ReLMM: Practical RL for Learning Mobile Manipulation Skills Using Only Onboard Sensors

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Abstract: In this paper, we study how robots can autonomously learn skills that require a combination of navigation and grasping. Learning robotic skills in the real world remains challenging without large scale data collection and supervision. Our aim is to devise a robotic reinforcement learning system for learning navigation and manipulation together, in an *autonomous* way without human intervention, enabling continual learning under realistic assumptions. Specifically, our system, ReLMM, can learn continuously on a real-world platform without any environment instrumentation, without human intervention, and without access to privileged information, such as maps, objects positions, or a global view of the environment. Our method employs a modularized policy with components for manipulation and navigation, where uncertainty over the manipulation success drives exploration for the navigation controller, and the manipulation module provides rewards for navigation. We evaluate our method on a room cleanup task, where the robot must navigate to and pick up items of scattered on the floor. After a grasp curriculum training phase, ReLMM can learn navigation and grasping together fully automatically, in around 40 hours of real-world training.

Keywords: Mobile Manipulation, Reinforcement Learning, Reset-Free

1 Introduction

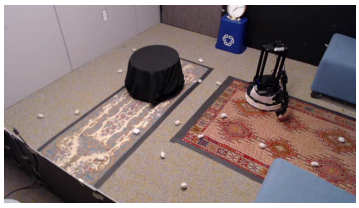

Figure 1: ReLMM enables learning mobile manipulation skills autonomously in the real world, using only on-board sensing.

Learning-based approaches have the potential to bring robots outside the lab setting, as vision-based policies enable agents to learn without external instrumentation, AR-tagging, or expensive sensors. In the mobile manipulation setting it is particularly important to reduce restrictions because, unlike stationary manipulation in a bin, the robot can explore a much wider range of different environments than is practical to instrument. In order to be deployed in a practical setting, a mobile robot must also handle the complexity of natural open-world environments that it itself is modifying as it operates, ideally continuing to learn throughout the process. In practice, however, most real-world reinforcement learning (RL) systems require careful environment instrumentation, large robot deployments, and/or human supervision or demonstrations during the training process to ensure that the robot performs effective exploration and resets between trials. These systems cannot simply be dropped into a natural environment to continue learning if they require controlled laboratory setting such as specially installed infrastructure that provides explicit resets [1, 2, 3, 4], or the presence of a person providing resets and monitoring the learning process [5, 6].

To address this issue and make it possible for mobile manipulators to learn with RL directly in the real world, we propose a system for learning mobile manipulation skills without instrumentation or demonstrations. We aim to produce a system that enables a robot to learn autonomously in settings

Submitted to the 5th Conference on Robot Learning (CoRL 2021). Do not distribute.

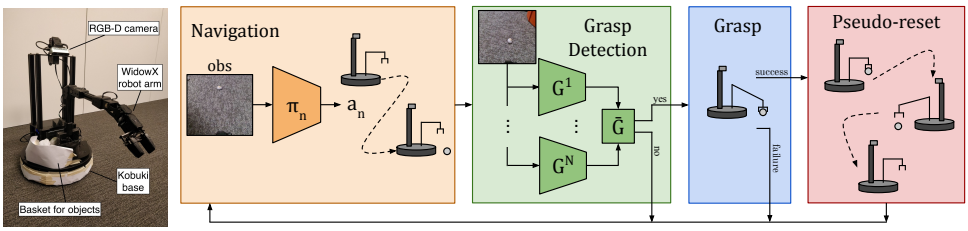

Figure 2: **Method overview.** ReLMM partitions the mobile manipulator into a navigation policy and grasping policy. Both policies are rewarded when an object is grasped. We use an ensemble of action-conditioned grasp success prediction functions estimate the success of a potential grasp better and use the uncertainty as an exploration bonus. If grasp succes is likely, a grasp action is sampled from the grasp predictors and executed. If the grasp is successful during training, the robot executes a pseudo-reset by placing the collected object back down in a random location.

such as homes and offices, such that anyone could simply place the robot down, start the learning process, and return to a trained robot. This goal dictates several constraints that shape our method: (1) the robot must learn entirely from its own sensors, both to select actions and to compute rewards; (2) the entire learning process must be efficient enough for real-world training; (3) the robot must be able to continually gathering data at scale without human effort.

