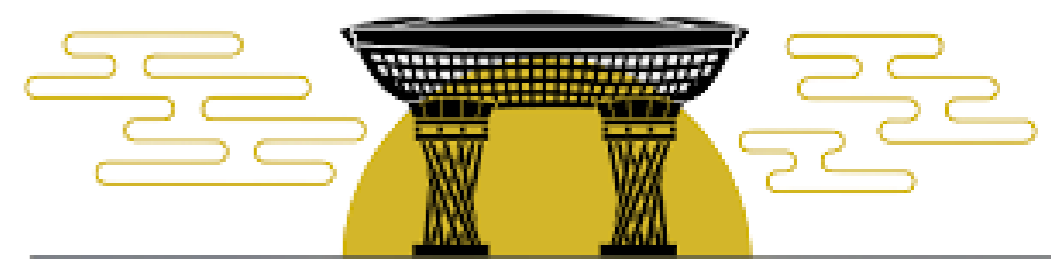


# Real-Time Simulation of Deformable Tactile Sensors in Robotic Grasping using Graph Neural Networks with Inductive Biases

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ROBOSOFT 2026

## Laboratoire d'InfoRmatique en Image et Systèmes d'information

LIRIS UMR 5205 CNRS / INSA de Lyon / Université Claude Bernard Lyon 1 / Université Lumière Lyon 2 / Ecole Centrale de Lyon

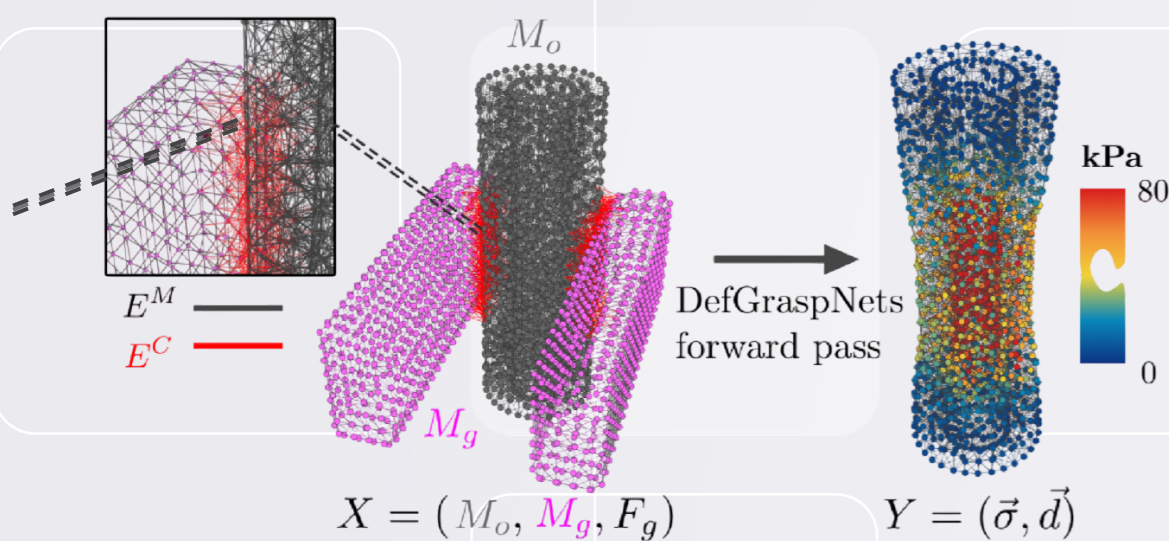
### Motivation

- More and more requirement in large scale dataset
- For Soft body, FEM remains the reference but can be slow
- GNN have shown good results in physics simulation
- Growing need of data using Visual Tactile Sensors

