Implicit Neural Representations for Generative Modeling of Living Cell Shapes

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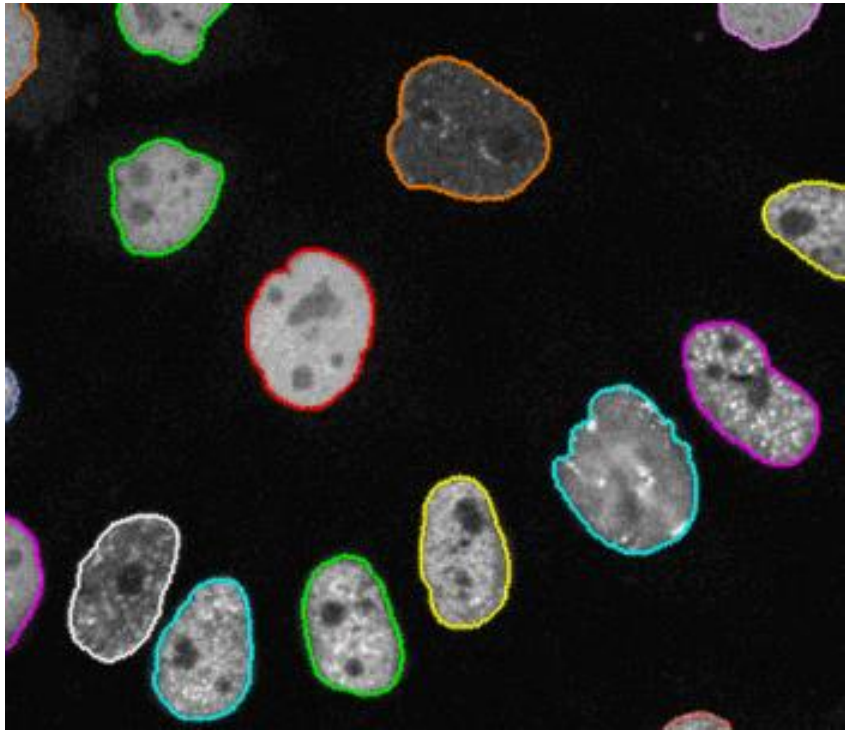
Introduction

- Performance of deep learning methods is heavily dependent on the amount, quality and diversity of the available **training data sets** with ground truth annotation
- Methods allowing the **synthesis of realistic cell shapes** could help generate training data sets to improve cell tracking and segmentation
- We propose a computationally efficient method for **modeling of realistic 3D time-evolving cell shapes** in high spatial and temporal resolution



Segmentation and tracking of living cells in time-lapse microscopy

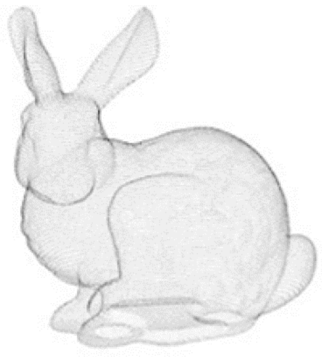
Goals and Challenges

- **Modeled data**
  - High dimensionality - 3D time-lapse sequences
  - High spatial and temporal resolution
- **Computational model**
  - Small and efficient
  - Easily customizable for arbitrary class of shapes
  - Able to model various phenomena occurring during the cell cycle, e.g., shape deformations, growth, or mitosis
- **Choosing the right data representation is important as it directly impacts the architecture of the corresponding model**

3D Shape Representation

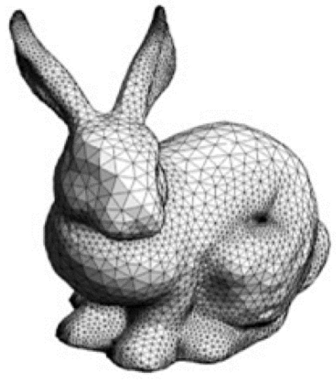
Voxel

- Cubically growing memory and computational requirements
- Not efficient for representing fine details



