Closed-loop estimation and detection for quadcopters

Du Ho

Division of Automatic Control
Department of Electrical Engineering
Linköping University
Linköping, Sweden

Motivation

Why do we consider multirotors

Wind turbine inspection

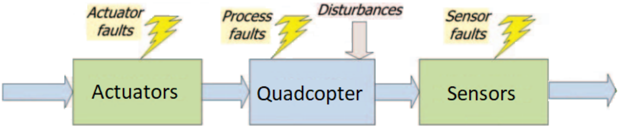
Agriculture irrigation

Catch a fixed-wing UAV

Multirotors can be used in many applications

Motivation

Goal: Detect/estimate system changes (process faults) with sensor biases (sensor faults) and actuator faults.



Typical problem: Limited sensors for the estimation and detection purposes.

- Disturbances (externals, sensors, model mismatch).
- Correlation between noises and signals due to closed-loop.

Can we simply apply a filtering problem?

- Sensors: Orientation measurements from AHRS (Altitude and heading reference system), $x - y$ body-fixed velocities.
- Complex: not always ensure an accurate estimation.
- Feedback: noises correlate with control inputs.

$\rightarrow$ Projection approach applied to the submodels of the quadcopter.

What kind of sensor information needed?

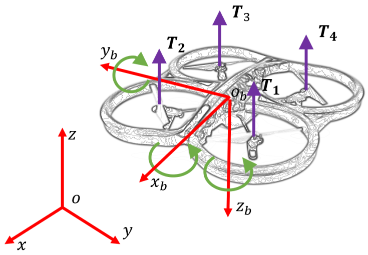
- IMU
- Command signals
- GPS

Outline

1. Motivation
2. Quadcopter modeling
3. Estimation
4. Detection
5. Conclusion

Quadcopter modeling

Modeling of an under-actuated quadcopter



$\xi = [x,\ y,\ z]^T$: position in inertial frame.
$\eta = [\phi, \theta, \psi]^T$: Euler angles.
$V_B = [u, v, w]^T$: linear velocities in the fixed-body frame.
$\omega = [p, q, r]^T$: angular velocities in the fixed-body frame.

$$m(\dot{V}_B + \omega \times V_B) = R^T mg + T_B + F_d + F_w \quad (1)$$

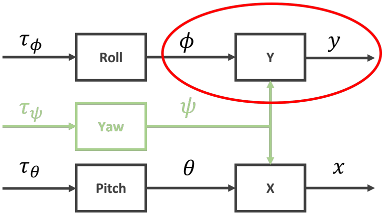
$$I\dot{\omega} + \omega \times (I\omega) = \tau_B - \Delta\omega \quad (2)$$

$T_B = [0,\ 0,\ T_z]^t$ and $\tau_B = [\tau_\phi,\ \tau_\theta,\ \tau_\psi]^T$ are control quantities.
F_d and $\Delta\omega$ are linear and angular drag, F_w is the wind forces.

Estimation

Subsystems (1) System change

Goal: Estimate quadcopter's payload.
Projecting the dynamics onto x-y body-fixed frame



Process model

$$\dot{u} = -g\sin\theta - \frac{\lambda_1}{m}u$$

$$\dot{v} = g\cos\theta\sin\phi - \frac{\lambda_1}{m}v$$

Measurement model

$$a_x = \frac{\lambda_1}{m}u + e_{a_x}, \quad a_y = \frac{\lambda_1}{m}v + e_{a_y}$$

$$p = \dot{\phi}, \quad q = \dot{\theta}$$

Sensor-to-sensor model

$$a_{y,s} = \frac{\frac{\lambda_1}{m}g}{p(p+\frac{\lambda_1}{m})}p_s + e$$

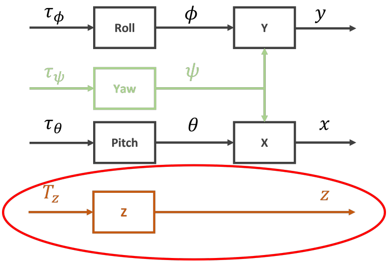
Experimental data

- Robust to actuator faults and load is fixed.
- Deal with feedback effect and coloured noises using IV-based method.
- Comparison performance with EKF, LS.

m_{ref}	m_c	$\hat{m}_c$ (LS)	$\hat{m}_c$ (EKF)	$\hat{m}_c$ (IV)
$455g$	$510g$	$1362.5 \pm 54.9g$	$505.6 \pm 258.8g$	$504.1 \pm 3.9g$
	$582g$	$2126.2 \pm 78.9g$	$384.4 \pm 161.2g$	$580.9 \pm 3.8g$
$510g$	$455g$	$170.3 \pm 6.9g$	$458.9 \pm 234.8g$	$460.3 \pm 3.4g$
	$582g$	$795.8 \pm 25.7g$	$387.3 \pm 187.3g$	$587.5 \pm 3.2g$
$582g$	$455g$	$124.5 \pm 4.6g$	$689.7 \pm 289.6g$	$456.1 \pm 3.0g$
	$510g$	$373.1 \pm 12.1g$	$766.4 \pm 370.7g$	$505.2 \pm 2.8g$

