RealAnt: An Open-Source Low-Cost Quadruped for Research in Real-World Reinforcement Learning

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Abstract—Current robot platforms available for research are either very expensive or unable to handle the abuse of exploratory controls in reinforcement learning. We develop RealAnt, a minimal low-cost physical version of the popular ‘Ant’ benchmark used in reinforcement learning. RealAnt costs only ∼350 € ($410) in materials and can be assembled in less than an hour. We validate the platform with reinforcement learning experiments and provide baseline results on a set of benchmark tasks. We demonstrate that the TD3 algorithm can learn to walk the RealAnt from less than 45 minutes of experience. We also provide simulator versions of the robot (with the same dimensions, state-action spaces, and delayed noisy observations) in the MuJoCo and PyBullet simulators. We open-source hardware designs, supporting software, and baseline results for ease of reproducibility.

I. INTRODUCTION

The field of reinforcement learning (RL) has advanced significantly in recent years, with numerous success stories in solving challenging control problems. This is largely due to the availability of simulators that allows for rapid testing of algorithmic performance, which are inexpensive, fast, and can be run in parallel. However, simulators often make unrealistic assumptions about the world. For example, the popular simulator benchmarks for RL [1]–[3] present no communications delays or noise, have simple dynamics, allow for environment resets, and have no concerns about the safety or durability of the robot hardware [4]. We have to bridge this gap by grounding the development of reinforcement learning on real-world problems such as robot learning.

Most research on robotics is conducted on industrial robots that are very expensive, costing thousands of dollars. This is not very affordable to all researchers. Traditional control algorithms require precise hardware that is easy to model. This places a lot of limitations on robot design. Reinforcement learning algorithms are able to learn controllers without modeling the dynamics and can also handle noisy observations and controls. However, aggressive exploratory actions taken by RL algorithms can easily damage the components of a robot. For example, plastic gears in RC servos or naively designed 3D parts can easily break during learning. In this paper, we present a minimal low-cost quadruped robot that can sustain research in reinforcement learning.

We develop and validate RealAnt, a physical version of the popular Ant benchmark available in OpenAI Gym [1], DeepMind Control Suite [2], and PyBullet [3] simulators.

The contributions of this paper are as follows. (i) We develop a low-cost minimal quadruped robot called RealAnt, a physical version of the popular Ant benchmark used in reinforcement learning research. (ii) We develop the supporting software stack to perform RL on the physical platform. We also provide simulated versions of the RealAnt robot (with same dimensions and state-action spaces, and delayed noisy observations) in PyBullet and MuJoCo simulators for rapid testing. (iii) We validate that the robot is suitable for real-world RL research, propose three benchmark tasks, and report baseline results on these tasks using TD3 and SAC algorithms. Hardware design, supporting software, RL baselines, and a video of learned gaits are available here: https://github.com/AaltoVision/realant-rl/
TABLE I
BILL OF MATERIALS GROUPED INTO CORE ROBOT PARTS, TRACKING EQUIPMENT, AND A WIRELESS EXTENSION PACKAGE.

| COMPONENT                        | QTY | UNIT PRICE (€) | TOTAL PRICE (€) |
|----------------------------------|-----|----------------|-----------------|
| Dynamixel AX-12A servos          | 8   | 40             | 320             |
| OpenCM9.04-A microcontroller     | 1   | 10             | 10              |
| OpenCM9.04 accessory set         | 1   | 6              | 6               |
| 3D printed parts                 | —   | —              | 3               |
| Screws and cables                | —   | —              | 15              |
| Total                            |     |                | 354             |

| Track                            |     |                |                 |
|----------------------------------|-----|----------------|-----------------|
| Web cam (e.g., Logitech Brio 4K) | 1   | 250            | 250             |
| Printed tags on office paper      | 1   | 1              | 1               |

| Wireless                         |     |                |                 |
|----------------------------------|-----|----------------|-----------------|
| Bluetooth-serial converter HC-06  | 1   | 9              | 9               |
| LiPo battery 4S 3.3Ah            | 1   | 30             | 30              |
| LM2596 12V buck converter        | 1   | 2              | 2               |
| Low voltage buzzer               | 1   | 3              | 3               |

Fig. 2. Schematic details of the RealAnt robot (all units in millimeters).