Point cloud

- Does not represent a watertight surface

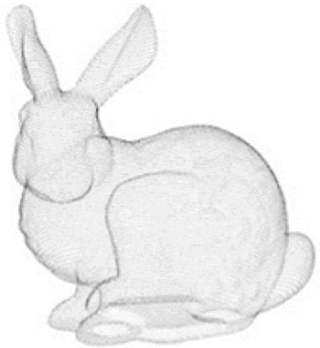


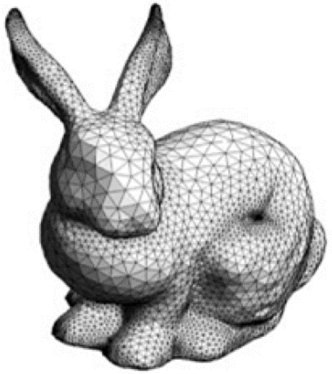
Polygon mesh

- Efficient for static shapes
- Modeling of shape deformations and division requires complex algorithms

Figure from: KATO, Hiroharu; USHIKU, Yoshitaka; HARADA, Tatsuya. **Neural 3d mesh renderer**. In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2018. p. 3907-3916.

3D Shape Representation





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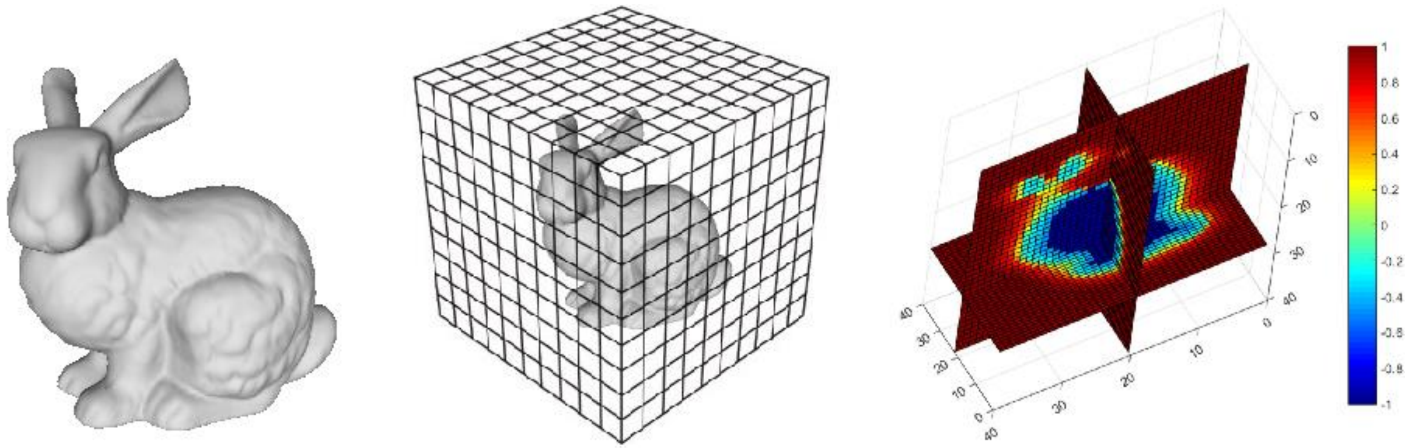
Implicit (Signed distance function)

- continuous; agnostic to sampling resolution
- computationally efficient
- suitable for representing fine details

Figure from: KATO, Hiroharu; USHIKU, Yoshitaka; HARADA, Tatsuya. **Neural 3d mesh renderer**. In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2018. p. 3907-3916.

