Mean Shift Gradient Vector Flow: A Robust External Force Field for 3D Active Surfaces

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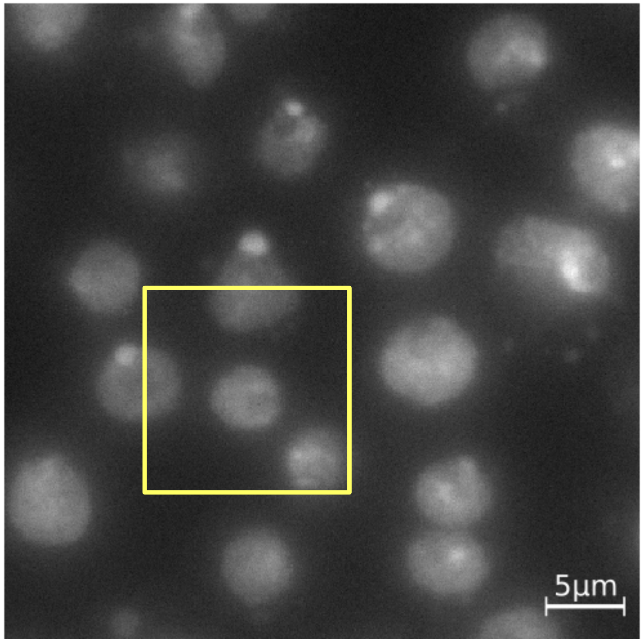
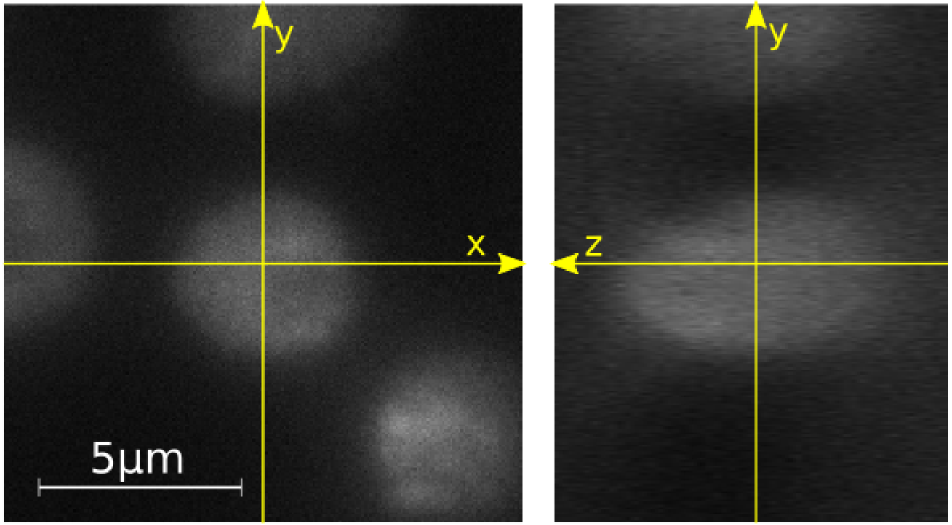
Motivation

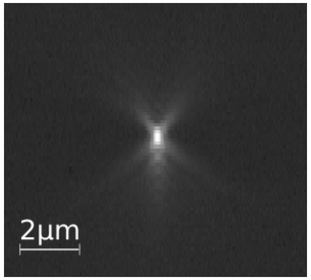
Segmentation of Drosophila S2 Cell nuclei recorded with widefield microscopy for high throughput screening



M. Keuper, J. Padeken, P. Heun, H. Burkhardt and O. Ronneberger, **A 3D Active Surface Model for the Accurate Segmentation of Drosophila Schneider Cell Nuclei and Nucleoli**, Proc. of the ISVC, Springer LNCS, 2009.

Orthogonal views of the recorded nucleus (DAPI staining)





yz-view of the PSF from a widefield fluorescence microscope

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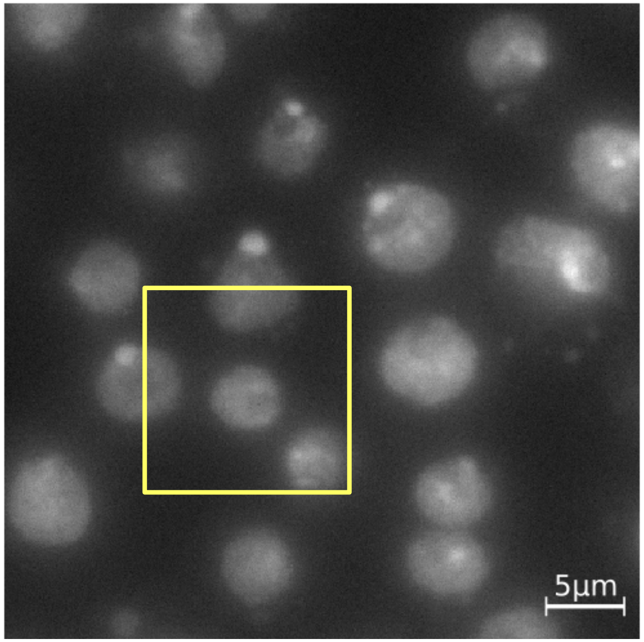

