

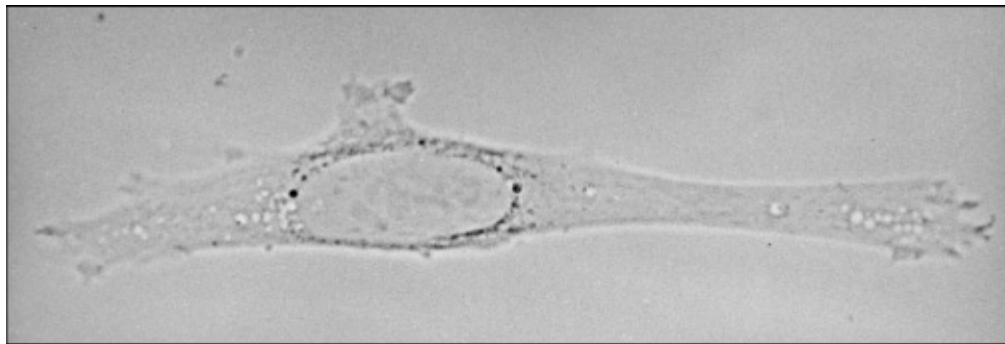
Cell Segmentation and Tracking in Phase Contrast Images using Graph Cut with Asymmetric Boundary Costs

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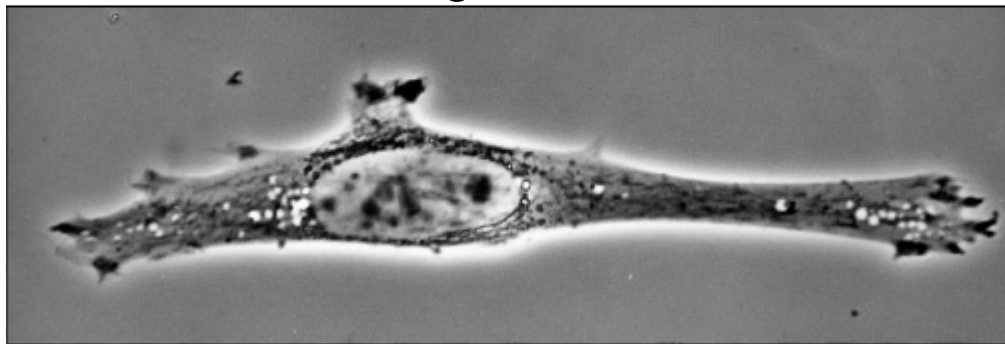


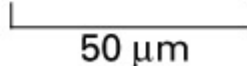
2015 IEEE International Symposium on Biomedical Imaging: From Nano to Macro
April 16-19, Brooklyn, NY, USA

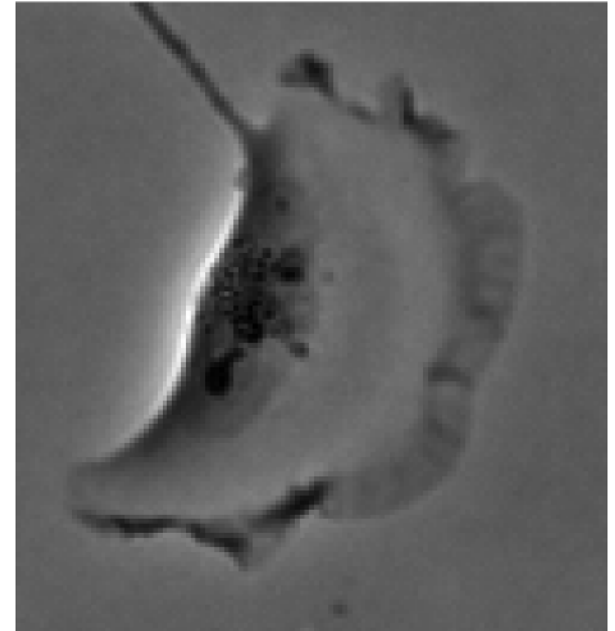
- Introduction
- Method
 - Segmentation
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- Conclusion



(A) Bright-field



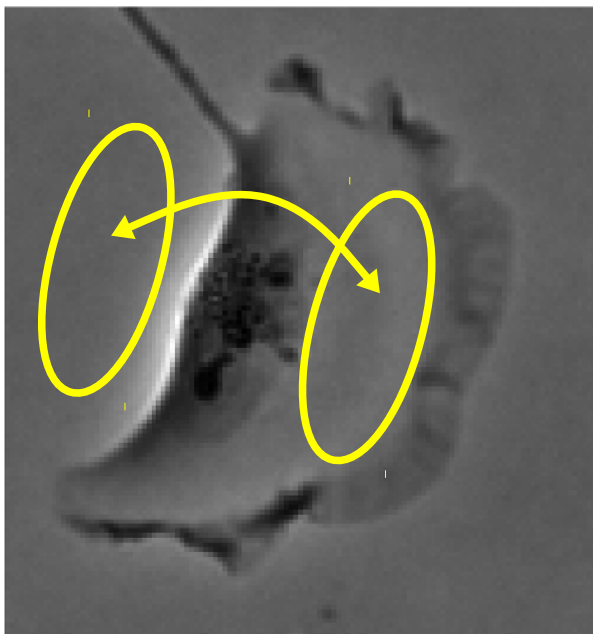
(B) Phase-contrast 



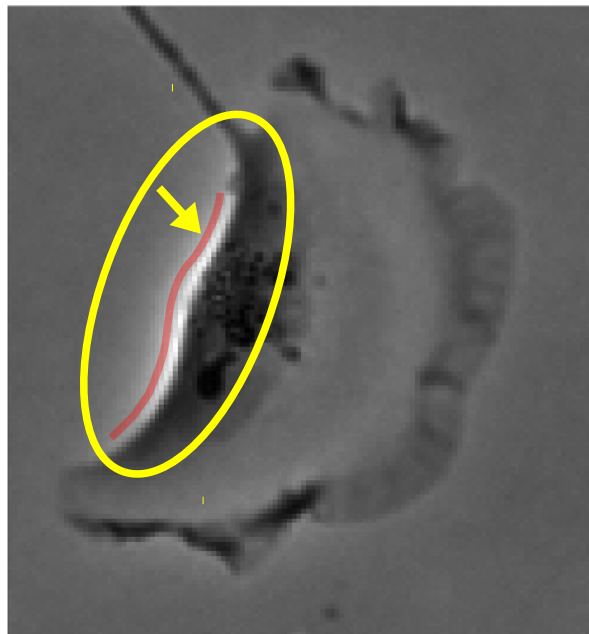
Phase-contrast

Figure: B. Alberts et al., Molecular Biology of the Cell, 4th Edition, 2002.

