On separation of closed-loop sensor and system faults for quadcopters

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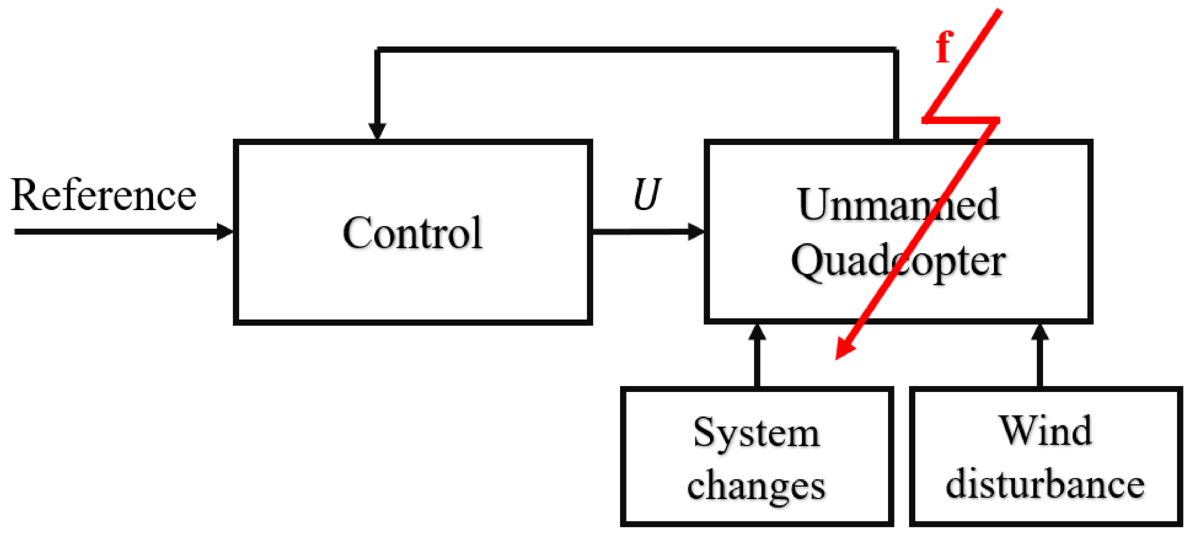
Summary

Change detection is important in many quadcopter applications. However, false alarms can occur due to inaccurate sensors and external disturbances. Here, it is shown that sensor faults can be estimated using a reduced dynamical model of the quadcopter. Based on the compensated sensor measurements, a sensor-to-sensor submodel can be used for robust detection of payload changes.

