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Unsupervised Contour Tracking of Live Cells by Mechanical and Cycle Consistency Losses

Junbong Jang, Kwonmoo Lee*, Tae-Kyun (T-K) Kim*

TUE-AM-022

KAIST

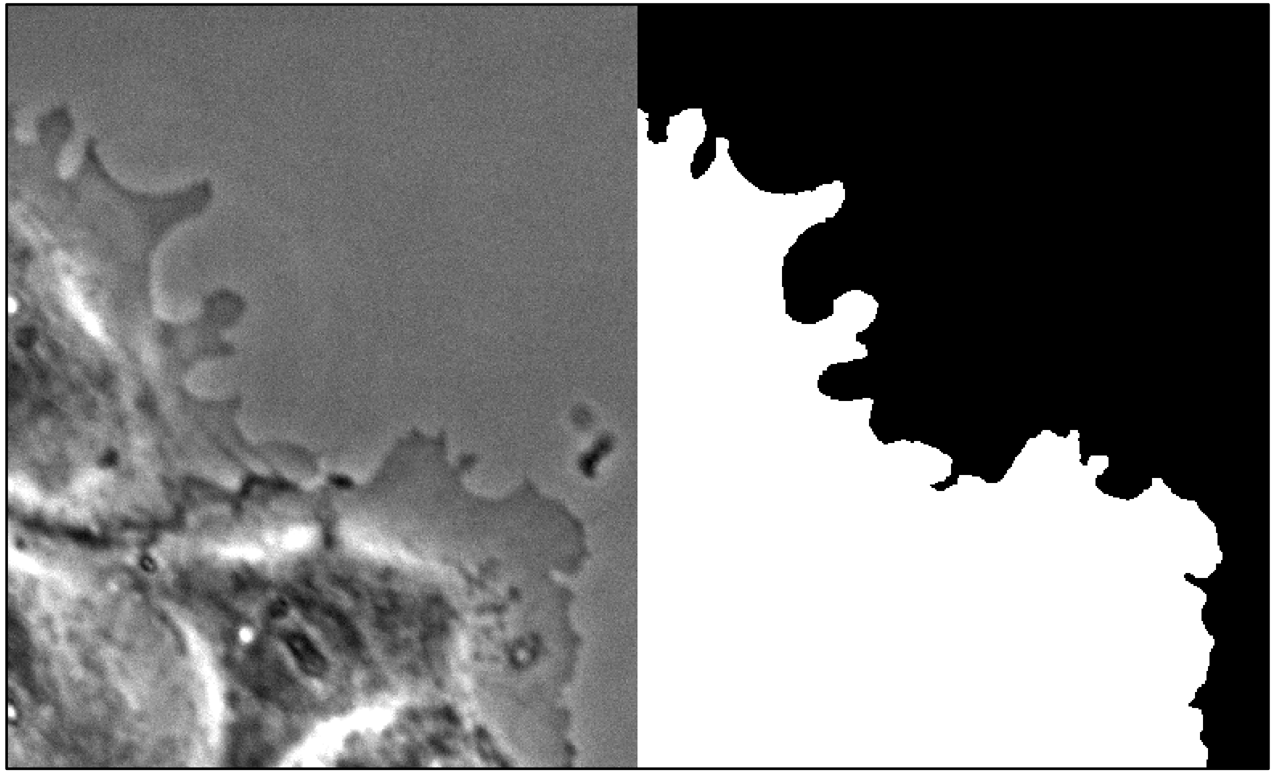
HARVARD MEDICAL SCHOOL

Imperial College London

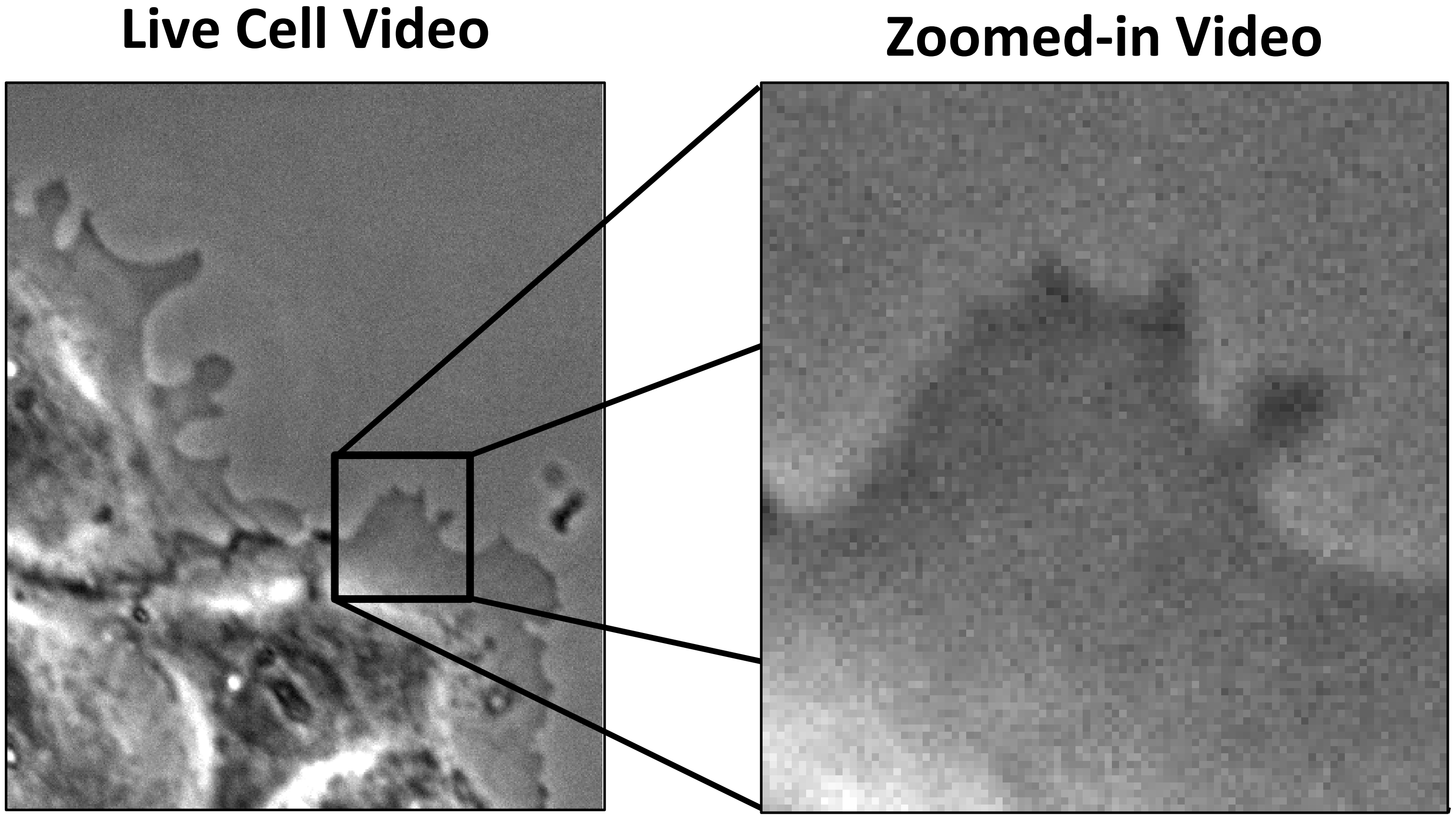
