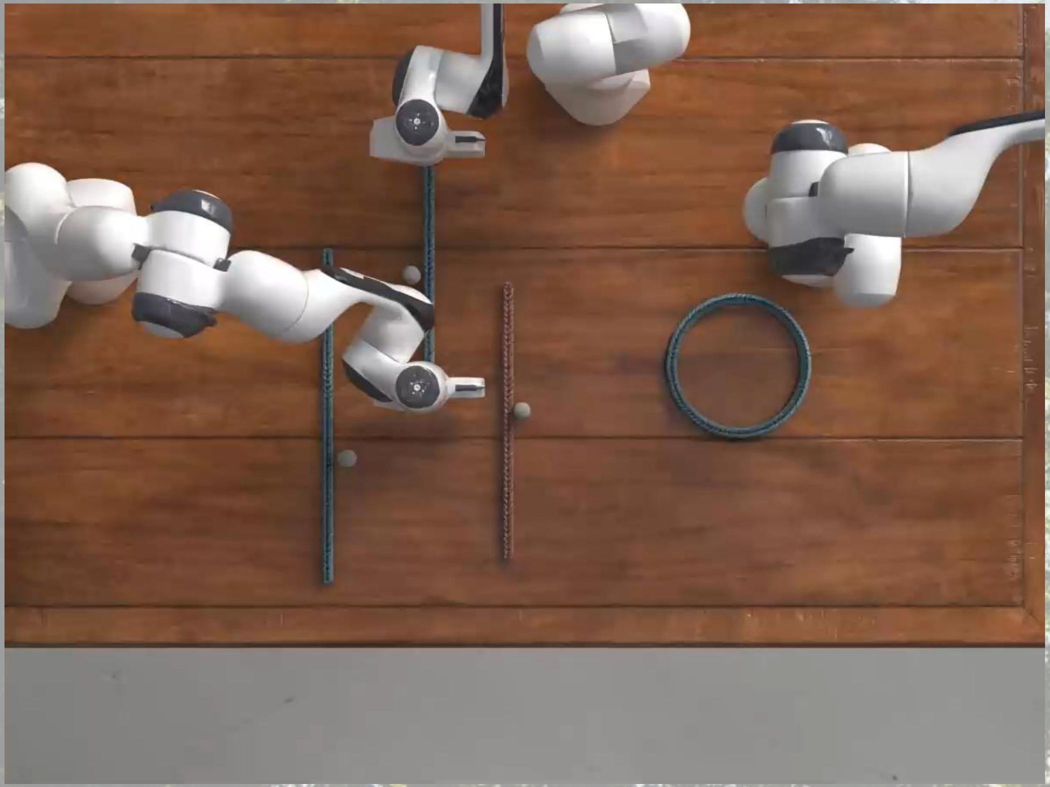

DLO-Lab:

Benchmarking Deformable Linear Object Manipulations with Differentiable Physics

JUNYI CAO | MAY 30, 2026 | DLO-LAB-26.GITHUB.IO/

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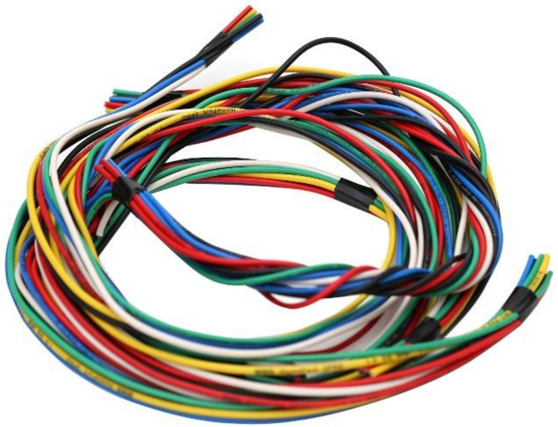
Overview

We encounter various deformable linear objects (DLOs) in our daily life.



Cables

Ropes

Rubber Bands

Wires

How can we teach machine intelligence to reliably manipulate these objects, especially given their *complex dynamics*, *unpredictable deformations*, and *varied topologies*?

