Self-supervised Learning of Reconstructing Deformable Linear Objects under Single-Frame Occluded View

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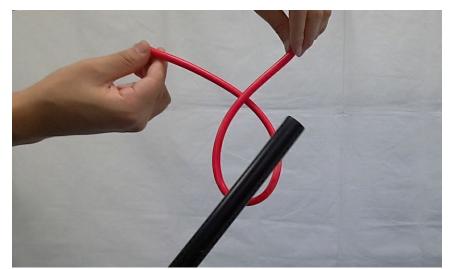


Highlights

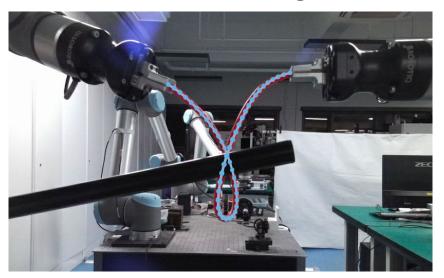
3D efficient self-supervised DLO reconstruction algorithm:

- Efficient No-Label Training: Enables data collection in real-world settings, even manually.
- Robust 3D State Inference: Reconstructs DLO from a single frame, even with severe occlusions.

Training Stage



Inference Stage



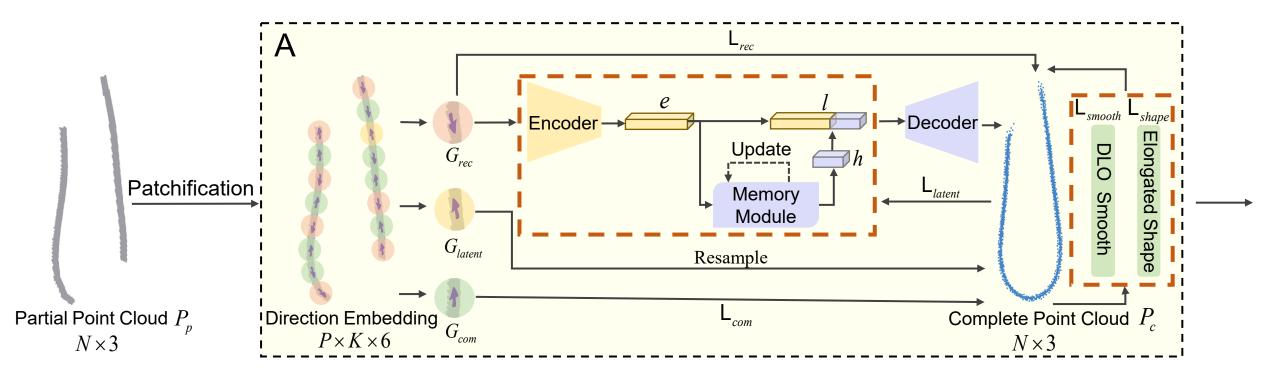




Framework

Self-supervised DLO occlusion single-frame reconstruction framework:

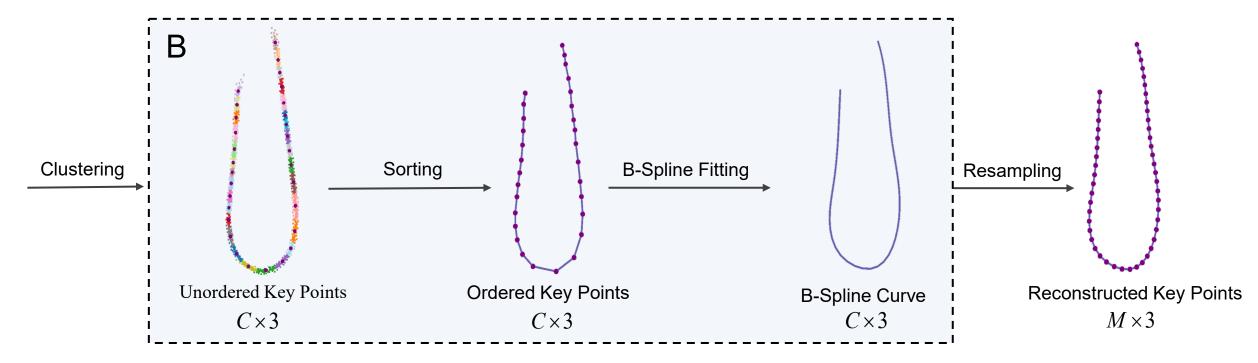
- A. Self-supervised DLO Point Cloud Completion
- B. Ordered Key Points Generation