II. RELATED WORK

Scalable low-cost robot platforms can enable a plethora of real-world applications like last-mile delivery and automate highly repetitive manually laborious tasks like object stacking. The robotics community is actively working towards more affordable robots, and in this section, we review recent works on low-cost platforms for robotics research.

Recent works have proposed designs for affordable quadruped robots. The MIT mini-cheetah [7], costing around $10k, is a small quadruped robot that can perform a wide range of locomotion behaviors. Solo [8], costing around 4k €, is an open-source, lightweight, and torque-controlled quadruped robot based on low complexity actuator modules using brushless motors. Stanford Doggo [9], costing less than 3k €, is an open-source quadruped robot based on a quasi-direct-drive mechanism. While these robots are designed for motion planning controllers, we propose RealAnt, costing less than 500 €, with a focus on research in real-world reinforcement learning. Unlike other available quadruped robots, RealAnt is designed as a direct analogy of the popular Ant benchmark.

Similar to RealAnt, ROBEL [10] is a recently introduced open-source platform for benchmarking real-world reinforcement learning. The ROBEL platforms consist of two robots: D’Claw and D’Kitty, for manipulation and locomotion tasks respectively. D’Kitty is a a 12 DoF quadruped robot, costing around $4.2k, with Dynamixel XM430-W210-R smart actuators. RealAnt is significantly cheaper as it is an 8 DoF robot with cheaper Dynamixel AX-12A servos. While D’Kitty relies on a HTC Vive Tracker setup (costing more than 500 €) for pose estimation, we use simple fiducial marker tracking (only requiring a web camera) for the same. Being so cheap, it is possible to build more than ten RealAnt robots at the cost of a D’Kitty, enabling scalable and broader real-world experiments.

While there exist cheap quadruped robots, mostly proposed for educational purposes, they were not designed to sustain the abuse of reinforcement learning. Reinforcement learning involves aggressive exploratory actions that can easily damage the servos or the 3D printed body of the robot. We validate that the proposed RealAnt robot can sustain such aggressive actions.

Wheeled robots tend to be more affordable. Examples of such research platforms include Donkey car, DeepRacer [11], JetBot, DuckieBot [12] and their costs fall in the range of $250 to $500. RealAnt enables research in contact-rich legged locomotion in a similar affordable cost range.

There has also been progress in reducing the cost of robot platforms for manipulation tasks. Recent works [13], [14] have proposed such platforms in the cost range of $2k to $5k. REPLAB [15], costing around $2k, is an easily reproducible benchmark for vision-based manipulation tasks.

Compared to existing solutions, RealAnt a direct analogy of the popular Ant benchmark, and is hence well suited for bridging the gap to real-world applications of RL.

III. REALANT

We design RealAnt, a minimal and low-cost physical version of the Ant benchmark for research in real-world reinforcement learning. Similar to the Ant benchmark, RealAnt is an 8 DoF quadruped robot (see Fig. [1] for a photo). RealAnt is based on easily available electronic components and a 3D printed body. List of all components used in RealAnt and their costs are in Table I. The RealAnt can be assembled from these components in less than an hour, by using a Phillips screwdriver, side cutters, and a soldering iron.

A. Mechanical Design

The minimally designed body of the robot consists of 1) four 3D printed legs, 2) eight Dynamixel AX-12A servos (and eight FP04-F2 frames sold with them), and 3) a 3D printed top and bottom torso. Each leg of the robot constitutes of two Dynamixel servos joints affixed to each other using Robotis FP04-F2 frames. Four of the leg assemblies are joined together using a 3D printed torso top and bottom plates. 3D printers are easily accessible and allows for rapid prototyping and cost-effective manufacturing. The schematic details are illustrated in Fig. [2].

