Sensitivity Approach for Prioritizing Unmanned Aerial Vehicles Simulator Design

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***Abstract*—There are plenty of dynamic parameters to be considered when designing unmanned aerial vehicle (UAV) simulators. In many scenarios, the simulator designer aims to accurately capture UAV motion dynamics and interaction with environment for direct simulation to reality transfer. In practice, modeling and estimation of some of those UAV dynamic parameters can be expensive and unpractical. In this paper, we provide an assessment for the use of relative sensitivity function for time-delay dynamic models. The relative sensitivity function allows for the analysis of the overall system performance in response to a change of a dynamic parameter. We provide sensitivity numerical results based on experimental identification of a UAV dynamics. Moreover, we investigate the system sensitivity when different sensor modalities are used. We draw conclusions on the relative importance of different parameters on the UAV closed-loop control performance based on the sensitivity results. Furthermore, we suggest possible future research directions based on the presented analysis and results.**

I. Introduction

The use of data-based approaches for control has been attracting increased attention recently from the robotics community. Data-based approaches promise to offer advantages over the classical model-based control approaches in some aspects; mainly in the handling of complex or impossible to model control problems. For example, reinforcement learning (RL) is one of the most prominent of these data-based approaches and its usage witnessed a surge in the robotics community following the notable success in other domains like computer games [1], in the hope that the same benefits would be claimed with real robots. Unfortunately, the application of data-based approaches to unmanned aerial vehicles (UAVs) was not as successful, mainly due to the discrepancy between the simulation models used for RL training, and the real robots [2]. Simulator design is quite challenging since many factors contribute to its accuracy, and having a perfect simulator is undoubtedly impossible. In this paper, we present our results investigating the use of sensitivity functions to drive the design of simulators used for data generation and training of data-based controllers. Sensitivity functions provide a relative metric for the importance of dynamic parameters and allow the designer to steer the resources in the right direction. We used the analytical time-delay cost functionals [3] to evaluate the sensitivity of the cost functional to UAV parameters variations.

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II. Constructing Cost Functionals

Consider the linearized UAV attitude and altitude parameters given by the following transfer function [4]:

$$G(s) = \frac{K_p e^{-\tau s}}{s(T_p s+1)(T_q s+1)} \tag{1}$$

which accounts for aerodynamic drag [5] (K_p and T_q), actuator dynamics [6] (T_p), and time delay [7] (τ) due to the cyber-physical nature of the system. We assume the use of a PD controller for each control loop since position and velocity measurements are available through sensors. With the use of a PD controller the error dynamics are written as:

$$E(s) = \frac{s(T_p s+1)(T_q s+1)}{s(T_p s+1)(T_q s+1) + (K_p K_c + K_p K_d s)e^{-\tau s}} R(s) \tag{2}$$

with K_c and K_d being controller gains.

A controller design is often performed through minimization of the integral of the square error (ISE) performance index. It was shown in [8] that the ISE performance index of linear systems can be found using Parseval's theorem as follows:

$$Q(C_i, G_i) = \int_0^{\infty} e^2(t)dt = \frac{1}{2\pi i}\int_{-i\infty}^{+i\infty} E(s)E(-s)ds \tag{3}$$

where C_i and G_i are the controller and dynamics of the system with index i, respectively. Note that for the PD case it the controller parameters are $[K_c\ K_d]^T$, which are optimized to minimize J. One cannot directly evaluate the integrand $E(s)E(-s)$ using Parseval's theorem in the delay case due to the infinite number of poles in the left and right half-planes. Yet, it is possible to analytically evaluate a cost functional associated with linear systems with a single time delay through the method suggested in [3]. In either of delay and delay-free cases, for the integral in Eq. (3) to exist, the steady-state error of the system must go to zero. The UAV dynamics could result in steady-state error for constant external disturbances are when trying to follow a ramp input [4]. Yet it is still possible to remove the contribution of the steady-state component and evaluate the error due to transients:

$$E'(s) = E(s) - \frac{1}{s}\lim_{s\longrightarrow 0} sE(s) \tag{4}$$

and then the cost functional optimization of Eq. (3) becomes a biobjective optimization:

$$Q = \alpha_1 Q' + \alpha_2 \lim_{s\longrightarrow 0} sE(s) \tag{5}$$

where α_1 and α_2 are weighing factors, and Q' is the cost functional in Eq. (3) evaluated with error function $E'(s)$ in

Fig. 1: QDrone research UAV from Quanser. The dimensions of the QDrone are $40 \times 40 \times 15$ cm, the mass is 1.21 kg, and a motion capture system connected over WiFi is used for position measurements.