The Idea of the Proposed Method

- We propose to model the cell surface using a **signed distance function** (SDF)
- We extend this representation to define the living cell shapes in both **space and time**
- We represent this SDF function implicitly using a multilayer perceptron (MLP) – a continuous **implicit neural representation**



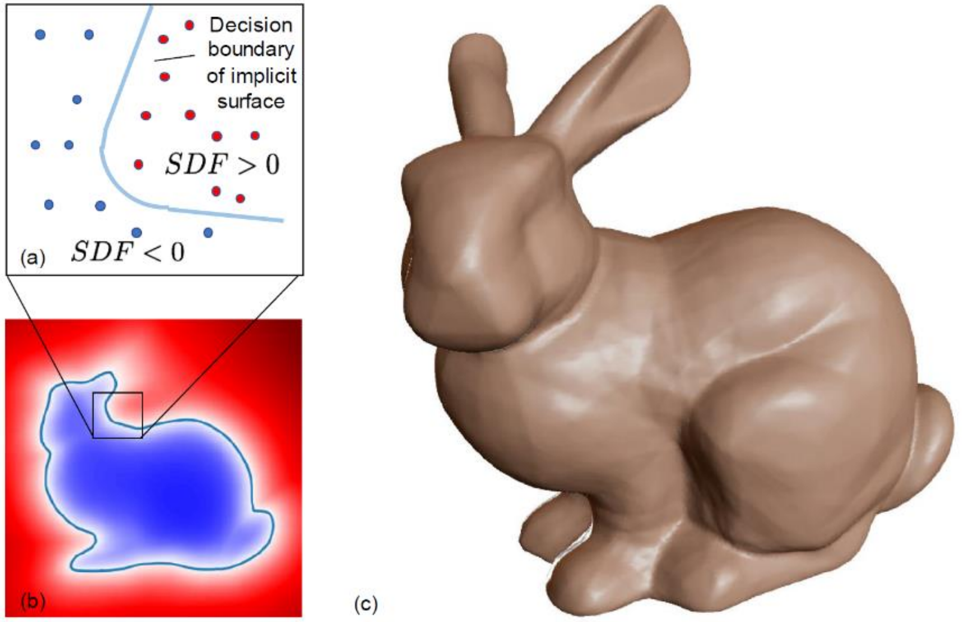
(a) Surface view. (b) Bounding volume. (c) Generated SDF.

Figure from: SLAVCHEVA, Miroslava. **Signed distance fields for rigid and deformable 3d reconstruction**. 2018. PhD Thesis. Technische Universität München.

The Proposed Method - Shape Representation

- $\Omega = [-1, 1]^3$ spatial domain
- $\tau = [-1, 1]$ temporal domain
- $\mathcal{M}_t$ 2D manifold embedded in Ω at a time $t \in \tau$
- For any point $\boldsymbol{x} = (x, y, z) \in \Omega$, the $SDF_{\mathcal{M}_t}: \Omega \to \mathbb{R}$ is defined as