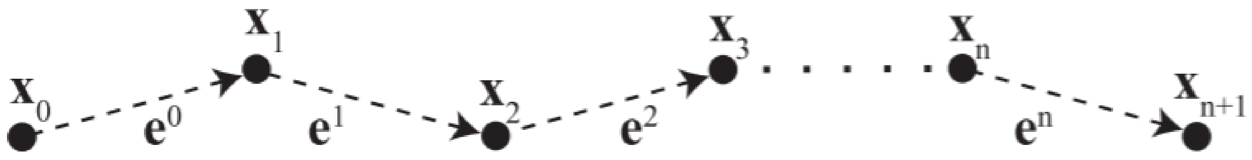
Overview

Existing DLO simulators only support a subset of the desired features.

Simulators	Solver	Bending Plasticity	Loop Topology	Coupling w/ Rigid & Soft	Differentiability
SoftGym	PBD			✅	
Elastica	Cosserat Rods			✅	
C-IPC	DER			✅	
DaXBench	MPM				✅
DEFORM	NN				✅
PhysTwin	Spring-Mass				✅
Ours	Customized	✅	✅	✅	✅

[1] SoftGym: Benchmarking deep reinforcement learning for deformable object manipulation. 2021.
[2] Elastica: A compliant mechanics environment for soft robotic control. 2021.
[3] Co-Dimensional incremental potential contact. 2021.
[4] DaXBench: Benchmarking deformable object manipulation with differentiable physics. 2023.
[5] Differentiable discrete elastic rods for real-time modeling of deformable linear objects. 2024.
[6] PhysTwin: Physics-informed reconstruction and simulation of deformable objects from videos. 2025

Simulation Environment

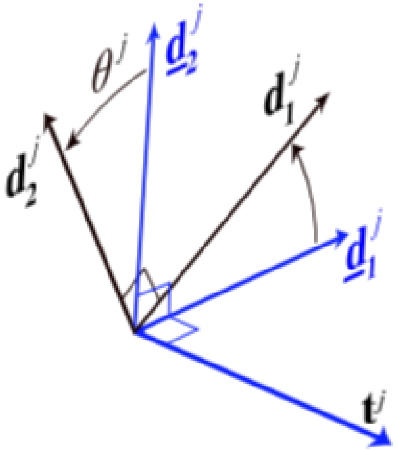


Vertex set $\mathcal{X} = \{\mathbf{x}_0, \mathbf{x}_1, \dots, \mathbf{x}_{n+2}\}$

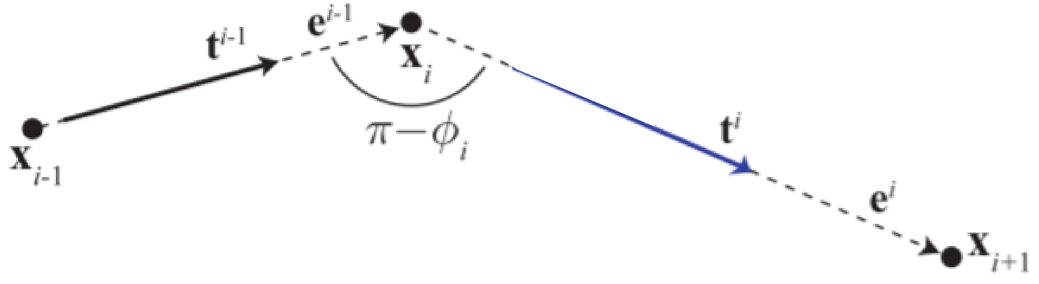
Edge set $\mathcal{E} = \{\mathbf{e}^0, \mathbf{e}^1, \dots, \mathbf{e}^{n+1}\}$

Reference frame at edge $\mathbf{e}^i$: $\{\underline{\mathbf{d}}_1^i, \underline{\mathbf{d}}_2^i, \underline{\mathbf{d}}_3^i\}$

Material frame at edge $\mathbf{e}^i$: $\{\mathbf{d}_1^i, \mathbf{d}_2^i, \mathbf{d}_3^i\}$



Twisting angle θ



Bending angle ϕ

Discrete Elastic Rods. SIGGRAPH 2008.
Discrete viscous threads. SIGGRAPH 2010.