The parts were printed in PLA (Prusament filament) using a consumer 3D printer (Creality Ender 3 v2). A complete set
of parts requires 13.5 h to print, for two torso plates and four legs. To lower the printing time and produce rigid enough parts, they were printed using 0.2 mm layer height, 20% gyroid [16] infill, and with open top and bottom layers. The printed parts weigh 106 g in total, costing \( \sim 2.5 \text{ } € \) in filament costs, assuming a filament price of 25 €/kg. The total robot weight is around 710 g.

Economical servo motors are challenging to use in an RL setting. The random actuation and hard hits to the floor can wear and break down the small gears in servo gearboxes. Also in long continuous operation under load, some servos tend to overheat and break. To overcome these issues, we designed the legs short and the platform lightweight enough to reduce sharp jerks, and we opted to do 10-second episodes, and let the servos cool down in a detached mode between the episodes for around 6 seconds. Also, in software, we limited the maximum torque of the servo motors to half.

Initially, we used high-torque RC hobby servos (such as Turnigy TS-910) for trials, but Robotis Dynamixels were eventually selected for the design due to their longevity in testing, owing mostly to adjustable torque limits, in-built temperature sensors, and overall build quality.

B. Electrical Design

For a simple and reliable experimental setup, we use an external lab power supply and directly control the robot using a wired USB connection from a computer. Both the USB and power wires are connected to the OpenCM9.04 microcontroller board. The leg servos are daisy-chained and each leg is connected to one of the four 3-pin servo ports on the board. Alternatively, a LiPo battery, a buck DC-DC voltage converter, a low battery voltage buzzer and a Bluetooth serial converter can be used for completely wireless operation without using wired power and data cables.

C. Pose Estimation

The state of the Ant robot involves the 6 DoF pose of the robot and this information is also necessary to derive reward functions for reinforcement learning. For example, the reward used in the simulated Ant benchmark is the forward velocity of the robot. We rely on augmented reality (AR) tag tracking using ArUco tags and the OpenCV version of the popular ArUco library [17]–[19] for pose estimation by detection of square fiducial markers. The tags are printed on A4 office paper and glued to cardboard for rigidity. We attach the tracking tag to the top of the robot body. We use a Logitech Brio 4K web camera and place a frame reference tag within the camera view. The camera model is calibrated by taking pictures of a chessboard pattern.

Using a consumer web camera for the position estimation can be challenging, due to camera latency and frame timing jitter. The latency can be as long as several hundred milliseconds, and frame timing jitter considerable. Using the Logitech Brio 4K web camera with 1280 × 720 resolution at 60 fps, we measured latency of around 110 ms. This latency requires a robust RL approach and is accordingly added and tested in the simulation model.

We also mount two 50W, 3800-lumen rated LED floodlights (costing 35 € each), approximately 1m above the floor, pointing downwards, so that the measured illuminance at floor level is approximately 3000 lux. Good illuminance is important so that shutter times with the webcam are short enough for precise positioning even when there is fast motion, so that the tracking is not lost due to motion blur.

Tag-based pose estimation is noisy, and deviates even more so. As velocity estimation is important in our tasks as a reward signal (see Sec. [V]), we used Holoborodko’s smooth noise-robust differentiator [20] to improve the velocity estimates. Furthermore, as the web camera is positioned on top of the tags, the z (depth) axis measurement is very noisy. We additionally smoothed this with a lowpass filter. We also add and test this estimation noise in our simulation model.

D. Software Design

We provide supporting software for the RealAnt platform so that it can be easily used and our experiments easily reproduced.

We decouple the software into three hierarchical processes: 1) a training client, 2) a rollout server, and 3) a control process. These processes communicate using ZeroMQ. The training client controls the whole learning process. It sends the latest policy weights to the rollout server at the beginning of each episode. The rollout server loads the policy weights, collects the latest observations from the control process, and sends the action computed using the policy network back to the control process. The control process continuously collects servo measurements from the microcontroller and the pose estimation from web camera (much like a lightweight ROS environment) and publishes them to the rollout server. It also subscribes to actions from the rollout server and applies them to the robot through the microcontroller. After completing an episode, the rollout server sends back the collected data to the train client. The newly collected data is added to a replay buffer and the agent is updated a few times by sampling from this replay buffer. Decoupling of these processes allow them to run seamlessly in different machines. For example, the data collection (with rollout server and control process) can be performed on a low-end computer and training can be performed on a high-end computer.

