Learning Robust Agents for Visual Navigation in Dynamic Environments: The Winning Entry of iGibson Challenge 2021

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Abstract—This paper presents an approach for improving navigation in dynamic and interactive environments, which won the 1st place in the iGibson Interactive Navigation Challenge 2021. While the last few years have produced impressive progress on PointGoal Navigation in static environments, relatively little effort has been made on more realistic dynamic environments. The iGibson Challenge proposed two new navigation tasks, Interactive Navigation and Social Navigation, which add displaceable obstacles and moving pedestrians into the simulator environment. Our approach to study these problems uses two key ideas. First, we employ large-scale reinforcement learning by leveraging the Habitat simulator, which supports high performance parallel computing for both simulation and synchronized learning. Second, we employ a new data augmentation technique that adds more dynamic objects into the environment, which can also be combined with traditional image-based augmentation techniques to boost the performance further. Lastly, we achieve sim-to-sim transfer from Habitat to the iGibson simulator, and demonstrate that our proposed methods allow us to train robust agents in dynamic environments with interactive objects or moving humans.

I. INTRODUCTION

To operate effectively in the real world, mobile robots must be able to skillfully navigate through their environment. For example, home assistant robots must be able to go from room to room in order to help humans with daily chores. But autonomous navigation is a difficult challenge that typically requires robots to understand and reason about its surroundings using visual sensors. Fortunately, several recent works have shown promising results using deep reinforcement learning (DRL) to successfully deploy robots that navigate in the real world [1], [2].

PointGoal Navigation [3] is a well-studied task, in which the agent is tasked to reach a target coordinate location in its environment. However, it typically assumes static environments without any dynamic obstacles, a far-cry from real homes and offices that may contain humans, pets, and small obstacles. To this end, the recent iGibson Challenge [4] at the 2021 CVPR conference was designed to encourage researchers to investigate two new tasks: Interactive Navigation (InteractiveNav) and Social Navigation (SocialNav). In InteractiveNav, the agent must reach the goal while pushing aside movable obstacles that obstruct the path. For SocialNav, the agent must avoid collisions with humans walking across the environment that may not yield.

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Fig. 1. Dynamic object data augmentation rendered in Habitat. During training, we add a population of moving pedestrians to the environment, who appear in agent’s egocentric depth camera (right). The agent must reason about their trajectories and dodge them, as a collision means episode failure.

These dynamic tasks impose new challenges previously unseen in static navigation settings. For InteractiveNav, the agent needs to distinguish moveable and unmovable objects, and learn how to push movable ones in the proper directions to form shorter paths to the goal. For SocialNav, the agent has to predict the trajectory of pedestrians and plan paths that avoid collisions. Furthermore, while there are large datasets for static 3D environments such as Gibson [5] and Matterport3D [6], datasets for dynamic environments that include properly arranged individually interactable furniture are much sparser; for iGibson Challenge 2021, only eight training and five evaluation scenes were available.

We present two key ideas for tackling these challenges: (1) large-scale reinforcement learning and (2) domain-specific data augmentation. First, we learn an agent using a large-scale reinforcement learning algorithm, DD-PPO [7], inspired by its near-perfect results on PointNav and ability to provide large batches of diverse experience through parallelization. Unfortunately, the iGibson simulator runs at approximately 100 frames per second (FPS) per simulator instance, which is too slow to scale to the hundreds of millions of steps of experience required for the performance shown in [7]. We thus propose to train our agents in Habitat simulator, which can run at 3,000 FPS per simulator instance [8]. We then demonstrate successful zero-shot sim-to-sim transfer of policies from Habitat to iGibson by achieving 1st place in the iGibson Challenge, despite the two using different rendering and physics engines. This suggests that our learned agents are robust, and opens a fruitful avenue for other researchers to pursue scalable experiments.

Second, we find training our agents with a domain-specific data augmentation technique in which we introduce a large number of dynamic pedestrians results in significantly more successful navigation policies even when evaluated on episodes containing only 0 to 3 dynamic pedestrians per house. This finding is surprising because it appears to be in
contrast with the conventional wisdom of matching training and test distributions. However, we explain this phenomenon by drawing an analogy to data augmentation techniques that are known to be highly successful in computer vision, where the input is purposely cropped, jittered, flipped, or corrupted to prevent the learner from picking up spurious correlations.