### Related works and GNN advantages

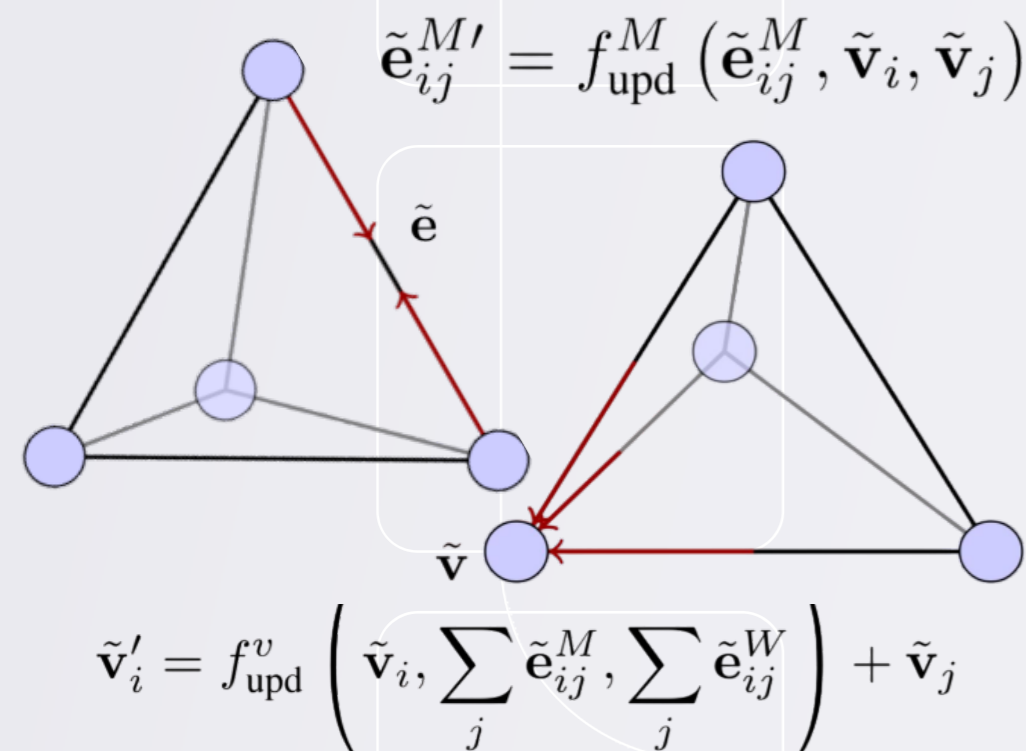
#### 1) DefGraspNet [1]

- Dataset generated with FEM simulator DefGraspSim [2]
- Object and gripper before grasp are expressed as input graph
- Mesh vertices are graph nodes, mesh edges graph edges



#### 2) Encode-Process-Decode GNN [3]

- Multi-Layer Perceptrons (MLPs) encode node and edge features to common 128D latent space
- Message passing propagates information:



- Decode deformation and stress prediction at each node

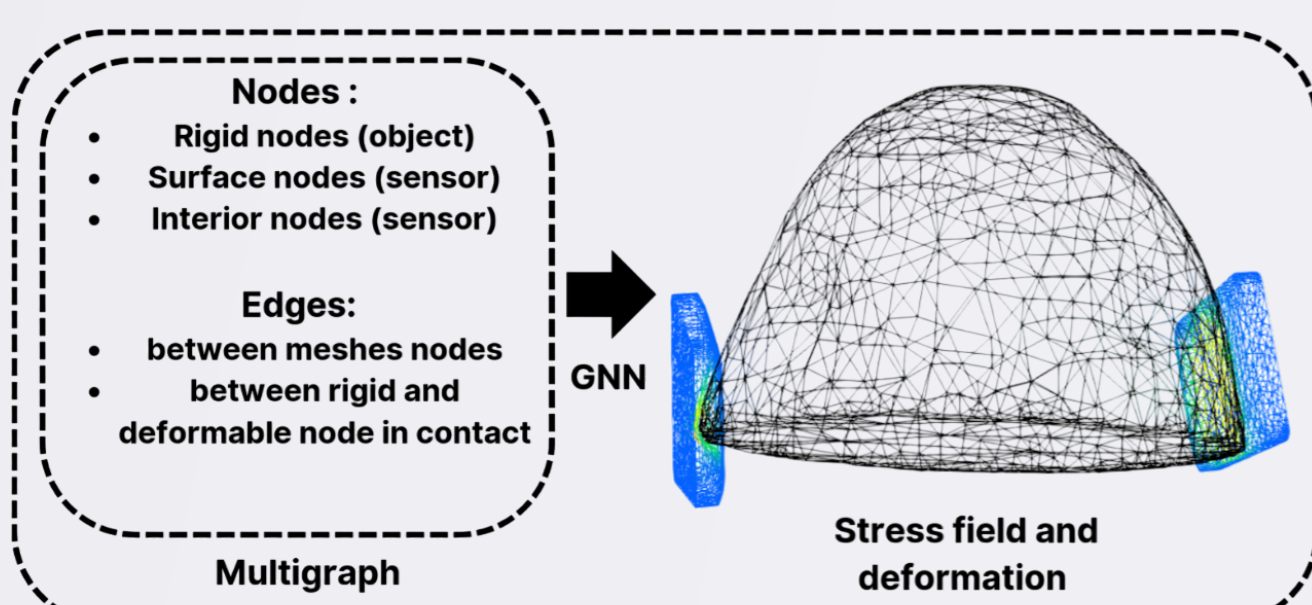
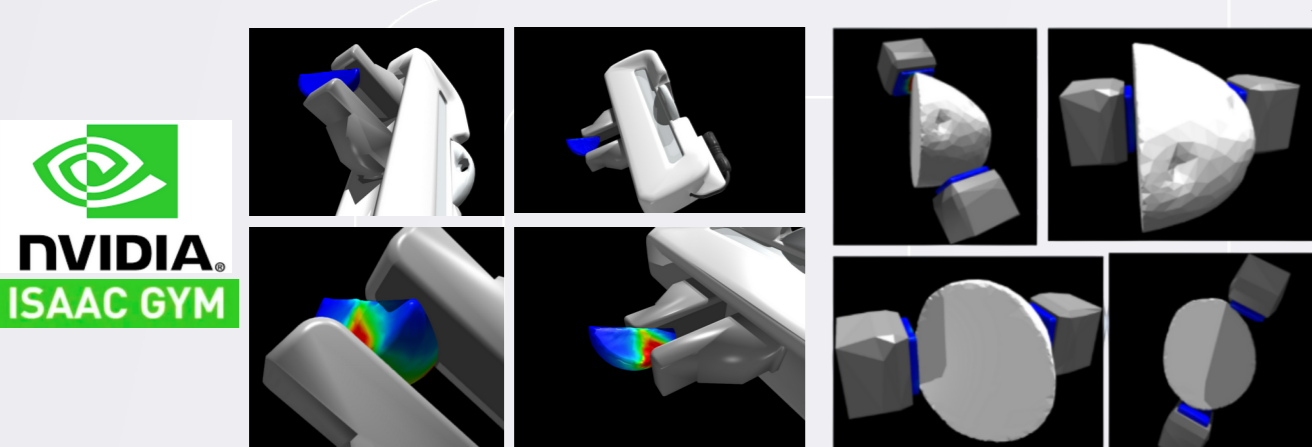
#### 3) Graph Neural Network advantages

- **Natural representation** : 3D scene with meshes and spatial relationships
- **Local information** : Message passing allows information to propagate locally, mimicking traditional FEM simulation and real continuum mechanics.
- **Inference takes a few ms**
- **End-to-End Differentiability** : Control optimization, parameter estimation and inverse design

