GDR Robotique: Drones 1^{er} Avril 2010

Guillaume Ducard



Fault-Tolerant Flight Control and Guidance System for a Small UAV

Introduction

- 1. Small UAV Configuration and Goals
- 2. Architecture of the Reconfigurable Flight Control System
- 3. Fault Detection and Isolation System
- 4. Supervision Module

Conclusions

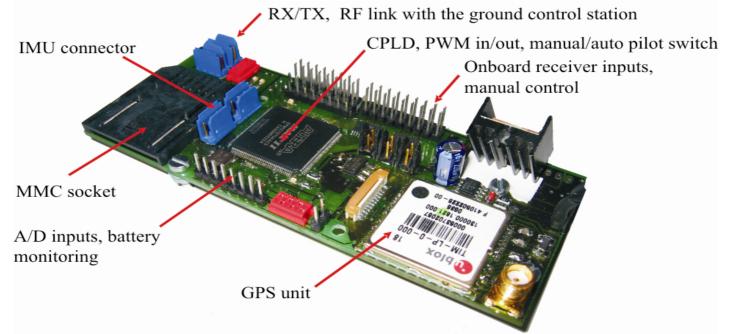
1. Small UAV Configuration



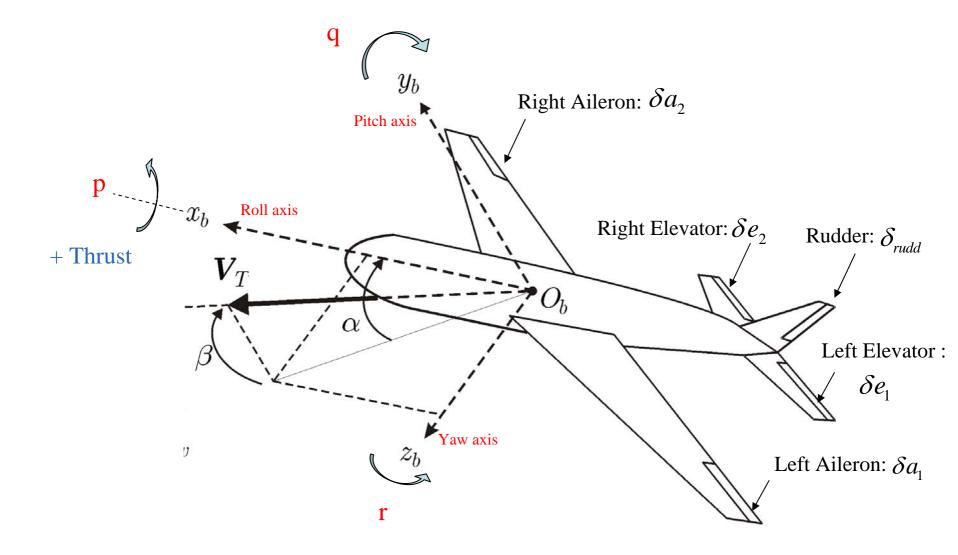
Small UAV at the IMRT, ETHZ

1. Small UAV Configuration





1. Small UAV Configuration



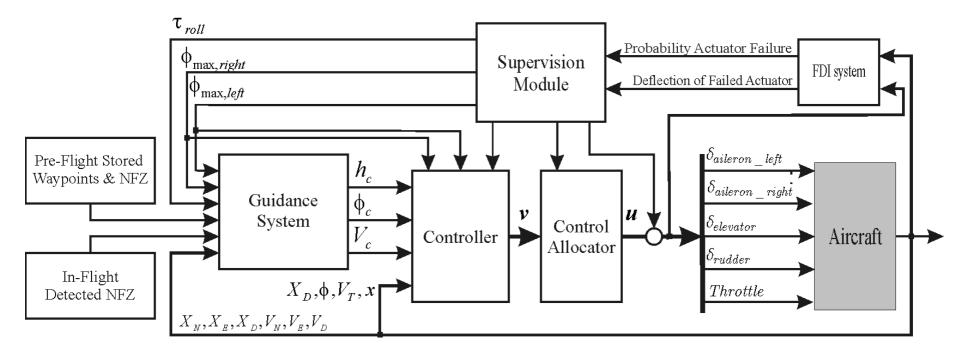
1. Small UAV : goals of this work

Design a safe and reliable control and guidance system for a small UAV under degraded flight performance

