Extending Task and Motion Planning with Feasibility Prediction: Towards Multi-Robot Manipulation Planning of Realistic Objects

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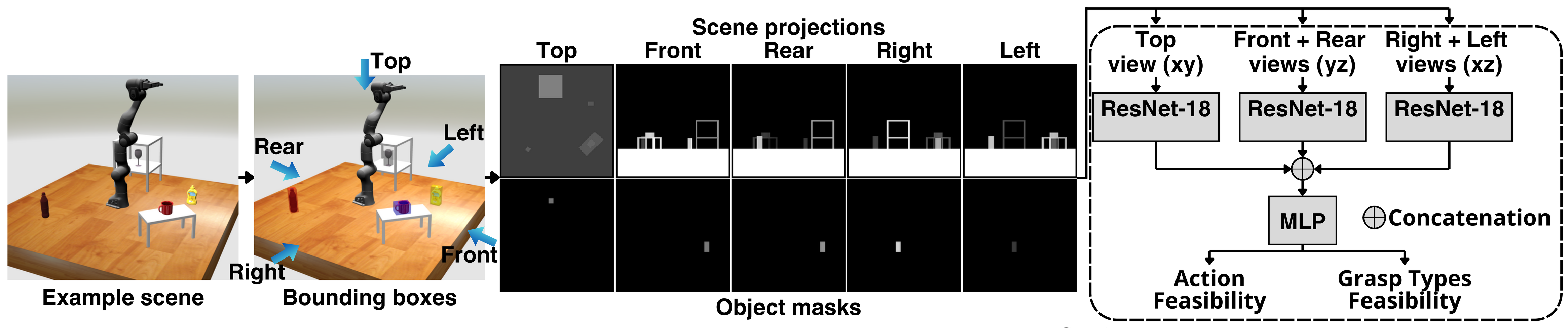
Motivation

- Due to the **high combinatorial complexity of TAMP**, geometric planning creates a **bottleneck** to the planning process
- Classical TAMP requires **numerous calls to motion planners** to verify the feasibility of actions
- A framework for **predicting the feasibility** of pick and place actions in 3D environments for **diverse-shaped objects** and **multi-robot settings.**
- A **feasibility-informed multi-robot TAMP algorithm** which prioritizes promising actions to accelerate the planning process

Action-Grasp Feasibility Prediction (AGFP-Net)

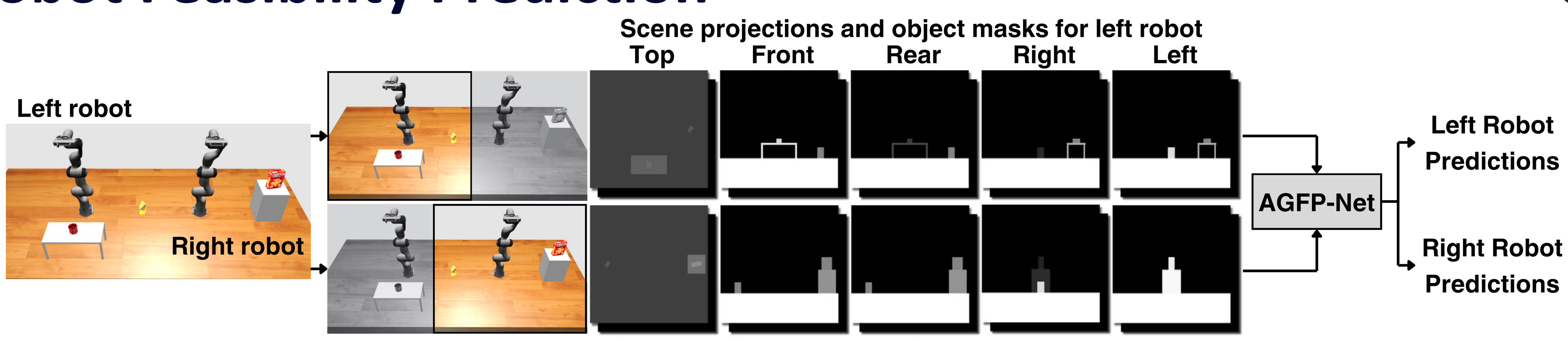
- A deep convolutional network that takes as input:
  - **3D scene** represented as **5 depth images** corresponding to **different views of the scene**
  - **Object of interest** represented as **masks**, showing its **bounding box** at the pose to be picked from or placed at.
- It outputs **the probability of feasibility** of the action as well as **the feasibility of 6 grasp classes simultaneously**