Our contribution is a system for autonomously training a mobile manipulation robot that satisfies the above constraints, which we call Reinforcement Learning for Mobile Manipulation (ReLMM). We apply ReLMM to the task of picking up items scattered across a room. Our system learns directly from on-board ego-centric camera observations and uses proprioceptive grasp sensing to assign itself rewards. To ensure the learning process is sample efficient and to facilitate exploration, we split the robot's controller into separate navigation and grasping neural network policy modules that choose when to act based on their predicted value and are continuously trained together for the same objective: successfully grasping objects in the environment. Separating the policies enables the use of uncertainty-based exploration for the grasping module, which uses an ensemble of Q-functions to explore grasp actions efficiently. Lastly, to reduce the need for humans to provide interventions in the form of resets, we develop an autonomous resetting behavior where the robot re-arranges the environment as it learns, so as to continually create new arrangements of objects for the agent continually "practice." Together, these components plus a brief grasping curriculum enable a system that can operate in real-world environments, learning how to navigate and grasp from its own collected experience. We evaluate our system on difficult room cleaning tasks in simulation and in real-world environments that have not been solved before.

2 Related Work

Robotic mobile manipulation tasks pose a number of unique challenges [7]. Many prior methods have addressed these challenges by requiring human effort for instrumentation and state estimation [8, 9, 10, 11], hand-coded controllers [12], or demonstrations [10, 13, 14] Several methods also require external instrumentation in the form of top-down camera views, oracle knowledge of object pose, or precomputed navigation maps [15, 16, 17, 18]. While these choices are pragmatic, they make it difficult to learn continually in uninstrumented real-world settings. In contrast, our proposed system is aimed at enabling reinforcement learning that is maximally autonomous, and does not require external instrumentation.

While RL-based methods allow agents to improve via interaction, enabling robots that can learn outside of instrumented laboratory settings is difficult. Such settings lack episodic structure and well-shaped reward functions [19, 20, 21, 22, 23] that are important for success [24, 25]. Large-scale uninterrupted deployment and training in the real world has been studied in several prior works [26, 27, 28, 29, 30, 31, 32]. While many of these works train robots in the real world without human interventions, they focus on navigation and do not consider how to interact with and manipulate objects. Large-scale real-world learning has also been successful for robotic grasping in laboratory settings. By letting robots learn from their own experience, prior approaches have shown that robots can learn to grasp from images [33, 34, 35, 36] or point clouds [37, 38]. These methods show real world learning can lead to robust robotic behavior, but they do not tackle challenging mobile manipulation tasks.

Gupta et al. show an approach to training a grasping policy on a mobile manipulator, but unlike our work, do not attempt to learn to navigate [39]. Wang et al. train a mobile manipulator with RL in simulation, but require known object pose, dense rewards, and episodic resets to a single initial state [16]. In contrast, our approach learns entirely from a sparse reward and onbaord sensors. Past approaches to learning without episodic resets have focused on stationary manipulation or simulation [40, 41, 2]. In this work we explicitly focus on how *mobile manipulation* robots can learn without external sources of resets or state estimation in the real world and lay out a set of design decisions that makes this process a practical one for acquiring robot skills.

