Semi-Supervised Learning of Edge Filters for Volumetric Image Segmentation

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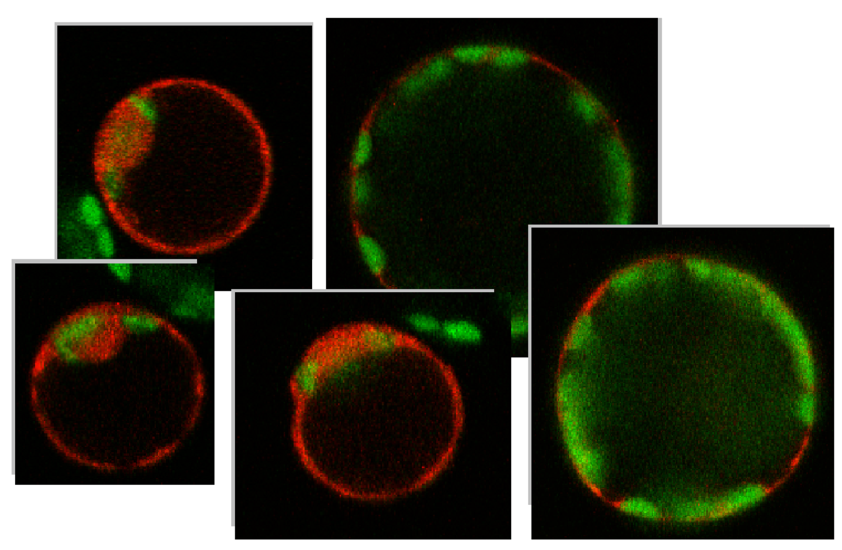
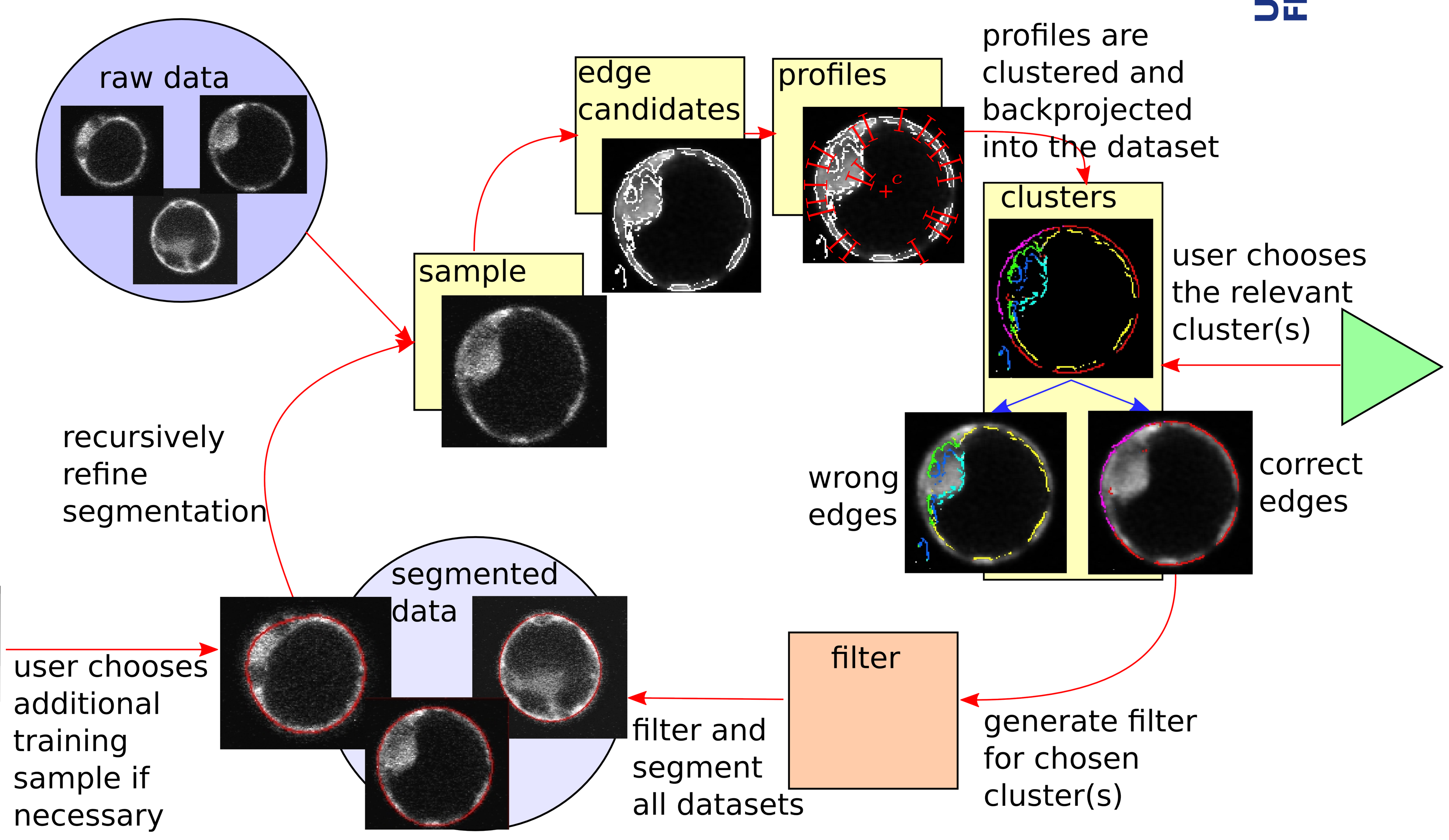
► Motivation and Approach