Our agent ranked 1st place in the InteractiveNav track of the iGibson Challenge, which demonstrates the effectiveness of the proposed sim-to-sim approach and domain-specific data augmentation technique. We further analyze the proposed method by evaluating it with various hyperparameters, such as the number of pedestrians, the number of scenes, and combination with other augmentation techniques. We show that our approach can train effective agents for dynamic environments, particularly with the limited number of scenes. Moreover, we show that this domain-specific augmentation technique is robust to distributional shifts in visual data, as it maintains good performance in a different simulator while the image-augmentation techniques do not.

II. RELATED WORK

A. PointGoal Navigation

PointGoal Navigation (PointNav), as formally defined in [3], is a task in which the robot must navigate from a start position to a goal coordinate in the environment. This is a challenging task to perform in the presence of obstacles, especially when the agent only has access to an egocentric camera and an egomotion sensor. This is the task setting used in several recent works that leverage deep reinforcement learning and photorealistic simulators [9], [10], [11], [12] to train agents to complete the task of PointNav successfully. Wijmans et al. [7] train a near-perfect PointGoal agent using only egocentric vision and an egomotion sensor via Decentralized Distributed Proximal Policy Optimization (DD-PPO). Other works [10], [13] also show that PointGoal Navigation could be solved via end-to-end training. However, these works use large amounts of training scenes, and do not study the effects of data augmentation on navigation performance; in this work, we focus on how our data augmentation technique can improve performance in scenarios in which only a small amount of scenes are available.

In this work, we utilize the DD-PPO framework to train our agents and the Habitat platform as our training simulator. We train a vision-based policy using egocentric depth vision and an egomotion sensor.

B. Navigation in Dynamic Environments

Though a vast amount of work on autonomous robot navigation exists, a very small subset of this research has focused on navigation that requires the robot to interact directly with elements in the environment. And while much of this work has studied how robots can open doors using manipulators, the recent work by Xia et al. [14] has introduced a new task in which the robot must instead interact with displaceable objects in order to reach the goal. This does not require the robot to use a manipulator; the robot can simply push past the objects using its base as it moves. The task that they introduce, InteractiveNav, evaluates how well the robot can balance taking the shortest path to the goal and how much it disrupts the obstacles present in the environment. The work in [14] showed that an agent can successfully learn to complete the task with deep reinforcement learning. In this work, we seek to investigate how such performance can be further improved using data augmentation techniques.

Additionally, the task of SocialNav, or visual navigation in the presence of dynamic humans, has recently received attention by researchers leveraging deep reinforcement learning (DRL) methods. However, earlier works using DRL such as [1] focus on spacious environments and do not use egocentric visual sensors for handling local interactions with humans. The recent work by Arpino et al. [15] is the most similar to ours, as they also tackle the task of SocialNav within constrained indoor environments using deep reinforcement learning. However, we do not use lidar data or motion planners in our approach.

C. Enhancing visual navigation performance

Several recent works have studied techniques to improve generalization to novel environments for visual navigation. Ye et al. [13] build upon DD-PPO [7] through the use of self-supervised auxiliary tasks, which proved to significantly improve sample efficiency. Sax et al. [16] incorporate visual priors about the world tp confer improve performance over training end-to-end from scratch. Chaplot et al. [17], [18] improve sample efficiency compared to typical end-to-end agents by having the agent infer information about mapping and localization, which can be supervised using privileged information from the simulator.

Unlike the works mentioned above, we propose a method that yields significant improvement without the use of additional auxiliary losses, extra heads to the network, or additional sensory information (e.g., local occupancy map). Our method also does not require tuning parameters for the reward function or other learning hyperparameters. In this work, we focus on data augmentation methods to improve how well our agent can generalize to new scenes for visual navigation, across various amounts of available training scenes. We study how these methods improve navigation both on their own and when combined with each other.