3 Preliminaries

In this work, we use reinforcement learning (RL) as a general purpose algorithm for learning robotic behaviors. Reinforcement learning has the advantage of being able to operate on autonomously collected data, and enables the robot to improve through trial and error. To this end, the mobile manipulation task is formulated as a partially observed Markov decision processes (POMDP) with an observation space $\mathcal{O}$ of first person images, action space $\mathcal{A}$, reward function $r(s_t, a_t)$, transition dynamics $\mathcal{P}(o_{t+1}|o_t, a_t)$, a discount factor γ, and an initial observation distribution $\rho(o_0)$. The goal of reinforcement learning is to learn a control policy $\pi(a_t|o_t)$ that can determine which actions to take in each state such that the expected sum of rewards is maximized. This objective can be written as $J(\pi) = \mathbb{E}_{a_t \sim \pi(o_t), o_{t+1} \sim \mathcal{P}(o_t, a_t)} \left[\sum_t \gamma^t r(o_t, a_t)\right]$, as for a standard RL problem.

4 ReLMM: RL For Mobile Manipulation

We develop the ReLMM system to enable training mobile manipulation robots with RL. While we specifically apply it to a room cleaning task, in principle ReLMM could be used to learn other mobile manipulation tasks as well. Each component of ReLMM is chosen in order to maximise the autonomy of learning while retaining the sample efficiency needed to train in the real world. The specific task that we study in our experiments involves training a robot to quickly navigate around in a room with obstacles, physically pick up many objects, and place them in a basket mounted on the robot, as shown in Figs 1, 3 and 5.

Our system provides for efficient autonomous learning by decomposing the policy into grasping and navigation policies, using an ensemble of grasping models to explore based on uncertainty, automatically rearranging the environment after successful grasps, and using a curriculum to bootstrap and stabilize the concurrent training of both policies. Our final system can learn room cleaning skills in a number of different room configurations in ~ 40 hours directly in the real world.

4.1 Grasping Policy Training

As noted previously, we decomposed the control problem into grasping and navigation. This gives the manipulation policy two objectives: given an image observation, accurately model the robots chance of success should it attempt a grasp and, if so, select an appropriate action to maximize success. We obtain the former by training an ensemble of grasping policies and using their uncertainty to efficiently explore grasping. For choosing *how* to grasp, the policy must learn with sufficiently low sample complexity so as to make real-world training feasible. To reduce the complexity of the exploration problem we formulate grasping as a discrete single-step top-down action. The grasp policy $\pi_g(a_g|o_g)$ is parameterized with the action a_g discretized in the x-y plane, and the observation o_g corresponding to an image from the robot's camera. Such single-step action selection formulations are amenable to more efficient training than more complex multi-step tasks [42, 43].

Algorithm 1 TrainGrasp($G^1, ..., G^N$, $\mathcal{D}_g$, N, pt)

for t = 0, . . . , N steps **do**
  Get grasp observation $\tilde{o}$.
  Sample $a_g \sim \pi_g(\cdot|\tilde{o})$. // see Equation 2
  Perform grasp a_g, receiving $r_g = 0$ or 1.
  Store $(\tilde{o}, a_g, r_g)$ in $\mathcal{D}_g$.
  Update $G^1, ..., G^N$ on $\mathcal{D}_g$
  if $r_g = 1$ and $pt = 1$, Drop object.
  elseif $r_g = 1$ and $pt = 0$, **return** r_g
return 0

Framed in this way, the grasping task corresponds to a contextual multi-armed bandit problem. Specifically, we train grasping policies that, given an image, predict the likelihood of grasp success

for each action.We use a soft-max over the action values to sample actions in proportion to their exponentiated probability of success. To create the ensemble, we train $M = 6$ independent grasp policies, $G^1 \dots G^M$ that are each by minimizing the cross-entropy loss on the same dataset:

$$\mathcal{L}_g^i = \mathbb{E}_{(o_g, a_g, r_g) \sim \mathcal{D}_g}[-r_g \log G^i(o_g, a_g) - (1 - r_g) \log(1 - G^i(o_g, a_g))]. \tag{1}$$