Simulation Environment

Stretching Energy U_s

$$\epsilon^j = \frac{|\mathbf{e}^j|}{|\bar{\mathbf{e}}^j|} - 1$$ stretching strain

$$U_s = \frac{1}{2}\sum_{j=1}^{N_e} k_s^j (\epsilon^j)^2 |\bar{\mathbf{e}}^j|$$

$$k_s^j = KA^j$$

Bending Energy U_b

$$(\kappa\mathbf{b})_i = \frac{2\mathbf{t}^{i-1} \times \mathbf{t}^i}{1 + \mathbf{t}^{i-1} \cdot \mathbf{t}^i}$$ bending strain

$$|(\kappa\mathbf{b})_i| = 2\tan(\phi_i/2)$$

$$\boldsymbol{\kappa}_i = \frac{1}{2}\sum_{j=i-1}^{i} \left((\kappa\mathbf{b})_i \cdot \mathbf{d}_2^j, (\kappa\mathbf{b})_i \cdot \mathbf{d}_1^j\right)$$

$$U_b = \frac{1}{2}\sum_{i=2}^{N_v-1} \frac{1}{\bar{l}_i}(\boldsymbol{\kappa}_i - \bar{\boldsymbol{\kappa}}_i)^\top B_i(\boldsymbol{\kappa}_i - \bar{\boldsymbol{\kappa}}_i)$$

$$B_i = \frac{EA_i}{4}\begin{pmatrix} r_i^2 & 0 \\ 0 & r_i^2 \end{pmatrix}$$

Twisting Energy U_t

$$\tau_i = m_i - \bar{m}_i$$ twisting strain

$$m_i = \theta^i - \theta^{i-1} + \underline{m_i}$$

$$U_t = \frac{1}{2}\sum_{i=2}^{N_v-1} \beta_i \frac{(\tau_i)^2}{\bar{l}_i}$$

$$\beta_i = \frac{GA_i r_i^2}{2}$$

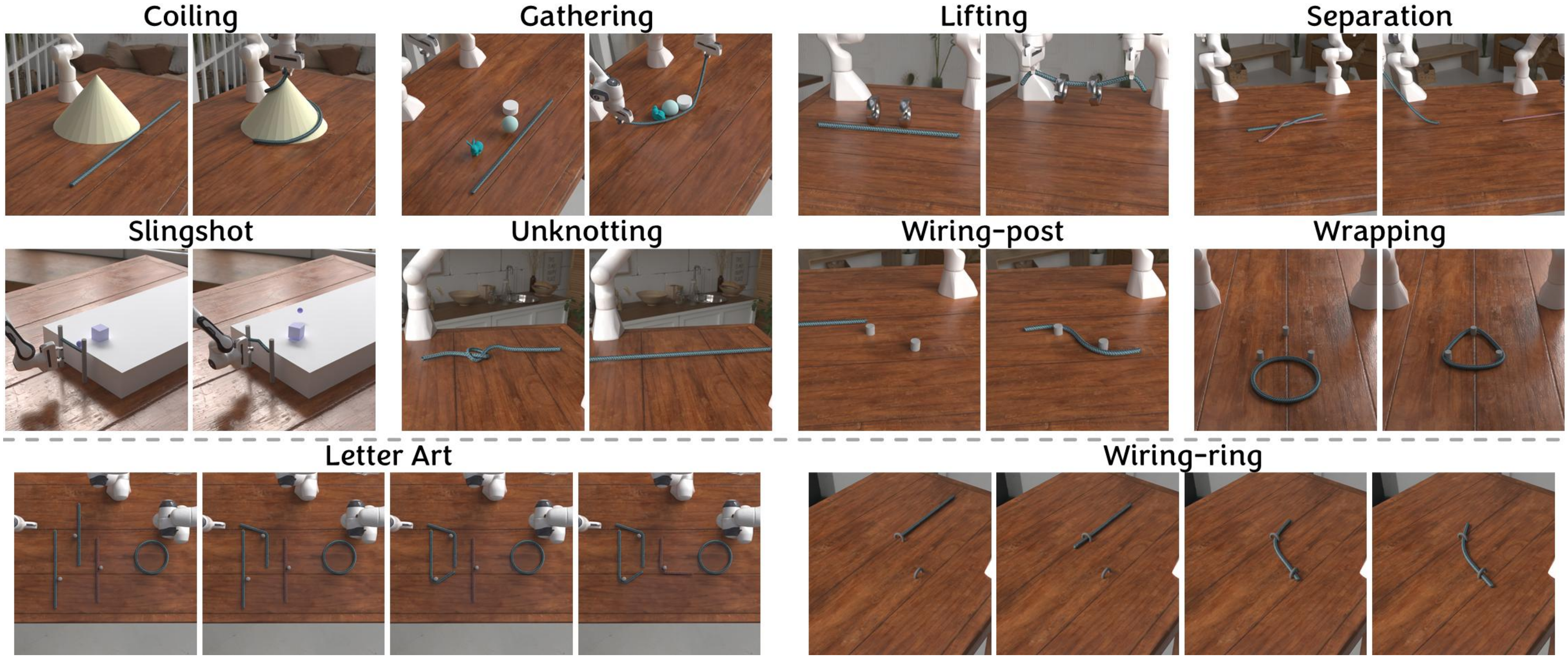
Discrete Elastic Rods. SIGGRAPH 2008.
Discrete viscous threads. SIGGRAPH 2010.

