Diffusion-Guided Multi-Arm Motion Planning

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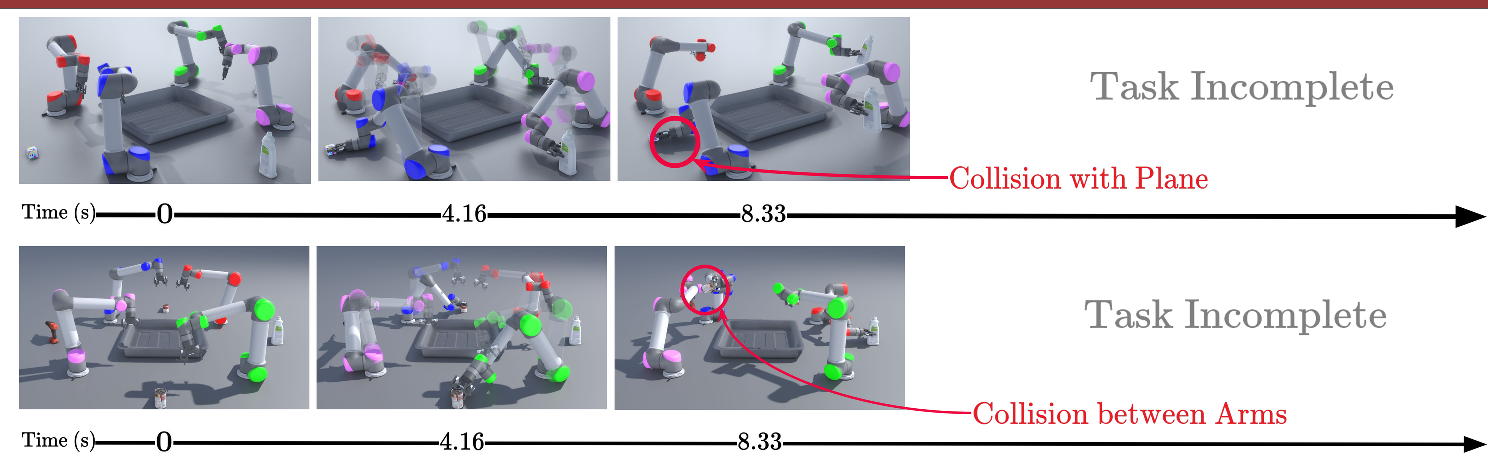
SCAN ME

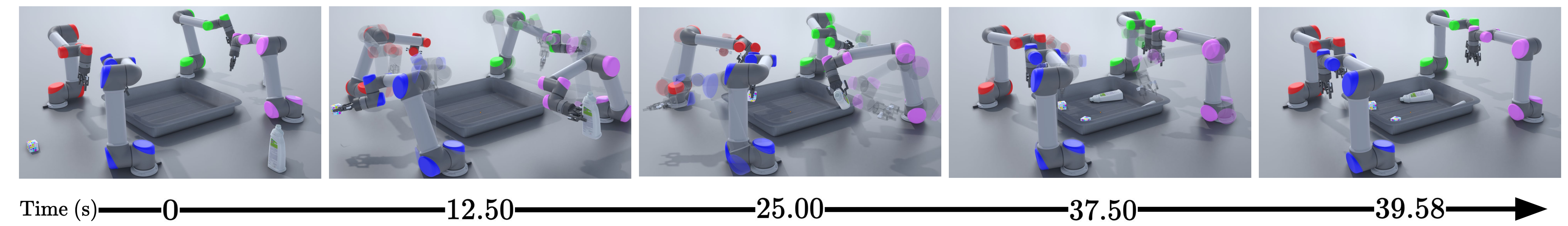
Enabling scalable coordination of multiple robotic arms by combining diffusion-based models with MAPF-inspired search without relying on massive datasets

