Visibility-Aware Mobile Grasping in Dynamic Environments

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***Abstract*—This paper addresses the problem of mobile grasping in dynamic, unknown environments where a robot must operate under a limited field-of-view. The fundamental challenge is the inherent trade-off between "seeing" around to reduce environmental uncertainty and "moving" the body to achieve task progress in a high-dimensional configuration space, subject to visibility constraints. Previous approaches often assume known or static environments and decouple these objectives, failing to guarantee safety when unobserved dynamic obstacles intersect the robot's path during manipulation. In this paper, we propose a unified mobile grasping system comprising two core components: (1) a low-level whole-body planner tightly coupled with velocity-aware active perception within a receding-horizon loop, enabling the robot to navigate dynamic environments more safely; and (2) a hierarchical, behavior-tree-based high-level planner that adaptively generates subgoals to drive exploration and recover from runtime failures. We provide experimental results across 400 randomized simulation scenarios and real-world deployment on a Fetch mobile manipulator. Results show that our system achieves a success rate of 68.8% and 58.0% in unknown static and dynamic environments, respectively, significantly boosting success rates by 22.8% and 18.0% over the navigation-and-manipulation approach in both unknown static and dynamic environments, with improved collision safety. The project page is available at https://visibility-aware-mobile-grasping.github.io/.**

I. Introduction

A robot that assists in the home must be able to retrieve everyday objects on command, such as picking up a can from a shelf across the room [25, 52]. This requires mobile grasping in a cluttered, unknown, and dynamic environment. With a pre-built, perfect map and static obstacles, this is a classical mobile manipulation problem [36, 44]. In a changing home, however, the robot must rely on its sensors to guarantee safety. In this realistic home setting, the robot has only minimal prior knowledge of the environment and must perceive it through a movable head sensor with a limited field-of-view [12]. As a result, the grasp configuration is underspecified, and the path to the target may be blocked by unknown, changing obstacles.

For this task, reliable manipulation and safe motion among obstacles are often in direct conflict. To successfully grasp the target, the robot must direct its sensors toward it to perceive and refine the underspecified grasping goal. To approach the target safely, it must also scan the environment for dynamic obstacles that may cross its path. Moreover, as the goal and obstacles keep changing, this conflict must be resolved continually, forcing real-time replanning of the whole-body trajectory.

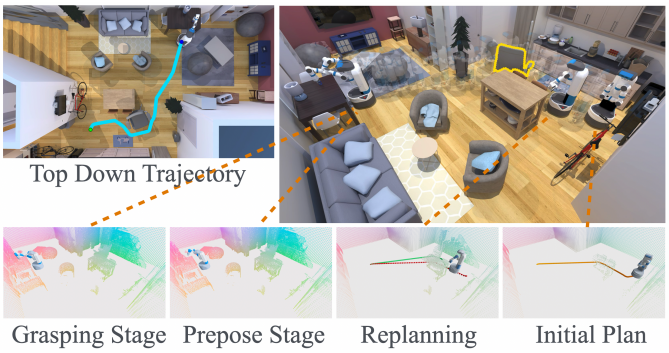

Fig. 1. **Visibility-Aware Mobile Grasping.** A mobile manipulator approaches a target while a chair appears in its path.

To address this issue, we propose a unified, hierarchical mobile grasping system that tightly couples perception and planning within a receding-horizon loop. At the low level, a whole-body motion planner is paired with a velocity-aware active perception policy that prioritizes observations along the planned swept volume, weighted by motion speed. At the high level, a behavior-tree-based policy monitors execution online, generates subgoals such as observation or pre-grasp poses, and recovers from runtime failures. During mobile manipulation, the system jointly optimizes whole-body trajectories and gaze directions, enabling the robot to traverse dynamic environments while progressively refining its manipulation goal.

We evaluate our system across 400 randomized simulation scenarios and real-world trials on a Fetch mobile manipulator. Results demonstrate that our approach achieves a success rate of 68.8% and 58.0% in unknown static and dynamic environments, respectively, improving by 22.8% and 18.0% over the navigation-and-manipulation baseline.

II. Related Work

Mobile manipulation systems have been deployed in service, household, and long-term human-shared scenarios [2, 5, 8, 31, 37, 50]. Many plan from a pre-built 3D map and use 2D lidar updates for moving obstacles, so observed 3D geometry near the target or robot body is not incorporated into the manipulation plan. Other studies address uncertainty through manipulator planning, scene reconstruction, and reactive informative planning [9, 13, 43, 45]. Base-placement

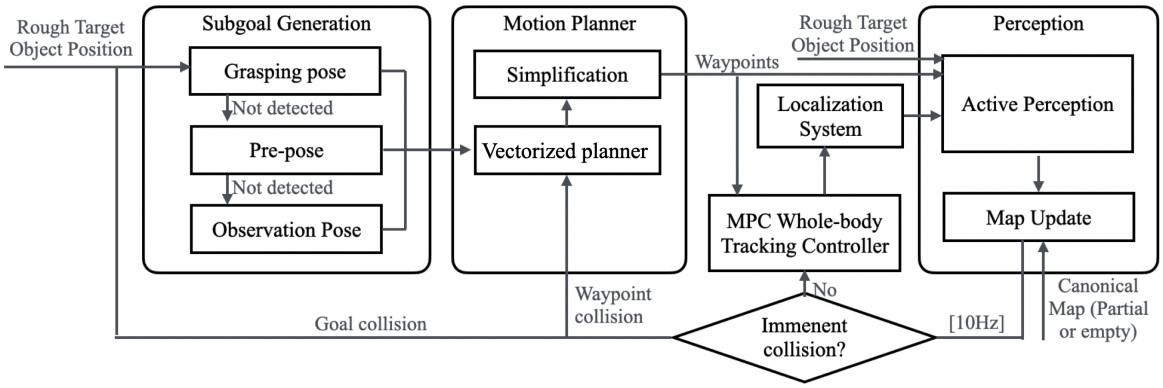

Fig. 2. **System Architecture Overview.** The system maintains belief state $b_t = (q_t, M_t, g_t)$ and couples subgoal generation, active perception, whole-body motion planning, and control in a receding-horizon loop.

methods reduce planning complexity by selecting a robot pose for a known manipulation goal [36, 44, 54, 56, 58]. These lines of work make individual modules effective, but usually study perception updates, goal selection, and motion replanning as separate problems. In partially observed scenes, new observations update the estimated target geometry and nearby obstacles, so the robot pose, intermediate configurations, and motion plan should be revised together during execution.

Visibility-aware planning and active perception address how robots should move under limited sensing. Visibility-aware planners constrain motion to observed free space [15, 19] or jointly optimize gaze and motion [30], but typically assume static observed regions or fixed manipulation goals. Active perception selects viewpoints for mapping [3, 4], grasping [6, 32, 57], belief-space reasoning [60], or occlusion reduction [22, 29]. These methods improve what the robot observes, but viewpoint selection is often planned independently of the current manipulation phase. In mobile grasping, the sensor must support both target observation for grasp refinement and observation along the current motion, so view selection should be coupled with goal and trajectory updates.

Real-time replanning is enabled by reactive control [17], optimization-based [33] and sampling-based planners [27, 48, 51], vectorized sampling [41], and tree search [47]. These methods reduce planning latency and make frequent trajectory updates practical. In mobile grasping under partial observation, however, replanning must jointly revise the map, the manipulation goal, and the whole-body trajectory as new observations arrive. Learning-based mobile manipulation has also explored modular language-grounded systems [1, 18, 25, 26, 52, 53], reinforcement learning [21, 34, 46, 55], and vision-language-action or embodied foundation models [7, 11, 20, 42, 49, 59]. These methods broaden task coverage, but often struggle to reason jointly about semantic goals, partial geometry, and whole-body motion during execution.

III. Problem Formulation

We address visibility-aware mobile grasping in dynamic, partially observed environments. Given an initial configuration q_0 and a target coordinate $p \in \mathbb{R}^3$, which may be derived from a user-specified image point or a visual grounding module [10], the robot must compute and execute a whole-body trajectory $\xi : [0, T] \to \mathcal{C}$ that achieves a stable grasp while avoiding collisions between its swept volume $V(\xi)$ and obstacles observed during execution.

We cast this as a decision-making problem defined by $\langle \mathcal{S}, \mathcal{A}, \mathcal{O}, \mathcal{T}, \mathcal{G} \rangle$. The state space $\mathcal{S}$ contains the robot configuration q and true 3D environment state $\underline{M}_t$; the action space $\mathcal{A} = \mathcal{A}_r \times \mathcal{A}_v$ contains whole-body motion and gaze actions; $\mathcal{O}$ is the observation space; $\mathcal{T}$ includes known robot transitions and unknown dynamic object transitions; and $\mathcal{G} \subset \mathcal{C}$ is the set of true grasp configurations. Since the robot cannot access $\underline{M}_t$, the dynamic object transitions, or $\mathcal{G}$, it maintains a belief state $b_t = (q_t, M_t, g_t)$, where q_t is the robot configuration, M_t is the partial 3D map updated by observations $o_t \in \mathcal{O}$, and g_t is the estimated grasp configuration.

A policy $\pi = (\pi_r, \pi_v, \pi_g)$ operates on b_t. The motion policy $\pi_r(b_t) \to \xi_t$ plans a whole-body trajectory to g_t under M_t, the perception policy $\pi_v(\xi_t, p) \to a_v \in \mathcal{A}_v$ selects a gaze action for updating M_t, and the subgoal policy $\pi_g(b_t, p) \to g_t$ selects or refines the grasp configuration.

