image

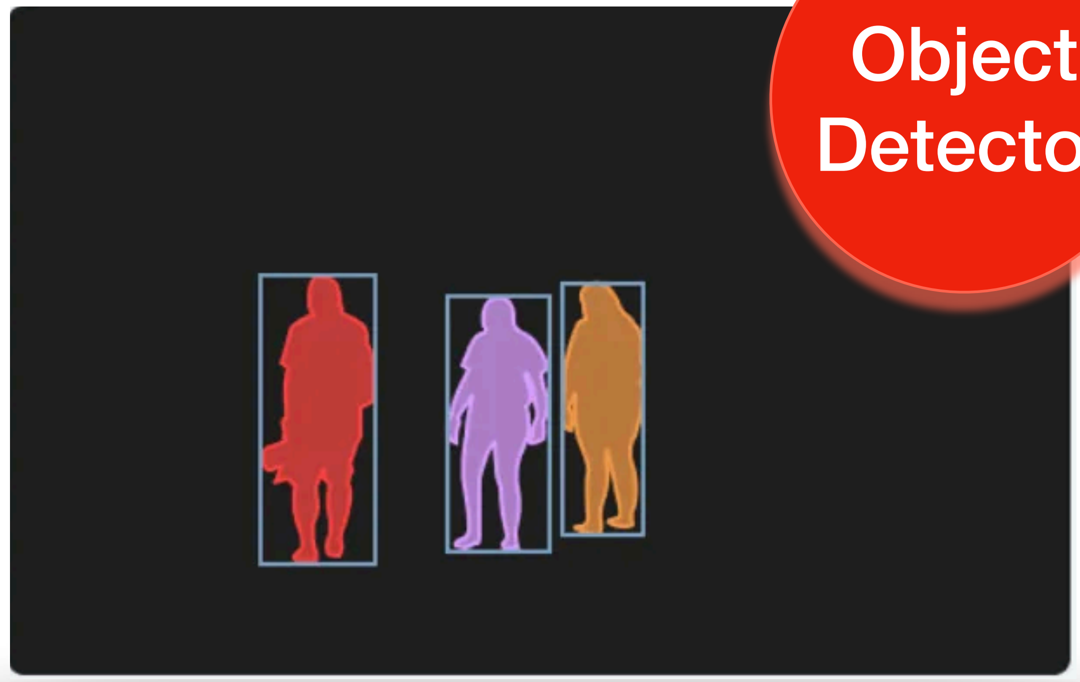
- ➡ Dimension
- ➡ Large number of objects, dense
- ➡ Highly variability: shape, color, ...
- ➡ Rare phenotype of interest