- Robust autopilot against:
 - External perturbations, Aircraft model uncertainties, Actuator or sensor failures
- Reconfigurable control allocation module
- Active fault detection and isolation (FDI) system
- Adaptive and reconfigurable guidance system:
 - Takes into account the flight performance of the UAV
 - · Generates on-line a suitable path for the aircraft given predefined waypoints
 - Avoids possible obstacles, and no-fly zone

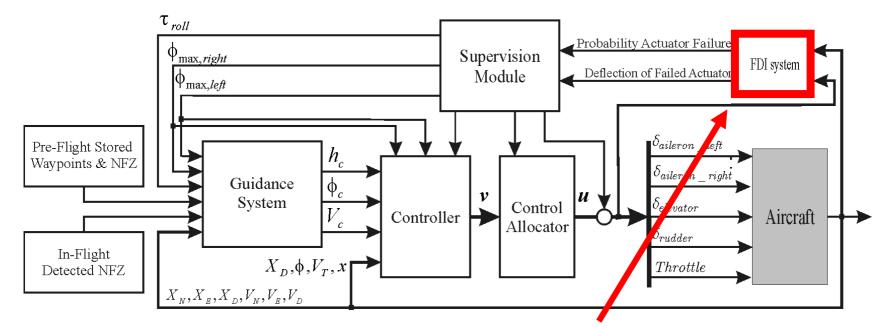
→ Each module has to be computationally efficient

2. Architecture of the Reconfigurable Flight Control System



FDI = Fault Detection and Isolation Module NFZ=No-fly Zones

2. Architecture of the Reconfigurable Flight Control System



FDI = Fault Detection and Isolation Module

1) Detection

detect a fault occurred: sensors or actuators detect damages on the aircraft

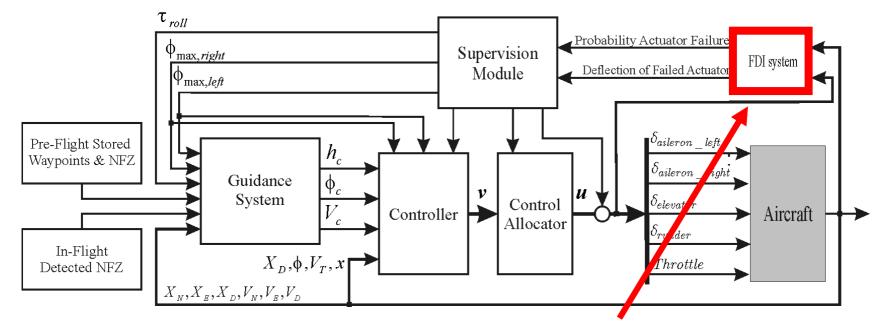
2) Isolation

locate precisely where the problem is (exact location of the fault/failure)

3) Identification

estimate the seriousness (size) of the fault or damage

2. Architecture of the Reconfigurable Flight Control System



FDI = Fault Detection and Isolation Module



1/ Direct measurements of the control surface deflection + decision logic

- Computationally efficient
- Requires additional sensors

2/ Model-based estimator

- Does not require additional sensor
- Computationally more intense

3. Fault Detection and Isolation System (FDI)

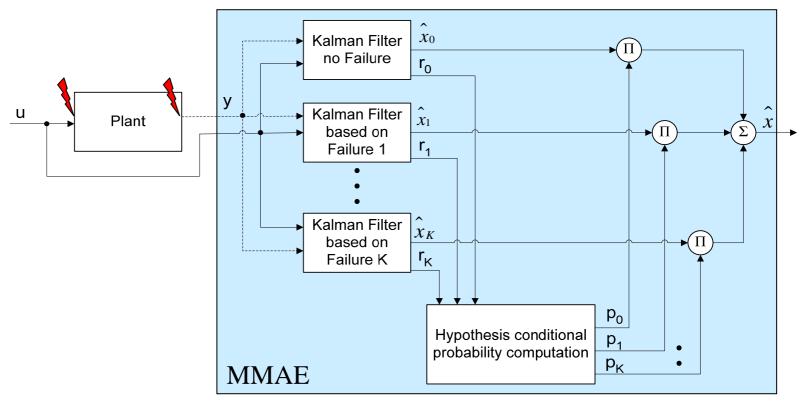
To achieve safer operation for small UAVs, we look for:

- Solutions that do not increase significantly the number of actuators or sensors,
- Algorithms that can run on processors or microcontrollers with limited processing capability.