For every segmentation task, prior knowledge about the object that shall be segmented has to be incorporated. This is typically performed either automatically by using labeled data to train the used algorithm, or by manual adaptation of the algorithm to the specific application. To avoid time consuming manual annotations and labellings in 3D, we developed a method that combines unsupervised and supervised learning.

First, the possible edge appearances are grouped, such that, in the second step, the expert only has to choose between relevant and non-relevant clusters. This way, even objects with very different edge appearances in different regions of the boundary can be segmented. In the presented work, the chosen edge clusters are used to generate a filter for all relevant edges. The filter response is used to generate an edge map based on which an active surface segmentation is performed.





1. Profile Extraction and Clustering

Candidates:
- chosen by their gradient magnitude
- non maximum suppression in gradient direction

Extracted Profiles:
- Describe the appearance at the respective position
- Robust to gray value variations

$$p(\mathbf{x}, l) = \frac{\mathrm{d}}{\mathrm{d}l} I\left(\mathbf{x} + l \cdot \frac{\mathbf{x}-\mathbf{c}}{|\mathbf{x}-\mathbf{c}|}\right)$$

center $\mathbf{c}$ from prior detection step

discrete:

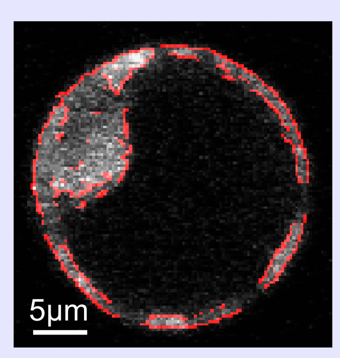
$$\mathbf{p}_\mathbf{x}(i) = p\left(\mathbf{x}, \lambda \cdot \left(i - \frac{\mathrm{L}}{2}\right)\right) \quad 0 \le i < \mathrm{L} \in \mathbb{N}$$

λ stepsize

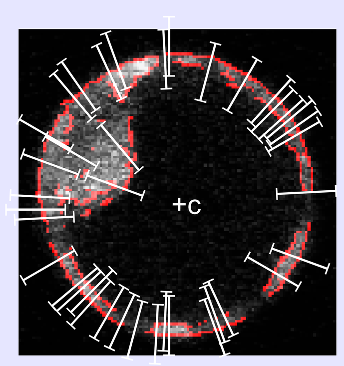
normalized:

$$\bar{\mathbf{p}}_\mathbf{x}(i) = \frac{\mathbf{p}_\mathbf{x}(i)}{\max_i(|\mathbf{p}_\mathbf{x}(i)|)}$$

