MICHIGAN ENGINEERING ROBOTICS
UNIVERSITY OF MICHIGAN

# Highly Deformable Proprioceptive Membrane for Real-time 3D Shape Reconstruction

Guanyu Xu†, Jiaqi Wang†, Dezhong Tong, Xiaonan Huang* | {xuguanyu, wangjq, dezhong, xiaonanh} @umich.edu
† Equal Contribution, *Corresponding author. Robotics Department, University of Michigan, Ann Arbor, MI 48109, USA

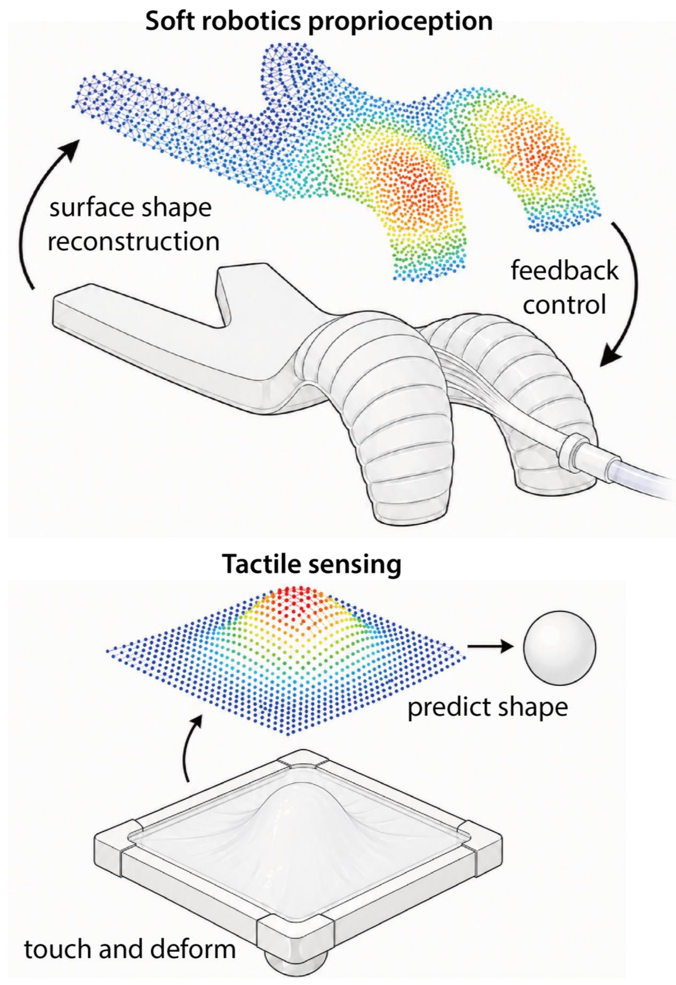
## Motivation

**Soft robots need real-time 3D shape reconstruction for**

- **Proprioception in deformable actuators:** recover body shape for feedback control.
- **Tactile sensing during contact:** estimate local deformation caused by touch.