Eq. (4). From experience, we found that the resultant controller gains are high, which would result in small steady-state errors which we can neglect for the practical interest [4]. Hence, we generally set $\alpha_2 = 0$ and perform the optimization on Q'.

III. Deriving Sensitivity Functions

There are multiple sensitivity functions that can be used to evaluate closed loop robustness to dynamics variations. For example, the relative sensitivity function is suitable for large variations [9] and the logarithmic sensitivity can be used locally to investigate variations in the vicinity of the nominal dynamics. In this work we use the relative sensitivity function since we are interested in the relative importance of modeling of parameters for possible large parametric variations. The relative sensitivity function is given by [9]:

$$J_{ij} = \frac{Q(C_i, G_j) - Q(C_j, G_j)}{Q(C_j, G_j)} \times 100\% \tag{6}$$

where J_{ij} represents the degradation in performance due to applying controller C_i, which is the optimal controller for the process G_i and a sub-optimal controller for the process G_j. Note that $J_{ij} \geq 0$, $J_{ii} \equiv 0$ and $J_{ij} \neq J_{ji}$. The relative sensitivity function depends on the nominal model parameters, controller tuning, varied parameter, and amount of parametric variation.

IV. Example Analysis

Consider the altitude dynamics in Eq. (1), with the following dynamic parameters:

$$\begin{aligned} K_p &= 5.004 \\ T_p &= 0.0321 \\ T_d &= 1.6886 \\ \tau &= 0.0237 \end{aligned} \tag{7}$$

these parameters were obtained experimentally using the DNN-MRFT identification algorithm from [10], for the QDrone platform from Quanser (QDrone is shown in Fig. 1). Now we may consider the relative sensitivity to variations in the linear aerodynamic drag defined in [11], and the time delay in the system. Variations in the aerodynamic drag are inversely proportional to the system gain K_p and the time constant T_d. Considering a numerical example for the increase of drag dynamics by 50%, the dynamics in Eq. (6) would be then given by (note that the nominal dynamics in Eq. (7) are indexed with $i = 1$ and the varied dynamics are indexed with $j = 2$):

$$\begin{aligned} C_1(s) &= 59.0265 + 8.304s \\ C_2(s) &= 59.6586 + 8.325s \\ G_1(s) &= \frac{5.004e^{-0.0237s}}{s(0.0321s+1)(1.6886s+1)} \\ G_2(s) &= \frac{4.17e^{-0.0237s}}{s(0.0321s+1)(1.4072+1)} \end{aligned} \tag{8}$$

and the corresponding ISE evaluations would be given by:

$$\begin{aligned} Q(C_1, G_2) &= 0.11578 \\ Q(C_2, G_2) &= 0.11576 \end{aligned}$$

which results in $J_{12} = 0.02\%$, i.e. no notable change in performance would be observed. These results, though simple to obtain, provide important insight into the performance of the nominal closed loop system to parametric variations that are expected to happen during the operation envelop.

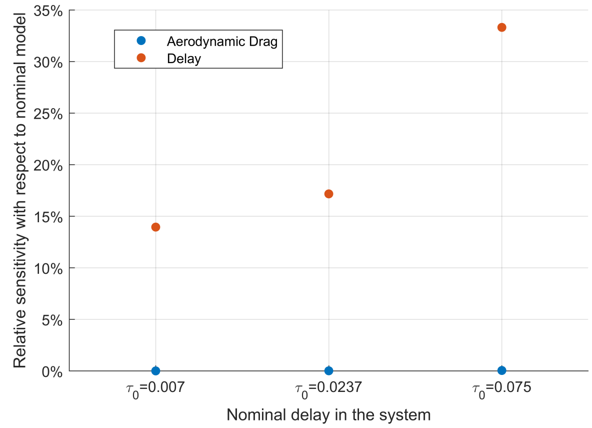

Fig. 2: Relative sensitivity to variations in aerodynamic drag and time delay with respect to three different nominal models of QDrone. The three different nominal models have three different nominal time delays, corresponding to the use of sensors with different latency dynamics.