- A. Multiple Model Adaptive Estimation (MMAE)
- B. The EMMAE* method
- C. Design example of a EMMAE-FDI system
- D. FDI simulation results

*EMMAE = Extended Multiple Model Adaptive Estimation

3. A. Classical Multiple Model Adaptive Estimation (MMAE)



MMAE Scheme for Fault Detection and Isolation

- The MMAE method is based on a bank of Kalman Filters, each of which matches a predefined fault status of the system.
- A hypothesis testing algorithm uses the residuals from each KF to assign a conditional probability to each fault hypothesis.

3.A. Classical MMAE Method

- 1 D. T. Magill, "Optimal Adaptive Estimation of Sampled Stochastic Processes", *IEEE Transactions on Automatic Control*, Vol. 10, No.4, Oct. 1965.
- 2 Maybeck, P. S., Stevens, R. D., "Reconfigurable Flight Control Via Multiple Model Adaptive Control Methods", *IEEE Trans. on Aerospace and Electronic Systems*, Vol.27, No 3, pp 470-479, May 1991.
- 3 Eide, P., Maybeck, P., "An MMAE Failure Detection System for the F-16", *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 32, No. 3, July 1996.
- 4 Maybeck, P. S., "Multiple Model Adaptive Algorithms for Detecting and Compensating Sensor and Actuator Failures in Aircraft Flight Control Systems", *Int. J. Robust Nonlinear Control 9*, 1051-1070 1999.
- 5 Lingli, Ni, *Fault-Tolerant Control of Unmanned Underwater Vehicles*, PhD Dissertation, Blacksburg, Virginia, June 29, 2001.

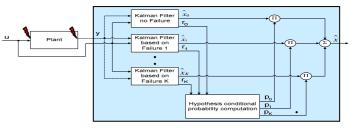
A KF designed to monitor a fault hypothesis on actuator *k* is based on the following linear system:

$$\dot{x} = A x + B_k u$$

$$\dot{x} = A x + \begin{bmatrix} b_{11} & b_{11} & \cdots & b_{1k}\lambda_k & \cdots & b_{1N} \\ b_{21} & b_{22} & \cdots & b_{2k}\lambda_k & \cdots & b_{2N} \\ b_{31} & b_{32} & \cdots & b_{3k}\lambda_k & \cdots & b_{3N} \\ b_{41} & b_{42} & \cdots & b_{4k}\lambda_k & \cdots & b_{4N} \\ b_{51} & b_{52} & \cdots & b_{5k}\lambda_k & \cdots & b_{5N} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_k \\ \vdots \\ u_N \end{bmatrix}$$

 $\lambda_k \in [0...1[, \text{loss of effectiveness}]$ $\lambda_k = 0$, for a complete loss of the actuator (stuck)

Limitations of the MMAE method:



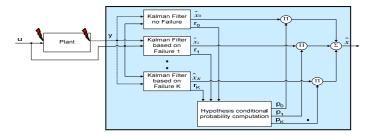
1) Number of filters to design

The method works properly as long as the occurring fault matches a predefined fault scenario (predefined value of λ_k).

➔ For one actuator, how many filters should we design to monitor it and to cover all the possible fault possibilities ?

In practice the number of addressable faults may quickly be rather restricted due to computational load, especially for several actuators.

Limitations of the MMAE method:



2) Actuator fault at an non-zero position:

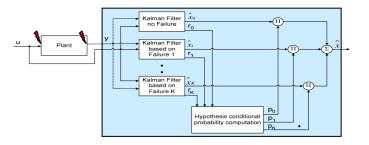
An actuator may fail at any arbitrary position that affects the dynamics of the system (not only at $u_k=0$).

The residuals in the KF are biased,

→ wrong fault detection and wrong state estimation.

Can we design a filter that takes into account any arbitrary actuator-fault?

Limitations of the MMAE method:



3) Operating conditions

Most of the MMAE systems encountered in the literature make use of linear KF based on a linear model of an aircraft flying at some operating conditions.

→The MMAE-FDI system will only work efficiently around the defined operating conditions.

→How to make the MMAE method applicable for any flight conditions?