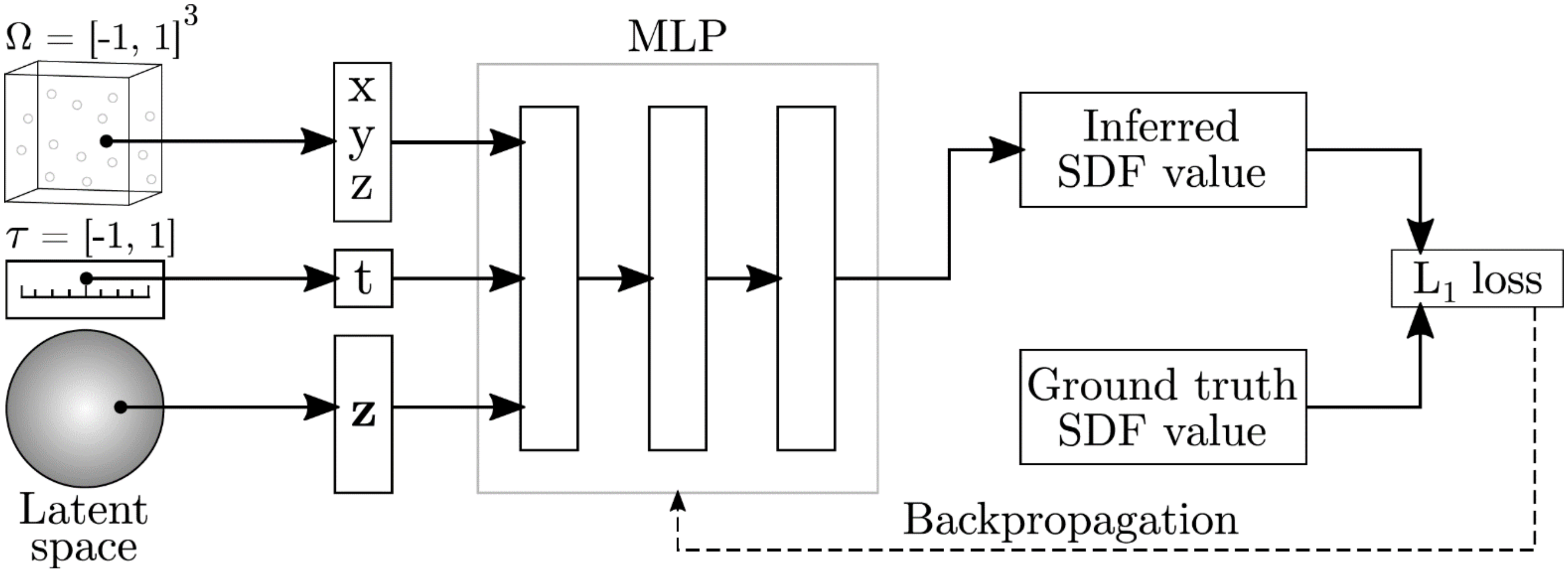
$$SDF_{\mathcal{M}_t}(\boldsymbol{x}) = \begin{cases} \min_{\boldsymbol{u} \in \mathcal{M}_t} \|\boldsymbol{x} - \boldsymbol{u}\|_2, & \boldsymbol{x} \text{ outside } \mathcal{M}_t \\ 0, & \boldsymbol{x} \text{ belonging to } \mathcal{M}_t \\ -\min_{\boldsymbol{u} \in \mathcal{M}_t} \|\boldsymbol{x} - \boldsymbol{u}\|_2, & \boldsymbol{x} \text{ inside } \mathcal{M}_t \end{cases}$$



Visualization of a 3D object and one slice of the corresponding SDF

Figure from: PARK, Jeong Joon, et al. **DeepSDF: Learning continuous signed distance functions for shape representation**. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019. p. 165-174..

