

Machine Intelligence for Manufacturing & Operations





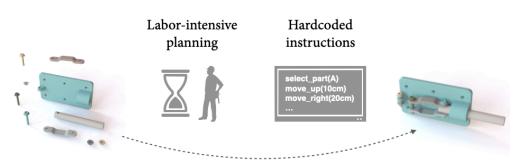


Motivation

Assembly is the core of modern industrial manufacturing!

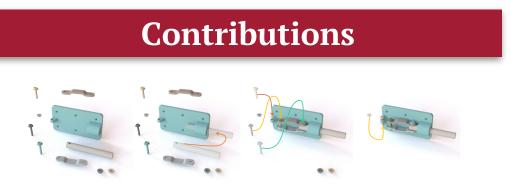


However, the assembly process is planned by human, which is tedious and time-consuming. Human needs to send hardcoded instructions to robots, and they only work for a specific assembly.



So, can we automate assembly planning for arbitrary assemblies? Challenges:

- The geometry of objects can be arbitrarily complex. It's non-trivial to plan collision-free paths for assembly.
- The number of potential assembly sequences scales exponentially with the number of parts, and most of the sequences are infeasible.
- How to make sure the assembly process is gravitationally stable and executable by only a few robotic grippers?



- An efficient assembly sequence planning algorithm that leverages an assembly-by-disassembly strategy and a physics-based simulation to generate physically-feasible sequences for complexshaped contact-rich assemblies.
- A novel physics-based planning method for translational and rotational assembly motion for arbitrary-shaped assemblies.
- A large-scale dataset and benchmark for assembly planning including thousands of physically valid assemblies.
- A state-of-the-art success rate, computational efficiency, and generalization performance.

Physics-Based Planning for Automated and Generalizable Assembly

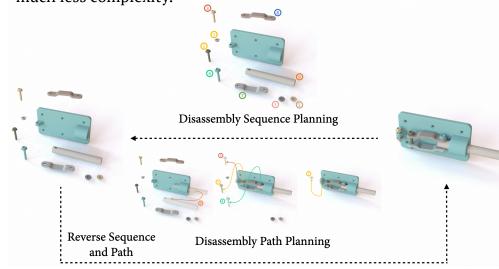
<Student Collaborators> Jie Xu¹, Yichen Li¹, Pingchuan Ma¹ <<u>Project Lead</u>> Yunsheng Tian¹ <PI> Wojciech Matusik¹ <<u>External Collaborators</u>> Karl D.D. Willis², Jieliang Luo², Bassel Al Omari², Farhad Javid², Shinjiro Sueda³, Hui Li², Sachin Chitta² ¹MIT CSAIL, ²Autodesk Research, ³Texas A&M University Part of the project^[1] was accepted to ACM Transactions on Graphics (SIGGRAPH Asia 2022)

Method

1. Assembly-by-disassembly

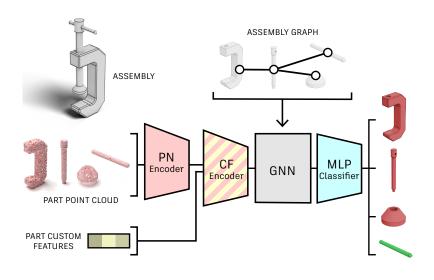
2. Disassembly tree search

Assuming all parts are rigid, a bijection exists between the assembly and disassembly sequences, meaning an assembly sequence can be obtained from the reverse order of its disassembly sequence with much less complexity.



3. Learning-based part selection

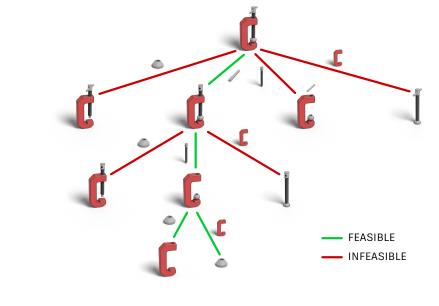
We introduce a supervised learning approach to predict the disassembly sequence order on complex contact-rich 3D assemblies using a GNN. Gathering training labels is made possible by our interactive data labeling tool for human-authored labels and a realistic physics-based simulation for synthetic labels. The network trained on a large dataset with diverse assemblies provides effective neural guidance to sequence planning on unseen assemblies.



5. Quasistatic stable pose generation

Since there is an infinite number of poses in a 3D space for a given assembly, to reduce the search space, we leverage a quasistatic pose estimator to provide a good set of candidate poses which have a higher chance to be dynamically stable during assembly.





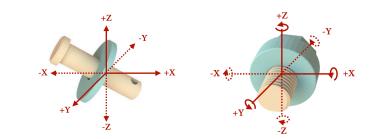
Each path of the tree represents a particular way of how the assembly is disassembled from top to bottom (or assembled from bottom to top).

4. Physics-based path planning

By applying forces/torques to assembly parts, we are able to infer the correct disassembly motion direction after the induced movement of the part is observed.



We propose a physics-based planner that efficiently plans the disassembly motion by leveraging feedback from physics. We formulate the disassembly path planning as another tree search problem, which starts from the assembled state and searches for a sequence of actions until a disassembled state has been found or some time/depth limitation of the search has been reached.



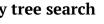
feasible or infeasible edge.





Paper/Video/Code/Dataset assembly.csail.mit.edu

Results



We formulate the disassembly sequence planning as a tree search framework where established tree-search techniques can be applied to search for feasible disassembly sequences efficiently.

6. Physics-based stability check

Finally, given the assembly and the part to disassemble with a candidate pose, we apply our custom-designed physics-based simulation for accurate gravitational stability check during the assembly process. The stability check result updates the disassembly tree with an either

99.8% success rate for collision-free path planning on a dataset of 8,000+ two-part assemblies.

Method	Two-Part	Rotational			
	Overall	Screw	Puzzle	Others	Overall
RRT	84.5	0.0	20.8	0.0	6.9
T-RRT	97.4	2.1	18.8	0.0	6.9
MV+T-RRT	97.8	12.5	18.8	0.0	10.4
BK-RRT	93.7	12.5	62.5	81.3	52.1
Ours	99.8	75.0	87.5	50.0	70.8
Ours (Rotated)	99.8	37.5	62.5	87.5	62.5

~30% success rate improvement over baselines for physically feasible sequence planning on a dataset of 240 complex multi-part assemblies.

Method		Success Rate (%) (Low Budget)			Success Rate (%) (High Budget)			
		2 Grippers	3 Grippers	4 Grippers	2 Grippers	3 Grippers	4 Grippers	
Ours	Random	44.17	52.92	62.50	66.25	76.25	81.25	
	Heuristics	50.42	60.83	69.17	66.67	75.00	82.08	
	Learning (from Sim)	54.17	62.50	69.58	67.50	76.25	82.08	
	Learning (from Human)	30.83	36.67	42.92	65.00	74.58	79.17	
Baseline	Random Permutation	14.58	25.42	41.25	27.92	43.33	55.42	
	Genetic Algorithm	14.17	25.83	40.00	30.83	41.25	51.25	

