Quad2Plane: An Intermediate Training Procedure for Online Exploration in Aerial Robotics via Receding Horizon Control

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Abstract—Data driven robotics relies upon accurate real-world representations to learn useful policies. Despite our best-efforts, zero-shot sim-to-real transfer is still an unsolved problem, and we often need to allow our agents to explore online to learn useful policies for a given task. For many applications of field robotics online exploration is prohibitively expensive and dangerous, this is especially true in fixed-wing aerial robotics. To address these challenges we offer an intermediary solution for learning in field robotics. We investigate the use of dissimilar platform vehicle for learning and offer a procedure to mimic the behavior of one vehicle with another. We specifically consider the problem of training fixed-wing aircraft, an expensive and dangerous vehicle type, using a multi-rotor host platform. Using a Model Predictive Control approach, we design a controller capable of mimicking another vehicles behavior in both simulation and the real-world.

I. INTRODUCTION

In the past decade Deep Reinforcement Learning has proven to be an effective tool to solve a variety of simulated [1][2] and real-world [3][4] control tasks. Real-world robotic learning is plagued by a host of practical issues [5] such as: resets, state-estimation and platform integrity. These practical limitations are easily solved by learning in simulation, but this often leads to a reality gap, where the policy learned by the agent learns to exploit attributes that are not present in the real-world, leading to poor performance. A common robotic learning pipeline is therefore to complete the majority of training in simulation, where demonstrations are cheap, and then fine-tune the learned policy on a real-world robot.

This approach works well in robotic domains where the vehicle can safely explore the environment without significant constraints, such as gripper [6] robots. However, in many field-robotic settings it is not safe to allow the robot to explore and fine-tune a policy in the real-world, as the vehicle can damage itself and 3rd parties. This is a challenge that is particularly constraining in fixed-wing aerial robotics, where the platform is often large and financially expensive. Further, we are often most interested in fine-tuning policies when the aircraft is slow and close to the ground [7] [8], where it is most likely to cause damage. This makes real-world fixed-wing robotic learning difficult constraining most research to simulation [9].

In comparison, multi-rotor drones are ubiquitous in aerial robotic research [10], and have been used for online robotic learning in a variety of safe [11] and constrained real-world environments [12]. Fixed-wing aircraft typically have superior range, endurance and load-carrying capabilities than rotary aircraft. However, this is not a constraint on the majority of learning tasks, because most stochastic control problems encountered by the robot, where using a DRL based controller would be useful, occur at the beginning or end of a flight and carrying a payload does not effect the learning process. Along with being safer, multi-rotors offer several distinct advantages, compared to fixed-wing aircraft, for online learning:

- Multi-rotors can hover and translate linearly in all three flight-axis, making it easier to reset the learning process online. [13].
- Multi-rotors are not as geometrically constrained as fixed-wing aircraft, allowing for easier installation of compute devices and sensors. This makes it easier to get accurate state-estimation and to perform online policy optimization [14].
- Multi-rotors have a larger low-speed flight envelope, easily being able to hover and navigate tight, constrained environments[15]. This allows us to train the robot in scenarios closer to the platforms limits without the risk of crashing, opening the door for safe-RL [16] and lifelong learning [17].

Given how much easier it is to learn control policies on multi-rotors than fixed-wing aircraft: can a multi-rotor mimic the mechanics of a fixed-wing aircraft? This would allow us to learn useful policies in the real-world, without the burden of reset-ability and safety imposed by a fixed-wing aircraft. All whilst providing access to the underlying real-world state-observation distribution, including wind and imaging data, which is difficult to entirely capture in simulation [18].

In this paper we present a general procedure to mimic the dynamics of a target vehicle on a dissimilar platform vehicle. Specifically we consider the problem of replicating the dynamics of a fixed-wing target vehicle on a multi-rotor platform. We make the following contributions:

- We pose the general platform-to-target control problem as a discrete time dynamic problem in section III. We then design an optimal model based controller to solve this problem in section IV.
- In section V we provide a description of the implementation of our controller for aerial robotics, along with the rationale behind the design of our vehicles state based cost function. This offers useful insights into how we need to design vehicles that are used for robotic
learning.

- In section [VI] we use a combination of simulated and real-world data to validate our approach and describe the key limitations of our approach.