The rollouts were done on a 2019 MacBook Pro 16” laptop, which was attached to the RealAnt board and to the webcam. Training was done on a Linux desktop machine equipped with an Nvidia GTX1080 GPU. One episode cycle took approximately 16 s wall clock time, including rollout and training. Between the rollouts, the robot was moved manually to a starting position, if necessary.

Based on our hardware design, we provide simulated versions of the robot on PyBullet and MuJoCo simulators, for rapid testing and development. The simulated robot has the same physical dimensions, state-action spaces, and roughly the same dynamics. We find that MuJoCo simulation is more stable and easy to modify while the PyBullet simulator is free and easily accessible. We run our experiments on both simulators for ease of reproducibility.
IV. REINFORCEMENT LEARNING

Reinforcement learning problems are often formalized as Markov decision processes (MDPs). An MDP consists of: a set of states $S$, a set of actions $A$, a transition probability function $s_{t+1} \sim p(\cdot|s_t, a_t)$ that represents the probability of transitioning to a state $s_{t+1}$ by taking action $a_t$ in state $s_t$ at timestep $t$, a reward function $r_t = R(s_t, a_t)$ that provides a scalar reward for taking action $a_t$ in state $s_t$, and a discount factor $\gamma \in [0, 1]$ to specify the weighing of future rewards.

The policy $\pi$ of a reinforcement learning agent is a mapping from observations to actions and defines the behavior of the agent. The state value function $V_\pi(s)$ of a policy $\pi$ is defined as the expected cumulative rewards from state $s$: $V_\pi(s) = E[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)|s_0 = s]$, where the expectation is taken over state transitions $s_{t+1} \sim p(\cdot|s_t, a_t)$ and policy function $a_t \sim \pi(s_t)$. The goal in RL is to learn an optimal policy function $\pi_\theta$ with parameters $\theta$, that maximizes the expected cumulative rewards, that is, $\arg\max_\theta V_{\pi_\theta}(s)$ for every $s \in S$.

In value-based actor-critic methods for RL, a critic network $Q_\phi$ is used to estimate the $Q^\pi(s, a)$ values (the expected cumulative rewards after taking action $a$ in state $s$) of the actor/policy network $\pi_\theta$. The critic network is trained to satisfy the Bellman equation: $Q^\pi(s_t, a_t) = r_t + \gamma Q^\pi(s_{t+1}, \pi_\theta(s_{t+1}))$, by sampling $(s_t, a_t, r_t, s_{t+1})$ transitions from a replay buffer. The actor network is trained to estimate a $Q$-optimal policy $\pi_\theta(s) = \arg\max_a Q_\phi(s, a)$.

We use the state-of-the-art TD3 [21] and soft actor-critic (SAC) [6], [22] algorithms in this paper. Function approximation in value-based RL algorithms is known to lead to overestimation of values and hence a sub-optimal policy [21]. TD3 deals with this by taking the minimum value between a pair of critic networks and also delaying the actor updates. SAC, based on the maximum entropy RL framework, uses a stochastic policy network that aims to maximize the cumulative rewards while also maximizing the entropy of the policy. SAC also makes use of the twin-critic technique proposed in TD3.

V. BENCHMARK TASKS

In this section, we define the MDP specifics of the robot including the observation and action spaces. We then introduce three benchmark tasks used to evaluate RL on the simulator and the physical platform.

We use an episodic formulation of reinforcement learning. Each training session is split into episodes lasting 200 steps. We manually reset the robot to the starting position of the task before each episode. We use a control frequency of 20Hz and each episode corresponds to 10 seconds of experience.