Segmentation in Computer Vision

Image

Pixel Classifier

Semantic Segmentation



Object Detector

Instance Segmentation

Panoptic Segmentation

Image classification

Deep learning - Classifier

CAT

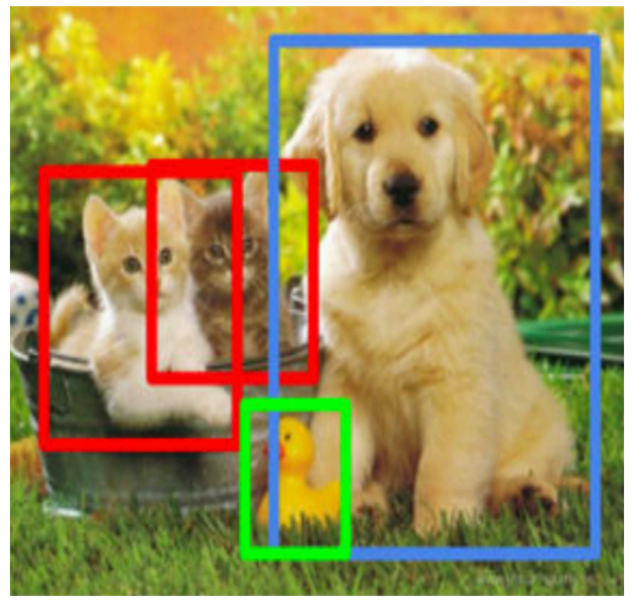
⊕

Localization

CAT

Object detection

Bounding box



CAT CAT DUCK DOG

1980 **Rule-based**

2000 Model-based

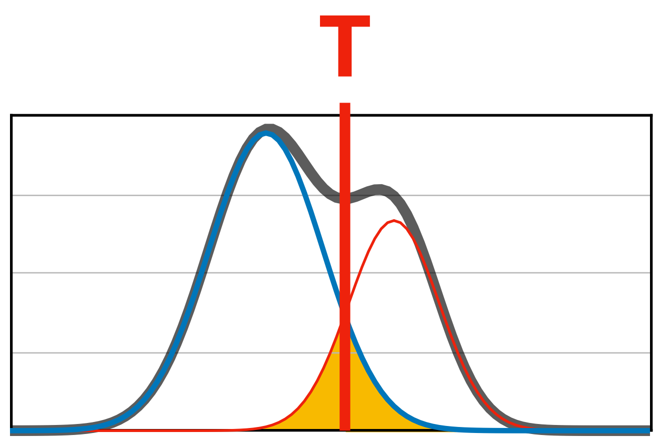
2000 Machine Learning

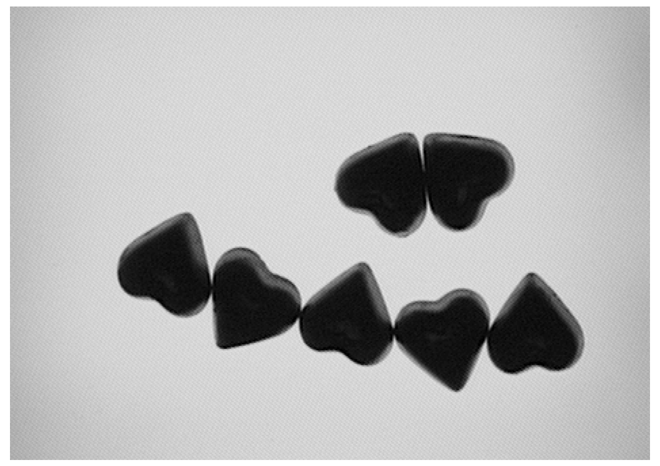
2020 Deep-Learning

Intensity-based

Bimodal histogram

Calibrated intensitiy



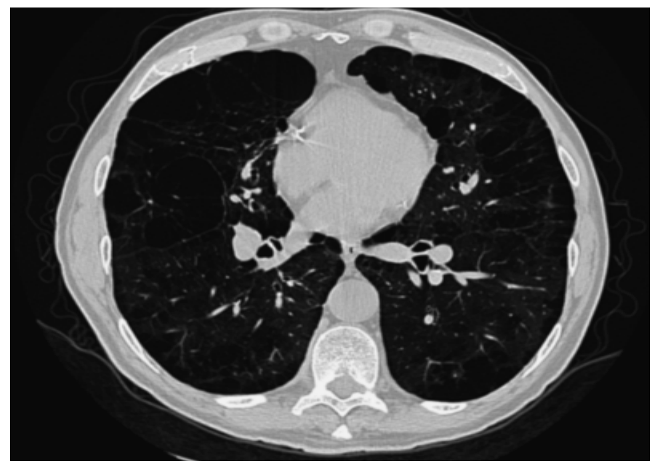


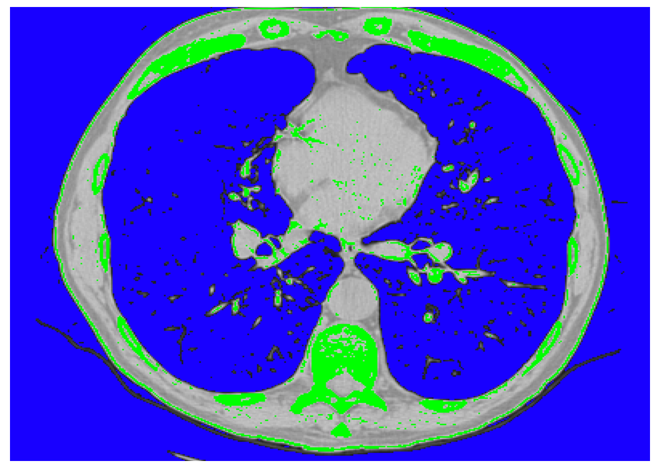
Threshold

Manual

Local adaptive

Otsu / k-means



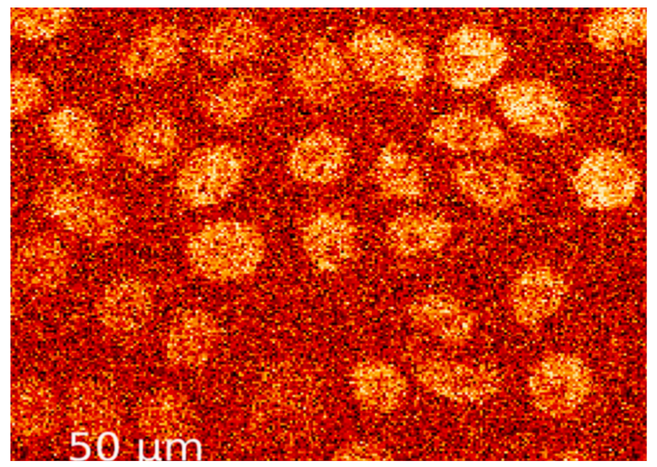


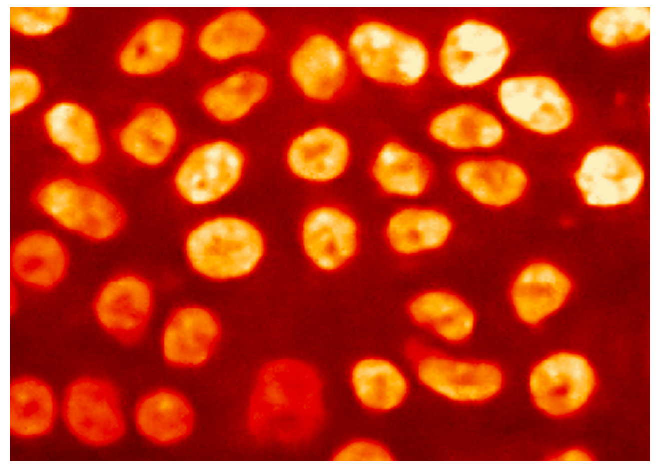
Preprocessing

Frequency filtering

Denoising

Flatten background



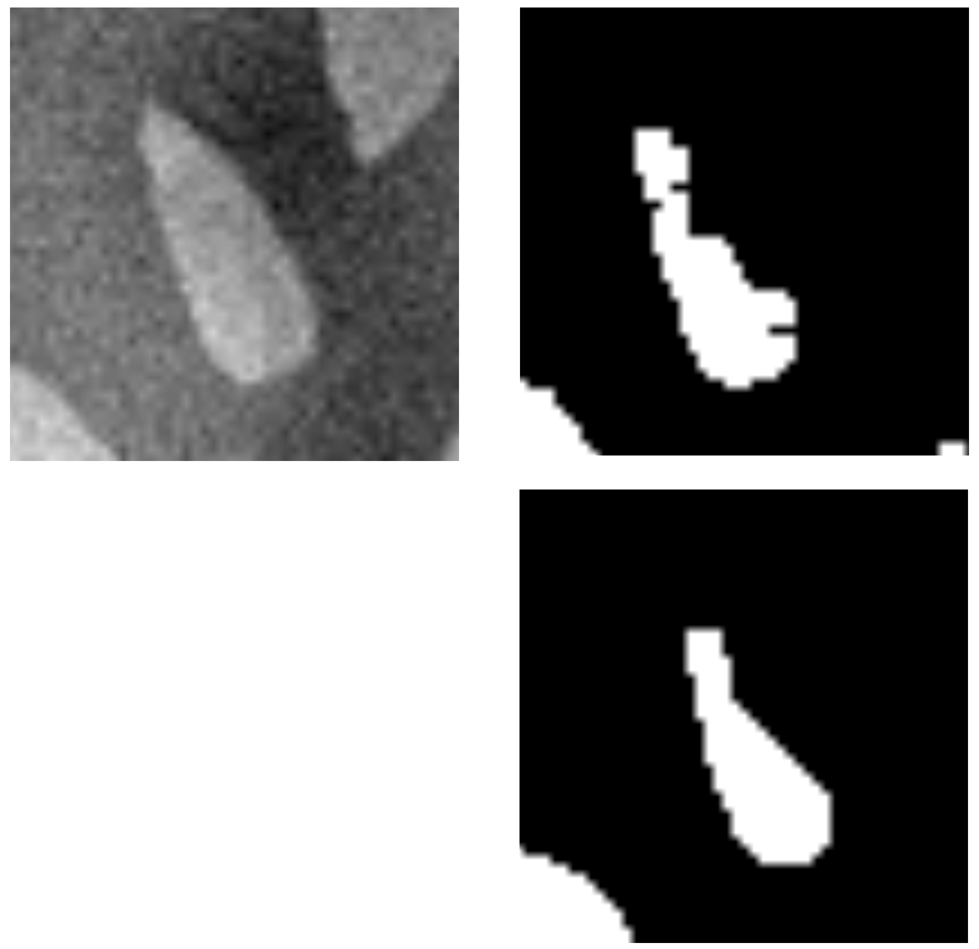


Postprocessing

Morphological operator

Fill holes

Watershed



1980 Rule-based

2000 Model-based

2000 Machine Learning

2020 Deep-Learning

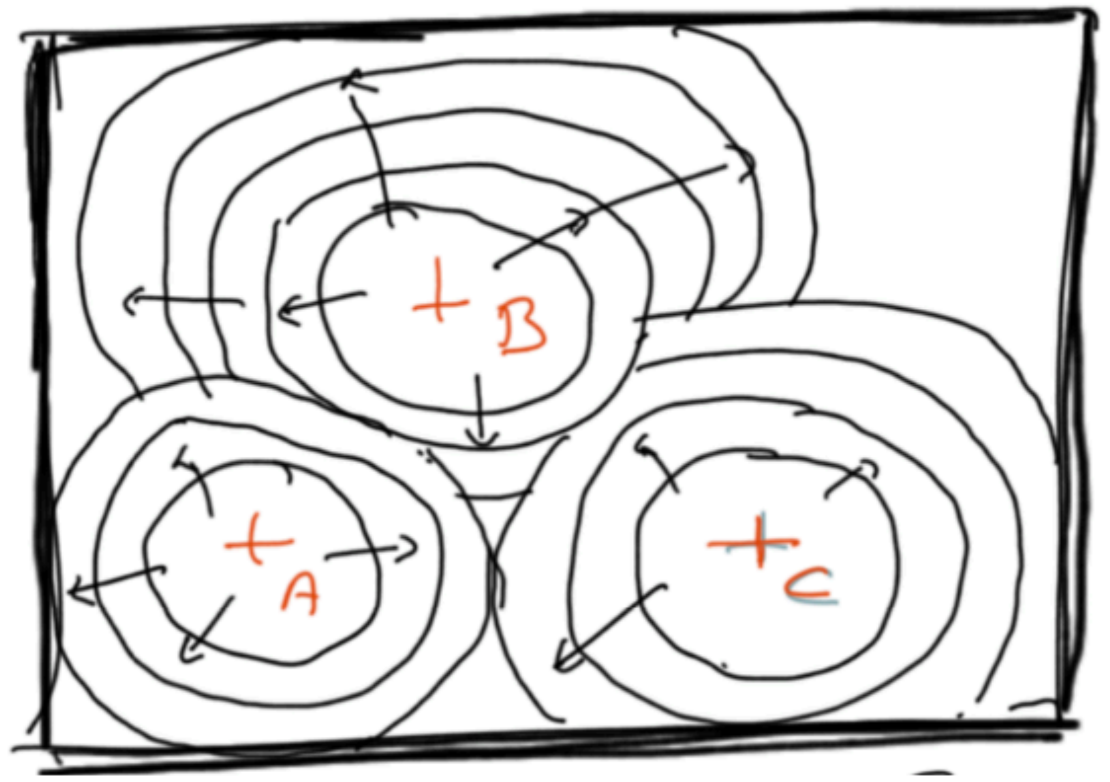
Aggregation

Achanta & Süsstrunk, SLIC Superpixel IEEE PAMI 2012.

Region Growing

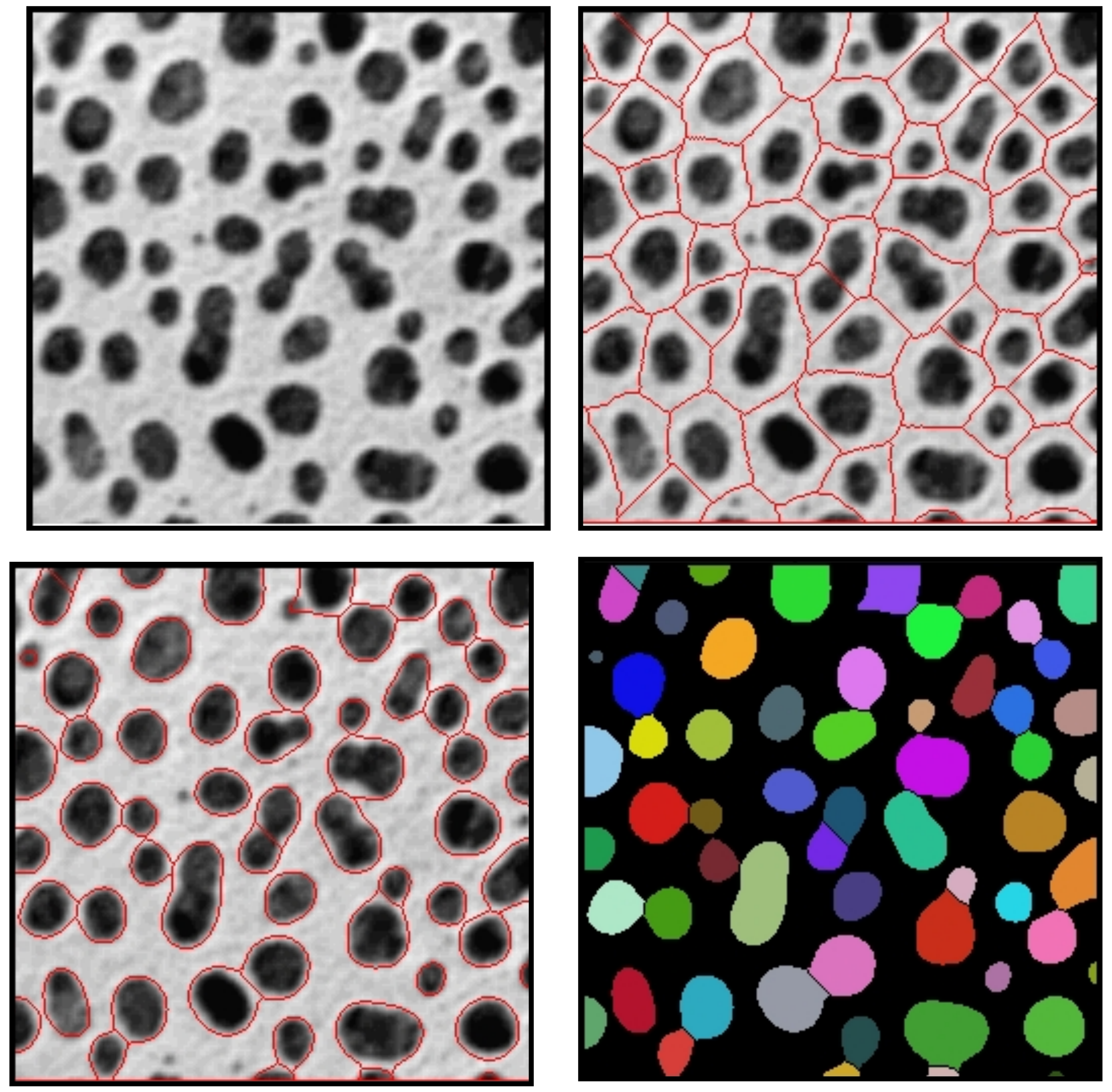
Seed

Cost of aggregation



Watershed on grayscale image

Denoise to avoid over-segmetation



Dam on top

Dam at 150

1980 Rule-based

2000 **Model-based**

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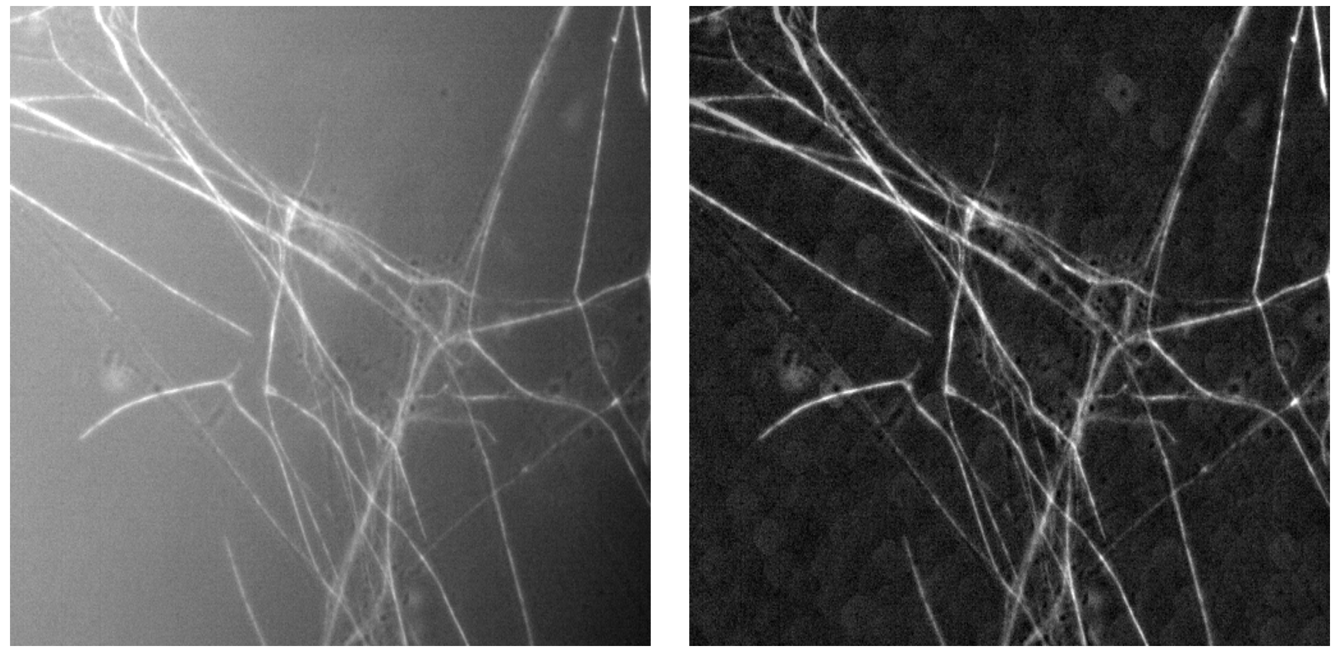
2020 Deep-Learning