Here, r_g is 1 when the robot successfully grasps an object, which is determined by presenting the gripper to the onboard camera. The grasping exploration policy is formed by constructing a Boltzmann distribution from optimistic estimates of grasp success, where the mean estimate from the ensemble, $\mathbb{E}[G^i(o_g, a_g)]$, is modified by adding a multiple of the ensemble variance $\sigma(G^i(o_g, a_g))$, which we expect to be larger for actions where success is more uncertain:

$$\tilde{G}(o_g, a_g) = \alpha \mathbb{E}[G^i(o_g, a_g)] + \beta \sigma(G^i(o_g, a_g)), \tag{2}$$

with $\pi_g(a_g|o_g) \propto \exp(\tilde{G}(o_g, a_g))$. The expectation and standard deviation are taken over the ensemble, and $\alpha, \beta \geq 0$ are hyperparameters. Other equivalent multi-step off-policy or contextual bandit algorithms can be used to train the grasping policy. However, we show in Section 6.3 that they are not as sample efficient for the mobile manipulation task in this work. Algorithm 1 describes the grasp training process in further detail.

4.2 Navigation Policy Training

For navigation, the policy must be able to control the mobile base to approach objects in a way that the current grasping policy can succeed. The navigation policy $\pi_n(a_n|o)$ outputs the action that controls the forward and turn velocities of the mobile robot base.

At every time step, the agent has to decide whether to perform a grasp or not by balancing the opportunity of receiving reward, the chance to collect novel data for the grasping policies, and the cost of wasting a timestep if there is no object within reach. This balancing act is done by reusing the same uncertainty measure described in Eq 2 when choosing whether to attempt a grasp. The probability of whether to attempt a grasp is

$$\mathbb{P}[\text{grasp}|o] = \max_{a_g} \tilde{G}(o, a_g). \tag{3}$$

Under this design, the navigation policy $\pi_n(a_n|o)$ continues to experience observations and output navigation actions, and at every step the choice of whether to perform a grasp or not is made by checking the grasp success probability of the current grasp model $\mathbb{P}[\text{grasp}|o]$ defined in Eqn 3. When the model decides attempting a grasp is worth the risk, the robot executes a grasp and evaluates the outcome to provide the navigation agent a reward. From the perspective of the navigation policy, the choice of whether to grasp or not is a part of the inherent dynamics of the environment. Even though these dynamics will change as the grasp policy is trained, the combined system results in an efficient and stable learning method. We compare two possible rewards for the the navigation policy. The first option is directly optimizing for the task by rewarding the navigation when a grasp is successful (i.e. where the current grasp ensemble has high performance): $r_n(o) = r_g(o) - 1$. The second option is to reward the navigation for reaching states that the current grasp ensemble will choose to grasp at, which is a function of its mean and uncertainty: $r_{n-\text{std}}(o) = (\max_{a_g} \tilde{G}(o, a_g) - 1)$ that we use to *relabel* states without successful grasps during SAC policy update. As this reward function only depends on the grasp ensemble and not on actual grasp success, this reward is computed at every policy update step and in Figure 4 we show how it can improve sample efficiency. The navigation policy is dependent on the performance of the grasping policy π_g to make successful grasps. The RL objective for navigation is $\max_{\pi_n} \mathbb{E}_{\pi_n(a_n|o_t)} \left[\sum_{k=0}^{\infty} \gamma^k r_n(o_{t+k})\right]$ or equivalently with $r_{n-\text{std}}$. We train the navigation policy for this objective using soft actor critic (SAC), which is data efficient and effective with continuous action spaces [44, 45].

The key design decisions that allow the navigation to be learned effectively are decoupling the navigation from grasping in order to allow for both policies to get more learning signal. Additionally, allowing the uncertainty of the grasping policies to decide when to pause navigation to attempt grasps ensures that grasping is not performed too frequently in situations where grasp success is impossible. In Section 6.3 we show how these design choices for the navigation and the grasping policy together allow for efficient exploration and learning, while being able to operate completely from on-board sensor readings, learning from high dimensional images and assigning rewards through proprioceptive grasp detection.