① Motivation

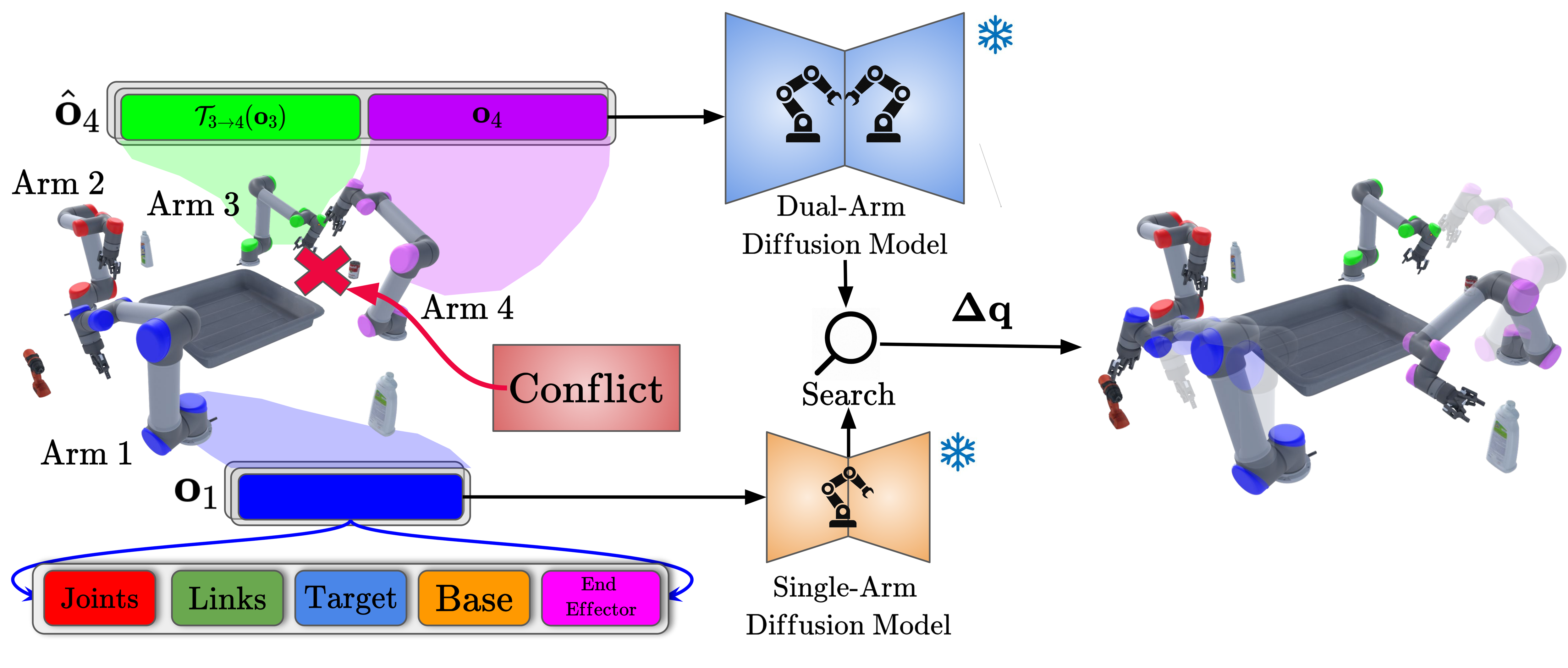
- Learning-based Multi-Arm Motion Planners [1]
  - Extremely fast
  - Reliance on massive datasets
- Search-based Multi-Arm Motion Planners [3]
  - Scale very well
  - Slower runtime



With Diffusion-Guided Search



② High-Level Overview



③ Algorithmic Details

Algorithm 1 Diffusion-Guided Multi-Arm Planner (DG-MAP)

Input: Models $\epsilon_{\theta_1}, \epsilon_{\theta_2}$
Output: Collision-free plan $\{\Delta q_i\}_{i=1}^N$ or best effort
Initialize: Frontier set $\mathcal{F} \leftarrow \emptyset$, collision cache $\mathcal{C} \leftarrow \emptyset$
for $i = 1 \dots N$ **do**
  $o_i \leftarrow \texttt{GetObs(i)}$
  $\mathcal{P}_i \leftarrow \epsilon_{\theta_1}(o_i, \cdot, \cdot)$
end for
// Generate initial plans independent of each other
$\mathcal{N}_0 \leftarrow \texttt{Node}(b = \vec{0}, \mathcal{K} = \emptyset)$
// Node stores indices and conflicting plan indices
$\mathcal{F}.\texttt{Insert}(\mathcal{N}_0, g(\mathcal{N}_0))$
while $\mathcal{F}$ not empty and time not exceeded **do**
  $\mathcal{N} \leftarrow \mathcal{F}.\texttt{ExtractMin}()$
  $\tau \leftarrow \{\Delta q_i^{\mathcal{N}.b_i}\}_{i=1}^N$
  $c \leftarrow \texttt{FindFirstCollision}(\tau, \mathcal{C})$
  if c is **null then**
    return τ, t^* // Solution found
  end if
  $(i, j, \hat{t}) \leftarrow c$ // Conflicting pair and time
  $t^* = \min(t^*, \hat{t})$ // Update earliest collision time
  $\kappa_i = \mathcal{N}.\mathcal{K} \cup \mathcal{N}.b_i$ // Attempt to fix for arm i
  $\texttt{Rebranch}(i, \kappa_i)$
  $\texttt{Repair}(i, j, \kappa_i)$
  $\kappa_j = \mathcal{N}.\mathcal{K} \cup \mathcal{N}.b_j$ // Attempt to fix for arm j
  $\texttt{Rebranch}(j, \kappa_j)$
  $\texttt{Repair}(j, i, \kappa_j)$
end while
return Best plan found in $\mathcal{F}$ based on cost // Timeout or failure

