

Learning Goal-Directed Object Pushing in Cluttered Scenes with Location-Based Attention

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Abstract—Non-prehensile planar pushing is a challenging task due to its underactuated nature with hybrid-dynamics, where a robot needs to reason about an object’s long-term behaviour and contact-switching, while being robust to contact uncertainty. The presence of clutter in the environment further complicates this task, introducing the need to include more sophisticated spatial analysis to avoid collisions. Building upon prior work on reinforcement learning (RL) with multimodal categorical exploration for planar pushing, in this paper we incorporate location-based attention to enable robust navigation through clutter. Unlike previous RL literature addressing this obstacle avoidance pushing task, our framework requires no predefined global paths and considers the target orientation of the manipulated object. Our results demonstrate that the learned policies successfully navigate through a wide range of complex obstacle configurations, including dynamic obstacles, with smooth motions, achieving the desired target object pose. We also validate the transferability of the learned policies to robotic hardware using the KUKA iiwa robot arm.

I. INTRODUCTION

Non-prehensile planar pushing is a highly researched topic in the field of robotic manipulation [1], used as a task to study broader concepts in modeling, planning, learning, and control. By extending the versatility of robots beyond typical pick-and-place tasks, it enables repositioning and reorienting specific objects [2], and achieving grasping configurations, that are otherwise unreachable [3]. Due to the underactuated nature of the task, it is necessary to reason about the long-term interaction between the robot and the object, where hybrid dynamics arise due to transitions between different contact modes [4], [5]. Furthermore, it is challenging to predict the motion of the object due to the uncertainty in the frictional interactions [6].

Incorporating obstacle avoidance introduces a new dimension of complexity, further necessitating spatial reasoning and responsiveness in the case of dynamic obstacles [7]. Most current research focuses either on precise and directed object pushing in free space [8]–[10], or on cluttered surfaces without any collision restriction between the objects [11], [12]. However, when the manipulated objects are fragile, or if it is essential to keep the layout of the objects on the surface untouched, the capability to avoid collisions becomes crucial.

Recently, Del Aguila Ferrandis *et al.* [13] proposed a reinforcement learning (RL) method that uses a categorical

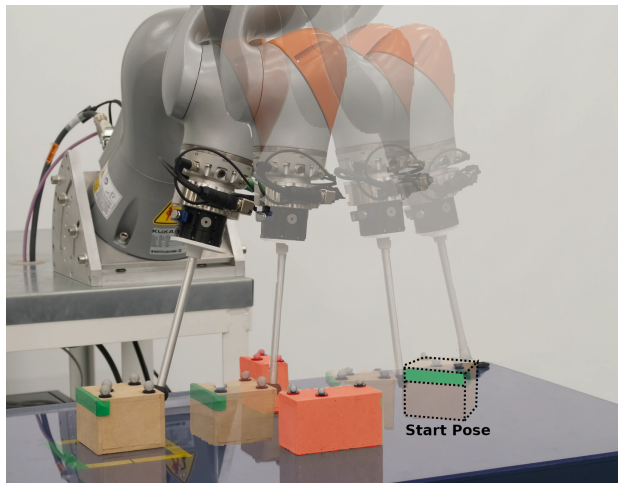


Fig. 1: Experimental setup for the pushing task in a cluttered workspace. The robot uses a pusher to move an object to a specified target pose while avoiding collisions with other objects on the table. Note that the box has to be oriented carefully in order to fit through the narrow passage.

exploration approach to capture the multimodal behavior in planar pushing arising from the different possible contact interaction modes between the robot and the manipulated object. The authors show the benefit of categorical exploration for goal-directed pushing to reach arbitrary target poses, i.e., arbitrary positions and orientations, but assume a workspace free of clutter.

This paper extends [13], tackling the problem of goal-directed non-prehensile pushing in cluttered scenes, with collision constraints on the clutter. In contrast to previous work [14], we introduce a model- and guidance-free learning approach to combine the robustness of RL with the improved feature extraction capabilities of attention-based methods to achieve goal-directed, collision-free pushing.

