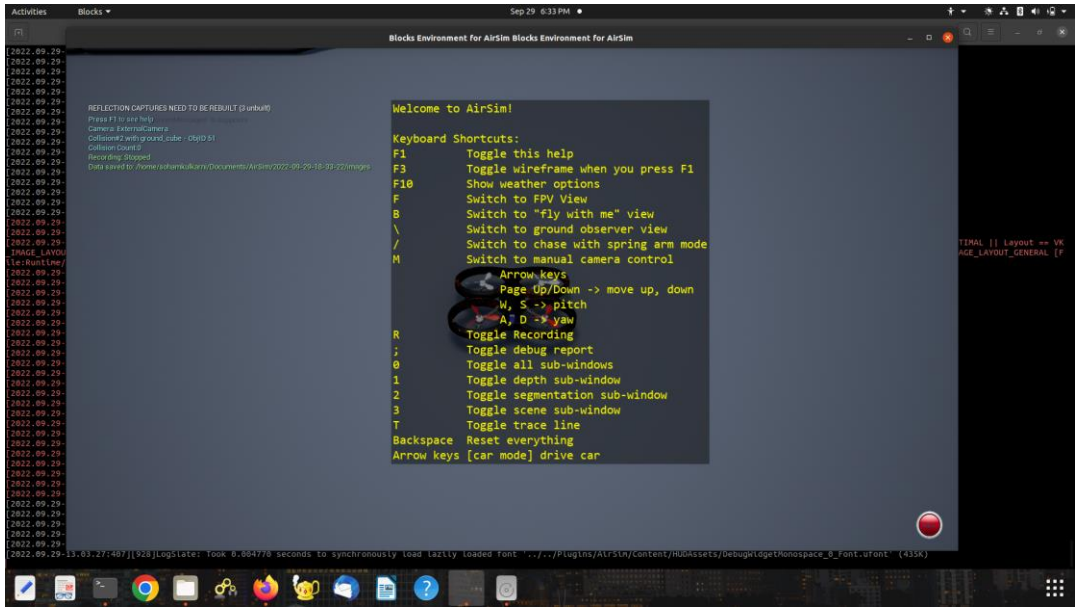
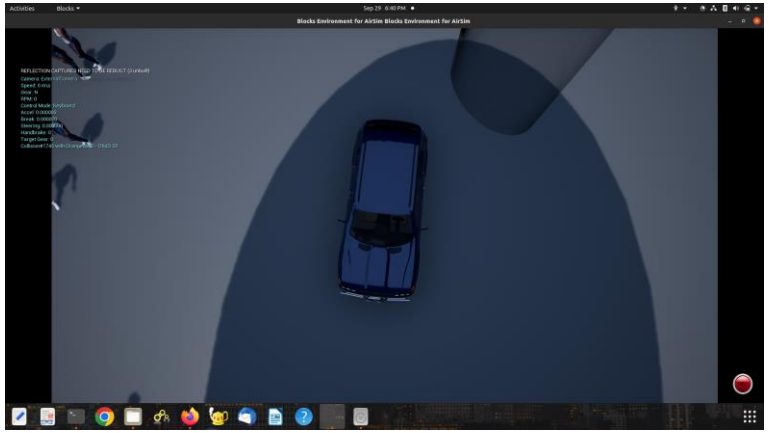
Review in project development #2

8th October 2022

AirSim

- Setup and installation for AirSim, Drone Racing Lab done





AirSim API and baselines

- Tried out different environment configurations, waypoints based navigation in the AirSim python API

Some baseline methods available are:

- Learning Visuomotor Policies for Aerial Navigation Using Cross-Modal Representations
- Representation Learning for Event-based Visuomotor Policies

- Available at: https://www.microsoft.com/en-us/research/group/autonomous-systems-group-robotics/publications/

AirSim Experiments

- Experiments tried out: Stereo matching and Obstacle Detection
- RL: DQN, PPO
- Holistic Parameters: # of people, speed (max)
- Policy: Stop and wait whenever there's obstacles within 0.2 m.
- The reward is defined as:

----moving forward in x direction: +1 x (V_x)
----Deviation in y direction: -1 x $|y|$
----Collision: -5

- Safe flight distance = 46.1 m (at slow speeds)

Safe Robot Learning

- The task is to design a controller/planner that enables a quadrotor (*Crazyflie 2.x*) to **safely fly through a set of gates and reach a predefined target despite uncertainties in the robot dynamics (e.g., mass and inertia) and the environment (e.g., wind and position of the gates)**. The algorithms will be evaluated regarding their safety (e.g., no collisions) and performance (e.g., time to target). We encourage participants to explore both control and reinforcement learning approaches (e.g., robust, adaptive, predictive, learning-based and optimal control, and model-based/model-free reinforcement learning). The controller/planner has access to the position and attitude measurements provided by a motion capture system and the noisy pose of the closest next gate. The controller can send position, velocity, acceleration and heading references to an onboard position controller.