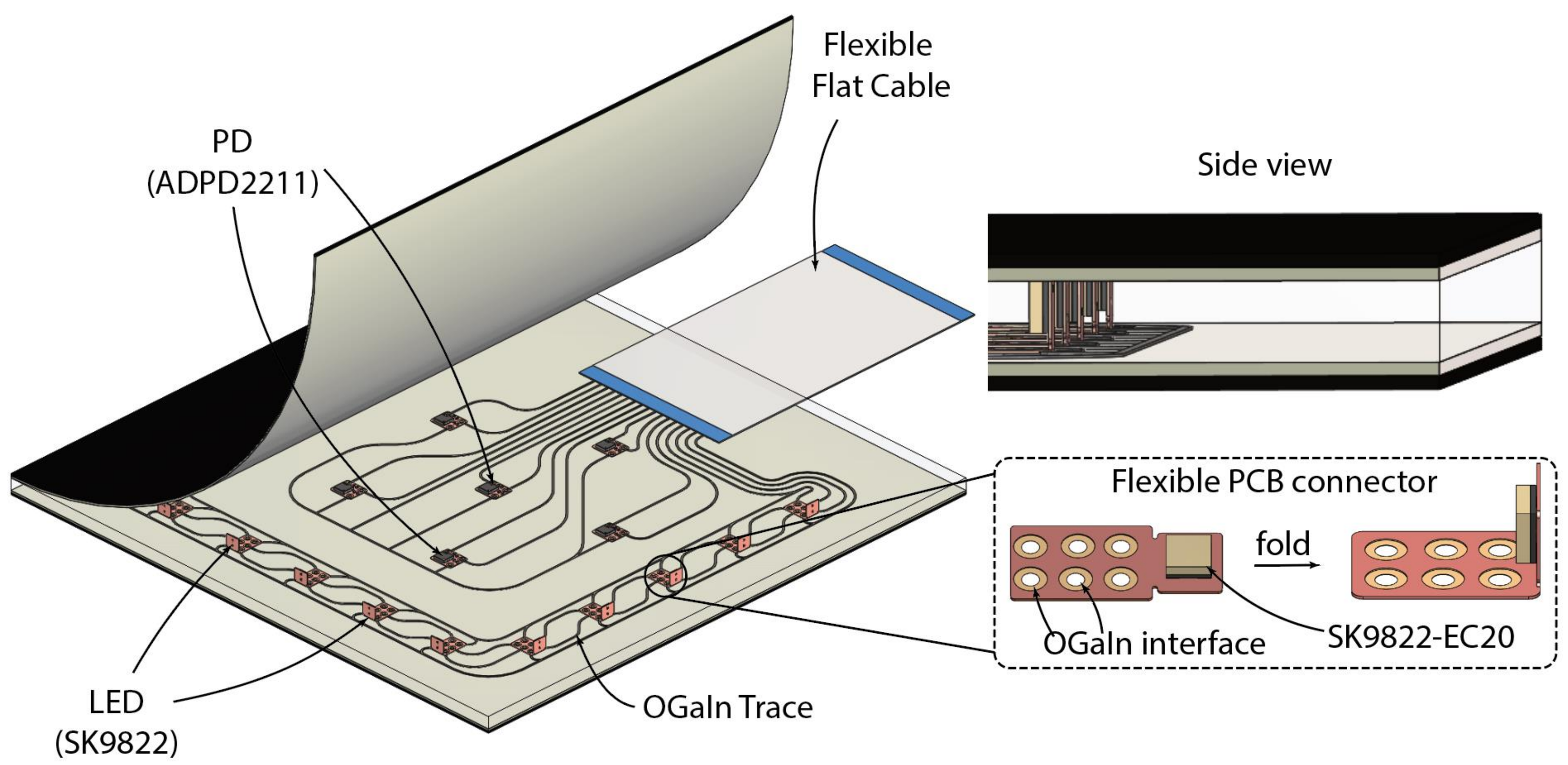
**Key Idea: Optical Waveguide Sensing**

- Decode the membrane shape from optical signals using a data-driven model.