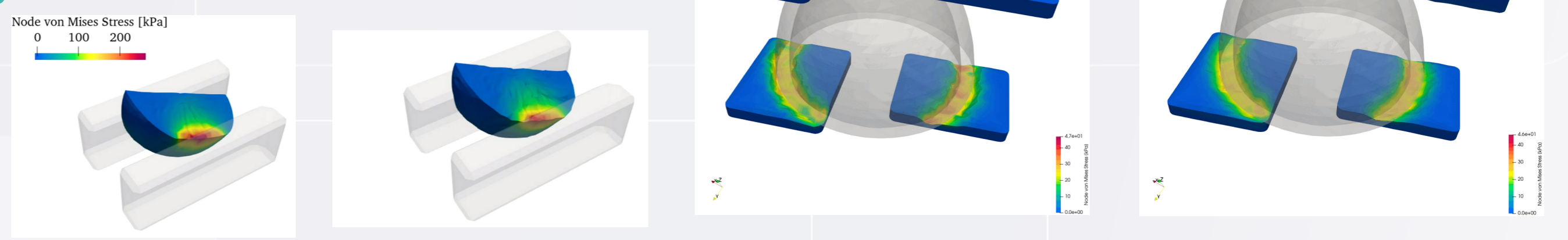
### Limitation

- Slow propagation through network hurts edge cases
- No preprocessing for DefGraspSim data
- No Visual tactile sensors

### Soft body Grasping and Visual tactile sensor dataset generation :



### Qualitative Results

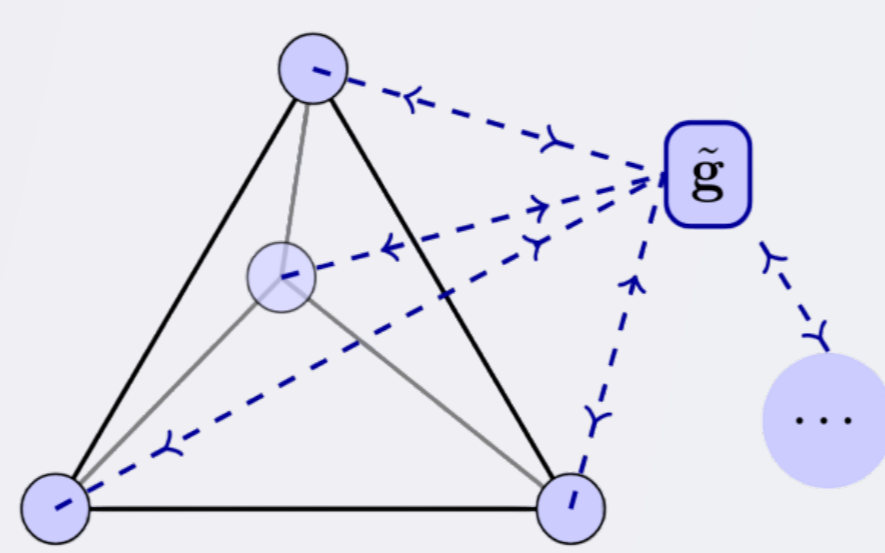


### Graph neural network Improvements :

#### 1) Tetrahedron features :

$$\tilde{t}_i' = f_{\text{upd}}^t(\tilde{t}_i, \{\tilde{v}_j\}_{j \in \mathbb{T}_i}) + \tilde{t}_i$$