Physic-driven Restoration

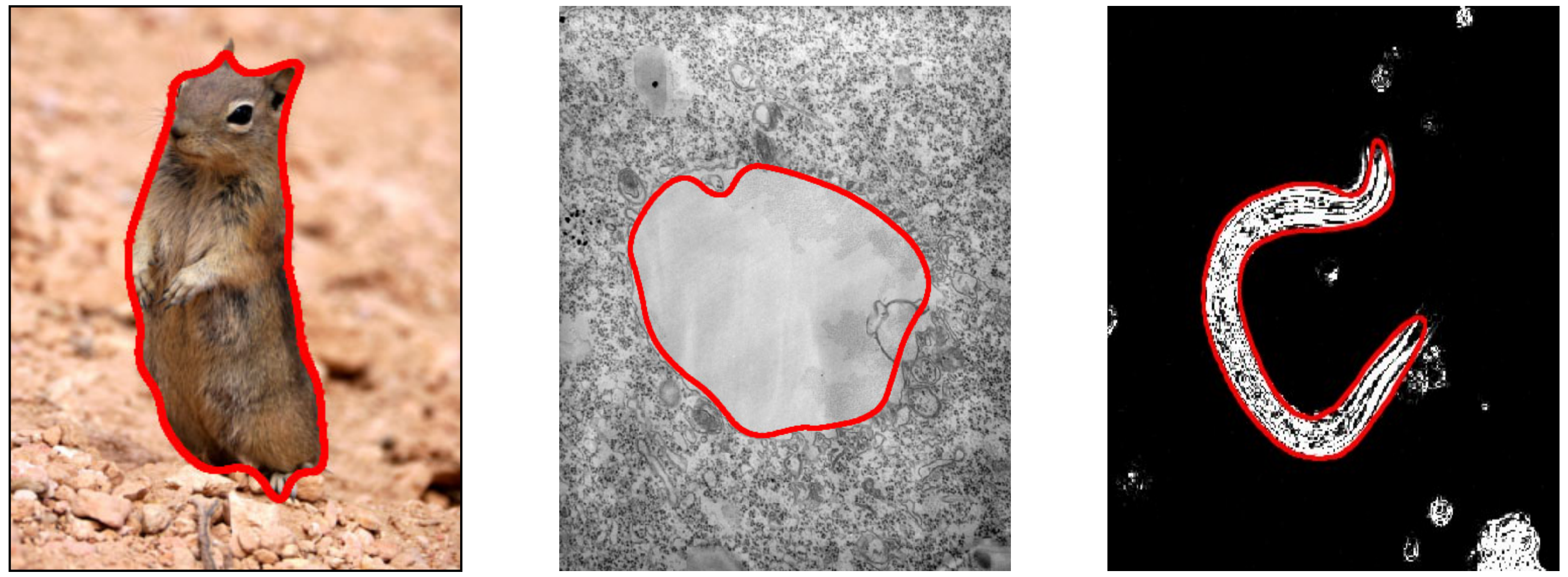
- ➡ Image reconstruction
- ➡ Deconvolution