*: corresponding author

Challenge: Cellular contour deforms with expansion and contraction

Live Cell Video **Segmentation**

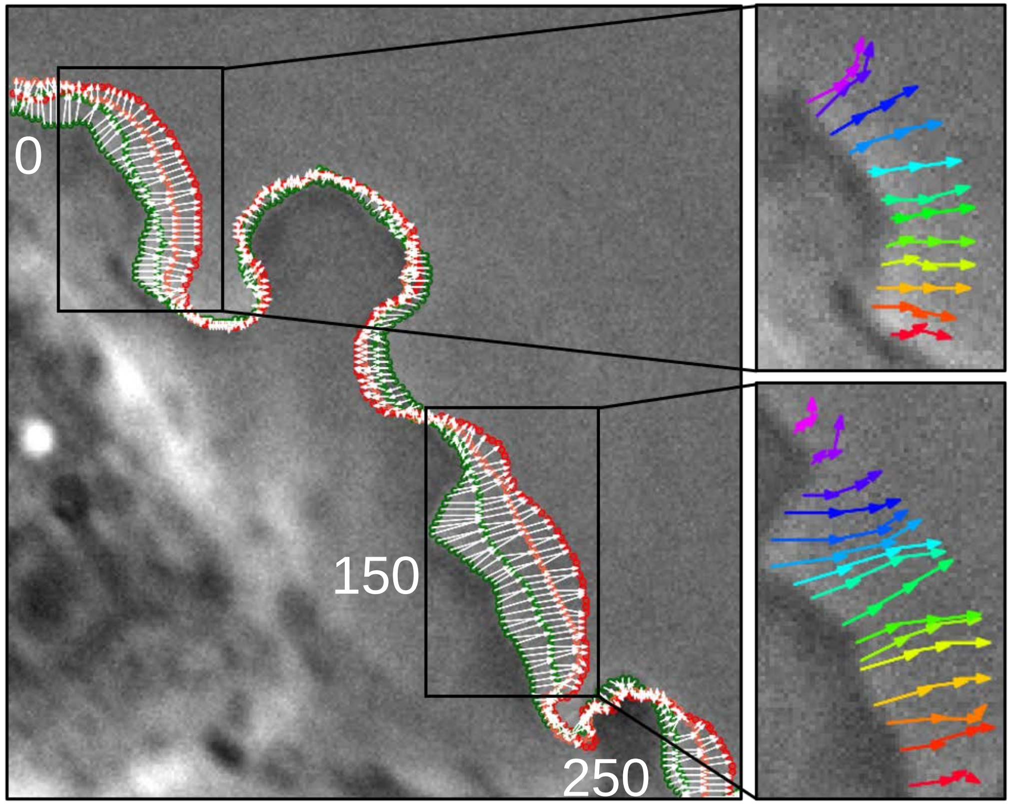


Challenge: Local shapes and textures on the contour are not evident

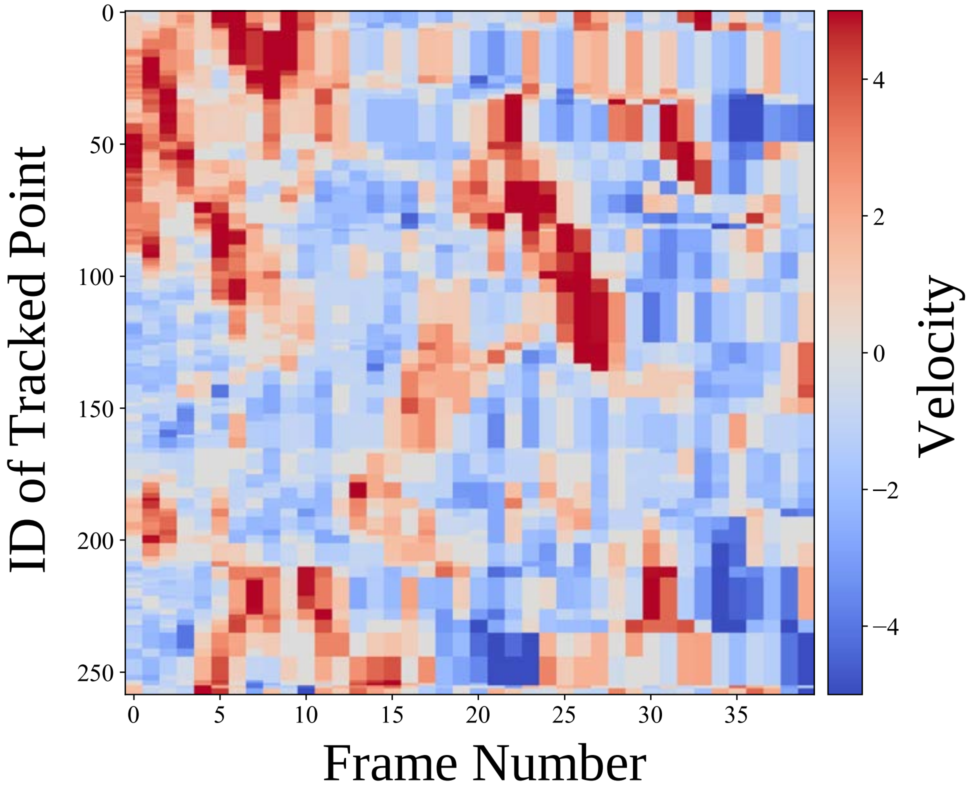


1-minute preview

Contour Tracking to Quantify Morphodynamics