Safe Robot Learning

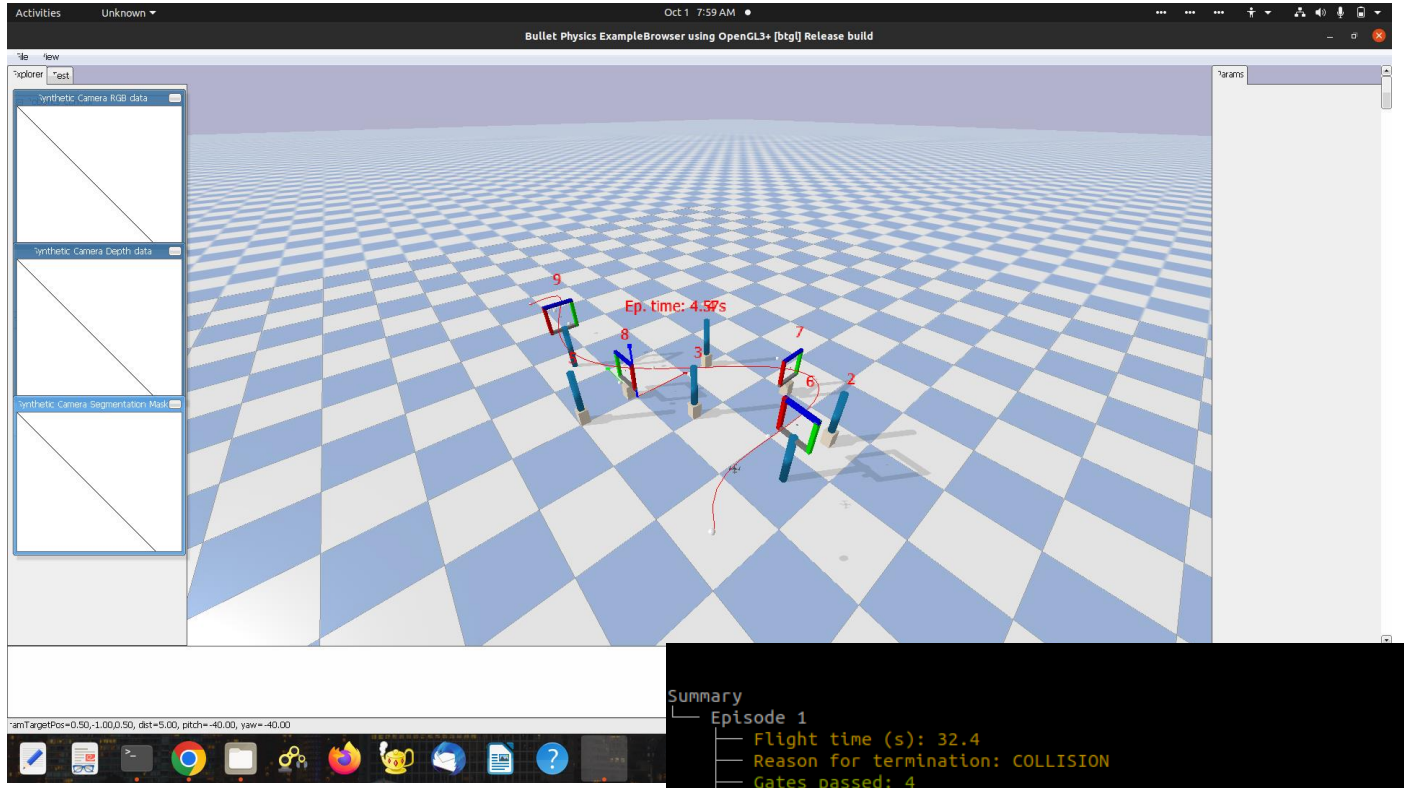
- Evaluation scenarios:

Evaluation Scenario	Constraints	Rand. Inertial Properties	Randomized Obstacles, Gates	Rand. Between Episodes	Notes
`level0.yaml`	**Yes**	*No*	*No*	*No*	Perfect knowledge
`level1.yaml`	**Yes**	**Yes**	*No*	*No*	Adaptive
`level2.yaml`	**Yes**	**Yes**	**Yes**	*No*	Learning, re-planning
`level3.yaml`	**Yes**	**Yes**	**Yes**	**Yes**	Robustness
sim2real	**Yes**	Real-life hardware	**Yes**, injected	*No*	Sim2real transfer

- Testing in Level 0 is done, presently working for Level 1.