IV. Method

Our system implements the policies in Section III with a receding-horizon loop (Figure 2). At each step, the robot updates $b_t = (q_t, M_t, g_t)$ from new observations, refines the subgoal when needed, plans a whole-body trajectory ξ_t under the current map, selects a gaze action, and executes the next motion command. Replanning is triggered when the map invalidates the trajectory or when the subgoal is reached.

A. Subgoal Policy π_g

In an unknown environment, g_t cannot be fixed before execution because grasp feasibility depends on observed geometry, collision constraints, and robot reachability that are only revealed as M_t is updated. A single-shot plan may also fail when the target is occluded or unreachable from the current base pose. We implement π_g as a behavior tree whose fallback structure encodes the priority among three stages: direct grasping when the current belief is sufficient, a pre-grasp whole-body configuration when base repositioning is needed,

and an observation pose when more information is required. This structure lets the robot use the least disruptive action that can make progress: it grasps when feasible, repositions when reach or visibility is limiting, and gathers observations when manipulation is blocked. The concrete sampling and validation procedures for these stages are given in Appendix B, Appendix C, and Appendix D.

B. Active Perception Policy π_v

A robot with a limited field of view must observe the target p for grasp refinement and monitor the swept volume $V(\xi_t)$ during execution. The active perception policy π_v selects a gaze action by maximizing visibility of a phase-dependent importance field. When no trajectory is being executed, the field is concentrated around p; during execution, it shifts to $V(\xi_t)$ and weights regions by temporal proximity and robot velocity. The map M_t is updated from RGB-D observations using ray casting, which adds newly observed surfaces, clears observed free space, and preserves occluded geometry. The gaze objective, velocity weighting, and map update pipeline are detailed in Appendix E and Appendix F.

C. Whole-Body Motion Policy π_r

The motion policy π_r replans whole-body trajectories as M_t changes. We follow the hierarchical mobile-manipulation planner of [48], sampling base placements with non-holonomic steering and connecting arm configurations with RRT-Connect [23]. To support real-time replanning, we discretize base and arm motions separately, synchronize them into whole-body configurations, and check them in parallel using vectorized collision checking [41]. The resulting path is shortened, smoothed, and passed to the controller; if planning fails or times out, execution halts and π_g selects a new subgoal. Planner details are provided in Appendix G.

D. Localization and Control

The execution layer tracks q_t and converts each planned trajectory ξ_t into velocity commands. Simulation uses ground-truth poses, while the real robot uses AMCL [28] for base localization against a static 2D map; dynamic obstacles remain represented in the separate 3D map M_t. An MPC controller runs at 20 Hz over the 11-DoF whole-body state and accepts updated trajectories during execution, enabling the receding-horizon loop to react to new observations. The controller formulation is given in Appendix H.

V. Experiments

a) Evaluation protocol: We evaluate our system across 400 randomized simulation scenarios and 40 real-world trials on a Fetch mobile manipulator. Simulation uses ManiSkill3 [40] with ReplicaCAD scenes [39]; the real robot uses ROS and AMCL for localization. The scenarios cover three settings: *unknown static environments*, which test perception and planning under visibility constraints with previously unseen layouts; *dynamic environments*, where obstacles suddenly appear along the robot's path; and *real robot deployments*, which introduce localization, sensing, and execution errors. All simulation scenarios guarantee that a collision-free path exists and operate at room scale (∼5–10 m navigation range). A trial succeeds if the robot approaches without collision, grasps the target, lifts it by 10 cm, and maintains a stable grasp for 2 seconds. We categorize failures as execution failures (collision, grasp, IK), system limitations (reachability, perception), and planning failures. Qualitative rollouts, real-robot setup, benchmark generation, and metric definitions are provided in Appendix A, Appendix I, Appendix J, and Appendix K.

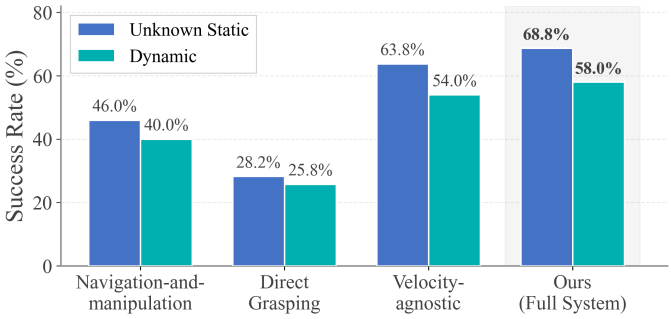

Fig. 3. **Success Rate Comparison.** Ablation study results across unknown static and dynamic simulation environments. Our full system achieves the highest success rates (68.8% and 58.0%), with subgoal generation providing the largest performance gain. Detailed failure breakdowns are provided in Appendix L.

b) Baselines: We compare against three baselines. navigation-and-manipulation follows the common decoupled paradigm [36, 44]: the robot navigates to a base pose using depth observations, replans navigation after collisions, resamples the target pose when needed, and then switches to arm motion planning from the fixed base. Direct Grasping retains whole-body planning and replanning but removes adaptive base repositioning and subgoal refinement, testing the role of the high-level policy π_g. Velocity-agnostic keeps all system components but removes velocity weighting from gaze optimization, using only volume-based safety weights [12]. Additional baseline definitions and system-level comparisons are provided in Appendix M.

c) Simulation results: Figure 3 summarizes the main simulation results: our system achieves 68.8% success in unknown static environments and 58.0% in dynamic environments, improving over navigation-and-manipulation by 22.8% and 18.0%. The decoupled navigation-and-manipulation baseline must commit to a base pose before observing the target's surroundings, causing unreachable final grasps (20.5% vs. 8.8% planning failures), while arm-only manipulation from a fixed base increases collisions in clutter (17.5% vs. 6.3%).

Removing the high-level subgoal policy causes the largest performance drop, reducing success by 40.5% in unknown static environments and 32.3% in dynamic environments. Without this policy, the robot lacks the structured logic for balancing task progress, failure recovery, and information

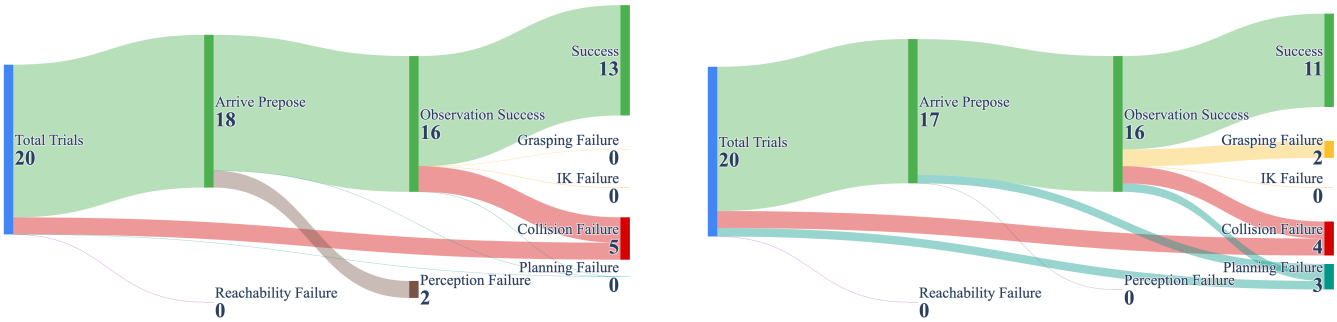

Fig. 4. Real robot evaluation results. Process flow and failure breakdown for static unknown (left) and dynamic (right) environments.

Fig. 5. **Spatial Distribution of Success and Failure.** Green and red circles represent successful and failed grasping attempts in a representative scene. Failures concentrate near walls, deep table regions, and cluttered object placements.

gathering. Velocity-aware active perception further improves safety in dynamic scenes, reducing collision failures from 13.8% to 9.8% by directing gaze to portions of the swept volume traversed at higher velocity, where collision consequences are most severe.

d) Failure modes: The remaining bottleneck is grasp detection: many geometrically plausible grasps are kinematically infeasible near walls, deep table regions, and clutter. Execution drift and small perception errors further block feasible approach directions in constrained regions. Figure 5 shows that these failures are not uniformly distributed: they concentrate around deep table placements, wall-adjacent objects, and cluttered support surfaces, where the grasp detector and whole-body planner face tightly coupled feasibility constraints. This pattern explains why success does not saturate even with active perception and fast replanning: the limiting factor is often whether a visually plausible grasp can be realized by the full robot in the revealed geometry. Detailed failure breakdowns are provided in Appendix L.

e) Real-world validation: We validate the full system on a real Fetch robot across five indoor locations with 40 test configurations (20 static, 20 dynamic). Figure 4 shows that the system achieves 65.0% and 55.0% success in static and dynamic settings, respectively, closely matching the simulation trend. Planning failures primarily come from noisy observations caused by localization-depth synchronization issues. Collision failures arise when ground-plane filtering removes low-lying obstacles such as chair legs, as well as from execution noise when the robot sticks and then accelerates, disrupting pose estimation. These results suggest that coupling active perception, subgoal refinement, and whole-body replanning transfers to real indoor deployments despite sensing and execution noise.

f) Robustness checks: Across five independent runs, our system achieves $69.5\% \pm 1.0\%$ success in unknown static environments and $61.2\% \pm 2.4\%$ in dynamic environments, with 95% Wilson confidence intervals that contain the single-run results in Figure 3. Per-scene success rates vary because room geometry, furniture density, and target placement change the feasible approach set, but this reflects layout difficulty rather than algorithmic instability. Under continuously moving obstacles at 0.2 m/s, the full system achieves 54.4% success, slightly below the sudden-appearance dynamic benchmark; this is consistent with a reactive system whose main failure mode is newly invalidated free space along the obstacle trajectory. Overall, the gains come from avoiding premature commitment to a fixed base pose and using gaze to actively monitor the current swept volume; additional analyses are provided in Appendix M.

