# Multi-skill Mobile Manipulation for Object Rearrangement

**Anonymous Author(s)**
Affiliation
Address
email

## Abstract

We study a modular approach to tackle long-horizon mobile manipulation tasks for object rearrangement, which decomposes a full task into a sequence of subtasks. To tackle the entire task, prior work chains multiple stationary manipulation skills with a point-goal navigation skill, which are learned individually on subtasks. Although more effective than monolithic end-to-end RL policies, this framework suffers from compounding errors in skill chaining, *e.g.*, navigating to a bad location where a stationary manipulation skill can not reach its target to manipulate. To this end, we propose that the manipulation skills should include mobility to have flexibility in interacting with the target object from multiple locations and at the same time the navigation skill could have multiple end points which lead to successful manipulation. We operationalize these ideas by implementing mobile manipulation skills rather than stationary ones and training a navigation skill trained with region goal instead of point goal. We evaluate our multi-skill mobile manipulation method **M3** on 3 challenging long-horizon mobile manipulation tasks in the Home Assistant Benchmark (HAB), and show superior performance as compared to the baselines.

## 1 Introduction

Building AI with embodiment is an important future mission of AI. Object rearrangement [2] is considered as a canonical task for embodied AI. The most challenging rearrangement tasks [1, 3, 4] are often long-horizon mobile manipulation tasks, which demand both navigation and manipulation abilities, *e.g.*, to move to certain locations and to pick or place objects. It is challenging to learn a monolithic RL policy for complex long-horizon mobile manipulation tasks, due to challenges such as high sample complexity, complicated reward design, and inefficient exploration. A practical solution to tackle a long-horizon task is to decompose it into a set of subtasks, which are tractable, short-horizon, and compact in state or action spaces. Each subtask can be solved by designing or learning a skill, so that a sequence of skills can be chained to complete the entire task [5–8]. For example, skills for object rearrangement can be picking or placing objects, opening or closing fridges and drawers, moving chairs, navigating in the room, *etc*.

Achieving successful object rearrangement using this modular framework requires careful subtask formulation such that skills trained for these subtasks can be chained together effectively. We define three desirable properties for skills to solve diverse long-horizon tasks: **achievability, composability, and reusability**. Note that we assume each subtask is associated with a set of initial states. Then, *achievability* quantifies the portion of initial states solvable by a skill. A pair of skills are *composable* if the initial states achievable by the succeeding skill can encompass the terminal states of the preceding

[1]Project website: https://sites.google.com/view/hab-mobile-manipulation

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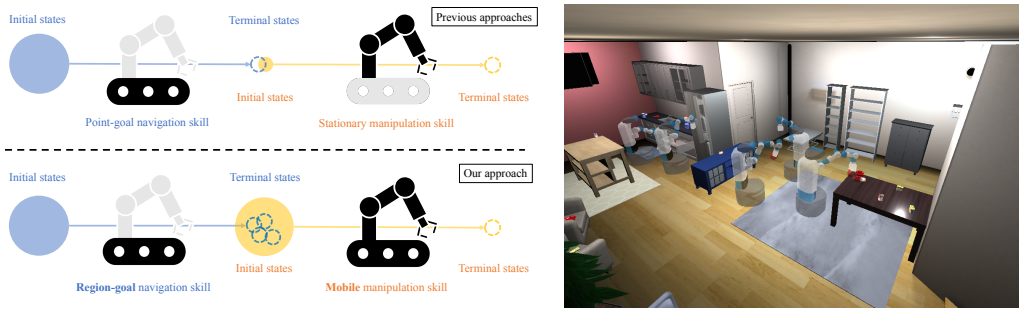



(a) Method Overview (b) The Home Assistant Benchmark

Figure 1: 1a provides an overview of our multi-skill mobile manipulation (**M3**) method. The inactive part of the robot is colored gray. Previous approaches exclusively activate either the mobile platform or manipulator for each skill, and suffer from compounding errors in skill chaining given limited composability of skills. We introduce mobility to manipulation skills, which effectively enlarges the feasible initial set, and a region-goal navigation reward to facilitate learning the navigation skill. 1b illustrates one task (*SetTable*) in the Home Assistant Benchmark [1], where the robot needs to navigate in the room, open the drawers or fridge, pick multiple objects in drawers or fridge and place them on the table. Best viewed in motion at the project website[1].

skill. This encompassment requirement is necessary to ensure robustness to mild compounding errors. However, trivially enlarging the initial set of a subtask increases learning difficulty and may lead to many unachievable initial states for the designed/learned skill. Last, a skill is *reusable* if it can be directly chained without or with limited fine-tuning [6, 8]. According to our experiments, effective subtask formulation is critical though largely overlooked in the literature.