Safe Robot Learning

- Simulation results:




```
Summary
└── Episode 1
    ├── Flight time (s): 32.4
    ├── Reason for termination: COLLISION
    ├── Gates passed: 4
    ├── Total reward: 36500
    ├── Number of collisions: 1
    ├── Number of constraint violations: 120
    ├── Total and average interstep learning time (s): 0.0033769607543945312,
    │   3.47066881232737e-06
    └── Interepisode learning time (s): 5.0067901611328125e-06
```

```
                Input: (f1, f2, f3, f4)
                Dynamics: @1=((mac(mac(mac(horzcat(horzcat(cos(psi),
(-sin(psi)), 0)', horzcat(sin(psi), cos(psi), 0)', horzcat(0, 0,
1)')',horzcat(horzcat(cos(theta), 0, sin(theta))', horzcat(0, 1, 0)',
horzcat((-sin(theta)), 0, cos(theta))')',zeros(3x3)),horzcat(horzcat(1, 0, 0)',
horzcat(0, cos(phi), (-sin(phi)))', horzcat(0, sin(phi),
cos(phi))')',zeros(3x3)),vertcat(0, 0,
(((f1+f2)+f3)+f4)),zeros(3x1))/0.03454)-[0, 0, 9.8]), vertcat(x_dot, @1[0],
y_dot, @1[1], z_dot, @1[2], mac(horzcat(horzcat(1, (sin(phi)*tan(theta)),
(cos(phi)*tan(theta)))', horzcat(0, cos(phi), (-sin(phi)))', horzcat(0,
(sin(phi)/cos(theta)), (cos(phi)/cos(theta)))')',vertcat(p, q, r),zeros(3x1)),
mac(
[[71428.6, 0, 0],
 [0, 71428.6, 0],
 [0, 0, 46082.9]],(vertcat((0.0280721*(((f1+f2)-f3)-f4)),
(0.0280721*(((f2-f1)+f3)-f4)),
(0.0251266*(((f1-f2)+f3)-f4)))-mac(mac(horzcat(horzcat(0, (-r), q)', horzcat(r,
0, (-p))', horzcat((-q), p, 0)')',
[[1.4e-05, 0, 0],
 [0, 1.4e-05, 0],
 [0, 0, 2.17e-05]],zeros(3x3)),vertcat(p, q, r),zeros(3x1))),zeros(3x1)))
Input constraints lower bounds: [0.02816169 0.02816169 0.02816169 0.02816169]
Input constraints upper bounds: [0.14834145 0.14834145 0.14834145 0.14834145]
State constraints active dimensions: [0, 2, 4]
State constraints lower bounds: [-3.  -3.  -0.1]
State constraints upper bounds: [3 3 2]
        Symbolic constraints:
                self.sym_func = lambda x: self.A @ self.constraint_filter @ x -
self.b
                self.sym_func = lambda x: self.A @ self.constraint_filter @ x -
self.b
INFO_0: Takeoff command sent.

0-th step.
        Applied action: [0.12238666 0.08342166 0.07503086 0.11097434]
        Observation: [-0.96661888 -0.02791138 -2.90698838 -0.0087332
0.04799449 -0.05957792
  0.02340707 -0.04683142  0.07295647 -0.60452617  1.66635592 -0.06054963]
        Reward: 0 (Cumulative: 0)
        Done: False
        Current target gate ID: 0
        Current target gate type: 0
        Current target gate in range: False
        Current target gate position: [0.5, -2.5, 0, 0, 0, -1.57]
        At goal position: False
        Task completed: False
        Constraints evaluations: [-0.02496828 -0.08704742 -0.10894883
-0.04954095 -0.09521148 -0.03313234
 -0.01123093 -0.07063881 -2.03338112 -0.09301162 -0.14799449 -3.96661888
 -5.90698838 -1.95200551]
        Constraints violation: False
        Collision: (None, False)
```

Safe Robot Learning

- *Tested Controllers (for basic trajectory tracking):*
- LQR
- iLQR
- Linear MPC
- GP-MPC
- SAC
- PPO
- DDPG
- Safety Layer
- RARL
- RAP
- MPSC
- CBF