VI. Conclusion

This paper presented a unified framework for mobile grasping in dynamic, unknown environments under visibility constraints. By integrating velocity-aware active perception, hierarchical subgoal generation, and fast whole-body replanning, our system improves success over the navigation-and-manipulation baseline by 22.8% and 18.0% in unknown static and dynamic environments, while reducing collisions through closed-loop perception and planning. Real-world trials further show that the same design transfers across diverse indoor settings. The results also highlight that future grasp scoring should account for full-body reachability rather than local grasp geometry alone; together with the spatial failure distribution, this suggests that visibility-aware mobile grasping should be evaluated as a coupled perception, base-placement, and whole-body feasibility problem. Future work will incorporate predictive models for human and object motion, broaden grasp coverage with multi-fingered hands, and develop probabilistic completeness guarantees for visibility-constrained planning, with extensions to multi-robot and contact-rich manipulation.

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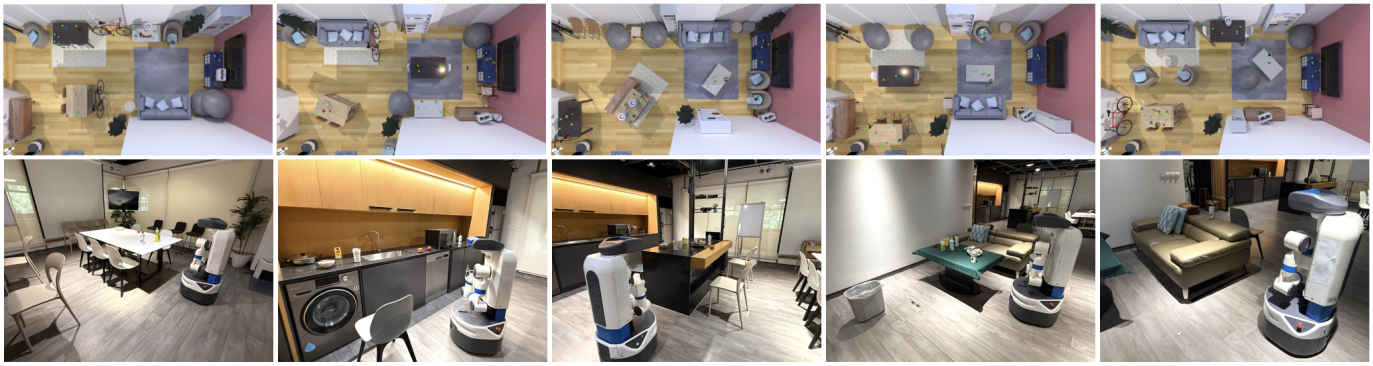

Fig. 6. **Evaluation Environments.** *Top.* Five of 20 simulation scenes (ReplicaCAD) with varied furniture layouts and target placements. *Bottom.* Real-world deployment across five indoor locations, including dining table, kitchen counter, workstation, coffee table, and sofa.

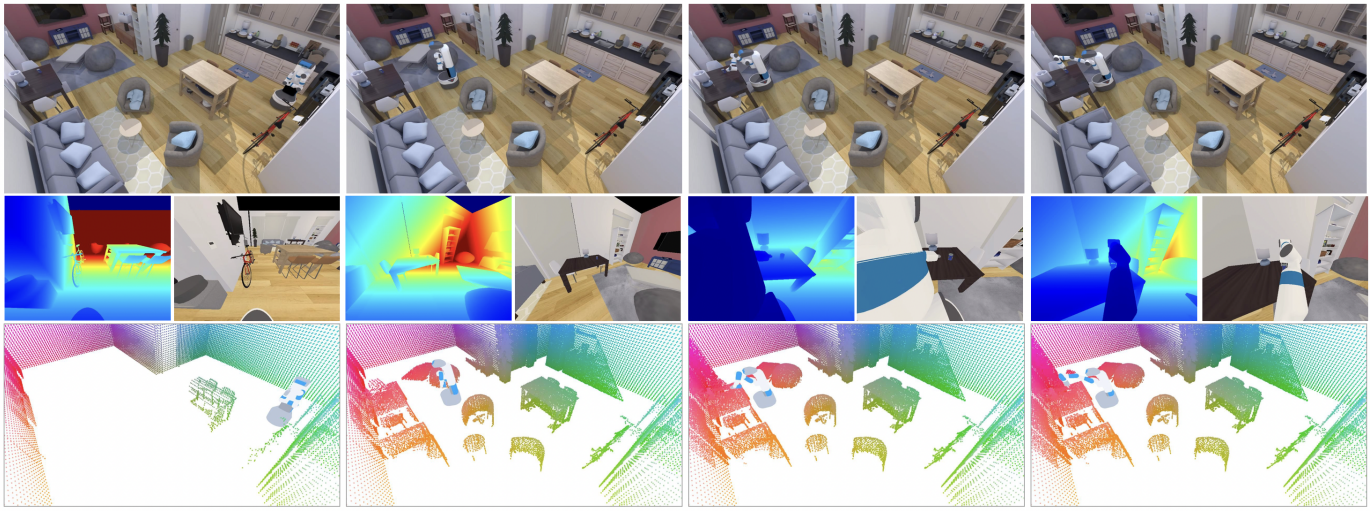

Fig. 7. Qualitative results showing the execution sequence in simulation. The columns show the starting pose, observation stage, pre-grasp stage, and grasping stage. The top row shows the third-person view, the middle row shows the first-person view from the robot head camera, and the bottom row displays the robot's belief map.

APPENDIX

This appendix provides supplementary material organized as follows: qualitative evaluation visualizations (Section A); implementation details for grasp sampling, pre-grasp configuration generation, kinematic map construction, active perception, environment mapping, whole-body motion planning, and path tracking (Sections B–H); real robot deployment specifics (Section I); benchmark generation and evaluation protocol (Sections J and K); detailed failure analysis (Section L); and additional experiments including baseline definitions, system-level comparisons, path efficiency, obstacle distance sensitivity, and sampling completeness (Section M).

A. *Evaluation Environments and Qualitative Rollouts*

Figure 6 shows representative simulation and real-world evaluation environments. Figure 7 shows a qualitative rollout in simulation, including the third-person view, robot camera view, and belief map.

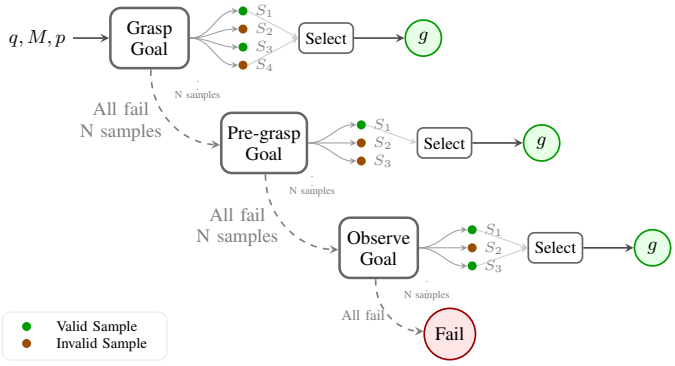

Fig. 8. **Subgoal Generation.** The process hierarchically attempts to generate a reachable subgoal (g) using three strategies: Grasp, Pre-grasp, and Observe. In each stage, N candidates ($S_1 \ldots S_N$) are sampled. If all samples in a stage are invalid, the system falls back to the next strategy.

B. Grasp Goal Sampling and Execution

Algorithm 1 details the grasp goal sampling procedure for in-place manipulation without base motion.

Algorithm 1 Grasp Goal Sampling

Require: Point cloud P, target p, current config q_{curr}, capability map $\mathcal{M}_{cap}$
Ensure: Valid grasp configuration g or failure

$\mathcal{G}_{raw} \leftarrow$ ContactGraspNet(P, p) ▷ Generate grasp candidates
$\mathcal{G}_{feas} \leftarrow \{T_{ee} \in \mathcal{G}_{raw} : \mathcal{M}_{cap}(T_{ee}) > 0\}$ ▷ Filter by capability
$\mathcal{G}_{div} \leftarrow$ FarthestPointSample$(\mathcal{G}_{feas}, N)$ ▷ Select diverse subset
Sort $\mathcal{G}_{div}$ by $\hat{s}(T_{ee})$ descending ▷ Rank by proximity-weighted score
for $T_{ee} \in \mathcal{G}_{div}$ **do**
  $q_{arm} \leftarrow \mathrm{IK}(T_{ee}, q_{curr})$ ▷ Solve inverse kinematics
  if $q_{arm} =$ `None` **then continue**
  end if
  $g \leftarrow (q_{curr,base}, q_{curr,torso}, q_{arm})$
  if CollisionFree(g, M) **then**
    return g
  end if
end for
return `Failure`

a) Grasp Candidate Generation: We use Contact-GraspNet [38] to generate 6-DoF grasp pose candidates from the observed point cloud. The network takes as input the segmented point cloud around the target and outputs a set of grasp poses $\{T_{ee}^{(i)}\}$ with associated confidence scores. We filter candidates to retain only those within a radius of 10 cm from the target centroid.

b) Capability Map Filtering: Each grasp candidate is transformed to the base frame and queried against the pre-computed capability map (Section D). Candidates mapping to voxels with zero visitation frequency are rejected, as they correspond to end-effector poses unreachable by the arm from the current base position.