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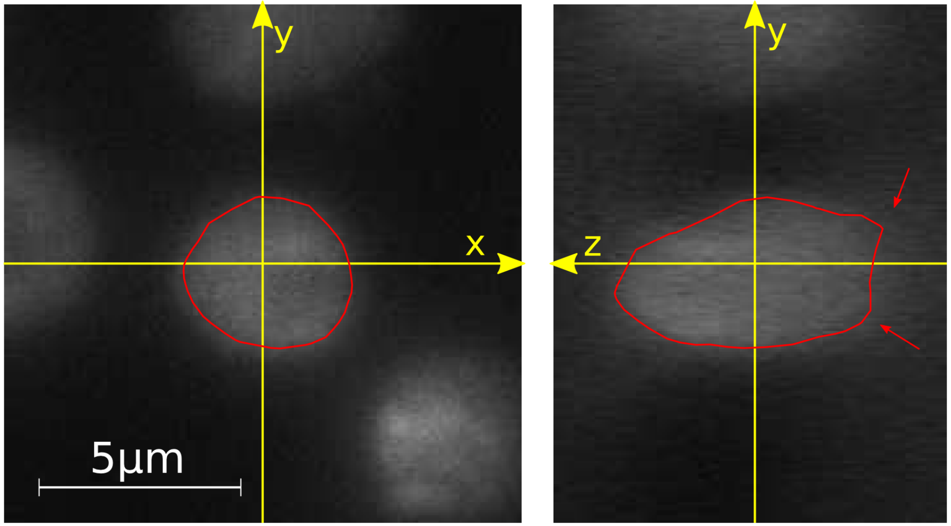
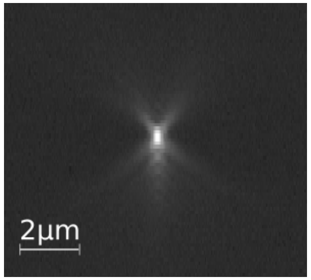




yz-view of the PSF from a widefield fluorescence microscope

Outline

- Gradient Vector Flow
- Mean Shift Filtering
  - Kernel Density Estimation
  - Density Gradient Estimation
  - Mean Shift on 3D Vector Fields
- Mean Shift GVF
- Results
- Conclusion

Gradient Vector Flow

Standard method to smooth vector fields:

- Preserve original gradient information in regions with strong edges
- Smooth vector field in regions with weak edges
- Diffuse gradient vectors according to their magnitude

$$\mathbf{v}(\mathbf{x}) : \mathbb{R}^3 \to \mathbb{R}^3$$

minimize:

$$E(M, \mathbf{v}) = \int_{\mathbb{R}^3} \mu(|\nabla \mathbf{v}|^2) + |\nabla M|^2 |\mathbf{v} - \nabla M|^2 \mathrm{d}\mathbf{x}$$

edge image

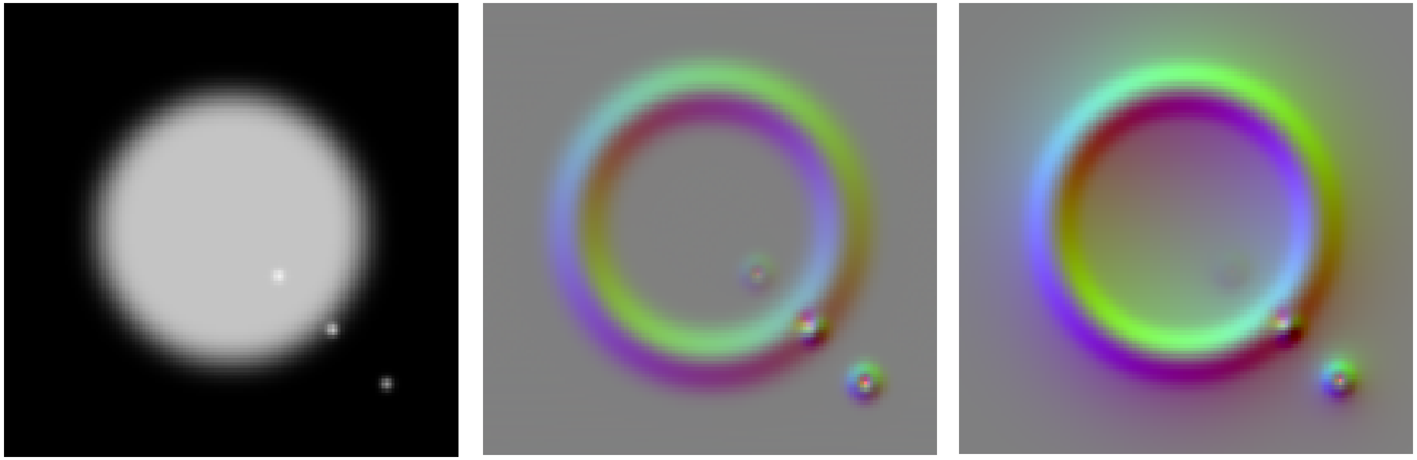
smoothing term

original gradient vectors

Gradient Vector Flow

Euler Lagrange Equation $$\mu\nabla^2\mathbf{v} - (\mathbf{v} - \nabla M)\,|\nabla M|^2 = 0$$

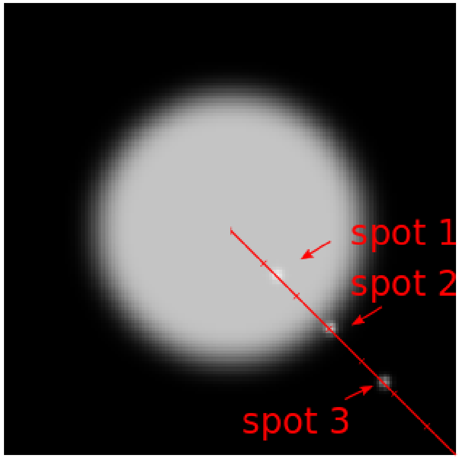
Partial Differential Equation $$\frac{\partial\mathbf{v}}{\partial t} = \mu\nabla^2\mathbf{v} - (\mathbf{v} - \nabla M)\,|\nabla M|^2$$