Framework

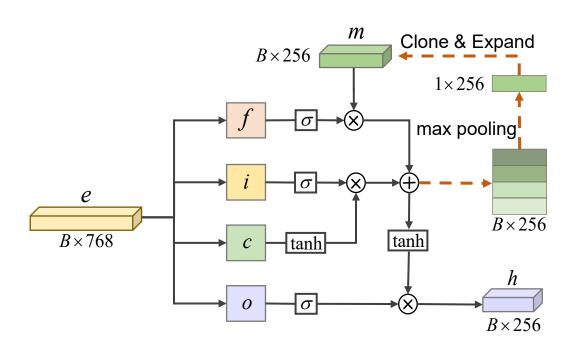
Self-supervised DLO occlusion single-frame reconstruction framework:

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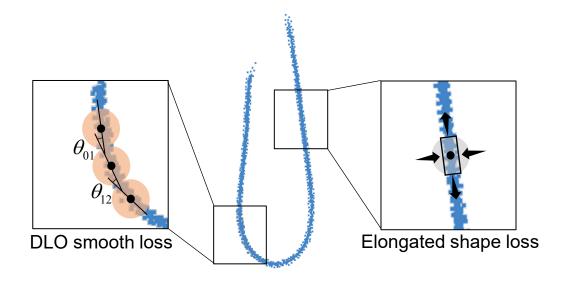
Innovations

Memory module



Extract memory across samples by **max pooling** to reinforce **the supervisory signals**.

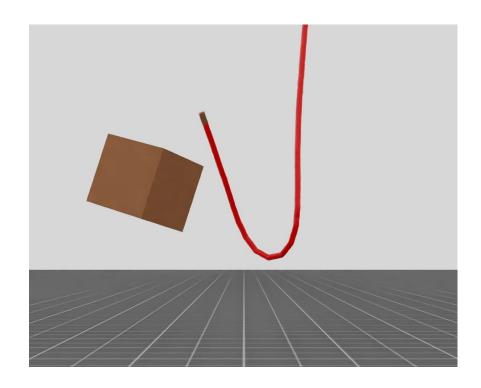
DLO shape constraints

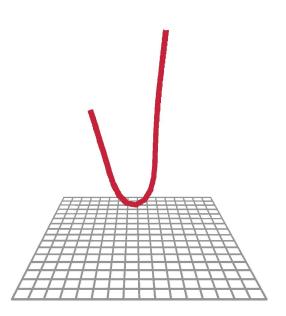


Integrate **DLO priors**, like **smooth and elongated shapes**, to enhance reconstruction performance.

Simulation Experiments—Synthetic Dataset Generation

- The DLO has randomly moving endpoints, while an occlusion cube moves to simulate occlusions.
- 7,000 DLO samples, split into training, validation, and test sets with an approximate 7:2:1 ratio.





Simulation Experiments—Results

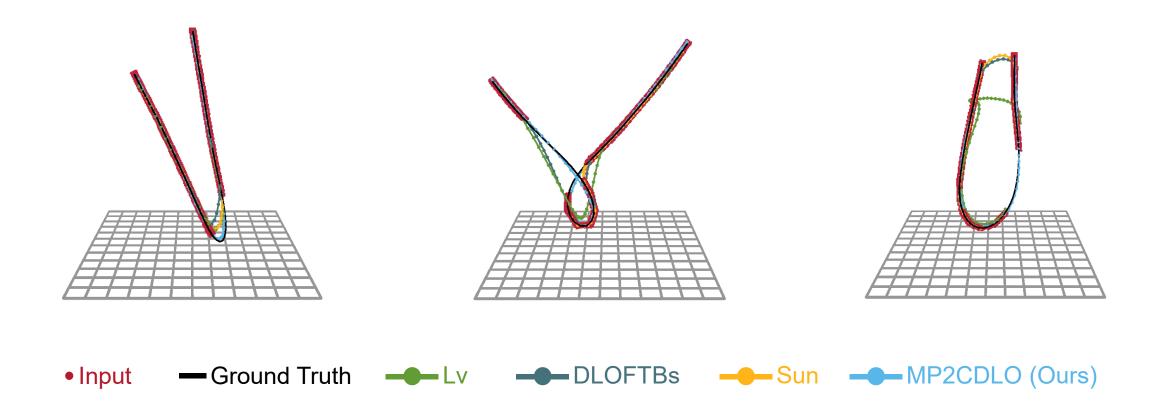
Evaluation metrics comparison and ablation study on synthetic DLO datasets.