In the context of mobile manipulation, skill chaining poses many challenges for subtask formulation. For example, an imperfect navigation skill might terminate at a bad location where the target object is out of reach for a stationary manipulation skill [1]. To tackle such "hand-off" problems, we investigate how to formulate subtasks for mobile manipulation. First, we replace stationary (fixed-base) manipulation skills with mobile counterparts, which allow the base to move when the manipulation is undertaken. We observe that mobile manipulation skills are more robust to compounding errors in skill chaining, and enable the robot to make full use of its embodiment to better accomplish subtasks, *e.g.*, finding a better location with less clutter and fewer obstacles to pick an object. We emphasize how to generate initial states of manipulation skills as a trade-off between *composability* and *achievability* in Sec 4.1. Second, we study how to translate the start of manipulation skills to the navigation reward, which is used to train the navigation skill to connect manipulation skills. Note that the goal position in mobile manipulation plays a very different role from that in point-goal [9, 10] navigation. On the one hand, the position of a target object (*e.g.*, on the table or in the fridge) is often not directly navigable; on the other hand, a navigable position close to the goal position can be infeasible due to kinematic and collision constraints. Besides, there exist multiple feasible starting positions for manipulation skills, yet previous works such as [1] train the navigation skill to learn a single one, which is selected heuristically and may not be suitable for stationary manipulation. Thanks to the flexibility of our mobile manipulation skills, we devise a region-goal navigation reward to handle those issues, detailed in Sec 4.2.

In this work, we present our improved multi-skill mobile manipulation method **M3**, where mobile manipulation skills are chained by the navigation skill trained with our region-goal navigation reward. It achieves an average success rate of 63% on 3 long-horizon mobile manipulation tasks in the Home Assistant Benchmark [1], as compared to 50% for our best baseline. Fig 1 provides an overview of our method and tasks. Our contributions are listed as follows:

1. We study how to formulate mobile manipulation skills, and empirically show that they are more robust to compounding errors in skill chaining than stationary counterparts;

2. We devise a region-goal navigation reward for mobile manipulation, which shows better performance and stronger generalizability than the point-goal counterpart in previous works;

3. We show that our improved multi-skill mobile manipulation pipeline can achieve superior performance on long-horizon mobile manipulation tasks without bells and whistles, which can serve as a strong baseline for future study.

# 2 Related Work

## 2.1 Mobile Manipulation

Rearrangement [2] is "to bring a given physical environment into a specified state". We refer readers to [2] for a comprehensive survey. Many existing RL tasks can be considered as instances of rearrangement, *e.g.*, picking and placing rigid objects [11, 12] or manipulating articulated objects [13, 14]. However, they mainly focus on stationary manipulation [11–13] or individual, short-horizon skills [14]. Recently, several benchmarks like Home Assistant Benchmark (HAB) [1], ManipulaTHOR [3] and ThreeDWorld Transport Challenge [4], are proposed to study long-horizon mobile manipulation tasks. They usually demand that the robot rearranges household objects in a room, requiring exploration and navigation [15, 16] between interacting with objects entirely based on onboard sensing, without any privileged state or map information.

Mobile manipulation [17] refers to "robotic tasks that require a synergistic combination of navigation and interaction with the environment". It has been studied long in the robotics community. [18] provides a summary of traditional methods, which usually require perfect knowledge of the environment. One example is task-and-motion-planning (TAMP) [19–21]. TAMP relies on well-designed state proposals (grasp poses, robot positions, *etc*.) to sample feasible trajectories, which is computationally inefficient and unscalable for complicated scenarios.

Learning-based approaches enable the robot to act according to visual observations. [22] proposes a hierarchical method for mobile manipulation in iGibson [23], which predicts either a high-level base or arm action by RL policies and executes plans generated by motion-planning to achieve the action. However, the arm action space is specially designed for a primitive action *pushing*. [24] develops a real-world RL framework to collect trash on the floor, with separate navigation and grasping policies. [3, 18] train an end-to-end RL policy to tackle mobile pick-and-place in ManipulaTHOR [3]. However, the reward function used to train such an end-to-end policy usually demands careful tuning. For example, [18] shows that a minor modification (a penalty for disturbance avoidance) can lead to a considerable performance drop. The vulnerability of end-to-end RL approaches restricts scalability. Most prior works in both RL and robotics separate mobile the platform and manipulator, to "reduce the difficulty to solve the inverse kinematics problem of a kinematically redundant system" [25, 26]. [27] trains an end-to-end RL policy based on the object pose and proprioception to simultaneously control the base and arm. It focuses on picking a single object up in simple scenes, while our work addresses long-horizon rearrangement tasks that require multiple skills.

