Supervision for drone flight safety

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Plan

Plan

Context and problem
Introduction

Me:

My research:

- Fault tolerant navigation
  - Sensor faults (GPS, IMU, ...)
  - Actuator faults (motors, ...)
- State estimation $\rightarrow$ Fault detection $\rightarrow$ Reconfiguration $\rightarrow$ Emergency procedure
- Application to a hexarotor drone

- Develop methods for robust drone navigation through:
  - The detection of faults
  - The localisation of their origin
  - The identification of their characteristics
  - The reduction of their impact on the continued navigation
- Define a modular architecture capable of performing the above tasks.

Plan

We consider the translational kinematics:

$$\begin{cases} \dot{X} = V \\ \dot{V} = A \end{cases}$$

Measurements:

$$\begin{cases} A_m = A + v_A \\ X_m = X + B + w_X \end{cases}$$

Hypothesis: If $B = 0$, the system is observable.

B can be a bias, a drift, etc.

$$\Rightarrow \begin{cases} \dot{X} = V \\ \dot{V} = A_m - v_A \\ \dot{B} = v_B \end{cases}$$

Measurement:

$$\{ \quad X_m = X + B + w_X$$

! The system is no longer observable (in a Kalman sense)

Typical solution: GLR[1]

Main hypothesis:

$B \to BY(t - T)$: A fault appears at time T

$\rightarrow$ System is (weakly) observable if T is known

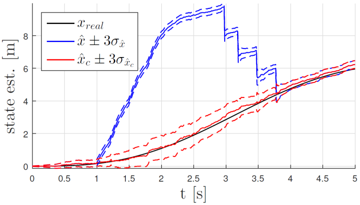
- Estimation of T in a max. likelihood sense.
- Estimation of the state X in a max. likelihood sense, given $T = \hat{T}$.

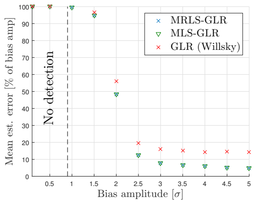
GLR: Generalized Likelihood Ratio

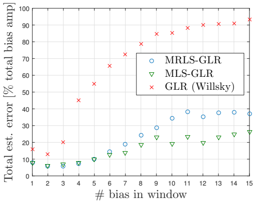
[1] Willsky, Jones, 1974

Method and results
Contribution: GLR for multiple frequent faults

Let's start from the back with some results...

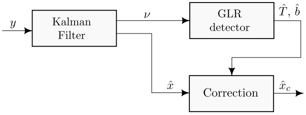






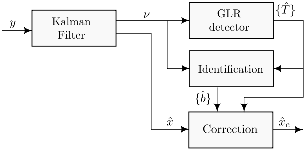
- GLR (Willsky): Nominal GLR defined by Willsky.
- MRLS-GLR: New GLR allowing detection/estimation of multiples faults, based on RLS (recursive least squares) estimation.
- MLS-GLR: New GLR allowing detection/estimation of multiples faults, based on LS (least squares) estimation.

Willsky's GLR algorithm:



- Compromise between fast detection and precise estimation of the fault.
- Corrected state $\hat{x}_c$ becomes unstable at frequent faults.

New MLS/MRLS-GLR[2] algorithm:



- Better compromise between speed and precision of the fault estimation.
- Corrected state more robust since the fault estimation is refined until it is no longer observable.

[2] Öman Lundin, Mouyon, Manecy, 2017

Attitude estimation: A non-linear problem

R is a rotation matrix from the body frame (B) to the inertial frame (I): $V_B = R^T V_I$

Non-linear kinematics:

$$\begin{cases} \dot{R} = f(R, \omega) \\ \omega_m = \omega + B_\omega + noise \quad \text{(Gyroscope)} \end{cases}$$

$$\begin{cases} M_m = M_B + B_M + noise \quad \text{(Magnetometer)} \\ \mathrm{A}_m = \mathrm{A}_B + B_\mathrm{A} + noise \quad \text{(Accelerometer)} \end{cases}$$

Assumption: $\begin{cases} \mathrm{A}_B = R^T \mathrm{A}_I \\ M_B = R^T M_I \end{cases} \quad (\dot{\mathrm{A}}_I = \dot{M}_I = 0)$

Problem:

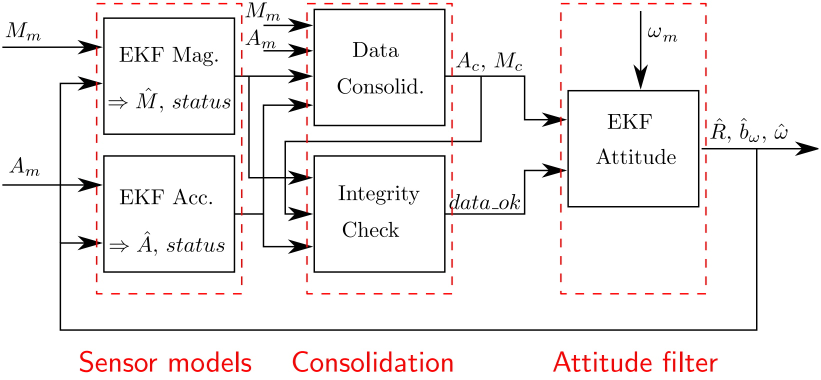
- B_ω is observable if $B_M = B_A = 0$.
- B_A and B_M are not observable.