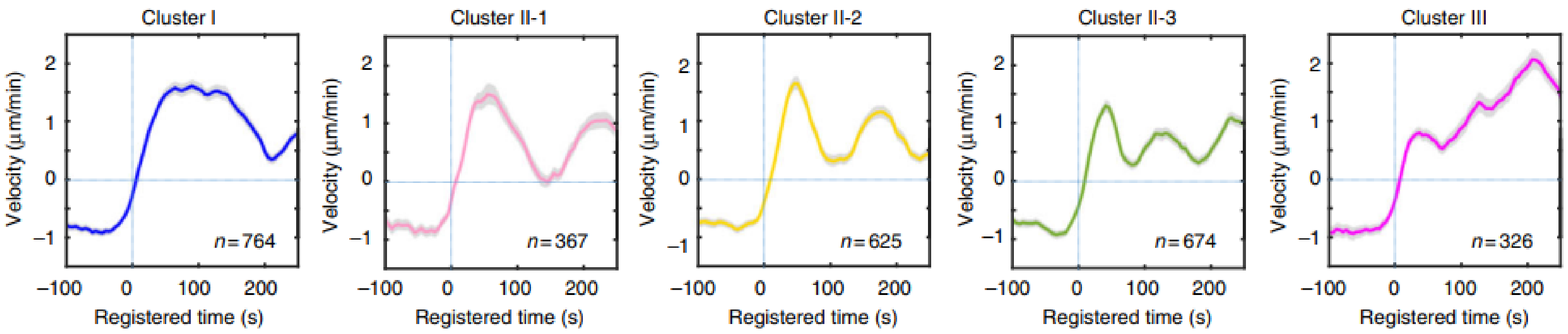
$$V = \frac{\Delta d}{\Delta t}$$

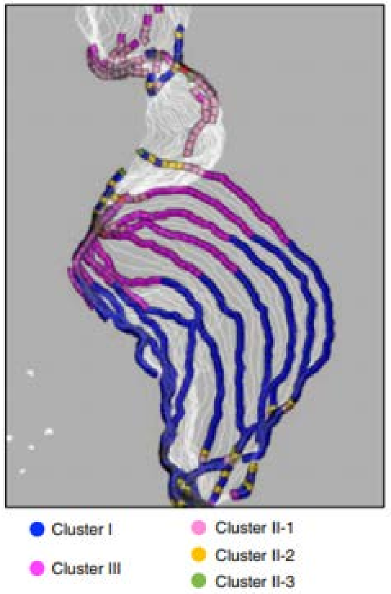


Motivation for Contour Tracking

- Cellular morphodynamics play vital roles in
  - Angiogenesis
  - Cancer invasiveness
  - Immune response
  - Tissue regeneration

- Characterize the drug-Sensitive morphodynamic phenotypes [1]