#### 2) Global features :

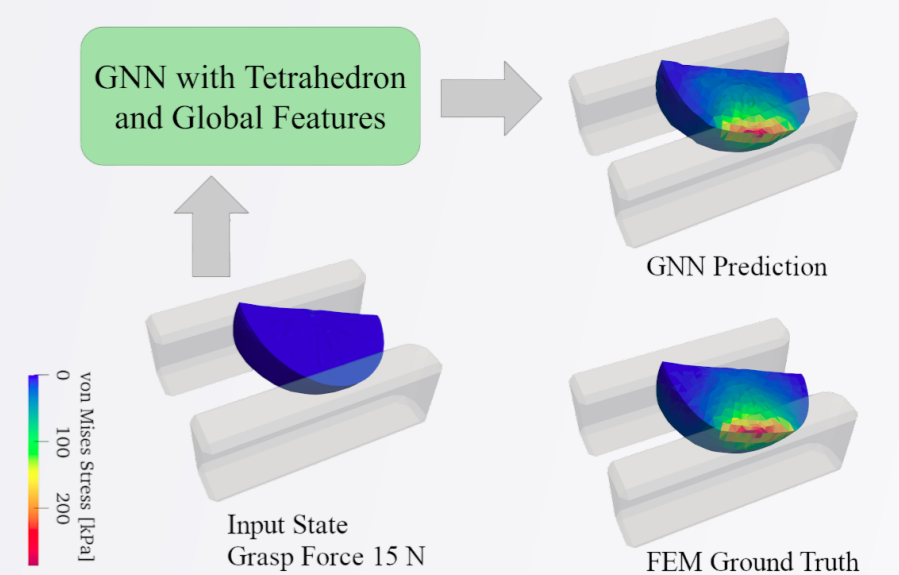


- Better physical meaning
- GNN is informed about mesh tetrahedrons by giving a tetrahedron set as input, similar to the edge set
- Decode stress prediction at tetrahedron

- Architectural extension to the GNN
- In message passing, global feature receives information from all nodes in graph, and sends to all nodes
- Act as shortcut for globally relevant information to be propagated through the graph

### Evaluations on Soft body Grasping

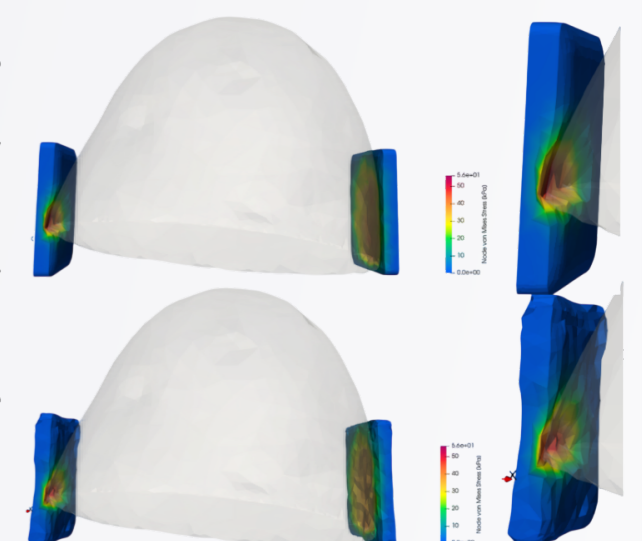
Object	8polygon06	cylinder07	lemon01	potato2	sphere03	strawberry01	u	σ
MAPE in %								
DefGraspNets [1]	3.24	1.52	3.00	3.23	4.66	1.39	<b>3.05</b>	2.46
Tet. Features	3.86	1.91	2.93	2.37	4.51	1.92	3.34	1.75
Tet. + Global Feat.	<b>2.04</b>	<b>0.93</b>	<b>1.84</b>	<b>1.04</b>	<b>3.48</b>	<b>0.77</b>	3.12	<b>0.53</b>



### Evaluations on Visual Tactile Sensors Grasping

Object	Trans.	Def. MAE	Stress MAE
Potato	✓	<b>6.57e-05</b>	<b>372.7</b>
	–	2.92e-04	382.8
Apple	✓	<b>7.20e-05</b>	<b>370.5</b>
	–	2.97e-04	427.9
Lemon	✓	<b>5.40e-05</b>	<b>212.1</b>
	–	2.38e-04	265.6

Object Set	Trans.	Def. MAE	Stress MAE
Known-10	✓	<b>6.30e-05</b>	<b>360.3</b>
	–	2.69e-04	420.2
Known-63	✓	<b>7.90e-05</b>	<b>352.0</b>
	–	2.54e-04	365.0
Unknown-12	✓	<b>8.54e-05</b>	<b>6.19e2</b>
	–	2.81e-04	6.43e2