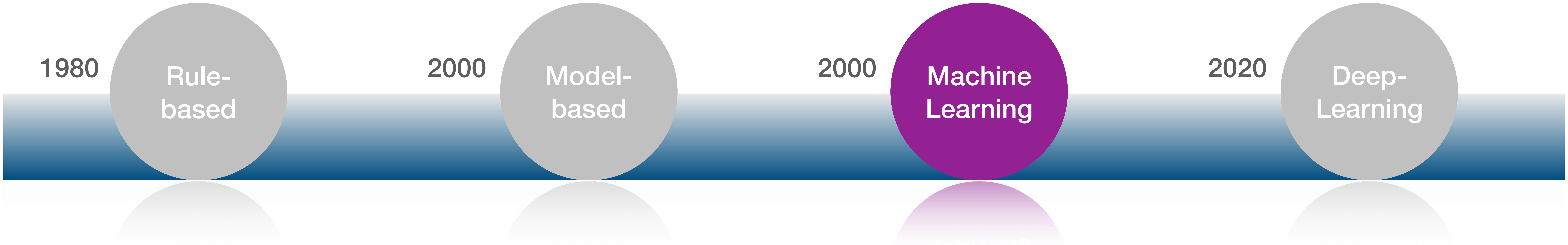
Design optimization scheme

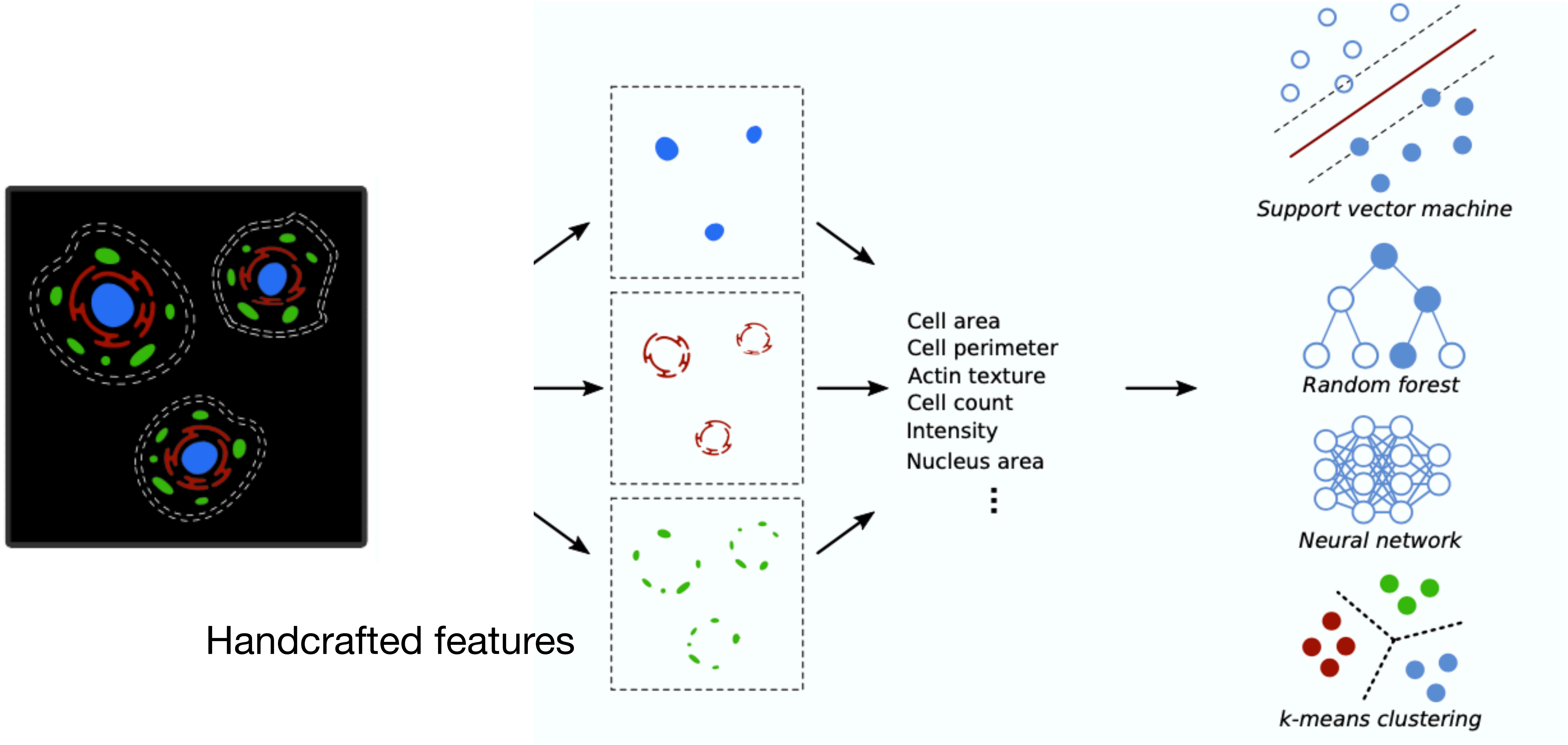
Deformable Shape

- ➡ Active contour
- ➡ Level-set
- ➡ Graph-Cut



Design optimization scheme





Handcrafted features

- Ilastik
- Weka
- Labkit
- QuPath

Few parameters to learn

1980 Rule-based

2000 Model-based

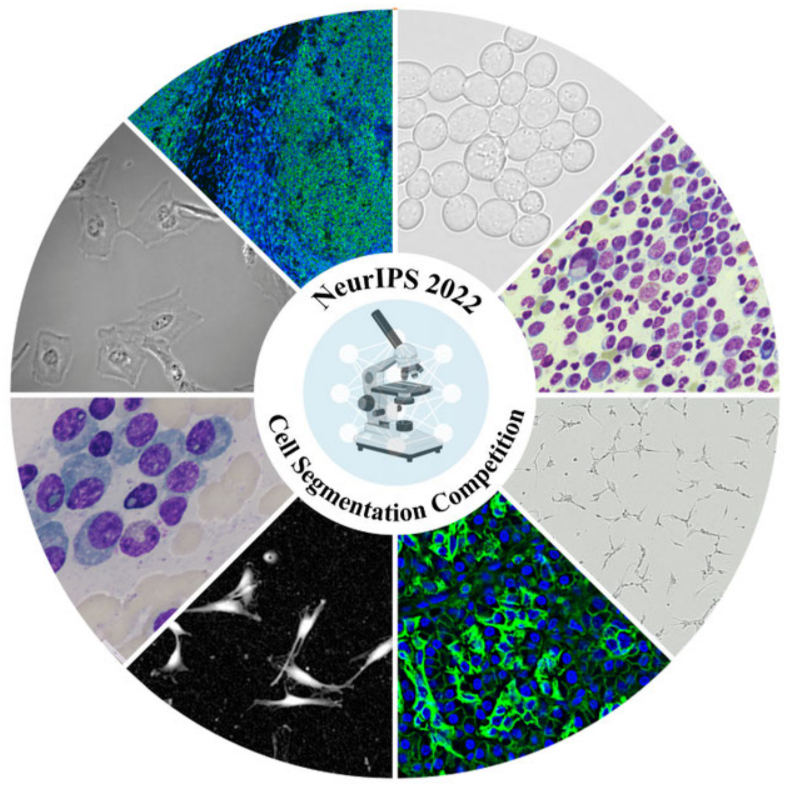
2000 Machine Learning

2020 Deep-Learning

Data

Learn for many data

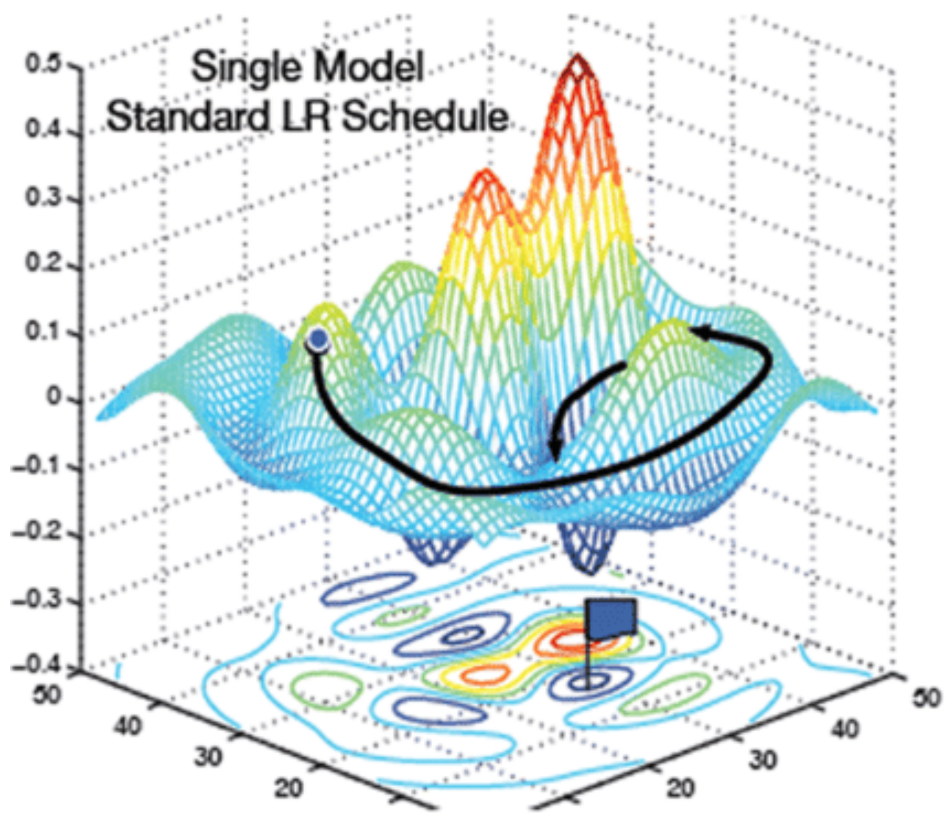
Annotated data



Training

Neural Network

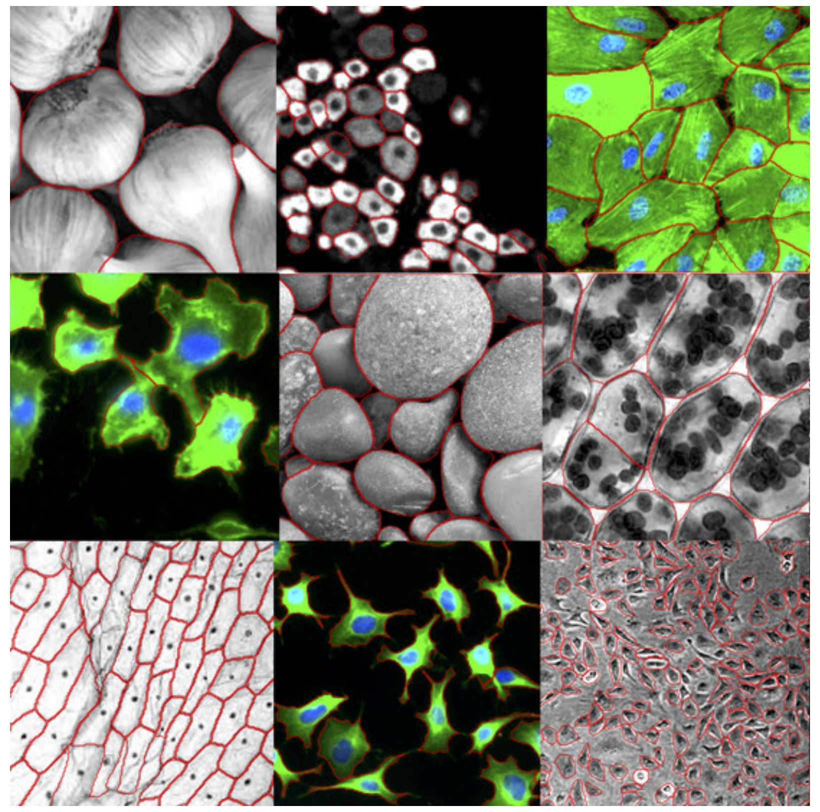
Supervised learning



Pretrained Models

Zoo of models

Generalist models



Foundation Models

Transformers

Big data

Image Analysis Paradigms

Model-driven relies on prior model		Data-driven learns from data
strong model	physical model	no model
highly generalization	generalizability	questionnable
limited	adaptivity	very adaptive
insight of structure	solver	blackbox
math. reconstruction	guarantees	none (Lipschitz)
interpretable	error analysis	no control

Input data
Algorithm **Code**

Output data

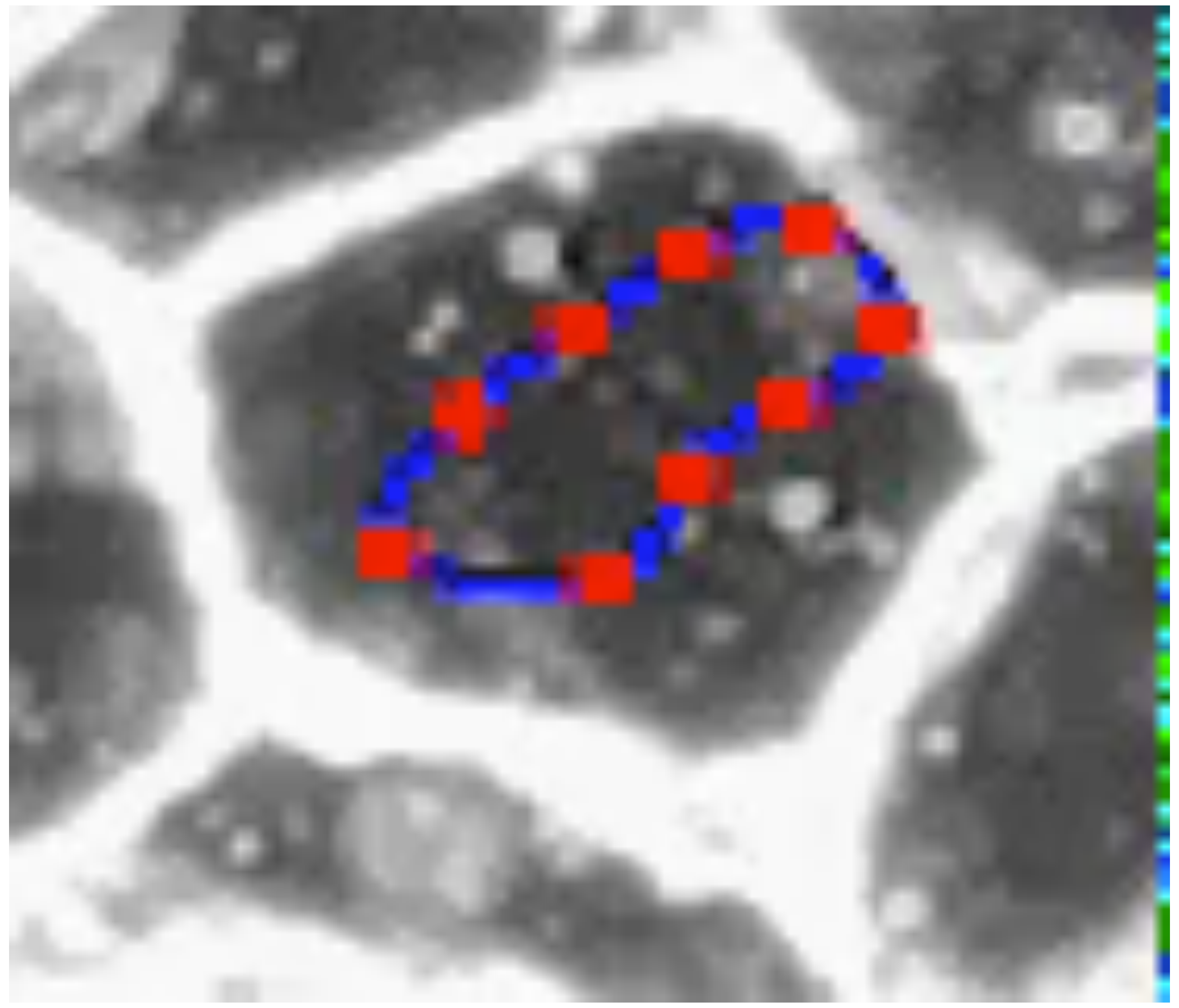
Input data
Truth data

Algorithm **Model**

The data is the code

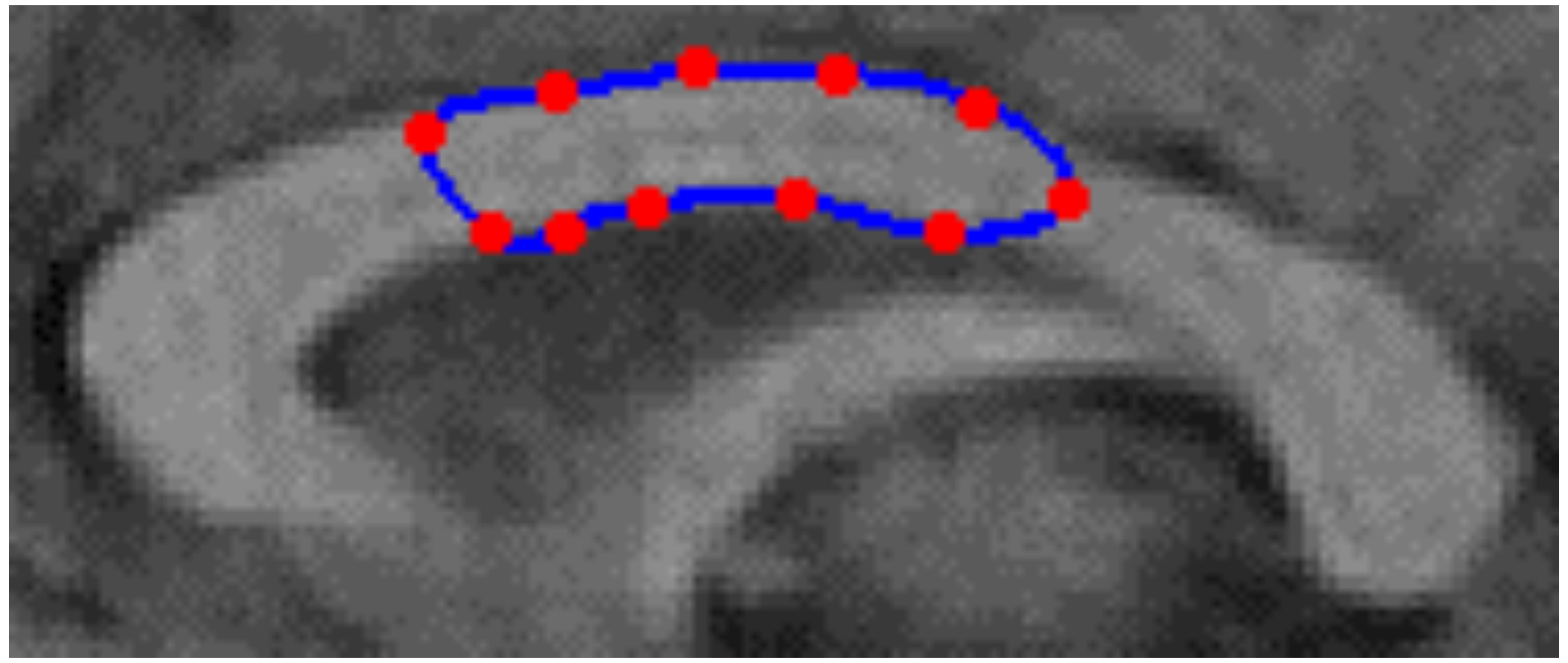
Advanced Segmentation Techniques

Active Contours



Definition

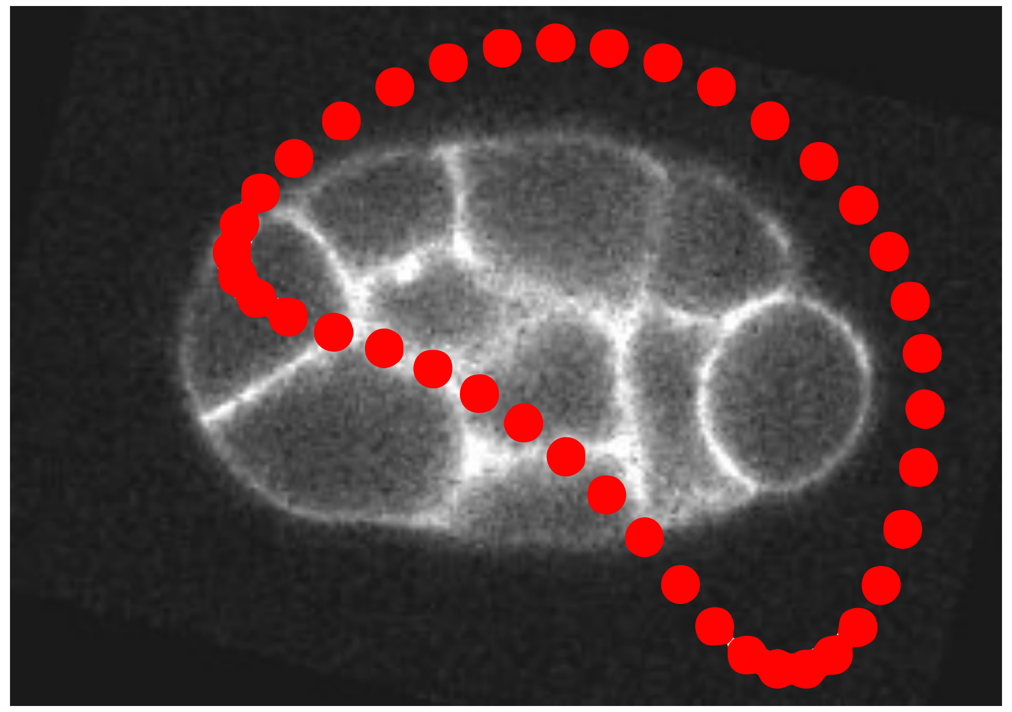
"Evolution of a curve ***toward the*** *boundary* ***of an object of interest through the*** *minimization* ***of an energy functional." [Kass 1988]***



- ✓ Effective and popular
- ✓ User-friendly (enable interaction)
- ✓ Possibility to incorporate a priori knowledge

Representation model	Energy	Optimization
Θ: parameters	$E_{\text{snake}}(f, \Theta)$	$\Theta_{\text{opt}} = \arg\min_{\Theta} E_{\text{snake}}(f, \Theta)$