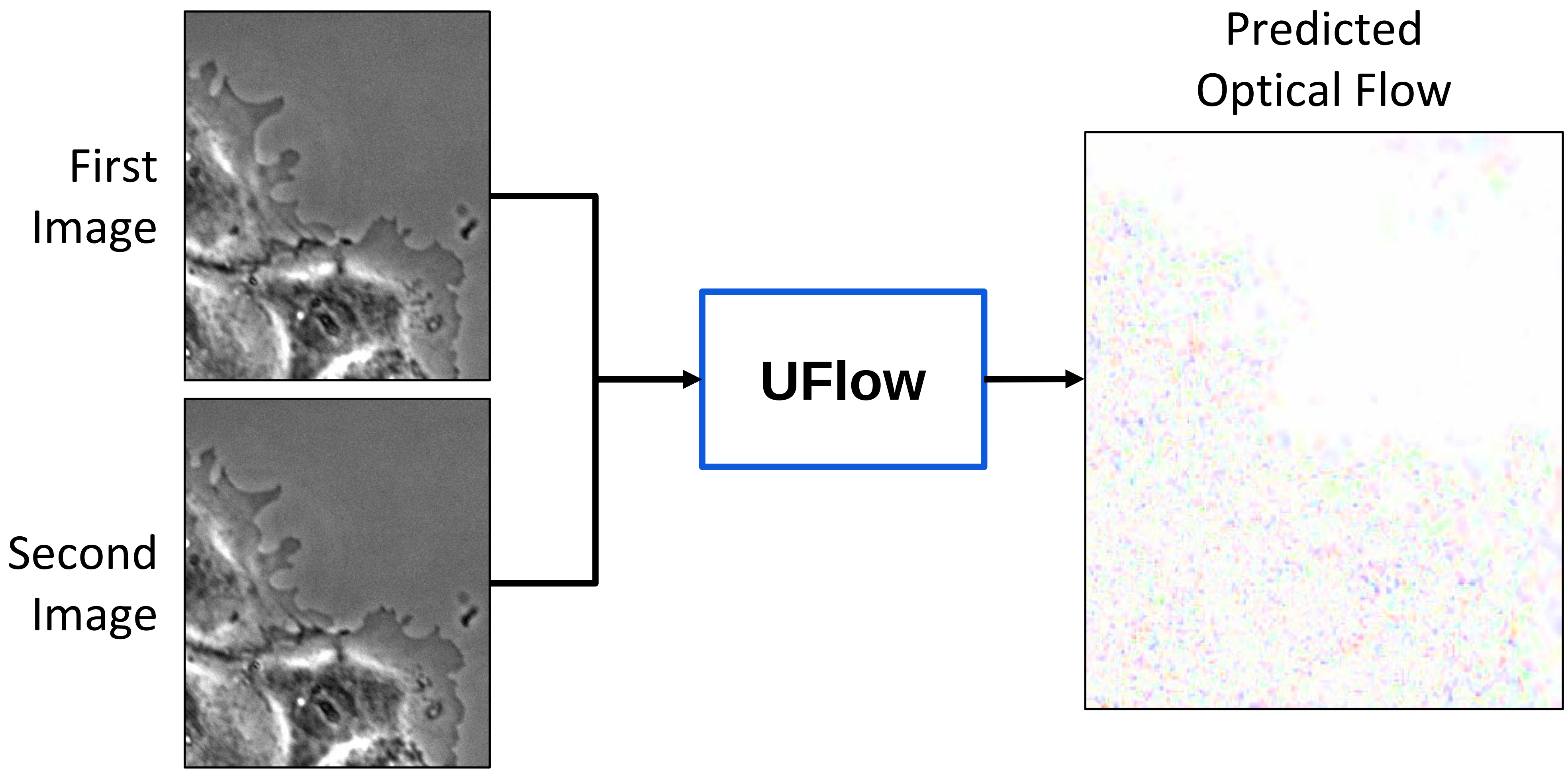
[1] Wang, C. et al. Deconvolution of subcellular protrusion heterogeneity and the underlying actin regulator dynamics from live cell imaging. Nat Commun 9, 1688, doi:10.1038/s41467-018-04030-0 (2018).

First deep learning-based model trained by unsupervised learning to densely track contour

	Deep Learning	Dense	Unsupervised	Contour
UFlow [1]	✓	✓	✓	
PoST [2]	✓			✓
Mechanical Model [3]		✓	✓	✓
Ours	✓	✓	✓	✓

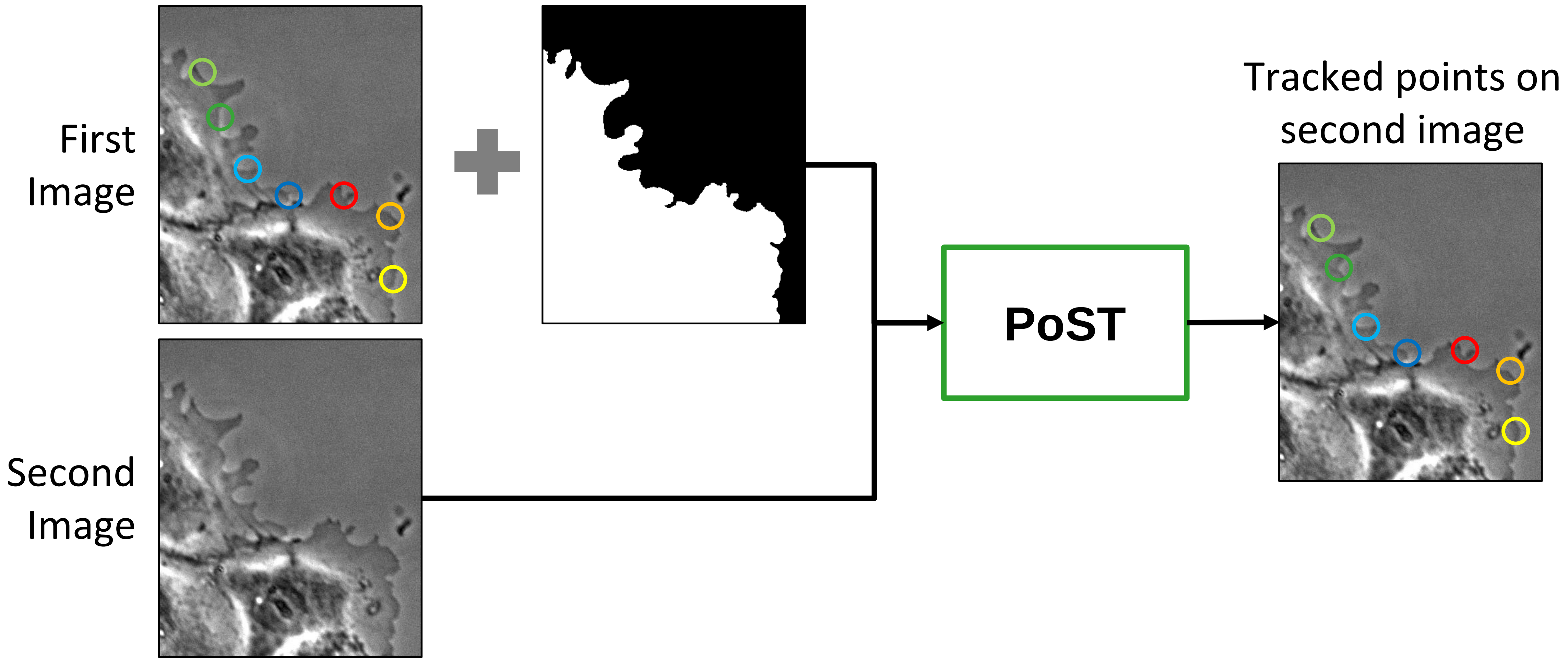
[1] Rico Jonschkowski, Austin Stone, Jonathan T Barron, Ariel Gordon, Kurt Konolige, and Anelia Angelova. What matters in unsupervised optical flow. In European Conference on Computer Vision, pages 557–572. Springer, 2020.
[2] Gunhee Nam, Miran Heo, Seoung Wug Oh, Joon-Young Lee, and Seon Joo Kim. Polygonal point set tracking. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5569–5578, 2021.
[3] Matthias Machacek and Gaudenz Danuser. Morphodynamic profiling of protrusion phenotypes. Biophysical journal, 90(4):1439–1452, 2006.