## Hardware Design

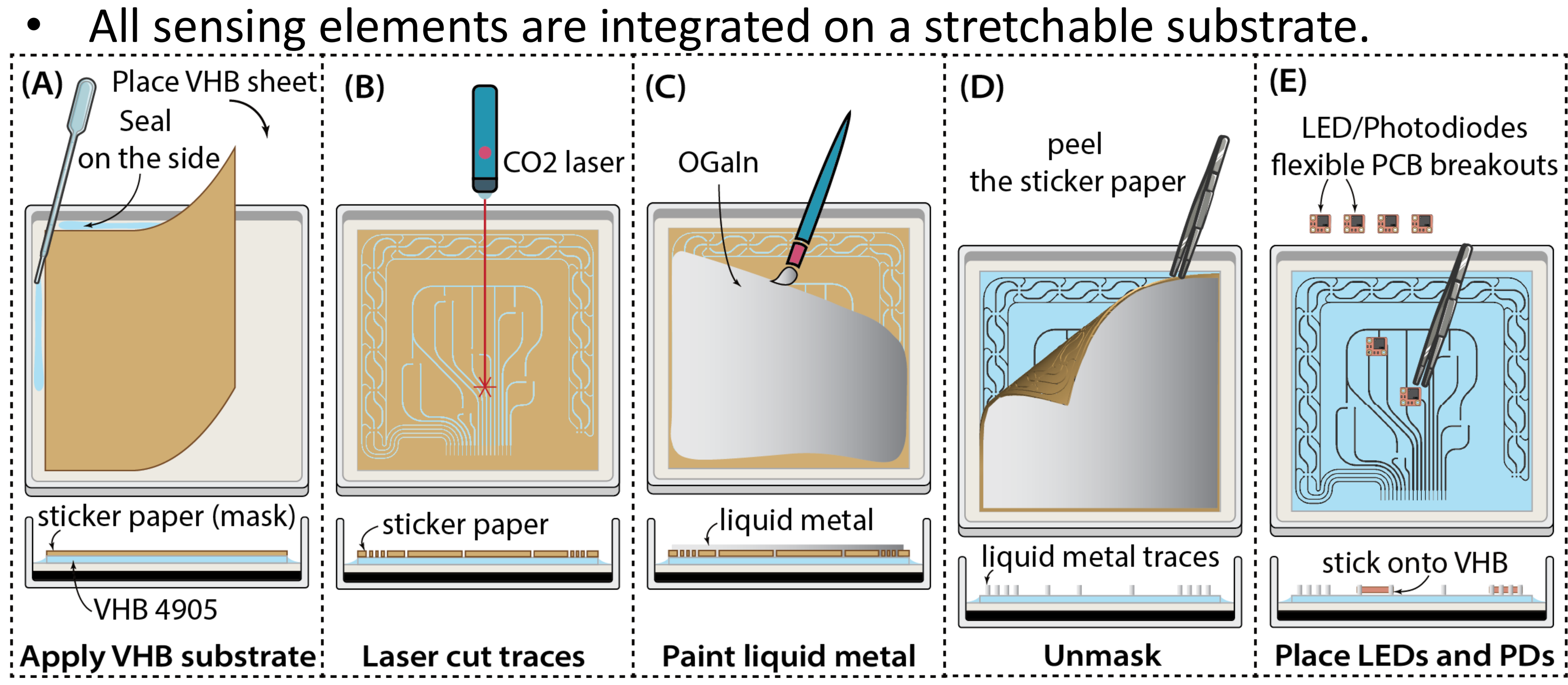
### ✓ Design of a Sensorized Highly Deformable Membrane




- LEDs placed along the edges, controlled to light up sequentially.
- PDs spread across the center, sampled by an external ADC.
- LEDs and PDs are soldered onto **flexible PCB** breakouts.
- Use **liquid metal** (OGaIn) for electrical connectivity.
- Body is made of a platinum-cured **silicone rubber** (Ecoflex 00-45).