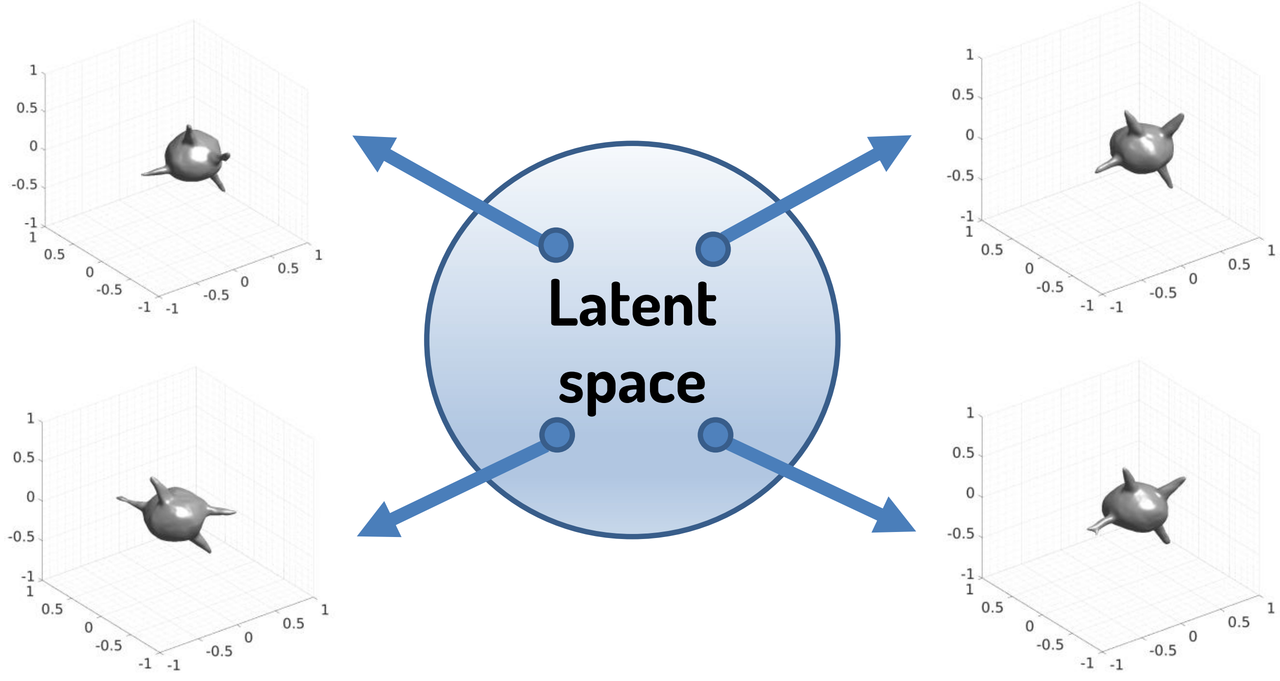
The Proposed Method – Model



- A fully-connected **auto-decoder** $f_\theta(x, t, z)$
- This model is orders of magnitude smaller than traditional voxel-based CNNs (e.g., GAN)

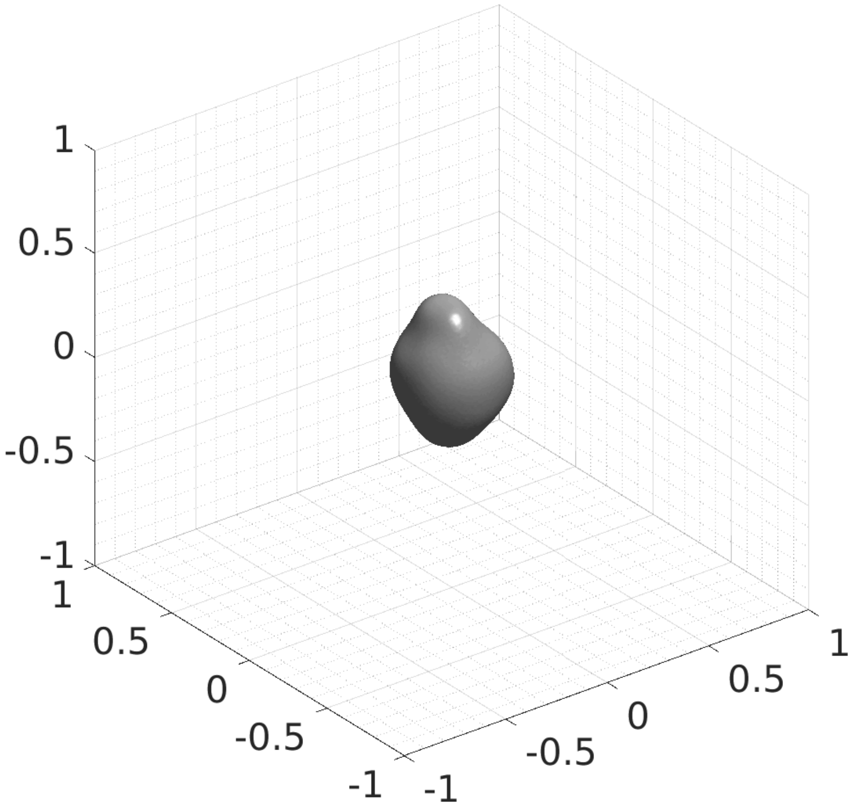
Latent Space of Shapes

- During training, the model learns a latent space corresponding to a specific class of shapes
- A latent code represents a point in this latent space and encodes a 3D time-evolving shape
- The model thus allows the synthesis of new and unseen time-evolving shapes