UFlow [1] densely estimates offset for every pixel without structural information of contour



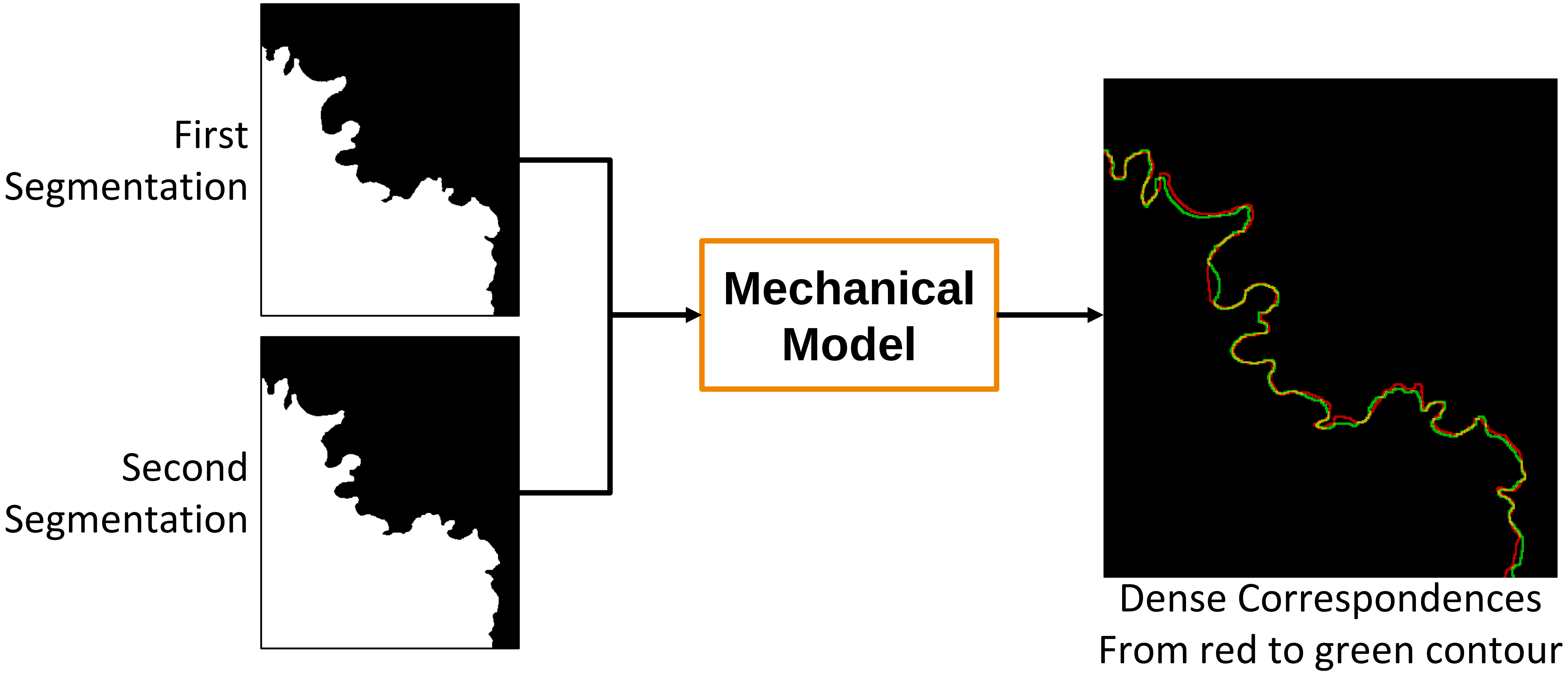
[1] Rico Jonschkowski, Austin Stone, Jonathan T Barron, Ariel Gordon, Kurt Konolige, and Anelia Angelova. What matters in unsupervised optical flow. In European Conference on Computer Vision, pages 557–572. Springer, 2020.
[2] Gunhee Nam, Miran Heo, Seoung Wug Oh, Joon-Young Lee, and Seon Joo Kim. Polygonal point set tracking. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5569–5578, 2021.
[3] Matthias Machacek and Gaudenz Danuser. Morphodynamic profiling of protrusion phenotypes. Biophysical journal, 90(4):1439–1452, 2006.

PoST [2] relies on the supervised learning of a fixed number of tracking points



[1] Rico Jonschkowski, Austin Stone, Jonathan T Barron, Ariel Gordon, Kurt Konolige, and Anelia Angelova. What matters in unsupervised optical flow. In European Conference on Computer Vision, pages 557–572. Springer, 2020.
[2] Gunhee Nam, Miran Heo, Seoung Wug Oh, Joon-Young Lee, and Seon Joo Kim. Polygonal point set tracking. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5569–5578, 2021.
[3] Matthias Machacek and Gaudenz Danuser. Morphodynamic profiling of protrusion phenotypes. Biophysical journal, 90(4):1439–1452, 2006.