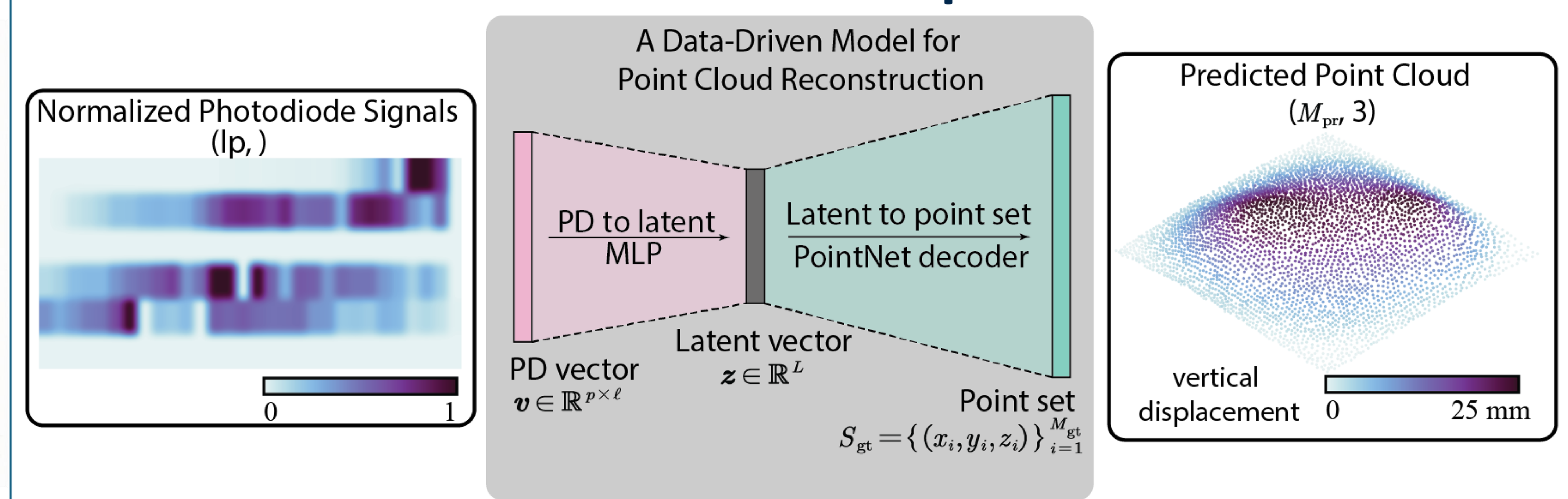
### ✓ Stretchable Circuit Fabrication

- All sensing elements are integrated on a stretchable substrate.




For more details about this work, please visit the project homepage by scanning the QR code.

## Reconstruction Pipeline




**Stage 1: Point cloud autoencoder**

- The encoder, $E(\cdot)$, compresses the point clouds into an $L$-dimensional latent space and a decoder, $D(\cdot)$, reconstructs them back.
- The training loss is the **chamfer distance** between the original point cloud $S_{gt}$ and the reconstructed point cloud $S_{pr}$

$$d_{CD}(S_{gt}, S_{pr}) = \sum_{x \in S_{pr}} \min_{y \in S_{gt}} \|x-y\|^2 + \sum_{y \in S_{pr}} \min_{x \in S_{gt}} \|x-y\|^2$$

- The autoencoder adopts the PointNet backbone to learn a compact representation of the geometry.

**Stage 2: PD-to-latent regression**

- A fully connected MLP, $h(\cdot)$, is trained on the MSE loss to map the PD vector to the latent vector.

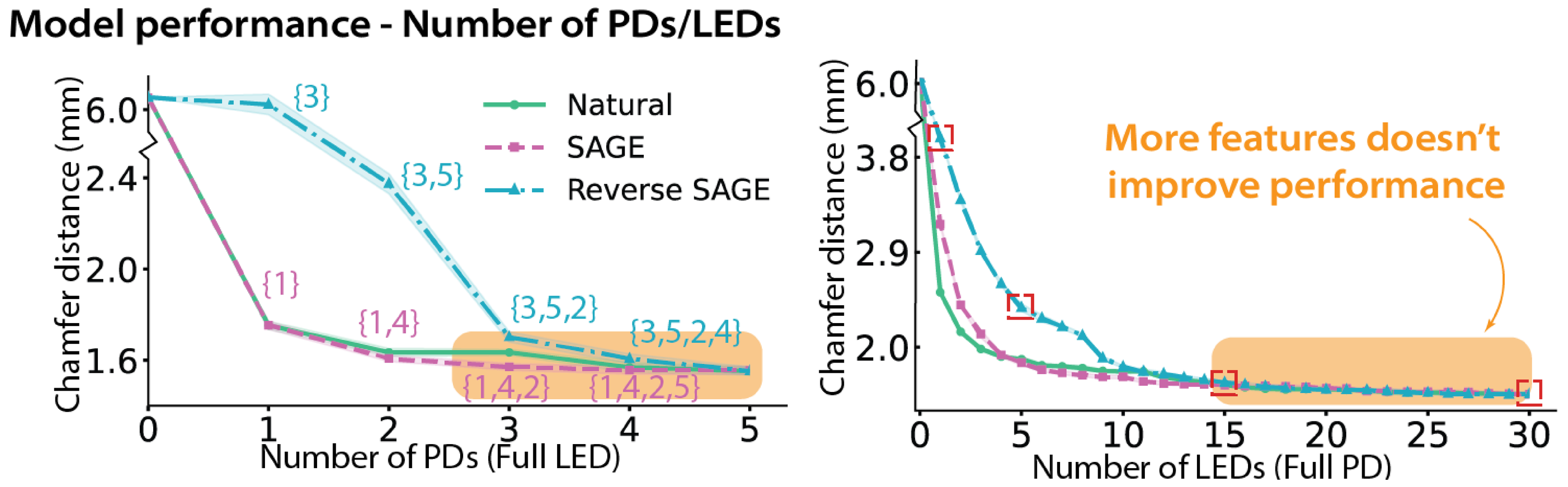
$$\mathcal{L}_{mse} = \|h(\boldsymbol{v}) - \boldsymbol{z}\|^2$$