c) Diversity Selection: From the feasible candidates, we select $N_{diverse} = 20$ poses using farthest point sampling in $SE(3)$ to maximize spatial coverage. Starting from the highest-confidence grasp, we iteratively add the candidate maximizing the minimum distance to already-selected grasps, using the metric:

$$d(T_1, T_2) = \|t_1 - t_2\| + \lambda \cdot \arccos\left(\frac{\mathrm{tr}(R_1^T R_2) - 1}{2}\right) \quad (1)$$

where $\lambda = 0.1$ balances translation and rotation differences.

d) Proximity-Aware Ranking: After diversity selection, candidates are sorted by a proximity-weighted score that provides a weak preference for grasps closer to the current end-effector pose:

$$\hat{s}(T_{ee}) = s(T_{ee}) - \lambda_d \cdot \|t_{ee} - t_{ee,curr}\| \quad (2)$$

where $s(T_{ee})$ is the grasp confidence from Contact-GraspNet, $t_{ee,curr}$ is the current end-effector position, and $\lambda_d = 0.01$. This small weight acts primarily as a tiebreaker among similarly confident grasps, favoring configurations that require less arm motion.

e) Validation and Execution: Each selected grasp is validated by: (1) solving whole-body inverse kinematics with the current base and torso configuration fixed; (2) checking the resulting configuration for collision against the current map M_t. The first valid configuration is selected as the grasp goal g_t. Note that this greedy first-valid strategy prioritizes computational efficiency over grasp quality optimization; tighter coupling between grasp selection and motion feasibility remains a direction for future work.

During execution, even in-place arm motion uses the same receding horizon framework as whole-body motion. Algorithm 2 details this procedure: the system plans an initial arm trajectory, then executes it asynchronously while continuously monitoring for collisions. At each control cycle, it updates the collision environment from the latest depth observation, checks the remaining trajectory for collisions, and triggers replanning if obstacles are detected. The gaze optimizer runs concurrently at 10 Hz—limited by the scene management and map update pipeline rather than the optimization itself (which completes in under 5 ms)—directing the camera toward regions along the planned trajectory, weighted by temporal proximity and velocity (Section E). The robot first moves to a pre-grasp pose (5 cm offset along the approach direction), then executes a linear approach motion before closing the gripper.

Algorithm 2 Arm Motion with Replanning

Require: Current config q_{curr}, goal config g, map M, max replan attempts K
Ensure: Motion success or failure

$\xi \leftarrow$ PlanArm(q_{curr}, g, M) ▷ Initial plan
StartAsyncExecution(ξ)
$k \leftarrow 0$
while not MotionComplete() **and** $k \leq K$ **do**
  $M \leftarrow$ UpdateMap(depth, T_{wc}) ▷ Ray casting update
  $i \leftarrow$ CurrentWaypointIndex()
  UpdateGaze(ξ, i) ▷ Look ahead at trajectory
  if CheckCollision$(\xi[i:], M)$ **then**
    StopMotion()
    $q_{curr} \leftarrow$ GetCurrentConfig()
    $\xi \leftarrow$ PlanArm(q_{curr}, g, M) ▷ Replan
    if $\xi =$ `None` **then return** `Failure`
    end if
    StartAsyncExecution(ξ)
    $k \leftarrow k + 1$
  end if
end while
if $k > K$ **then return** `Failure`
end if
return `Success`

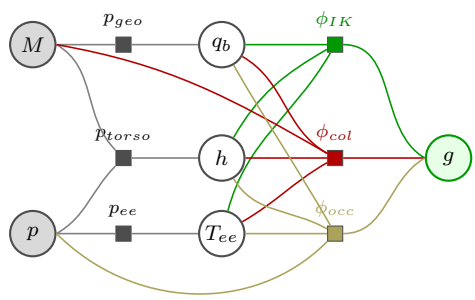

Fig. 9. **Constrained sampling for pre-grasp configuration.** Given map M and target p, we sample base pose q_b, torso height h, and end-effector pose T_{ee} via proposal distributions (black). Constraint checks enforce IK feasibility (ϕ_{IK}, green), collision-free (ϕ_{col}, red), and occlusion-free (ϕ_{occ}, yellow) via rejection sampling to produce valid goal g.

C. Pre-Grasp Configuration Sampling

Algorithm 3 details the constrained sampling procedure for generating pre-grasp configurations when direct grasping fails.

Algorithm 3 Pre-Grasp Configuration Sampling

Require: Map M, target p, current config q_{curr}, number of samples N
Ensure: Valid pre-grasp configuration g or failure

```
for i = 1 to N do
    q_b ~ p_geo(q_b | M)          ▷ Sample base pose from SDF
    h ~ p_torso(h | q_b, p)       ▷ Query torso height map
    T_ee ~ p_ee(T_ee | p)         ▷ Sample EE pose around target
    q_arm ← IK(T_ee, q_b, h)      ▷ Solve inverse kinematics
    if q_arm = None then continue
    end if
    g ← (q_b, h, q_arm)
    if CollisionFree(g, M) ∧ OcclusionFree(g, p) then
        return g
    end if
end for
return Failure
```

a) Base Pose Sampling (p_{geo}): We maintain a 2D costmap derived from the 3D belief point cloud. The SDF generation proceeds as follows: (1) filter points by height (0.05–1.5 m) to capture obstacles at robot operating height; (2) project filtered points onto the XY ground plane; (3) rasterize into a 2D occupancy grid at 0.05 m resolution; (4) apply binary closing (3×3 kernel) to fill small gaps; (5) identify the navigable region as the largest connected free-space component; (6) compute the Euclidean distance transform from obstacle cells; (7) convert distances to costs via exponential decay $c = \exp(-d/d_{max})$ where $d_{max} = 2.0$ m. Base poses are sampled with probability proportional to $(1-c)^2$, biased toward low-cost regions within manipulation radius of the target. Orientation is set to face the target.

b) Torso Height Selection (p_{torso}): We pre-compute a torso height map $H : \mathbb{R}^3 \to \mathbb{R}$ that maps end-effector position (relative to the base frame) to the optimal torso height that maximizes the end-effector's reachability. This map is computed offline by selecting the torso height that maximizes the volume of feasible joint configurations reaching each position bin (Section D).

c) End-Effector Pose Sampling (p_{ee}): Candidate end-effector poses are sampled on a sphere of radius 10 cm centered at the target p. Orientations are sampled from approach directions pointing toward p, filtered by the pre-computed capability map to ensure kinematic feasibility.

D. Pre-computed Kinematic Maps

We pre-compute three maps offline to accelerate online sampling. All maps are robot-specific and computed once.

a) Reachability Map: We construct a 6D reachability map by uniformly sampling $N = 1.28 \times 10^8$ joint configurations within joint limits and computing forward kinematics for each. End-effector poses are discretized into a 6D voxel grid (position at 5 cm resolution, orientation at $\pi/8$ rad resolution). For each voxel, we store the visitation frequency and the maximum Yoshikawa manipulability $\sqrt{\det(JJ^T)}$ across all configurations mapping to that voxel. Voxels below the ground plane are filtered out.

b) Capability Map: The capability map [31] is derived by inverting the reachability map transforms, converting from "given base pose, where can the end-effector reach?" to "given a desired end-effector pose relative to the base, is it reachable?" At runtime, we query this map to filter candidate grasp poses: voxels with zero visitation frequency are marked unreachable, allowing early rejection before expensive IK computation.

c) Torso Height Map: For robots with a prismatic torso joint (e.g., Fetch), we build a torso height policy map. We sample 3×10^8 joint configurations uniformly, compute FK, and discretize the end-effector position into 3D bins (2 cm resolution) while separately binning the torso height (5 cm resolution). For each position bin (x, y, z), we select the torso height with the highest sample count:

$$h^*(x,y,z) = \underset{h}{\operatorname{argmax}} \operatorname{Count}\big[\mathrm{FK}(q) \in \mathrm{bin}(x,y,z) \wedge \mathrm{torso}(q) \in \mathrm{bin}(h)\big] \quad (3)$$

This yields the torso height that maximizes the volume of feasible joint configurations reaching each position, providing a kinematically-informed default without online search.

E. Active Perception Details

The safety weight $w_{safety}(x)$ in the gaze optimization combines temporal, spatial, and velocity terms. The distance weight $w_d(x, q^{(i)})$ is a Gaussian function centered at moderate distance:

$$w_d(x, q^{(i)}) = \exp\left(-\frac{1}{2}\left(\frac{d(x, q^{(i)}) - d_{mid}}{\sigma}\right)^2\right) \quad (4)$$

where $d(x, q^{(i)})$ is the distance from point x to the robot at configuration $q^{(i)}$, d_{mid} is the center distance (regions too close offer no reaction time; regions too far pose less

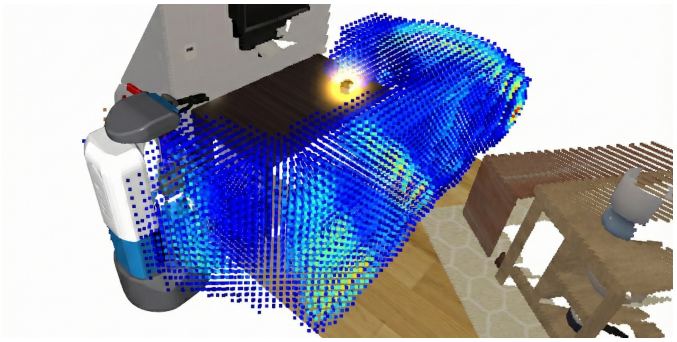

Fig. 10. **State-Dependent Gaze Optimization.** During planning ($\xi_t = \emptyset$), the importance field concentrates on the target region to enable grasp pose generation. During execution ($\xi_t \neq \emptyset$), the field shifts to the swept volume $V(\xi_t)$, weighted by velocity and temporal proximity to prioritize observation of collision-critical regions.

immediate threat), and $\sigma = \max(1.0, 0.25 \cdot N)$ controls the width based on the lookahead window N.