Architecture of the proposed neural network AGFP-Net

Multi-Robot Feasibility Prediction

- In a multi-robot setting, **AGFP-Net** can be queried for **each robot individually** while making sure that:
  - The input depth images **only show the workspace of the considered robot** and the objects inside it
  - **Objects' poses** are shown **in the frame of the considered robot**



Feasibility-Informed Multi-Robot TAMP

- The TAMP algorithm is a **best-first tree search**, nodes represent the state of the environment and the robot, and edges represent actions.
- **AGFP-Net** is queried to compute the probability of feasibility of each action and each grasp class as:

$$p_F^a = p_F^{Pick} \times p_F^{Place} \times max(\mathbf{p}_G^a) \qquad \text{Where} \qquad \mathbf{p}_G^a = \mathbf{p}_G^{Pick} \otimes \mathbf{p}_G^{Place}$$

- **For actions involving two robots**, the **collaborative feasibility (CF)** is computed as:

$$p_{CF}^{a_{pass}} = p_F^{a_{pass}}(r_1, O, s(O)^{r_1}, \mathbf{q}^{r_1}) \times p_F^{Pick}(r_2, O, \mathbf{q}^{r_2})$$

- During the search, the task planner incorporates this **heuristic** into the cost to **sort the set of nodes to expand**, and **prioritize feasible actions**:

$$C_{Total} = C_{SoFar} + C_{ToGoal} + C_{Feasibility} \qquad \text{Where} \qquad C_{Feasibility} = \frac{1}{p_F(a)} - 1 \in]0, \infty[$$

Algorithm 1 Task and motion planner

```
Input: E, s_0, s_goal, Γ          ▷ Environment, Initial and goal states, robots graph
Q ← {s_0}                                               ▷ Set of nodes to expand
while Solution not found do
    s ← argmin_cost Q
    if s ∈ s_goal then
        [τ, Π] ← retrieveSolution(s)]
        if Π is feasible then
            return τ, Π
        end if
    else
        Q ← Q ∪ findChildren(s, E, s_goal, Γ)
    end if
end while
```