Quadcopter dynamics

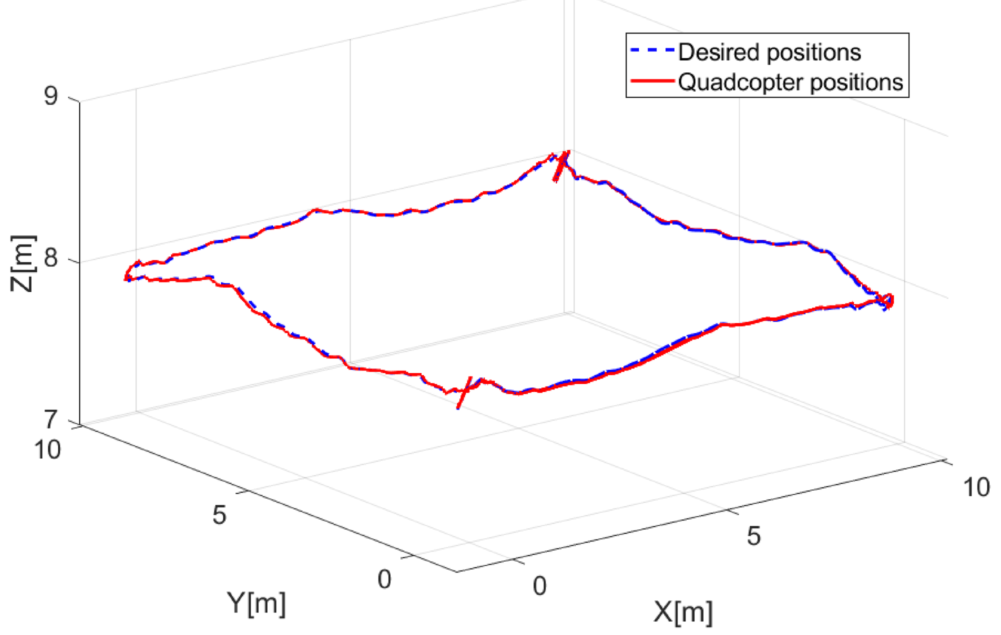


In the body-fixed frame, the dynamic equations of a rigid body quadcopter using the Newton-Euler equations are given by

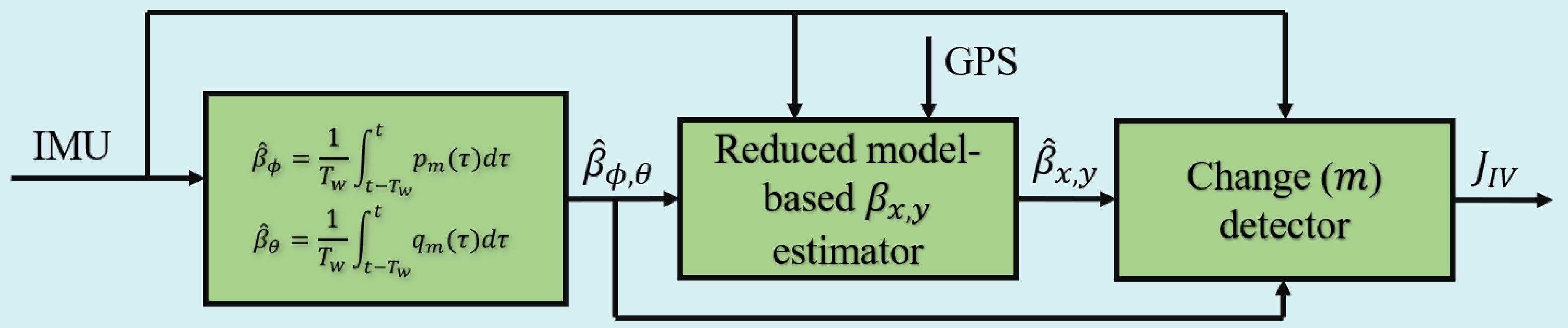
$$\begin{aligned} m\dot{V}_B + m\nu \times V_b &= mR^T g + E_B^F(\Omega) + D_B^F(V_b) \\ I\dot{\nu} + \nu \times (I\nu) &= O_B^\tau(\nu, \Omega) + E_B^\tau(\Omega) \end{aligned} \tag{1}$$

where m is the mass of the quadcopter.

The wind turbulence can be modeled using the Dryden wind model. The controller reacts to the disturbances and drives the quadcopter to follow the desired path.



Detector overview



Sensor fault estimator

With an augmented state vector $x_a = [\phi,\, \theta,\, u,\, v,\, x,\, y,\, \beta_x,\, \beta_y]^T \in \mathbb{R}^8$, a reduced model of (1) can be written as