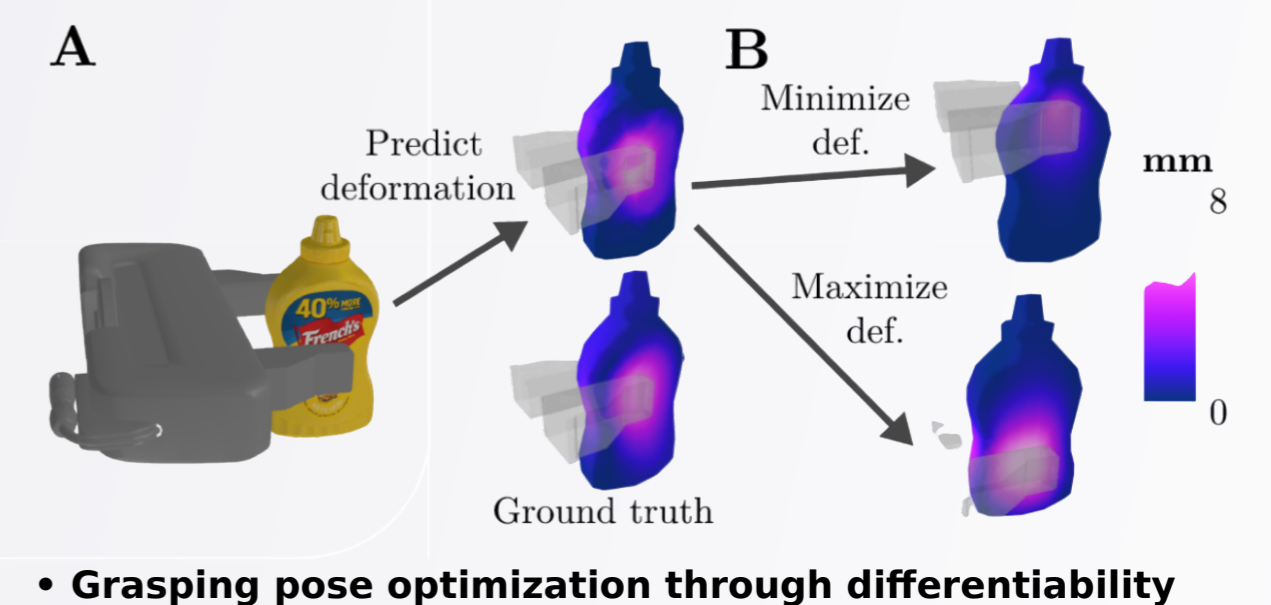
Method	Inference Time	Speedup vs. FEM	Hardware
FEM Simulation	100–200 s	1×	GPU
GNN (Ours)	<b>5–50 ms</b>	<b>10<sup>3</sup>–10<sup>4</sup>×</b>	GPU

### Contributions

- Full PyTorch re-implementation of the DefGraspNets baseline
- Tetrahedron and global features improvement
- Extend DefGraspSim to Visual tactile sensors
- Extensive evaluation of the GNN on visual tactile sensor, including generalization to new objects
- First application of GNN on Visual tactile sensors
- Evaluation of the new features on Soft body grasping

### Future works

- Extend the Graph Neural network to new Tactile sensors
- Extend the dataset generation (More objects, soft body parameters, Gravity, Soft-Soft interactions...)
- Use differentiability to parameter finding for Control optimization



### References

- [1] I. Huang, Y. Narang, R. Bajcsy, F. Ramos, T. Hermans, and D. Fox, "DefGraspNets: Grasp planning on 3D fields with graph neural nets," in 2023 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2023, pp. 5894–5901.
- [2] I. Huang, Y. Narang, C. Eppner, B. Sundaralingam, M. Macklin, R. Bajcsy, T. Hermans, and D. Fox, "DefGraspSim: Physics-based simulation of grasp outcomes for 3D deformable objects," IEEE Robotics and Automation Letters, vol. 7, no. 3, pp. 6274–6281, 2022.
- [3] T. Pfaff, M. Fortunato, A. Sanchez-Gonzalez, and P. Battaglia, "Learning mesh-based simulation with graph networks," in International conference on learning representations, 2020.