[1] adopts a different hierarchical approach for mobile manipulation in the HAB [1]. It uses task-planning [28] to generate high-level symbolic goals, and individual skills are trained by RL to accomplish those goals. It outperforms the monolithic end-to-end RL policy and the classical sense-plan-act robotic pipeline. It is scalable since skills can be composited to solve different tasks, and benefit from progress in individual skill learning [12, 14]. Moreover, different from other benchmarks, the HAB features continuous motor control (base and arm), interaction with articulated objects (opening drawers and fridges), and complicated scene layouts. Thus, we choose the HAB as the platform to study long-horizon mobile manipulation.

## 2.2 Skill Chaining for Long-horizon Tasks

[1] observes that sequentially chaining multiple skills suffers from "hand-off" problems, where a preceding skill terminates at a state that the succeeding skill has either never seen during training or is infeasible to solve. [5] proposes to learn a transition policy to connect primitive skills, but assumes that such a policy can be found through random exploration. [8] regularizes the terminal state distribution of a skill to be close to the initial set of the following skill, through a reward learned with adversarial training. Most prior skill chaining methods focus on fine-tuning learned skills. In this work, we instead focus on subtask formulation for skill chaining, which directly improves composability and reusability without additional computation.

# 3 Preliminary

## 3.1 Home Assistant Benchmark (HAB)

The Home Assistant Benchmark (HAB) [1] includes 3 long-horizon mobile manipulation rearrangement tasks (*TidyHouse, PrepareGroceries, SetTable*) based on the ReplicaCAD dataset, which contains a rich set of 105 indoor scene layouts. For each episode (instance of task), rigid objects from the YCB [29] dataset are randomly placed on annotated supporting surfaces of receptacles, to generate clutter in a randomly selected scene. Here we provide a brief description of these tasks.

**TidyHouse**: Move 5 objects from starting positions to goal positions. Objects and goals are located in open receptacles (*e.g.*, table, kitchen counter) rather than containers. Complex scene layouts, diverse receptacles, dense clutter all pose challenges. The task implicitly favors collision-free behavior since a latter target object might be knocked out of reach when a former object is moved by the robot.
**PrepareGroceries**: Move 2 objects from the fridge to the counters and move an object from the counter to the fridge. The fridge is fully open initially. The task requires picking and placing an object in a cluttered receptacle with restricted space.
**SetTable**: Move a bowl from a drawer to a table, and move a fruit from the fridge to the bowl on the table. Both the drawer and fridge are closed initially. The task requires interaction with articulated objects as well as picking objects from containers.

All the tasks use the GeometricGoal [2] specification $(s_0, s_*)$, which describes the initial 3D (center-of-mass) position $s_0$ of the target object and the goal position $s_*$. For example, *TidyHouse* is specified by 5 tuples $\{(s_0^i, s_*^i)\}_{i=1...5}$.

## 3.2 Subtask and Skill

In this section, we present the definition of subtask and skill in the context of reinforcement learning. A long-horizon task can be formulated as a Markov decision process (MDP) [1] defined by a tuple $(\mathcal{S}, \mathcal{A}, R, P, \mathcal{I})$ of state space $\mathcal{S}$, action space $\mathcal{A}$, reward function $R(s, a, s')$, transition distribution $P(s'|s, a)$, initial state distribution $\mathcal{I}$. A subtask $\omega$ is a smaller MDP $(\mathcal{S}, \mathcal{A}_\omega, R_\omega, P, \mathcal{I}_\omega)$ derived from the original MDP of the full task. A skill (or policy), which maps a state $s \in \mathcal{S}$ to an action $a \in \mathcal{A}$, is learned for each subtask by RL algorithms.

[1] introduces several parameterized skills for the HAB: *Pick, Place, Open fridge, Close fridge, Open drawer, Close drawer, Navigate*. Each skill takes a single 3D position as input, either $s_0$ or $s_*$. See Appendix C for more details. Here, we provide a brief description of these skills.

**Pick**($s_0$): pick the object initialized at $s_0$
**Place**($s_*$): place the held object at $s_*$
**Open [container]**($s$): open the container containing the object initialized at $s$ or the goal position $s$
**Close [container]**($s$): close the container containing the object initialized at $s$ or the goal position $s$
**Navigate**($s$): navigate to the start of other skills specified by $s$

Note that $s_0$ is constant per episode instead of a tracked object position. Hence, the target object may not be located at $s_0$ at the beginning of a skill, *e.g.*, picking an object from an opened drawer. Next, we will illustrate how these skills are chained in the HAB.

## 3.3 Skill Chaining

Given a task decomposition, a hierarchical approach also needs to generate high-level actions to select a subtask and perform the corresponding skill. Task planning [28] can be applied to find a sequence of subtasks before execution, with perfect knowledge of the environment. An alternative is to learn high-level actions through hierarchical RL. In this work, we use the subtask sequences generated by a perfect task planner [1]. Here we list these sequences, to highlight the difficulty of tasks [2].