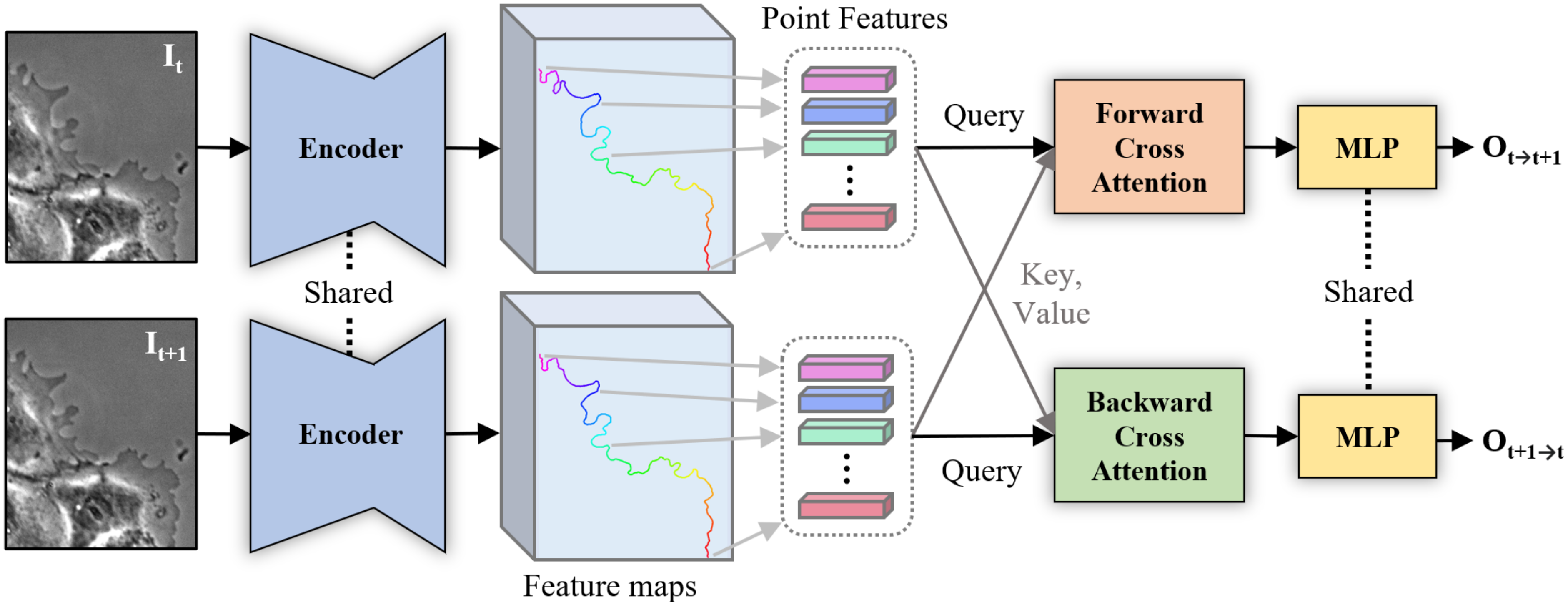
Mechanical model [3] only uses the segmentation mask, not the visual features in the raw image



[1] Rico Jonschkowski, Austin Stone, Jonathan T Barron, Ariel Gordon, Kurt Konolige, and Anelia Angelova. What matters in unsupervised optical flow. In European Conference on Computer Vision, pages 557–572. Springer, 2020.
[2] Gunhee Nam, Miran Heo, Seoung Wug Oh, Joon-Young Lee, and Seon Joo Kim. Polygonal point set tracking. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5569–5578, 2021.
[3] Matthias Machacek and Gaudenz Danuser. Morphodynamic profiling of protrusion phenotypes. Biophysical journal, 90(4):1439–1452, 2006.

Deep Learning Architecture for Contour Tracking

- Extract feature map from VGG16 ImageNet pre-trained encoder
- Feature sampling along the contour
- Fuse the features from the previous and current frame by Cross Attention
- Predict the offset vector for each contour point by MLP



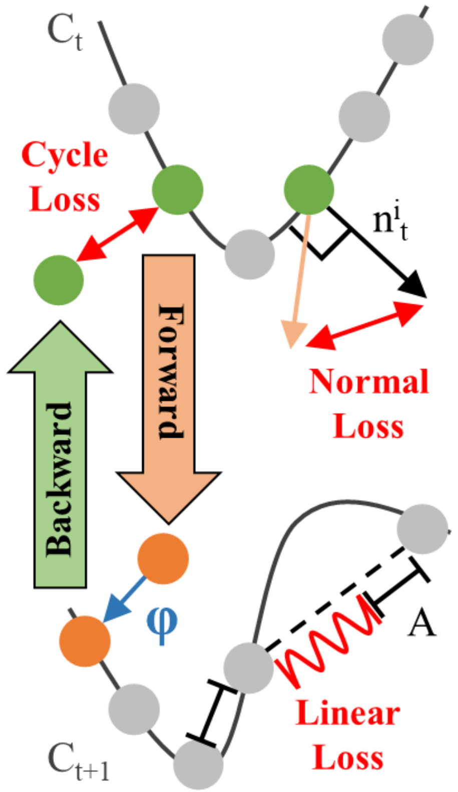
Unsupervised Learning

- **Cycle consistency loss** to utilize visual features

$$L_{forward} = \sum_{i=0}^{N_t-1} \|p_t^i - O_{t+1\to t}(\phi(O_{t\to t+1}(p_t^i)))\|_2 \quad (1)$$