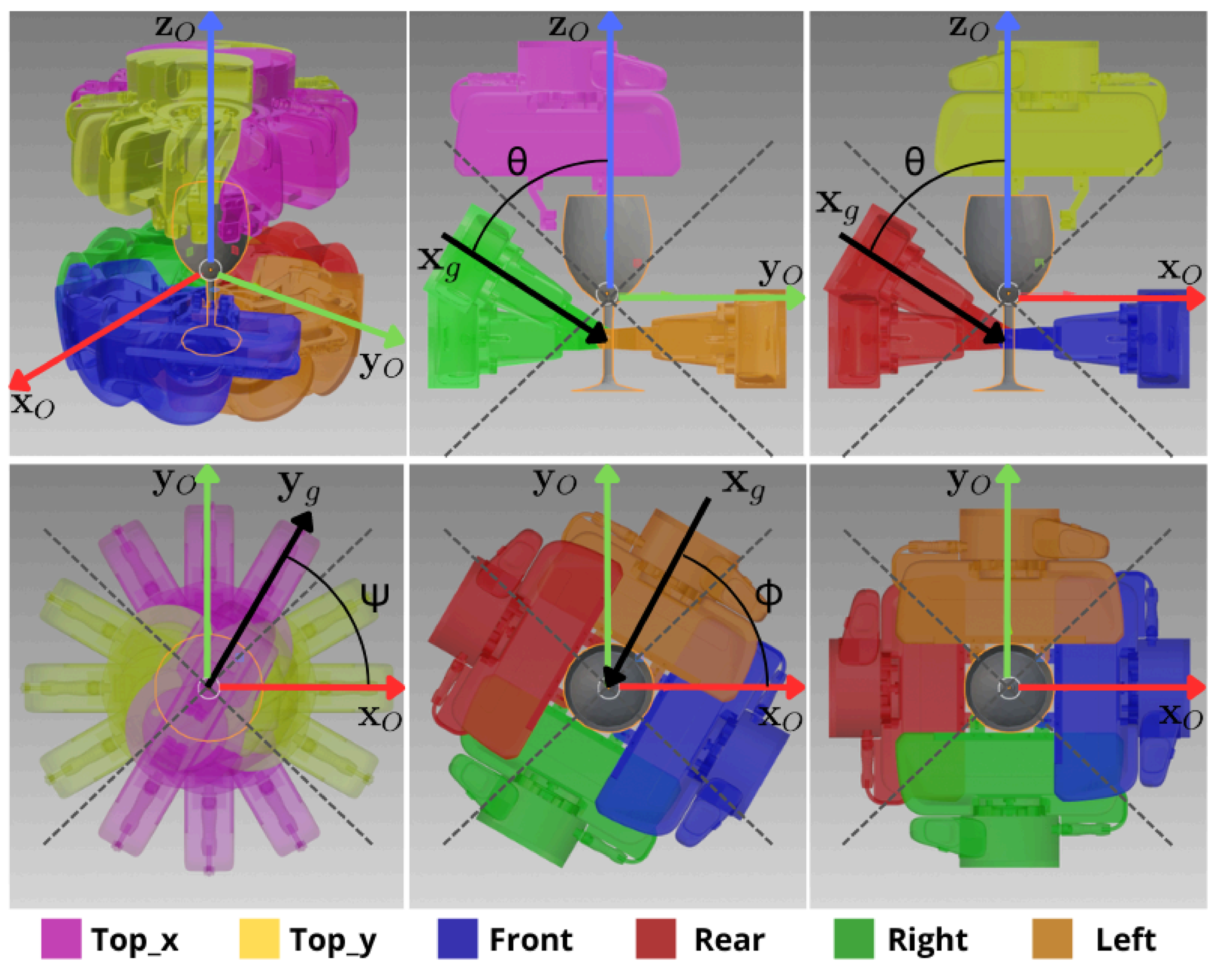
Algorithm 2 findChildren

```
Input: s, E, s_goal, Γ
children ← ∅
A ← findPossibleActions(s, E, s_goal, Γ)
for each a in A do
    [p_F^a, p_G^a)] ← predictFeasibility(s, E, a)
    child ← nextState(s, a)
    child.cost ← computeCost(child, s_goal, p_F(a), E)
    children ← children ∪ child
end for
return children
```

Grasp Feasibility

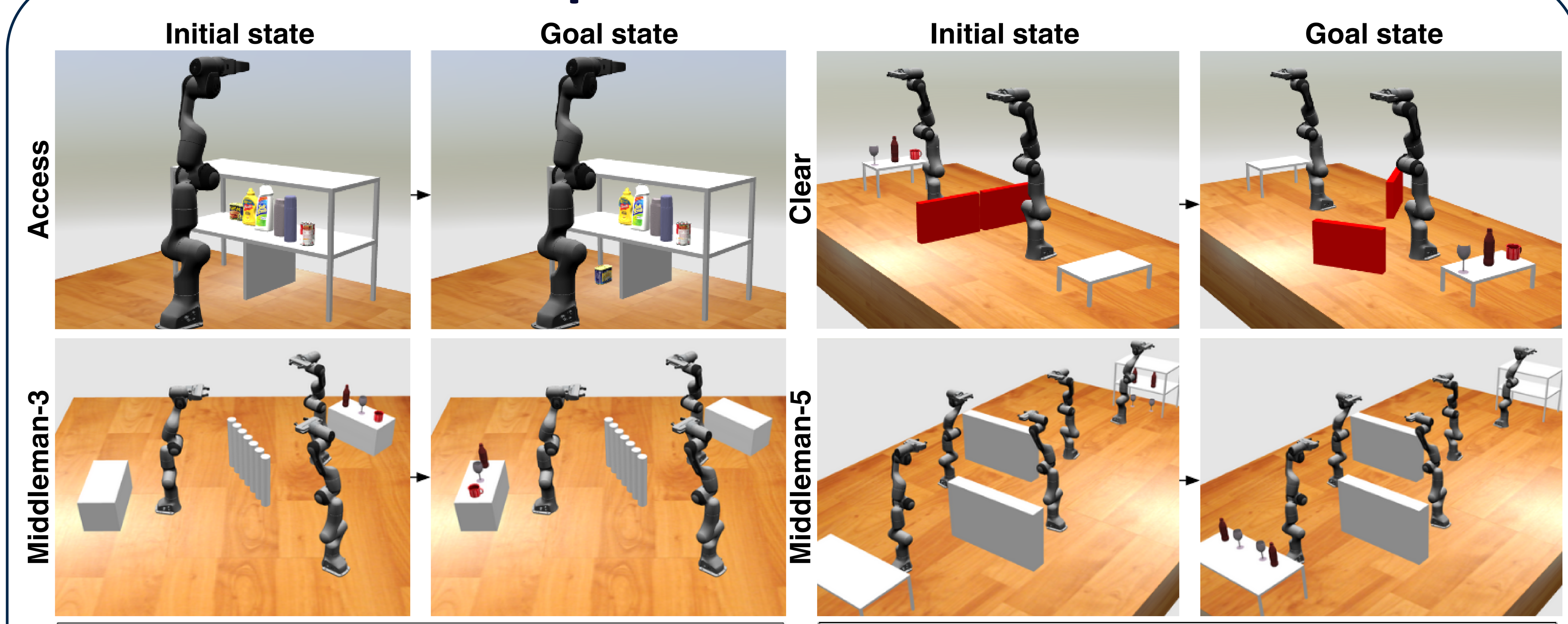
- The feasibility of each grasp is associated with the probability of feasibility of its type.
- Grasp types are **defined by the angles of approach of the end-effector** w.r.t the object.

