Learning to Fly—a Gym Environment with PyBullet Physics for Reinforcement Learning of Multi-agent Quadcopter Control

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Abstract—Robotic simulators are crucial for academic research and education as well as the development of safety-critical applications. Reinforcement learning environments—simple simulations coupled with a problem specification in the form of a reward function—are also important to standardize the development (and benchmarking) of learning algorithms. Yet, full-scale simulators typically lack portability and parallelizability. Vice versa, many reinforcement learning environments trade-off realism for high sample throughputs in toy-like problems. While public data sets have greatly benefited deep learning and computer vision, we still lack the software tools to simultaneously develop—and fairly compare—control theory and reinforcement learning approaches. In this paper, we propose an open-source OpenAI Gym-like environment for multiple quadcopters based on the Bullet physics engine. Its multi-agent and vision-based reinforcement learning interfaces, as well as the support of realistic collisions and aerodynamic effects, make it, to the best of our knowledge, a first of its kind. We demonstrate its use through several examples, either as control (trajectory tracking with PID control, multi-robot flight with downwash, etc.) or reinforcement learning (single and multi-agent stabilization tasks), hoping to inspire future research that combines control theory and machine learning.

I. INTRODUCTION

Over the last decade, the progress of machine learning—and deep learning specifically—has revolutionized computer science by obtaining (or surpassing) human performance in several tasks, including image recognition and game playing [1]. New algorithms, coupled with shared benchmarks and data sets have greatly contributed to the advancement of multiple fields (e.g., as the KITTI suite [2] did for computer vision in robotics). While reinforcement learning (RL) looks as a very appealing solution to bridge the gap between control theory and deep learning, we are still in the infancy of the creation of tools for the development of realistic continuous control applications through deep RL [3].

As automation becomes more pervasive—from healthcare to aerospace, from package delivery to disaster recovery—better tools to design robotic applications are also required. Simulations are an indispensable step in the design of both robots and their control approaches [4], especially so when building a prototype is expensive and/or safety (of the hardware and its surroundings) is a concern. Besides platform-specific and proprietary software, many of today’s open-source robotic simulators are based on ROS’s plumbing and engines like Gazebo and Webots. While these solutions can leverage a host of existing plugins, their limited portability can hinder typical machine learning workflows, based on remote, highly parallel, computing cluster execution.

In an attempt to standardize and foster deep RL research, over the last few years, RL environments have multiplied. OpenAI’s Gym [5] emerged as a standard that comprises (i) a suite of benchmark problems as well as (ii) an API for the definition of new environments. Because of the inherent similarities between the decision-making loops of control theory and RL, many popular environments are inspired by control tasks (e.g. the balancing of a pole on a cart). However, because deep RL algorithms often rely on large amounts of data, some of these environments trade-off realism for high sample throughputs. A reason for concern is that developing—and benchmarking—algorithms on environments that are not necessarily representative of practical scenarios might curb the progress of RL in robotics [6].

With this work, we want to provide both the robotics and machine learning (ML) communities with a compact, open-source Gym-style environment that supports the definition of multiple learning tasks (multi-agent RL, vision-based RL, etc.) on a practical robotic application: the control of one or more nanoquadcopters. The software provided with this paper, gym-pybullet-drones, can help both roboticists and ML engineers to develop end-to-end quadcopter control with model-free or model-based RL. The main features of gym-pybullet-drones are:

1) Realism: support for realistic collisions, aerodynamic effects, and extensible dynamics via Bullet Physics [10].

Fig. 1. Rendering of a gym-pybullet-drones simulation with 10 Crazyflie 2.x on a circular trajectory and a rubber duck for scale.
2) **RL Flexibility**: availability of Gym-style environments for both vision-based RL and multi-agent RL—simultaneously, if desired.

3) **Parallelizability**: multiple environments can be easily executed, with a GUI or headless, with or without a GPU, with minimal installation requirements.

4) **Ease-of-use**: pre-implemented PID control, as well as stable Baselines3 [11] and RLlib workflows [12].

Section III of this paper reviews similar simulation environments for RL, in general, and quadcopters, specifically. Section IV details the inner working and programming interfaces of our Gym environment. In Sections V and VI, we analyze its computing performance and provide control and learning use cases. Section VII suggests the possible extensions of this work. Finally, Section VIII concludes the paper.