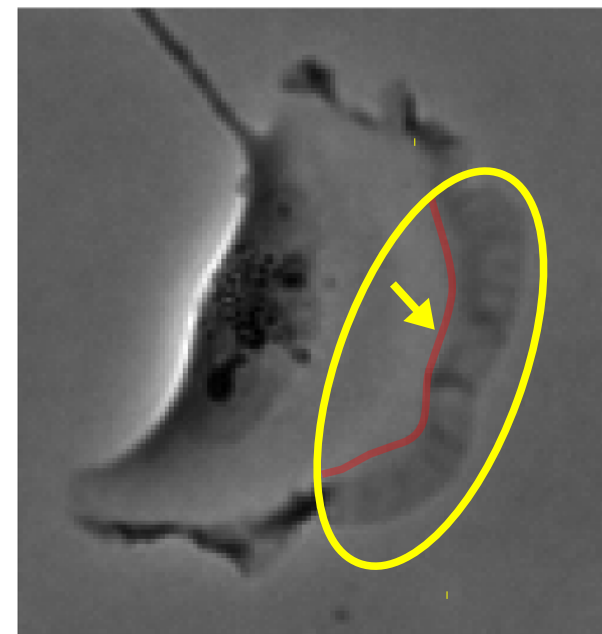
- **Visualize transparent objects** with high contrast at cell borders



Shade-off

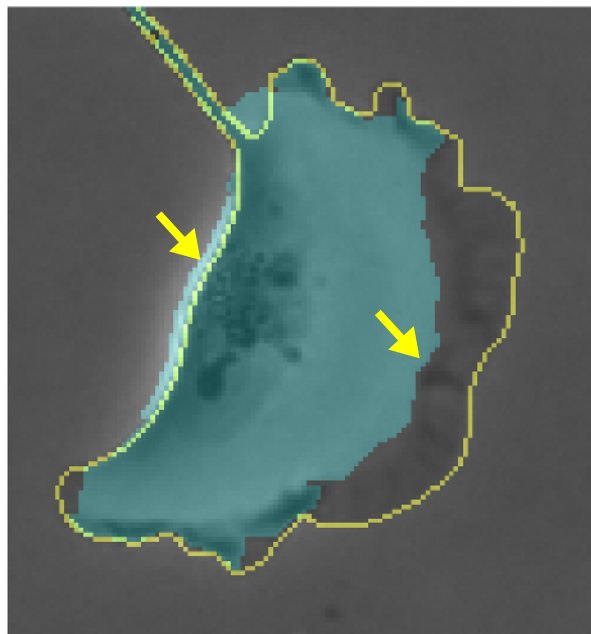


Halo pattern



Strong edges inside
and outside the cell

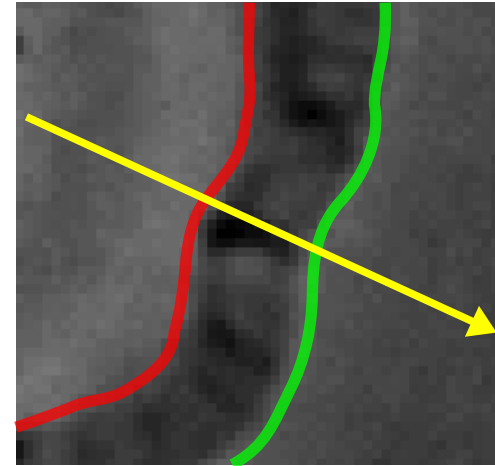
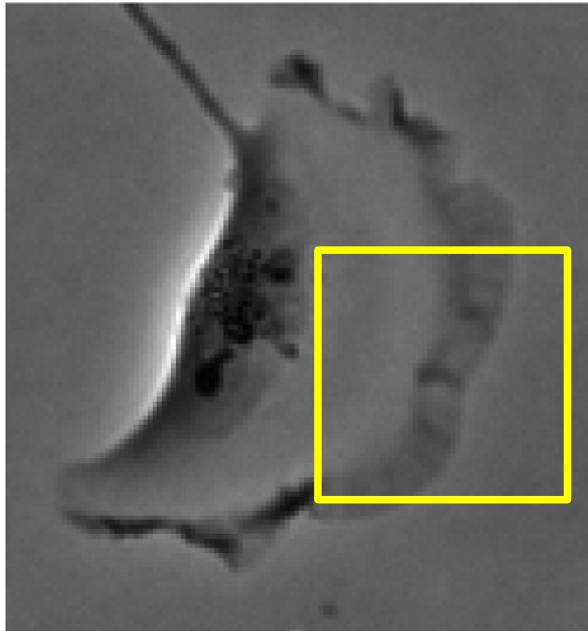
- Drawback: **Various artifacts**



Cyan: Graph cut segmentation result
Yellow: Our manual ground truth

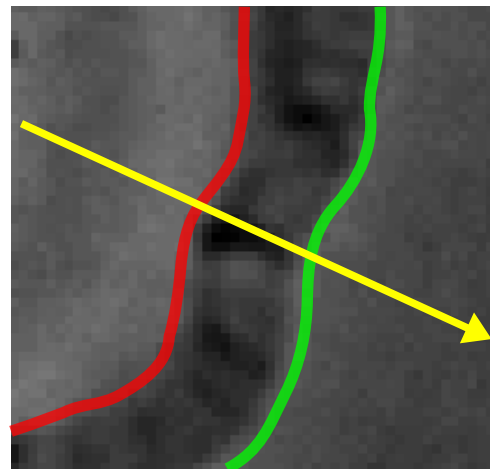
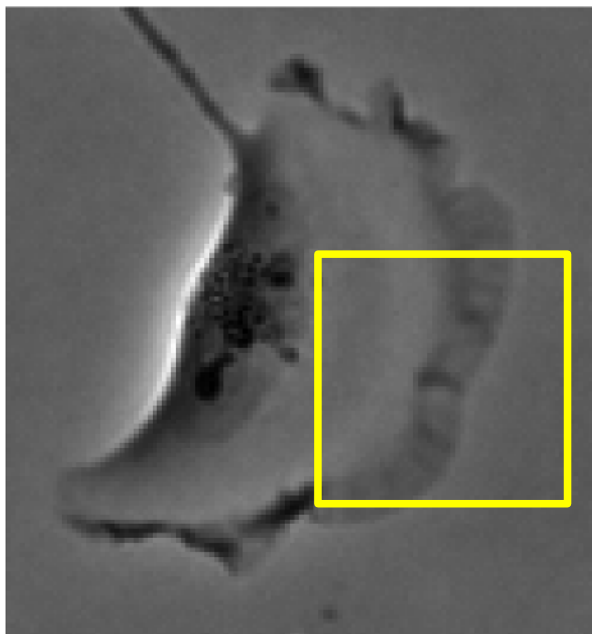
- Standard edge-based segmentation algorithms fail
- Traditional graph cut with **symmetric boundary costs**.