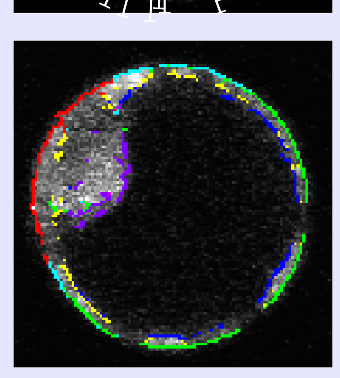
Clustering:
The extracted profiles are grouped by their similarity using K-Means Clustering



Found positions of high gradient magnitude



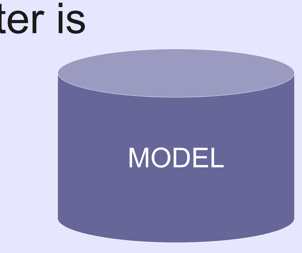
Profiles are extracted in radial direction from the object's center $\mathbf{c}$.


Clustered candidates

3. Filtering

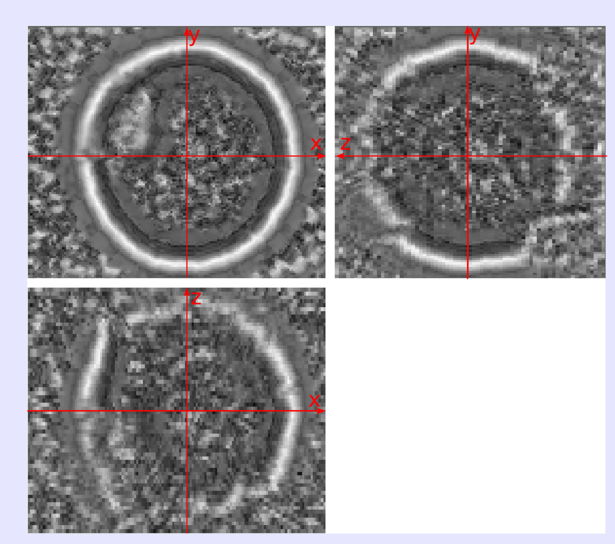
For each point $\mathbf{x}$, the radial profiles are extracted. The distance to one cluster is defined with the Mahalanobis Distance as

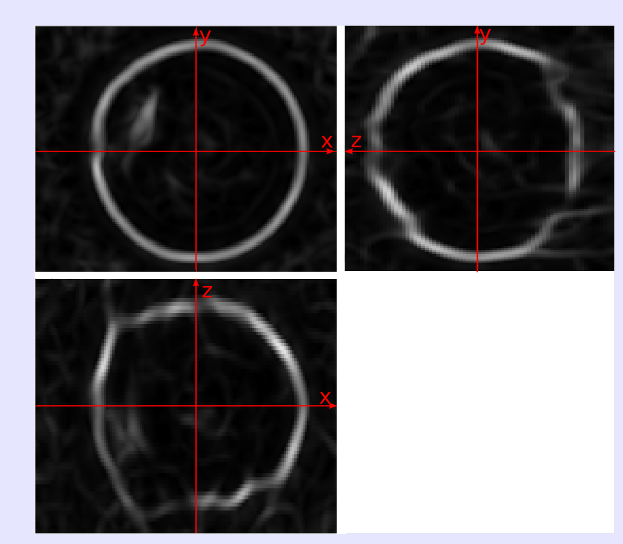
$$D_\mathrm{M}(\bar{\mathbf{p}}_\mathbf{x}, \mathrm{C}_j) = \sqrt{\left(\bar{\mathbf{p}}_\mathbf{x} - \mu_{\mathrm{C}_j}\right)^T \Sigma^{-1} \left(\bar{\mathbf{p}}_\mathbf{x} - \mu_{\mathrm{C}_j}\right)}$$