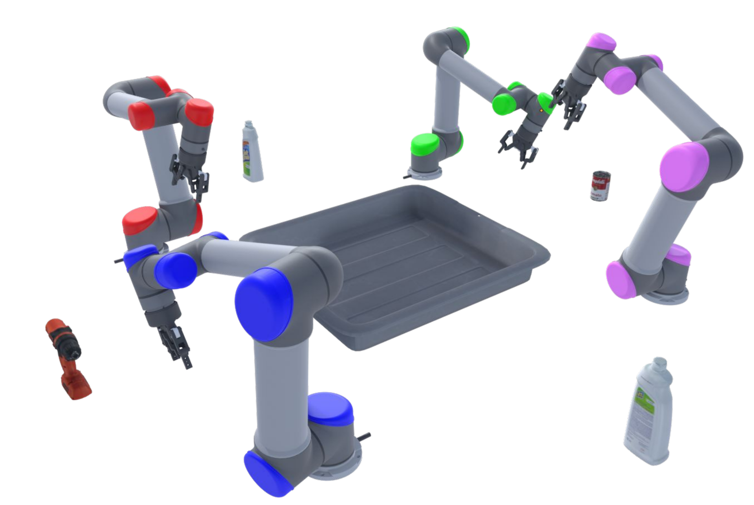
Algorithm 2 Generate Successors by Rebranch

Input: ego arm, conflicts κ
for $m = 1 \dots |\mathcal{P}_{\text{ego}}|$ **do**
  if $m \notin \kappa$ **then**
    $b_{\text{ego}}^{\text{new}} \leftarrow m$
    $b' \leftarrow (b_1, \dots, b_{\text{ego}}^{\text{new}}, \dots, b_N)$
    $\mathcal{N}' \leftarrow \texttt{Node}(b = b', \mathcal{K} = \kappa)$
    $\mathcal{F}.\texttt{Insert}(\mathcal{N}', g(\mathcal{N}'))$
  end if
end for

Algorithm 3 Generate Successors by Repair

Input: ego arm, other arm, conflicts κ, Model ϵ_{θ_2}
$\hat{o}_{\text{ego}} \leftarrow \texttt{GetPairedObs(ego, other)}$
Sample $\{\Delta q_{\text{ego}}^{\text{new},m}\}_{m=1}^B$ using $\epsilon_{\theta_2}(\hat{o}_{\text{ego}}, \cdot, \cdot)$
for $m = 1 \dots B$ **do**
  $b_{\text{ego}}^{\text{new}} \leftarrow \mathcal{P}_{\text{ego}}.\texttt{Update}(\Delta q_{\text{ego}}^{\text{new},m})$
  $b' \leftarrow (b_1, \dots, b_{\text{ego}}^{\text{new}}, \dots, b_N)$
  $\mathcal{N}' \leftarrow (b = b', \mathcal{K} = \kappa)$
  $\mathcal{F}.\texttt{Insert}(\mathcal{N}', g(\mathcal{N}'))$
end for

④ Pick-and-Place



Method	Success (↑)	Steps (↓)
Baseline-LD	0.375	**4479**
Baseline-ED	0.714	6018
DG-MAP	**0.890**	5390

Table 3: Success rate (%, higher is better) along with average number of steps (lower is better) taken by the methods to complete the full cycle of multi-arm pick-and-place task.

⑤ Comparison with Limited Data Baseline

Arms	Easy		Medium		Hard		Average	
	Baseline LD	DG-MAP Ours (↑)	Baseline LD	DG-MAP Ours (↑)	Baseline LD	DG-MAP Ours (↑)	Baseline LD	DG-MAP Ours (↑)
3	0.349	**0.984**	0.426	**0.975**	0.460	**0.965**	0.412	**0.975**
4	0.032	**0.981**	0.024	**0.969**	0.060	**0.953**	0.039	**0.968**
5	0.224	**0.972**	-	**0.958**	-	**0.905**	0.075	**0.945**
6	0.145	**0.976**	0.011	**0.921**	0.008	**0.888**	0.055	**0.928**
7	0.113	**0.955**	-	**0.918**	-	**0.907**	0.038	**0.926**
8	0.067	**0.951**	-	**0.933**	-	**0.888**	0.022	**0.924**

⑥ Comparison with Extended Data Baseline

Arms	Easy		Medium		Hard		Average	
	Baseline ED	DG-MAP Ours (↑)	Baseline ED	DG-MAP Ours (↑)	Baseline ED	DG-MAP Ours (↑)	Baseline ED	DG-MAP Ours (↑)
3	0.980	**0.984**	0.973	**0.975**	0.943	**0.965**	0.965	**0.975**
4	0.973	**0.981**	0.961	**0.969**	0.950	**0.953**	0.961	**0.968**
5	0.963	**0.972**	0.947	**0.958**	0.891	**0.905**	0.934	**0.945**
6	0.950	**0.976**	0.887	**0.921**	0.882	**0.888**	0.906	**0.928**
7	0.950	**0.955**	0.913	**0.918**	0.891	**0.907**	0.917	**0.926**
8	**0.951**	**0.951**	0.911	**0.933**	0.859	**0.888**	0.907	**0.924**

References

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Acknowledgements

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