### II. RELATED WORK

Several reinforcement learning environments and quadcopter simulators are already available to the community, offering different features and capabilities. Here, we briefly discuss (i) the current landscape of RL environments, (ii) the learning interfaces of existing quadcopter simulators, and (iii) how they compare to gym-pybullet-drones.

#### A. Reinforcement Learning Environments

The OpenAI Gym toolkit [5] was created in 2016 to address the lack of standardization among the benchmark problems used in reinforcement learning research and, within five years, it was cited by over 2000 publications. Besides the standard API adopted in this work, it comprises multiple problem sets. Some of the simplest, “Classical control” and “Box2D”, are two-dimensional, often discrete action problems—e.g., the swing-up of a pendulum. The more complex problems, “Robotics” and “MuJoCo”, include continuous control of robotic arms and legged robots in three-dimensions (Swimmer, Hopper, HalfCheetah, etc.) that are based on the proprietary MuJoCo physics engine [13].

MuJoCo’s physics engine also powers DeepMind’s dm_control [14]. While dm_control’s environments do not expose the same API as Gym, they are very similarly structured and DeepMind’s suite includes many of the same articulated-body locomotion and manipulation tasks. However, because of smoothing around the contacts and other simplifications, even locomotion policies trained successfully with these environments do not necessarily exhibit gaits that would easily transfer to physical robots [3].

The need for MuJoCo’s licensing also led to the development and adoption of open-source alternatives such as Georgia Tech/CMU’s DART and Google’s Bullet Physics [10] (with its Python binding, PyBullet). Open-source Bullet-based re-implementations of the control and locomotion tasks in [5] are also provided in pybullet-gym. Community-contributed Gym environments like gym-minigrid [15]—a collection of 2D grid environments—were used by over 30 publications between 2018 and 2021.

Both OpenAI and Google Research have made recent strides to include safety requirements and real-world uncertainties in their control and legged locomotion RL benchmarks with safety-gym [16] and realworldrl_suite [17], respectively.

One of the most popular Gym environment for quadcopters is gymfc [18]. While having a strong focus on the transferability to real hardware, the work in [18] only addresses the learning of an attitude control loop that exceeds the performance of a PID implementation, using Gazebo simulations. Work similar to [18], training a neural network in simulation for the sim2real stabilization of a Crazyflie 2.x (the same quadcopter model used here), is presented in [19].

To the best of our knowledge, gym-pybullet-drones is the first general purpose multi-agent Gym environment for quadcopters.

#### B. Quadcopter Simulators

RotorS [20] is a popular quadcopter simulator based on ROS and Gazebo. It includes multiple AscTec multicopter models and simulated sensors (IMU, etc.). However, it does not come with ready-to-use RL interfaces and its dependency on Gazebo can make it ill-advised for parallel execution or vision-based learning applications. CrazyS [9] is an extension of RotorS that is specifically targeted to the Bitcraze Crazyflie 2.x nanoquadcopter. Due to its accessibility and popularity in research, we also chose the Crazyflie to be the default quadcopter model in gym-pybullet-drones. However, for RL applications, CrazyS suffers from the same limitations as RotorS.

Microsoft’s AirSim [8] is one of the best known simulators supporting multiple vehicles—car and quadcopters—and photorealistic rendering through Unreal Engine 4. While being an excellent choice for the development of self-driving applications, its elevated computational requirements and overly simplified collisions—using FastPhysicsEngine in multirotor mode—make it less than ideal for learning control. AirSim also lacks a native Gym interface, yet wrappers for velocity input control have been proposed [21].

The most recent and closely related work to ours is ETH’s Unity-based Flightmare [7]. This simulator was created to simultaneously provide photorealistic rendering and very fast, highly parallel dynamics. Flightmare also implements Gym’s API and it includes a single agent RL workflow. Unlike gym-pybullet-drones, however, Flightmare does not include a Gym with vision-based observations nor one compatible with multi-agent reinforcement learning (MARL).
III. METHODS

To explain how gym-pybullet-drones works, one needs to understand (i) how its dynamics evolve (Subsections III-A to III-C), (ii) which types of observations, including vision and multi-agent ones, can be extracted from it (Subsection III-D), (iii) what commands one can issue (Subsection III-E), and (iv) which learning and control workflows we built on top of it (Subsections III-F and III-G).