Providing precomputed guidance, such as global paths, can restrict the RL-agent in its exploration process, potentially leading to sub-optimal or even failed manipulation. Furthermore, by using a more general representation of the surrounding clutter, i.e., an occupancy grid map, our agent can better adapt and generalize to other or unseen scenarios, such as dynamic or differently shaped objects, than with fixed representations. However, high-dimensional representation comes at the cost of higher computational effort. To enhance the system’s scene understanding and to focus its attention on important parts of the current state representation, we investigate the influence of a lightweight attention mechanism, called location-based attention [15]. In

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our experiments, we show sophisticated pushing behavior when combining the concepts of categorical exploration with attention-based feature extraction. For example, Fig. 1 shows a challenging scenario, where the robots pushes the object through a gap between two obstacles while avoiding any collisions.

To summarize, the key contributions of our work are:

- A guidance- and model-free RL framework leveraging categorical exploration during training and location-based attention for goal-oriented pushing of objects in cluttered table-top scenes.
- A quantitative evaluation in simulation, with different quantities and configurations of unseen obstacles, and a study of the effect of the location-based attention module, with different design choices.
- Qualitative and quantitative hardware experiments with a KUKA iiwa robot, showcasing the efficacy of our method in various challenging scenarios, such as avoiding dynamic obstacles.

II. RELATED WORK

A. Model-Based Planar Pushing

Previous works developing model-based robot controllers for planar pushing generally use Model Predictive Control (MPC) to track nominal trajectories computed offline [5], [7]. These approaches achieve smooth and highly precise pushing motions. However, due to the short-horizon MPC used for trajectory tracking, large disturbances to the manipulated object or significant changes in the obstacle layout require offline re-computation of the nominal trajectory.

These MPC approaches also lack scalability to scenarios involving switching the contact between the object faces, due to the combinatorial complexity of the discrete decisions regarding the making and breaking of contact and which face to push. Recent works address this issue by proposing sampling-based [16] and demonstration-guided [17] optimization approaches. In particular, Pasricha *et al.* [16] use Rapidly-exploring Random Trees (RRT) to poke an object while avoiding obstacles in the workspace. Nevertheless, this method results in non-smooth motions which are unable to accurately control the resulting object pose.

B. Model-Free Planar Pushing

Other works approach the planar pushing task through model-free methods, primarily using RL. Many of these works focus on learning pushing policies for clutter-free environments [8], [13], [18]. Another prominent research direction is the synergy of pushing and grasping actions to retrieve objects from clutter [11], [19], [20]. While this is also an important task, the characteristics are very different from the task we consider, since their goal is to move the clutter away to reach and retrieve the target object through a grasping action, hence disregarding collision constraints.

To the best of our knowledge, the work proposed by Dengler *et al.* [14] is the only other model-free learning-based approach that addresses the problem we consider in this paper. However, their approach relies on various assumptions

that reduce the complexity of the problem. Most significantly, they use sub-goals from a pre-computed global path in order to guide the policy towards the target position. Furthermore, the authors only consider a 2D target centroid position, neglecting the orientation of the object.

C. RL with Attention Mechanism

Attention based approaches have gained significant popularity, primarily in navigation tasks [21], [22], due to their ability to extract relevant features from the input and to require low computational cost [23]–[25], which is crucial when training RL policies with highly parallelized environments. One subclass of these algorithms is location-based attention [15], [26], which assigns attention weights to selectively focus on input features based on their spatial location without needing to compute relationships between all pairs of the input data. Recently, Heuvel *et al.* [22] effectively used location-based attention within an RL approach for robot navigation among obstacles. However, their method still relies on sub-goals sampled from a global path, which we aim to overcome. We claim that no global guidance is needed and the features extracted by the attention module are sufficient to achieve sophisticated goal-directed pushing behaviour.