The complete safety weight is:

$$w_{safety}(x) = \sum_{i=0}^{N} \gamma^i \cdot w_d(x, q^{(i)}) \cdot \|\dot{q}^{(i)}\| \tag{5}$$

where $\gamma = 0.999$ provides temporal decay (prioritizing near-term waypoints), and $\|\dot{q}^{(i)}\|$ is the velocity magnitude at waypoint i. This formulation emphasizes regions that are (1) temporally imminent, (2) at moderate distance where corrective action is still possible, and (3) near fast-moving links where collision consequences are most severe.

The gaze action space $\mathcal{A}_v$ is discretized into a grid of pan-tilt angles for the head camera. At each control cycle, we evaluate the importance field integral for each candidate gaze direction and select the maximum. With typical discretization of 8 pan $\times$ 5 tilt angles, this optimization completes in under 5 ms.

F. Dynamic Environment Mapping

The map M_t is maintained as a point cloud that evolves through ray casting updates. Each RGB-D observation triggers the following pipeline:

a) Point Cloud Generation: The depth image is converted to a world-frame point cloud by back-projecting pixels using the camera intrinsics K and transforming via the camera-to-world pose T_{wc}. Points are filtered by depth range (0.2–3.0 m) and cropped to a 2.5 m radius sphere around the camera to focus on the relevant workspace.

b) Filtering Pipeline: Before integration, points undergo two filtering stages: (1) ground plane removal, which discards points below a height threshold ($z < 0.3$ m) to eliminate floor returns that would interfere with navigation planning; (2) robot self-filtering, which removes points that fall within the robot's own body volume using the current joint configuration to prevent self-collision artifacts in the map.

c) Ray Casting Update: The core update uses ray casting to distinguish free space from occluded regions. For each existing point $x \in M_t$, we project it into the current camera frame and compare its depth z_x against the measured depth z_{obs} at the corresponding pixel:

- If $z_x < z_{obs} - \delta$: the point lies in free space (between camera and observed surface) and is removed.
- If $z_x \geq z_{obs} - \delta$: the point is either on the surface or occluded behind it, and is preserved.

Here $\delta = 0.03$ m is a merge tolerance. This approach enables the robot to detect when dynamic obstacles have moved away while preserving geometry that remains occluded.

d) Point Merging: New observation points are merged with the existing map using voxel-based deduplication. Points are quantized to a voxel grid (resolution 0.03 m), and only points falling in previously unoccupied voxels are added. This prevents unbounded point cloud growth while maintaining surface detail.

G. Whole-Body Motion Planning

Reactive execution in dynamic environments requires re-planning whole-body trajectories as the map M_t updates. Existing approaches face a trade-off: vectorized planners like VAMP [41] achieve real-time performance but assume homogeneous configuration spaces, while state-of-the-art planners for non-holonomic mobile manipulators [48] handle heterogeneous base-arm spaces but require more computation per planning cycle.

We combine these directions by decomposing planning hierarchically following [48]. The algorithm samples candidate base placements using a non-holonomic steering kernel that combines Hybrid A* [24] for global guidance with Reeds-Shepp curves for local connections. For each base placement, arm configurations are connected using standard RRT-Connect [23].

To enable vectorization across this heterogeneous space, we discretize base and arm motions separately, apply Reeds-Shepp curves for the base and linear interpolation for the arm, and synchronize them into whole-body configurations at matching time steps. These synchronized configurations are checked in parallel using SIMD operations [41]. Raw paths are refined through randomized shortcutting [14, 16], B-spline fitting [35], and dense re-interpolation before tracking.

In our system, this implementation typically achieves planning times of 50–80 ms. When planning fails or exceeds the time limit, the system halts execution and the subgoal policy generates a new goal for the next planning attempt.

H. Whole-Body Path Tracker

We implement a whole-body velocity controller running at 20 Hz to track planned trajectories. The whole-body state is defined as $\mathbf{x} = [x, y, \theta, h, \mathbf{q}_{arm}]^\top \in \mathbb{R}^{11}$, comprising the base pose (x, y, θ), torso height h, and 7 arm joint angles $\mathbf{q}_{arm}$. The control input is $\mathbf{u} = [v, \omega, \dot{h}, \dot{\mathbf{q}}_{arm}]^\top \in \mathbb{R}^{10}$, consisting of the base linear and angular velocities, torso velocity, and 7 arm joint velocities.

At each control cycle, the controller selects a look-ahead reference $\mathbf{x}_{ref}$ from the planned waypoint sequence. The controller first identifies the nearest waypoint to the current state using a weighted distance metric that combines base position error, heading error, and joint error. From this nearest waypoint, it selects the reference state at a fixed look-ahead offset along the trajectory.

The control law is derived by linearizing the nonholonomic base dynamics around the current heading θ:

$$\mathbf{x}_{k+1} \approx \mathbf{x}_k + \mathbf{B}(\theta)\,\mathbf{u}_k \tag{6}$$

where the input matrix $\mathbf{B}(\theta) \in \mathbb{R}^{11\times 10}$ encodes the unicycle kinematics for the base and identity mappings for the joints:

$$\mathbf{B}(\theta) = \begin{bmatrix} \cos\theta & 0 & 0 & \cdots & 0 \\ \sin\theta & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & \mathbf{I}_7 \end{bmatrix} \tag{7}$$

Given the state error $\Delta\mathbf{x} = \mathbf{x}_{ref} - \mathbf{x}$, the controller solves a one-step quadratic program:

$$\min_{\mathbf{u}} \; \|\Delta\mathbf{x} - \mathbf{B}\mathbf{u}\|^2_{\mathbf{Q}} + \|\mathbf{u}\|^2_{\mathbf{R}} \tag{8}$$

where $\mathbf{Q} = \mathrm{diag}(20, 20, 15, 12, \ldots, 12)$ weights the tracking error and $\mathbf{R} = \mathrm{diag}(0.5, 0.8, 1.0, \ldots, 1.0)$ regularizes the control effort. The closed-form solution is:

$$\mathbf{u}^* = (\mathbf{B}^\top\mathbf{Q}\mathbf{B} + \mathbf{R})^{-1}\mathbf{B}^\top\mathbf{Q}\,\Delta\mathbf{x} \tag{9}$$

The resulting command is scaled by a gain factor $\alpha = 2.5$ and clamped to velocity limits ($v_{max} = 1.5$ m/s, $\omega_{max} = 1.0$ rad/s, with per-joint velocity limits of 0.1 rad/s for the torso and 1.0 rad/s for arm joints).

I. Real Robot Deployment

a) Goal Specification and Target Tracking: The user specifies the target by pointing at an object in an initial RGB-D image. We extract the target's 3D pose via instance segmentation and establish a semantic label using open-vocabulary object detection from a predefined list of graspable objects (e.g., apple, mug, bottle). During execution, as the robot observes from different viewpoints, we re-identify the target by finding the detected object that (1) matches the semantic label and (2) has the nearest bounding box center to the projected previous target coordinate. This semantic-geometric association enables robust tracking despite viewpoint changes and localization drift.

b) ROS Integration: Our system integrates several ROS packages: `ros_control` and MoveIt for arm trajectory execution, `message_filters` for synchronized RGB-D observation callbacks, `tf` for coordinate frame transformations, and the ROS Navigation stack (AMCL) for localization.

J. Benchmark Generation

We generate a benchmark of 400 test scenarios (20 scenes $\times$ 20 objects per scene) through a multi-stage validation pipeline.

a) Scene Selection: We select 20 scenes from ReplicaCAD [39] that represent diverse indoor environments: living rooms, kitchens, bedrooms, and offices. Scenes are chosen to vary in room size (15–50 m^2), furniture density (3–12 major pieces), and navigational complexity (open spaces vs. narrow passages).

b) Object Placement: For each scene, we procedurally place YCB objects on horizontal support surfaces (tables, counters, shelves). Placement surfaces are detected via point-cloud-based plane segmentation: we sample surface points, filter by upward-facing normals (> 0.95 dot product with Z-axis), cluster spatially adjacent cells, and retain only the topmost surface for each horizontal footprint. Objects are sampled from 50 YCB objects: master chef can, sugar box, tomato soup can, mustard bottle, tuna fish can, potted meat can, banana, strawberry, apple, lemon, peach, pear, orange, plum, bleach cleanser, bowl, mug, power drill, flat screwdriver, hammer, medium clamp, extra large clamp, mini soccer ball, softball, baseball, tennis ball, racquetball, golf ball, foam brick, marbles (a, b), cups (a–j), colored wood blocks, toy airplane, lego duplo (a–f), and rubiks cube. Initial placement positions are sampled with rejection sampling to ensure minimum separation between object centers (20 cm).

c) Drop Checking: Each placed object undergoes stability validation. We spawn the object 20 cm above the sampled surface point and simulate 100 physics steps using ManiSkill3. An object passes drop checking if:

1) The object's final height is within the expected range relative to the support surface ($\pm$5 cm below to 30 cm above)
2) The object's total displacement from spawn is less than 30 cm (no excessive rolling/bouncing)
3) No collision with existing objects at spawn time

Objects failing these checks are re-sampled at alternative positions until a stable placement is found or the maximum attempts (100) are exceeded.

d) Oracle Grasp Checking: Stable objects undergo graspability validation to ensure each benchmark object is actually graspable under ideal conditions. The procedure is:

1) **Multi-view rendering:** We render 20 RGB-D images of each object from viewpoints distributed on a circle (radius 0.3 m, height 0.3 m above the object center, uniformly spaced in azimuth).
2) **Grasp candidate generation:** For each view, we run Contact-GraspNet [38] on the segmented point cloud, filter by confidence score (≥ 0.4), and aggregate candidates across views. We apply farthest-point sampling to select up to 256 diverse grasps.
3) **Physics-based validation:** Each grasp candidate is tested using a virtual parallel-jaw gripper (box approximation with 10 cm finger length, 10 cm max opening):
   - The gripper approaches from a 10 cm pre-grasp offset along the approach direction
   - The gripper closes to 2 mm opening width
   - The gripper retreats to the pre-grasp pose, then lifts vertically by 10 cm

- Success requires: both fingers contact the object, object displacement <3 cm during a 30-step stability hold, and object lifts at least 3 cm

4) **Inclusion criterion:** An object is included in the benchmark if at least one grasp candidate succeeds. Objects with zero successful grasps are replaced with alternative placements.

e) Dynamic Scenario Generation: For dynamic environment evaluation, we augment static scenarios with sudden obstacle appearances:

- **Pedestrian obstacles:** A cylindrical obstacle (radius 0.3 m, height 1.7 m) appears at a predefined position along the robot's path when the robot approaches within 1.7 m. Positions are manually selected to block the initial planned trajectory while ensuring alternative paths exist.
- **Table-top obstacles:** A small object appears on the table surface near the target when the robot reaches the pre-grasp pose. This tests perception updates and grasp replanning under tight spatial constraints.

We note that these dynamic scenarios use suddenly appearing static obstacles rather than continuously moving agents (e.g., walking pedestrians). This design ensures reproducibility and guarantees that an alternative path to the target always exists, enabling controlled evaluation of reactive replanning. Evaluating under continuously moving obstacles remains a direction for future work.

K. Evaluation Metrics

We evaluate system performance using grasp success rate as the primary metric and categorize failures to diagnose system behavior.

a) Success Criterion: A trial is marked successful if the robot:

1) Approaches the target object without collision
2) Executes a grasp that achieves stable contact with the object
3) Lifts the object above a height threshold (10 cm above the support surface)
4) Maintains stable grasp for 2 seconds after lifting

This physics-based validation accounts for the robot's full kinematic and dynamic constraints during execution.

b) Failure Categories: We categorize failures into three groups to identify system bottlenecks:

Execution Failures occur during physical interaction:

- **Collision:** Any contact between the robot body (excluding gripper fingers) and environment obstacles or the target object before grasp initiation.
- **Grasp Failure:** The gripper closes but fails to establish stable contact, or the object slips during lifting. This includes cases where the grasp pose is geometrically valid but execution errors (positioning, timing) cause failure.
- **IK Failure:** The inverse kinematics solver cannot find a valid joint configuration for the commanded end-effector pose during execution.

System Limitations represent fundamental constraints:

- **Reachability:** No valid whole-body configuration exists that places the end-effector at any feasible grasp pose. This occurs when the target is too far, too high, or in a confined space that the robot cannot physically access.
- **Perception:** The target object cannot be reliably detected or localized due to occlusion, lighting conditions, or sensor noise. Also includes cases where environmental geometry is incorrectly estimated, leading to invalid planning.

Planning Failures indicate algorithmic limitations:

- **Planning Timeout:** The motion planner cannot find a collision-free path within the allocated time budget (200 ms per attempt, up to 3 attempts). While the average planning time is 50–80 ms for feasible problems, failures at the timeout typically indicate that the target configuration is infeasible under the current map or that the environment is too constrained for a collision-free path to exist, rather than reflecting mere computational limitations.
- **Subgoal Generation Failure:** No valid pre-grasp or observation configuration can be sampled that satisfies all constraints (collision-free, reachable, non-occluded).

c) Evaluation Scenarios: Figure 11 shows all 20 simulation scenes with test case distributions. Green and red dots indicate robot starting positions and target object locations, respectively.

d) Real-World Locations: We test in five indoor settings: (1) dining table, (2) kitchen counter, (3) workstation, (4) coffee table, and (5) sofa. These locations span different approach constraints and obstacle configurations. For each location, we configure 4 unique object–start pairs (varying target object identity and robot starting position), yielding 20 static configurations and 20 dynamic configurations (40 total). This doubled evaluation set (compared to a minimal 10+10 split) improves statistical reliability of real-world results. We evaluate only the full system in real-world experiments; baseline methods lacking safety-critical components (e.g., active perception, reactive replanning) pose risks of physical damage to the robot and environment during unguarded execution.

L. Detailed Failure Analysis

a) Spatial Failure Patterns: Figure 5 visualizes the spatial distribution of successes and failures in a representative scene. Figure 12 shows the aggregate failure flow across unknown static and dynamic simulation environments. Three distinct failure regions emerge: (1) objects located deep on tables fail due to limited arm reachability from feasible base positions; (2) objects near walls fail because environmental constraints eliminate viable approach directions, yet the grasp detector lacks kinematic awareness to account for this; (3) objects in cluttered areas fail due to the difficulty of isolating individual items for precision grasping.

b) Grasping Failures: Grasping represents the most significant bottleneck (13–16% of trials). The grasp detection model exhibits sensitivity to out-of-distribution scenarios: large objects frequently produce low-quality grasp poses due

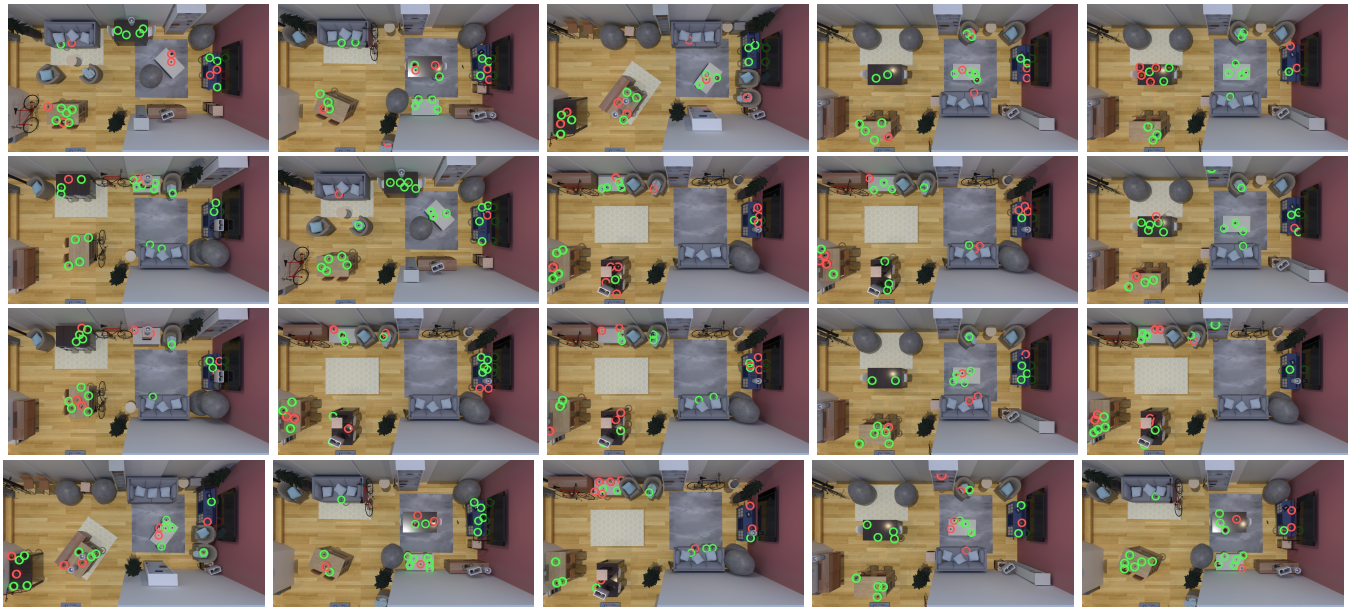

Fig. 11. **Simulation Test Scenarios.** Top-down views of all 20 ReplicaCAD scenes used for evaluation. Green dots indicate robot starting positions; red dots indicate target object locations. Scenes vary in room layout, furniture density, and navigational complexity.