**TidyHouse**$(s_0^i, s_*^i)$: Navigate$(s_0^i) \rightarrow$ Pick$(s_0^i) \rightarrow$ Navigate$(s_*^i) \rightarrow$ Place$(s_*^i)$
**PrepareGroceries**$(s_0^1, s_*^1, s_0^2, s_*^2, s_0^3, s_*^3)$: Navigate$_{\text{fr}}(s_0^1) \rightarrow$ Pick$_{\text{fr}}(s_0^1) \rightarrow$ Navigate$(s_*^1) \rightarrow$

[1] To be precise, the tasks studied in this work are partially observable Markov decision process (POMDP).

[2] We only list the subtask sequence of *TidyHouse* for one object here for illustration. The containers are denoted with subscripts $fr$ (fridge) and $dr$ (drawer) if included in the skill.

Place($s_*^1$) $\rightarrow$ Navigate$_{\text{fr}}$($s_0^2$) $\rightarrow$ Pick$_{\text{fr}}$($s_0^2$) $\rightarrow$ Navigate($s_*^2$) $\rightarrow$ Place($s_*^2$) $\rightarrow$ Navigate($s_0^3$) $\rightarrow$ Pick($s_0^3$) $\rightarrow$ Navigate$_{\text{fr}}$($s_*^3$) $\rightarrow$ Place$_{\text{fr}}$($s_*^3$)

**SetTable**($s_0^1, s_*^1, s_0^2, s_*^2$): Navigate$_{\text{dr}}$($s_0^1$) $\rightarrow$ Open$_{\text{dr}}$($s_0^1$) $\rightarrow$ Pick$_{\text{dr}}$($s_0^1$) $\rightarrow$ Navigate($s_*^1$) $\rightarrow$ Place($s_*^1$) $\rightarrow$ Navigate$_{\text{dr}}$($s_0^1$) $\rightarrow$ Close$_{\text{dr}}$($s_0^1$) $\rightarrow$ Navigate$_{\text{fr}}$($s_0^2$) $\rightarrow$ Open$_{\text{fr}}$($s_0^2$) $\rightarrow$ Navigate$_{\text{fr}}$($s_0^2$) $\rightarrow$ Pick$_{\text{fr}}$($s_0^2$) $\rightarrow$ Navigate($s_*^2$) $\rightarrow$ Place($s_*^2$) $\rightarrow$ Navigate$_{\text{fr}}$($s_0^2$) $\rightarrow$ Close$_{\text{fr}}$($s_0^2$)

# 4 Subtask Formulation and Skill Learning for Mobile Manipulation

Following the proposed principles (*composability*, *achievability*, *reusability*), we revisit and reformulate subtasks defined in the Home Assistant Benchmark (HAB) [1]. The core idea is to enlarge the initial states of manipulation skills to encompass the terminal states of the navigation skill, given our observation that the navigation skill is usually more robust to initial states. However, manipulation skills (*Pick*, *Place*, *Open drawer*, *Close drawer*) in [1], are stationary. The *composability* of a stationary manipulation skill is restricted, since its feasible initial states are limited due to kinematic constraints. For instance, the robot can not open the drawer if it is too close or too far from the drawer. Therefore, these initial states need to be carefully designed given the trade-off between *composability* and *achievability*, which is not scalable and flexible. On the other hand, the navigation skill, which is learned to navigate to the start of manipulation skills, is also restricted by stationary constraints, since it is required to precisely terminate at a small set of "good" locations for manipulation. To this end, we propose to replace stationary manipulation skills with mobile counterparts. Thanks to mobility, mobile manipulation skills can have better *composability* without sacrificing much *achievability*. For example, a mobile manipulator can learn to first get closer to the target and then manipulate, to compensate for errors from navigation. It indicates that the initial states can be designed in a more flexible way, which also enables us to design a better navigation reward to facilitate learning.

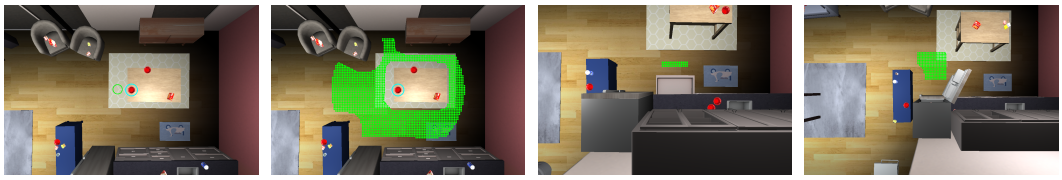
In the context of mobile manipulation, the initial state of a skill consists of the robot base position, base orientation, and joint positions. For simplicity, we do not discuss the initial states of rigid and articulated objects in the scene, which are usually defined in episode generation. Moreover, we follow previous works [1, 8] to initialize the arm at its resting position and reset it after each skill in skill chaining. Such a reset operation is common in robotics [21]. Each skill is learned to reset the arm after accomplishing the subtask as in [1]. Furthermore, for base orientation, we follow the heuristic in [1] to make the robot face the target position $s_0$ or $s_*$.

