System change detection for quadcopters with sensor biases and winds

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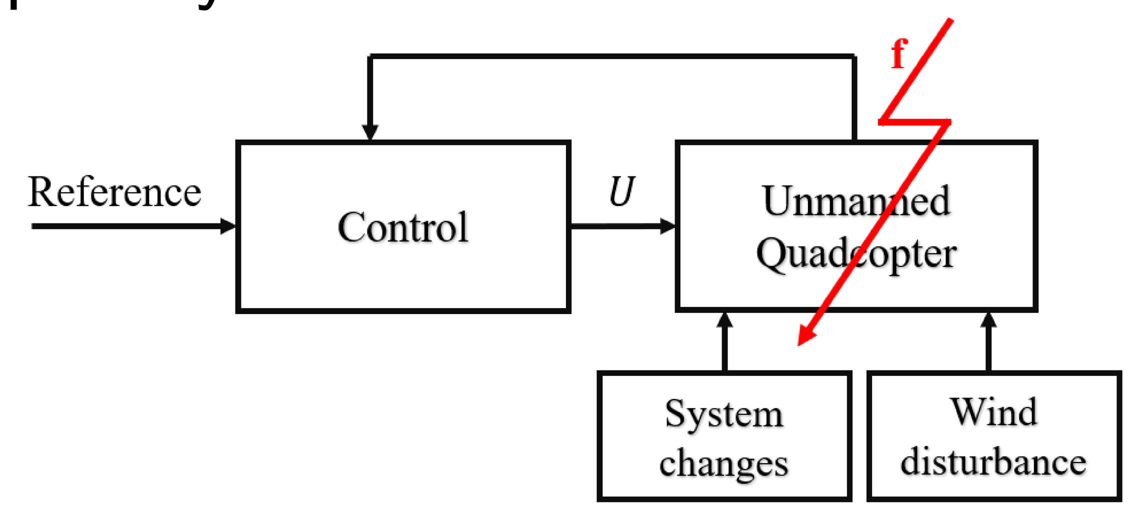
Summary

Change detection is essential in many quadcopter applications. However, inaccurate sensors and external disturbances can result in false alarms. Here, it is shown that a quadcopter's navigation model can be used to estimate sensor biases, requiring only IMU and GPS measurements. Based on the compensated IMU measurements, a sensor-to-sensor submodel is employed for the robust detection of payload changes.

Quadcopter dynamics



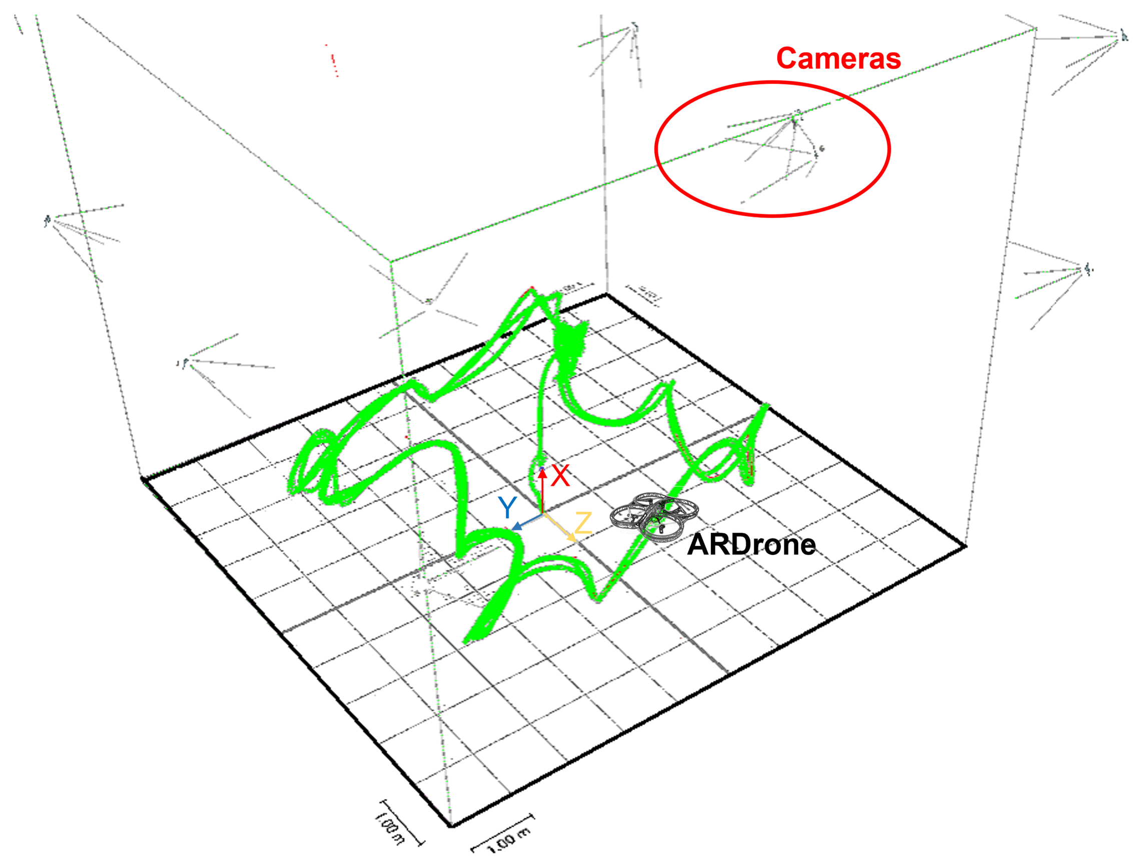
In the body-fixed frame, the quadcopter's dynamics are given by