4.3 Training with Autonomous Pseudo-Resets

While the training schemes described above allow ReLMM to learn efficiently, both the contextual bandit grasping formulation and the navigation training setup requires an episodic training setup, where the environment is reset between trials, for example by replacing the objects into the world at random positions. To enable the robot to learn mobile manipulation skills without manually provided resets, we construct an automated pseudo-reset system that allows our method to learn autonomously without human intervention. After a successful grasp, the environment would ideally be reset by relocating the object to a new, randomly selected location. In stationary bin grasping setups, this can be automated simply by dropping the object back into the bin. However, for a mobile manipulator, dropping the object back to where it was grasped would promote policies that fail to search for new objects, and simply remain in the same location. To force the policies to learn to grasp in varied situations, we perform an automated random pseudo-reset, by commanding random navigation actions while the robot is holding the object, placing down the object in this new location, and then navigating randomly away. This ensures the robot will not always be near an object during training and must instead learn to seek objects out. We outline the overall algorithm used for training in Algorithm 2.

Algorithm 2 ReLMM

1: Init: function estimators π_n, $G^1, \ldots, G^M$.
2: Replay buffers $\mathcal{D}_n = \{\}$, $\mathcal{D}_g = \{\}$
3: TrainGrasp(G^1, .., G^N, D_g, N_{pt}, 1)
4: **for** $t = 0, \ldots, T$ steps **do**
5: Get navigation observation o_t
6: Sample $a_n \sim \pi_n(\cdot|o_t)$ and perform a_n
7: **if** *uniform*() $\leq \mathbb{P}[\text{grasp}|o_t]$ **then**
8: $r_g =$TrainGrasp(G^1,.., G^M,D_g,N_{grasp},0)
9: **else** $r_g = 0$
10: Compute reward $r_n = r_g - 1$
11: Get next navigation observation o_{t+1}
12: Store (o_t, a_n, r_n, o_{t+1}) in $\mathcal{D}_n$.
13: Update π_n with $\mathcal{D}_n$ using SAC.
14: Pseudo-reset
15: **end for**

4.4 Training Curricula

The separate grasping and navigation policies lend themselves naturally to curricular training, where the grasping policy, which needs to have some successes to provide rewards to the navigation policy, can be prioritized at the beginning of the learning process. We propose two types of curricula, which both break the potential "chicken-and-egg" training problem of providing poor reward signals for navigation from an untrained grasping model.

Stationary curriculum. The simplest curriculum is to place a single object in front of the robot and run Algorithm 1 with $pt = 1$ for N_{pt} steps. After each successful grasp, the robot places the object down randomly. If the object is knocked into an area the robot can not reach (because the base is stationary), which happens about 5% of the time, a human observer must push the object back into the graspable area. This curriculum is very time efficient, but does require occasional human intervention.

Autonomous curriculum. For fully autonomous learning, we develop a grasping curriculum that favors collecting grasping data early on by performing a high number of grasps at the beginning of training. This is accomplished by developing a type of practicing curricula that focuses the agent to find objects quickly and practice with them thoroughly. To find objects quickly the robot attempts $N_{grasp} = N_{start}$ (Alg 2, line 8) grasps after every navigation step. If the robot succeeds at grasping an object it will practice with this object by placing it down randomly and picking it up from that same location. The robot often looses track of the object and will navigate to another location after $N_{grasp} = N_{stop}$ unsuccessful grasps. This initial automatic grasping curricula ends when a total of N_{max} grasps are complete. More details on the grasping curriculum algorithm are in Appendix B.