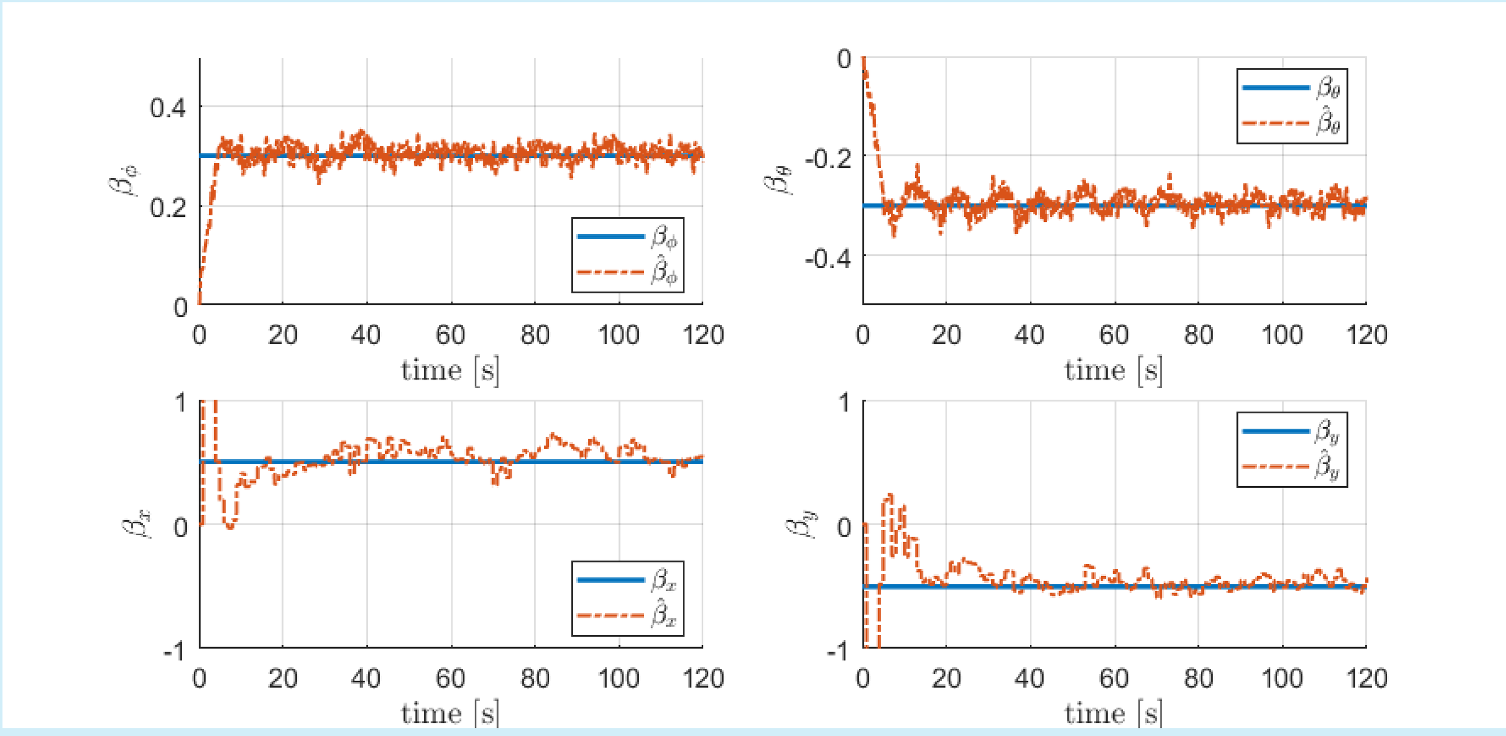
$$\dot{x}_a = F(\psi_m, r_m)x_a + B\left[p_m - \hat{\beta}_\phi,\, q_m - \hat{\beta}_\theta,\, -a_x,\, -a_y\right]^T \tag{2a}$$

$$y_a = H(\psi_m, r_m)x_a \tag{2b}$$

where ψ_m and r_m are the noisy yaw angle and yaw rate, respectively. An IMU gives the input vector in (2) including the roll rate p_m, pitch rate q_m and accelerations a_x and a_y at 200 Hz. A GPS receiver provides the output vector y_a containing measurements of the absolute positions x, y and velocities $\dot{x}$, $\dot{y}$ at 1 Hz.

Sensor fault estimation result

A linear Kalman filter can be applied to the time-varying model (2) to estimate the accelerometer biases and the gyro biases can be estimated using integration over a time window and mild assumptions about the quadcopter movements.



The gyro and accelerometer biases can be compensated before using in the change detection.