Simulation Environment

Rigid body: Time-varying Signed Distance Field (SDF)

Soft body: Material Point Method (MPM)

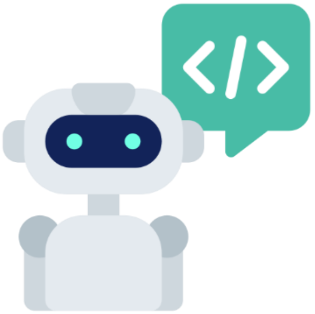
Manipulation Benchmark



DLO Agent

➢Many of these tasks mimic practical applications like cable routing, wire forming, and unknotting, which are inherently *long-horizon* and *constrained by topology*.

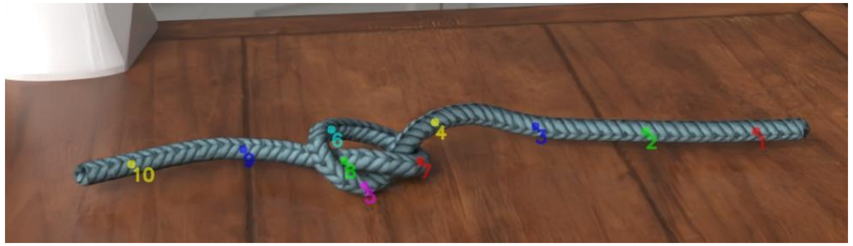
➢In such scenarios, the success of a task also depends on *identifying suitable grasping points* and implementing *strategic re-grasping*, making simple end-to-end policy learning impractical.



