Dynamics and control of quadcopter in uncertain environment

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Abstract

We consider problem of dynamics, control, and uncertainty quantification for quadcopter. We use the 6DOF model of quadcopter dynamics, linear quadratic regulator and linear quadratic Gaussian control of quadcopter in the presence of dynamical disturbances, measurement noise, hidden dynamical variables, dashing GPS signal, and wind gusts to predict quadcopter trajectory. We identify key sources of uncertainties and report on progress in development of a system that estimates the probability of safety-critical events using a set of algorithms based on the trajectory predictions.

1. Introduction. Most engineering applications are subject to uncertainty. There are multiple sources of uncertainty including those due initial conditions, weather, system health, surroundings, navigation sensors, control systems etc. The uncertainty quantification of unmanned aerial systems (UAS) such as quadcopters is crucial for their safe operation. The latter quantification present a significant challenge due to nontrivial dynamics and control of UAS in the presence of a large number of uncertainties.

The vehicle configuration (Chovancová, Fico, Chovanec, & Hubinsk, 2014) is shown in Fig. 1. The state vector of the system has four triplets

\[ x = [(\phi, \theta, \psi), (p, q, r), (x, y, z), (\dot{x}, \dot{y}, \dot{z})] \]

representing Euler angles of the vehicle frame \( \eta = [\phi, \theta, \psi]^T \), angular velocities \( \nu = [p, q, r]^T \), coordinates of the center of mass \( \xi = [x, y, z]^T \), and the corresponding velocities in the inertial frame.

The vehicle dynamics is analyzed using two sets of equations for translational dynamics in inertial frame

\[ m\ddot{\xi} = -mg\ddot{a}_3 + R_M^T \cdot T_B + F_x + W + D_x, \]

and rotational dynamics in the body frame

\[ J\ddot{\nu} + \nu \times (J\nu) + \Gamma = \tau + D_{\eta}, \]

where forces on the rhs of the first equation are due to gravity \( g \), rotor thrust \( T_B = [0, 0, \sum_{i=1}^{4} k_i\omega_i^2]^T \) where \( R_M^T \) is the full rotation matrix, drag \( F_x = [-A_x\dot{x}, A_y\dot{y}, A_z\dot{z}]^T \) with drag coefficients \( A_i \), wind gusts (Tran, Bulka, & Nahon, 2015) \( W = [W_x, W_y, W_z]^T \) that may accelerate the whole air block as a random not necessarily Gaussian disturbance, the rest of the disturbances \( D_x = [d_x, d_y, d_z]^T \) modeled as zero-mean Gaussian random variables.
The rotational dynamics is controlled by the diagonal inertia matrix
\( J = \text{diag}(J_{xx}, J_{yy}, J_{zz}) \), torque \( \tau = [lk(\omega^2_2 - \omega^2_1), lk(\omega^2_3 - \omega^2_1), \sum_i b_i \omega^2_i]^T \) with drag coefficient \( b_i \) of each rotor, the gyroscopic forces \( \Gamma \) (neglected in this presentation), and random force \( D_0 \).

Figure 2. (left) Lost LQR control when measurements of the \( p, q, \) and \( r \) are missing and the dynamical disturbances \( (D_d = 0.05) \) and measurement noise \( (D_m = 0.05) \) are present. (right) Recovered control using LQR with the same model parameters.

To model control the dynamic equations without wind disturbance are linearized as follows
\[
\dot{x}(t) = Ax(t) + Bu(t) + w(t) \quad \text{and} \quad y(t) = Cx(t) + v(t)
\]

The LQR control is applied when no measurement or disturbance noise is present and the full set of dynamical variables is available for measurement. In simulation the LQR control was reasonably robust in the presence of noise, but was lost if a number of variables could not be measured. The results of the simulation of this model with lost LQR control in the presence of noise and incomplete measurements are shown in Fig. 2 (left).

The recovery of the control using LQG for the same dynamical variables is shown in Fig. 2 (right).

We apply this model for development of a simulation environment (see Fig. 3) for the quadrotor that allows to specify obstacles, way points, dynamical and measurement noise, wind gusts characteristics, and measurement matrix with incomplete set of measurements.

Next, in the spirit of (Roy & Oberkampf, 2011) we specify a list of uncertainties and categorizing them (i.e. identify model related, environmental, numerical etc uncertainties), we characterize them, i.e. assign probabilities/intervals for known/unknown uncertainties.

The system response quantities (SRQ) of interest in these analysis are the probabilities of: (i) impact with the obstacles (which is reduced to the probability of deviation from the desired trajectory); (ii) total time of the flight exceeding threshold value; (iii) delay of arrival beyond limiting value; (iv) total requested energy during flight exceeding approaching critical value etc.

Finally, the effect of uncertainties on the SRQ is estimated using a set of algorithms proposed in (Roy & Oberkampf, 2011; Sankararaman & Daigle, 2017). This work is in progress.

REFERENCES