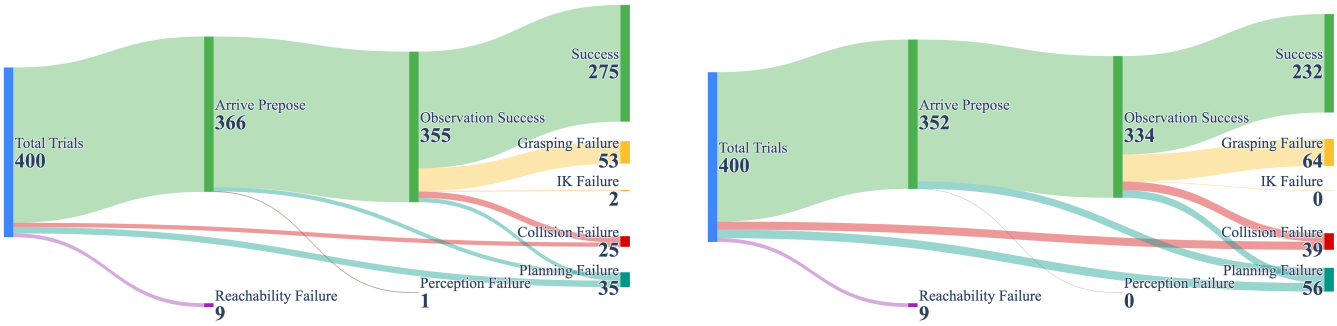

Fig. 12. Failure flow in unknown static (left) and dynamic (right) environments in simulation benchmark.

to training data bias toward smaller objects, and grasp quality degrades with distance from the observation point as depth uncertainty increases. The core limitation stems from decoupling grasp detection from kinematic feasibility. In constrained spaces like shelf corners, the model often predicts top-down grasps that are unreachable due to gripper-environment collisions or joint limit violations. Additionally, small lightweight objects exhibit high sensitivity to positioning errors, and certain geometries (e.g., objects with handles) are incompatible with parallel-jaw grippers. To further diagnose this bottleneck, we manually labeled 46 grasp failures into four modes (Table I): *infeasible* (all motion planning attempts fail or the IK solution lies in collision), *inaccurate* (the grasp pose is a false positive—geometrically misaligned with the object), *instability* (the grasp completes but the object slips during lift), and *out-of-distribution* (no valid candidate is returned by the grasp network). The dominance of the *infeasible* mode (43.5%) reveals a domain shift between mobile grasping and tabletop grasping: the off-the-shelf grasp detector ranks candidates by geometric quality alone, so geometrically optimal grasps are frequently kinematically infeasible in the constrained spaces our robot encounters (e.g., shelves, walls, deep tables). These failures are largely independent of the system architecture and would affect any pipeline that uses decoupled grasp detection. Kinematically-informed grasp scoring is therefore a clear direction for future work.

TABLE I
DISTRIBUTION OF GRASP FAILURE MODES ACROSS 46 LABELED TRIALS.

Mode	Infeasible	Inaccurate	Instability	OOD
Count (%)	20 (43.5%)	14 (30.4%)	11 (23.9%)	1 (2.2%)

c) Planning Failures: Planning failures (8–14% of trials) arise from four sources: (1) perception noise creating false obstacle detections that block valid paths; (2) planner false negatives where feasible paths exist but are not found within time limits; (3) insufficient path smoothness causing controller tracking errors; (4) paths passing too close to obstacles with insufficient safety margin. Our system incorporates fallbacks and multiple planning attempts, but these issues still contribute to failures, highlighting the importance of robust planning under perceptual uncertainty.

d) Collision Failures: Collision failures (6–10% of trials) expose perception and execution limitations. The active perception system prioritizes high-velocity and near-target regions, creating blind spots where thin or non-convex objects (plant stems, chair legs) are missed. Conservative ground plane removal, necessitated by sensor noise, inadvertently filters low-lying obstacles. Execution uncertainty also contributes: in-place rotations exhibit translational drift sufficient to cause collisions in tight spaces. In dynamic environments, sensor synchronization delays create spurious obstacle detections during reactive replanning. The static-to-dynamic gap further reflects two compounding effects: the planner produces tighter trajectories around newly appearing obstacles (raising collisions from 6.3% to 9.8%), and new obstacles occlude previously observed regions, degrading observation efficiency and contributing to the rise in planning failures (8.8% to 14.0%). These effects motivate two future directions: incorporating predictive motion models for humans and dynamic objects to reduce reactive replanning, and developing probabilistic completeness guarantees for visibility-constrained planning.

M. Additional Experiments

1) Main Baseline Implementations:

a) Navigation-and-manipulation: This baseline represents the dominant mobile manipulation paradigm [36, 44], where navigation and arm motion planning are decoupled into separate phases. The robot uses current depth observations for collision avoidance, executes closed-loop navigation with replanning upon collisions, and enables target pose resampling. Navigation terminates when the robot reaches a fixed distance from the target, after which arm motion planning begins.

b) Direct Grasping: This baseline attempts manipulation without base repositioning. It retains whole-body planning with replanning capability but executes a fixed sequence (observe, navigate, grasp) without adaptive goal resampling or gaze control. It ablates the benefit of the subgoal policy π_g, which provides priors for efficient task planning.

c) Velocity-agnostic: This baseline retains all system components except velocity awareness in Eq. 5. It uses only volume-based safety weights [12], ablating the velocity-aware active perception module to evaluate its effect on task performance and safety.

Table II provides detailed failure breakdowns for all six methods across both simulation environments. The reported numbers are stable across 5 independent runs of the 400-scenario benchmark (2,000 trials per condition): our system achieves $69.5\% \pm 1.0\%$ (static) and $61.2\% \pm 2.4\%$ (dynamic) mean $\pm$ std, with 95% Wilson confidence intervals of $[67.4\%, 71.5\%]$ and $[59.0\%, 63.3\%]$ that contain the single-run results reported in the main paper. Per-scene success rates range from 51%–81% (static) and 47%–73% (dynamic), with cross-scene standard deviations of $\sigma_{\text{scene}} = 8.2\%$ and 6.9%, reflecting layout and clutter diversity rather than system instability.

2) System-Level Comparisons: We evaluate two alternative system designs that make different architectural choices for integrating navigation and manipulation, complementing the ablation study in the main paper.

a) CapMap Placement: This system design follows the sequential navigation-then-manipulation paradigm but incorporates manipulation-aware base placement using the capability-map-based method of Reister et al. [36]. Rather than terminating navigation at a fixed distance from the target (as in the navigation-and-manipulation design), this architecture uses the pre-computed capability map to select a base pose that ensures the target lies within the arm's reachable workspace.

The system uses the same pre-grasp sampler as ours (Section C), which samples complete configurations (base + torso + arm). However, by design only the base pose is extracted for navigation. Once the robot reaches the selected base pose, it switches to arm-only motion planning for the grasping phase, maintaining a strict separation between the navigation and manipulation stages.

As shown in Table II and Figure 13, this design achieves 44.25% and 40.00% success rates in the unknown static and dynamic environments, respectively. Interestingly, despite the kinematically-informed base placement, it performs slightly *worse* than the simpler fixed-distance navigation design (46.00% and 40.00%) in the static environment. The manipulation-awareness constraints narrow the set of feasible base poses: by requiring the target to lie within the arm's reachable workspace, the capability map excludes base positions that, while not optimal for reachability, would have been safer in terms of collision avoidance. This over-constraining effect is evident in its collision rate (23.25% static, 23.50% dynamic)—among the highest of all methods—as the robot is forced into tighter base placements near furniture and obstacles. Planning failures remain significant (17.25% static, 22.25% dynamic), as the fixed base pose may not provide feasible arm trajectories once the full scene geometry is revealed. These results highlight a fundamental limitation of the sequential paradigm: even with manipulation-aware positioning, decoupling navigation and manipulation prevents the system from jointly optimizing for both reachability and safety.

b) Closed-Loop Replanning: This system design integrates navigation and manipulation into a single planning loop, similar to our approach, but forgoes structured task management. The system continuously replans whole-body motions toward the sampled pre-grasp configuration until the robot reaches it, then initiates the grasping phase. Unlike our behavior tree architecture, which provides distinct observation, navigation, and manipulation stages with explicit state transitions, this design relies solely on continuous replanning to handle environmental changes without high-level task coordination.

This design achieves 61.25% and 56.75% success rates in the unknown static and dynamic environments, respectively (Figure 13). While substantially better than the sequential designs, it still falls short of our full system (68.75% and 58.00%). Without the structured state transitions of a behavior tree, continuous replanning can oscillate between configura-

TABLE II

SIMULATION EVALUATION RESULTS. SUCCESS RATES AND FAILURE BREAKDOWN (EXECUTION: COLLISION/GRASP/IK; SYSTEM LIMITATIONS: REACHABILITY/PERCEPTION; PLANNING) FOR ALL METHODS ACROSS TWO SIMULATION SCENARIOS. ALL VALUES ARE PERCENTAGES (%).

Method	Success	Execution			System Limitations		Planning
		Collision	Grasp	IK	Reachability	Perception	
Unknown Environment (Simulation)							
Navigation-and-manipulation	46.00	17.50	15.75	0.00	0.00	0.25	20.50
CapMap Placement	44.25	23.25	14.50	0.00	0.25	0.50	17.25
Direct Grasping	28.25	3.25	4.00	8.75	1.75	0.75	53.25
Closed-Loop Replanning	61.25	6.75	15.25	0.75	0.50	0.25	15.25
Velocity-agnostic	63.75	8.00	15.50	0.25	2.50	0.25	9.75
Ours (Full System)	68.75	6.25	13.25	0.50	2.25	0.25	8.75
Dynamic Environment (Simulation)							
Navigation-and-manipulation	40.00	24.75	14.25	0.00	0.00	1.50	19.50
CapMap Placement	40.00	23.50	13.00	0.00	0.00	1.25	22.25
Direct Grasping	25.75	1.50	2.00	5.75	1.00	0.75	63.25
Closed-Loop Replanning	56.75	8.50	14.75	0.50	0.75	0.25	18.50
Velocity-agnostic	54.00	13.75	15.50	0.75	3.25	0.00	12.75
Ours (Full System)	58.00	9.75	16.00	0.00	2.25	0.00	14.00

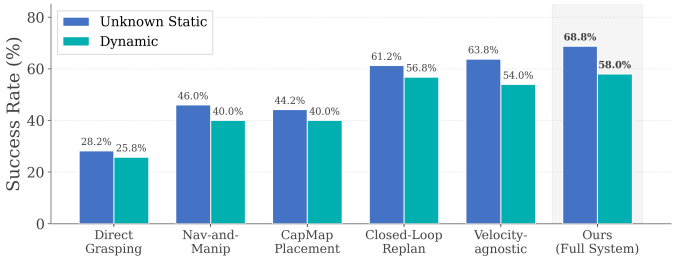

Fig. 13. **System-level comparison.** Success rates for all six methods across unknown static and dynamic environments. The CapMap Placement design suffers from high collision rates due to its sequential architecture, while the Closed-Loop Replanning design improves over sequential designs but lacks the structured task management of our behavior tree.

tions without converging, leading to higher planning failures (15.25% static, 18.50% dynamic). Collision rates (6.75% static, 8.50% dynamic) are comparable to our system, confirming that the integrated approach to navigation and manipulation is inherently effective for collision avoidance. However, the absence of explicit observation and subgoal management stages limits the system's ability to gather sufficient environmental information before committing to a plan, reducing overall task success.