II. RELATED WORK

The problem of transferring learned skills from simulation to the real-world is well documented within the robotic learning community [19][20][21]. This reality gap is caused by a distributional shift from simulated to real-world observations, due to un-modelled physical effects such as noise in a collected image or friction in an actuator. One approach to solve this problem is to vary the state distribution of the simulation, either by randomizing the domain [22][23] or dynamics [24]. However, Domain Randomization (DR) has some key limitations: the creation of suitable simulated training environments is time consuming, and deciding what to randomize requires care to ensure the final distributions match. Additionally there is no guarantee that DR can achieve zero-shot sim-to-real transfer [25].

Alternatively, demonstrations can be used to help fine-tune the policy [26][27][28], but for many settings it is difficult to obtain expert demonstrations to learn from. Learning in the real-world is perhaps the simplest way to ensure we don’t have a reality gap, either by fine-tuning [29], or without simulation altogether [30]. Unfortunately this requires our robotic platform to be capable of safe exploration, something that cannot be assured for our target vehicle. We offer an intermediary solution to this, by learning on a surrogate vehicle, we contribute a procedure to train inherently dangerous vehicles in the real-world safely.

Mimicking the dynamics of one vehicle with another has been used by the aerospace community for flight crew training [31] and aircraft flying quality evaluation [32] since the late 1950s [33]. These In Flight Trainer (IFT) aircraft [34] [35] typically use linear state-space model reference adaptive controllers based on LQI or LQR to mimic another aircraft’s flight mechanics. This makes sense for IFT aircraft, where the objective is typically to provide proprioceptive information to the flight crew. However, it is desirable for our system to also be capable of replicating the vehicles non-linear dynamics, linear state-space control is therefore inappropriate.

Model Predictive Control (MPC) is an effective method to control non-linear systems [36], especially when constraints are imposed on exploration [37]. Classical MPC provides a complete trajectory to solve an optimal control problem, for which receding horizon MPC [38], offers a useful framework. We assume that the transition of the vehicles dynamics $F$ is deterministic, and the model representation entirely captures the vehicles dynamics. We can frame the control design problem for $G^{t2p}$, as in (2), so that when $F_{plat}$ receives a control input $u^{plat}_t$ it undergoes the same state-transition as $F_{tar}$, receiving an input $u^{tar}_t$, as shown in figure [1]

$$u^{tar}_t = G^{t2p}(u^{tar}_t, x^{plat}_t)$$

Fig. 1. Problem Formulation Block Diagram

We assess the performance of $G^{t2p}$ using a loss function between the target and platform trajectory terms $S_r = L(\tau_{x_{plat}}, \tau_{x_{tar}})$.

IV. MODEL PREDICTIVE CONTROL

We can frame the control design problem for $G^{t2p}$ as an optimal control problem, for which receding horizon MPC offers a useful framework. We assume that the transition of the vehicles dynamics $F$ is deterministic, and the model representation entirely captures the vehicles dynamics.

Consider the cost function $J(u;x)$, composed of state $q(x)$ and control $p(u)$ dependant costs, as in

$$J(u;x) = q(x) + p(u) \ s.t. \ u_{min} \leq u \leq u_{max}$$

The objective is then to find the optimal control sequence $u^*$ that minimizes $J$ over a finite time-horizon $T$, subject to the linear bounding constraint $[u_{min}, u_{max}]$. To help reduce the computational cost at each time $t$ the optimization problem is warm-started with the previous control sequences solution, reducing the computational cost of the online optimization problem.

Control sequence $\tau^{tar}_t$ with finite length $T$ is the control input sequence received by $G^{t2p}$. This is the command sequence produced by the outer controller we are aiming to train. In a typical model-free RL setting only a single next time-step would be provided and the MPC time-horizon would effectively be one step. We found that this often causes
instability in our platform vehicle as the MPC controller is unable to solve the non-linear control problem, effectively getting stuck in a local optima. To learn an RL policy it is therefore necessary to rollout a control trajectory $T$ steps ahead. When the policy is deployed online only the first state from the policies action trajectory will be selected.

Algorithm 1 is a general MPC based procedure to mimic the dynamics of a target vehicle. We denote the target vehicle model and platform model as $F^{tar}$ and $F$ respectively.