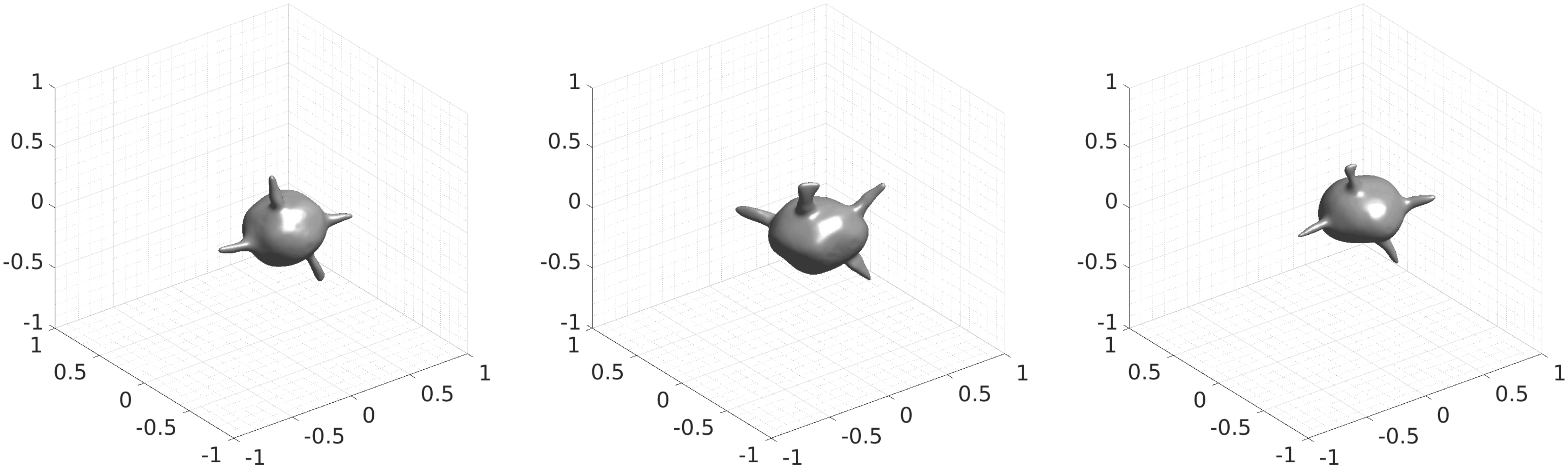
Results – New Time-Evolving Shapes

- Modeling of cell growth and mitosis – *C. elegans* embryo cells



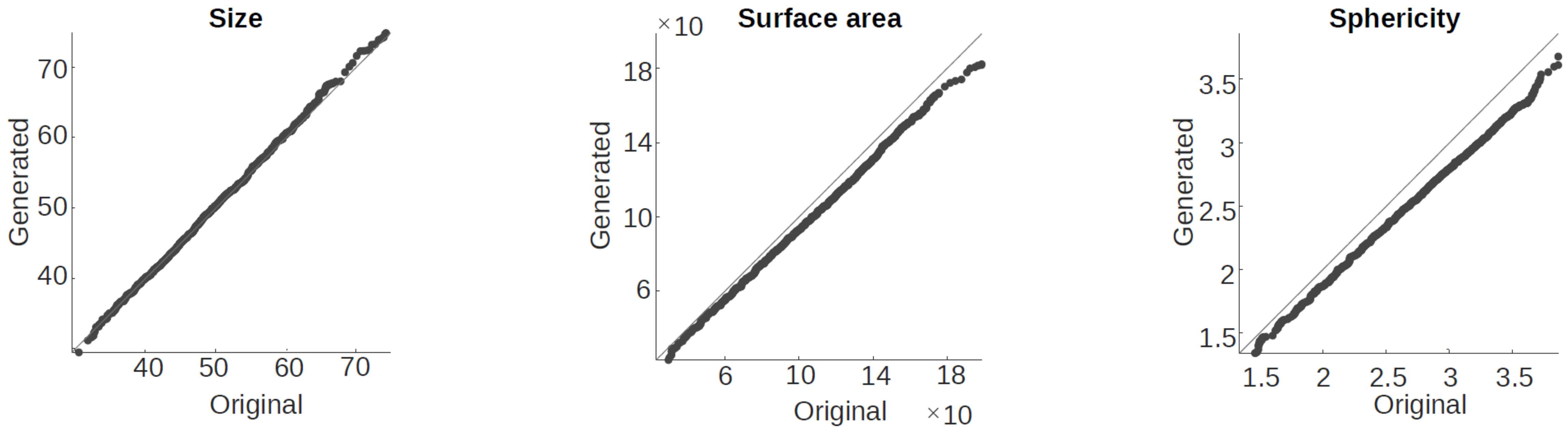
Results – New Time-Evolving Shapes

- Modeling of growing and branching filopodial