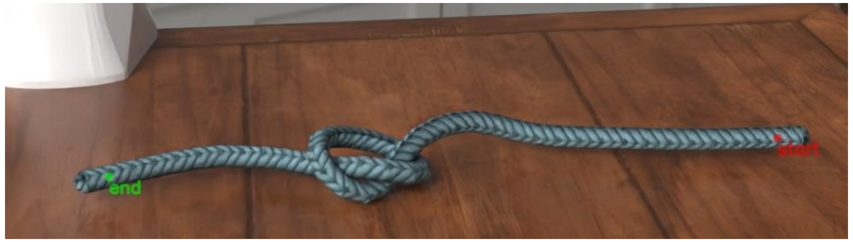
Grasp Proposal

Task Decomposition

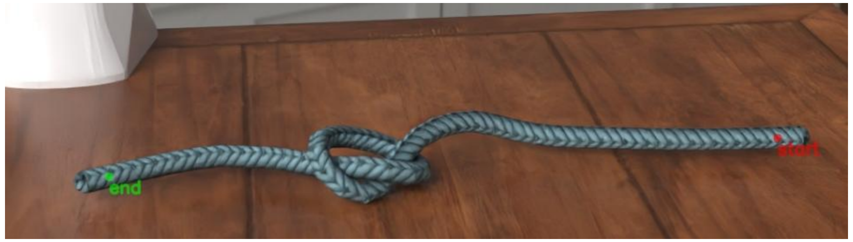
DLO Agent



Candidate Mode:
Choose from candidate points



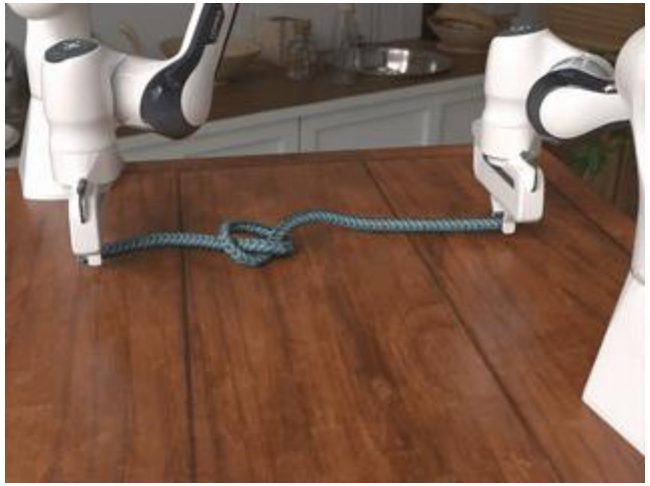
Coefficient Mode:
Select from [0, 1]



Marker Mode:
Pinpoint points on the image

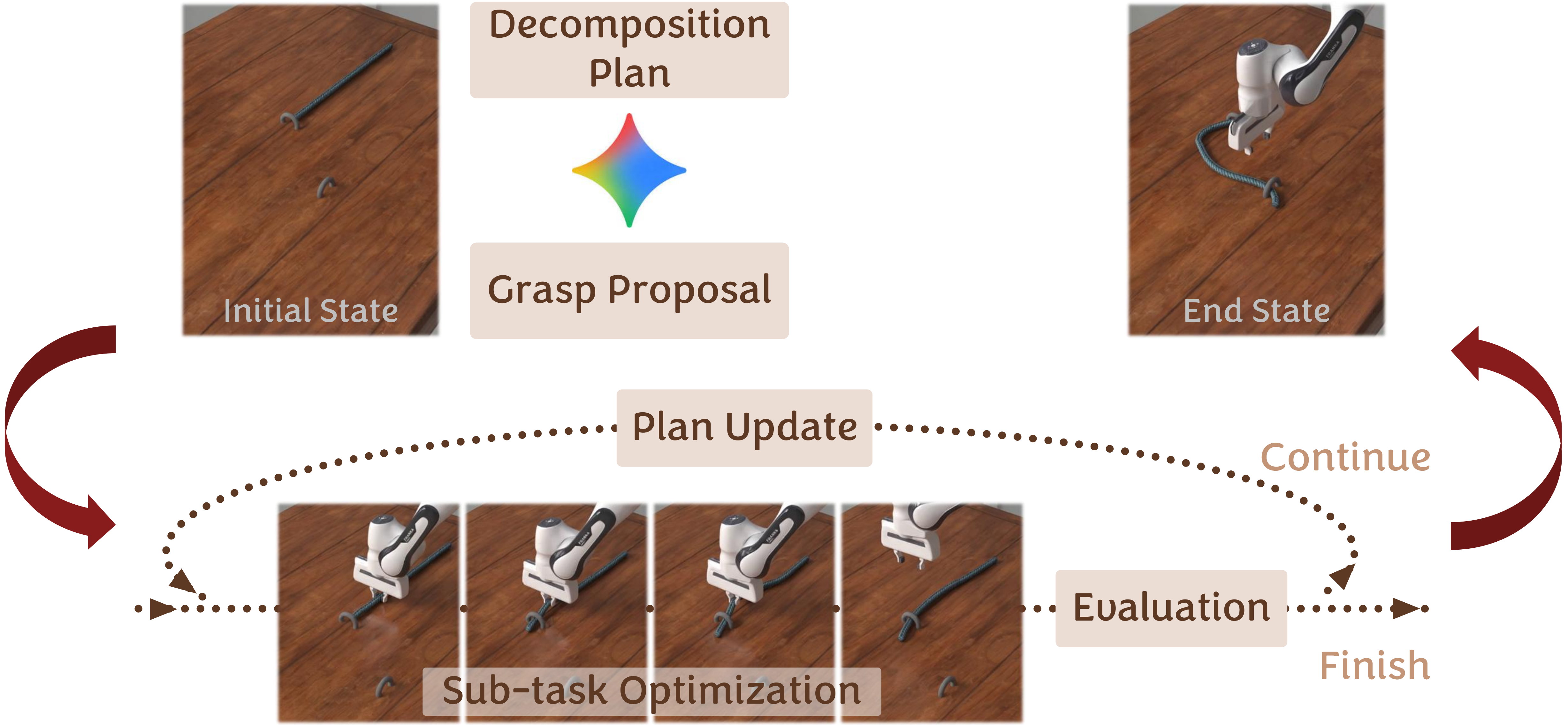
Tasks	Lifting	Unknotting	Wrapping
Candidate Mode	**335.59±14.21**	**57.21±1.51**	**162.68±0.86**
Coefficient Mode	330.57±9.03	3.06±0.01	144.78±3.23
Marker Mode	330.57±9.03	3.06±0.01	136.39±1.14