III. PROBLEM DEFINITION

In this work, we consider the following problem. A robotic arm must push an object from its current pose to a target pose configuration (x, y, θ) , within a bounded planar workspace. To achieve this, we consider the end effector (pusher) of the arm moving in planar space (x, y) . In addition to the pushed object, there are other objects in the workspace which we regard as obstacles and might obstruct the direct path to the target configuration. The pusher must avoid colliding with the obstacles while also avoiding any collisions between the manipulated object and the obstacles.

IV. METHOD

To tackle the described problem, we apply RL with the categorical exploration approach as presented in [13]. Furthermore, we use a location-based attention pipeline to extract relevant features from the workspace occupancy grid and achieve active obstacle avoidance without relying on guidance from a global path. We now describe the design of our RL framework, as summarized in Fig. 2, in more detail.

A. Feature Extraction

We begin with the preprocessing of the input data as well as the architecture of the neural networks, all of which are implemented and optimized using PyTorch [27].

1) **Preprocessing:** At the beginning of each episode, we generate a binary occupancy grid of the workspace, where 1 represents obstacle and 0 free space. We use a resolution of $0.005 \text{ m} \times 0.005 \text{ m}$ per grid cell. To reduce the computational cost during training, we keep the grid layout fixed throughout each episode. Nevertheless, we show in our

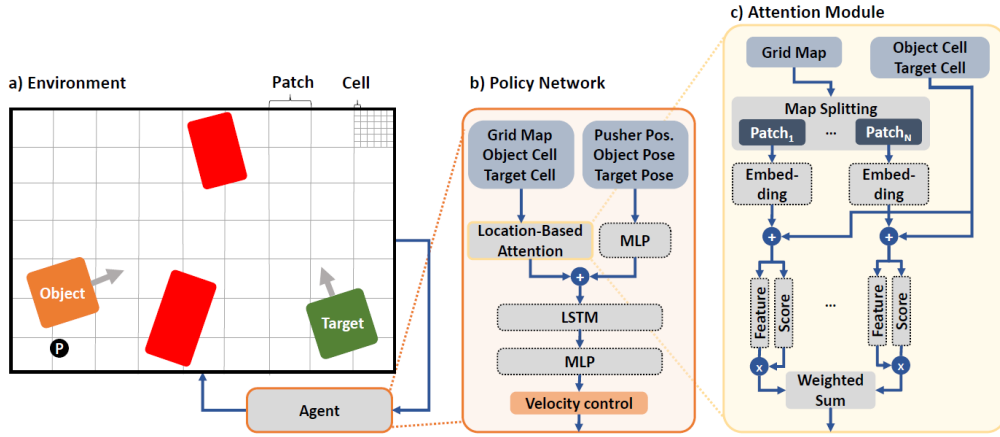


Fig. 2: Overview of our framework for learning goal-directed pushing using location-based attention. The grid map of the environment together with the object and target pose, as well as the position of the pusher (a) is fed to the RL-agent (b). In comparison to previous work [14], we use a location-based attention module (c) for feature extraction of the cluttered scene. The action of the agent is the velocity in x and y direction for the next time step.

hardware experiments that the learned policies are robust to dynamic changes in the obstacle layout. Since we divide the grid into patches for the input to the attention module (see the next subsection), we add padding to the grid such that the axis dimensions are a multiple of the patch size P_s .

2) **Location-Based Attention:** We leverage the concept of location-based attention to enable our system to focus on the obstacles and the potential pushing paths around them, effectively ignoring less relevant information. Since we use grid maps as workspace representation, we adapted [22] to successfully encode the spatial features. In particular, we decompose the occupancy map into n patches P , each of size $P_s = 16 \times 16$, where $n \cdot P_s$ matches the size of the original map. Three fully connected layers embed each patch, encoding its features. This encoding process allows us to capture the essential characteristics of each patch, including obstacles and potential paths.

To provide positional context for each patch in the current task configuration, we concatenate them with the object and target positions, relative to the upper-left corner of each patch and compute the weighted attention features, as depicted in Fig. 2.c. The output of the location-based attention module is fed to the RL agent, enabling it to focus on the most relevant spatial information for the current pushing scenario.