A. Gym Environment Classes

OpenAI’s Gym toolkit was introduced to standardize the development of RL problems and algorithms in Python. As in a standard Markov decision process (MDP) framework, a generic environment class receives an action, uses it to update (step) its internal state, and returns a new state (observation) paired with a corresponding reward. This, of course, is akin to a simple feedback loop in which a controller feeds an input signal to a plant to receive a (possibly noisy) output measurement. An OpenAI Gym environment also exposes additional information about whether its latest state is terminal (done) and other standard APIs to (i) reset it between episodes and (ii) query it about the domains (spaces) of its actions and observations.

B. Bullet Physics

Physics engines are particularly appealing to researchers working on both robotics and ML because they (i) expedite the development and test of new applications for the former, while (ii) yielding large data sets for the latter [4]. The work in this paper is based on the open-source Bullet Physics engine [10]. Our choice was motivated by its collision management system, the availability of both CPU- and GPU-based rendering, the compatibility with the Unified Robot Description Format (URDF), and its steppeable physics—allowing to extract synchronized rendering and kinematics, as well as to control, at arbitrary frequencies.

C. Quadcopter Dynamics

We use PyBullet to model the forces and torques acting on each quadcopter in our Gym and leverage the physics engine to compute and update the kinematics of all vehicles.

1) Quadcopter models: The default quadcopter model in gym-pybullet-drones is the Bitcraze Crazyflie 2.0. Its popularity and availability meant we could leverage both a wealth of system identification work [22]–[24] and real-world experiments to pick the parameters used in this section. Its arm length $L$, mass $m$, inertial properties $J$, physical constants, and a convex collision shape are described through separate URDF files for the $\times$ and $+$ configurations (see Figure 2). We also provide the URDF for a generic, larger quadcopter based on the Hummingbird described in [25].

2) PyBullet-based Physics Update: First, PyBullet lets us set the gravity acceleration $g$ and the physics stepping frequency (which can be much finer grained than the control frequency at which the Gym steps). Besides the physical properties and constants, PyBullet uses the URDF information to load a CAD model of the quadcopter. The forces $F_i$’s applied to each of the 4 motors and the torque $T$ induced around the drone’s $z$-axis are proportional to the squared motor speeds $P_i$’s in RPMs. These are linearly related to the input PWMs and we assume we can control them near-instantaneously [25]:

$$ F_i = k_F \cdot P_i^2, \quad T = \sum_{i=0}^{3} (-1)^{i+1} k_T \cdot P_i^2, $$

where $k_F$ and $k_T$ are constants.

a) Explicit Python Dynamics Update: As an alternative implementation, we also provide an explicit Python update that is not based on Bullet. This can be used for comparison, debugging, or the development of ad hoc dynamics [7]. In this case, the linear acceleration in the global frame $\vec{x}$ and change in the turn rates in the local frame $\vec{\psi}$ are computed as follows:

$$ \ddot{\vec{x}} = \left( R \cdot [0, 0, k_F \sum_{i=0}^{3} P_i^2] - [0, 0, mg] \right) m^{-1}, $$

$$ \dot{\vec{\psi}} = J^{-1} \left( \kappa_x (L, k_F, k_T, [P_0^2, P_1^2, P_2^2, P_3^2]) - \dot{\vec{x}} \times (J \dot{\vec{\psi}}) \right), $$

where $R$ is the rotation matrix of the quadcopter and $\kappa_+$, $\kappa_-$ are functions to compute the torques induced in the local frame by the motor speeds, for the $\times$ and $+$ configuration.
3) Aerodynamic Effects: While the model presented in [1] captures simple quadcopter dynamics, flying in a medium, in the proximity of the ground, or near other vehicles can result in additional aerodynamic effects (Figure 2). PyBullet allows to model these separately and use them jointly.

a) Drag: The spinning propellers of a quadcopter produce drag $D$, a force acting in the direction opposite to the one of motion. Our modeling is based on [23] and it states that the air resistance is proportional to the quadcopter velocity $\dot{x}$, the angular velocities of the rotors, and a matrix of coefficients $k_D$ experimentally derived in [23]:

$$D = -k_D \left( \sum_{i=0}^{3} \frac{2 \pi P_i}{60} \right) \dot{x}. \tag{4}$$

b) Ground Effect: When hovering at a very low altitude, a quadcopter is subject to an increased thrust caused by the interaction of the propellers’ airflow with the surface, i.e., the ground effect. Based on [26] and real-world experiments with Crazyflie hardware (see Figure 4), we model contributions $G_i$’s for each motor that are proportional to the propellers’ radius $r_p$, speeds $P_i$’s, altitudes $h_i$’s, and a constant $k_G$:

$$G_i = k_G k_F \left( \frac{r_p}{4h_i} \right)^2 P_i^2. \tag{5}$$

c) Downwash: When two quadcopters cross paths at different altitudes, the downwash effect causes a reduction in the lift of the bottom one. For simplicity, we model it as a single contribution applied to the center of mass of the quadcopter whose module $W$ depends on the distances in $x$, $y$, and $z$ between the two vehicles ($\delta_x$, $\delta_y$, $\delta_z$) and constants $k_{D1}$, $k_{D2}$, $k_{D3}$ that we identified experimentally:

$$W = k_{D1} \left( \frac{r_p}{4\delta_z} \right)^2 \exp \left( -\frac{1}{2} \left( \frac{\sqrt{\delta_x^2 + \delta_y^2}}{k_{D2} \delta_z + k_{D3}} \right)^2 \right). \tag{6}$$

Figure 3 compares a flight simulation using this model with data from a real-world flight experiment.

D. Observation Spaces

Every time we advance gym-pybullet-drones by one step—which might include multiple steps of the physics engine—we receive an observation vector. In our code base, we provide several implementations. Yet, they all include the following kinematic information: a dictionary whose keys are drone indices $n \in [0..N]$ and values contain positions $x_n = [x, y, z]_n$’s, quaternions $q_n$’s, rolls $r_n$, pitches $p_n$, and yaws $j_n$’s, linear $\dot{x}_n$, and angular velocities $\omega_n$’s, as well as the motors’ speeds $[P_0, P_1, P_2, P_3]_n$’s for all vehicles.

$$\{n : [x_n, q_n, r_n, p_n, j_n, \dot{x}_n, \omega_n, [P_0, P_1, P_2, P_3]_n] \} \tag{7}$$

1) Adjacency Matrix of Multi-Robot Systems: In networked multi-robot systems, it is convenient to express the notion of neighboring robots (those within a certain radius $R$) through adjacency matrix $A \in \mathbb{R}^{N \times N} A_{ij}$. In this type of observation, the value of each drone’s key also includes the drone’s corresponding row (of Booleans) in $A$:

$$\{n : \{\ldots, \text{neighbors} : [A_{n0}, \ldots , A_{nN}] \} \} \tag{8}$$

2) Vision and Rendering: Furthermore, leveraging PyBullet’s bindings to TinyRenderer/OpenGL3 and inspired by Bitcraze’s AI-deck, gym-pybullet-drones observations can include video frames in each drone’s perspective (towards the positive direction of the local x-axis) for the RGB ($C_n \in \mathbb{R}^{48 \times 48 \times 4}$), depth, and segmentation ($U_n, O_n \in \mathbb{R}^{48 \times 48}$) views (Figure 5).

$$\{n : \{\ldots, \text{rgb} : C_n, \text{dep} : U_n, \text{seg} : O_n \} \} \tag{9}$$

E. Action Spaces

Advancing a gym-pybullet-drones environment by one step requires to pass an action (or control input) to it. For the sake of flexibility, and acknowledging that different robotic applications (e.g., stabilization vs. path planning) require different levels of abstractions, we provide multiple implementations.

1) Propellers’ RPMs: The default action space of gym-pybullet-drones is a dictionary whose keys are the drone indices $n \in [0..N]$ and the values contain the corresponding 4 motor speeds, in RPMs, for each drone:

$$\{n : [P_0, P_1, P_2, P_3]_n\}. \tag{10}$$

2) Desired Velocity Input: Alternatively, drones can be controlled through a dictionary of desired velocity vectors, in the following format:

$$\{n : [v_x, v_y, v_z, v_M]_n\}, \tag{11}$$

where $v_x$, $v_y$, $v_z$ are the components of a unit vector and $v_M$ is the desired velocity’s magnitude. In this case, the translation of the input into PWMs and motor speeds is delegated to a PID controller comprising of position and attitude control subroutines [27].

3) Other Control Modes: Developing additional RL and MARL applications will likely require to tweak and customize observation and action spaces. The modular structure of gym-pybullet-drones is meant to facilitate this. In Section [8] we provide learning examples based on one-dimensional action spaces. The inputs of class DynAviary are the desired thrust and torques—from which it derives feasible RPMs using non-negative least squares.