$$type(g) = \begin{cases} Front & |\Theta| > \frac{\pi}{4} \text{ and } |\Phi| > \frac{3\pi}{4} \\ Rear & |\Theta| > \frac{\pi}{4} \text{ and } |\Phi| \leq \frac{\pi}{4} \\ Right & |\Theta| > \frac{\pi}{4} \text{ and } \frac{-3\pi}{4} \leq \Phi < \frac{-\pi}{4} \\ Left & |\Theta| > \frac{\pi}{4} \text{ and } \frac{\pi}{4} < \Phi \leq \frac{3\pi}{4} \\ Top_x & |\Theta| \leq \frac{\pi}{4} \text{ and } \frac{\pi}{4} < |\Psi| \leq \frac{3\pi}{4} \\ Top_y & |\Theta| \leq \frac{\pi}{4} \text{ and } (|\Psi| \leq \frac{\pi}{4} \text{ or } |\Psi| > \frac{3\pi}{4}) \end{cases}$$



Visualization of the 6 grasp types depending on the angle of approach of the robot's gripper

Experimental Results



Problem	Method	Success Rate (%)	Total Planning Time (s)	Infeasible Task Plans	Speedup
Access	Baseline	0%	> 900	> 303.3	> 10.4
	Ours	**100%**	**86.6**	**1.7**	
Clear	Baseline	70%	299.8	21.4	> 13.7
	Ours	**100%**	**35.0**	**0.4**	
Middleman-3	Baseline	0%	> 900	> 146.6	> 33
	Ours	**100%**	**27.3**	**0.4**	
Middleman-5	Baseline	0%	> 900	> 54.4	> 3.4
	Ours	90%	**198.0**	**1.4**	

Results comparison with and without using AGFP-Net

Problem	CF	Success Rate	Planning Time (s)	Expanded Nodes	Feasibility Checks
Clear	-	90%	**31**	60	1635
	+	**100%**	35	**40**	**1025**
Middleman-3	-	50%	106	1093	14417
	+	**100%**	**27**	**16**	**598**
Middleman-5	-	0%	> 900	> 4616	> 104433
	+	**90%**	**198**	**797**	**6271**

Results comparison with and without using collaborative feasibility (CF)

References

- Bouhsain et al. "Learning to predict action feasibility for task and motion planning in 3d environments." 2023 IEEE International Conference on Robotics and Automation (ICRA).
- Bouhsain et al. "Simultaneous Action and Grasp Feasibility Prediction for Task and Motion Planning through Multi-Task Learning." 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).
- Bouhsain et al. "Extending Task and Motion Planning with Feasibility Prediction: Towards Multi-Robot Manipulation Planning of Realistic Objects." 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).

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