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Physically Compatible 3D Object Modeling from a Single Image

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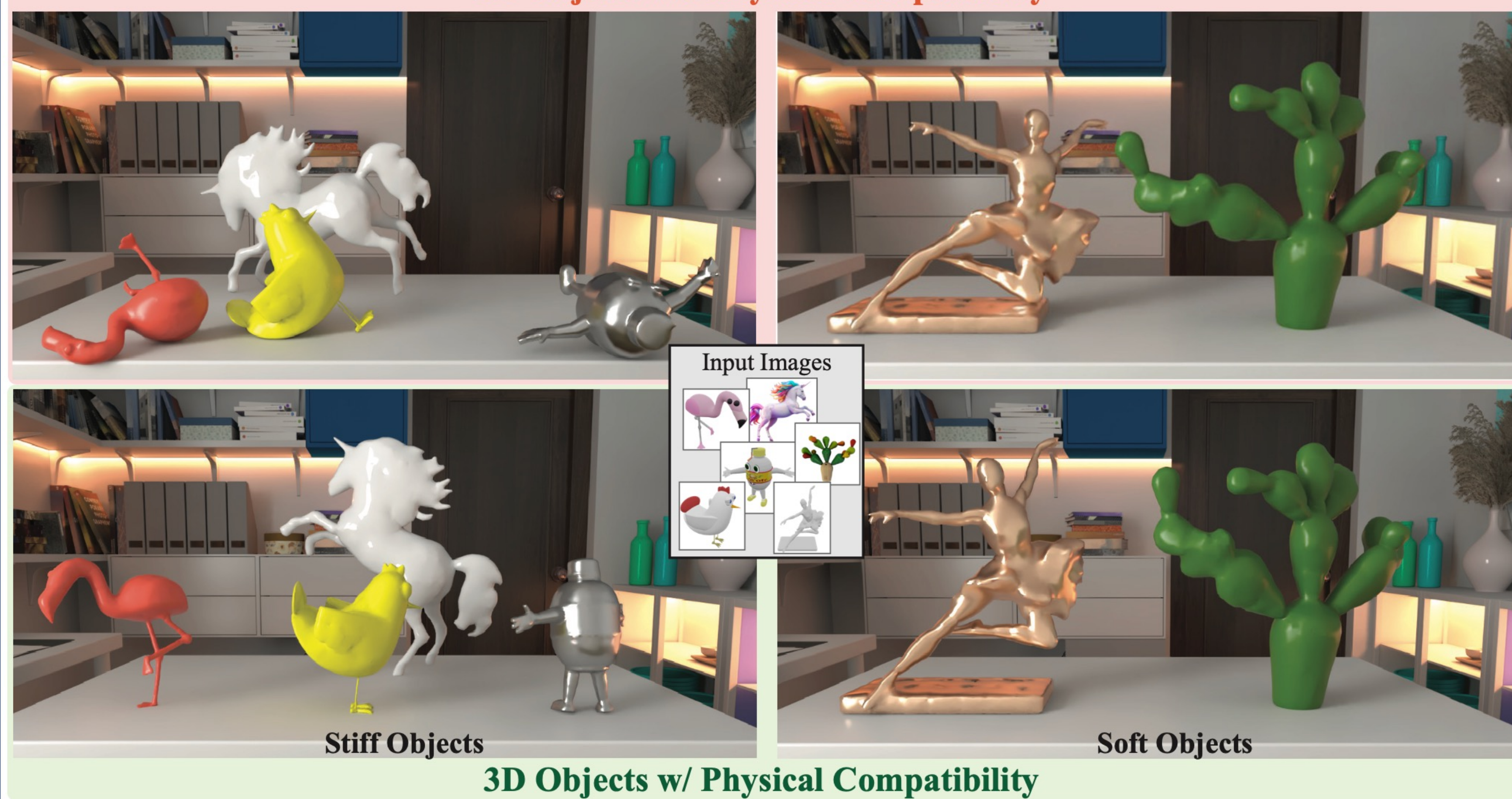