Subsystems (2) Actuator and system change

Goal: Estimate quadcopter's drag coefficient and mass.
Projecting the dynamics onto z body-fixed frame



Process model

$$\dot{w} = -\frac{T_z}{m} - \frac{k_w}{m} w + g\cos\theta\cos\phi$$

Measurement model

$$a_z = \frac{T_z}{m} + \frac{k_w}{m} w + e_{a_z}$$

Refined thrust

$$a_z = \frac{p}{p+\frac{k_w}{m}}\left(\frac{k_1}{m}u_t^2 + \frac{k_2}{m}u_t\right) + \frac{\frac{k_w g}{m}}{p+\frac{k_w}{m}} + e_{a_z}$$

Experimental data

- Standard model Hammerstein nonlinear model.
- Unmodeled actuator dynamics.
- Feedback effect, and nonlinear-related and coloured noises

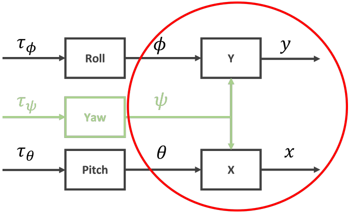
Param		Mass $455\,g$	Mass $530\,g$	Mass $586\,g$
k_w	LS	0.2590 ± 0.0848	0.3068 ± 0.1475	0.1713 ± 0.1473
	IV	0.3040 ± 0.0063	0.2904 ± 0.0083	0.3052 ± 0.0022
k_1	LS	0.1217 ± 0.1298	-0.1067 ± 0.3205	0.4957 ± 0.2078
	IV	0.5198 ± 0.0482	0.5165 ± 0.0833	0.4921 ± 0.0217
k_2	LS	-0.0988 ± 0.1248	0.1870 ± 0.2326	-0.6443 ± 0.1893
	IV	1.5115 ± 0.0305	1.5574 ± 0.0565	1.5247 ± 0.0171

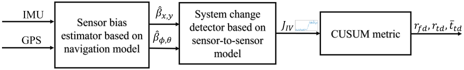
Detection

Subsystems (3) Sensor fault and system change

Goal: Detect payload change with wind disturbances and sensor biases.

Consider roll-pitch dynamics under yaw effect.





Navigation model

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

$$y_a = C(\psi_m, r_m)x_a$$

Sensor-to-sensor model:

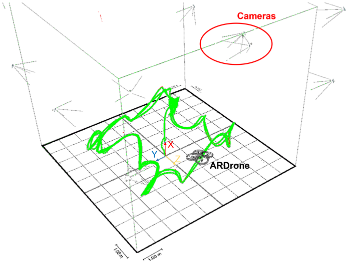
$$\dot{u} = -g\sin\theta - \frac{\lambda_1}{m}u, \; a_x = \frac{\lambda_1}{m}u + e_{a_x}$$

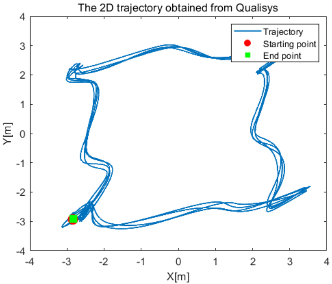
$$\dot{v} = g\cos\theta\sin\phi - \frac{\lambda_1}{m}v, \quad a_y = \frac{\lambda_1}{m}v + e_{a_y}$$

Experimental study

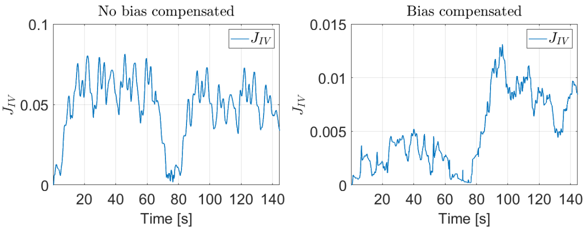
Settings

- Flights: 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





For single flight



For multiple flights

Type	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

Conclusion

Summary

- Interesting physical coefficients of quadcopters have been estimated using the IV method despite closed-loop and sensor-to-sensor setups (1, 2).
- Sensor bias estimation and system change detection under windy condition is considered (3).

Take-home message: unknown dynamic parameters can be estimated accurately and validated using multiple datasets (with changes of measurable quantities).

Future work

- Working with (slung) payload detection application in quadcopters.
- Multiple quadcopters application can be studied.

Thanks for your attention!

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