The 8-dimensional action space of the RealAnt robot defines the set-point for the angular position of the torso joints. The observation space of RealAnt is computed from 6D pose estimates and joint positions. The 3D positions ($x$, $y$, and $z$) and 3D angles (roll $\alpha$, pitch $\beta$, and yaw $\gamma$) of the torso are obtained from pose estimation using AR tag tracking. The torso velocities are computed using differences of consecutive pose estimates. The angular positions and velocities of the joints are obtained from the joint servos. The 29-dimensional observation space of the RealAnt robot consists of:

1) $x$, $y$, and $z$ velocities of the torso (3),
2) $z$ position of the torso (1),
3) $\sin$ and $\cos$ values of Euler angles of the torso (6),
4) velocities of Euler angles of the torso (3),
5) angular positions of the joints (8), and
6) angular velocities of the joints (8).

The three benchmark tasks introduced below share the same observation and action spaces. Only the reward functions are different.

a) Stand / Sleep: This is a very simple task that involves attaining a goal torso height ($z_g$). That is, $R(s_t, a_t) = -\|z_t - z_g\|^2$, where $z_t$ is the $z$ position of the robot torso at timestep $t$. In the simulator, the robot starts each episode standing upright and the goal is to sleep (that is, $z_g = 0$) and in the physical experiments, the robot starts each episode lying down and the goal is to stand upright (that is, $z_g = 0.12$).
b) Turn: This task involves the robot turning 180° to face the other direction. Each episode starts with the robot lying down. The robot has to balance itself and coordinate all joints to turn the whole body around. The initial yaw $\gamma_0$ of the robot is 0 and the goal in this task is to rotate to a yaw of 180° or 3.14 radians. The rewards are computed based on this angular distance:

$$R(s_t, a_t) = -\|\gamma_t - 3.14\|^2.$$ 

This challenging task can also be used to ensure that pose estimation and tracking is accurate.

c) Walk: This task is the same as for the original Ant benchmark used in simulated RL experiments: learning to walk forward as fast as possible. Each episode starts with the robot lying down. This challenging task involves the robot coordinating all its joints to walk forward as fast as possible. The reward in this task is the forward velocity of the robot:

$$R(s_t, a_t) = \dot{x}_t,$$

where $\dot{x}_t$ is the velocity of the robot along the $x$ axis.

VI. EXPERIMENTS

We begin each training session with ten episodes of data collected using a random policy. We alternate between data collection and training for every episode. We perform 200 learning updates of the learning algorithm at the end of each episode. We use the Adam optimizer (learning rate 0.0003).

We use fully-connected networks with dense connections for our policy and value networks. As reported in [23], we find that dense connections (concatenation of network inputs to the input of each layer) enable stable training of deeper networks, which allows for improved sample-efficiency. We use dense connections, three hidden layers, and 256 hidden units for our policy and value networks.

Reinforcement learning on the physical robot has to inevitably deal with latencies and noise in the observations. This makes the environment non-Markovian. To deal with this, we construct the robot state (to be used by the RL algorithm) by stacking the past four observations. Note that noise in the observations also leads to noisy rewards, which makes learning even more challenging. We introduce such noise and delays into the simulator environments to better match real-world conditions.

A. Results on Simulator

We first test the state-of-the-art SAC and TD3 algorithms on the simulated versions of our RealAnt robot. The results of our experiments on the MuJoCo simulator are shown in Fig. 3. We observe that TD3 performs similarly to SAC in the turn task and significantly outperforms SAC in the sleep and walk tasks. We also test the RL algorithms on the PyBullet simulator. RL algorithms are able to exploit the instabilities of the PyBullet simulator, and we only test on the walk task. The results of our experiments are shown in Fig. 4. Similar to our observations in experiments on the MuJoCo simulator, we find that TD3 performs better than SAC.

B. Ablation Studies on Simulator

Since TD3 works better than SAC in our experiments, we use TD3 for ablation studies and physical experiments. Real-world experiments inevitably consist of delays and noise. The pose estimation and tracking used in robots are usually noisy. We study the effect of such delays and noise on the learning efficiency of TD3. We use the MuJoCo simulator for these ablation studies.