- True cell borders appear as **dark-to-bright** transition (positive phase contrast microscopy)



Yellow: Cell outwards direction
Green: True cell border
Red: Wrong cell border

- True cell borders appear as **dark-to-bright** transition (positive phase contrast microscopy)



Yellow: Cell outwards direction
Green: True cell border
Red: Wrong cell border

- Search for segmentation mask that favors dark-to-bright transitions at its boundary
- Graph cut with **asymmetric boundary costs**

- Kanade et al.: Two-step reconstruction approach
 - Reconstruct abs. phase image & apply basic threshold techniques
 - Fails if sample contains light absorbing structures
- Ambühl et al.: Morphological image processing and level sets
 - Handle halo artifacts by changing image during level set evolution
- Magnusson et al.: Winner ISBI Cell Tracking Challenge 2014
 - Strong tracking approach & Segmentation based on bandpass filtering, thresholding and watershed transform

- (1) K. Li and T. Kanade, “Nonnegative mixed-norm preconditioning for microscopy image segmentation,” Proceedings of IPMI, pp. 362–373, 2009.
- (2) M.E. Ambül, C. Brepsant, J.-J. Meister, A.B. Verkhovsky, and I.F. Sbalzarini, “High-resolution cell outline segmentation and tracking from phase-contrast microscopy images,” JOM, vol. 245, no.2, pp. 161–170, 2012.
- (3) K. Magnusson, J. Jaldén, and H. M. Blau, Cell tracking using bandpass filtering and the viterbi algorithm, Description of the algorithm available at: <http://www.codesolorzano.com/celltrackingchallenge/>

- Kanade et al.: Two-step reconstruction approach
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- Magnusson et al.: Winner ISBI Cell Tracking Challenge 2014
 - Strong tracking approach & Segmentation based on bandpass filtering, thresholding and watershed transform
- Boykov et al.: Asymmetric boundary costs in min-cut
 - Propose asymmetric boundary costs for segmentation
 - *Never been applied to phase contrast microscopy*

- (1) K. Li and T. Kanade, “Nonnegative mixed-norm preconditioning for microscopy image segmentation,” Proceedings of IPMI, pp. 362–373, 2009.
- (2) M.E. Ambül, C. Brepsant, J.-J. Meister, A.B. Verkhovsky, and I.F. Sbalzarini, “High-resolution cell outline segmentation and tracking from phase-contrast microscopy images,” JOM, vol. 245, no.2, pp. 161–170, 2012.
- (3) K. Magnusson, J. Jaldén, and H. M. Blau, Cell tracking using bandpass filtering and the viterbi algorithm, Description of the algorithm available at: <http://www.codesolorzano.com/celltrackingchallenge/>
- (4) Y. Boykov and G. Funka-Lea, “Graph cuts and efficient n-d image segmentation,” IJCV, vol. 70, no. 2, pp. 109–131, 2006.

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- Cost function (Region & boundary term)

$$E(M) = \lambda \cdot R(M) + B(M)$$

Mask $M : \Omega \rightarrow \{0, 1\}$,
 $\Omega \subset \mathbb{R}^2$

- Boundary term

$$B(M) = \int_{\Omega} C_{\text{edge}} \left(\underbrace{\langle \nabla M(\mathbf{x}), -\nabla I(\mathbf{x}) \rangle}_{\substack{\text{intensity derivative } d \\ \text{(perpendicular to mask boundary)}}} \right) d\mathbf{x}$$

Image I
 ∇M unit normal vector
 on mask boundary, and
0 elsewhere

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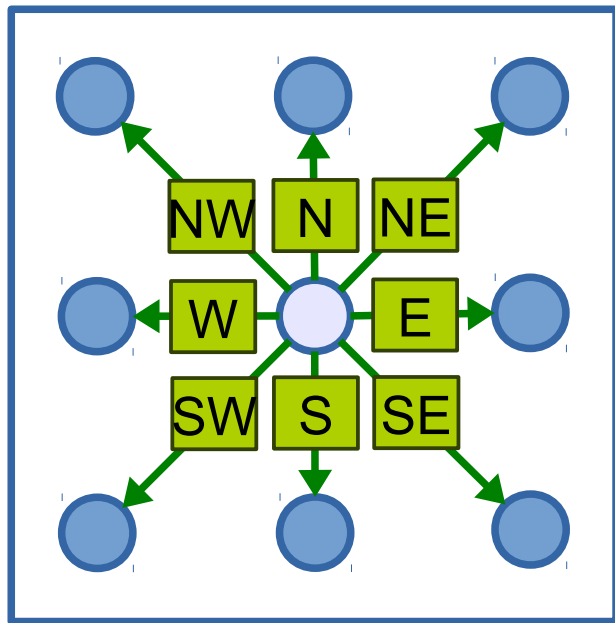
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Image I
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 $\mathbf{0}$ elsewhere

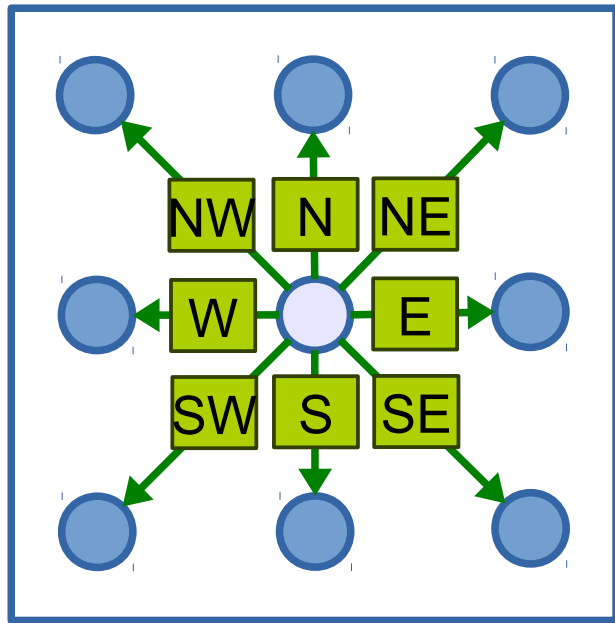
- **Asymmetric** boundary penalties (**dark-to-bright**)

$$C_{\text{edge}}(d) = \begin{cases} \exp\left(-\frac{d^2}{2\sigma^2}\right) & \text{if } \boxed{d > 0} \\ 1 & \text{else.} \end{cases}$$

