Implicit Neural Representations for Generative Modeling of Living Cell Shapes

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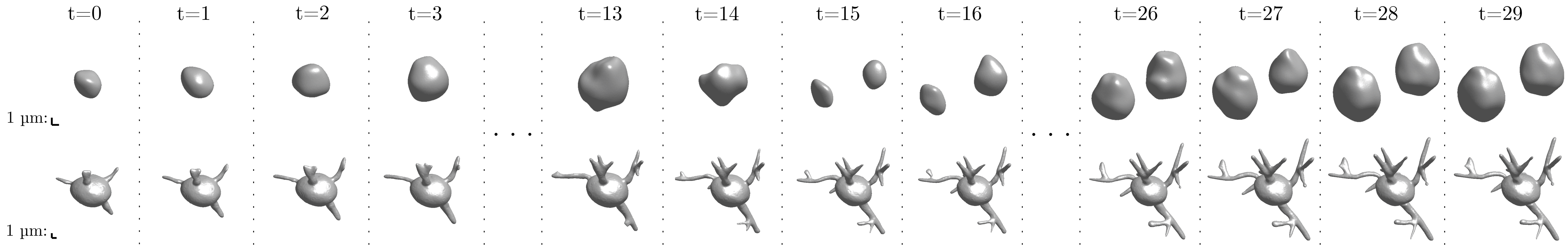
- **Fig. 1:** Synthetic shapes of **C. elegans embryo cell** (top) and **A549 lung cancer cell** (bottom) produced using the proposed method



INTRODUCTION

- Methods allowing the **synthesis of realistic cell shapes** could help generate training data sets to improve cell tracking and segmentation in biomedical images
- In this work, we propose to use an efficient data representation for cell shapes, level sets of **signed distance functions** (SDFs)
- We optimize a neural network as an implicit neural representation of the SDF value at any point in a **3D+time** domain
- The model is conditioned on a latent code, thus allowing the synthesis of new and unseen shape sequences

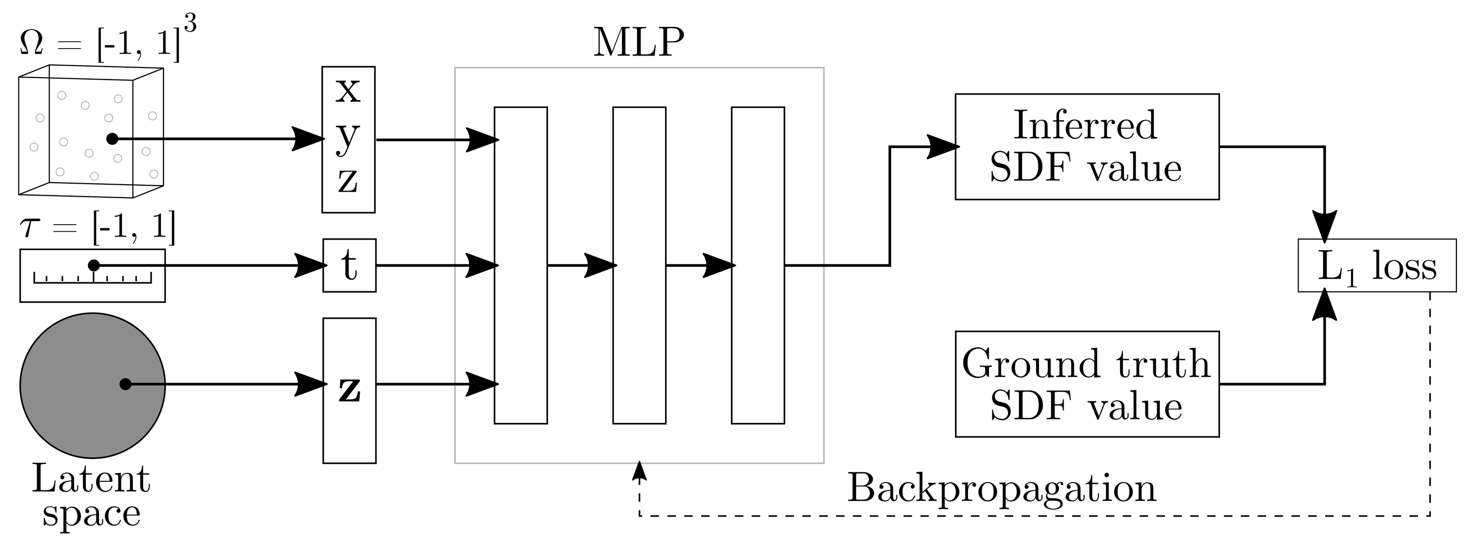
METHODOLOGY

- **Shape Representation**
  - $\Omega = [-1,1]^3$ spatial domain
  - $\tau = [-1,1]$ temporal domain
  - $\mathcal{M}_t$ 2D manifold embedded in Ω at time $t \in \tau$

For any point $\boldsymbol{x} = (x,y,z) \in \Omega$, the $SDF_{\mathcal{M}_t} : \Omega \rightarrow \mathbb{R}$ is defined as:

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

- **Neural Network**



The $SDF_{\mathcal{M}_t}(\boldsymbol{x})$ is approximated using a multi-layer perceptron (MLP) f_θ. The MLP takes as an input a coordinate vector $\boldsymbol{x}$, time parameter t, and a latent vector $\boldsymbol{z}$ initialized from a Gaussian distribution. Combining these terms results in an **auto-decoder** [1] $f_\theta(\boldsymbol{x}, t, \boldsymbol{z})$ that approximates the SDF of the manifold $\mathcal{M}_t$ for an arbitrary $t \in \tau$, given latent vector $\boldsymbol{z}$.