1) Effect of tracking latency: We test the effect of tracking latency by delaying the observation of body position and orientation values in the simulator. To deal with this latency, we simply stack observations from past steps (larger than latency). The results of our experiments are shown in Fig. 4. We find that observation stacking is able to effectively deal with even significant delays of 10 steps or 500 ms.

2) Effect of tracking noise: We test the effect of tracking noise by adding different levels of noise to observations of body position and orientation values. The results of our
C. Results on Physical Robot

In this section, we validate the RealAnt robot by evaluating the best performing TD3 algorithm on the three proposed benchmark tasks of stand, turn, and walk. We use the same network architecture (with dense connections) and hyperparameters as in our simulator experiments. The results of our experiments are shown in Fig. 5. We are able to successfully learn all three tasks from 250 episodes or 40 min of real-world experience. An example of a learned walking gait and a turn is shown in Fig. 6.

VII. CONCLUSIONS AND FUTURE WORK

We introduce a very low-cost and minimal robot platform called RealAnt, for real-world research in reinforcement learning for legged locomotion. RealAnt is based on the Ant benchmark that is very familiar to researchers in RL, allowing for straightforward testing of existing models and algorithms. We provide the supporting software to perform RL research on RealAnt. We validate the robot with RL experiments on three benchmark tasks and demonstrate successful learning using TD3 and SAC algorithms. Model-based RL algorithms have demonstrated significantly better sample-efficiency on the simulated Ant benchmark [24], [25]. However, such algorithms also require significantly more computational resources, and testing them on RealAnt is a line of future work.

We found that off-the-shelf tracking cameras such as Intel RealSense T265 are highly sensitive to the high-frequency vibrations in legged robots like RealAnt, leading to significant drift in tracking. Visual-inertial odometry algorithms that are robust to such vibrations can be used for pose estimation and tracking without any external AR tag tracking or motion capture systems. While reinforcement learning could damage the components of a robot, the learning does not take this into account. Feedback from energy usage, foot contact sensors, servo temperature, etc. can be used for safety-aware learning. Sparse negative feedback can also be provided when RL causes significant damage to the robot such as breaking of 3D printed parts or servo gears. Safe exploration in RL is an active research area.

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REFERENCES

[1] G. Brockman, V. Cheung, L. Pettersson, J. Schneider, J. Schulman, J. Tang, and W. Zaremba, “OpenAI Gym,” arXiv preprint arXiv:1606.01540, 2016.

[2] Y. Tassa, Y. Doron, A. Muldal, T. Erez, Y. Li, D. d. L. Casas, D. Budden, A. Abdolmaleki, J. Merel, A. Letfrancq, et al., “Deepmind control suite,” arXiv preprint arXiv:1801.00690, 2018.

[3] E. Coumans and Y. Bai, “PyBullet, a Python module for physics simulation for games, robotics and machine learning,” http://pybullet.org 2016–2019.

[4] G. Dulac-Arnold, D. Mankowitz, and T. Hester, “Challenges of real-world reinforcement learning,” arXiv preprint arXiv:1904.12901, 2019.

[5] J. Schulman, P. Moritz, S. Levine, M. Jordan, and P. Abbeel, “High-dimensional continuous control using generalized advantage estimation,” in Proceedings of the International Conference on Learning Representations (ICLR), 2016.

[6] T. Haarnoja, A. Zhou, K. Hartikainen, G. Tucker, S. Ha, J. Tan, V. Kumar, H. Zhu, A. Gupta, P. Abbeel, et al., “Soft actor-critic algorithms and applications,” arXiv preprint arXiv:1812.05905, 2018.

[7] B. Katz, J. Di Carlo, and S. Kim, “Mini cheetah: A platform for pushing the limits of dynamic quadruped control,” in 2019 International Conference on Robotics and Automation (ICRA). IEEE, 2019, pp. 6295–6301.

[8] F. Grimminger, A. Meduri, M. Khadiv, J. Viereck, M. Wüthrich, M. Naveau, V. Berenz, S. Heim, F. Widmaier, T. Flayols, et al., “An open torque-controlled modular robot architecture for legged locomotion research,” IEEE Robotics and Automation Letters, vol. 5, no. 2, pp. 3650–3657, 2020.