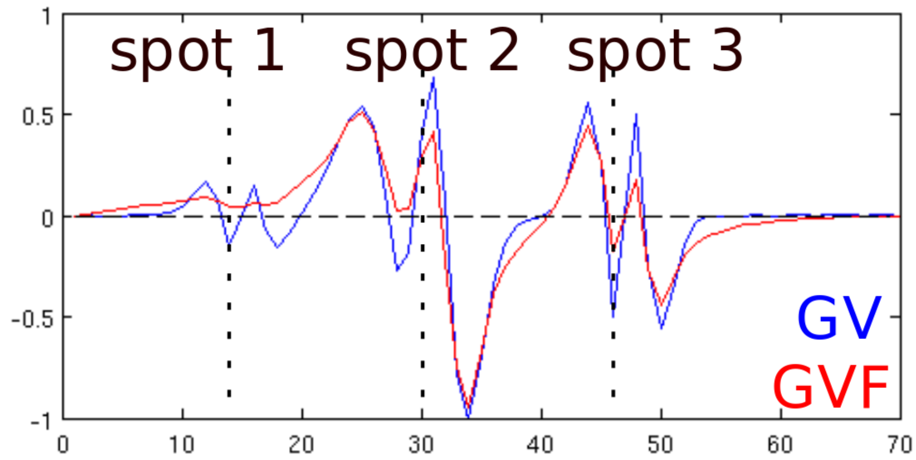
toy data gradient vectors gradient vector flow (μ=0.15)

Gradient Vector Flow

GVF on toy data, μ=0.15



toy data



magnitude profile
along the red line

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Mean Shift Filtering

Mean Shift: n-dimensional points (e.g. features, colors, vectors) are shifted towards their local density modes.

Image Processing:

D. Comaniciu and P. Meer, Mean Shift: A Robust Approach Toward Feature Space Analysis, PAMI, 24/5, 2002.

- Edge Preserving Filtering
- Segmentation

Idea: use **local density information** for the vector field generation

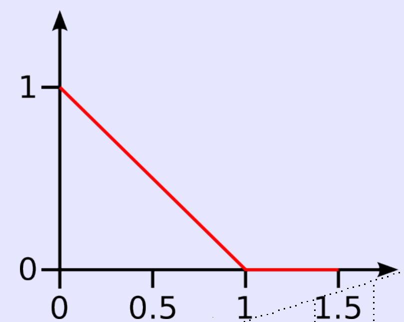
Mean Shift Filtering

Kernel Density Estimate $\hat{f}_{h,K}(\mathbf{x}) = \frac{c_{k,d}}{nh^d} \sum_{i=1}^{n} k\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{h}\right\|^2\right)$

with radially symmetric kernel $K(\mathbf{x}) = c_{k,d}k(\|\mathbf{x}\|^2)$

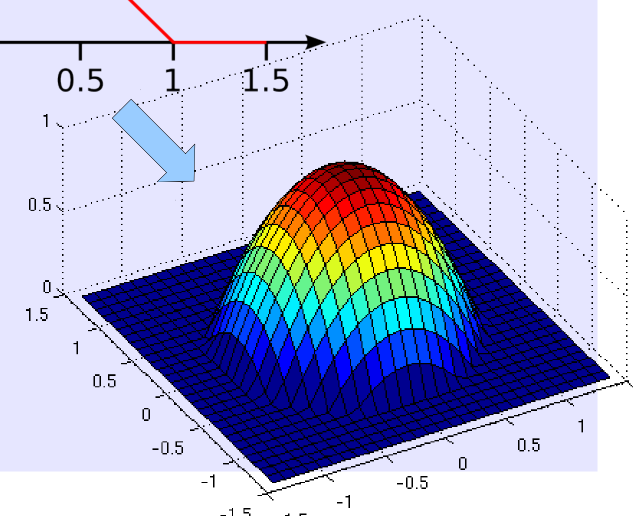
Example: Epanechnikov kernel

profile $k_E(x) = \begin{cases} 1-x & \text{if } 0 \leq x \leq 1 \\ 0 & \text{if } x > 1 \end{cases}$



kernel

$$K_E(\mathbf{x}) = \begin{cases} \frac{1}{2}c_d^{-1}(d+2)(1-\|\mathbf{x}\|^2) & \text{if } \|\mathbf{x}\| \leq 1 \\ 0 & \text{otherwise} \end{cases}$$



Mean Shift Filtering

Density Gradient Estimation

$$\nabla \hat{f}_{h,K}(\mathbf{x}) = \frac{2c_{k,d}}{nh^{d+2}} \left[\sum_{i=1}^{n} k' \left(\left\| \frac{\mathbf{x}-\mathbf{x}_i}{h} \right\|^2 \right) \right] \underbrace{\left[\mathbf{x} - \frac{\sum_{i=1}^{n} \mathbf{x}_i k' \left(\left\| \frac{\mathbf{x}-\mathbf{x}_i}{h} \right\|^2 \right)}{\sum_{i=1}^{n} k' \left(\left\| \frac{\mathbf{x}-\mathbf{x}_i}{h} \right\|^2 \right)} \right]}$$

Mean Shift:

$$\mathbf{m}_{h,G}(\mathbf{x}) = \frac{\sum_{i=1}^{n} \mathbf{x}_i g \left(\left\| \frac{\mathbf{x}-\mathbf{x}_i}{h} \right\|^2 \right)}{\sum_{i=1}^{n} g \left(\left\| \frac{\mathbf{x}-\mathbf{x}_i}{h} \right\|^2 \right)} - \mathbf{x}$$

Iteration Scheme:

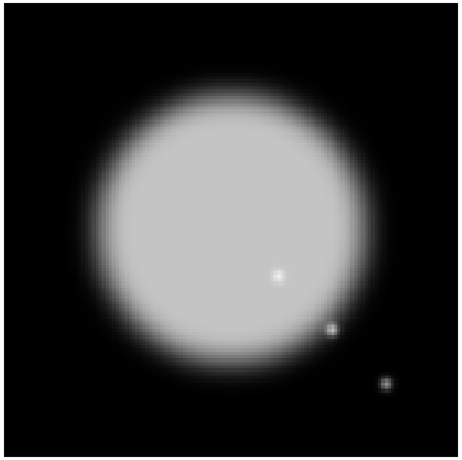
$$\mathbf{y}_{j+1} = \frac{\sum_{i=1}^{n} \mathbf{x}_i g \left(\left\| \frac{\mathbf{y}_j-\mathbf{x}_i}{h} \right\|^2 \right)}{\sum_{i=1}^{n} g \left(\left\| \frac{\mathbf{y}_j-\mathbf{x}_i}{h} \right\|^2 \right)}$$

Mean Shift Filtering

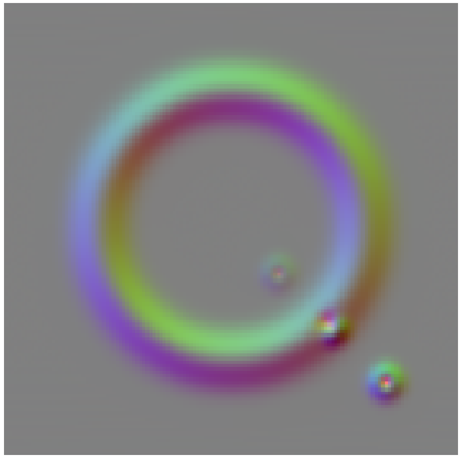
Mean Shift on 3D Vector Fields

$$K_{h_s,h_r}(\mathbf{x}) = \frac{C}{h_s^3 h_r^3} k\left(\left\|\frac{\mathbf{x}^s}{h_s}\right\|^2\right) k\left(\left\|\frac{\mathbf{x}^r}{h_r}\right\|^2\right)$$

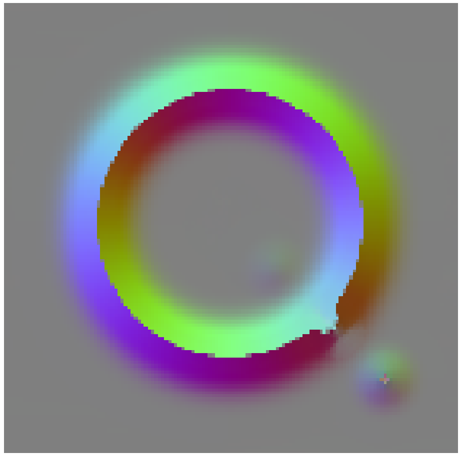
Mean shift on vectors containing spatial information **and** gradient information.



toy data



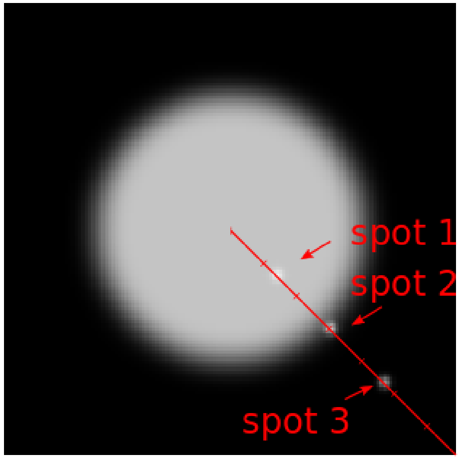
gradient vectors



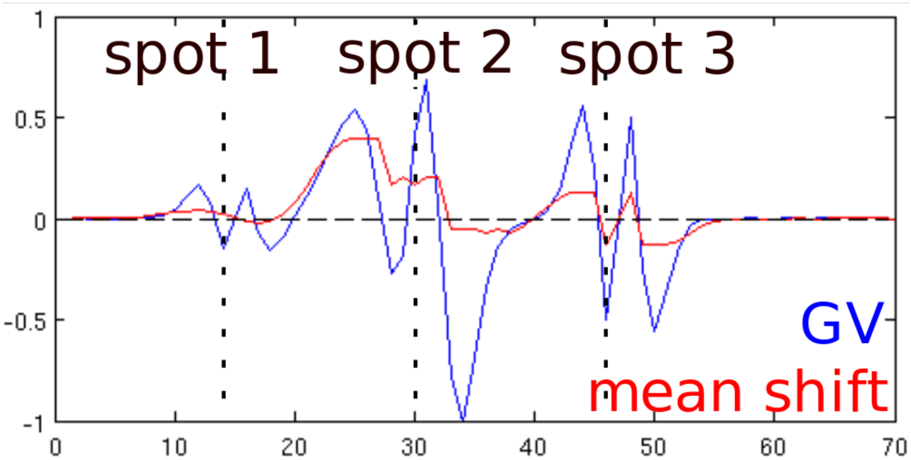
ms vector field (h_s=6, h_r=0.4)

Mean Shift Filtering

Mean Shift on toy data: h_s=6, h_r=0.4



toy data



magnitude profile along the red line

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Mean Shift Gradient Vector Flow

Mean Shift GVF

- Low Energy $$E(M,\mathbf{v}) = \int_{\mathbb{R}^3} \mu(|\nabla \mathbf{v}|^2) + |\nabla M|^2 |\mathbf{v} - \nabla M|^2 \mathrm{d}\mathbf{x}$$
- High Kernel Density $$\hat{f}_{h_s,h_r,K}(\mathbf{v}) = \frac{c_{k,d}}{n h_s^3 h_r^3} \sum_{i=1}^{n} k\left(\left\|\frac{\mathbf{v}-\mathbf{v}_i}{h}\right\|^2\right)$$