5 Robotic Mobile Manipulator: System Overview

Our choice of robotic system reflects the need for a robust robotic platform that can operate autonomously for long periods of time, and is unlikely to cause damage to itself and its surroundings. Ensuring safety during autonomous operation is itself a significant research challenge, which is outside of the scope of this work. Therefore, we utilize a small-scale low-cost mobile manipulation platform based on the LocoBot design [39, 46], shown in Figure 2 (left), which consists of an iClebo

Kobuki mobile base and a WidowX200 5-DoF arm. The robot sensors include an Intel RealSense D435 camera at the top of the robot, as well as bump sensors on the base. We use an onboard Intel NUC to command the robot, and connect wirelessly to a server for data processing and training. Random exploration is generally safe with the LoCoBot as it is small, light, and will automatically stop the arm's motors if they encounter resistance. The robot learns in a real-world office space, with varied lighting conditions, distractors, and surface textures. Our experiments utilize small objects that the robot can feasibly pick up, which consist of socks and toys – a representative sampling of objects one may want a robot to pick up off the floor.

To control the robot, we separately command the iClebo mobile base and the WidowX200 robotic arm with the corresponding navigation and a grasping policies. The navigation policy stops the robot during a grasp. For grasping, we use a directed end-effector control space. Assuming the floor is flat, the vertical position for grasping is always chosen to be just above the floor, and the learning algorithm chooses a point in $X - Y$ space in front of the robot to perform a grasp at. This chosen position then dictates where to move the gripper using inverse kinematics. Details on the learned network architectures are in Appendix A.2.

To ensure that we can continue training the robot for extended periods of time, the robot must be able to safely navigate in environments with obstacles without breaking. To support safe navigation, we use the depth channel of the robot's camera to detect obstacles and walls in front of the robot. When an obstacle is detected as being inside the graspable area of the robot's arm, the robot's base rotates in a random direction until the obstacle is no longer obstructing the grasp space. We also simulate this setup for more exhaustive comparisons, with details of the simulation provided in Appendix A.1.

6 Experimental Results

Our experiments aim to evaluate our autonomous reinforcement learning system in a number of real-world environments, as well as to provide ablation experiments and analysis in simulation. In particular, we aim to study the following questions: (1) Can ReLMM learn autonomously in the real world? (2) How does the control hierarchy affect learning performance? (3) How does ReLMM compare to other policy designs and prior methods? Our goal is to study real-world reinforcement learning, rather than necessarily provide the best possible solution to the room clearing task, and hence we design our system to be general, with only the reward determining the task.

6.1 Experiment details

For all real-world experiments, the entire training procedure is performed in the real world on the LoCoBot platform, with about 40 hours of training. The training is autonomous with the exception of the stationary curriculum (if used), and battery changes every 5 hours, during which time we also replace any objects that become stuck near corners, walls, or furniture.

As our task is non-episodic, the policies are evaluated at the end of training. This is done by scattering the objects, executing the policy (without pseudo-resets) for 15 minutes, and counting the number of objects collected in that time. We use four real environments in our evaluation (no obstacles, with obstacles, with diverse objects, and with obstacles and rugs, as shown in Figure 3) and two simulated environments (Figure 5). Each room has a different size and number of objects, so we report the percent of objects collected. However, we plot a proxy for training performance by measuring the number of timesteps between successful grasps. Simulation results are evaluated in a similar way with a few differences. Instead of 15 minutes for evaluation, we use 250 timesteps. We evaluate our system in the simulated room shown in Figure Figure 5.

We compare our approach to several prior methods and baselines to comparatively evaluate our method. The baselines include: **Rand all**, a policy that selects navigation and manipulation actions randomly, as a lower baseline; **Rand nav**, a method similar to Gupta et al. [39] that collects grasping data in the same way as our method, but has a random navigation controller. These baselines disentangle the benefits we get from learning both the grasping and the navigation. We also include a hand-coded controller (**Scripted**) specifically engineered for this task that locates objects by thresholding the image pixels and grasps at their centroids, which provides a strong hand-designed baseline. Our goal is not to improve on the Scripted baseline, which incorporates considerable do-