protrusions – A549 lung cancer cells



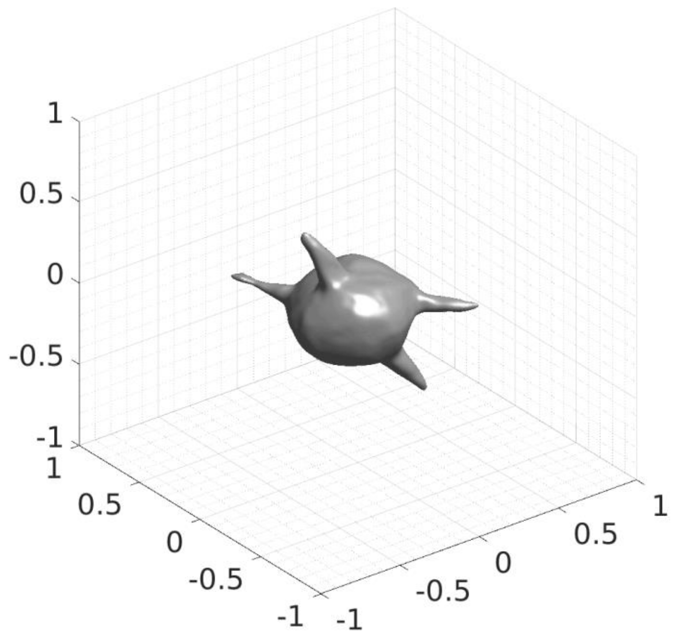
Results – Quantivative Evaluation

- **Graphical comparison of distributions of selected shape descriptors** on ground truth shapes (O) and new generated shapes (G) of lung cancer cells