⇒ minimize $$E(M,\bar{\mathbf{v}}) = \int_{\mathbb{R}^3} \mu\left(|\nabla(\bar{\mathbf{v}})|^2\right) + |\nabla M|^2 \, |\bar{\mathbf{v}} - \nabla M|^2 \, \mathrm{d}\mathbf{x}$$

with $$\bar{\mathbf{v}} := \mathbf{v} + \hat{c}\underbrace{\frac{\nabla \hat{f}_{\mathbf{h},K}(\mathbf{v})}{\hat{f}_{\mathbf{h},G}(\mathbf{v})}}_{} = \mathbf{v} + \mathbf{m}_{\mathbf{h},G}(\mathbf{v})$$

0 at density maximum

Mean Shift Gradient Vector Flow

Mean Shift GVF

- Find Steady State Solution to

$$\frac{\partial \mathbf{v}}{\partial t} = \mu \nabla^2 (\mathbf{v} + \mathbf{m}_{h,G}(\mathbf{v})) \\ - ((\mathbf{v} + \mathbf{m}_{h,G}(\mathbf{v})) - \nabla M) \, |\nabla M|^2$$

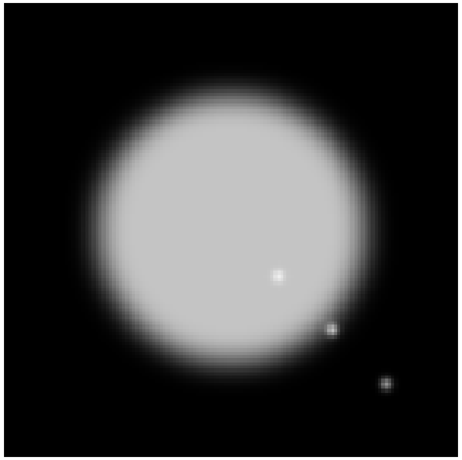
⇨ Alternate GVF and Mean Shift iteration scheme.

(PDE from GVF: $\frac{\partial \mathbf{v}}{\partial t} = \mu \nabla^2 \mathbf{v} - (\mathbf{v} - \nabla M) \, |\nabla M|^2$)

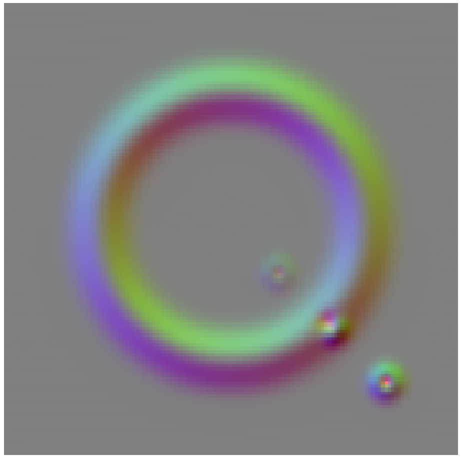
Mean Shift Gradient Vector Flow

Properties:

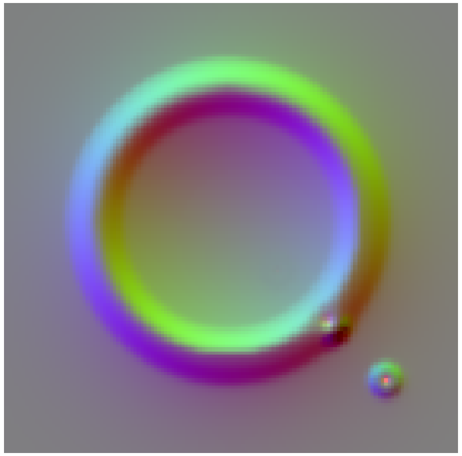
- Preserve original gradient information in regions with strong edges
- Diffuse gradient vectors according to their magnitude **and density**
- Smooth vector field in regions with weak edges and low density



toy data



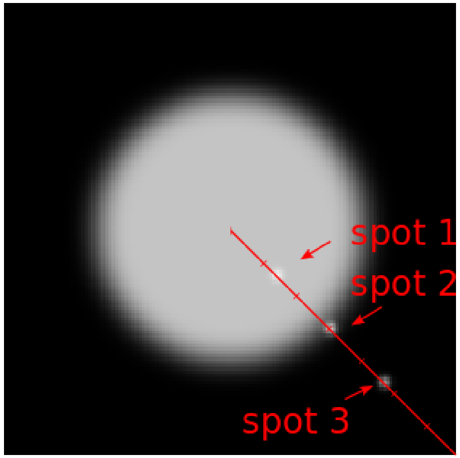
gradient vectors



mean shift gvf
(μ=0.15, h_s=6, h_r=0.2)