Figure 3: **Left**: Learning curves for training the real robot, averaged over the last 250 actions, with number of objects collected on top (higher is better) and time steps between grasp successes on bottom (lower is better). The results show that ReLMM learns in the real world without instrumentation or resets. **Right**: Snapshots from the evaluation tasks without obstacles in a $4m^2$ room (top-left, *no obst*, top-right, *diverse*), with obstacles *obst* in a $9m^2$ room (top-middle), and with obstacles and rugs *obst+rugs* in a $10m^2$ room (bottom). Videos are available in the supplementary material.

main knowledge, but rather to study real-world RL, but we still include it to provide a point of reference for the task. For more detail on the implementation of these baselines, see Appendix A.3.

6.2 Real Robot Evaluation

Our real-world experiments evaluate how well ReLMM can learn a mobile grasping policy autonomously in a variety of rooms. We conducted separate experiments for each of the rooms shown in Fig 3 which differ in terms of size, furniture, layout, and objects. The learning progress of the robot averaged over the last 250 training actions is shown in Fig 3 (left). ReLMM can train using both the *stationary* and *autonomous* grasping curricula, with the *autonomous curriculum* requiring less human effort, at the cost of increased training time.

Env	no obst	obst	diverse	obst+rugs
ReLMM-StatCurr	$\mathbf{88 \pm 2}$	76 ± 2	$\mathbf{63 \pm 8}$	59 ± 14
ReLMM-AutoCurr	77 ± 8	–	–	–
Scripted	75 ± 4	$\mathbf{88 \pm 6}$	56 ± 3	$\mathbf{65 \pm 9}$
Rand nav [39]	52 ± 12	38 ± 10	22 ± 9	20 ± 7
Rand all	12 ± 6	2 ± 2	2 ± 3	5 ± 4

Table 1: Percent of objects collected after training in each of the four real-world environments. ReLMM outperforms the baselines by learning both grasping and navigation jointly, without requiring environment instrumentation. Due to ReLMM-AutoCurr's slower learning, we only evaluate it in *no obst* with *relabel*.

After training, we conduct an evaluation run in each room, measuring the percentage of objects collected after 15 minutes of policy execution. The result are summarized in Table 1. Examples of the learned behaviors are also shown in Figure 3, and are illustrated in more detail in the supplementary video and Appendix C. To provide context for these results, we compare ReLMM to the previously described baselines. The *Rand all* and *Rand nav* [39] baselines perform poorly, since neither method learns a directed navigation behavior, making is difficult to effectively navigate the room to collect objects, though *Rand nav* [39] is effective at picking up the objects if it stumbles upon them. This illustrates the importance of an intelligent navigational strategy in these settings. The policy in the *Scripted* baseline performs well in some settings (as it was designed for this task), but still falls short of the policy learned by ReLMM in half the settings, and crucially cannot improve from these results autonomously. Our method will continue to improve given more training time. This is particularly important in the *diverse* environment where it is difficult to find a pixel threshold that works for all objects, ReLMM can automatically learn how to identify objects to grasp via interaction.

6.3 Simulation Analysis

To study questions (2) and (3), we perform a detailed ablation analysis in simulation. As discussed in Appendix C, we find that a discretized grasping policy learns with $\frac{1}{3}$ the samples compared to a continuous one. In Figure 4, we show the performance of various ablations of our system in the simulated environment with the *stationary curriculum*. First, we ablate the policy decomposition by training a *single policy* with reinforcement learning using grasp success as the reward. The joint