B. Reinforcement Learning

For our obstacle avoidance pushing task, we extend the RL approach proposed by Del Aguila Ferrandis *et al.* [13], which exhibits promising learning and pushing behavior. Accordingly, we use the on-policy algorithm Proximal Policy Optimization (PPO) [28] with a discretized action space for categorical exploration.

1) **Observation:** The policy observation of the environment consists of the object and target poses (x, y, θ) , the pusher position (x, y) , and the binary occupancy grid that encodes the clutter layout. As previously described, we process the binary occupancy grid with an attention module to extract spatially relevant weighted attention features.

2) **Policy and Value Networks:** We use the same architecture for the policy and value networks, which is illustrated in Fig. 2.b. The attention module extracts weighted attention features (size 64) from the occupancy grid. We also use a multilayer perceptron (MLP) (size 64) to extract features from the remaining observation, which consists of the object and target pose, as well as the pusher position. We concatenate these two feature vectors and feed them through a Long Short-Term Memory (LSTM) (size 256) layer and an MLP (size 128) layer. The final output of the value network is of size 1, while the policy network returns a vector of size 22, i.e., 11 categorical bins for the velocity on the x and y axes.

3) **Action:** Similar to [13] we compute (v_x, v_y) , which correspond to the x and y velocity of the pusher and limit the velocity on each axis to the range $[-0.1, 0.1] \text{m s}^{-1}$, with 0.02m s^{-1} velocity steps for each categorical bin.

4) **Reward:** The reward is a crucial part for training convergence so we simplify its design as much as possible. Our reward function r_{total} consists of four components,

$$r_{total} = r_{term} + k_1(1 - r_{dist}) + k_2(1 - r_{ang}) + r_{coll}, \quad (1)$$

with k_1, k_2 being scaling factors. r_{term} is a large sparse termination reward, which is positive when the episode is successful, and otherwise negative. r_{dist} is the Euclidean distance to the target position, normalized to the range $[0, 1]$, and r_{ang} the angular distance to the target orientation, also normalized to $[0, 1]$. In addition, we use, r_{coll} which is a binary negative reward to penalize at every step any kind of obstacle contact by the pusher or the object. If there is no collision during one time step then $r_{coll} = 0$.

V. EXPERIMENTS AND RESULTS

In this section, we evaluate the performance and generalization capabilities of our system in different scenarios in terms of success rate and number of collisions. Furthermore, we show that the method proposed by Dengler *et al.* [14] fails when the global path information is not available, highlighting the need for an alternative approach, such as our

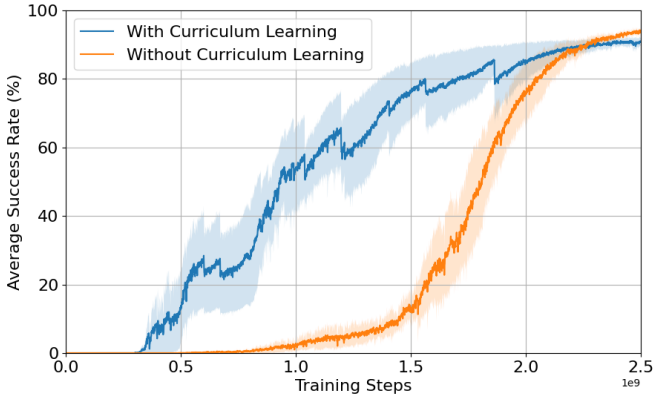


Fig. 3: Policy training performance on our obstacle avoidance pushing task, with and without curriculum learning.

Parameter	Method	Value
Parallel Environments	RL	1,440
Batch Size	RL	14,400
Rollout Length	RL	120
Update Epochs	RL	5
Learning Rate	RL	KL-Adaptive
Control Frequency	RL	10 Hz
Max. Episode Length	RL	160
Grid Size	Attention	100 × 140
Patch Size	Attention	16 × 16
Grid Embedding	Attention	MLP (192, 128)
Feature and Score Network	Attention	MLP (128, 100, 64)

TABLE I: Hyperparameter values for the RL algorithm and the attention module.

proposed attention mechanism. We also present an ablation study on the influence of the location-based attention module. Finally, we conduct a domain shift analysis using an unseen physics simulator and a physical hardware set-up.