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Motivation

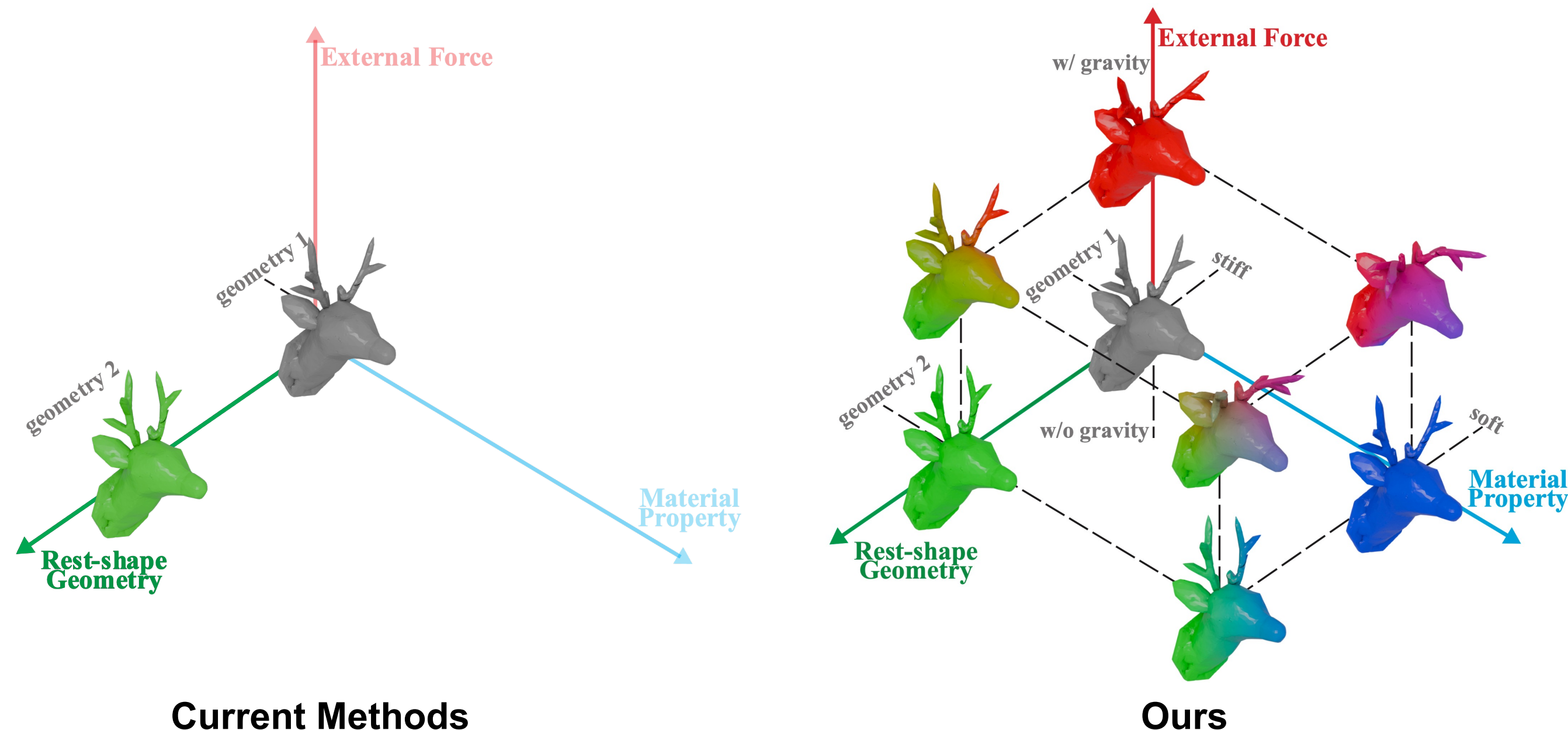
- Existing single-view reconstruction methods output 3D objects failing to withstand real-world physical forces.
- We propose **physical compatibility optimization**, ensuring that the optimized physical shapes exhibit desired physical behavior.