F. Learning Workflows

Having understood how gym-pybullet-drones’s dynamics and observations/actions spaces work, using it in an RL workflow only requires a few more steps.
while (i) Python node. This node continuously steps an environment reading actions from a separate topic it subscribed to. gym-pybullet-drones for community, we also implemented a minimalist wrapper G. ROS2 Wrapper Node
its best performing policies. To run a 2-agent centralized critic training example and replay MADDPG, QMIX) algorithms. In Section V, we show how many popular RL (e.g., PPO, DDPG, DQN) and MARL (e.g., Stable Baselines3 can be used with either kinematics or Baselines3 [11], [2] RLlib Workflow. We provide a complete training workflow for single agent RL based on Stable Baselines3 [12]. RLlib is a library built on top of Ray’s API for distributed applications, which includes TensorFlow and PyTorch implementations of many popular RL (e.g., PPO, DDPG, DQN) and MARL (e.g., MADDPG, QMIX) algorithms. In Section [V] we show how to run a 2-agent centralized critic training example and replay its best performing policies.

G. ROS2 Wrapper Node
Finally, because of the significance of ROS for the robotics community, we also implemented a minimalist wrapper for gym-pybullet-drones’s environments using a ROS2 Python node. This node continuously steps an environment while (i) publishing its observations on a topic and (ii) reading actions from a separate topic it subscribed to.

IV. Computational Performance
To demonstrate our proposal, we first analyze its computational efficiency. Being able to collect large data sets—through parallel execution and running faster than the wall-clock—is of particular importance for the development of reinforcement learning applications. We chose to adopt Gym’s Python API [5], while leveraging Bullet’s C++ back end [10], to strike a balance between readability and portability, on one hand, and computational performance, on the other.

As we believe that closed-loop performance is the better gauge of a simulation at work, we used a stripped-down version of the PID control [27] example in Figure 6 to generate the data presented in Table II. The script—with no GUI, no debug information, fewer obstacles, and less front end reporting between physics steps—is available in folder: gym-pybullet-drones/experiments/performance/.

Unlike simulations that rely on game engines like Unreal Engine 4 and Unity [7], [8], PyBullet has less demanding rendering requirements and can run with either the CPU-based TinyRenderer or OpenGL3 when GPU acceleration is available. We collected the results in Table II using two separate laptop workstations: (i) a 2020 MacBook Pro with an Intel i7-1068NG7 CPU and (ii) a Lenovo P52 with an Intel i7-8850H CPU and an Nvidia Quadro P2000 GPU.

For a single drone with physics updates at 240Hz, we achieved speed-ups of over 15x the wall-clock. Exploiting parallelism (i.e., multiple vehicles in multiple environments), we could generate 80x the data of the elapsed time. This is slightly slower, but comparable, to Flightmare’s dynamics open-loop performance. Although on simpler scenes, a visual observations throughput of ~750kB/s with TinyRenderer is also comparable to Flightmare, and 10x faster when OpenGL3 acceleration is available.

V. EXAMPLES
In practice, we show how one can jointly use gym-pybullet-drones with both control approaches and reinforcement learning algorithms. We do so through a set of six examples. All of our source code is available online and it can be installed using the following steps (please refer to the repository for a full list of requirements):

```
$ git clone -b paper git@github.com:utiasDSL/gym-pybullet-drones.git
$ cd gym-pybullet-drones/
$ pip3 install -e
```

A. Control
The first four examples demonstrate how to command multiple quadcopters using motor speeds or desired velocity...
control inputs as well as two of the aerodynamic effects discussed in Section 3.1 ground effect and downwash.

\$ cd gym-pybullet-drones/examples/

1) Trajectory tracking with PID Control: The first example includes 4 Crazyflies in the x configuration, using PyBullet’s physics update (1), and external PID control. The controllers receive the kinematics observations (7) and return commanded motors’ speeds (10).

\$ python3 fly.py --num_drones 4

Figure 6 plots position x, velocity \( \dot{x} \), roll r, pitch p, yaw j, angular velocity \( \omega \), and motors’ speeds \( P_0, P_1, P_2, P_3 \) for all vehicles, during a 12 seconds flight along a circular trajectory (the three top-left subplots).

2) Desired Velocity Input: The second example also uses kinematics observations (7) but it is controlled by desired velocity inputs (11). These are targeted by PID controllers embedded within the environment.

\$ python3 velocity.py --duration_sec 12

Figure 7 shows the linear velocity response to step-wise changes in the velocity inputs (the three top-right subplots).