A. Experimental Setup

We train our policies using the Isaac Sim [29] physics simulator, for which we develop a custom environment for pushing in clutter. The standard training setup contains a single rectangular obstacle, and we also fine-tune trained policies using two rectangular obstacles. At the start of each episode, we sample random poses for the object, the obstacle, and the target, such that the obstacle is between the object and the target. Note that for the hardware experiments, we decided to fix the target pose to simplify the setup, but our simulation experiments fully randomize it.

The policies run at a frequency of 10 Hz and, during training, we enforce a maximum episode length of 160 steps. During evaluation, since we consider more complex scenarios, such as unseen obstacle shapes and multiple obstacles, we increase the maximum episode length to 200 steps. For the reward function, we use a termination reward $r_{term} = 50$, when the episode is successful, and $r_{term} = -10$ when it is unsuccessful due to a violation of workspace boundaries. Furthermore, the collision penalty is $r_{coll} = -5$, and we use scaling factors $k_1 = 0.1$, $k_2 = 0.02$ for the position and angular distance reward terms.

We use the PPO algorithm with the hyperparameter values as specified in Tab. I. Note that we use an adaptive learning

Parameter	Sampling Distribution
Static Friction	$\mathcal{U}[0.5, 0.7]$
Dynamic Friction	$\mathcal{U}[0.2, 0.4]$
Restitution	$\mathcal{U}[0.4, 0.6]$
Object Mass	$\mathcal{U}[0.4, 0.6]$ kg
Object Scale	$\mathcal{U}[0.9, 1.1]$
Obstacle Scale	$\mathcal{U}[0.8, 1.2]$
Pusher Scale	$\mathcal{U}[0.95, 1.05]$
Position Noise	$\mathcal{N}[0, 0.001^2]$ m
Orientation Noise	$\mathcal{N}[0, 0.02^2]$ rad

TABLE II: Sampling distributions for the dynamics randomization and observation noise. \mathcal{U} is the uniform distribution and \mathcal{N} the normal distribution.

rate schedule based on the KL divergence of the policy network, as in [30], with a target KL divergence of 0.01. Furthermore, if an episode terminates due to reaching the maximum episode length, we bootstrap the final reward with the state value estimate from the value network, as discussed in [31]. For the remaining hyperparameters we use the same values as in [13].

To bridge the sim-to-real gap, we use dynamics randomization and synthetic observation noise during policy training. Table II shows the randomized parameters and corresponding sampling distributions. As in [13], we generate correlated noise, sampled at the beginning of every episode, as well as uncorrelated noise, sampled at every step, and add it to the policy observation of the object pose and the pusher position. The code of our system will be made available after publication.

B. Policy Training

Curriculum learning is a popular technique in RL to speed up policy convergence so we explored its applicability for our task. In particular, we designed a curriculum such that the learning begins with a larger 3 cm position success threshold and the target orientation is disregarded. Then, as the policy reaches a higher success rate, we gradually enforce progressively smaller orientation success thresholds, from $3\pi/4$ rad to $\pi/6$ rad, and lastly reduce the position success threshold to 1.5 cm.

We trained our policies with curriculum learning as well as without, using the final position and orientation success thresholds directly ($\pi/6$ rad and 1.5 cm). The results are shown in Fig. 3. We found that the curriculum does not provide a significant advantage in terms of convergence speed, and the asymptotic performance is slightly higher without curriculum learning.

C. Baseline and Influence of Path Guidance

To the best of our knowledge, Dengler *et al.* [14] is the closest related approach that addresses the task we consider. Therefore, in order to establish a baseline, we re-implemented their proposed approach in PyBullet [32] and applied it to our obstacle avoidance pushing task. Note that Dengler *et al.* [14] did not perform hardware validation, so their method does not incorporate dynamics randomization or synthetic observation noise. Our re-implementation does include these aspects to enable a more accurate comparison.