## 4.1 Manipulation Skills with Mobility

We first present how initial base positions are generated in previous works. For stationary manipulation, a feasible base position needs to satisfy several constraints, *e.g.*, kinematic (the target is reachable) and collision-free constraints. [1] uses heuristics to determine base positions. For *Pick, Place* without containers (fridge and drawer), a navigable position closest to the target position is selected. For *Pick, Place* with containers, a fixed position relative to the container is selected. For *Open, Close*, a navigable position is randomly selected from a handcrafted region relative to each container. Noise is added to base position and orientation in addition, and infeasible initial states are rejected by constraints. See Fig 2 for examples.

The above example indicates the difficulty and complexity to design feasible initial states for stationary manipulation. One naive solution is to enlarge the initial set with infeasible states, but this can hurt learning as shown later in Sec 5.4. Besides, rejection sampling can be quite inefficient in this case, and [1] actually computes a fixed number of feasible initial states offline.

**Manipulation Skills with Mobility.** To this end, we propose to use mobile manipulation skills instead. The original action space (only arm actions) is augmented with base actions. We devise a unified and efficient pipeline to generate initial base positions. Concretely, we first discretize the floor map with a resolution of $5 \times 5cm^2$, and get all navigable (grid) positions. Then, different candidates are computed from these positions based on subtasks. Candidates are either within a radius (*e.g.*, 2m) around the target position for *Pick, Place*, or a region relative to the container for *Open, Close*. Finally, a feasible position is sampled from the candidates with rejection and noise. Compared to stationary manipulation, the rejection rate of our pipeline is much lower, and thus can be efficiently employed on-the-fly during training. See Fig 2 for examples.



(a) Pick(stationary) (b) Pick(mobile) (c) Close drawer (d) Close fridge

Figure 2: Initial base positions of manipulation skills. We only show the examples for *Pick, Close drawer, Close fridge*, as *Place, Open drawer, Open fridge* share the same initial base positions respectively. Positions are visualized as green points on the floor. The target object in *Pick* is highlighted by a circle in cyan. Note that the initial base position of *Pick(stationary)* is a single navigable position closest to the object.

### 4.2 Navigation Skill with Region-Goal Navigation Reward

The navigation skill is learned to connect different manipulation skills. Hence, it needs to terminate within the set of initial achievable states of manipulation skills. We follow [1] to randomly sample a navigable base position and orientation as the initial state of navigation skill. The challenge is how to formulate the reward function, which implicitly defines desirable terminal states. A common navigation reward [9] is the negative change of geodesic distance to a single 2D goal position on the floor. [1] extends it for mobile manipulation, which introduces the negative change of angular distance to the desired orientation (facing the target). The resulting reward function, $r_t(s, a)$, for state $s$ and action $a$ is the following (Eq 1):

$$r_t(s,a) = -\Delta_{geo}(g) - \lambda_{ang}\Delta_{ang} I_{[d_t^{geo}(g) \leq \tilde{D}]} + \lambda_{succ} I_{[d_t^{geo}(g) \leq D \wedge d_t^{ang} \leq \Theta]} - r_{slack} \quad (1)$$

$\Delta_{geo}(g) = d_t^{geo}(x_t^{base}, g) - d_{t-1}^{geo}(x_{t-1}^{base}, g)$, where $d_t^{geo}(x_t^{base}, g)$ is the geodesic distance between the current base position $x_t^{base}$ and the 2D goal position $g$. $d_t^{geo}(g)$ is short for $d_t^{geo}(x_t^{base}, g)$. $\Delta_{ang} = d_t^{ang} - d_{t-1}^{ang} = \|\theta_t - \theta^*\|_1 - \|\theta_{t-1} - \theta^*\|_1$, where $\theta_t$ is the current base orientation, and $\theta^*$ is the target orientation. Note that the 2D goal on the floor is different from the 3D goal specification for manipulation subtasks. $I_{[d_t^{geo} \leq \tilde{D}]}$ is an indicator of whether the agent is close enough to the 2D goal, where $\tilde{D}$ is a threshold. $I_{[d_t^{geo} \leq D \wedge d_t^{ang} \leq \Theta]}$ is an indicator of navigation success, where $D$ and $\Theta$ are thresholds for geodesic and angular distances. $r_{slack}$ is a slack penalty. $\lambda_{ang}, \lambda_{succ}$ are hyper-parameters.