Algorithm 1 t2p-MPC

**Input:** $\tau_{tar}$: target control input sequence, $\tau_u$: last control prediction sequence (up to $T-1$)

**Output:** $u_{t+1}$: next control input to platform

1: $\tau_{tar} \leftarrow \emptyset$
2: for $t$ to $T$ do
3: $\tau_{tar} \leftarrow F^{tar}(x_t; u_{tar})$; add to $\tau_{tar}$
4: end for
5: $J \leftarrow 0$
6: while not converged do
7: for $t$ to $T$ do
8: $x_t \leftarrow F(x_t; u_t)$
9: $j \leftarrow q(x_t) + p(u_t)$
10: $J \leftarrow J + j$
11: end for
12: $\tau_u \leftarrow \text{argmin } J \text{ s.t. } u_{min} \leq u \leq u_{max}$
13: end while

V. IMPLEMENTATION

A. Simulation

For the target fixed-wing ($fw$) we use the x8 Skywalker model from [40], and simulate the aircraft using JSBSim [41]. For the multi-rotor ($mr$) we provide our own implementation contained within this paper's associated repository [1]. Both aircraft have the same 6 degree of freedom 12 state representation form: 6 translational components $[x, y, z; u, v, w]$ and 6 rotational components $[roll, pitch, yaw; p, q, r]$. Both aircraft have 4 controls $u$ with normalized inputs for control-deflection and thrust:

- The multi-rotor has 4 thrust control commands, one for each prop: $u_{mr} = [T_0, T_1, T_2, T_3]$, where $T_i$ is bound from $[0, 1]$.
- The fixed-wing airplane is modelled with 3 control surface commands and one throttle command: $u_{fw} = [ail, elev, tla, rud]$, with bounds: $[\{-1, +1\}, [-1, +1], [0, +1], [-1, +1]]$.

The actual x8 airplane flown, shown in figure 2 has 2 full wing control surfaces (cs) which are transformed into equivalent elevator & aileron within the x8 wind tunnel model [40]. The x8’s large control surfaces provide lots of control authority in pitch and roll, but the lack of vertical tailplane results in poor directional control and balance.

Our multi-rotor simulator includes models for drag, motor-thrust and gravitational effects. The vehicle states are updated with a two-step forward euler method using the linear and rotational accelerations generated by these forces. We specified the vehicles performance to satisfy the x8 target platforms required flight envelope, principally by observing when the multi-rotor’s motors became saturated when responding to a step-control disturbance on the airplane. This produced a thrust to weight requirement of $\approx 2 : 1$, performance that is not unrealistic for many small to medium size off-the-shelf quad-copters [42].

B. MPC

For our MPC control task we use a state-dependent cost function $q(x)$ of the form

$$q(x) = w_x |x^{fw} - x^{mr}|^2$$

Where the state weight matrix $w_x$ has parameters

$$w_x = [1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0]$$

This corresponds to minimizing the $(x, y, z)$ position error between the fixed-wing and multi-rotor aircraft. This is suitable for higher order fixed-wing control tasks, based on temporal position based objectives [43]. If mimicking rotational vehicle states is desirable, it would not be difficult to include a gimbal controller to directly passthrough the fixed-wing rates from the model. Allowing us to train a vision encoded policy as the attitude of the fixed-wing aircraft has a direct relation to the perspective of the policy. For the control-dependant cost function $p(u)$ we apply a constant cost weight to all thrust terms of 0.5. This improves the convergence rate when close to an optimal solution and helps to reduce jittering. To minimize the cost function, argmin $J(u, x)$ s.t. $u_{min} \leq u \leq u_{max}$, we use the Sequential Least Squares Programming (SLSQP) routine from the Python based SciPy optimization library [44] with constraints $[u_{min}, u_{max}] \leftarrow [0, 1]$. We use a constant time-horizon $T$ of 1.0s.

VI. EXPERIMENTS

To investigate the limitations of our surrogate learning approach we consider the following procedures:

- A disturbance in roll and pitch, to investigate the quadcopter’s limitations to mimic the dynamics of the fixed-wing at the limits of the flight envelope.
- A comparison to real-world flight data, to investigate our procedures ability to mimic the aeroplane.
A. Disturbance Tracking

Figures 3 & 4 plot the 3 dimensional position and linear velocity states for the two vehicles respectively. The orange dash-dot vertical line in both figures is the point the disturbance was initiated. For the pitch and roll disturbances we apply an instantaneous up elevator and left aileron deflection for 0.2s respectively. In both cases we use 50% of the maximum control deflection for the disturbance.