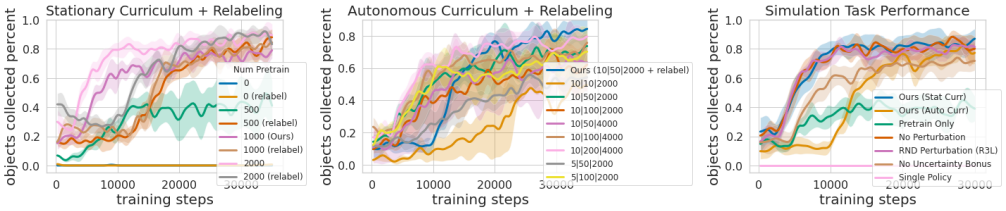

Figure 4: **Left**: Ablation of different number of grasp pretraining samples (N_{pt}) and navigation reward relabeling (described in subsection 4.2) in simulation. Increased pretraining of the grasping policy increases overall mobile manipulation performance. **Center**: Analysis to find the best parameters for the *autonomous* curriculum compared to the *stationary* curriculum. With the proper settings ($N_{start}|N_{stop}|N_{max}$) the *autonomous* curriculum can be almost as efficient as the *stationary*, without requiring as much manual effort. **Right**: Ablation of ReLMM, all use the stationary curriculum and no relabeling except for *Ours (AutoCurr)*. The *Single Policy* does not use our grasp/navigation decomposition and fails to learn in a reasonable time. *Pretrain Only* freezes the mediocre grasping policy from the stationary phase and only trains the navigation. Removing the grasp policy's *Uncertainty Bonus* reduces performance due to lack of exploration. Learned perturbation using RND [47] like [2] does not improve performance in this simulation environment.

action space poses a much larger exploration problem, and the policy is unable to make headway on the task in a reasonable number of samples. This indicates that the hierarchical decomposition used by ReLMM significantly improves training performance. Next we see that freezing the grasp policy after the stationary phase and only training the navigation is much worse than training both together. This illustrates the interplay between the two policies, as the navigation is dependent on the grasping for obtaining rewards. As shown in the plot, training the grasp policy without the uncertainty bonus (i.e. $\beta = 0$) leads to significantly lower performance for ReLMM, as it is less incentivized to explore. Finally, we see that the autonomous curriculum with reward relabeling can get similar final performance as the stationary curriculum with less human intervention at the cost of longer training time.

Lastly, we examine the choice of curriculum. While the stationary curriculum performs well with 2000 stationary grasps (Figure 4 left), the stationary period can require human supervision to move the objects back to the robot. The autonomous curriculum instead bootstraps the grasp learning by attempting many more grasps at the beginning of the navigation training whenever an object has been picked up. This requires no human involvement, but incurs additional unsuccessful grasps due to more grasped attempts in locations without an object. After tuning the *autonomous* curriculum with reward relabeling in Figure 4 (center) it learn almost as fast as *stationary*. Further comparisons in other simulated environments can be found in Appendix C. Using either the stationary or autonomous with relabeling curriculum, ReLMM is able to train its policies concurrently and as a result achieves large gains in total objects collected.

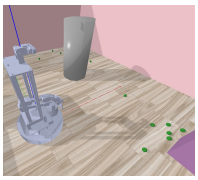

Figure 5: Simulation task is to collect the green balls.

7 Conclusion

We presented ReLMM, a system for autonomously learning mobile manipulation skills in the real world, without instrumentation, and with minimal human intervention. Our real-world experiments, conducted in four separate rooms, show that ReLMM can train continuously for several days (40 hours) with only occasional interventions, and that the resulting policies are effective at cleaning up the room. Our simulated ablation studies further provide support for the design decisions in ReLMM, indicating that the hierarchical decomposition of navigation and grasping greatly improves learning performance, autonomous practicing with a suitable exploration bonus enhances learning speed, and our automated curriculum can provide effective performance when learning from scratch. Even when using the manually-provided curriculum, the grasp pretraining phase does not need to be long: only 1000 attempted grasps were needed to get reasonable room-cleaning performance, although more pretraining can improve performance further. Extending this system to more complex manipulation tasks would be an exciting direction for future work. We hope that this system for practical RL on mobile manipulators will make mobile manipulation more accessible to outside lab spaces and to users who need maximally autonomous learning algorithms.

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