This reward has several drawbacks: 1) A single 2D goal needs to be assigned, which should be an initial base position of manipulation skills. It is usually sampled with rejection, as explained in Sec 4.1. It ignores the existence of multiple reasonable goals, introduces ambiguity to the reward (hindering training), and leads the skill to memorize (hurting generalization). 2) There is a hyperparameter $\tilde{D}$, which defines the region where the angular term $\Delta_{ang}$ is considered. However, it can lead the agent to learn the undesirable behavior of entering the region with a large angular distance, *e.g.*, backing onto the target.

**Region-Goal Navigation Reward.** To this end, we propose a region-goal navigation reward for training the navigation skill. Inspired by object-goal navigation [30], we use the geodesic distance [3] between the robot and a region of 2D goals on the floor instead of a single goal. Thanks to the flexibility of our mobile manipulation skills, we can simply reuse the candidates (Sec 4.1) for their initial base positions as the navigation goals. However, these candidates are not all collision-free. Thus, we add a collision penalty $r_{col} = \lambda_{col} C_t$ to the reward, where $C_t$ is the current collision force and $\lambda_{col}$ is a weight. Besides, we simply remove the angular term, and find that the success reward is sufficient to encourage correct orientation. Our region-goal navigation reward is the following (Eq 2):

$$r_t(s,a) = -\Delta_{geo}(\{g\}) + \lambda_{succ} I_{[d_t^{geo}(\{g\}) \leq D \wedge d_t^{ang} \leq \Theta]} - r_{col} - r_{slack} \quad (2)$$

[3] The geodesic distance to a region can be approximated by the minimum of all the geodesic distances to grid positions within the region.

# 5 Experiments

## 5.1 Experimental Setup

We use the ReplicaCAD dataset [1] and the Habitat 2.0 simulator [1] for our experiments. The ReplicaCAD dataset contains 5 macro variations, with 21 micro variations per macro variation [4]. We hold out 1 macro variation to evaluate the generalization of unseen layouts. For the rest of the 4 macro variations, we split 84 scenes into 64 scenes for training and 20 scenes to evaluate the generalization of unseen configurations (object and goal positions). For each task, we generate 6400 episodes (64 scenes) for training, 100 episodes (20 scenes) to evaluate cross-configuration generalization, and another 100 episodes (the hold-out macro variation) to evaluate cross-layout generalization. The robot is a Fetch [31] mobile manipulator with a 7-DoF arm and a parallel-jaw gripper.

**Observation space:** The observation space includes head and arm depth images ($128 \times 128$), arm joint positions (7-dim), end-effector position (3-dim) in the base frame, goal positions (3-dim) in both base and end-effector frames, as well as a scalar to indicate whether an object is held. The goal position, depending on subtasks, can be either the initial or desired position of the target object. We assume a perfect GPS+Compass sensor and proprioceptive sensors as in [1], which are used to compute the relative goal positions. For the navigation skill, only the head depth image and the goal position in the base frame are used.

**Action space:** The action space is a 10-dim continuous space, including 2-dim base action (linear forwarding and angular velocities), 7-dim arm action, and 1-dim gripper action. Grasping is abstract as in [1–3]. If the gripper action is positive, the object closest to the end-effector within 15cm will be snapped to the gripper; if negative, the gripper will release any object held. For the navigation skill, we use a discrete action space, including a stop action, as in [1, 32]. A discrete action will be converted to continuous velocities to move the robot, while arm and gripper actions are masked out.

**Hyper-parameters:** We train each skill by the PPO [33] algorithm. The visual observations are encoded by a 3-layer CNN as in [1]. The visual features are concatenated with state observations and previous action, followed by a 1-layer GRU and linear layers to output action and value. We use 64 parallel environments and train each skill for 100M steps with 16 CPU cores and 1 2080Ti GPU. Each skill is trained with 3 different seeds. See Appendix C.1 for more details.

**Metrics:** Each HAB task consists of a sequence of subtasks to accomplish, as illustrated in Sec 3.3. The completion of a subtask is conditioned on the completion of its preceding subtask. We report progressive completion rates of subtasks, and the completion rate of the last subtask is thus the success rate of the full task. For each evaluation episode, the robot is initialized at a random base position and orientation without collision, and its arm is initialized at the resting position. The completion rate is averaged over 9 different runs (3 seeds for RL training multiplied by 3 seeds for initial states).