- **Network Optimization**

The auto-decoder is given a training set of N shape sequences. The training procedure optimizes both the network parameters θ and a latent code $\boldsymbol{z}$. The loss function thus consists of two components, L_1 distance between the inferred and ground truth SDF values:

$$\mathcal{L}_{recon}(f_\theta(\boldsymbol{x}, t, \boldsymbol{z}), SDF_{\mathcal{M}_t}(\boldsymbol{x})) = \|f_\theta(\boldsymbol{x}, t, \boldsymbol{z}) - SDF_{\mathcal{M}_t}(\boldsymbol{x})\|_1$$

And the latent code regularization term:

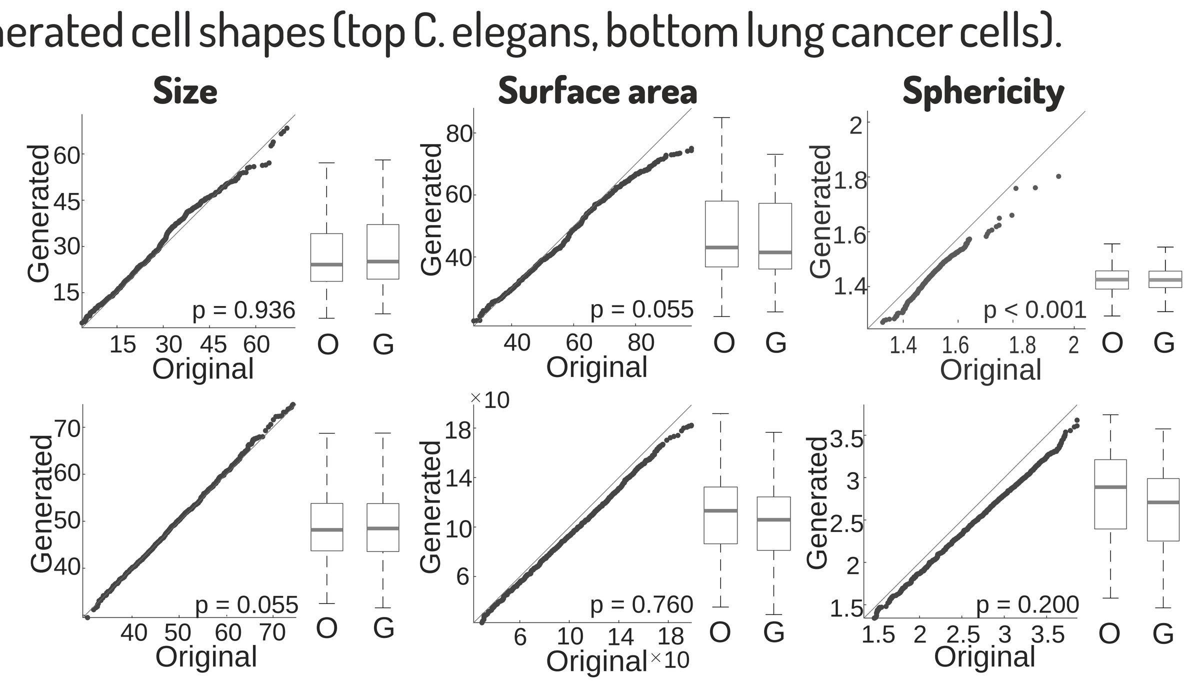
$$\mathcal{L}_{code}(\boldsymbol{z}, \sigma) = \frac{1}{\sigma^2}\|\boldsymbol{z}\|_2^2$$

The overall loss then becomes:

$$\mathbb{E}_{(\boldsymbol{x},t)}\left(\sum_{i=1}^{N} \mathcal{L}_{recon}(f_\theta(\boldsymbol{x}, t, \boldsymbol{z}_i), SDF_{\mathcal{M}_t^i}(\boldsymbol{x})) + \mathcal{L}_{code}(\boldsymbol{z}_i, \sigma)\right)$$

EXPERIMENTAL RESULTS

By giving new randomly generated latent codes to the auto-decoder, we produced new sequences of living shapes (see **Fig. 1**). For quantitative evaluation, we computed quantile-quantile plots and boxplots showing distributions of selected shape descriptors and p-values of the respective Kolmogorov-Smirnov tests on real and generated cell shapes (top C. elegans, bottom lung cancer cells).



CONCLUSION

- The proposed model is simple, easy to train, and can be **easily customized to produce a desired class of shapes**
- Owing to the implicit continuous representation, the model is able to produce evolving shapes in **virtually unlimited spatial and temporal resolution**
- The proposed method can be used for generating brand-new data sets, for data augmentation, or for increasing spatial and temporal resolution of existing data

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