3D Objects w/o Physical Compatibility

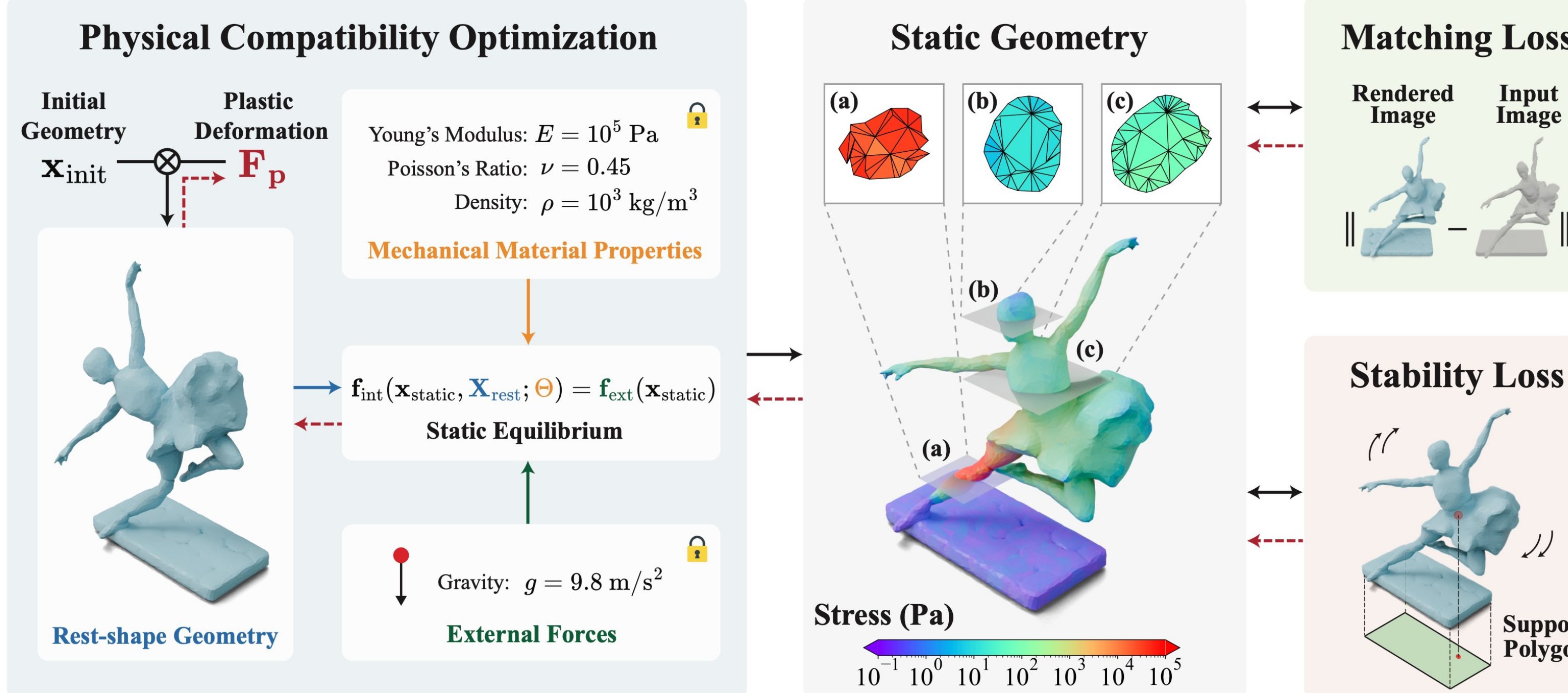


An Image is a Physical Snapshot of an Object

- The object in an image is in a state of **static equilibrium**, under the influence of real-world forces.



Formulation of Physical Compatibility



- Optimization Objective:**

$$\min_{\mathbf{X}_{\text{rest}}, \mathbf{X}_{\text{static}}} \mathcal{J}(\mathbf{X}_{\text{rest}}, \mathbf{X}_{\text{static}}) = \mathcal{L}(\mathbf{x}_{\text{static}}) + \mathcal{L}_{\text{reg}}(\mathbf{X}_{\text{rest}})$$

$$\text{s.t. } \mathbf{f}_{\text{int}}(\mathbf{x}_{\text{static}}, \mathbf{X}_{\text{rest}}; \Theta) = \mathbf{f}_{\text{ext}}(\mathbf{x}_{\text{static}}).$$

Parameterization of Rest Geometry

- Plastic Deformation:** $\mathbf{X}_{\text{rest}} := \phi(\mathbf{F}_p; \mathbf{X}_{\text{init}})$, with $\mathbf{f}_{\text{int}}(\mathbf{X}_{\text{rest}}, \mathbf{X}_{\text{init}}; \Theta) = 0$.
- Implicit Differentiation-based Optimization:**