Control saturation is shown following the disturbance in roll at 5 seconds on figure 5 as the quad-copter encounters a slight (10m) departure from tracking in altitude. The system effectively runs out of power required to maintain rate of climb whilst turning. The controller is able to maintain higher power for longer however and recaptures the control by effectively leading the velocity of the fixed-wing aircraft, shown from 9.0s to 12.0s on figure 4. We find this analysis useful to understand the limitations of our platform vehicle, if tracking closely in this domain was desirable we could increase the performance of our vehicle to maintain position.

Fig. 5. The control input to each of the quad-copter’s 4 motors under the pitch and roll disturbances. The roll disturbance is saturated from 5.5s to 10.0s

Figure 6 shows the control input required to mimic the disturbances of the fixed wing for each disturbance. The noise at the beginning of each control plot is caused by cold-starting the optimizer, as the control sequence $t_n$ starts with all values set to zero. The solution for the optimizer is then progressively improved by warm-starting the optimizer with the last best solution. Once converged to a local optimum the variance in control input decays and the noise in the system reduces. Importantly this doesn’t cause the aircraft to diverge from the mimicked dynamics, despite following a sub-optimal solution.

To simulate the effect of un-modelled dynamics we add a first-order lag filter to the multi-rotor’s motors given as

$$y_t = (1 - a)y_{t-1} + au_t \quad a = \frac{\delta_t}{\delta_t + T_{lag}}$$  \hspace{1cm} (6)

Where $y_t$ is the command sent to the linear motor model at time $t$, $\delta_t$ is the step-size of the simulation, and $T_{lag} = \frac{1}{30}$s is the size of the lag. But, we do not include the lag model within the MPC model. We found this did not cause any
significant effects on the ability of the quad-copter to track the commanded signal but, as expected, slightly increases the noise of the motor input command, shown in figure 6.

B. Real-World Comparison

To validate our approach on a real-world dataset we use our algorithm to mimic the motion of an x8 on a gas-sensing mission to the summit of Volcán de Fuego in Guatemala using the same platform drone. We consider a demanding 60 second climbing turn section, shown in figure 7.

Fig. 7. Climbing Turn section starting at 15,000’, around Volcán de Fuego. Solid orange segment indicates flight track used over the 60 second period.

We find the multi-rotor platform is capable of tracking the fixed-wing demonstration with little to no error through the whole manoeuvre with relatively small control noise, shown in figure 8. Interestingly the controller approaches saturation during the level out from the turn, where it needs to turn aggressively and continue the climb.

We find that the trajectory tracking error of the real world data in figure 8 is relatively small, with mean squared error in $[x, y, z]$ positions of $[0.00182, 0.00357, 0.310]$ respectively.

VII. FUTURE WORK & LIMITATIONS

A key limitation of our approach is the time taken to calculate trajectories for our MPC loop. Even in the best case the frequency of our controller to update on modern hardware is 10 to 100 times slower than is required to run online. A large constraint to this is the need to use a sequential quadratic programming solver, as the core algorithm is fundamentally serial and the computational expense to calculate gradients and simulate model state roll-outs is significant. Information Theoretic MPC methods such as MPPI [45] offer a solution to this challenge, via a sampling based MPC procedure, based on KL divergence and free energy. This allows us to take full advantage of parallel compute and does not require gradients to be calculated for the optimization procedure. Initially, we found that running MPPI, with the quad-copter simulator on parallel CPU compute, provided insufficient samples to converge to a stable solution. We therefore aimed to use a neural-network to represent our model dynamics, allowing us to take advantage of accelerated parallel GPU compute and collect many more samples faster. To train our network we investigated bootstrapping from demonstrations collected with both random actions and an MPC oracle along with simply training within the MPPI framework. A unique challenge that stems from the quad-copters fundamental instability is that random actions frequently lead to the aircraft rotating into an uncontrolled state. The original MPPI paper [45] solves this on the quad-copter task by including angular rates as part of the control input. We found that whilst position and linear/angular velocities can be predicted with small error, angles could only be learned to within 1° of error, which is far too large of an error to use with MPPI.

More recent Model-Based RL algorithms such as MBPO [46] or PETS [47] may offer a better solution to solving our control problem, with their CMA-ES ensemble maximum likelihood [48] based model learning procedure. Alternatively, we may simply need to collect more demonstrations for supervised training, either from the MPC oracle or human demonstrations.

Once this computational bottleneck is overcome we aim to experiment with the controller in the real-world. Such as: online episodic reinforcement learning and safety constrained RL tasks, for example flying at high speed around a car-park or navigating to landing spots in built-up areas.

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