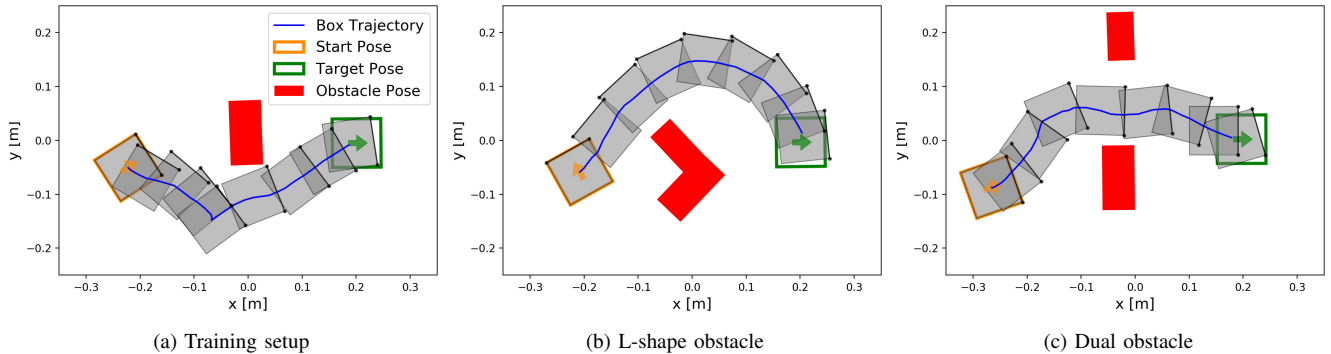


Fig. 4: Different obstacle configurations and the corresponding trajectories generated by the RL policy with location-based attention in the physical hardware setup. The three experiments show pushing behaviour with contact surface switching (a), a smooth trajectory around an L-shaped obstacle (b), and a precise pushing maneuver to fit the object through a narrow gap between two obstacles (c).

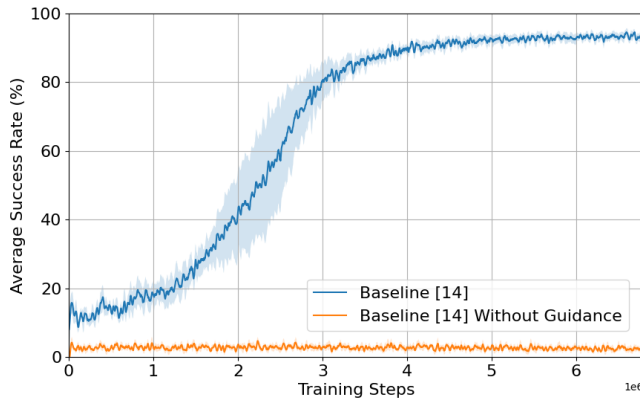


Fig. 5: Training performance of the baseline approach [14] (blue), as well as a variant without global path guidance (orange).

Most importantly, their approach relies on a precomputed global path providing guidance to avoid obstacles. Since we aim to overcome this limitation, we trained a baseline with the re-implemented method from Dengler *et al.* [14], as well as a variation that does not have access to the global path information. Fig. 5 shows the resulting learning curves. As can be seen, the baseline with guidance demonstrates convergence; however, removing the global path guidance leads to a convergence failure. This shows that the method from Dengler *et al.* [14] is unable to handle the guidance-free pushing task that we consider, and highlights the need for improved processing of the clutter layout, as proposed in our approach.