## 5.2 Baselines

We denote our method by **M3**, short for a multi-skill mobile manipulation pipeline where mobile manipulation skills (**M**) are chained by the navigation skill trained with our region-goal navigation reward (**R**). We compare our method with several RL baselines. All baselines follow the same experimental setup in Sec 5.1 unless specified. We refer readers to [1] for a task-and-motion-planning (TAMP) baseline, which is shown to be inferior to the skill chaining pipeline emphasized in this work. Stationary manipulation skills and point-goal navigation reward are denoted by **S** and **P**.

**Monolithic RL (mono)**: This baseline is an end-to-end RL policy trained with a combination of reward functions of individual skills. See Appendix D for more details.

**Stationary manipulation skills + point-goal navigation reward (S+P)**: This baseline is TaskPlanning+SkillsRL (TP+SRL) introduced in [1], where stationary manipulation skills are chained by the navigation skill trained with the point-goal navigation reward. Compared to the original implementation, we make several improvements, including better reward functions and training schemes. For reference, the original success rates of all HAB tasks are nearly zero. See Appendix A for more details.

**Mobile manipulation skills + point-goal navigation reward (M+P)**: Compared to our **M3**, this

[4] Each macro variation has a different, semantically plausible layout of large furniture (*e.g.*, kitchen counter and fridge) while each micro variation is generated through perturbing small furniture (*e.g.*, chairs and tables).

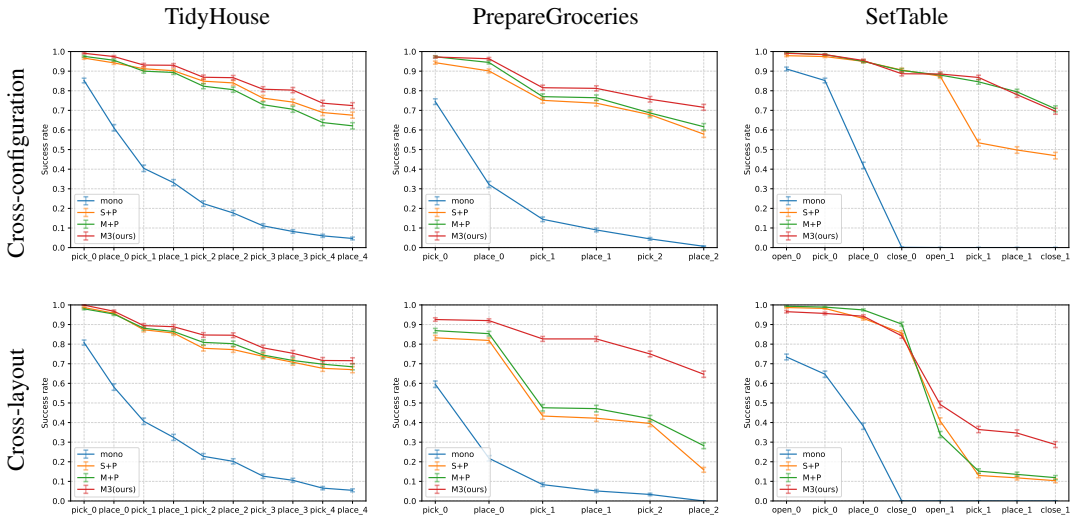



Figure 3: Progressive completion rates for HAB [1] tasks. The x-axis represents progressive subtasks. The y-axis represents the completion rate of each subtask. The mean and standard error for 100 episodes over 9 seeds are reported. Best viewed zoomed.

baseline does not use the region-goal navigation reward. It demonstrates the effectiveness of proposed mobile manipulation skills. Note that the point-goal navigation reward is designed for the start of stationary manipulation skills.

### 5.3 Results

Fig 3 shows the progressive completion rates of different methods on all tasks. Our method **M3** achieves an average success rate of 71.2% in the cross-configuration setting, and 55.0% in the cross-layout setting, over all 3 tasks. It outperforms all the baselines in both settings, namely **mono** (1.8%/1.8%), **S+P** (57.4%/31.1%) and **M+P** (64.9%/36.2%). First, all the modular approaches show much better performance than the monolithic baseline, which verifies the effectiveness of modular approaches for long-horizon mobile manipulation tasks. Mobile manipulation skills are in general superior to stationary ones (**M+P** *vs*.**S+P**). Fig 4 provides an example where mobile manipulation skills can compensate for imperfect navigation. Furthermore, our region-goal navigation reward can reduce the ambiguity of navigation goals to facilitate training (see training curves in Appendix C). Since it does not require the policy to memorize ambiguous goals, the induced skill shows better generalizability, especially in the cross-layout setting (55.0% for **M3** *vs*.36.2% for **M+P**).

### 5.4 Ablation Studies

We conduct several ablation studies to show that mobile manipulation skills are more flexible to formulate than stationary ones, and to understand the advantage of our navigation reward.