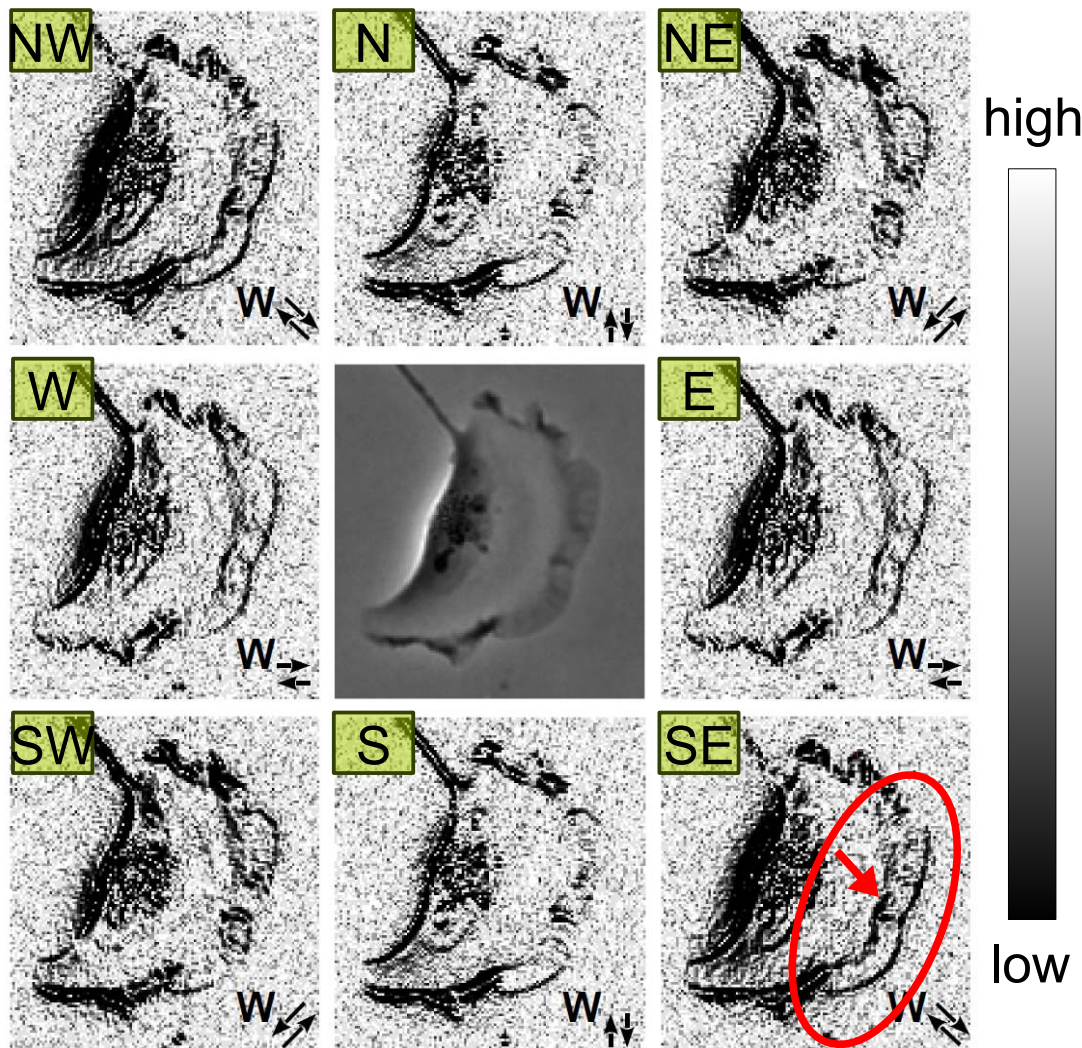
→ **directed graph**
 with asymmetric
 edge weights



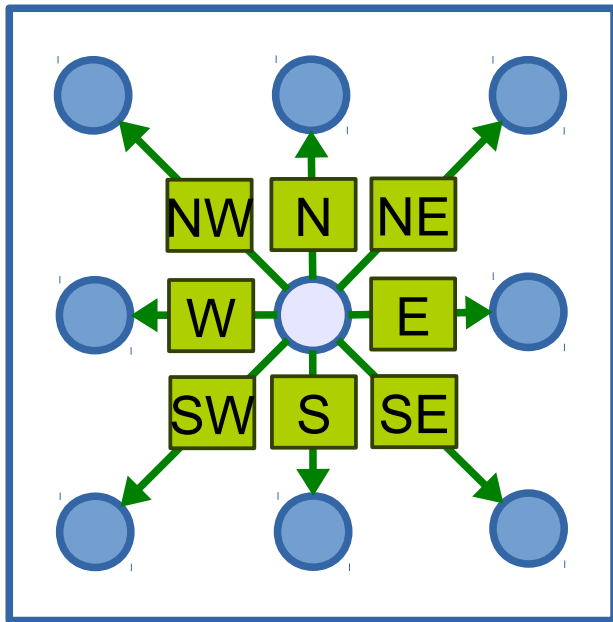
3x3 pixel neighborhood,
Edges and weights (only
outwards edges shown)



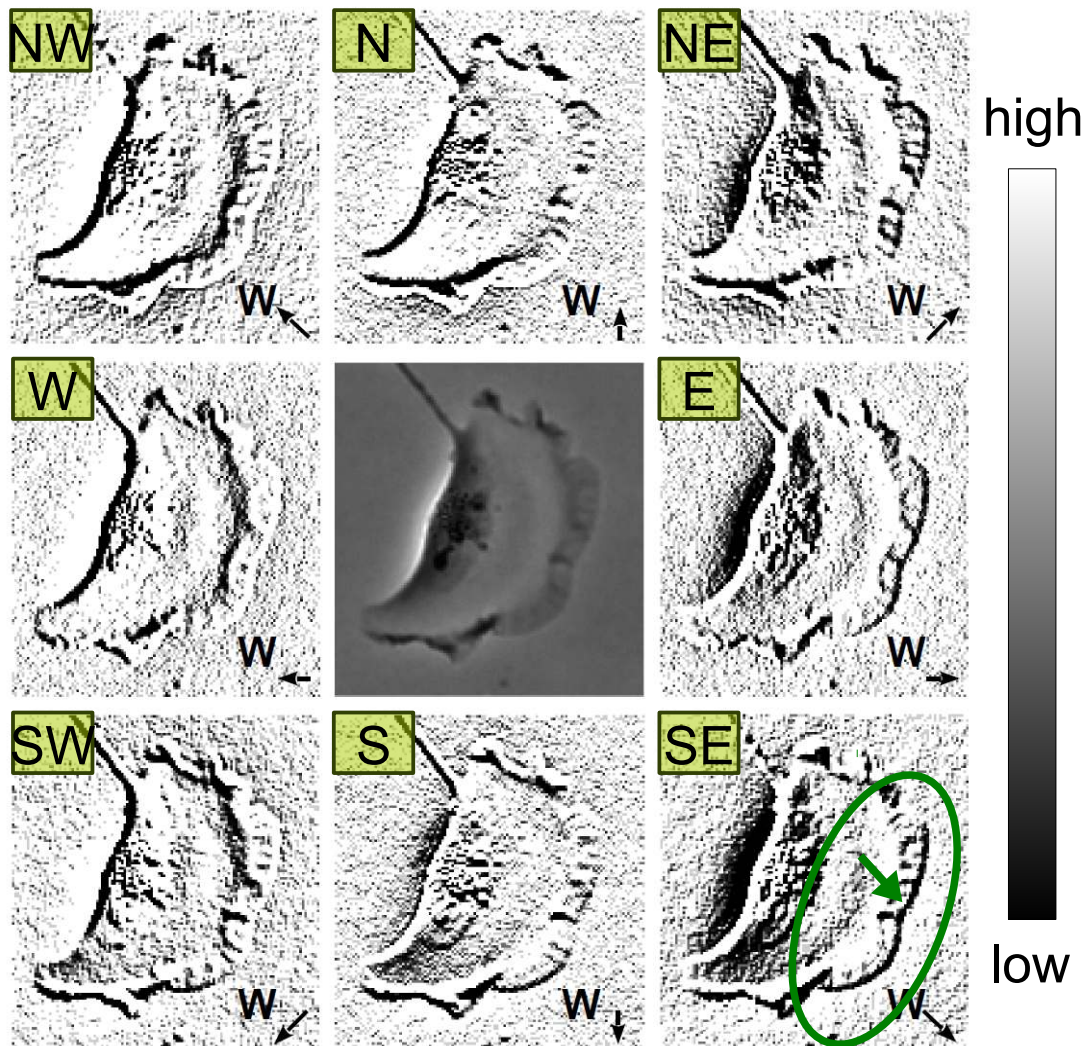
3x3 pixel neighborhood,
Edges and weights (only
outwards edges shown)