ID	Algorithms	Success Rate(%) ↑	$D_{1bi}(\text{mm}) \downarrow$	$D_1(\text{mm}) \downarrow$	$D_2(\text{mm}) \downarrow$	$D_3 \downarrow$	$D_4 \downarrow$
1	L _V [1]	85	23.92	10.38	23.81	.276	5.20
2	DLOFTBs [2]	95	17.35	7.76	19.54	.085	5.47
3	Sun [3]	87	20.77	7.34	20.09	.065	4.96
	P2C	100	13.02	6.44	16.17	.028	4.90
4	MP2C	100	12.79	6.22	12.58	.026	4.81
	MP2CDLO	100	12.89	6.24	11.68	.025	4.66

- **P2C:** Original P2C[4] in **our framework.**
- MP2C: P2C with our memory module.
- MP2CDLO: MP2C with our DLO shape constraints.
- [1] K. Lv, M. Yu, Y. Pu, X. Jiang, G. Huang, and X. Li, "Learning to estimate 3-d states of deformable linear objects from single-frame occluded point clouds," in 2023 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2023, pp. 7119–7125.
- [2] P. Kicki, A. Szymko, and K. Walas, "Dloftbs–fast tracking of deformable linear objects with b-splines," in 2023 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2023, pp. 7104–7110.
- [3] S. Zhaole, H. Zhou, L. Nanbo, L. Chen, J. Zhu, and R. B. Fisher, "A robust deformable linear object perception pipeline in 3d: From segmentation to reconstruction," IEEE Robotics and Automation Letters, vol. 9, no. 1, pp. 843–850, 2023.
- [4] R. Cui, S. Qiu, S. Anwar, J. Liu, C. Xing, J. Zhang, and N. Barnes, "P2c: Self-supervised point cloud completion from single partial clouds," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023, pp. 14 351–14 360.

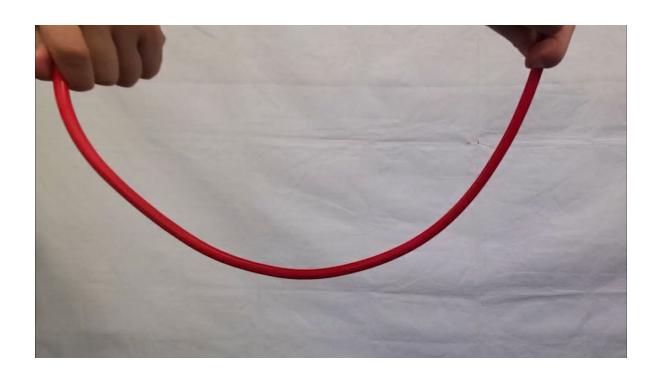
Simulation Experiments—Results

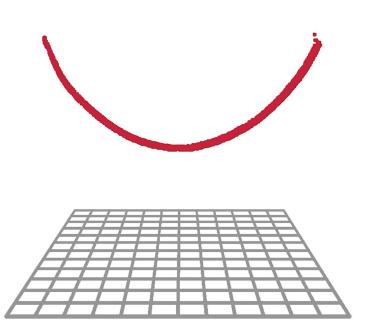
Reconstruction visualization comparison on synthetic DLO datasets.



Real-world Experiments—Training Stage

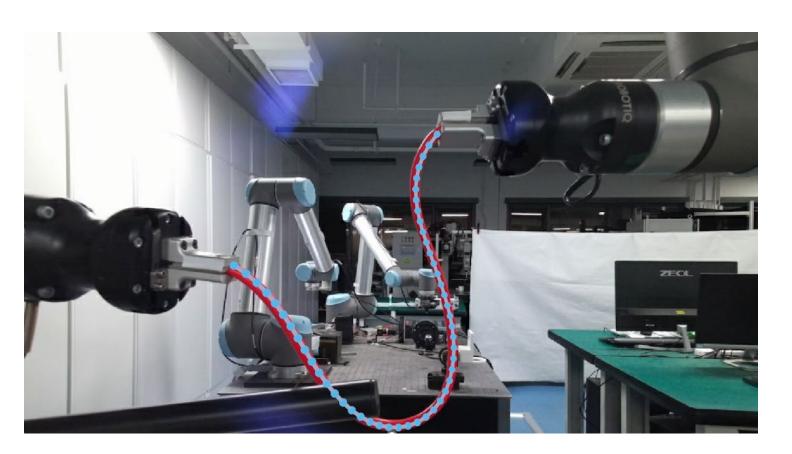
• Simplify data collection by **manual manipulation** of both ends of the DLO under an RGB-D camera.