Mean Shift Gradient Vector Flow

MSGVF on toy data, $\mu=0.15$, $h_s=6$, $h_r=0.2$



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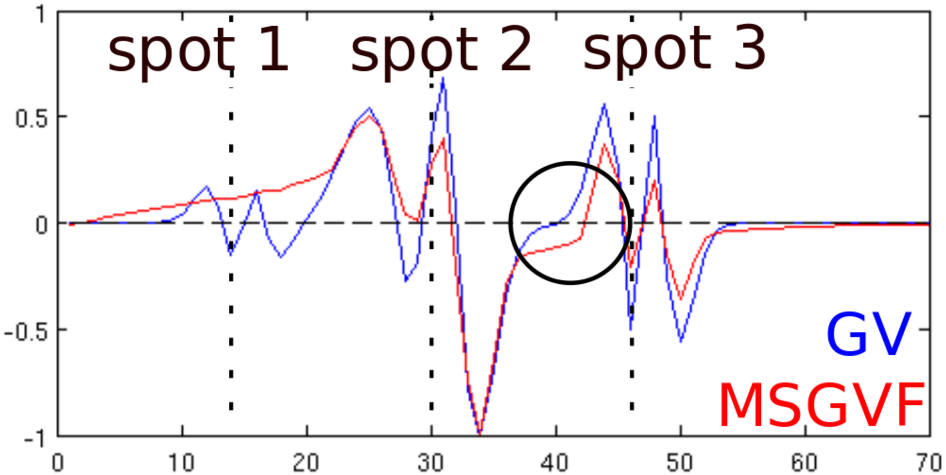
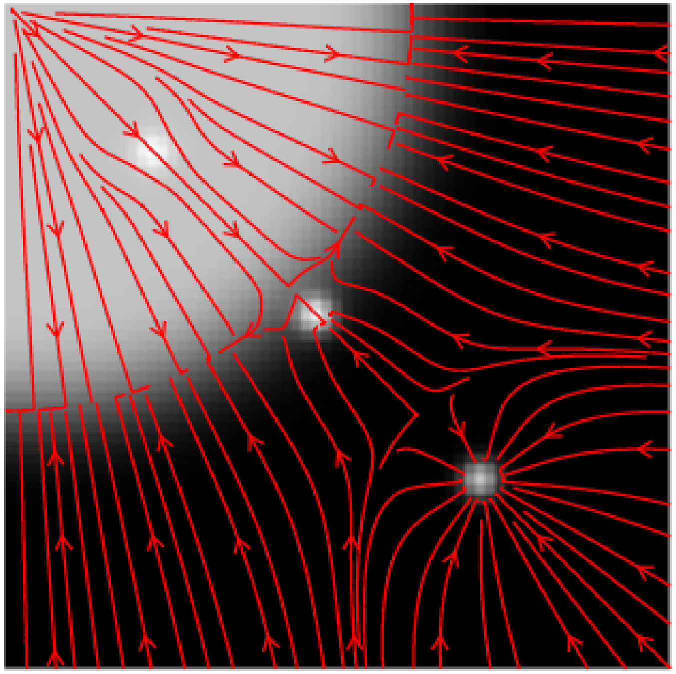