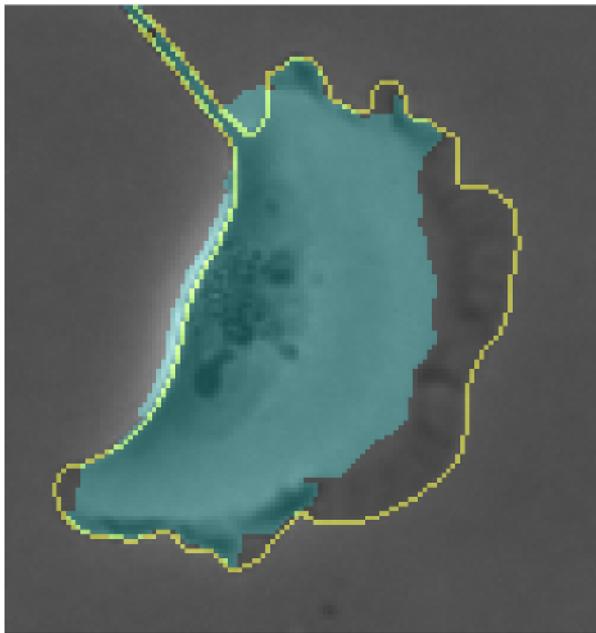
- Low costs at **wrong cell borders**
(bright-to-dark transitions)



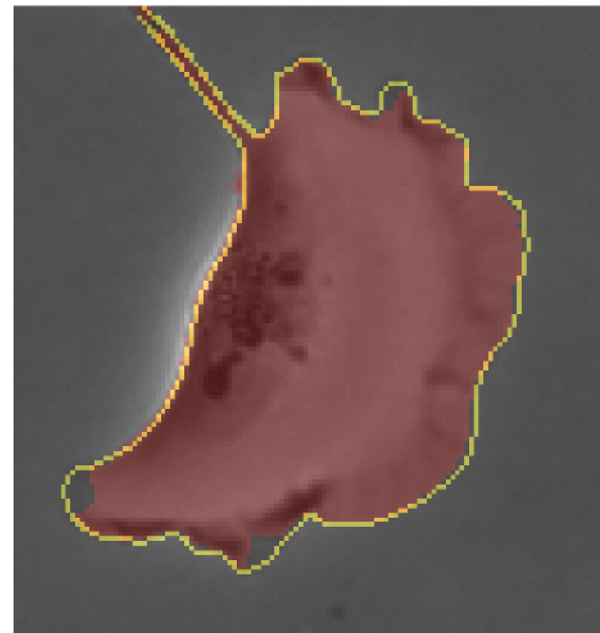
3x3 pixel neighborhood,
Edges and weights (only
outwards edges shown)



- Low costs at **correct cell borders**
(dark-to-bright transitions)



Cyan mask: Segmentation result of graph cut with **symmetric costs**
Yellow: Our manual ground truth



Red mask: Segmentation result of **proposed method**
Yellow: Our manual ground truth

- Standard graph cut (**negative log-likelihood**)

$$R(A) = \sum_{p \in \mathcal{P}} R_p(A_p) \quad (\text{regional term})$$

$$R_p(\text{"obj"}) = -\ln \Pr(I_p | \text{"obj"}) \quad (\text{object penalty})$$

$$R_p(\text{"bkg"}) = -\ln \Pr(I_p | \text{"bkg"}) \quad (\text{background penalty})$$

→ **hard constraint**

- Standard graph cut (**negative log-likelihood**)

$$R(A) = \sum_{p \in \mathcal{P}} R_p(A_p) \quad (\text{regional term})$$

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→ **hard constraint**

- In our approach

$$R(M) = \int_{\Omega} M(\mathbf{x}) \cdot C_{\text{obj}}(I(\mathbf{x})) d\mathbf{x} \quad (\text{regional term})$$

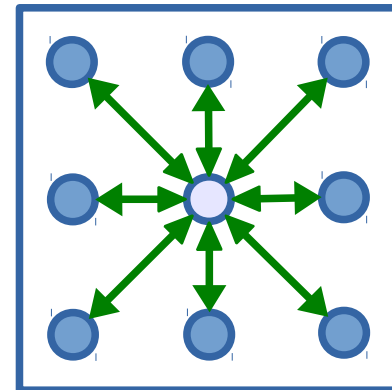
$$C_{\text{obj}}(v) = \frac{P(v|\mathcal{B}) - P(v|\mathcal{O})}{P(v|\mathcal{O}) + P(v|\mathcal{B})} \quad (\text{data costs})$$

Intensity v
 $P(v|\mathcal{O})$ and $P(v|\mathcal{B})$
from fore-/background
intensity histograms

→ **soft constraint**

$$E(M) = \lambda \int_{\Omega} M(\mathbf{x}) \cdot C_{\text{obj}}(I(\mathbf{x})) d\mathbf{x} + \int_{\Omega} C_{\text{edge}} (\langle \nabla M(\mathbf{x}), -\nabla I(\mathbf{x}) \rangle) d\mathbf{x}$$

- Energy minimization problem
- Discretize edge term into 8 directions
→ combinatorial optimization problem
- Solve efficiently by a **min-cut approach**



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1) Propagate Segmentation Information

a) Foreground information

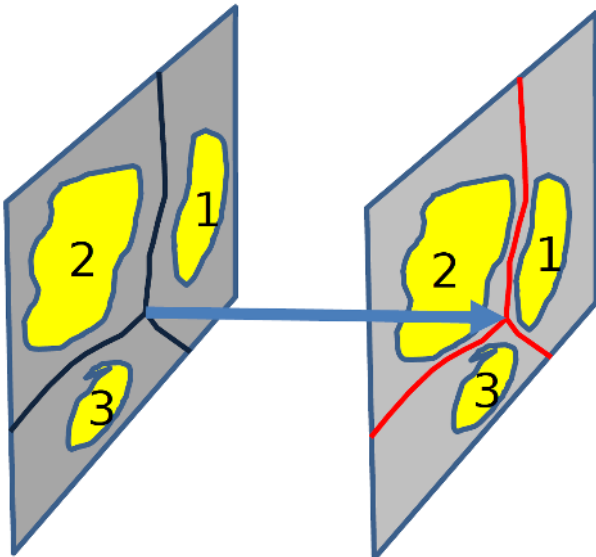
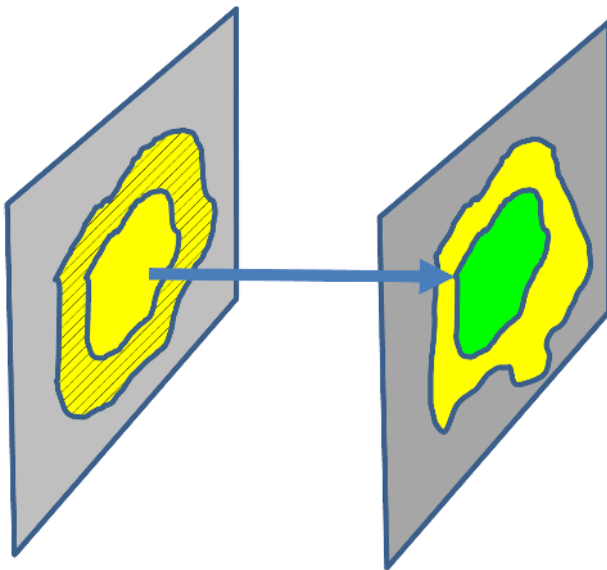
using eroded mask