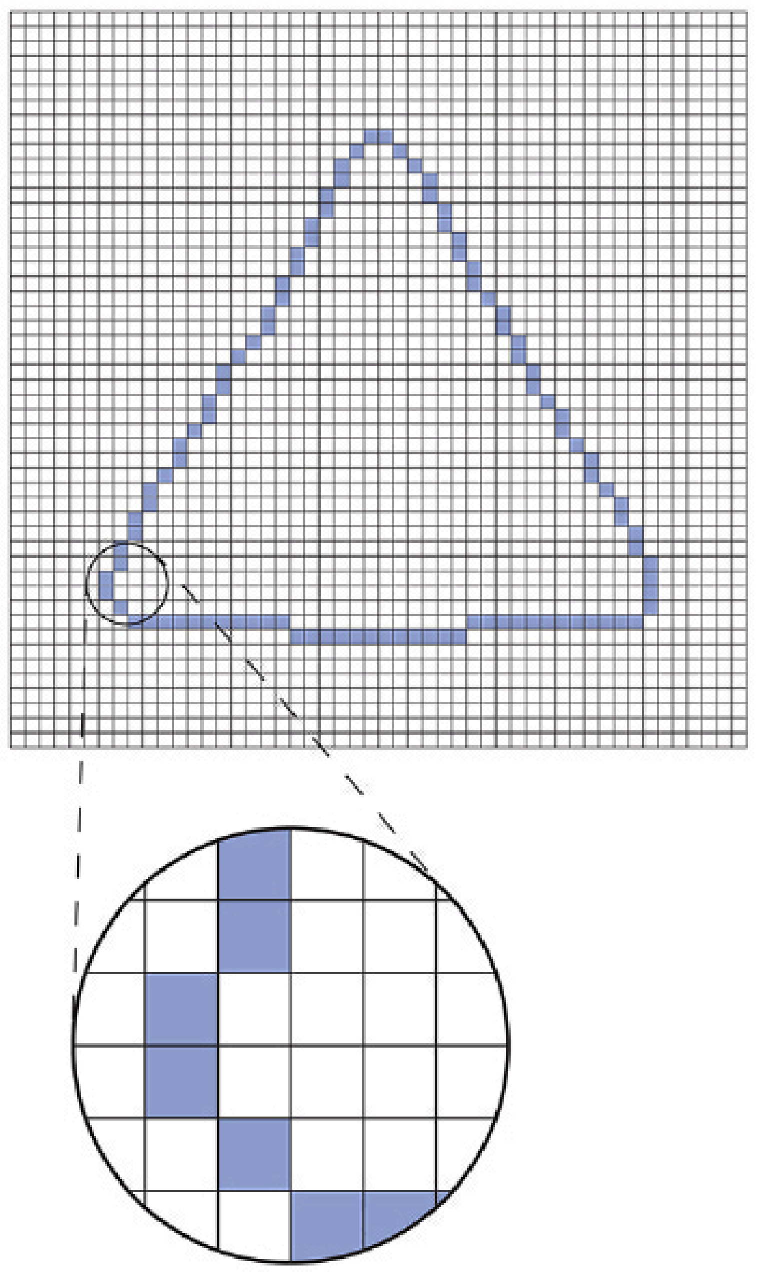
The energy functional of the snake drives the evolution of the curve to fit object boundaries



Representation of 2D Curves

POINT CURVES

- Discrete representation
- Many points

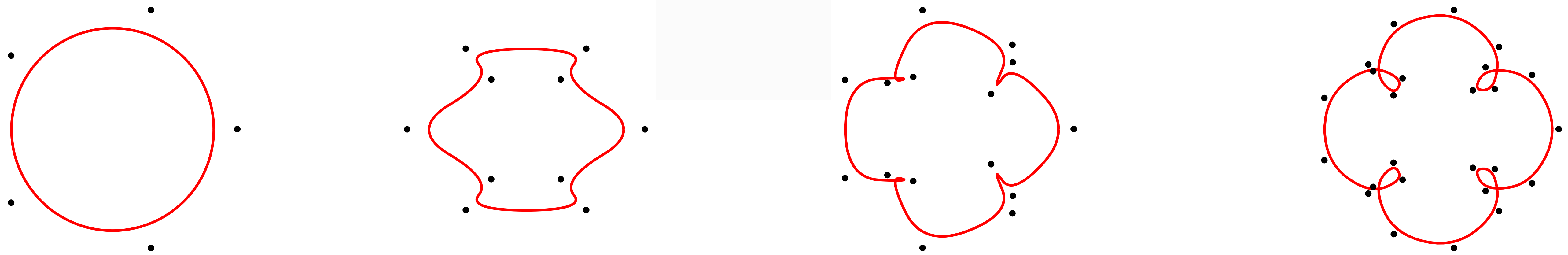


PARAMETRIC CURVES

Cubic Spline curve

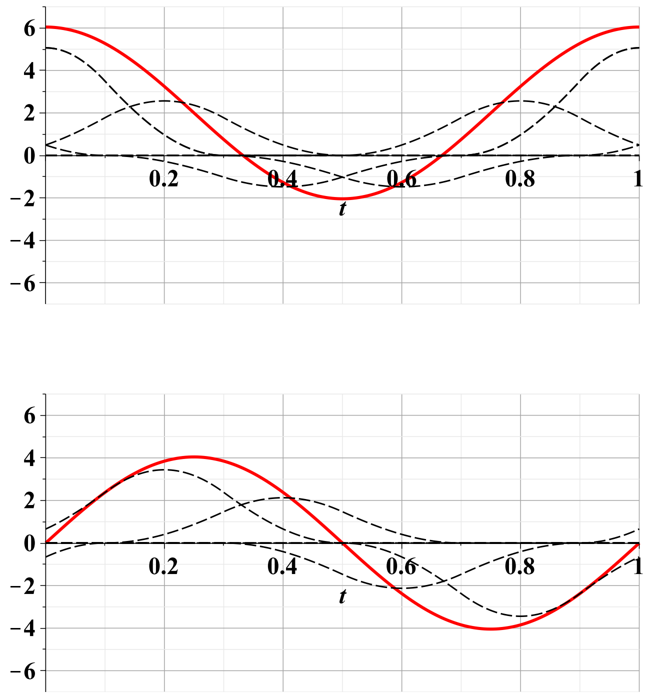
- Continuous representation
- Few control points
- Guarantee smoothness

Compact support of spline ➜ Intuitive user-interaction



$r_1(t)$

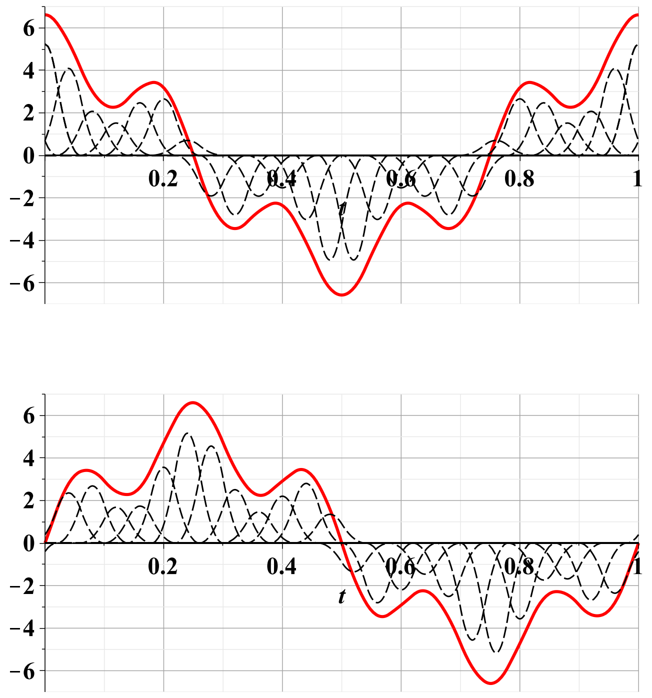
$r_2(t)$



$$\mathbf{r}(t) = \begin{pmatrix} r_1(t) \\ r_2(t) \end{pmatrix} = \sum_k \mathbf{c}[k]\varphi(t-k)$$

control points

basis functions



N controls the degree of freedom

Energy

- The curve evolution is formulated as an energy minimization problem

$$E_{\text{snake}}(\Theta) = E_{\text{image}}(\Theta) + E_{\text{internal}}(\Theta) + E_{\text{constraint}}(\Theta)$$

Image energy (data driven)

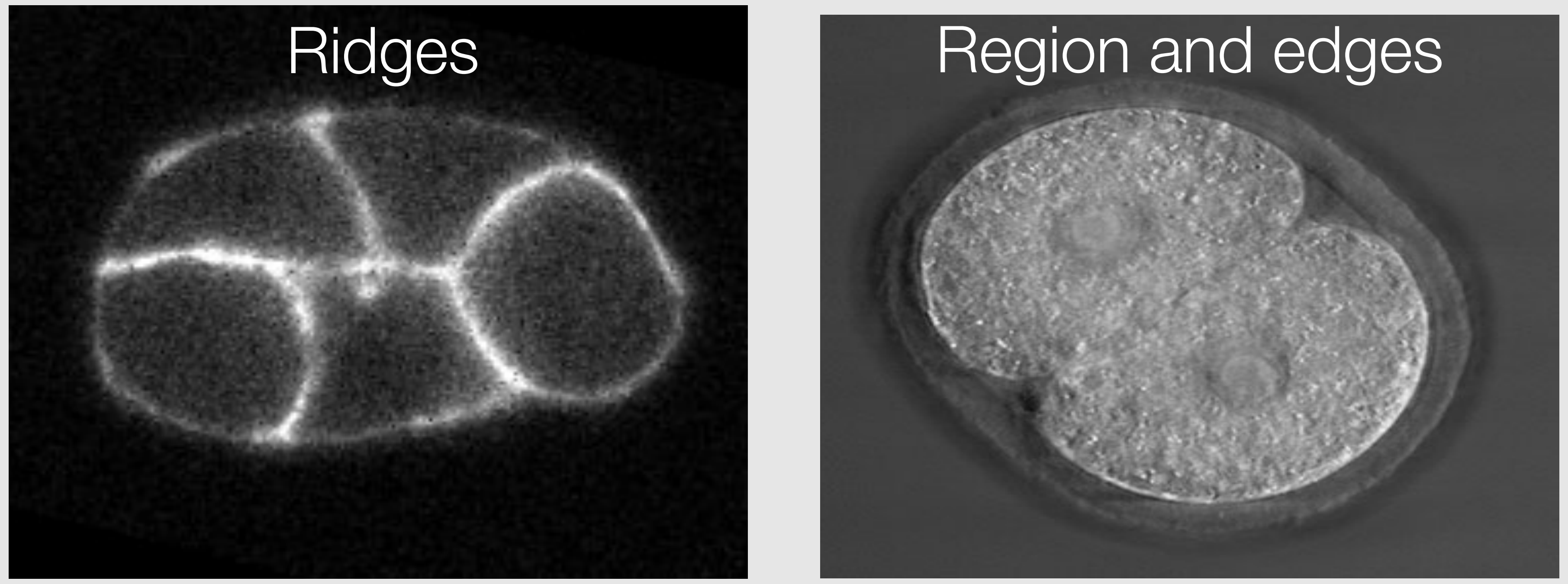
Guides the snake toward the boundary of interest

Internal energy

Ensures smooth boundaries of the segmented object

Constraint energy

Provides a means for the user to interact with the snake



The quality of the segmentation depends on the choice of the energy terms

Contour-based Image Energy

- Use of local image information (edges or ridges)

- Accurate contour localization
- Small basin of attraction
- Sensitivity to noise