- The ground truth latent vector is pre-computed using the encoder trained in stage 1.

Full reconstruction pipeline is the composition of $h$ and $D$.

## Number of Sensing Elements

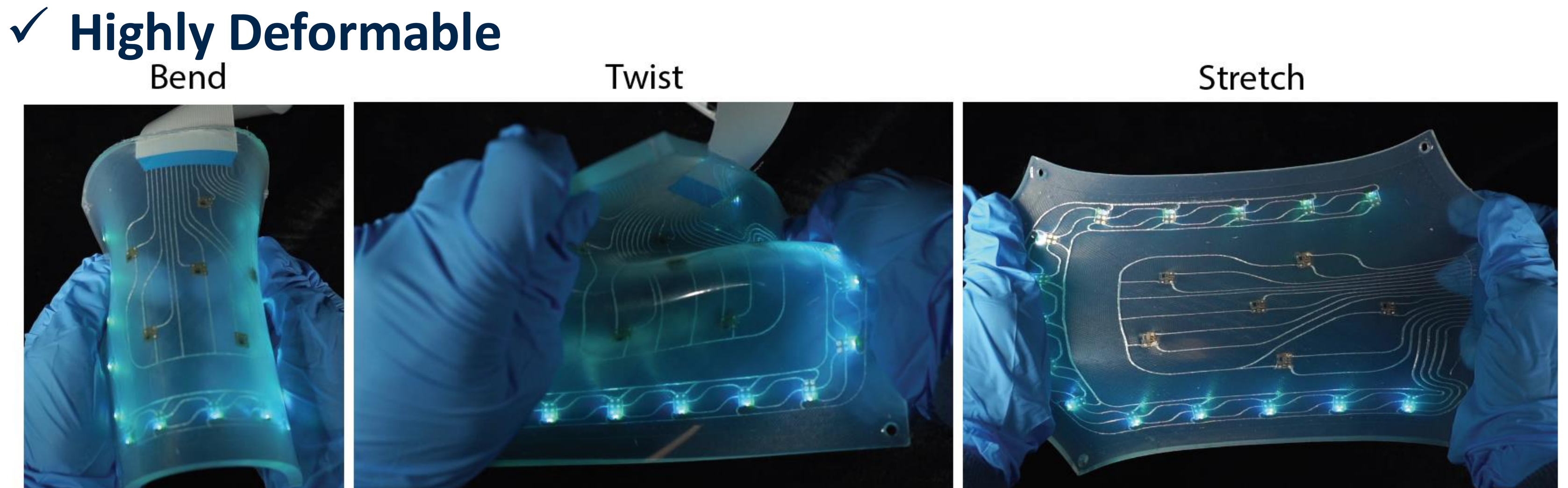
**Model performance - Number of PDs/LEDs**