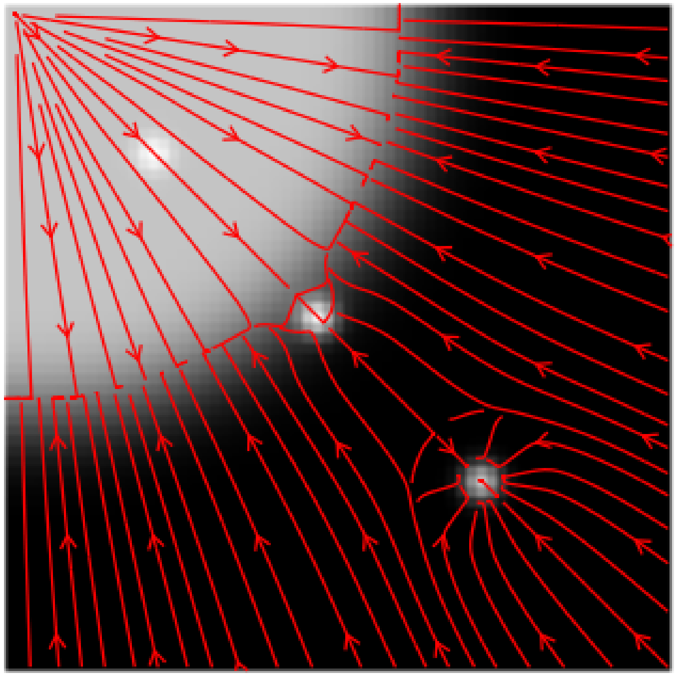
magnitude profile
along the red line

GVF vs Mean Shift GVF

Influence on the capture range: Streamline plots



GVF



MSGVF

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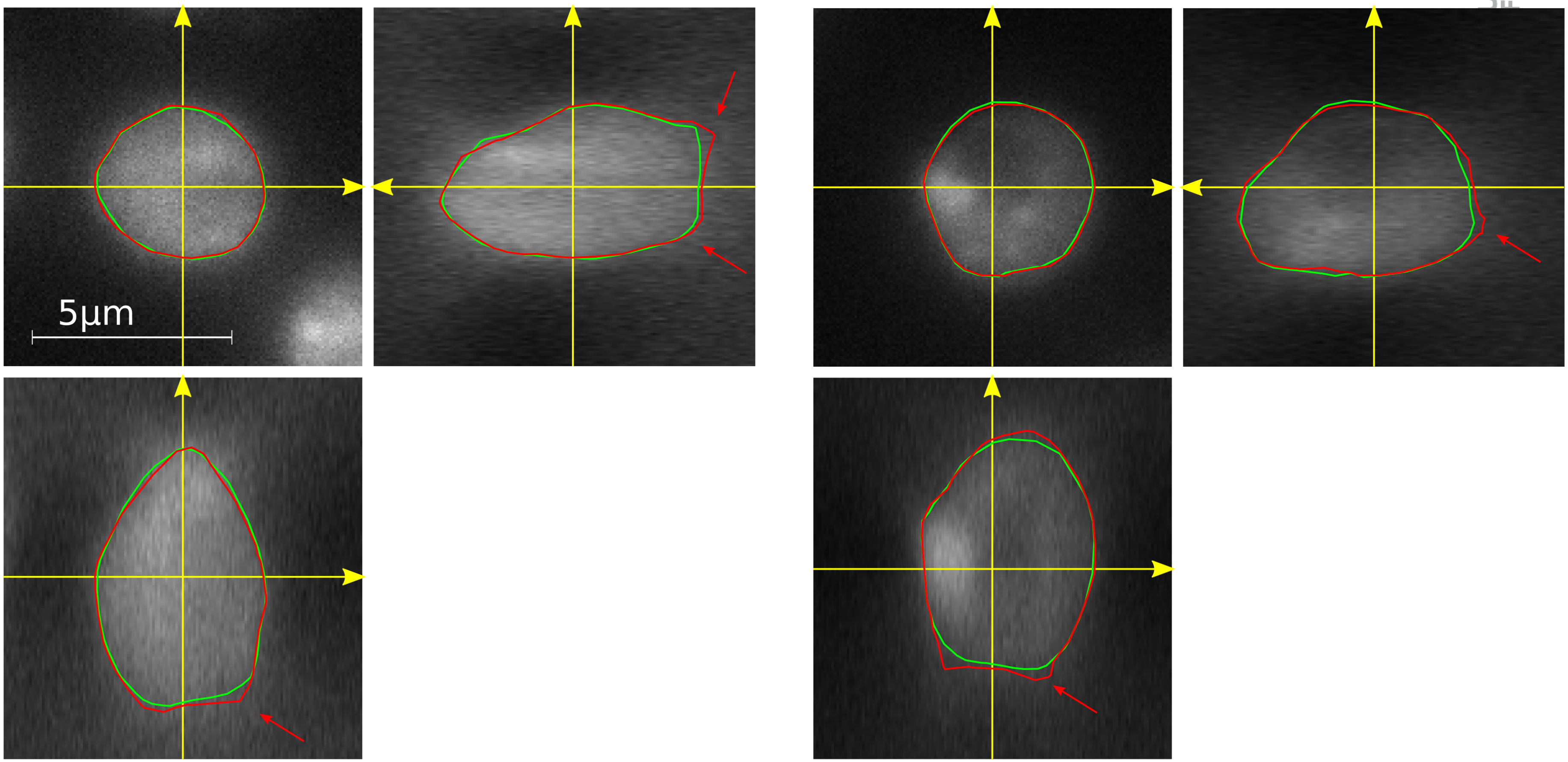
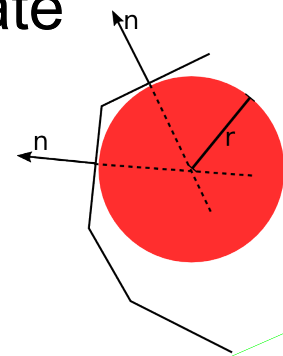
Results

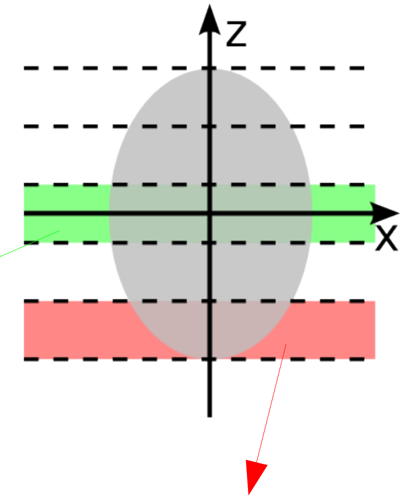


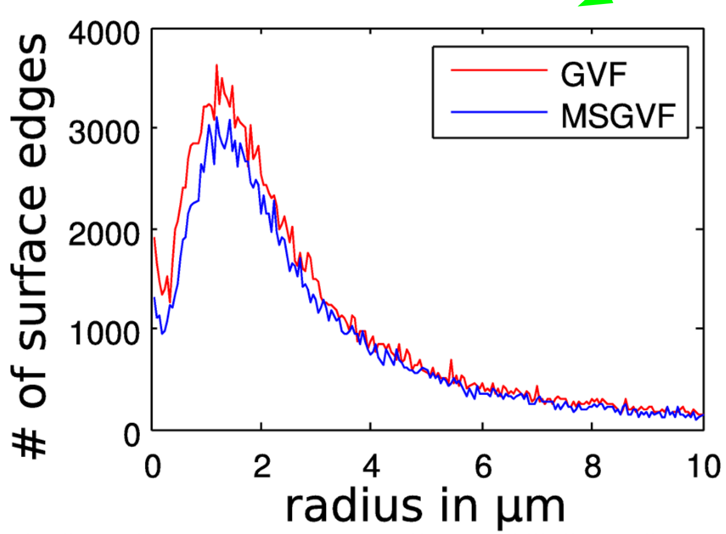
red contour: standard GVF
green contour: MSGVF

Results

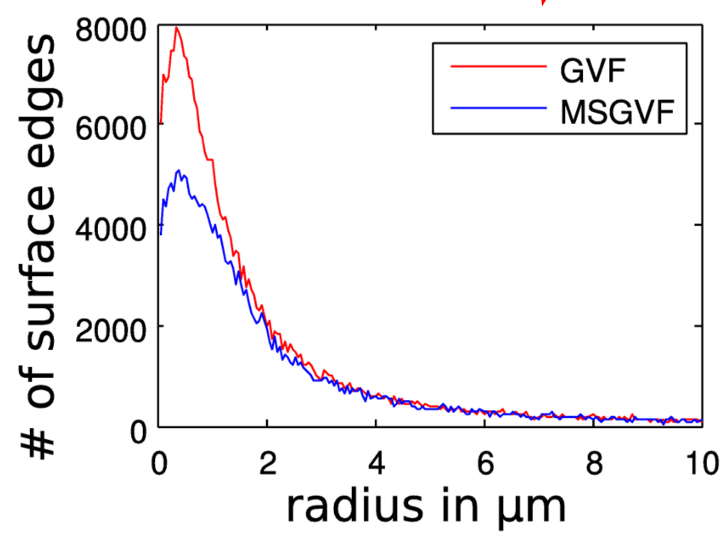
Measure: Locally approximate the surface by spheres and estimate their radii. These radii should be similar to the cell radius (i.e. ~2µm).