D. Quantitative Evaluation

We conduct a quantitative evaluation of our system in Isaac Sim using various environment configurations, including unseen obstacle shapes, sizes, and quantities. Specifically, in addition to the standard training setup, we consider obstacles with circular, cross, T, and L shapes, as well as a dual obstacle setup. We run our trained policy for 2,000 episodes in each environment, randomizing the start and target configurations as well as the size and pose of the obstacles, and report the average success rate and the collision rate within the successful runs. Note that an episode is successful when

Experiment Setup	Success Rate	Collision Rate
Training Setup	0.986	0.018
Circular Obstacle	0.982	0.030
Cross-Shape Obstacle	0.980	0.031
T-Shape Obstacle	0.979	0.058
L-Shape Obstacle	0.975	0.084
Dual obstacle	0.976	0.439
Dual obstacle fine-tuned	0.961	0.055

TABLE III: Performance across different obstacle configurations in size, shape, and quantity, in terms of success and collision rates from tests conducted on 2,000 episodes each. The results indicate high success rates across all configurations, with a slight increase in collision rates as obstacle complexity rises.

the object is within 1.5 cm and $\pi/6$ rad of the target position and orientation respectively.

The results of this evaluation are shown in Table III. For the single obstacle setups, our system consistently achieves a high success rate, with a slight increase in the collision rate as the complexity of the obstacle configuration increases. In particular, the policy achieves a 98.6% success rate, with a 1.8% collision rate, in the training setup. In the more complex scenarios, the success rate decreases at most by 1.1% and the collision rate increases at most by 6.6%. This shows the robustness of our system to unseen obstacle configurations.

Extending the task to scenarios with multiple obstacles leads to substantially more complex configurations, for instance requiring highly accurate robot motions to push the object through a narrow gap. As shown in Table III, when we apply our policy, which was trained on a single obstacle environment, to a dual obstacle setup, the success rate remains high at 97.6% while the collision rate increases to 43.9%. However, after fine-tuning the policy in the dual obstacle environment for only $5 \cdot 10^8$ steps, it achieves a 96.1% success rate with a significantly reduced collision rate of 5.5%. This demonstrates the adaptability of our system in handling more complex obstacle avoidance scenarios through targeted fine-tuning.

E. Influence of Location-Based Attention

To study the influence of the location-based attention module, we trained our policy with and without attention.

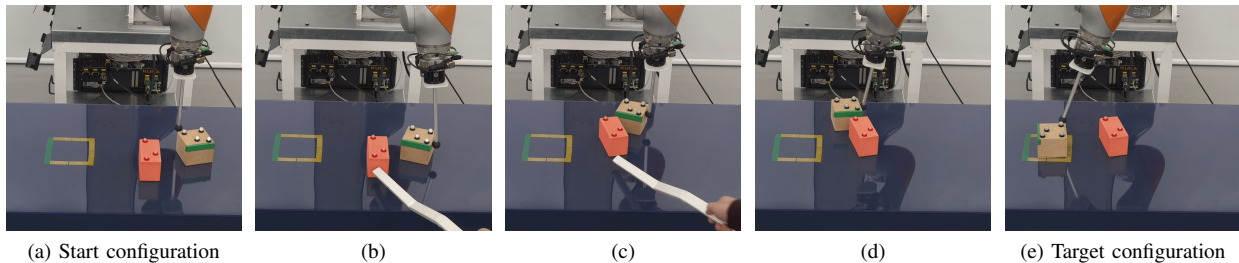


Fig. 6: Key frames of the Kuka iiwa robot pushing an object from the start (a) to the target (e) configuration while avoiding an obstacle (red). As the robot pushes the object, we dynamically change the obstacle pose (b - c) to intersect the path of the object. Our policy successfully reaches the target pose without any collisions, demonstrating its robustness to such dynamic changes in the clutter layout.

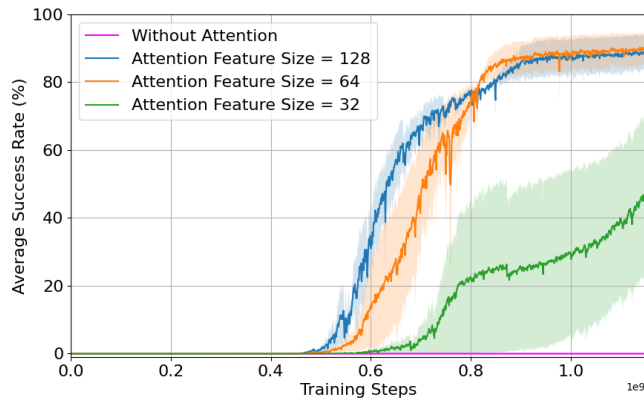


Fig. 7: Ablation study on the influence of the attention module. Without attention (magenta), the policy fails to converge, while a feature and score size of 64 (orange) yields the best result in terms of convergence and network size.

