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ICRA2024 YOKOHAMA | JAPAN

ASAP: Automated Sequence Planning for Complex Robotic Assembly with Physical Feasibility

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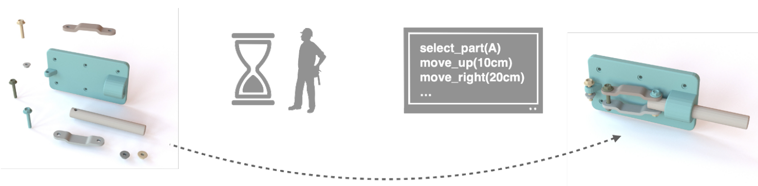
Motivation

Impact: Assembly automation is the core problem of industrial manufacturing.

Current limitations: The assembly process is always planned by human, which is labor-intensive, slow, tedious, error-prone and inflexible. Human needs to send hardcoded instructions to robots, and they only work for a specific assembly.



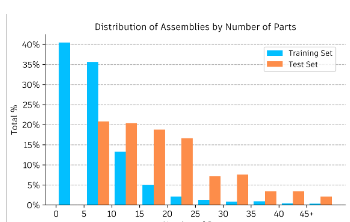
Challenges: The assembly plan is physically feasible only if the order is correct, collision-free paths can be found, poses are stable, and proper parts are held.

Questions: How to solve for such physically feasible plans autonomously? Is it possible to generalize to many arbitrarily complex assemblies?

Contributions

1. An automated approach to generate physically feasible assembly sequences.
2. Efficient planning through tree-search, geometric heuristics, and GNNs.
3. Stability guarantee considering supporting surface and grippers.
4. Integrated grasp planning and inverse kinematics for robotic execution.
5. SOTA performance on hundreds of complex product assemblies.

Quantitative Results



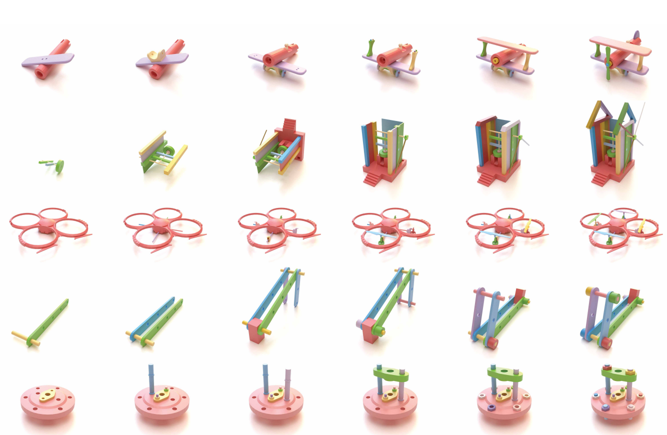
Method		Success Rate (%) (Low Budget) 2 Parts Held	3 Parts Held	4 Parts Held	Success Rate (%) (High Budget) 2 Parts Held	3 Parts Held	4 Parts Held
ASAP (Ours)	Heuristics	51.25	61.25	68.75	66.67	74.17	80.83
	Learning	**54.58**	**62.92**	**69.58**	**67.08**	**76.25**	**82.08**
Baseline	Random Permutation	14.58	25.42	41.25	27.92	43.33	55.42
	Genetic Algorithm [9]	14.17	25.83	40.00	30.83	41.25	51.25
	Assemble Them All [5]	19.17	27.08	35.42	30.42	46.25	56.67

We achieve ~30% higher success rate than baseline methods on hundreds of complex product assemblies (up to 50 parts) within given evaluation budgets.