(a) Histogram of radii in the central layers.



(b) Radii in the lower 20% of the surface.

Conclusion

- New method for the generation of external force fields for 2D and 3D active contours
- Robust against noise and small structures that should not influence the overall force field
- Improved segmentation results on strongly blurred data from 3D widefield microscopy (less PSF artifacts)

Outlook

- No 3D segmentation benchmark available for cell nuclei
- No segmentation ground truth available for our data
- Try the method on a broader range of data

Acknowledgments

MPI (Max Planck Institute for Immunobiology):

- Jan Padeken , Patrick Heun

LMB (Computer Science Department, University of Freiburg):

- Junior Prof. Olaf Ronneberger, Prof. Hans Burkhardt

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Questions?

Literatur

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6. M. Keuper, **Mean Shifting Gradient Vector Flow, an Improved Force Field for Active Surfaces in Widefield Microscopy**, Technical Report, IIF-LMB, University of Freiburg, 2010.

Mean Shift Gradient Vector Flow

Mean Shift GVF

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- High Kernel Density

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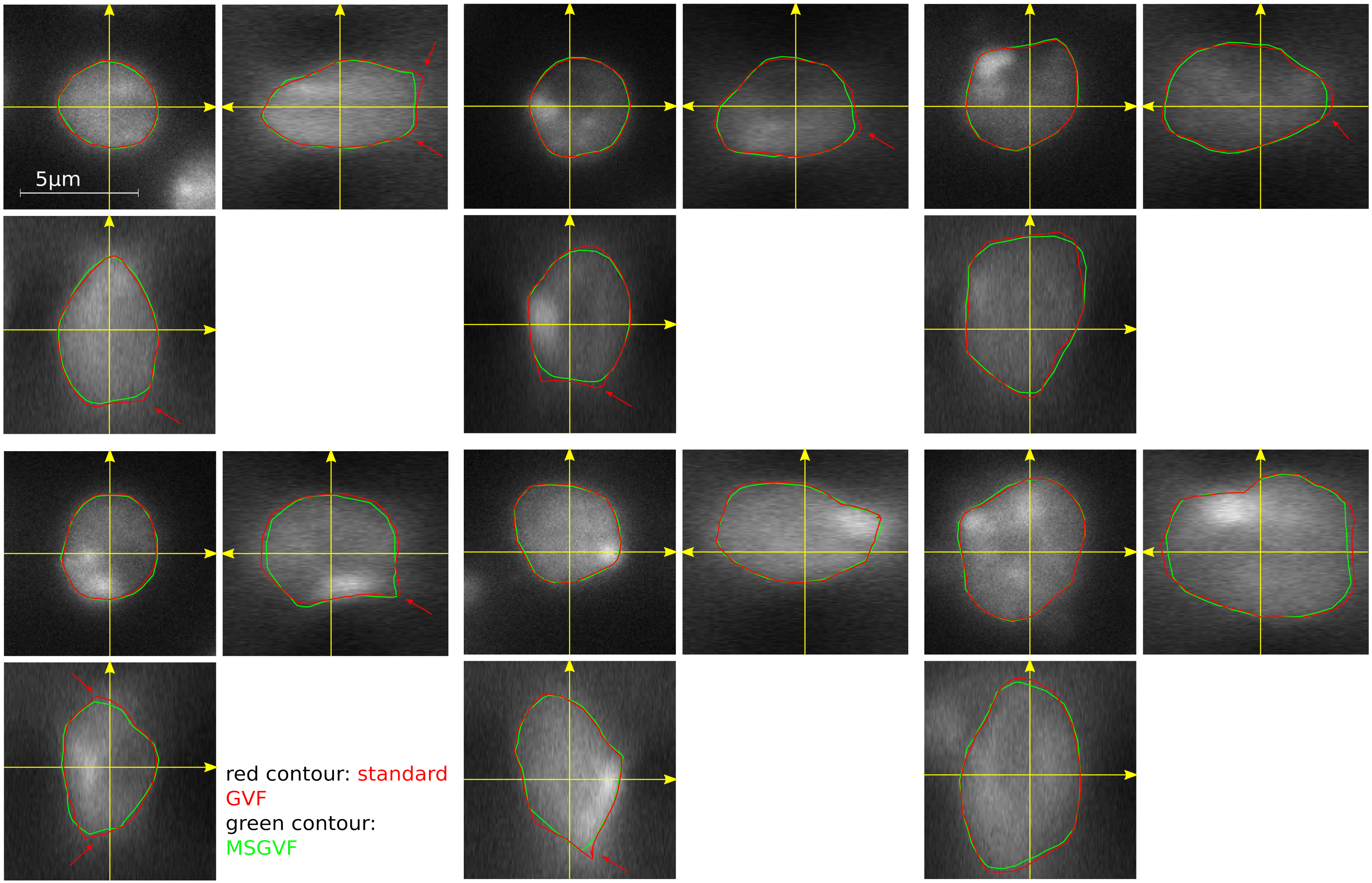
- Find Steady State Solution to

$$\begin{aligned}\frac{\partial \mathbf{v}}{\partial t} = {} & \mu \nabla^2 (\mathbf{v} + \mathbf{m}_{h,g}(\mathbf{v})) \\ & - ((\mathbf{v} + \mathbf{m}_{h,g}(\mathbf{v})) - \nabla M) |\nabla M|^2\end{aligned}$$

➡ Alternate GVF and Mean Shift iteration scheme.

Results



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