Solution:

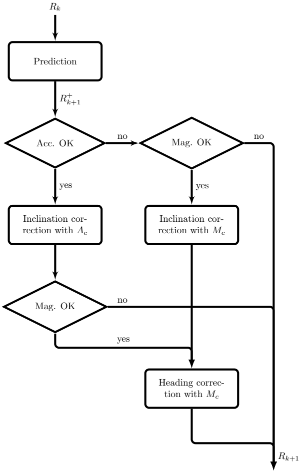
- Detect the presence of B_A and B_M and adapt the attitude estimation.

General approach:

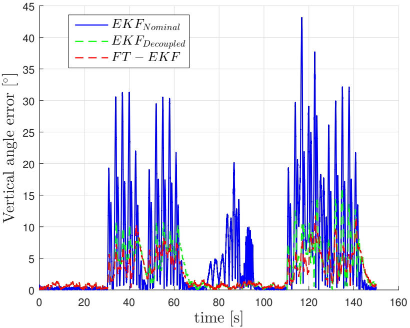
1. A set of sensor models based on expected sensor performance are used to estimate the sensor output (acc. and mag.).
2. The estimation error is used to determine whether a bias (B_A or B_M) is present on the sensor output.
3. A data consolidation stage decides whether to use the estimated sensor data or the actual measurement for the attitude update, or to inhibit correction of the attitude.
4. An attitude filter based on an EKF formalism corrects the inclination and the yaw estimates by using the consolidated sensor information.

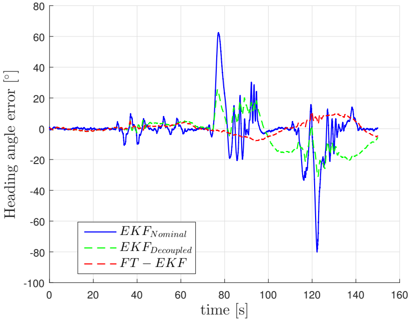

M_m
A_m
EKF Mag.
$\Rightarrow \hat{M}$, $status$
EKF Acc.
$\Rightarrow \hat{A}$, $status$
M_m
A_m
Data
Consolid.
Integrity
Check
A_c, M_c
$data\_ok$
ω_m
EKF
Attitude
$\hat{R}$, $\hat{b}_\omega$, $\hat{\omega}$
Sensor models
Consolidation
Attitude filter

- The attitude filter is based on an EKF-formalism, i.e. a linearised predictor-corrector.
- The gyroscope bias is modelled as a saturated white noise process.
- The consolidated acceleration is used for inclination update and associated gyroscope biases $B_{\omega,1}$ and $B_{\omega,2}$.
- The consolidated acceleration is used for yaw update and associated gyroscope bias $B_{\omega,3}$.
- Attitude correction is inhibited if the sensor integrity check is not passed.



Method and results
Attitude estimation: Simulation results





Plan

- Integration of detection/estimation (modified GLR, ...) and detection/isolation (FT-EKF, ...) methods for robust full state estimation (position, velocity, attitude).
- Creation of a modular estimation architecture for robust navigation of multi rotor drones.

Plan

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THE FRENCH AEROSPACE LAB

Gustav Öman Lundin, Philippe Mouyon, Augustin Manecy
A GLR algorithm for multiple consecutive measurement bias estimation, REDUAS 2017

Questions ?

Appendix
Attitude estimation: Sensor bias detection

Method applied to detect B_A (same applies to B_M):

1. Performance model for A_m (and M_m):

$$\dot{\mathrm{A}}_B = -\omega \times \mathrm{A}_B + \dot{\mathrm{A}}_I$$

where $\dot{\mathrm{A}}_I = -\frac{1}{\tau}\left(\mathrm{A}_B - R^T \mathrm{A}_I\right)$

$$\Rightarrow \quad \mathrm{A}_B \to R^T A_I$$

2. Kalman filter to estimate A_B:

$$\dot{\hat{\mathrm{A}}}_B = -\omega \times \mathrm{A}_B + \dot{\mathrm{A}}_I + K\left(\mathrm{A}_m - \hat{\mathrm{A}}_B\right)$$

$$\Rightarrow \quad \mathrm{A}_B \to \mathrm{A}_m$$

3. Statistical test on residual $\mathrm{A}_m - \hat{\mathrm{A}}_B$