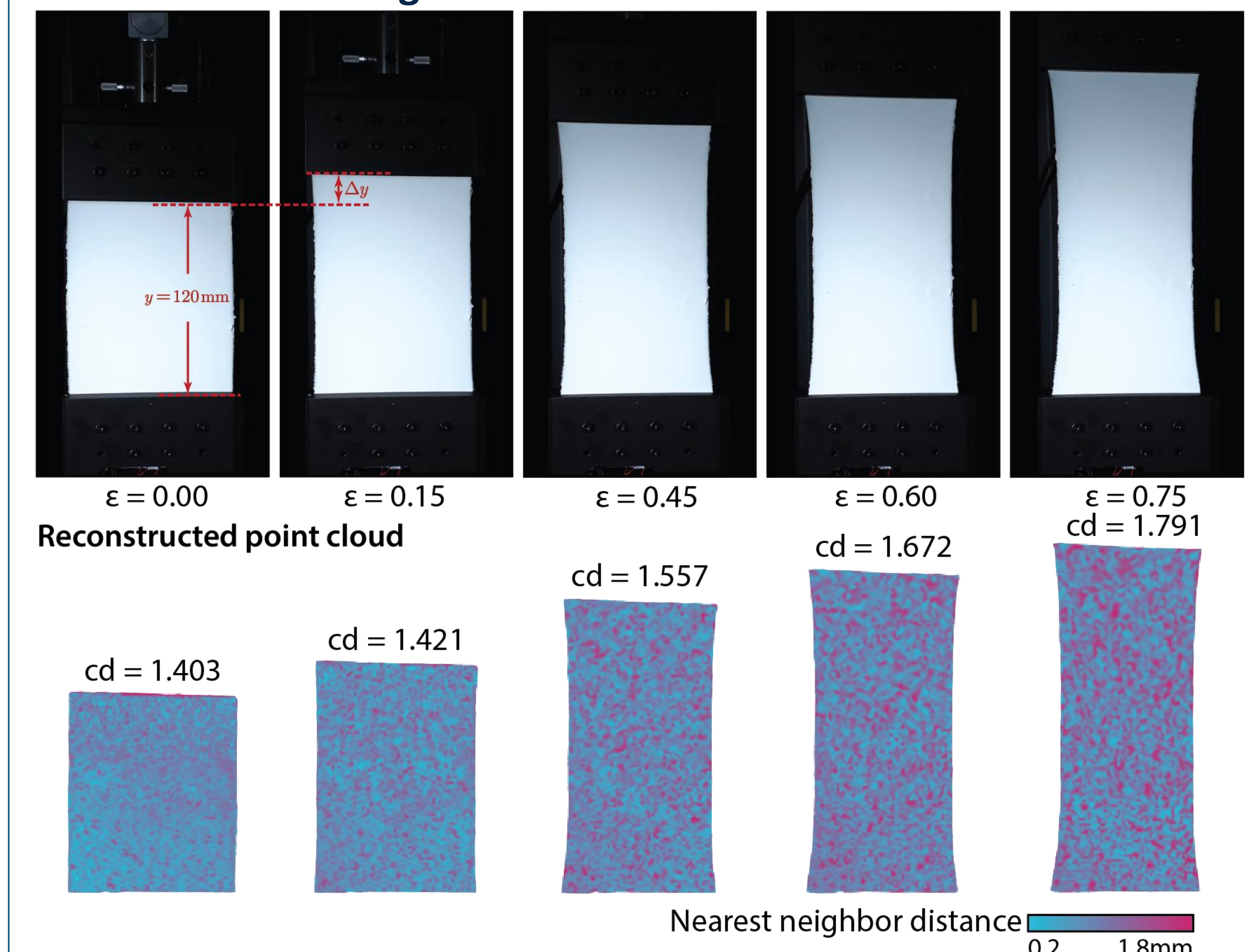

- Track the model performance (using ground-truth to reconstruction chamfer distance) while progressively adding sensing element.
- Performance plateau when LED number is greater than 15.