The distance to the closest cluster $A(\mathbf{x})$ is the filter response at $\mathbf{x}$.

$$A(\mathbf{x}) = \min_{\mathrm{C}_j}\left(D_\mathrm{M}(\bar{\mathbf{p}}_\mathbf{x}, \mathrm{C}_j)\right)$$

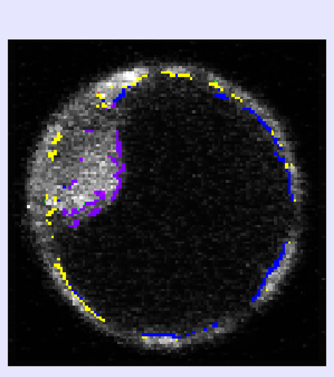

Filter response of the example data in three orthogonal views.

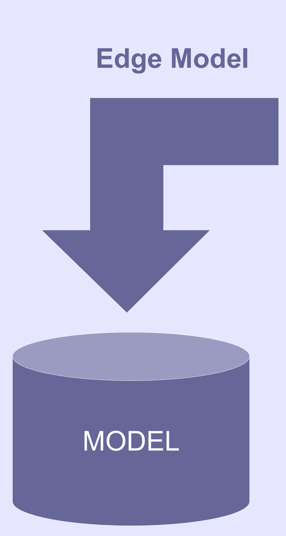

Generate Edge Map (EM) from filter response by applying a steerable filter for plane detection (Aguet, 2005)

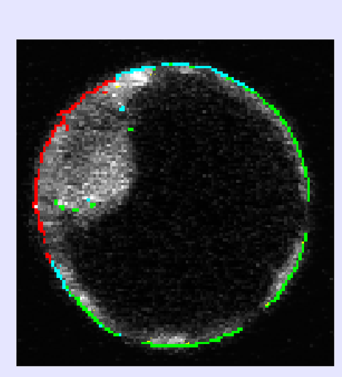
2. Learning Edge Model

User Interaction:
The user chooses the relevant clusters.
These are used to design an edge profile model.

Irrelevant Clusters







Relevant Clusters

Edge Model Generation:
For each chosen cluster C_j, mean $\boldsymbol{\mu}_{C_j}$ and covariance Σ_{C_j} of the profiles are computed.
We use a Gaussian PDF to describe each cluster.

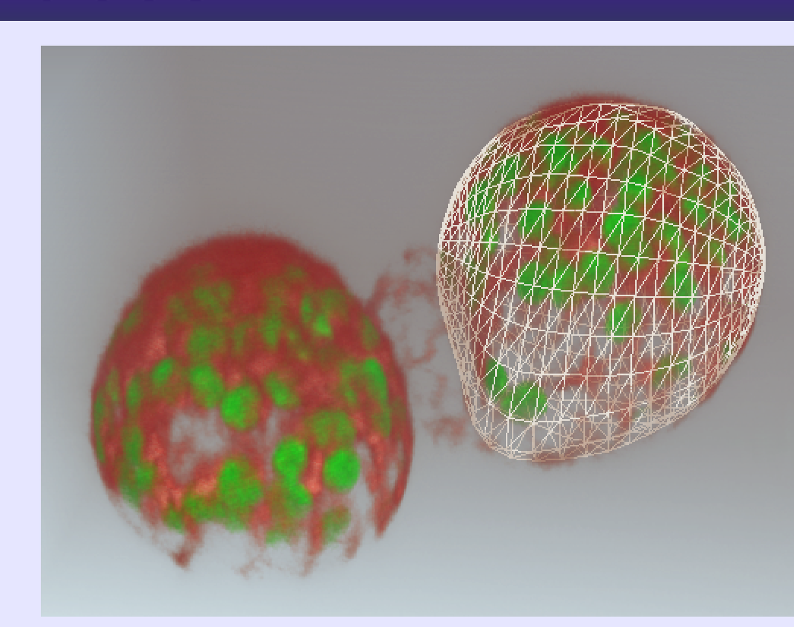
$$f_{\mathrm{C}_j}(\bar{\mathbf{p}}) = \frac{1}{(2\pi)^{l/2}|\Sigma_{\mathrm{C}_j}|^{1/2}} \cdot \mathrm{e}^{-\frac{1}{2}(\bar{\mathbf{p}}-\mu_{\mathrm{C}_j})^T \Sigma_{\mathrm{C}_j}^{-1}(\bar{\mathbf{p}}-\mu_{\mathrm{C}_j})}$$