Candidate Mode



Coefficient/Marker Mode

DLO Agent


Decomposition Plan
Grasp Proposal
Initial State
End State
Plan Update
Continue
Evaluation
Finish
Sub-task Optimization

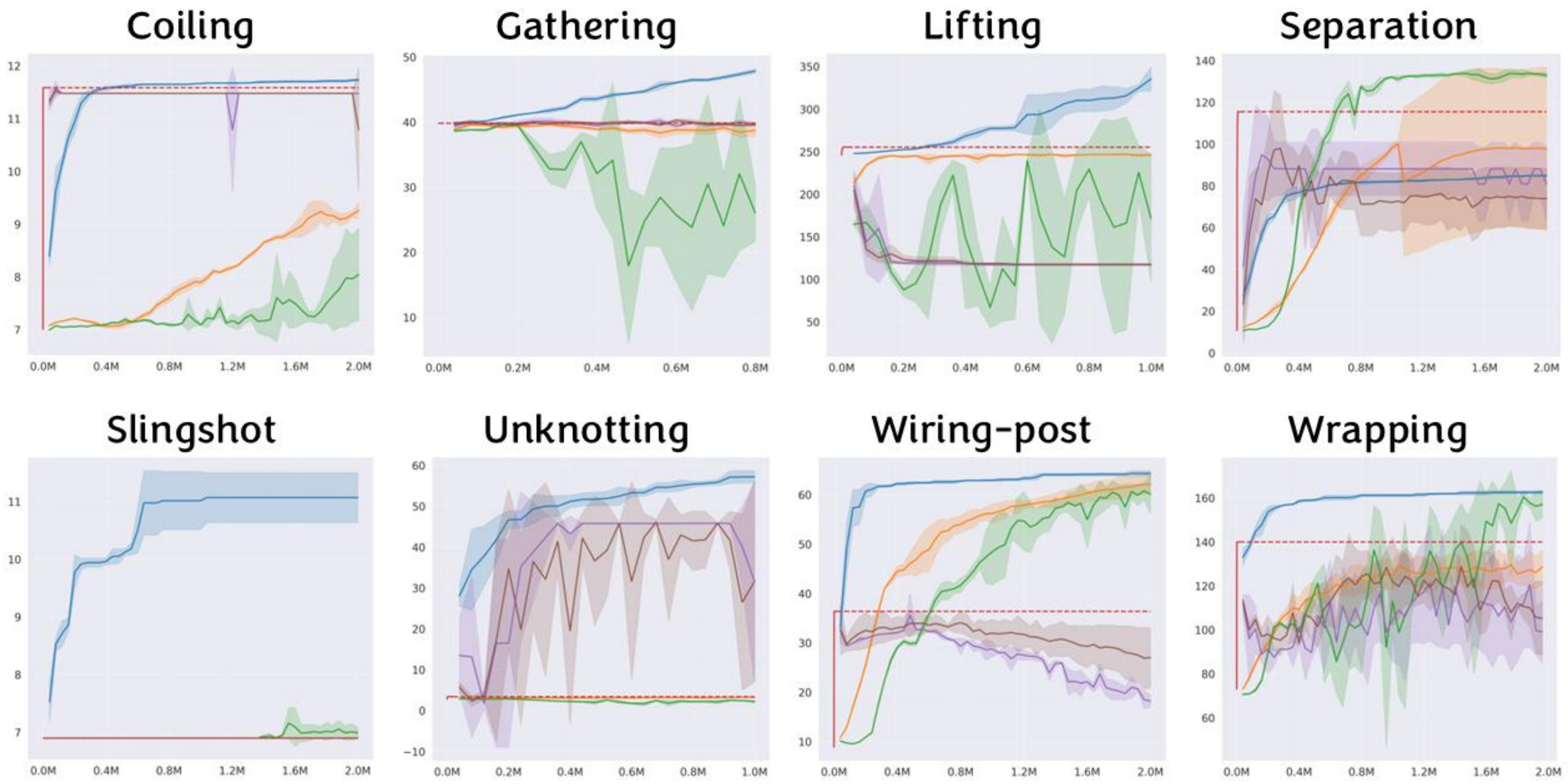
Benchmark Comparison

Tasks	Coiling	Gathering	Lifting	Separation	Slingshot	Unknotting	Wiring-post	Wrapping	Avg.
PPO	67%	0%	0%	100%	0%	0%	67%	0%	29.25%
SAC	0%	0%	0%	100%	33%	0%	0%	0%	16.63%
SHAC	93%	0%	0%	100%	0%	73%	0%	0%	33.25%
SAPO	100%	0%	0%	100%	0%	80%	0%	0%	35.00%
GD	100%	0%	0%	100%	0%	0%	0%	0%	25.00%
CMA-ES	100%	100%	87%	100%	93%	93%	93%	27%	86.63%

Task Success Rates

Model-Free Reinforcement Learning: PPO, SAC
First-Order Model-based Reinforcement Learning: SHAC, SAPO
Trajectory Optimization: GD, CMA-ES

Benchmark Comparison



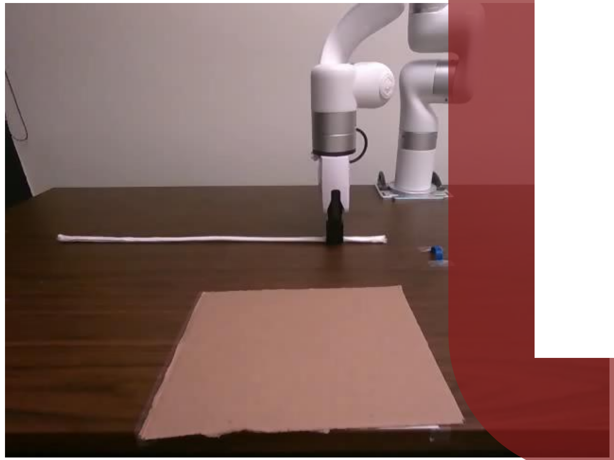
PPO, SAC, SHAC, SAPO, GD, CMA-ES