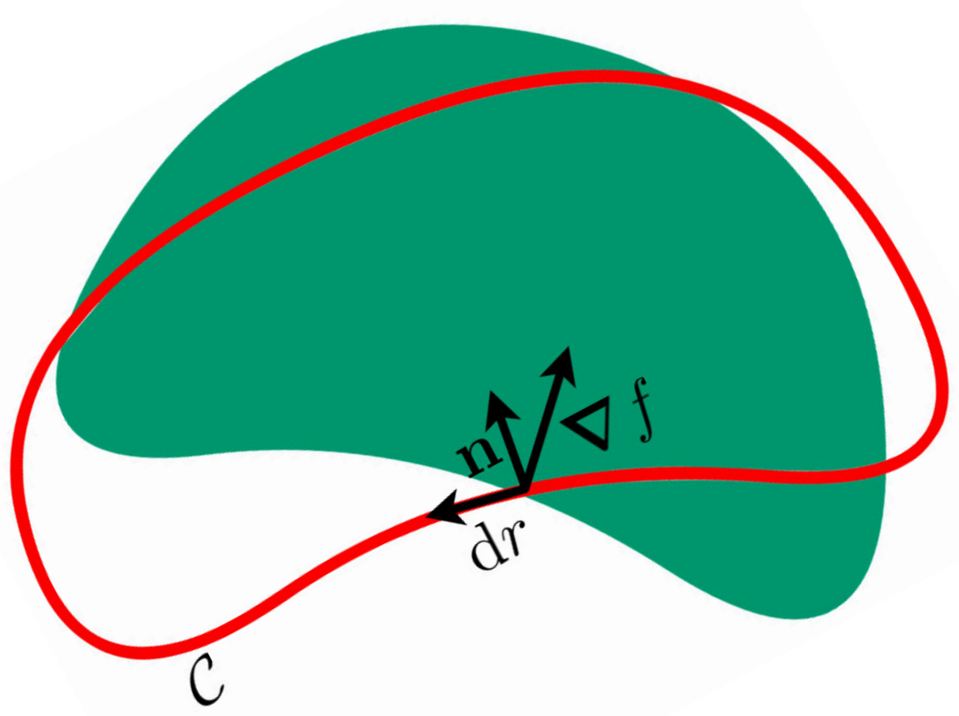
Edge attraction

- Based on the **magnitude** of the gradient

$$E_{\text{edge}}(\Theta) = -\oint_{\mathcal{C}} |\boldsymbol{\nabla} f(\mathbf{r})| \, \mathrm{d}r$$

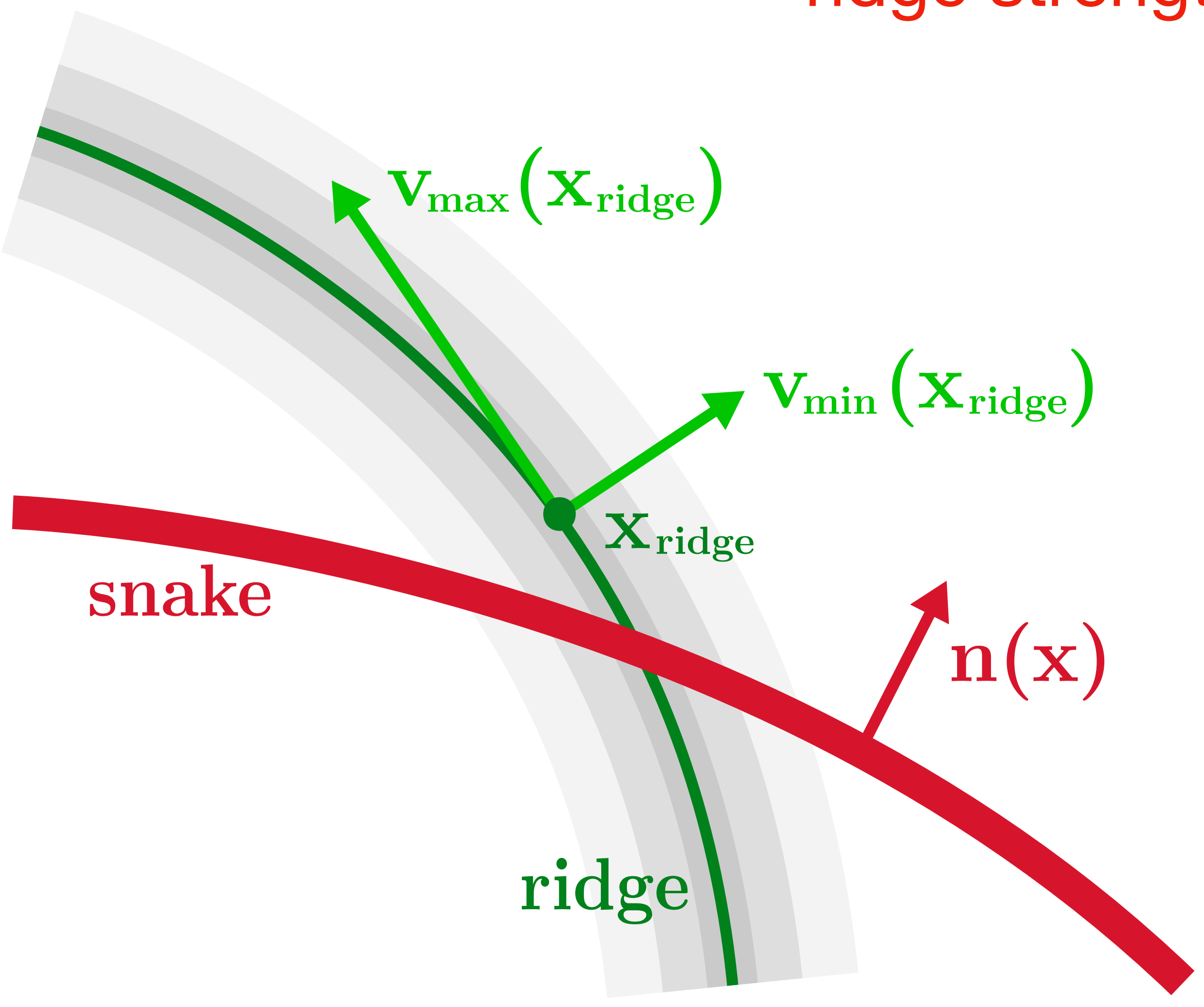
- Improvement using the **direction** of the gradient

$$E_{\text{edge}}(\Theta) = -\oint_{\mathcal{C}} \langle \boldsymbol{\nabla} f(\mathbf{r}), \mathbf{n}(\mathbf{r}) \rangle \, \mathrm{d}r$$



Ridge attraction

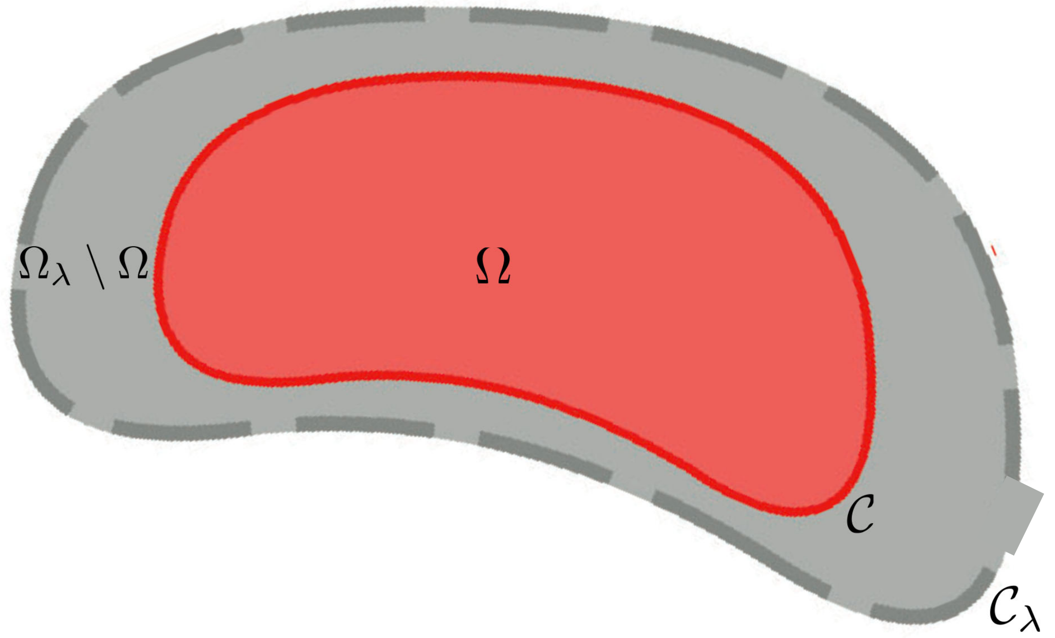
$$E_{\text{ridge}}(\Theta) = -\oint_{\mathcal{C}} \underbrace{\xi(\mathbf{r})}_{\text{ridge strength}} \frac{|\langle \mathbf{v}_{\min}(\mathbf{r}), \mathbf{n}(\mathbf{r}) \rangle|}{\|\mathbf{v}_{\min}(\mathbf{r})\|} \mathrm{d}r$$



Slides of **Anaïs Badoual**

Region-based Image Energy

- Use of mean information (intensity distribution or texture)
  - Large basin of attraction
  - Robust to noise
  - Poor contour localization



$\mathbf{r}_\lambda$: dilated version of $\mathbf{r}$

Ω_λ : surface enclosed by $\mathbf{r}_\lambda$

Ω : surface enclosed by $\mathbf{r}$

$\Omega_\lambda \setminus \Omega$: shell

$$E_{\text{region}}(\Theta) = -\frac{1}{|\Sigma|}\left|\iint_\Omega f(\mathbf{x})\mathrm{d}x_1\mathrm{d}x_2 - \iint_{\Omega_\lambda\setminus\Omega} f(\mathbf{x})\mathrm{d}x_1\mathrm{d}x_2\right|$$

- Fast implementation ➜ Green's theorem

All surface integrals reduce to line integrals by using a pre-integrated image

$$E_{\text{region}}(\Theta) = -\frac{1}{|\Sigma|}\left|2\oint_{\mathcal{C}} F(\mathbf{r})\mathrm{d}r_2 - \oint_{\mathcal{C}_\lambda} F(\mathbf{r}_\lambda)\mathrm{d}r_{2,\lambda}\right|$$

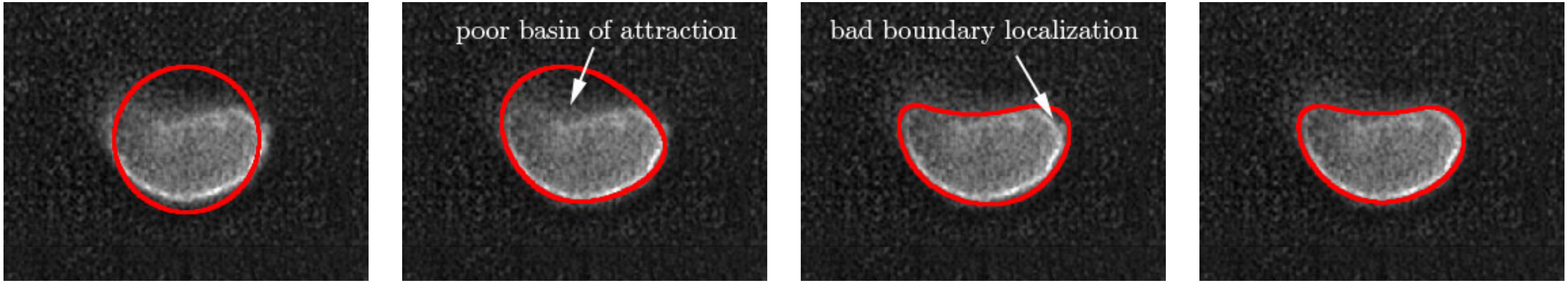
pre-integrated images

Slides of **Anaïs Badoual**

Image Energy Contour + Region

- To benefit from the advantages of both methods, we use the following combination

$$E_{\text{image}}(\Theta) = bE_{\text{contour}}(\Theta) + (1-b)E_{\text{region}}(\Theta) \qquad b \in [0,1]$$



Initialization | E_{contour} | E_{region} | $0.5(E_{\text{contour}} + E_{\text{region}})$