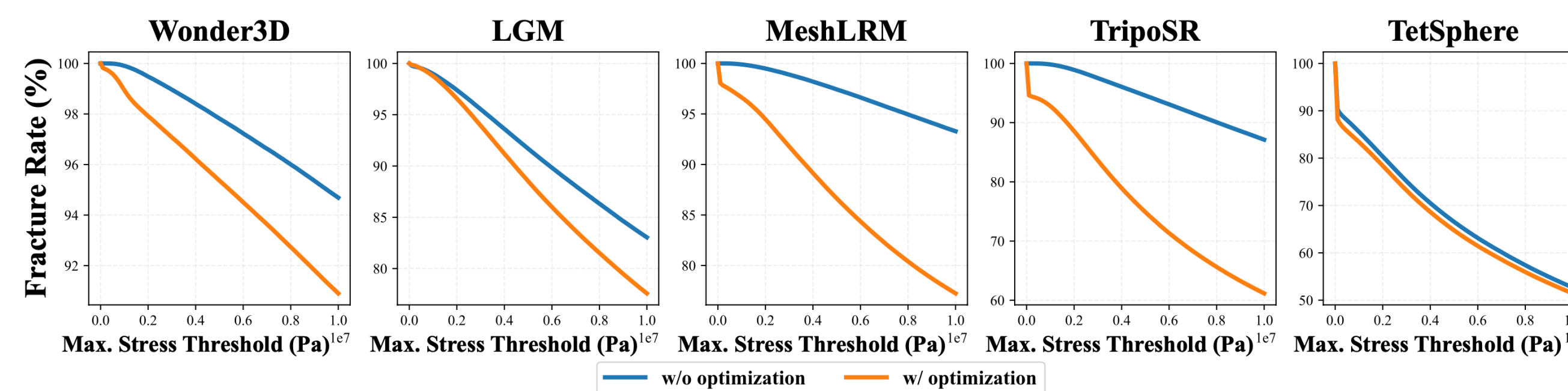
$$\min_{\mathbf{F}_p, \mathbf{X}_{\text{static}}} \mathcal{J}(\mathbf{F}_p, \mathbf{x}_{\text{static}}) = \mathcal{L}(\mathbf{x}_{\text{static}}) + \mathcal{L}_{\text{reg}}(\mathbf{F}_p)$$

$$\text{s.t. } \mathbf{f}_{\text{int}}(\mathbf{x}_{\text{static}}, \phi(\mathbf{F}_p; \mathbf{X}_{\text{init}}); \Theta) = \mathbf{f}_{\text{ext}}(\mathbf{x}_{\text{static}}).$$

$$\frac{\partial \mathcal{J}}{\partial \mathbf{F}_p} = - \left(\frac{\partial \mathcal{L}}{\partial \mathbf{x}_{\text{static}}} \right) \left[\frac{\partial \mathbf{f}_{\text{net}}}{\partial \mathbf{x}_{\text{static}}} \right]^{-1} \frac{\partial \mathbf{f}_{\text{net}}}{\partial \mathbf{F}_p} + \frac{\partial \mathcal{L}_{\text{reg}}}{\partial \mathbf{F}_p}$$