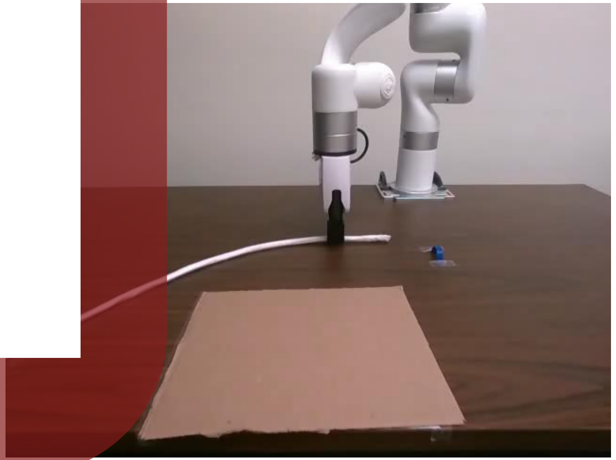
Video Results

Benchmark Results

Open-loop Sim-to-Real

↑ Project Page ↑





Closed-loop Sim-to-Real

Conclusion

↑ Project Page ↑

- Introduced DLO-Lab, a *versatile and differentiable simulation platform* tailored to the complexities of robotic DLO manipulation.

- Developed a specialized DLO agent that employs *hierarchical task decomposition* and *strategic grasp proposals* to make complex planning feasible.

- Established *a comprehensive benchmark suite* of tasks that mirror real-world skills and analyzed the performance of different policies.

- Verified that the proposed simulation environment adequately captures physical realism to effectively *bridge the simulation-to-reality gap* for zero-shot real-world deployment.

Thank you for watching!