$$L_{backward} = \sum_{i=0}^{N_t-1} \|p_{t+1}^i - O_{t\to t+1}(\phi(O_{t+1\to t}(p_{t+1}^i)))\|_2 \quad (2)$$

$$L_{cycle} = L_{forward} + L_{backward} \quad (3)$$

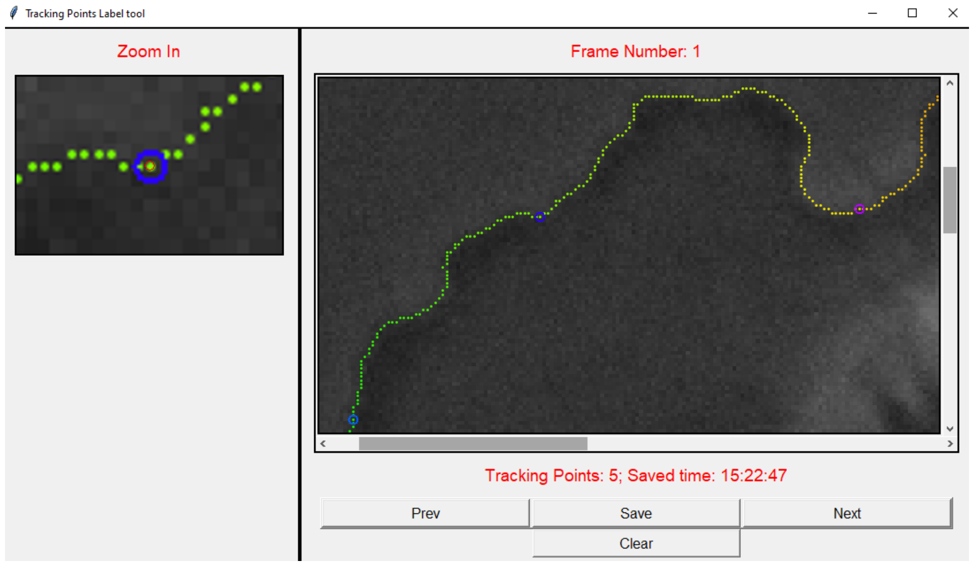


- **Mechanical Normal loss** to utilize morphological features

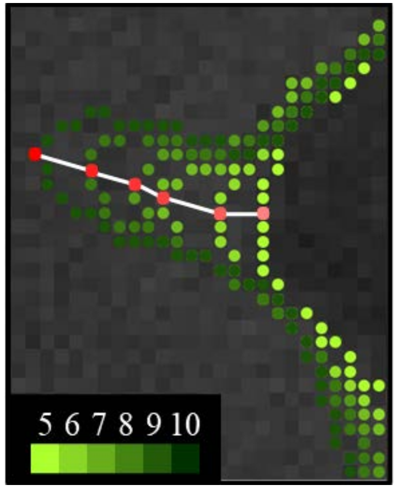
$$L_{\text{mech-normal}} = \sum_{i=1}^{N_t-2} \left\| \frac{n_t^i}{\|n_t^i\|_2} - \frac{O_{t\to t+1}(p_t^i)}{\|O_{t\to t+1}(p_t^i)\|_2} \right\|_1$$

Labeling Live Cell Tracking Points

- Developed a GUI to facilitate annotation of tracking points



- Labeled a few contour points in every fifth frame
- Use high-temporal information from consecutive frames



Finding Optimal Loss and Architecture

Supervised	Cycle	Photo	Normal	Linear	$SA_{.02}$	$SA_{.04}$	$SA_{.06}$	$CA_{.01}$	$CA_{.02}$	$CA_{.03}$
✓					0.549	0.813	0.904	0.614	0.821	0.900
	✓				0.632	0.869	0.953	0.676	0.849	0.925
		✓			0.198	0.383	0.471	0.234	0.402	0.489
			✓		0.640	0.858	0.948	0.674	0.853	0.922
			✓	✓	0.378	0.593	0.686	0.400	0.594	0.674
	✓		✓	✓	0.426	0.611	0.738	0.469	0.627	0.710
	✓		✓		**0.729**	**0.937**	**0.974**	**0.762**	**0.925**	**0.971**