→ hard foreground constraint

b) Partitioning information

using borders of „support regions“

→ hard background constraint



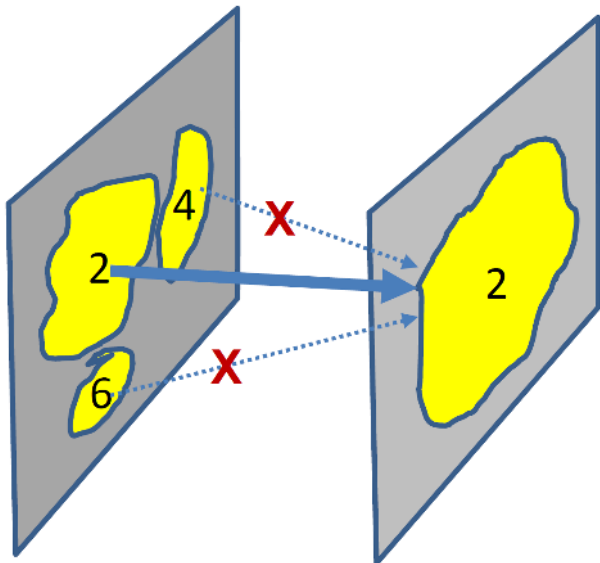
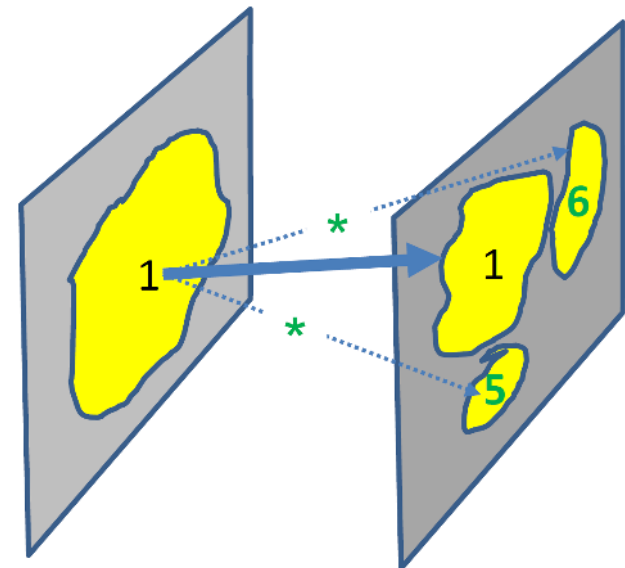
2) Propagate Labels to overlapping Segments using max. IoU

a) Resolve **one-to-many** correspondences

- start new tracks (with new label)

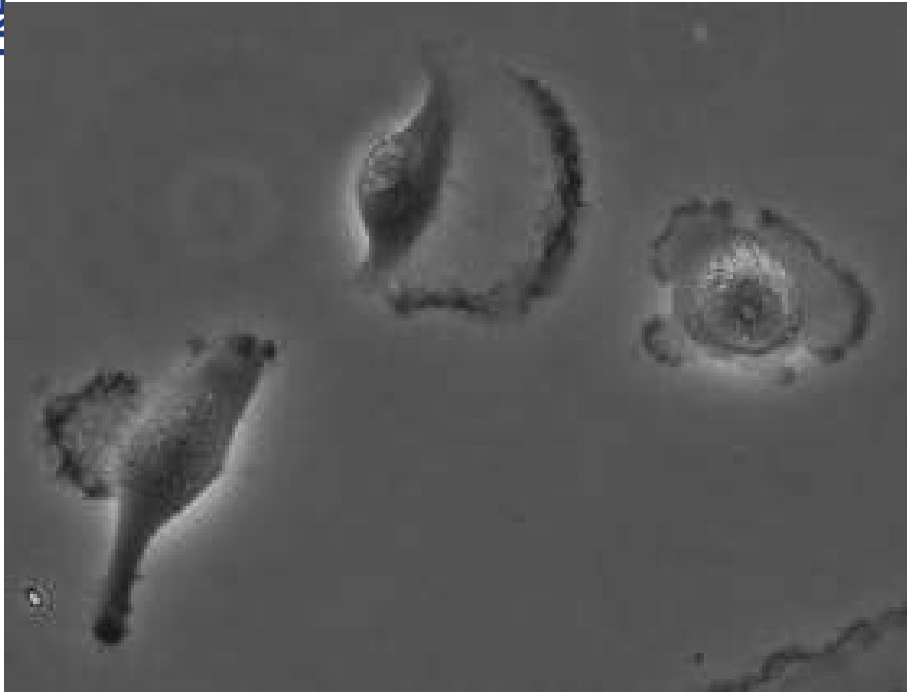
b) Resolve **many-to-one** correspondences

- stop other tracks



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Datasets: ISBI cell tracking challenge^{1,2}



Glioblastoma-astrocytoma U373 cells
on a polyacrylimide substrate*
Phase contrast microscopy

- Strong **shape** variations
- Weak outer **borders**, strong irrelevant inner borders
- **Cytoplasm** has same structure as background

(1) ISBI Cell Tracking Challenge, Available at: <http://www.codesolorzano.com/celltrackingchallenge>.

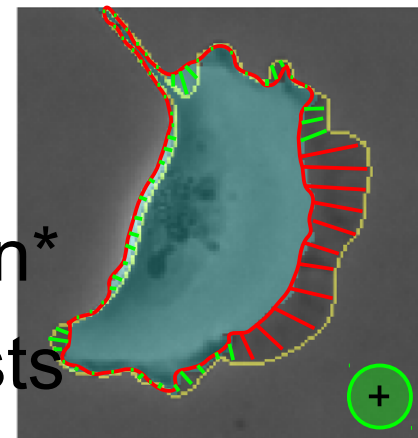
(2) M. Maška, V. Ulman, D. Svoboda, P. Matula, and P. Matula, et al., “A benchmark for comparison of cell tracking algorithms,” *Bioinformatics*, vol. 30, no. 11, pp. 1609–1617, 2014.

*Data provided by Dr. Sanjay Kumar, Department of Bioengineering University of California at Berkeley, Berkeley CA (USA).