Qualitative Results

ASAP generates feasible assembly plans for diverse complex assemblies. →

We also integrate ASAP with a robotic setup for real-world deployment, powered by grasp planning, inverse kinematics and collision detection. ↓

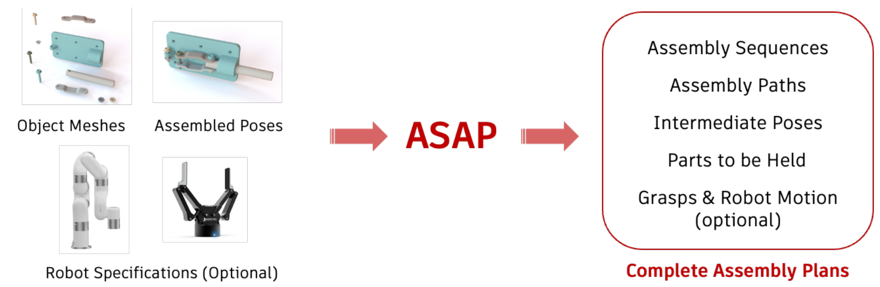


The sim-to-real transfer can be made more robust by incorporating vision or force feedback and adaptive manipulation skills.

Please see more comprehensive demos on our website! –> asap.csail.mit.edu

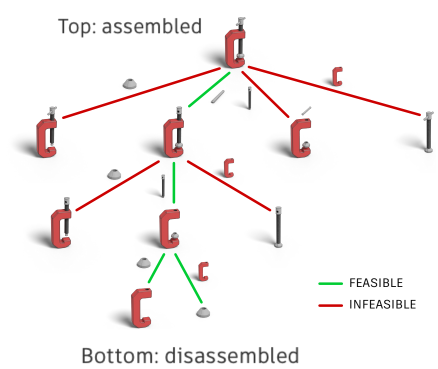
Methodology

ASAP only takes object meshes and target assembly poses (w/ optional robot specs) as input, then generates complete and executable assembly plans.



Disassembly Tree Search

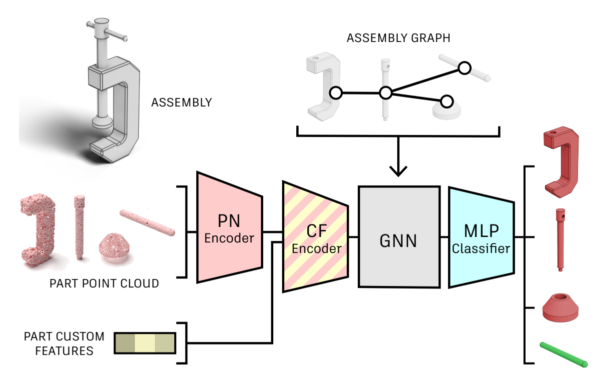
```
def asap():
    tree.add_node(root_node)
    for node in select_node(tree):
        for part in select_part(node):
            for pose in select_pose(node):
                check_assemblable(node, part, pose)
                check_stable(node, part, pose)
                if success:
                    child_node = node \ {part}
                    tree.add_edge(node, child_node)
    return tree
```



Our core method is a disassembly tree search paradigm using an assembly-by-disassembly strategy for discovering feasible assembly sequences. We use DFS for node selection. Other key components of the search are described below.

Part Selection

We introduce a learning approach to predict disassembly sequences on complex assemblies using a GNN. Training on a large dataset with diverse assemblies provides effective neural guidance for unseen assemblies.

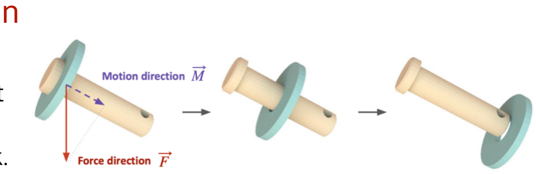


Pose Selection

We leverage a quasistatic pose estimator to provide good candidate poses with higher chances to be stable during assembly.

Assemblability Evaluation

We adopt a physics-based path planner (Assemble Them All) that robustly plans the disassembly motion through physics feedback.



Stability Evaluation

We use physics to check if any parts fall under gravity after certain time steps. Since stability is conditioned on the pose and parts to hold, we propose a greedy strategy for identifying the minimal sets of parts to be held to guarantee stability, speeding evaluation up by 14-23x with 85-95% accuracy.

Future Work

- Fast and accurate physics assembly simulation
- Learning sequence from human demonstration
- Integration into CAD tools for design verification
- Real robot deployment with adaptive tools and skills