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

where m is the mass of the quadcopter.

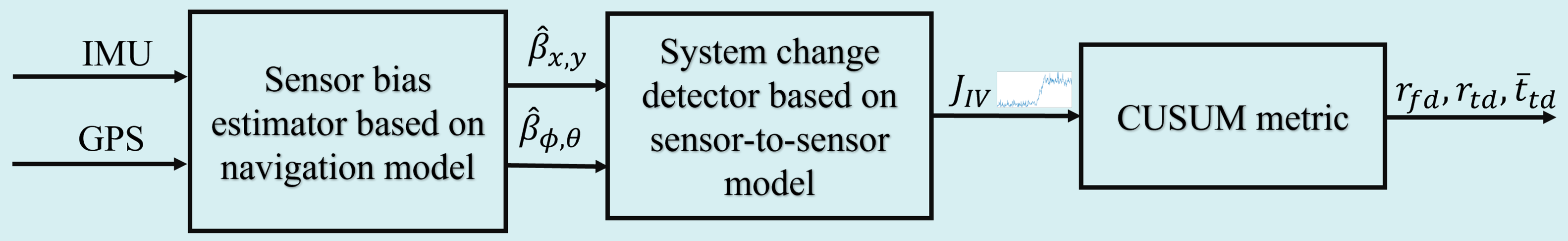
The controller reacts to the disturbances and drives the quadcopter to follow the desired path consisting of two parts:

- Nominal part: for a mission.
- Additional excitation: for estimation and detection purpose.



Detector overview

Estimating unknown quantities using an augmented model and a nonlinear estimator might not always be accurate due to closed-loop control and imperfect noise modeling. Therefore an alternative is proposed by viewing the system dynamics differently.



Sensor bias estimation result

A navigation model can be written as

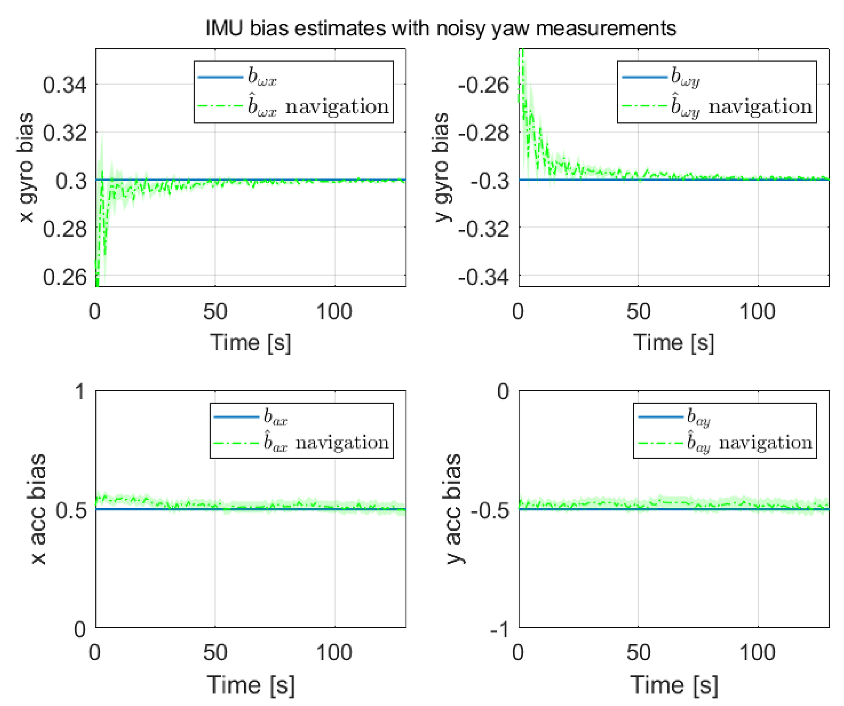
$$\dot{x}_a = A(\psi_m, r_m)x_a + B\left[p_m,\, q_m,\, -a_x,\, -a_y\right]^T \tag{2a}$$

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

where $x_a = [\phi,\, \theta,\, u,\, v,\, x,\, y,\, \hat{\beta}_\phi,\, \hat{\beta}_\theta,\, \beta_x,\, \beta_y]^T \in \mathbb{R}^{10}$ is an augmented state vector. ψ_m and r_m are the noisy yaw angle and yaw rate, respectively.