Note that, due to computational constraints, we simplify our task for this study such that the target orientation of the object is disregarded. Training the policy without attention involves forwarding the feature outputs, rather than performing a weighted sum with the attention scores. In particular, we concatenate and compress the feature vectors by feeding them through an MLP (2048, 512, 64). We also evaluate the effect of the feature and attention score sizes.

Fig. 7 shows the resulting learning curves. We find that, after removing the attention scores, the agent fails to converge, which highlights the critical role of the attention module. Furthermore, the attention module with a feature and score size of 64 yields the best performance in terms of convergence speed and network size, which is why we decided to use this configuration for our other training runs. It is worth mentioning that we also attempted to reduce the attention scores to a size of 1 per patch. This failed to converge, and hence we opted to use the same size for the features and attention scores. We believe this can be attributed to excessive loss of information when compressing each patch to a score of size 1.

F. Domain Shift and Hardware Experiments

We study the robustness of our system in terms of its transferability to a physics simulator different from the one used for training, and to a physical planar pushing hardware setup. Other simulators have distinct computational models

for physical phenomena such as contacts, leading to different interactions between the environment, the objects, and the robot. Therefore, after training our system in Isaac Sim, we evaluate it for 2,000 episodes in PyBullet. The policy achieves a 97.6% success rate with a 1.3% collision rate. Both metrics are close to those achieved in the Isaac Sim training environment, shown in Table III.

For the physical hardware set-up, as depicted in Fig. 1, we use the KUKA iiwa robot arm. We track the current and target box pose, as well as the obstacle poses, using the Vicon motion capture system. Additionally, we use OpTaS [33] to map the task-space policy actions to robot joint configurations, and test our software implementation for reading the environment state and controlling the robotic arm using the ROS-PyBullet Interface [34].

To quantitatively evaluate the performance of our system in hardware, we run it from 10 random starting configurations for three different scenarios: (a) the standard training setup with a single rectangular obstacle, (b) a single obstacle with unseen shape, and (c) dual separated obstacles. Fig. 4 shows sample trajectories generated by the physical robot in each of these scenarios. The learned policy achieved a success rate of 10/10 in each scenario, with collision rates 0/10, 0/10, and 1/10, respectively.

Finally, we qualitatively evaluate our system’s adaptability to unforeseen changes in the clutter layout. Fig. 6 shows a sequence of key frames where the robot pushes the object to the target pose while actively avoiding a moving obstacle. After the robot starts pushing the object, we dynamically change the obstacle pose to intersect the object’s trajectory toward the target, thereby significantly increasing the complexity of the obstacle avoidance task. Fig. 6b – Fig. 6e show our system’s adaptive behavior, enabling the policy to successfully maneuver the object around the moving obstacle and reach the target pose. The supplemental video¹ clearly demonstrates this adaptive behavior, along with showing additional scenarios.

VI. CONCLUSION

In this paper, we presented a model-free RL approach for non-prehensile planar pushing in cluttered environments that leverages location-based attention for improved feature

¹<https://youtu.be/47B6VWEI0sA>

extraction. In contrast to the closest related approach [14], our framework does not require guidance from a global path and considers the target orientation of the manipulated object. By choosing to represent the clutter layout with an occupancy grid, the proposed system is highly adaptable to diverse environments and even dynamic changes in the environment configuration. Our experiments demonstrate that the learned policies achieve high success rate with minimal collisions, even in configurations with unseen obstacle shapes, and can be efficiently fine-tuned for more complex scenarios involving multiple obstacles. Finally, we evaluated the robustness of our approach in a physical hardware setup, demonstrating smooth and precise trajectories under various challenging clutter layouts, including dynamic obstacles.

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