III. METHOD

A. Learning in A Scalable Simulator: Habitat

The simulator used for evaluation in the iGibson Challenge prioritizes using realistic physics to animate each of the many objects that collectively make up the environment, such as articulated doors, chairs beneath tables, and other pieces of furniture. Although a straightforward approach is to train agents in iGibson, we instead opt to train agents in Habitat [10] for its high performance parallel computing capabilities, relating to both simulation and synchronized learning. We believe that speed and scalability are high priority for training intelligent embodied agents with reinforcement learning, especially for the investigations presented in this work, in
In addition, we investigate Crop&Cutout relative to the original frame can be between \[0, 3 \times 3\] \[33\], and its scale relative to the original frame can be between \[0.02, 0.33\]. In addition, we investigate Crop&Cutout, which applies Crop and Cutout sequentially.

**Domain-specific Data Augmentation.** To this end, we introduce an additional data augmentation technique (illustrated in Figure 1) which rather than adding noise to image observations, leverages the capabilities of the simulator to add more dynamic obstacles to the scene. Our intuition is that this domain-specific technique can improve the robustness of the agent for visual navigation, even for static environments used in PointNav; by forcing the agent to predict trajectories for both itself and the dynamic obstacles in the environment in an effort to reach the goal without any collisions, the agent learns to use its visual data to gain a better understanding of the spatial layout of its environment. As we explain later, this is shown by the fact that this method produces successful agents in previously unseen scenes, even in data-constrained training configurations, in which the amount of training scenes is low (1-2 apartments).

In our experience, adding more dynamic objects, such as pedestrians, generates even more variances in depth camera images than adding stationary objects. Further, this domain-specific data augmentation is effective even in tandem with other image-based data augmentation techniques, and allows us to achieve performance better than any other combination of image-based transformations. We investigate combinations of different augmentation techniques in Section V.

During training, each dynamic object is represented by a 3D model of a human from the iGibson Challenge [4], which we have found to be sufficiently large while having a small enough radius for the agent to maneuver around. For each of these pedestrians, two navigable points that are at least 3 meters apart are randomly sampled from the environment, and the pedestrian moves back and forth along the shortest path connecting these points. It has the same maximum linear and angular speed as the agent, but its speed is randomly decreased from the maximum value by up to 10% on a per-episode basis. Different pedestrians within the same episode can be moving at different velocities.

**C. Problem Formulation and Learning Method**

**Observation and Action Spaces.** The policy takes as inputs a depth image and its relative distance and heading to the goal point; the latter is derived from the agent’s egomotion sensor, which indicates its relative distance and heading to its initial position. We do not use RGB data, as Wijmans et al. [7] has shown that including it can hurt performance. The policy outputs a two-dimensional diagonal Gaussian distribution, from which a pair of actions are sampled (linear and angular velocity). The maximum speeds are 0.5 m/s and 90\(^{\circ}\)/s, and the policy is polled at 10 Hz. If the magnitude of the velocities are below a certain threshold (10% of their maximum values for our experiments), it is perceived as the agent invoking a stop action, which terminates the episode.

**Reward Function.** The reward function that we use when training our agent is the same whether it is being trained with or without dynamic pedestrians in the scene. The definition is as follows:

\[
 r(a_t, s_t) = -\Delta_d - w_1 - w_2(I_{back} + I_{col}) + w_3 I_{suc},
\]
Fig. 3. Five frames from an example navigation episode of training with six dynamic pedestrians. Red denotes the pedestrian trajectories, while blue denotes the agent’s trajectory. In this episode, the agent arrives at the destination without any collisions with the six pedestrians.

where \( -\Delta_d \) is the change in geodesic distance since the previous state, and \( I_{\text{back}}, I_{\text{col}}, \) and \( I_{\text{suc}} \) are binary flags indicating whether the agent has moved backwards, collided with the environment, or terminated the episode successfully (based on the criteria in the following subsection), respectively. The weights \( w_1, w_2, \) and \( w_3 \) are set to 0.002, 0.02, and 10.0 for all experiments. We penalize backward motion since we have observed that it often leads to poor visual navigation performance. However, we do not prevent it altogether, as backward movement can be helpful for avoiding an incoming obstacle that suddenly appears into view.

**Success Criteria.** For all tasks, episodes are considered successful only if the agent both (1) invokes a stop action that terminates the episode, and (2) the agent is within 0.2 m of the goal point. Episodes are terminated and deemed unsuccessful after 500 steps, or if the agent collides with a dynamic pedestrian either for SocialNav or when training with our augmentation method. A collision occurs if the agent is within 0.3 m of the pedestrian.