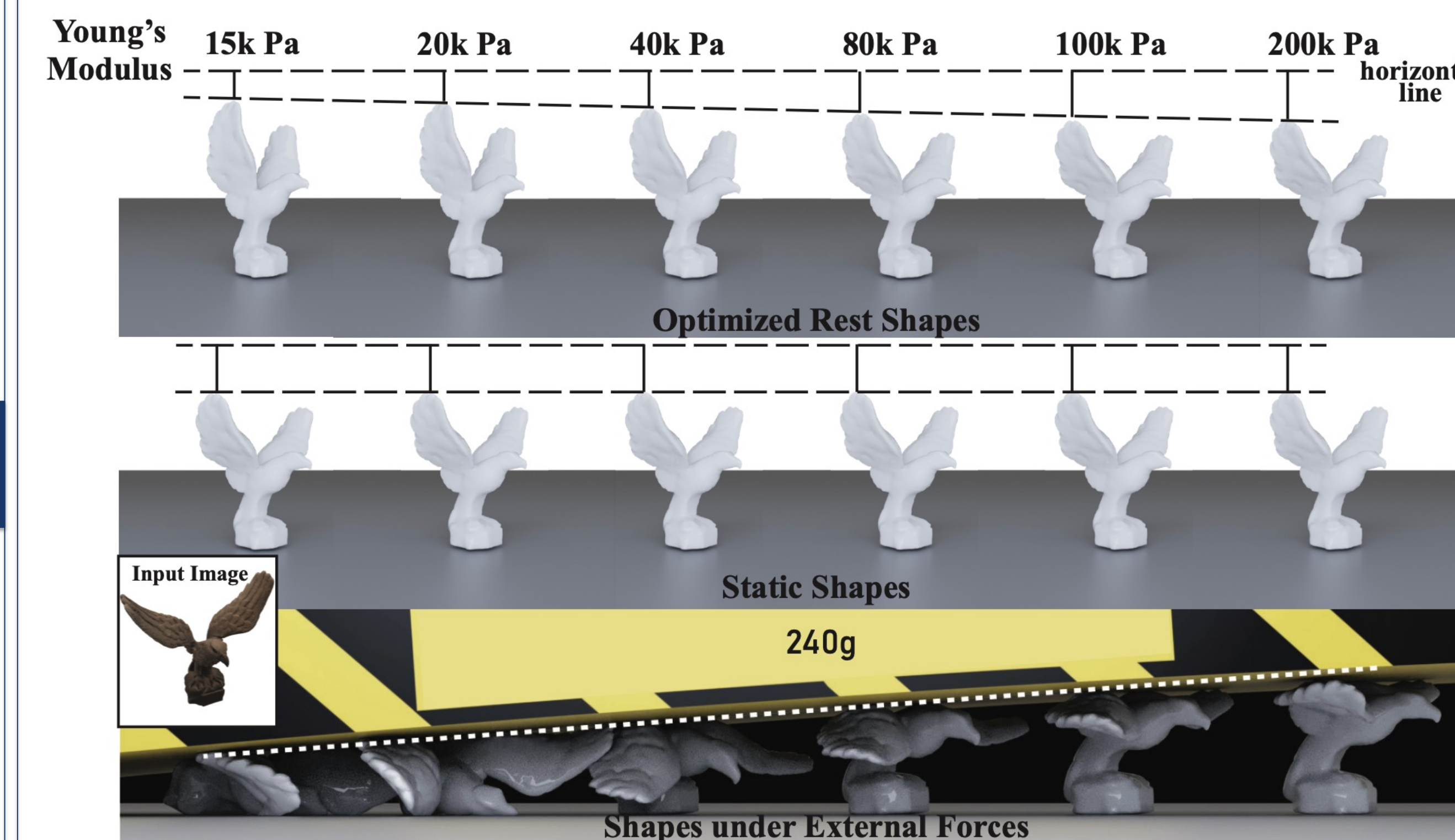
Experimental Results

- Main Results**



Method	Init. Geo.	#CC. ↓	Mean Stress ↓ (kPa)	Standable. ↑ (%)	Img. Loss ↓	
Wonder3D	Baseline	NeuS	2.54 ± 2.64	10.68 ± 17.47	6.9	0.073 ± 0.063
	Ours	NeuS	2.54 ± 2.64	0.45 ± 0.96	72.4	0.069 ± 0.048
LGM	Baseline	Gaussian splatting	2.67 ± 2.13	1.14 ± 2.03	20.3	0.121 ± 0.091
	Ours	Gaussian splatting	2.67 ± 2.13	1.01 ± 1.34	85.9	0.116 ± 0.065
MeshLRM	Baseline	surface mesh	1.55 ± 2.13	0.54 ± 1.41	28.6	0.065 ± 0.042
	Ours	surface mesh	1.55 ± 2.13	0.38 ± 1.05	73.8	0.064 ± 0.042
TripoSR	Baseline	NeRF	1.43 ± 1.12	0.29 ± 1.28	24.2	0.066 ± 0.047
	Ours	NeRF	1.43 ± 1.12	0.22 ± 0.94	80.6	0.059 ± 0.039
TetSphere	Baseline	tet-sphere	1.00 ± 0.00	0.22 ± 0.51	32.8	0.061 ± 0.045
	Ours	tet-sphere	1.00 ± 0.00	0.19 ± 0.78	92.4	0.057 ± 0.040

- Ablation Study on Young's Modulus**



- Applications on Dynamic Simulation and Fabrication**