## Experiments and Results

### ✓ Highly Deformable

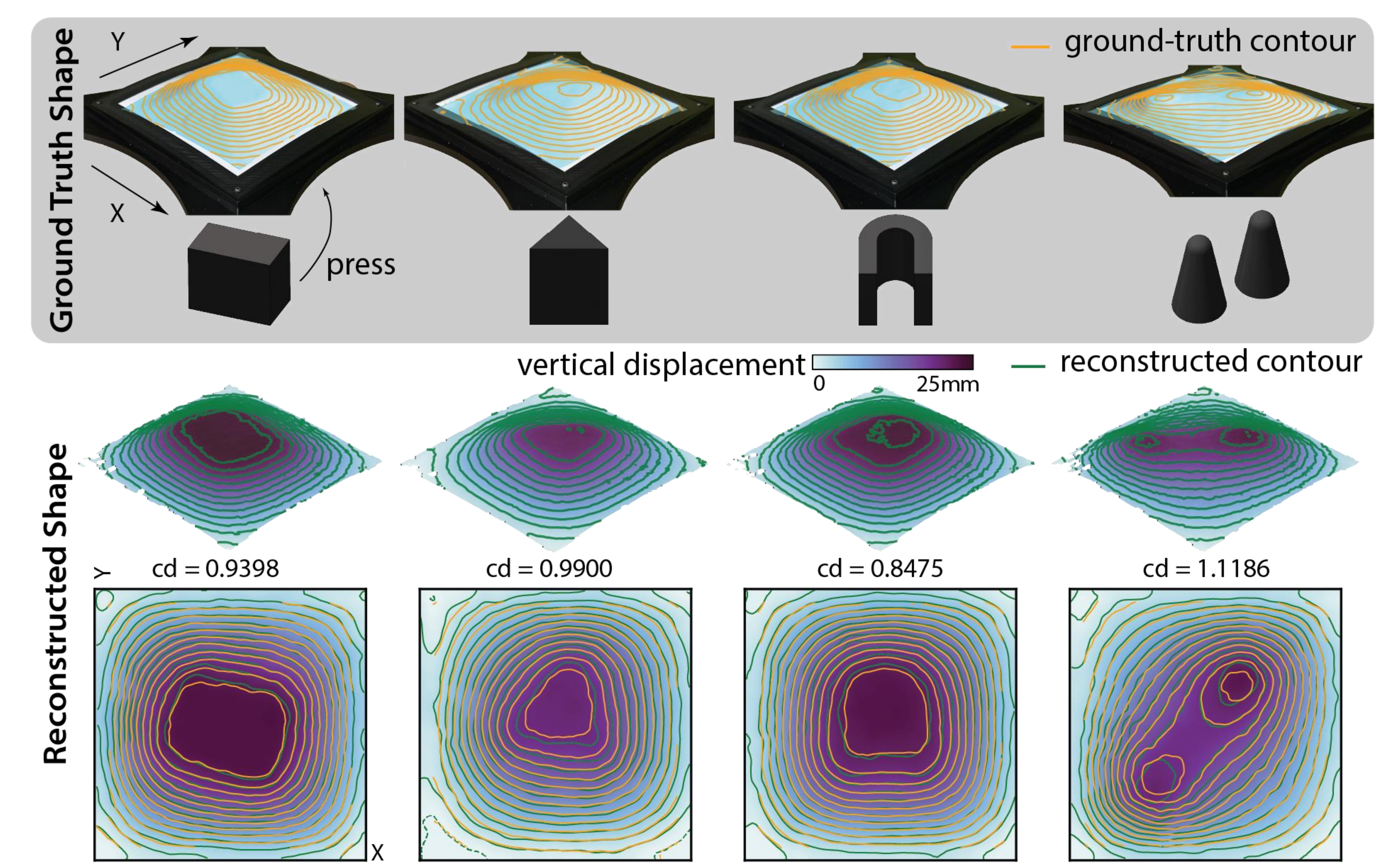



### ✓ Uniaxial stretching




- Achieve high accuracy reconstruction of **uniaxial stretching up to 75%**.
- Average chamfer distance (cd) **1.214 mm**.

### ✓ Out-of-plane Indentation




- Achieve real-time reconstruction with **90 Hz update rate**.
- Average chamfer distance (cd) **1.307 mm**.

## Future Work

- Develop scalable optical simulation for highly deformable waveguide membranes.
- Generate paired datasets covering broader deformation modes.
- Reduce training data collection cost through simulation.

## Acknowledgement

This work is supported by the Start-up Funding from the Robotics Department. The authors would like to thank their lab mates in the Hybrid Dynamic Robotics Lab for their help and assistance.