3) Ground Effect: The third example compares the takeoff of a Crazyfly with and without the ground effect contribution (5), using the coefficient identified in Figure 4.

\$ python3 groundeffect.py

Figure 8 compares positions and velocities along the global z-axis, during the first half-second of simulation time, showing a small but noticeable overshooting and the larger maximum velocity of the drone experiencing the ground effect.

4) Downwash: The last control example subjects two Crazyflies—moving in opposite directions along sinusoidal trajectories in x and different altitudes of 0.5 and 1 meter—to the downwash model in (6).

\$ python3 downwash.py --gui False

Figure 9 compares the simulation results with the experimental data collected to identify the parameters used in (6). Figure 9 shows a very close match in the x and z positions between our simulation and the real-world.

As we would expect, however, our simplified single contribution modeling does not fully capture the impact of downwash on the bottom drone—e.g., in the pitch p and its ramifications on velocity \( \dot{x} \).
B. Reinforcement Learning

The last two examples let one or more quadcopters learn policies to reach a target altitude and hover in place. These are based on normalized kinematics observations and a normalized, one-dimensional RPMs action space.

1) Single Agent Take-off and Hover: For a single agent, the goal is to reach a predetermined altitude and stabilize. The reward function is simply the negation of the squared Euclidean distance from the set point:

$$ r = -\| x_0 - x \|^2 $$

We use the default implementations of three popular RL algorithms (PPO, A2C, and SAC) provided in Stable Baselines3 [11]. We do not tune any of the hyperparameters. We choose MLP models with ReLU activation and 4 hidden layers with 512, 512, 256, and 128 units, respectively. For PPO, the training workflow can be executed as follows:

```python
$ python3 singleagent.py --algo ppo
```

To replay the best trained model, execute the following script:

```python
$ python3 test_singleagent.py --exp ./results/save
```

Figure [10] compares (i) the three algorithms’ learning and (ii) the trained policies performance. While SAC performs best, all algorithms succeed albeit with very different learning curves. These were not expected, as we deliberately omitted any parameter tuning to avoid cherry-picking.

2) Multi-agent Leader-follower: The last example is a MARL problem in which a leader agent is trained as in [12] and a follower is rewarded by tracking its altitude:

$$ r_0 = -\| x_0 - x_f \|^2, \quad r_1 = -0.5(z_1 - z_0)^2. $$

The workflow is built on top of RLlib [12] using a central critic with 25 inputs and two action models with 12 inputs, all having two hidden layers of size 256 and tanh activations.

```python
$ python3 multiagent.py --alg one_d_rpm
```

To replay the best trained model, execute the following script:

```python
$ python3 test_multiagent.py --exp ./results/save
```

Figure [11] shows a stable training leading to successfully trained policies. The leader presents minor oscillations that are, expectedly, reflected by the follower. The RPMs commanded by these policies, however, appear to be erratic.

VI. EXTENSIONS

We developed gym-pybullet-drones to provide a compact and comprehensive set of features to kick-start RL in quadcopter control. Yet, we also structured its code base for extensibility. Some of the enhancements in the works include: (i) the support for heterogeneous quadcopter teams—this can be achieved by importing multiple URDF
files, where the inertial properties are stored; (ii) the development of more sophisticated aerodynamic effects—e.g., a downwash model made of multiple components instead of a single contribution applied to the center of mass; (iii) the inclusion of symbolic dynamics—e.g., using CasADi to expose an analytical model that could be leveraged by model predictive control approaches; (iv) new workflows to support additional MARL frameworks beyond RLlib [12]—e.g., PyMARL; and finally, (v) Google Colaboratory support and Jupyter Notebook examples—to facilitate adoption by those with limited access to computing resources.

VII. CONCLUSIONS

In this paper, we presented an open-source, OpenAI Gym-like [5] multi-quadcopter simulator written in Python on top of the Bullet Physics engine [10]. When compared to similar existing tools, the distinguishing and innovative features of our proposal include (i) a more modular and sophisticated physics implementation, (ii) vision-based Gym’s observations, and (iii) a multi-agent reinforcement learning interface. We showed how gym-pybullet-drones can be used for low- and high-level control through trajectory tracking and target velocity input examples. We also demonstrated the use of our work in separate workflows for single and multi-agent RL, based on state-of-the-art learning libraries [11], [12]. We believe our work will contribute to bridging the gap between reinforcement learning and control research, helping the community to develop realistic MARL applications for aerial robotics.

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