3) Additional Analysis:

a) Path Efficiency Analysis: We evaluate path efficiency using Success weighted by Path Length (SPL), which measures how efficiently the robot reaches the target relative to the optimal path length. SPL is defined as:

$$\text{SPL} = \frac{1}{N}\sum_{i=1}^{N} S_i \cdot \frac{l_i}{\max(p_i, l_i)} \tag{10}$$

where N is the number of episodes, $S_i \in \{0, 1\}$ is a binary success indicator, l_i is the shortest path distance from start to goal, and p_i is the actual path length taken by the robot. This metric rewards successful episodes while penalizing inefficient paths. A perfect score of 1.0 indicates all episodes succeeded via optimal paths.

To compute the optimal path length l_i, we build a 2D occupancy grid from the scene point cloud by projecting points within a height range of $[0.06, 1.5]$ m onto the XY plane at 0.05 m resolution. Obstacles are inflated by the robot's base radius (0.29 m) using a circular structuring element, so that paths on the grid are guaranteed to be collision-free for the robot footprint. We then run BFS on the 8-connected grid from the robot's initial position to the nearest reachable cell to each target object, yielding the shortest collision-free path in meters. We note that this 2D shortest path is an approximation of the true optimal whole-body path, as computing the optimal trajectory in the full configuration space is intractable; nevertheless, it provides a consistent and comparable baseline across all methods.

Figure 14 shows the SPL results for all methods. Our full system achieves the highest SPL in both environments (62.2% static, 48.0% dynamic), indicating that it not only succeeds more often but also follows more efficient paths. The Velocity-agnostic ablation (56.4% static, 47.0% dynamic) and Closed-Loop Replanning (54.7% static, 45.8% dynamic) achieve similar SPL, despite different success rates, suggesting that the closed-loop baseline takes longer paths when it does succeed. The sequential baselines (Nav-and-Manip: 42.6%/37.2%, CapMap Placement: 40.8%/36.5%) show moderate SPL, while Direct Grasping (25.7%/21.2%) has the lowest SPL due to both low success rate and the absence of navigation planning. Notably, the gap between our system and baselines is larger in SPL than in raw success rate, confirming that our integrated approach produces more direct, efficient trajectories.

b) Obstacle Distance Analysis: We analyze the system's reactive capability by measuring success rate as a function of obstacle appearance distance, i.e., the distance between the robot and a dynamic obstacle when it first appears. This characterizes the minimum reaction distance required for

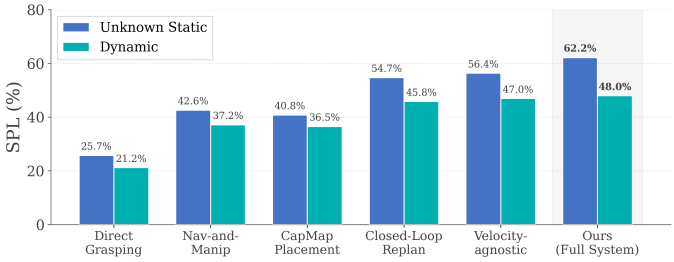

Fig. 14. **Path efficiency analysis (SPL).** Success weighted by Path Length for all methods. Higher SPL indicates both higher success rate and more efficient paths relative to the shortest collision-free path. Our system achieves the highest SPL across both environments.

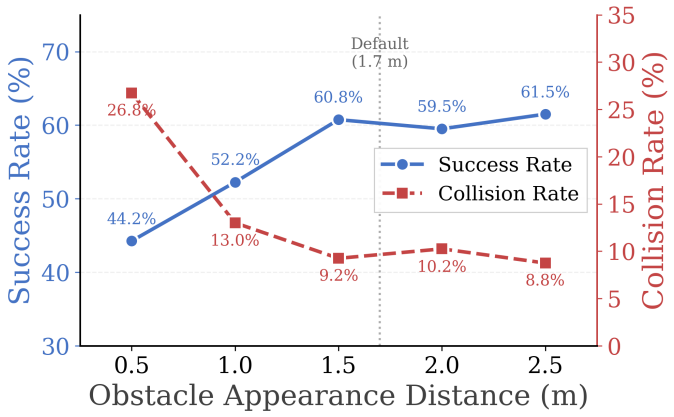

Fig. 15. **Obstacle distance analysis.** Success rate and collision rate as a function of obstacle appearance distance. The system requires at least 1.5 m of reaction distance to achieve near-optimal avoidance performance. Beyond this threshold, success rate plateaus as collision avoidance saturates and remaining failures are dominated by grasp and planning limitations.

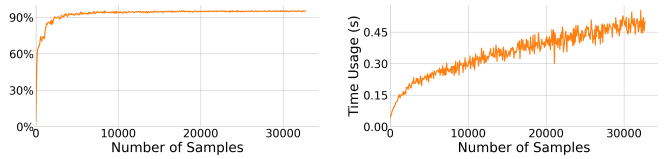

Fig. 16. **Sampling completeness analysis.** Empirical completeness of pre-grasp configuration sampling. **Left:** Success rate as a function of the number of samples, showing rapid convergence to approximately 95%. **Right:** Computational time scales approximately linearly with the number of samples.

successful obstacle avoidance. We evaluate trigger distances from 0.5 m to 2.5 m rather than starting from zero because the dynamic obstacles in our benchmark are manually positioned along likely robot paths, with each placement verified to leave at least one alternative route to the target (Section J). Since the motion planner is stochastic, at very short trigger distances the robot's planned path may not pass through the trigger zone at all, causing the obstacle to never appear and reducing the experiment to the static setting. Starting at 0.5 m ensures the obstacle reliably triggers across the majority of trials.

Figure 15 shows the results across five trigger distances (0.5–2.5 m). Success rate increases sharply from 44.2% at 0.5 m to 60.8% at 1.5 m, then plateaus at approximately 60–61% for distances beyond 1.5 m. The primary driver of this trend is collision rate, which drops from 26.8% at 0.5 m to 9.2% at 1.5 m as the robot gains sufficient reaction time and distance to replan around suddenly appearing obstacles. At trigger distances below 1.0 m, the robot often cannot decelerate or replan quickly enough to avoid the obstacle, as the perception–planning–execution loop requires a minimum reaction distance to execute corrective maneuvers. Beyond 1.5 m, collision rates stabilize at 8.8–10.2%, suggesting the system achieves near-optimal reactive avoidance at this range. Grasp and planning failure rates remain relatively stable across all distances (9.5–13.8% and 12.0–18.0%, respectively), confirming that these failure modes are independent of obstacle appearance timing and instead reflect inherent task difficulty. The default trigger distance of 1.7 m used in our dynamic environment experiments (Section J) lies within the plateau region, confirming it provides sufficient reaction margin.

To verify that the conclusions hold under continuously moving obstacles rather than the suddenly-appearing obstacles used by default, we re-ran the same 400 dynamic scenarios with the obstacles moving across the robot's planned path at 0.2 m/s. Our full system achieves a success rate of 54.4%, slightly lower than the sudden-appearance setting (58.0%). The small difference is consistent with our system being purely reactive: a moving obstacle entering the camera's field of view via closed-loop detection is algorithmically equivalent to a suddenly appearing one from the planner's perspective. The slight degradation arises from the moving obstacle additionally invalidating recently observed free space along its trajectory, which is not the case in the sudden-appearance setting.

c) Sampling Completeness Analysis: We analyze the empirical completeness of the proposed pre-grasp configuration sampling procedure (Section C) by examining how the success rate and computational time scale with the number of samples. As shown in Figure 16, the success rate increases rapidly with the number of samples and converges to approximately 95% at around 2,000 samples, after which additional samples yield diminishing returns. Note that the success rate plateaus below 100% because a fraction of target configurations are inherently infeasible due to kinematic reachability limits, rather than due to insufficient sampling. This confirms that the sampler efficiently covers the feasible configuration space with a moderate number of samples. Meanwhile, the computational time grows approximately linearly with the number of samples. In practice, we use 2,560 samples (20 base poses $\times$ 128 arm/torso configurations), which achieves near-convergence success rates while maintaining real-time computational performance.

d) Computational Cost Breakdown: We profile the runtime of each module to characterize the real-time feasibility of the full pipeline. Each control cycle comprises three components that run on every iteration: map update via ray casting (69 ms on average), gaze optimization (26 ms), and collision checking against the current trajectory (3 ms), totaling approximately 100 ms. When motion replanning is triggered (e.g., by a

path collision or subgoal change), the cycle extends to roughly 150 ms. Pre-grasp subgoal sampling and grasp detection are invoked only at phase transitions and not on every cycle: subgoal sampling takes 369 ms on average and is invoked roughly 3.6 times per task, while grasp detection (Contact-GraspNet [38]) takes 1.2 s and is invoked roughly 1.3 times per task. The velocity-aware gaze policy itself contributes only 26 ms per cycle on top of the volume-based variant; all other modules are shared between our system and the baselines, so this overhead is the primary computational difference between our system and the velocity-agnostic ablation.