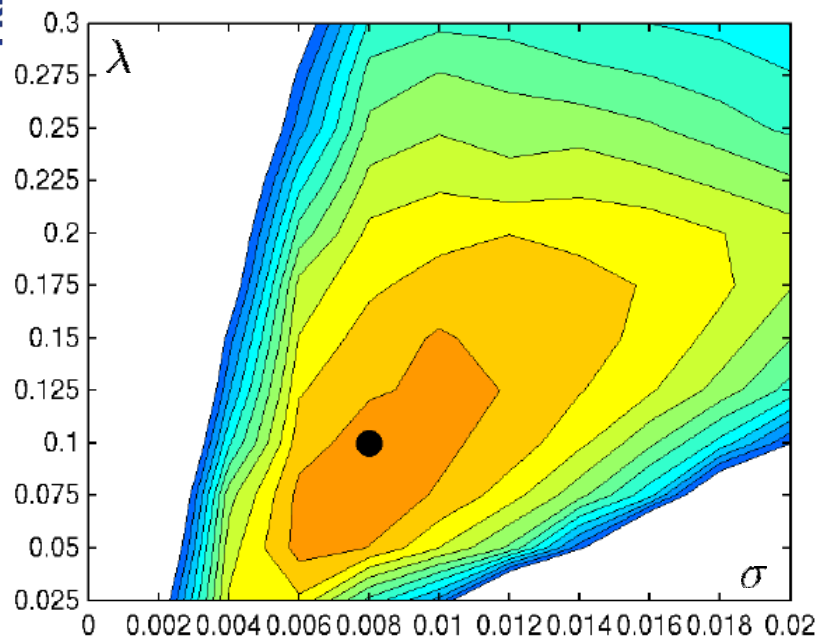
Boundary costs	Seq. 1			Seq. 2		
	F-meas.	Recall	Prec.	F-meas.	Recall	Prec.
Symm.	0.863	0.838	0.889	0.768	0.732	0.808
Asymm. (Equ. 2)	0.896	0.894	0.897	0.835	0.822	0.847

Boundary detection F-measure, recall and precision (4 pixels tolerance)

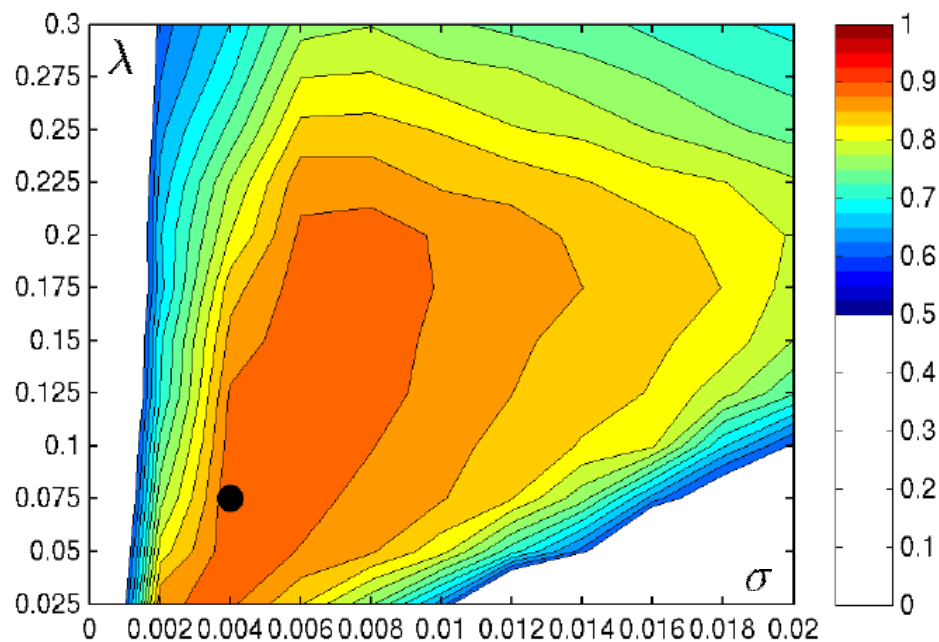
- **Boundary detection** recall and precision*
- Symmetric vs. asymmetric boundary costs



*Computed using code from „The Berkeley Segmentation Dataset and Benchmark“, Available at: <http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/>.



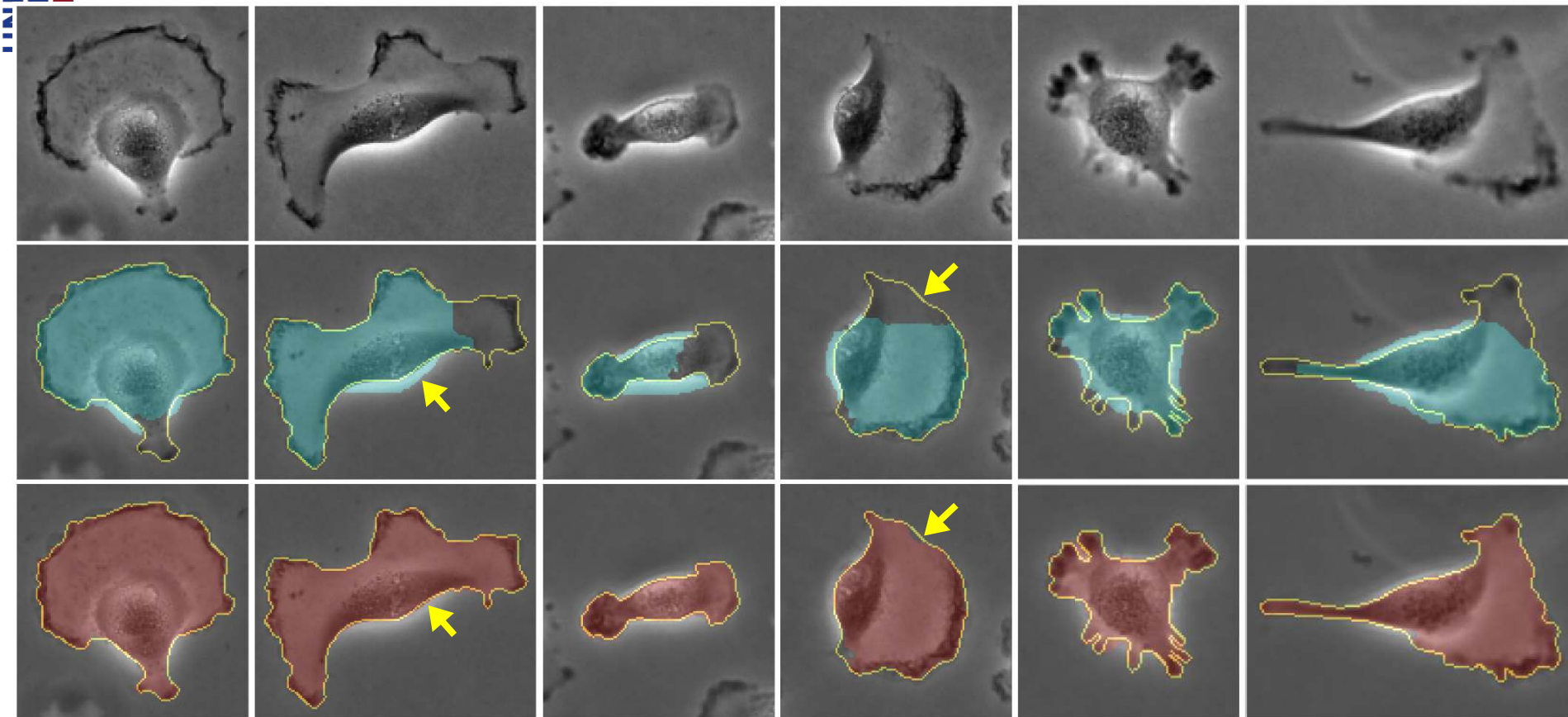
Symmetric boundary costs,
F-measure isolines



Asymmetric boundary costs, F-
measure isolines

- Boundary detection results across **varying min-cut parameters** lambda and sigma.