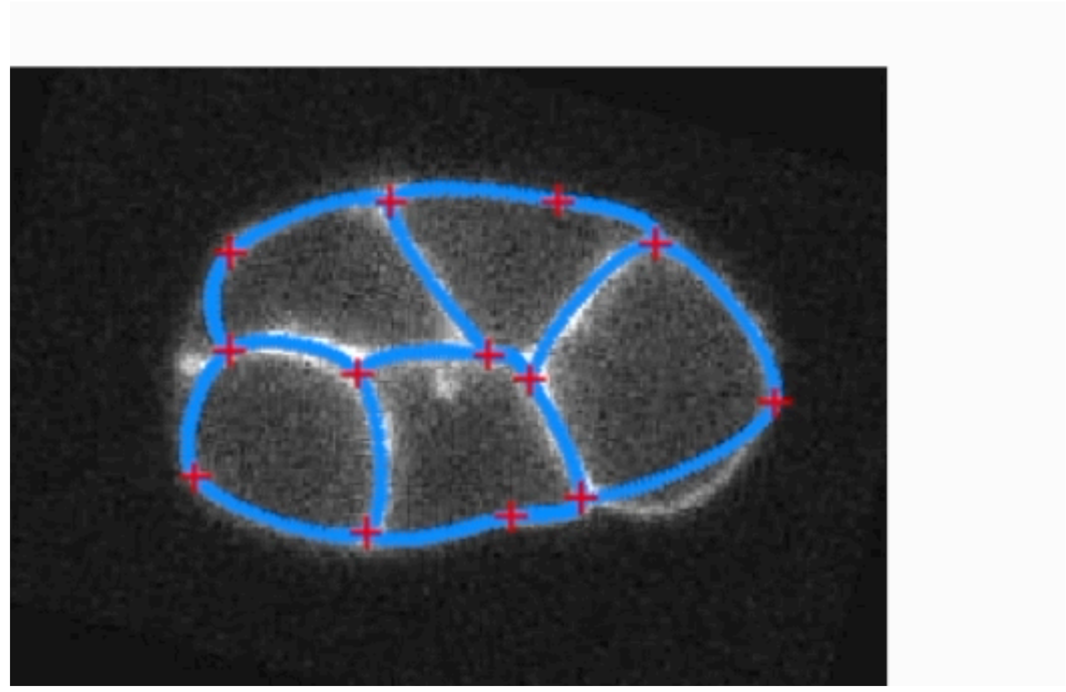
Slides of **Anaïs Badoual**

Application Cases

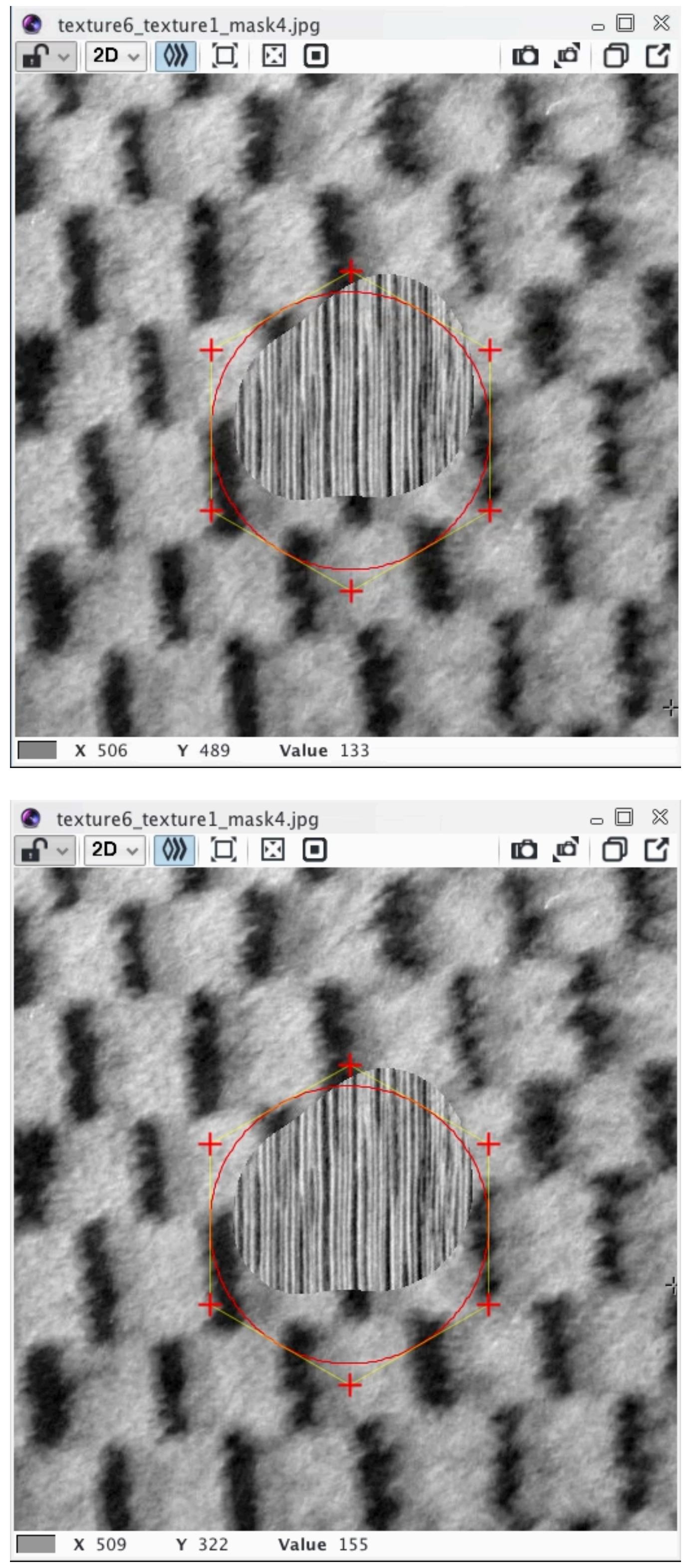
Active Tessellation

[Badoual, 2019]

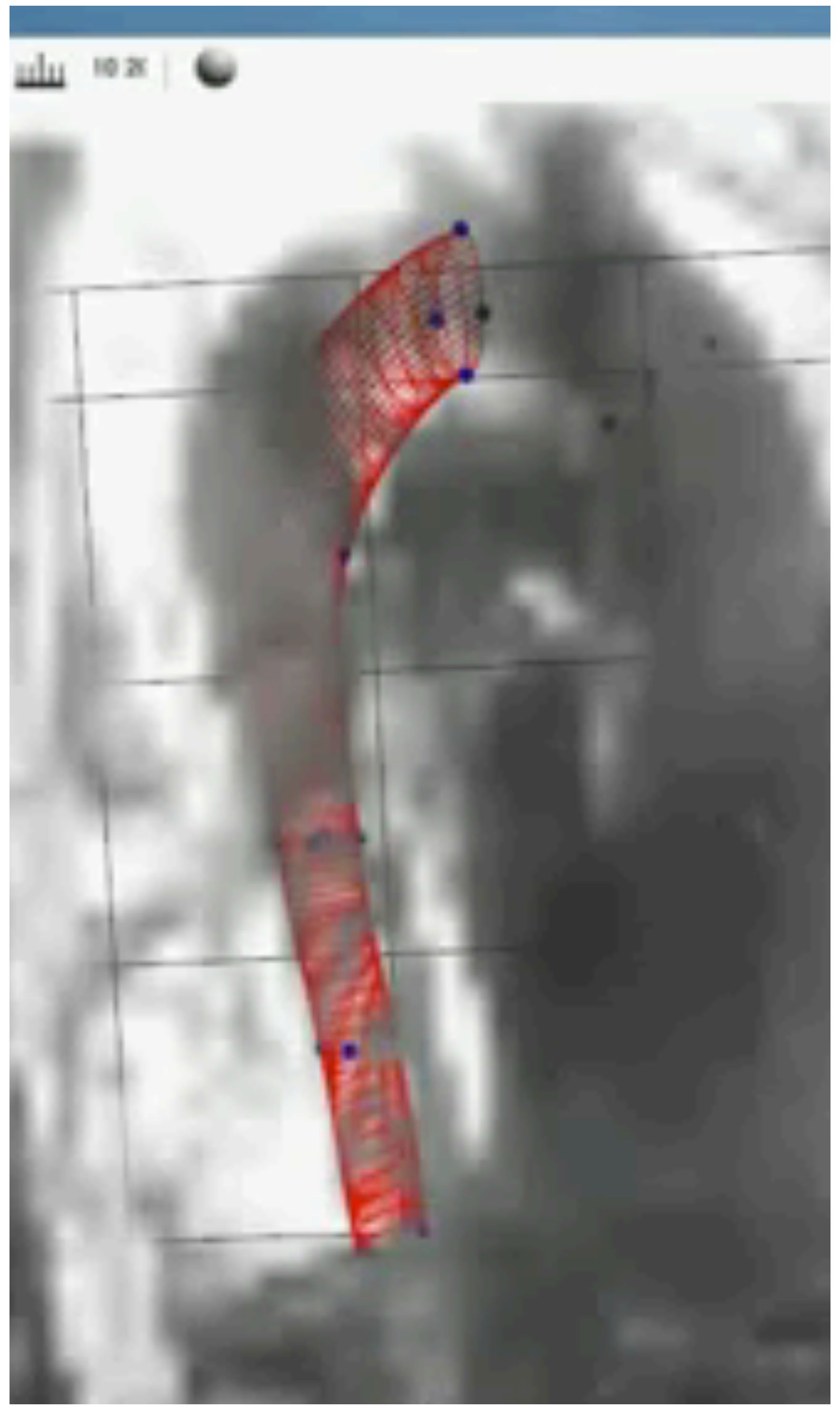
Find complex structure at once



Texture

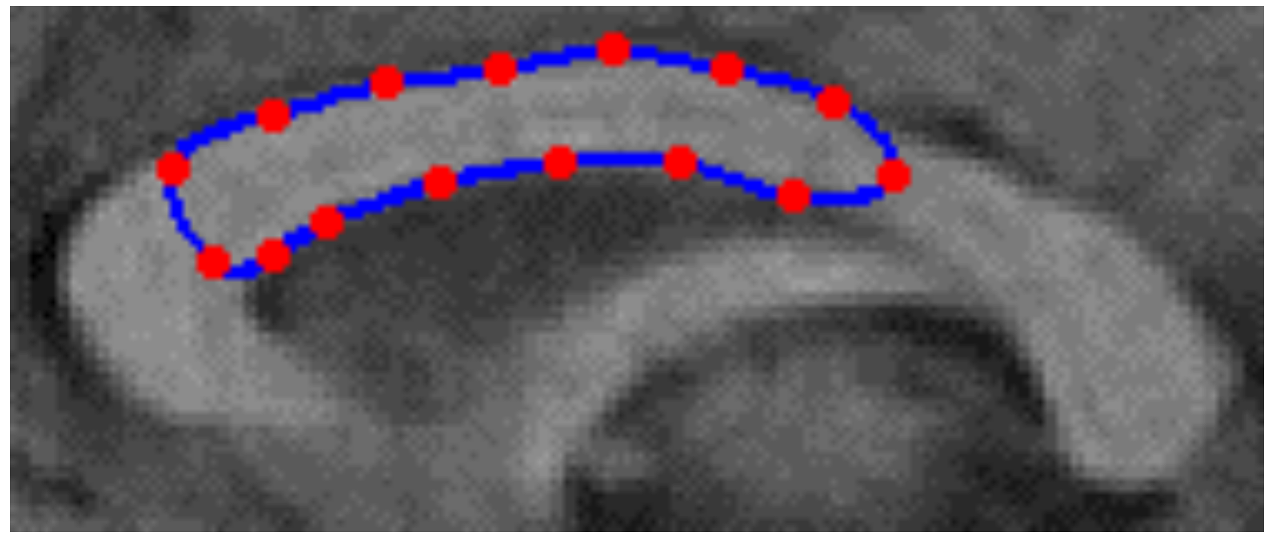


Aorta segmentation 3D



Soline Snake

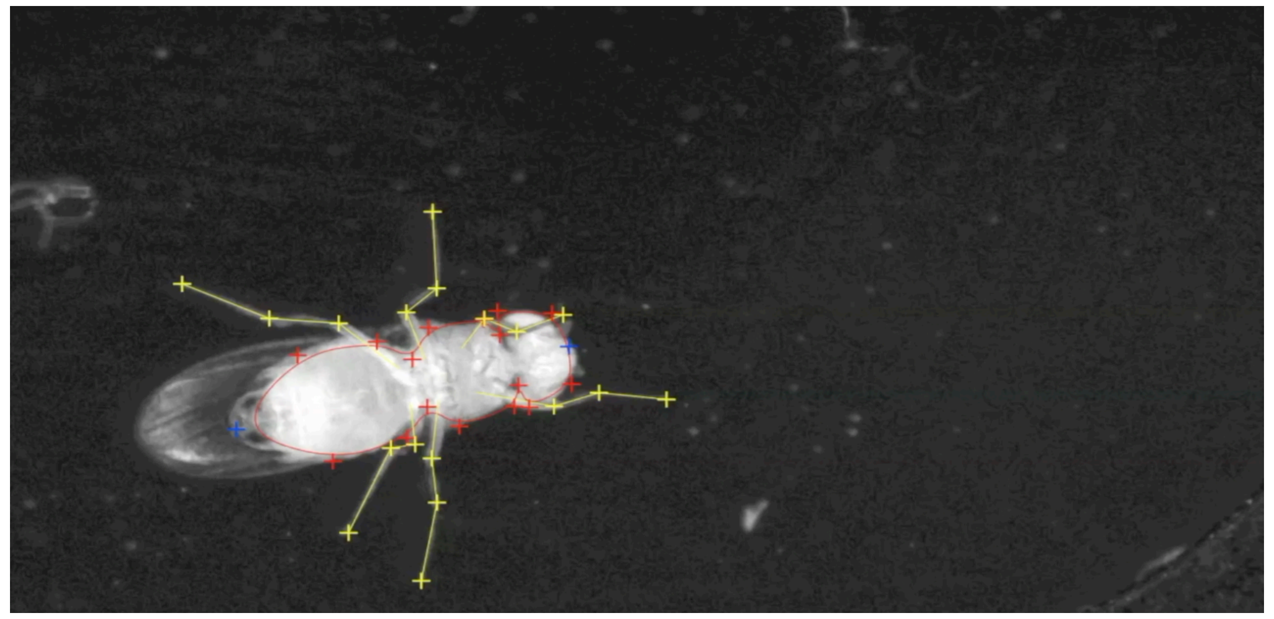
[Jacob, 2004]

