Online Learning and Control for Data-Augmented Quadrotor Model

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1 Introduction

The ability to adapt to changing conditions is a key feature of a successful autonomous system. In this work, we use the recursive Gaussian Processes for identification of the quadrotor air drag model *online*, without the need of training data. The identified drag model then augments a physics-based model of the quadrotor dynamics, which allows for more accurate quadrotor state prediction with increased ability to adapt to changing conditions. This *hybrid* model is utilized for precise quadrotor trajectory tracking using the suitably modified Model Predictive Control (MPC) algorithm. The proposed modelling and control approach is evaluated using the Gazebo simulator and we show that the proposed approach tracks a desired trajectory with a higher accuracy compared to the MPC with the non-augmented (purely physics-based) model.

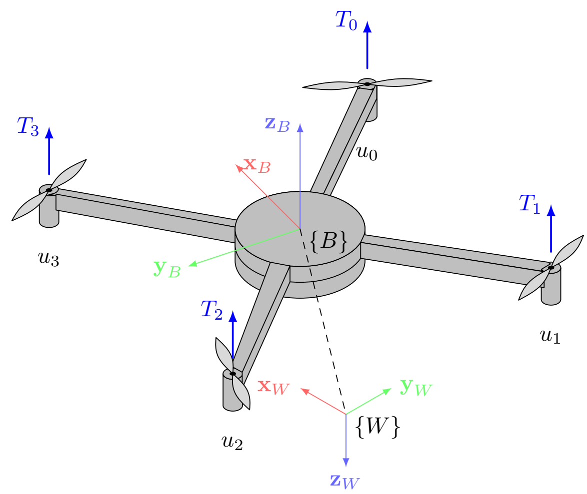

Figure 1: Quadrotor schematic. Thrust T_i is generated by individual rotors given inputs u_i.

2 Recursive Gaussian Process

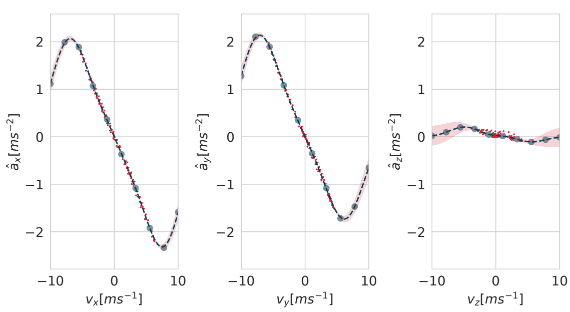

Figure 2: RGP fit to the aerodynamic drag data.

Recursive Gaussian process regression (RGP) (Huber, 2014) is a generalization of the Gaussian process regression (GP) (Rasmussen et al., 2005) to the online setting. It is able to fit data recursively, as it arrives, without the need to store the entire dataset. It is also able to change its fit in domains that were previously visited, which is not possible with the standard GPR. This allows us to use the RGP to identify the quadrotor drag model online, without the need of training run.

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3 Hybrid Model

We developed a hybrid model that combines a physics-based model with a data-driven model. The physics-based model derived from first principles models the rigid body dynamics of the quadrotor, its thrust and rotational dynamics. The data-driven model augments the physics-based model with a model of the aerodynamic forces, difficult to model analytically. In this way, we make the two modeling approaches complementary, making use of both their strengths.

First Principles Quadrotor Model

$$\boldsymbol{f}_{\text{PHYS}}(\boldsymbol{x_k}) = \begin{bmatrix} \boldsymbol{v}_{WB} \\ \boldsymbol{q}_{WB} \cdot \begin{bmatrix} 0 \\ \boldsymbol{\omega}_B/2 \end{bmatrix} \\ \boldsymbol{q}_{WB} \odot \left(\frac{1}{m}\boldsymbol{T}_B\right) + \boldsymbol{g}_W \\ \boldsymbol{J}^{-1}(\boldsymbol{\tau}_B - \boldsymbol{\omega}_B \times \boldsymbol{J}\boldsymbol{\omega}_B) \end{bmatrix}$$

Data-Driven RGP Drag Model

$$\boldsymbol{f}_{\text{DATA}}(\boldsymbol{x}_k) = \begin{bmatrix} \mathbf{0}^{7\times1} \\ \tilde{a}_x \\ \tilde{a}_y \\ \tilde{a}_z \\ \mathbf{0}^{3\times1} \end{bmatrix} = \begin{bmatrix} \mathbf{0}^{7\times1} \\ \mu_x^{\bullet,k}(v_{x,k}) \\ \mu_y^{\bullet,k}(v_{y,k}) \\ \mu_z^{\bullet,k}(v_{z,k}) \\ \mathbf{0}^{3\times1} \end{bmatrix}$$

Parameters of the RGP change during flight

Hybridized Quadrotor Model

$$\boldsymbol{f}_{\text{HYB}}(\boldsymbol{x}_k, \boldsymbol{u}_k) = \boldsymbol{f}_{\text{PHYS}}(\boldsymbol{x}_k, \boldsymbol{u}_k) + \boldsymbol{f}_{\text{DATA}}\left(\boldsymbol{x}_k; \boldsymbol{\mu}^{+,k}\right).$$

4 Results

The hybrid model $\boldsymbol{f}_{\text{HYB}}$ is employed in a MPC framework with the task of precise trajectory tracking under wind disturbances which we call RGP−MPC. We performed experiments in the simulation environment Gazebo+ROS[1]. Using the hybridized model $\boldsymbol{f}_{\text{HYB}}$, we achieved up to **69%** improvement in trajectory tracking accuracy compared to solely using the physics-based model $\boldsymbol{f}_{\text{PHYS}}$ as seen in Table 1. We also demonstrated that the RGP can be used to identify the quadrotor drag model online, without the need of training run, allowing the quadrotor to adapt to changes in its aerodynamic properties.

		RMSE pos [mm]	
Trajectory	$v_{\max}$ **[ms^{-1}]**	**Nominal**	**RGP−MPC**
Random	3	75.9	40.6 (53%)
	6	110.1	65.1 (59%)
	9	128.5	88.2 (69%)
	12	142.9	99.6 (69%)
Circle	3	57.5	23.6 (41%)
	6	102.7	43.5 (42%)
	9	145.1	69.7 (47%)
	12	183.9	98.2 (53%)
	avg. opt. dt [ms]	0.60	1.21

Table 1: RMSE position error for the circle trajectory generated using Gazebo with both $\boldsymbol{f}_{\text{PHYS}}$ and $\boldsymbol{f}_{\text{HYB}}$.

References

Huber, M.F. (2014) Recursive Gaussian process: On-line regression and learning. *Pattern Recognition Letters*, Volume 45, pp. 85–91.

Rasmussen, C.E. and Williams, C.K.I. (2005) *Gaussian Processes for Machine Learning*. Adaptive Computation and Machine Learning series, MIT Press.

[1]Source code available at: `https://github.com/smidmatej/mpc_quad_ros`