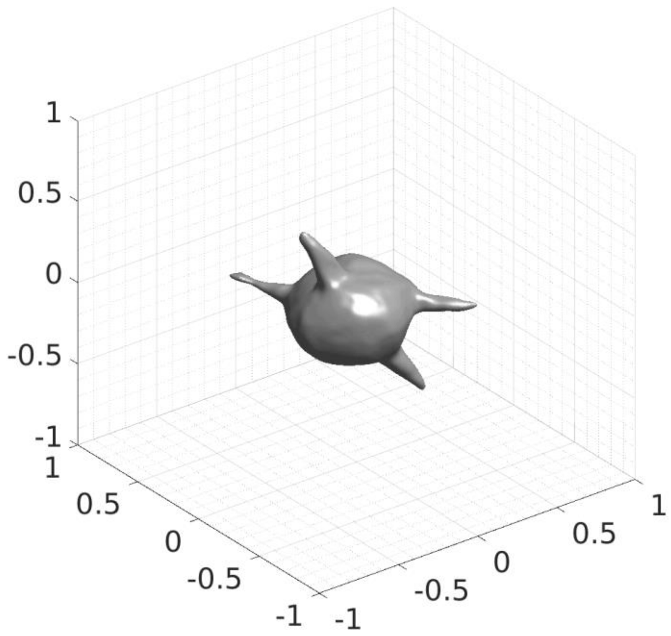


Results – Temporal Sampling

- Owing to the continuous representation, we can choose the number of samples taken from the temporal domain t and thus **infer time-evolving shapes with arbitrary temporal resolution**



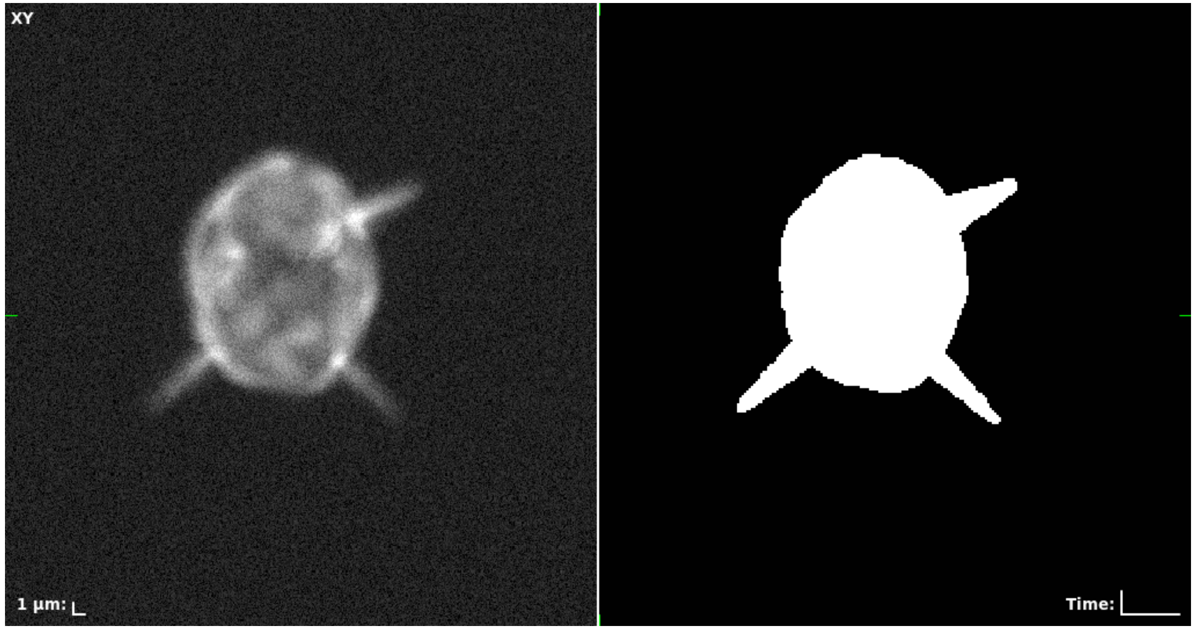
Coarsely sampled



Finely sampled

Method's Application – Producing Annotated Data Sets

- The produced cell shapes are used as ground truth for segmentation
- The corresponding cell texture is generated using a conditional model (e.g., GAN)



Conclusion

- We presented an efficient method to **synthesize realistic 3D time-evolving shapes using continuous implicit neural representations**
- Owing to the implicit continuous representation, the model is able to produce time-evolving shapes in **virtually unlimited spatial and temporal resolution**
- Conditional implicit neural representations or auto-decoders are a feasible representation for generative modeling of 3D time-lapse sequences of living cells
- The source code, models and produced datasets are publicly available at

  https://cbia.fi.muni.cz/research/simulations/implicit_shapes
- **Poster T053** at poster session 5 (14:30 – 15:30)