4. Parametric Active Surfaces

Active Surfaces with parameterization on the sphere

$$S = \{(\theta, \phi) \in \mathbb{R}^2 | 0 \le \theta \le \pi, \; 0 \le \phi < 2\pi\}$$

$$s : S \to \mathbb{R}, (\theta, \phi) \to s(\theta, \phi)$$



Spherical Harmonic Expansions:

$$s(\theta, \phi) = \sum_{l=0}^{B} \sum_{m=-l}^{l} \hat{s}_l^m Y_l^m(\theta, \phi)$$

$$Y_l^m(\theta, \phi) = \sqrt{\frac{(2l+1)(l-m)!}{4\pi(l+m)!}} P_l^m(\cos\theta) e^{jm\phi}$$

Regularization by bandwidth limitation.

External Forces:
Projection onto the radial unit vector $\hat{\mathbf{r}}(\theta, \phi)$

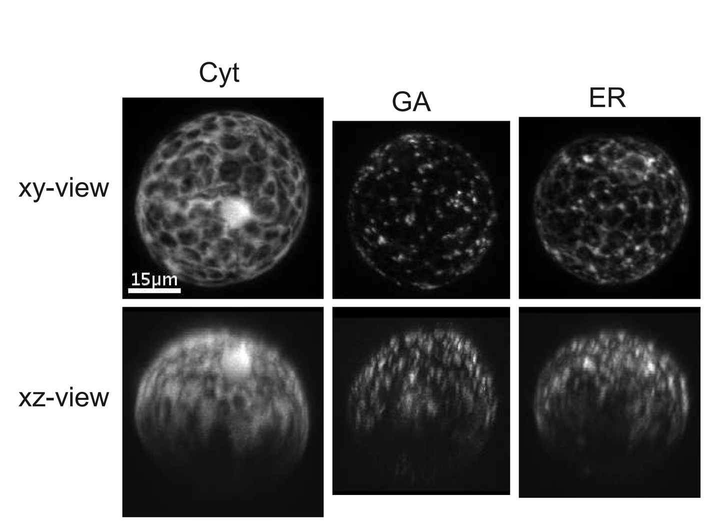
$$\mathbf{F}_{ext}(\theta, \phi) = \left\langle \mathrm{GVF}\left(\nabla \mathrm{EM}\right)\left(\mathbf{c} + s\left(\theta, \phi\right) \cdot \hat{\mathbf{r}}\left(\theta, \phi\right)\right), \hat{\mathbf{r}}\left(\theta, \phi\right) \right\rangle \cdot \hat{\mathbf{r}}\left(\theta, \phi\right)$$

► Experiments and Results

Data:
- Tobacco Leaf Protoplasts (187 cells)
- Recordings from Confocal Laser Scanning Microscopy
- Resolution: 0.28x0.28x0.4 µm³

3 different proteins stained:

- Cytoplasm
- Golgi Apparatus
- Endoplasmic Reticulum



Results:
Segmentation results were labeled as correct or incorrect by two experts

Experiment	# of cells	Iteration 1	Iteration 2	Iteration 3
Cyt	55	**85,5%**	**94,6%**	**94,6%**
GA	86	68,1%	88,4%	**96,5%**
ER	46	91,3%	95,7%	**97,8%**