**Can initial states be trivially enlarged?** We conduct experiments to understand to what extent we can enlarge the initial states of manipulation skills given the trade-off between *achievability* and *composability*. In the **S(L)+P** experiment, we simply replace the initial states of stationary manipulation skills with those of mobile ones. The success rates of stationary manipulation skills on subtasks drop by a large margin, *e.g.*, from 95% to 45% for *Pick* on *TidyHouse*. Fig 5 shows that **S(L)+P** (37.7%/18.1%) is inferior to both **S+P** (57.4%/31.1%) and **M+P** (64.9%/36.2%). It indicates that stationary manipulation skills have a much smaller set of feasible initial states compared to mobile ones, and including infeasible initial states during training can hurt performance significantly. Besides, we also study the impact of initial state distribution on mobile manipulation skills in Appendix F.

**Is the collision penalty important for the navigation skill?** Our region-goal navigation reward benefits from unambiguous region goals and the collision penalty. We add the collision penalty to the point-goal navigation reward (Eq 1) in **S+P(C)** and **M+P(C)** experiments. Fig 5 shows that the collision penalty significantly improves the success rate: **S+P(C)** (65.2%/44.6%) *vs*.**S+P**

(a) Stationary Manipulation (S+P)

(b) Mobile Manipulation (M+P)

Figure 4: Qualitative comparison between stationary and mobile manipulation. In this example, the point-goal navigation skill terminates between two drawers (1st image). Mobile manipulation manages to open the correct drawer containing the bowl (last image in the bottom row) while stationary manipulation gets confused and finally opens the wrong drawer (last image in the top row).

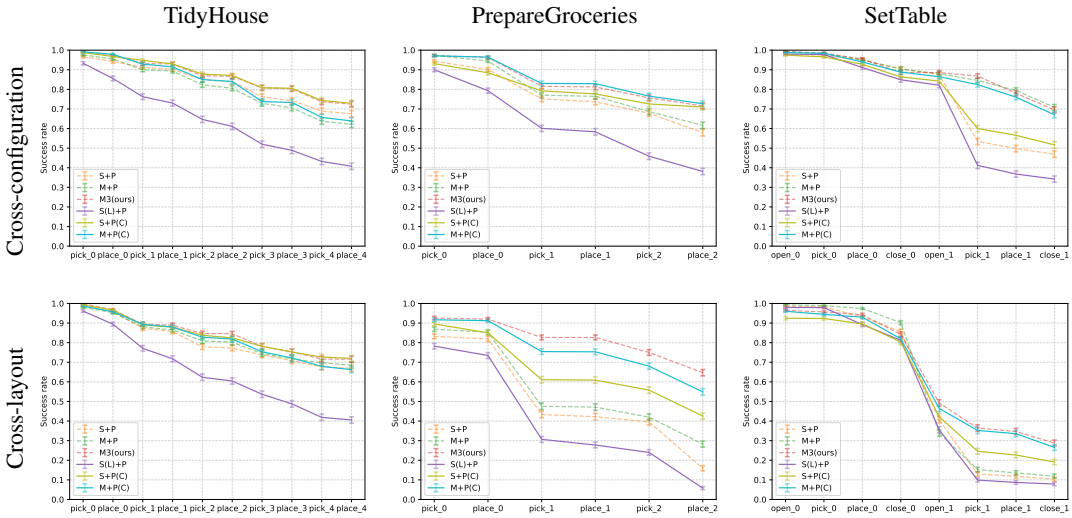



Figure 5: Progressive completion rates for HAB [1] tasks. The x-axis represents progressive subtasks. The y-axis represents the completion rate of each subtask. Results of ablation experiments are presented with solid lines. The mean and standard error for 100 episodes over 9 seeds are reported.

(57.4%/31.1%) and **M+P(C)** (67.9%/49.2%) *vs*.**M+P** (64.9%/36.2%). A collision-aware navigation skill can avoid disturbing the environment, *e.g.*, accidentally closing the fridge before placing an object in it. Besides, **M+P(C)** is still inferior to our **M3** (71.2%/55.0%). It implies that reducing the ambiguity of navigation goals helps learn more robust and generalizable navigation skills.

## 6 Conclusion and Limitations

In this work, we present a modular approach to tackle long-horizon mobile manipulation tasks in the Home Assistant Benchmark (HAB), featuring mobile manipulation skills and the region-goal navigation reward. Given the superior performance, our approach can serve as a strong baseline for future study. Besides, the proposed principles (*achievability, composability, reusability*) can serve as a guideline about how to formulate meaningful and reusable subtasks. However, our work is still limited to abstract grasp and other potential simulation defects. We leave fully dynamic simulation and real-world deployment to future work.

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