Change detector

Sensor-to-sensor models are obtained by projecting (1) onto the $x-y$ plane in the body-fixed frame

$$\begin{aligned} \dot{u} &= -g\sin\theta - \frac{\lambda_1}{m}u, \quad a_x = \frac{\lambda_1}{m}u + e_{a_x} \\ \dot{v} &= g\cos\theta\sin\phi - \frac{\lambda_1}{m}v, \quad a_y = \frac{\lambda_1}{m}v + e_{a_y} \end{aligned} \tag{3}$$

where λ_1 is the drag coefficient.

The IV cost functions are computed based on the sensor-to-sensor models as

$$J_{IV1,2}(t) = \left\| \sum_{i=t-N_w+1}^{t} \lambda^{t-i} Z_{1,2}(i) r_{1,2}(i) \right\|_2 \tag{4}$$

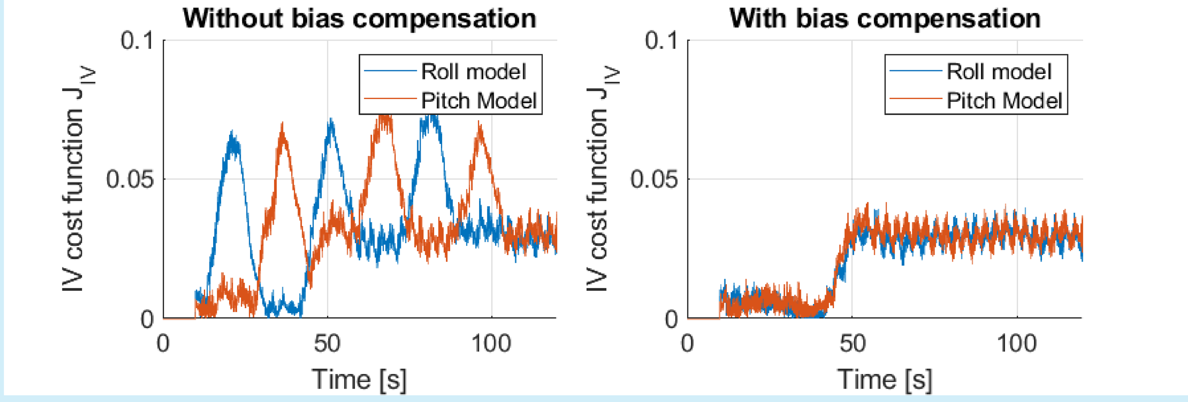
where λ is the forgetting factor. The residual $r_{1,2}(t)$ are computed using $m = 0.5kg$ as

$$r_1(t) = a_x(t) - \varphi_x^T(t)\vartheta_x, \quad r_2(t) = a_y(t) - \varphi_y^T(t)\vartheta_y \tag{5}$$

where $\varphi_x^T(t) = [-a_x(t-1), -a_x(t-2), q_m(t-2)]$, $\varphi_y^T(t) = [-a_y(t-1), -a_y(t-2), p_m(t-2)]$ and $\vartheta_x = \vartheta_y = [-2 + \frac{\lambda_1}{m}T,\, 1 - \frac{\lambda_1}{m}T,\, \frac{\lambda_1}{m}gT^2]^T$. $Z_1(t)$ and $Z_2(t)$ are the noise-free versions of $\varphi_x(t)$ and $\varphi_y(t)$, respectively.

Change detection result

The mass of the quadcopter increases linearly from $m = 0.5kg$, $\forall t \le 40s$ to $m = 1kg$, $\forall t \ge 42s$.



The payload changes are detected using the IV cost function.

Papers

1. Ho, D., Hendeby, G., and Enqvist, M. On separation of closed-loop sensor and system faults for quadcopters, to be submitted, 2020.
2. Ho, D., Hendeby, G., and Enqvist, M. A sensor-to-sensor model-based change detection approach for quadcopters, In the 21st IFAC World Congress in Berlin, Germany, 2020.