[9] N. Kau, A. Schultz, N. Ferrante, and P. Slade, “Stanford doggo: An open-source, quasi-direct-drive quadruped,” in 2019 International Conference on Robotics and Automation (ICRA). IEEE, 2019, pp. 6309–6315.

[10] M. Ahn, H. Zhu, K. Hartikainen, H. Ponte, A. Gupta, S. Levine, and V. Kumar, “ROBEL: Robotics benchmarks for learning with low-cost robots,” in Conference on Robot Learning. PMLR, 2020, pp. 1300–1313.

[11] B. Balaji, S. Mallya, S. Genc, S. Gupta, L. Dirac, V. Khare, G. Roy, T. Sun, Y. Tao, B. Townsend, et al., “DeepRacer: Educational autonomous racing platform for experimentation with sim2real reinforcement learning,” arXiv preprint arXiv:1911.01562, 2019.

[12] L. Paull, J. Tani, H. Ahn, J. Alonso-Mora, L. Carlone, M. Cap, Y. F. Chen, C. Choi, J. Dusek, Y. Fang, et al., “Duckietown: an open, inexpensive and flexible platform for autonomy education and research,” in 2017 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2017, pp. 1497–1504.

[13] A. Gupta, A. Murali, D. P. Gandhi, and L. Pinto, “Robot learning in homes: Improving generalization and reducing dataset bias,” in Advances in Neural Information Processing Systems, 2018, pp. 9094–9104.

[14] D. V. Gealy, S. McKinley, B. Yi, P. Wu, P. R. Downey, G. Balke, A. Zhao, M. Guo, R. Thomasson, A. Sinclair, et al., “Quasi-direct drive for low-cost compliant robotic manipulation,” in 2019 International Conference on Robotics and Automation (ICRA). IEEE, 2019, pp. 437–443.

[15] B. Yang, J. Zhang, D. Jayaraman, and S. Levine, “REPLAB: A reproducible low-cost arm benchmark platform for robotic learning,” ICRA, 2019.

[16] A. H. Schoen, Infinite periodic minimal surfaces without self-intersections. National Aeronautics and Space Administration, 1970.

[17] S. Garrido-Jurado, R. Munoz-Salinas, F. J. Madrid-Cuevas, and R. Medina-Carnicer, “Generation of fiducial marker dictionaries using mixed integer linear programming,” Pattern Recognition, vol. 51, pp. 481–491, 2016.

[18] F. J. Romero-Ramirez, R. Munoz-Salinas, and R. Medina-Carnicer, “Speeded up detection of squared fiducial markers,” Image and vision Computing, vol. 76, pp. 38–47, 2018.

[19] G. Bradski, “The OpenCV Library,” Dr. Dobb’s Journal of Software Tools, 2000.

[20] P. Holoborodko, “Smooth noise robust differentiators,” http://www.holoborodko.com/pavel/numerical-methods/numerical-derivative/smooth-low-noise-differentiators/, 2008.

[21] S. Fujimoto, H. Hoof, and D. Meger, “Addressing function approximation error in actor-critic methods,” in International Conference on Machine Learning, 2018, pp. 1587–1596.

[22] T. Haarnoja, A. Zhou, P. Abbeel, and S. Levine, “Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor,” in International Conference on Machine Learning, 2018, pp. 1861–1870.

[23] Anonymous, “D2RL: Deep dense architectures in reinforcement learning,” in Submitted to International Conference on Learning Representations, 2021, under review. [Online]. Available: https://openreview.net/forum?id=mYNfmvt8oSv

[24] M. Janner, J. Fu, M. Zhang, and S. Levine, “When to trust your model: model-based policy optimization,” in Advances in Neural Information Processing Systems, 2019, pp. 12 519–12 530.

[25] R. Boney, J. Kannala, and A. Ilin, “Regularizing model-based planning with energy-based models,” in Conference on Robot Learning. PMLR, 2020, pp. 182–191.