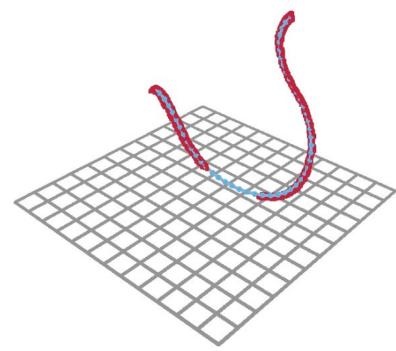




Real-world Experiments—Inference Stage

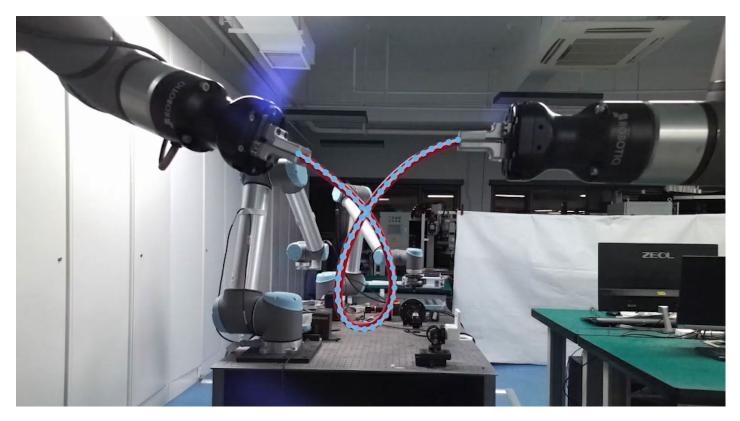
Normal Scenario: Occasional occlusions occur when two arms manipulate the DLO.

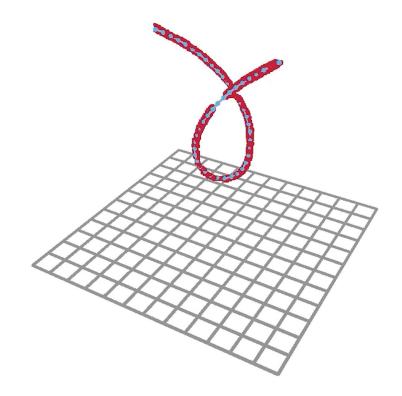




Real-world Experiments—Inference Stage

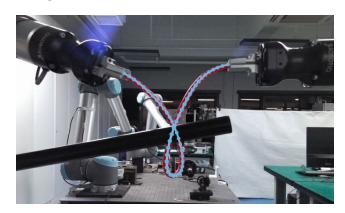
• Complex Scenario: Both occlusions and various self-intersections may occur simultaneously.

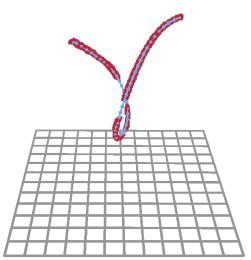




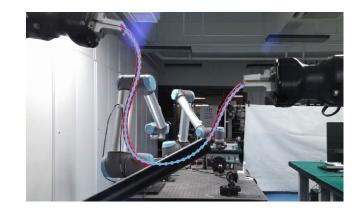
Real-world Experiments—Inference Cases

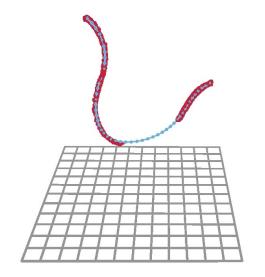
Viewpoint Occlusion Self-intersection



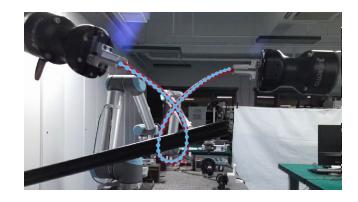


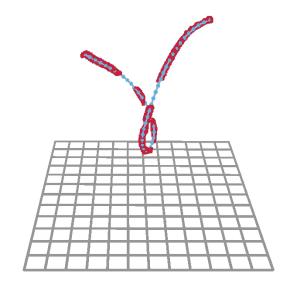
Extensive Occlusion





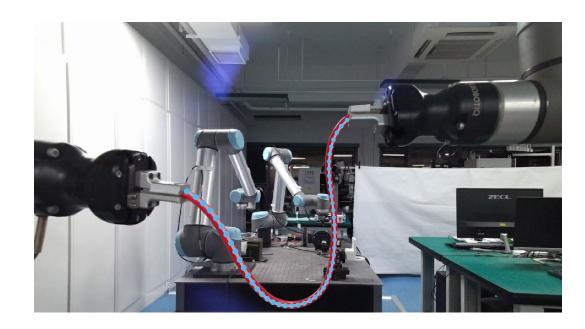
Spatial Proximity Self-intersection

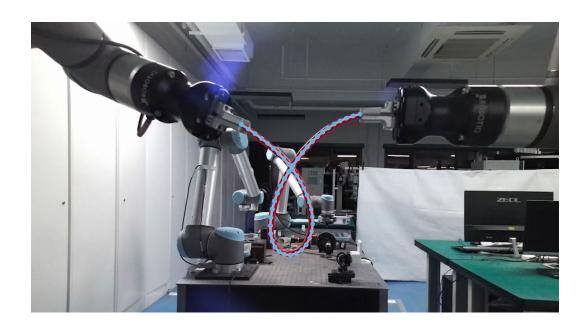




Contributions

- Self-supervised Reconstruction Framework: Efficiently reconstructs DLO from partial point clouds.
- Memory Module: Enhances completion by consolidating prototype information across samples.
- DLO Shape Constraints: Leverages structural priors for better DLO representations.





Thank you!