- Inputs (IMU): roll rate p_m, pitch rate q_m, and accelerations a_x and a_y at 200 Hz.
- Outputs (GPS+IMU): naive estimates (IMU) β_ϕ, β_ϕ, and absolute positions (GPS) x, y and velocities (GPS) $\dot{x}$, $\dot{y}$ at 1 Hz.

A linear Kalman filter can be applied to the time-varying model (2) to estimate the accelerometer and gyro biases.



The gyro and accelerometer signals are bias-compensated before using them in the change detection.

System change detection result

Projecting (1) onto the $x-y$ plane in the body-fixed frame gives

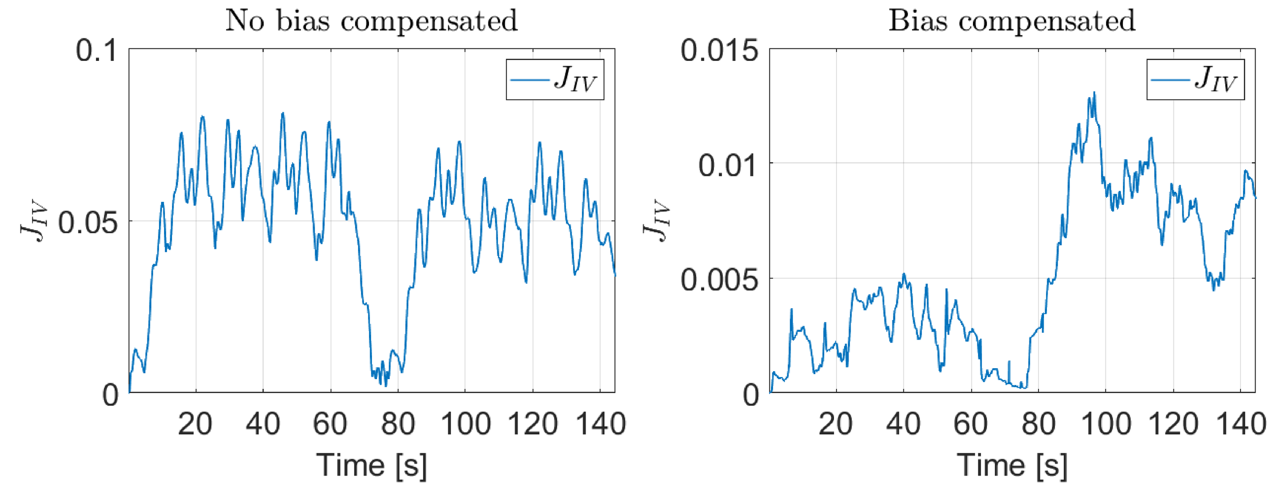
$$\begin{aligned} \dot{u} &= -g\sin\theta - \frac{\lambda_1}{m}u, \quad & a_x &= \frac{\lambda_1}{m}u + e_{a_x} \\ \dot{v} &= g\cos\theta\sin\phi - \frac{\lambda_1}{m}v, \quad & a_y &= \frac{\lambda_1}{m}v + e_{a_y} \end{aligned} \tag{3}$$

where λ_1 is the drag coefficient.

The IV cost functions are computed based on the regression form of the sensor-to-sensor model as

$$J_{IV}(t) = \sum_{j=1}^{2} \Big\| \sum_{i=t-N_{IV}+1}^{t} Z_j(i) r_j(i) \Big\|^2 \tag{4}$$

Payload added to the quadcopter, from $m = 0.519kg$ to $m = 0.595kg$ at 71 s. The quadcopter needs few seconds for restabilization.



CUSUM metric

- A (slow V, small r), B (fast V, large r), C (fast V, fairly large r)
- r_{fd}, r_{td}: false/true detection rate, $\bar{t}_{td}$: avarage time-to- detection

trajectory (flights)	100% CUSUM params			115% CUSUM params		
	$r_{fd}[s^{-1}]$	$r_{td}[s^{-1}]$	$\bar{t}_{td}$ [s]	$r_{fd}[s^{-1}]$	$r_{td}[s^{-1}]$	$\bar{t}_{td}$ [s]
A (3)	0	0.0845	9.0609	0	0.0578	11.4482
B (3)	0.0047	0.1646	4.2607	0	0.0980	7.1100
C (5)	0.0082	0.7717	1.0378	0	0.5998	1.3109

Papers

1. Ho, D., Hendeby, G., and Enqvist, M. System change detection of quadcopters with sensor biases and wind disturbances, submitted to R-AL, 2021.
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.

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