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.

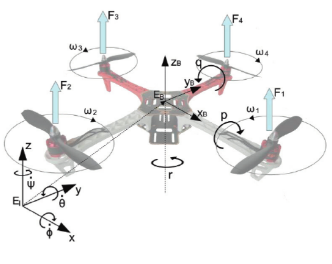

Figure 1. Quadrotor configuration with a free body diagram.

Here we report on development of the computational framework built to model realistically quadcopter dynamics and control in mission-critical and safety-critical situations. The dynamical model of quadcopter accounts dynamical disturbances and measurement noise that incorporates some simplified planning of quadcopter trajectory through a set of arbitrary way points. We apply linear quadratic regulator (LQR) and linear quadratic Gaussian (LQG) trajectory tracking to model the system control. We analyze the effect of disturbances, measurement noise, wind, and flickering/dashing GPS signal on vehicle dynamics and control. We formulate the uncertainty quantification problem for quadrotor and initiate uncertainty quantification analysis of the vehicle.

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

$$x = [(\phi, \theta, \psi), (p, q, r), (x, y, z), (\dot{x}, \dot{y}, \dot{z})] \tag{1}$$

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

$$m\ddot{\xi} = -mg\vec{a}_3 + R_M^T \cdot T_B + F_\xi + W + D_\xi, \tag{2}$$

and rotational dynamics in the body frame

$$J\dot{\nu} + \nu \times (J\nu) + \Gamma = \tau + D_\eta, \tag{3}$$

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 $J = diag(J_{xx}, J_{yy}, J_{zz})$, torque $\tau = [lk(\omega_4^2 - \omega_2^2), lk(\omega_3^2 - \omega_1^2), \sum_{i=1}^{4} b_i \omega_i^2]^T$ with drag coefficient b_i of each rotor, the gyroscopic forces Γ (neglected in this presentation), and random force D_η.

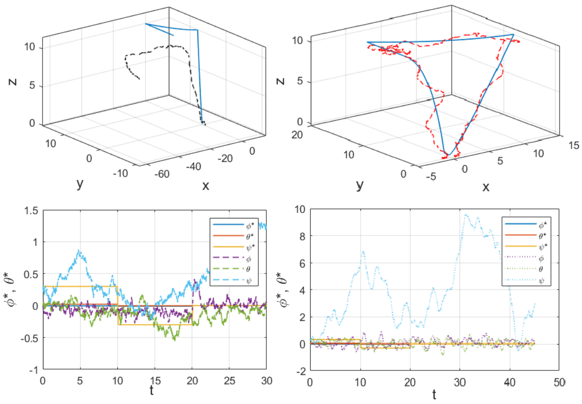

Figure 2. (left) Lost LQR control when measurements of the p, q, and r are missing and the dynamical disturbances ($D_d = 0.05$) and measurement noise ($D_m = 0.05$) are present. (right) Recovered control using LQR with the same model parameters.

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.

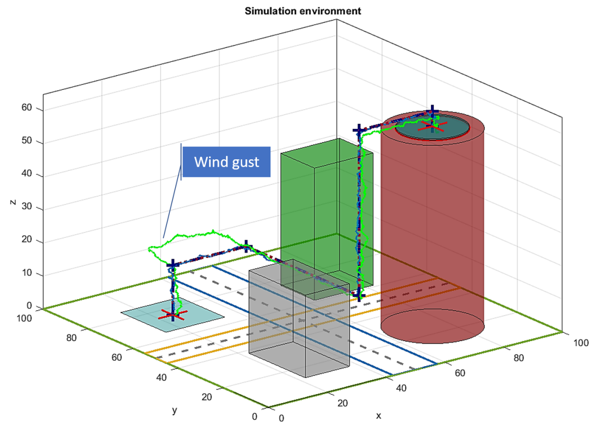

Figure 3. The simplified simulation environment with obstacles and a set of way points, and planned trajectory. Example of the LQR control of the nonlinear set of equations in the presence of the wind gust, dynamical and measurement noise and incomplete measurements.

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

Chovancová, A., Fico, T., Chovanec, Ľ., & Hubinsk, P. (2014). Mathematical modelling and parameter identification of quadrotor (a survey). *Procedia Engineering*, *96*, 172–181.

Roy, C. J., & Oberkampf, W. L. (2011, jun). A comprehensive framework for verification, validation, and uncertainty quantification in scientific computing. *Computer Methods in Applied Mechanics and Engineering*, *200*(25-28), 2131–2144.

Sankararaman, S., & Daigle, M. (2017, jan). Uncertainty quantification in trajectory prediction for aircraft operations. In *AIAA guidance, navigation, and control conference.* American Institute of Aeronautics and Astronautics.

Tran, N. K., Bulka, E., & Nahon, M. (2015, jun). Quadrotor control in a wind field. In *2015 international conference on unmanned aircraft systems (ICUAS).* IEEE.