**Network Architecture and Training.** Our network architecture has two main components; a visual encoder and a recurrent policy. The visual encoder is a convolutional neural net based on ResNet-18 [21], and takes the depth image as input. The policy is a 2-layer LSTM [22] with a 512-dimensional hidden state. As input, it takes the visual encoder’s features, the relative distance and heading to the goal, the previous action, and the previous LSTM hidden state. In addition to a head that outputs actions, the policy has a critic head that outputs an estimate of the state’s value, which is used for reinforcement learning as described in [7].

We use Decentralized Distributed Proximal Policy Optimization by Wijmans et al. [7] to train our agents, and use the same learning hyperparameters. We use 8 GPUs to train 8 copies of the agent per GPU, for a total of 64 parallel workers. Each agent is trained for 500M steps (~280 GPU hours, or ~35 hours wall-clock).

IV. EXPERIMENTAL SETUP

**A. Simulator and dataset**

We configure Habitat to match the simulation configuration of the iGibson Challenge. In particular, the agent’s maximum linear and angular velocities are the same, the agent’s height and radius are modeled after the LoCoBot platform [23], and the policy is polled at the same frequency. Though our entry to the iGibson Challenge featured an agent trained on the small iGibson dataset of eight apartments imported into Habitat, we center this work on the Gibson-4+ dataset [10] instead, in order to investigate the impact our method has across both large and small amounts of available training scenes. Gibson-4+ contains 86 high-quality 3D scans and meshes curated manually from the much larger Gibson dataset [5]. The full training split contains 3.6M episodes distributed across 72 scenes, while the validation split contains 994 episodes across 14 scenes. When using less than 72 scenes for training, we reduce the amount of scenes through random selection of scenes to remove. Each subset of scenes we consider (e.g., 1, 2, or 4 scenes) is a superset of the sets that contain less scenes; in other words, the set of 8 scenes contain all scenes from the sets containing 4, 2 and 1 scenes, and so on.

**B. Evaluation Details**

During evaluation, the agent’s behavior was set to be deterministic for reproducibility, by sampling only the means from the policy’s output Gaussian action distribution. We trained each agent configuration three times using different seeds. For each seed, the checkpoint that yielded the highest success rate on val1 was selected, and reported evaluation metrics are based on that checkpoint’s performance on val2.

There are no pedestrians present during PointNav evaluation, and three pedestrians for SocialNav evaluation. For InteractiveNav, objects from the YCB dataset [24] are placed on the shortest path from the start to the goal spaced 0.5 m apart.

**C. Evaluation Metrics**

We use success rate as our primary evaluation metric. Apart from that, to evaluate InteractiveNav performance in
iGibson, we use Success weighted path length (SPL) [3], as well as Effort Efficiency and Interactive Navigation Score (INS) [4], [12] as our evaluation metrics. Effort Efficiency penalizes excessive displacement and forces that are applied to movable obstacles, while INS is an average of Path Efficiency (SPL) and Effort Efficiency. INS was used as the primary metric performance for InteractiveNav in the iGibson Challenge.

V. RESULTS

In this section, we evaluate the performance of our approach of large-scale reinforcement learning with domain-specific data augmentation for visual navigation tasks. We design the experiments to answer the following questions:

1) Can we learn successful navigation agents using large-scale reinforcement learning and sim-to-sim transfer?
2) Does our domain-specific data augmentation improve navigation performance?
3) Can our method be successfully combined with other image-based data augmentation techniques, or be robust to sim-to-sim transfer?