Suppose that a possible 20% increase in aerodynamic drag or 20% increase of time delay is specified within the operation envelope of QDrone. Fig. 2 shows the relative sensitivity results for three different nominal cases. Note that we varied the time delay of the nominal model while keeping other model parameters as specified in Eq. (7). Changing the nominal time delay corresponds to changing the sensor and processing algorithms used for positioning, which incurs different overall

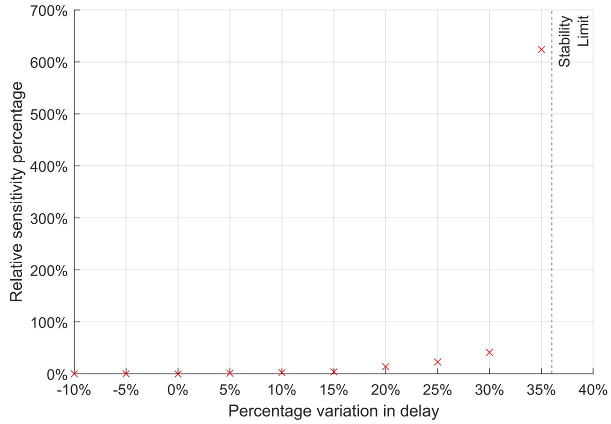

Fig. 3: Relative sensitivity to variations of delay for QDrone nominal dynamics with $\tau_0 = 0.007$ s. Decrease of delay in the loop merely changed the system performance. The system performance deteriorates rapidly beyond 30% increase of delay, eventually leading to instability.

latency. In particular, we used 0.007 s nominal delay to denote the case when a fast sensor like event camera is used for positioning, and used 0.075 s nominal delay to denote the case when a slow sensor like vision camera or thermal camera is used. The significant difference in latency between different sensor modalities was demonstrated in [12]. In all three nominal cases, the relative sensitivity predicts low sensitivity of optimal performance to variations in aerodynamic drag and a much higher sensitivity to time delay variations. These results suggest that simulated models are more sensitive to certain parametric mismatches when deployed in reality. For example, when using QDrone or another platform of similar dynamics, more efforts should be devoted to modeling of time delay and its possible variations compared to aerodynamic drag for best transferability results from simulation to reality.

The relative sensitivity can also be used to predict the drop in system performance up until instability. Fig. 3 shows the percentage drop from optimal performance in response to percentage variations in time delay, when nominal dynamics with time delay of 0.007 s are used. The results in Fig. 3 shows that a decrease in the time delay of the system has little effect on system performance. On the other hand, increasing the time delay in the controller system causes the system performance to drop until instability is reached at around $\tau = 0.00956$ s corresponding to time delay increase of approximately 37% from the nominal delay value. Since parametric variations are invetible in practice, lower bounds of performance can be predicted using relative sensitivity for a given upper bounds of parametric uncertainty.

V. Conclusions

This paper provided a theoretical investigation supported by simulation results for the use of relative sensitivity to evaluate the drop of optimal performance due to variations introduced to the nominal model parameters. The effect of variations of both time delay and aerodynamic drag was investigated. It was found that a small sized planar UAV similar to QDrone was more sensitive to variations in delay compared to aerodynamic drag. Such analysis provides an insight on the design of simulators for robust simulation to reality transfer. For example, accounting for small aerodynamic drag forces is not important for the investigated UAV design. On the other hand, ensuring that the delay in the position measurement (e.g. WiFi delay) is within a certain bound is essential for the overall performance of the system. Moreover, it is advised that delay greater than the measured nominal should be used in simulation design since lower delay in experimentation would not lead to noticeable change in system performance, yet it will lead to better robustness of the system.

Some future research directions are suggested based on the presented results. First, the sensitivity function can be used for the effective design of adversarial training of RL agents or domain randomization of dynamic parameters. Second, the selection of the nominal dynamics of the system used for RL training can be done through the analysis of the sensitivity. Lastly, different trajectories can be included in the sensitivity analysis, which leads to RL agents that can perform well for certain tasks.

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