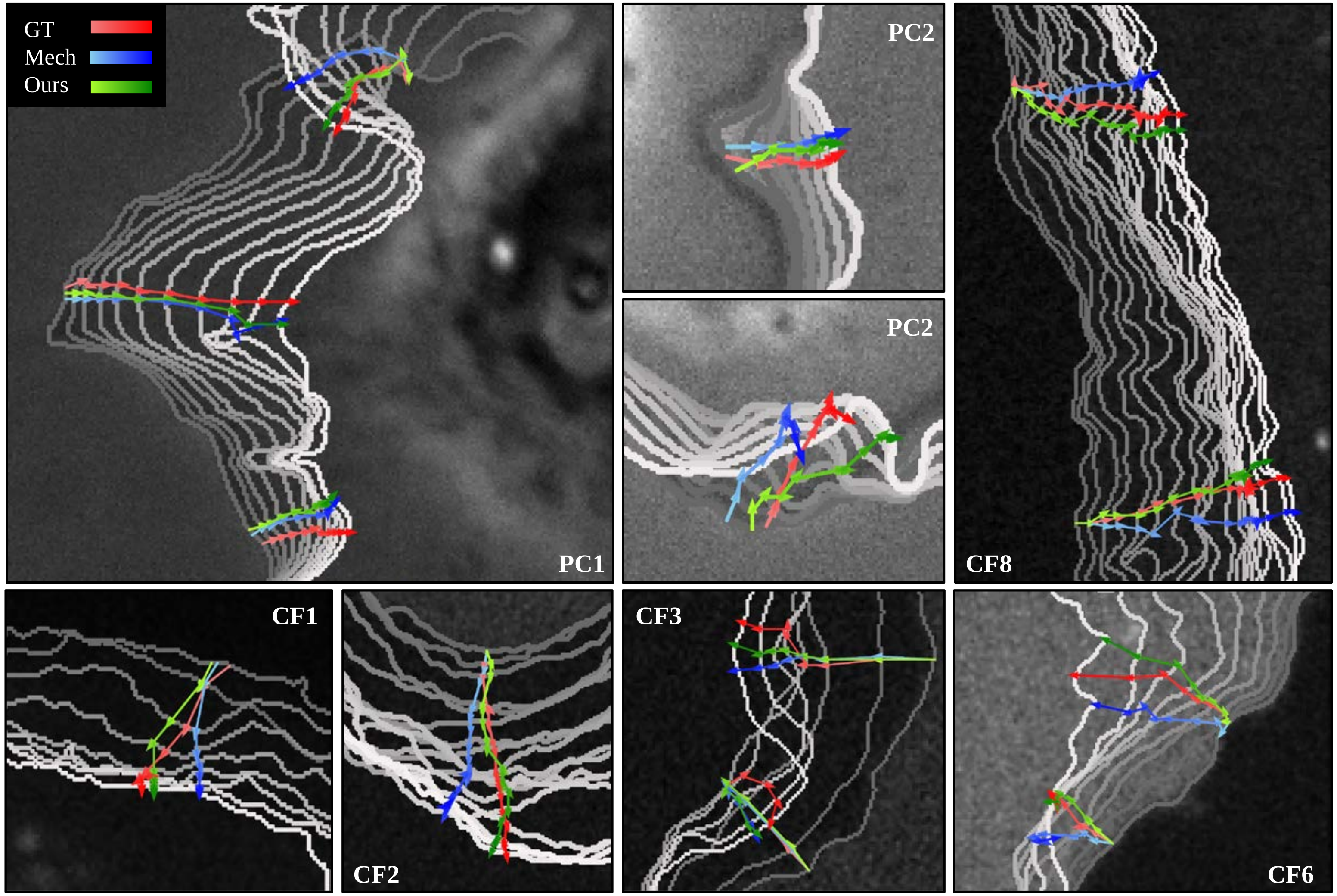
Method	$SA_{.02}$	$SA_{.04}$	$SA_{.06}$	$CA_{.01}$	$CA_{.02}$	$CA_{.03}$
No Cross	0.659	0.858	0.969	0.696	0.851	0.939
Single Cross	0.677	0.864	0.930	0.734	0.854	0.913
Circ Conv	0.643	0.931	**0.983**	0.718	0.910	0.965
1D Conv	0.692	0.909	0.976	0.736	0.881	0.948
Ours	**0.729**	**0.937**	0.974	**0.762**	**0.925**	**0.971**

Accurate Contour Tracking on Two Live Cell Datasets

	Phase Contrast Dataset [1]						Confocal Fluorescence Dataset [2]					
Method	$SA_{.02}$	$SA_{.04}$	$SA_{.06}$	$CA_{.01}$	$CA_{.02}$	$CA_{.03}$	$SA_{.02}$	$SA_{.04}$	$SA_{.06}$	$CA_{.01}$	$CA_{.02}$	$CA_{.03}$
UFlow [3]	0.585	0.809	0.881	0.632	0.802	0.857	0.605	0.785	0.863	0.520	0.685	0.791
PoST [4]	0.629	0.850	<u>0.947</u>	0.693	<u>0.872</u>	<u>0.939</u>	<u>0.614</u>	0.805	**0.888**	<u>0.531</u>	0.706	<u>0.807</u>
Mechanical [5]	<u>0.683</u>	<u>0.853</u>	0.938	<u>0.722</u>	0.863	0.927	0.603	<u>0.798</u>	0.876	0.517	<u>0.711</u>	0.804
Ours	**0.729**	**0.937**	**0.974**	**0.762**	**0.925**	**0.971**	**0.632**	**0.824**	<u>0.882</u>	**0.555**	**0.728**	**0.826**

[1] Junbong Jang, Chuangqi Wang, Xitong Zhang, Hee June Choi, Xiang Pan, Bolun Lin, Yudong Yu, Carly Whittle, Madison Ryan, Yenyu Chen, and Kwonmoo Lee. A deep learning-based segmentation pipeline for profiling cellular morphodynamics using multiple types of live cell microscopy. Cell Reports Methods, Oct 2021.
[2] Chuangqi Wang, Hee June Choi, Sung-Jin Kim, Aesha Desai, Namgyu Lee, Dohoon Kim, Yongho Bae, and Kwonmoo Lee. Deconvolution of subcellular protrusion heterogeneity and the underlying actin regulator dynamics from live cell imaging. Nature Communications, 9(1):1688, Apr 2018.
[3] Rico Jonschkowski, Austin Stone, Jonathan T Barron, Ariel Gordon, Kurt Konolige, and Anelia Angelova. What matters in unsupervised optical flow. In European Conference on Computer Vision, pages 557–572. Springer, 2020.
[4] Gunhee Nam, Miran Heo, Seoung Wug Oh, Joon-Young Lee, and Seon Joo Kim. Polygonal point set tracking. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5569–5578, 2021.
[5] Matthias Machacek and Gaudenz Danuser. Morphodynamic profiling of protrusion phenotypes. Biophysical journal, 90(4):1439–1452, 2006.

Contour Tracking against Labeled Tracking Points



Contour Tracking of Phase Contrast Live Cell with Dense Correspondences

Contour Tracking of Confocal Fluorescence Live Cell with Dense Correspondences

Contour Tracking of Jellyfish with Dense Correspondences

Project Website & Code

https://junbongjang.github.io/projects/contour-tracking/