### TABLE I

**POIN NAV (0 PPL) SUCCESS RATES**

| # of train scenes | # of dynamic pedestrians during training | 0 ppl | 3 ppl | 6 ppl | 12 ppl | 18 ppl |
|-------------------|----------------------------------------|-------|-------|-------|--------|--------|
| 1                 | 74.93 ± 1.91                          | 73.90 ± 2.36 | 78.64 ± 1.76 | 76.53 ± 2.65 | 78.12 ± 0.57 |
| 2                 | 81.41 ± 2.03                          | 80.85 ± 1.30 | 81.22 ± 0.89 | 81.69 ± 1.17 | 82.86 ± 2.16 |
| 4                 | 82.39 ± 0.87                          | 86.15 ± 0.87 | 84.37 ± 1.79 | 84.32 ± 2.07 | 85.77 ± 0.61 |
| 8                 | 87.89 ± 1.31                          | 91.41 ± 0.86 | 88.97 ± 1.65 | 90.99 ± 1.52 | 89.44 ± 0.34 |
| 16                | 91.60 ± 1.68                          | 90.99 ± 0.98 | 91.69 ± 0.53 | 92.07 ± 0.81 | 91.69 ± 0.70 |
| 32                | 90.80 ± 0.78                          | 92.68 ± 0.40 | 93.90 ± 0.65 | 92.68 ± 1.33 | 92.39 ± 0.69 |
| 64                | 94.84 ± 1.90                          | 95.26 ± 0.46 | 93.43 ± 1.16 | 94.93 ± 0.83 | 94.08 ± 0.61 |

### TABLE II

**SOCIAL NAV (3 PPL) SUCCESS RATES**

| # of train scenes | # of dynamic pedestrians during training | 3 ppl | 6 ppl | 12 ppl | 18 ppl |
|-------------------|----------------------------------------|-------|-------|--------|--------|
| 1                 | 65.26 ± 2.47                          | 68.78 ± 2.35 | 65.40 ± 3.77 | 68.40 ± 2.26 |
| 2                 | 68.97 ± 0.96                          | 69.20 ± 2.92 | 72.68 ± 2.03 | 71.31 ± 1.66 |
| 4                 | 74.60 ± 1.45                          | 77.32 ± 0.64 | 76.10 ± 0.24 | 75.77 ± 1.52 |
| 8                 | 80.38 ± 1.27                          | 80.89 ± 1.94 | 79.91 ± 3.37 | 78.64 ± 1.04 |
| 16                | 83.00 ± 1.37                          | 83.71 ± 0.59 | 82.96 ± 2.61 | 80.47 ± 0.63 |
| 32                | 84.04 ± 1.09                          | 84.41 ± 0.74 | 83.99 ± 1.29 | 81.27 ± 0.87 |
| 64                | 85.26 ± 1.27                          | 84.79 ± 1.33 | 86.43 ± 1.75 | 83.10 ± 2.93 |

**A. Number of pedestrians vs. number of training scenes**

We evaluated the performances of various training configurations with different numbers of training scenes and different numbers of dynamic pedestrians present during training. Table I represents the success rates for PointNav, while Table II shows the success rates for SocialNav. We did not evaluate agents trained with zero pedestrians for SocialNav due to their inability to adapt to the presence of dynamic objects, which led to poor performance.

Both results showed that making the environment more dynamic improves performance, as the best performance is achieved when more dynamic pedestrians were present in the training environments (PointNav: >3, SocialNav: 6–12). The results of SocialNav evaluation indicates that performance peaks when the agent is trained with 6 to 12 pedestrians in the environment.

Furthermore, both tables showed that the performance gains provided by our technique are more substantial with a small number (<8) of training scenes. The significant improvements in performance our method confers for the task of PointNav, in which no dynamic objects exist during evaluation, implies that our method is improving performance as a result of better generalization to unseen scenes. These gains were more significant than the gains observed when more (>16) training scenes were available. Therefore, we conclude that our data augmentation is more effective when few training scenes are available, such as the scenario imposed by the iGibson Challenge.

### B. Comparison with image augmentation methods

![Fig. 4. Heatmaps comparing augmentation methods when trained with 8 scenes. Our augmentation method can further increase performance gains when combined with image augmentation methods, while combining image augmentation methods decreases performance. Mean over three seeds.](image)

In this section, we compare our technique against image augmentation techniques, **Crop** and **Cutout**, as defined in Section III-B. To narrow the scope of our investigation, we only used agents trained with eight scenes. When testing with our augmentation method, six pedestrians were used during training. When not testing with our method, agents were trained with zero pedestrians for PointNav, or three pedestrians for SocialNav. As shown along the diagonal cells of Figure 4, **Crop** and **Cutout** are competitive with our method when each are used alone, with **Cutout** outperforming our dynamic object augmentation by a slight margin.