Experiments: Symmetric vs. asymmetric costs



Cyan masks: Graph cut with symmetric costs, Red masks: Our approach with asymmetric costs, Yellow borders: Our manual ground truth

- Improved detection of very **weak boundaries**
- **Halo boundaries** are handled well

Group	Av. SEG	Av. TRA
KTH-SE	0.7953	0.9818
HOUS-US	0.5323	0.9206
IMCB-SG	0.2669	0.9595

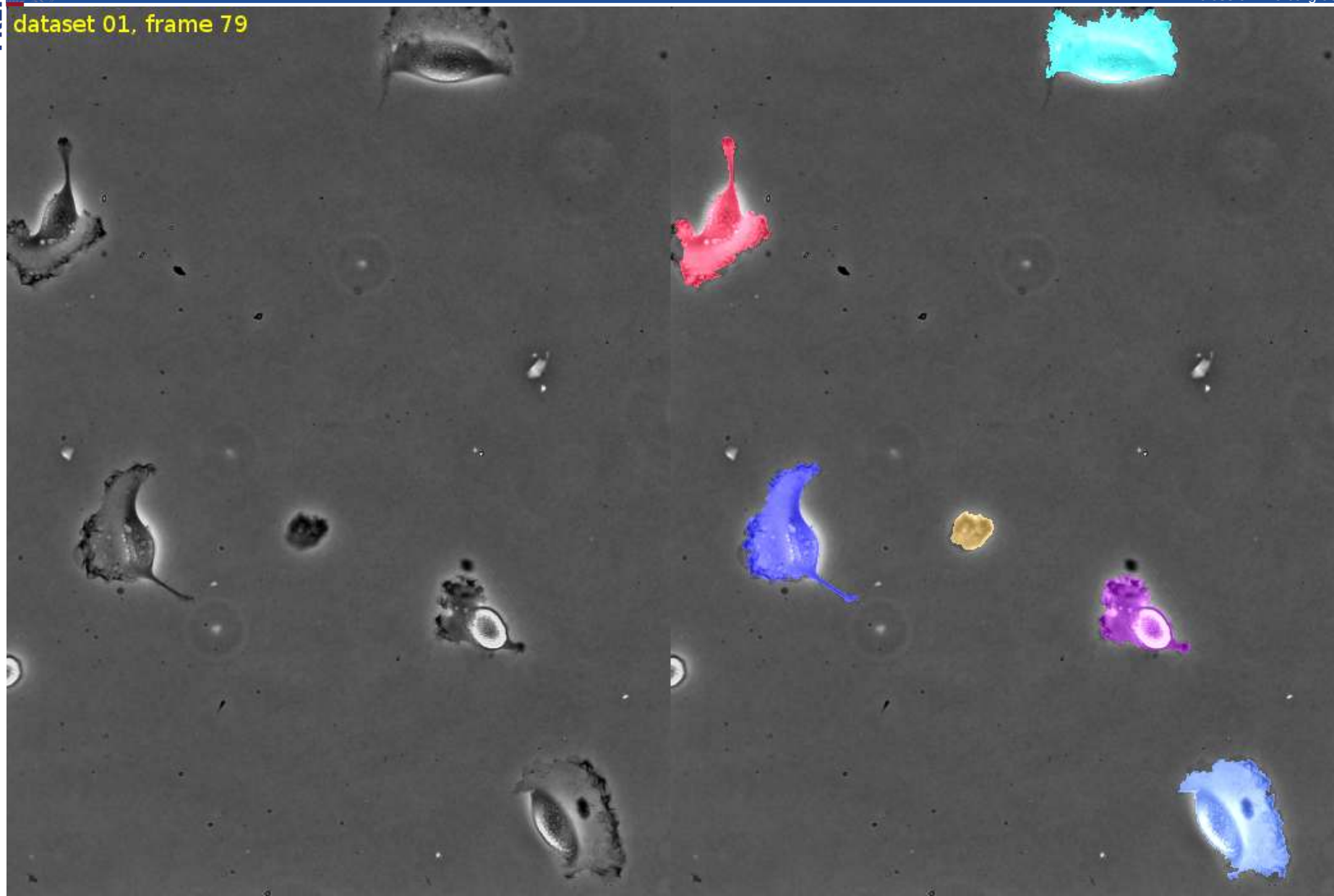
Reported results on the „challenge dataset“

Sequence	Av. SEG	Av. TRA
Seq. 1	0.8648	0.9830
Seq. 2	0.7563	0.9150
Seq. 1+2	0.8105	0.9490

Our preliminary results on the „training dataset“

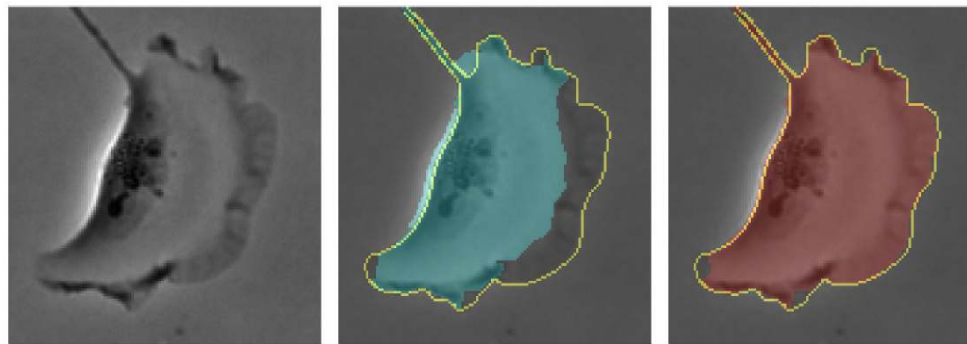
- Comparison against top ranked methods from last years **ISBI cell tracking challenge**
- Phase contrast dataset: PhC-C2DH-U373

dataset 01, frame 79





- Direction dependent boundary costs improve segmentation in phase contrast microscopy
- Our approach outperforms standard min-cut segmentation with symmetric costs
- Preliminary results suggest competitive performance with top-ranked methods in the ISBI CTC



→ *Profit for cell segmentation in other modalities*

→ *Open-source MATLAB code (and ImageJ plugin):*

<http://lmb.informatik.uni-freiburg.de/resources/opensource/CellTracking/>



Thank you!



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