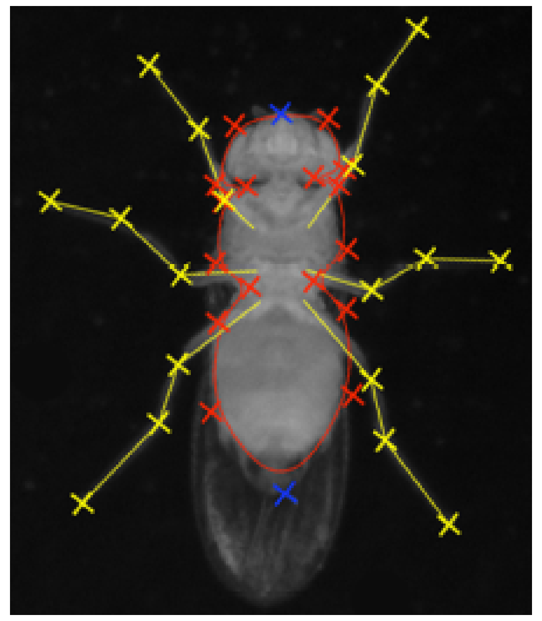


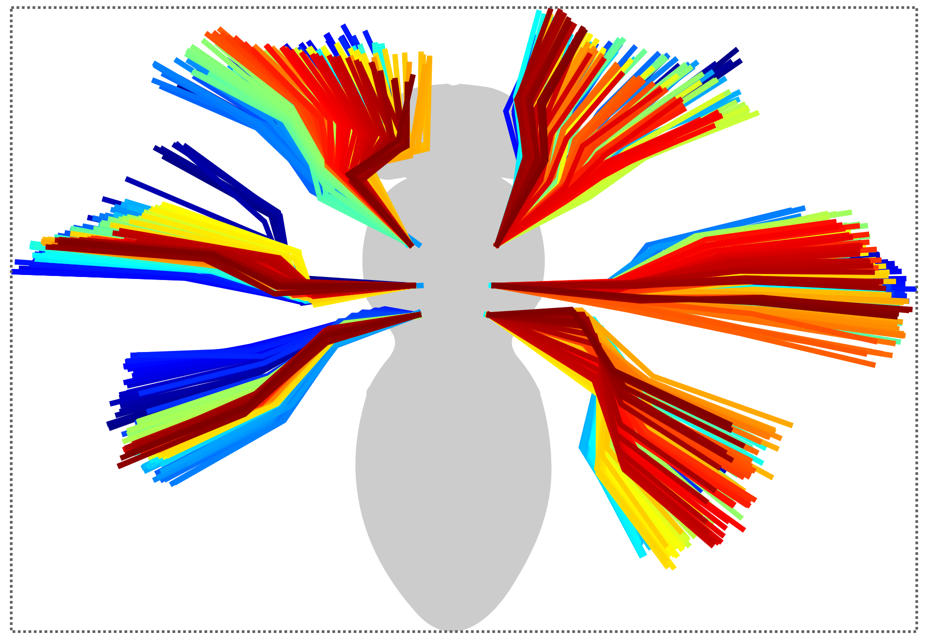
Segmentation legs

[Uhlmann, 2017]

- 1 close snake for body
- 6 open snakes for legs

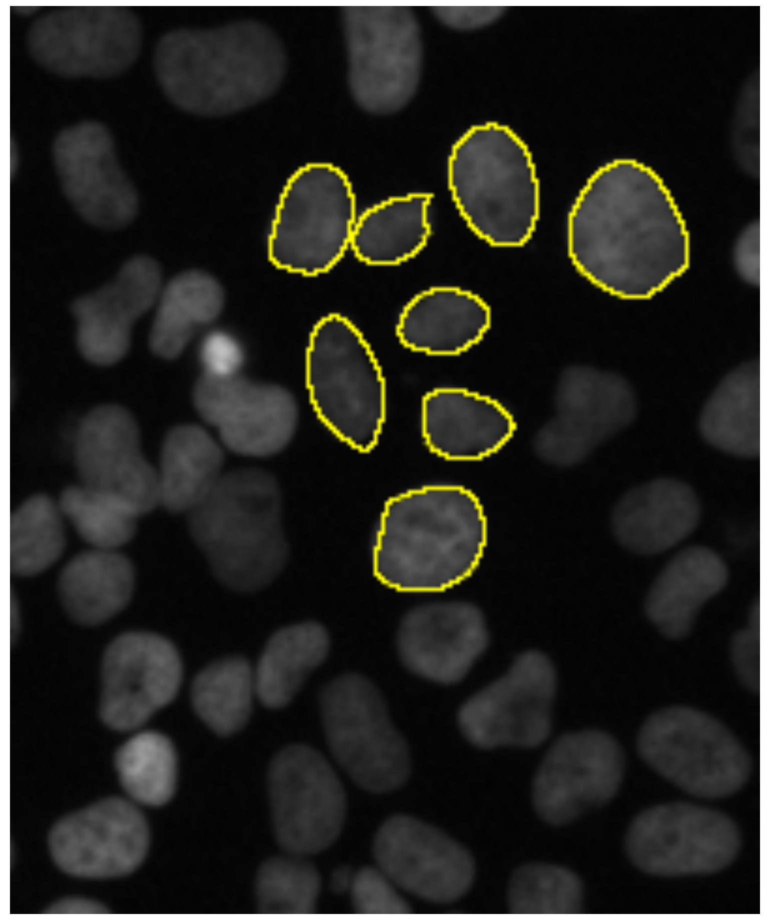






Recap on Active Contour

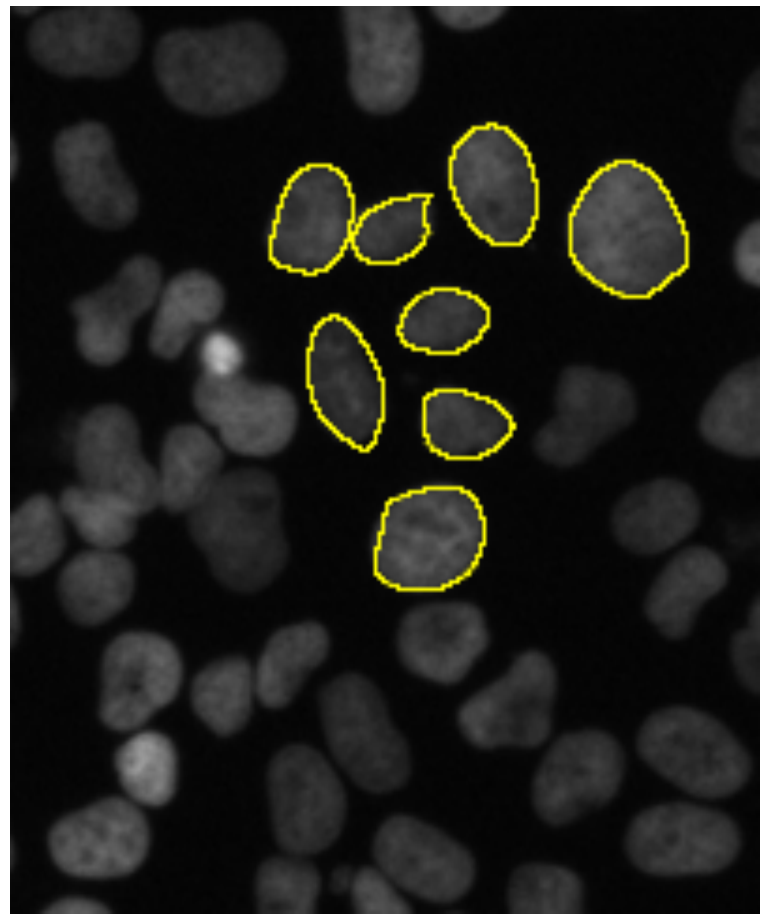
*"Evolution of a curve **toward the** boundary **of an object of interest through the** minimization **of an energy functional."***



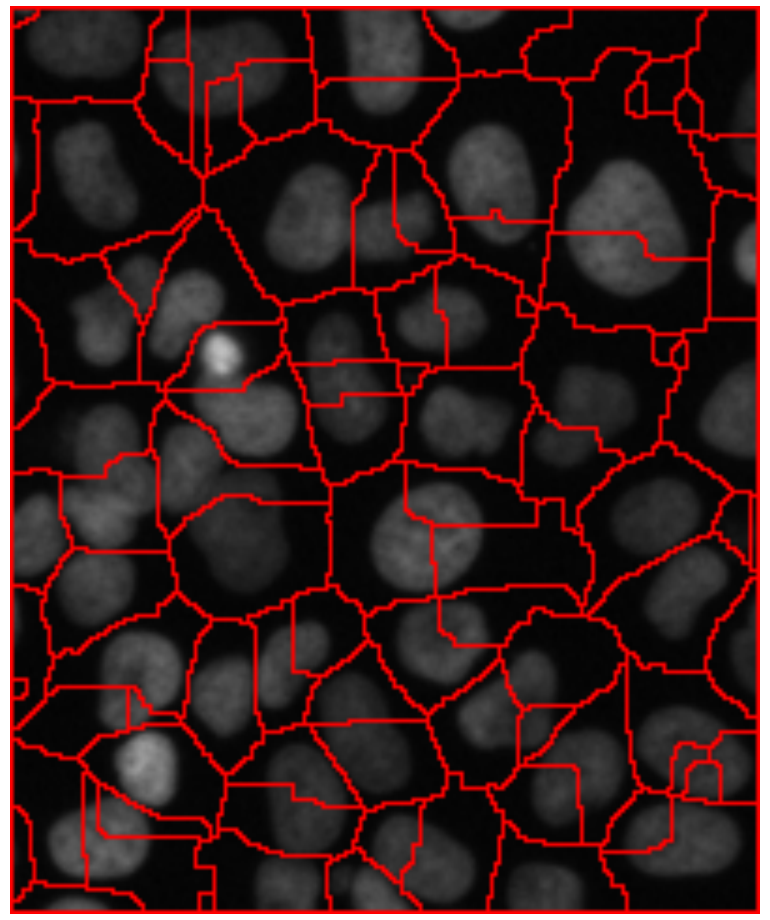
Segment-Anything
- Required manual prompt
- Data-driven model
- User edition by points
- Processing objects

Advantages on active contour
- Robustness to noise
- Does not suffer from leakage issue
- Easy to introduce prior knowledge
- User-interaction
- Computational efficiency

Limitations
- Initialization
- Self-intersection
- Dense objects



Snake
- Required initial curve
- Strong model
- User edition by controls
- Processing objects



Watershed
- Required seed
- Over-segment, leakage
- No edition
- Processing pixel image