We also evaluated the effects of combining the augmentation techniques. When training with deep reinforcement learning, applying different data augmentation techniques in conjunction does not necessarily improve performance over a single isolated technique. For example, in [19], Laskin et al. showed that random cropping, when not combined with any of the other several data augmentation techniques tested, performed the best on the DMControl500k Walker environment [25]. However, as shown in Figure 4, when our technique was combined with **Crop** and **Cutout**, it did not experience a drop in performance, and instead conferred further improvement to the success rate. In contrast, we
observed that combining Crop and Cutout leads to worse performance than using Cutout alone.

C. Sim-to-sim transfer for iGibson InteractiveNav

Though we can evaluate our agents for PointNav and SocialNav in Habitat, emulating the InteractiveNav task in Habitat requires a large amount of engineering and remained out of our reach despite prolonged effort. Instead, we evaluated the agents trained in Habitat directly in iGibson. This is the same approach we used to win the iGibson Challenge.

As in the previous section, all agents were trained with eight Habitat scenes, and those trained with our augmentation method were trained with six pedestrians (no pedestrians otherwise). We evaluated our agents in the eight iGibson scenes from the training set for the InteractiveNav task. Currently, the evaluation set from the iGibson Challenge is not public.

As shown in Table III, while all data augmentation methods improve performance, our dynamic object augmentation did so by the greatest amount (~11% more success). Notably, compared to the results from the previous subsection, the results yielded by the image augmentation methods have become much less competitive with our dynamic method. In fact, when using Crop or Cutout in conjunction with our method, performance is actually slightly reduced. Whereas Cutout by itself conferred one of the highest gains in performance in the previous subsection, it now provides the least gains over the baseline, beating only Crop&Cutout.

We attribute this to the visual gap between the iGibson scenes and the Gibson-4+ scenes that our agents were trained on; Gibson-4+ scenes are collected from the real world using a 3D camera and may contain some irregularities or artifacts, whereas iGibson scenes are completely synthetic, comprised wholly by 3D computer-aided design (CAD) files made by artists, and thus contain no artifacts and much cleaner surfaces and edges (see Figures 1 and 5 for comparison). Because image augmentation methods such as Crop and especially Cutout encourage the agent to infer the removed information from the remaining context available in the visual input, we believe that the agents trained with these methods are more sensitive to changes in how that context is represented visually. This is because these image-based augmentation methods are not designed to accommodate shifts in the image distribution. In contrast, our method is more robust to the shift from Gibson-4+ to iGibson scenes, and continues to provide substantial performance gains despite the sim-to-sim transfer. We attribute this to the fact that we use a domain-specific approach to data augmentation rather than image-based, in which we aim to encourage the agent to learn a better spatial understanding of its surroundings rather than learn to recover from perturbations to its input from the existing visual context.

We note that while the Effort Efficiency of the best agent is high, its INS score is significantly lowered due to its low SPL score, which denotes that the agent took longer paths. To achieve higher INS, we plan to investigate in future work how our augmentation method (which prioritizes collision avoidance) can be better balanced so the agent is encouraged to collide with movable obstacles to open much shorter paths to the goal, without excessively lowering Effort Efficiency.

VI. CONCLUSION AND FUTURE WORK

In this work, we propose a set of techniques to improve the performance of visual navigation in dynamic scenarios with interactable objects or moving pedestrians. Our first idea is to use large-scale reinforcement learning by leveraging a Habitat simulator, which is 30 times faster than iGibson and highly scalable. In addition, we train a more robust agent using the domain-specific data augmentation of adding more pedestrians to environments. We show that our approach can learn effective agents from a large scale of data while overcoming the sim-to-sim gap. We also demonstrate that the proposed domain-specific data augmentation can improve the agents’ performance in all three tasks, PointNav, InteractiveNav, and SocialNav, even when training scenes are scarce.

There are several directions in which our work can be extended. We suspect that while using dynamic pedestrians can boost performance, overcrowding can make the agent overly conservative and result in suboptimal behaviors. In the future, we plan to introduce curriculum learning to gradually increase the number of pedestrians during training, in order to find or potentially increase the number of pedestrians that will maximize performance.

We also plan to investigate sim-to-real transfer of the proposed technique by deploying it to real-world with pedestrians. However, we expect that the sim-to-real gap will lead to significant drops in performance, especially since the pedestrians that we use within the simulator are single rigid bodies (i.e., limbs are not independently animated). This could be addressed by adding more realistic motions and gestures for simulated humans to reduce the sim-to-real gap.