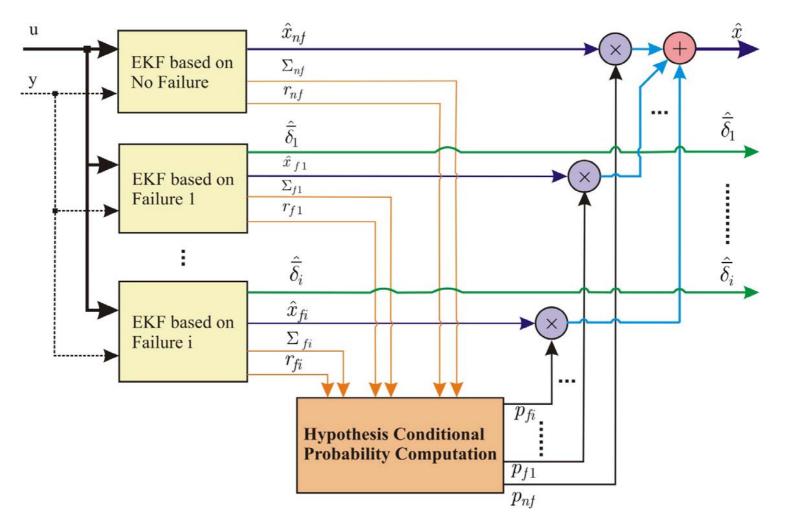
3.B. FDI System: EMMAE Method

EMMAE (Extended Multiple Model Adaptive Estimation)

With this method:

 Any actuator faulty position can be addressed.
 The EMMAE method can operate at any flying conditions (nonlinear filtering technique).
 Only one filter is needed to completely monitor one actuator.

3.B. FDI System: EMMAE Method



EMMAE method. EKF are designed for the estimation of state variables and of the position of the faulty actuator.

3.B EMMAE–FDI Design Example (relevant equations)

State vector:
$$x = [p, q, r, \alpha, \beta]^T$$

Input vector: $u = [\delta_{a_1}, \delta_{a_2}, \delta_{e_1}, \delta_{e_2}, \delta_{rudd}]^T$

Turn rates dynamics:

$$\begin{bmatrix} \dot{p} \\ \dot{q} \\ \dot{r} \end{bmatrix} = I^{-1} \left(\begin{bmatrix} L \\ M \\ N \end{bmatrix}^b - \begin{bmatrix} p \\ q \\ r \end{bmatrix} \times I \begin{bmatrix} p \\ q \\ r \end{bmatrix} \right)$$

Dynamics of the angle of attack α and the sideslip angle β

$$\dot{\alpha} = q + \frac{g}{V_T} \left\{ 1 + \frac{\overline{q}S}{mg} ([CX_1 + CZ_2]\alpha + CZ_1) \right\}$$
$$\dot{\beta} = -r + \frac{\overline{q}SCY_1}{mV_T} \beta$$

The measurement vector is $y = [p, q, r, \alpha, \beta]^T$

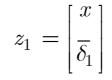
3.C. EMMAE–FDI Design Example (No fault Filter matrices)

$$F_{NF}(k) = \begin{bmatrix} \frac{I_{zz}Sb^2C_{L3}}{2D_{l}V_{T}}\overline{q} - \frac{N_{1}}{D_{1}}q & \frac{-N_{1}}{D_{1}}p + \frac{N_{2}}{D_{1}}r & \frac{(I_{zz}C_{L4} - I_{xz}C_{N3})Sb^{2}}{2D_{l}V_{T}}\overline{q} + \frac{N_{2}}{D_{1}}q & 0 & \frac{Sb[I_{zz}C_{L2} - I_{xz}C_{N2}]}{D_{1}}\overline{q} \\ \frac{I_{xx} - I_{zz}}{I_{yy}}r - \frac{2I_{zx}}{I_{yy}}r & \frac{S\overline{c}^{2}C_{M4}}{2V_{T}I_{yy}}\overline{q} & -\frac{I_{xx} - I_{zz}}{I_{yy}}p - \frac{2I_{xz}}{I_{yy}}r & \frac{S\overline{c}C_{M3}}{I_{yy}}\overline{q} & 0 \\ \frac{-I_{xz}Sb^{2}C_{L3}}{2D_{l}V_{T}}\overline{q} + \frac{N_{3}}{D_{1}}q & \frac{N_{3}}{D_{1}}p + \frac{N_{1}}{D_{1}}r & \frac{(-I_{xz}C_{L4} + I_{xx}C_{N3})Sb^{2}}{2D_{l}V_{T}}\overline{q} + \frac{N_{1}}{D_{1}}q & 0 & \frac{Sb[I_{xx}C_{N2} - I_{xz}C_{L2}]}{D_{1}}\overline{q} \\ 0 & 1 & 0 & \frac{\rho V_{T}SC_{Z2}}{2m} & 0 \\ 0 & 0 & -1 & 0 & \frac{\rho V_{T}SC_{Y1}}{2m} \end{bmatrix}_{\hat{x}_{NF}(k|k|)}$$

Discrete transition matrix for the no fault filter $\phi_{k,NF} = I + F_{NF}(k)T_s$

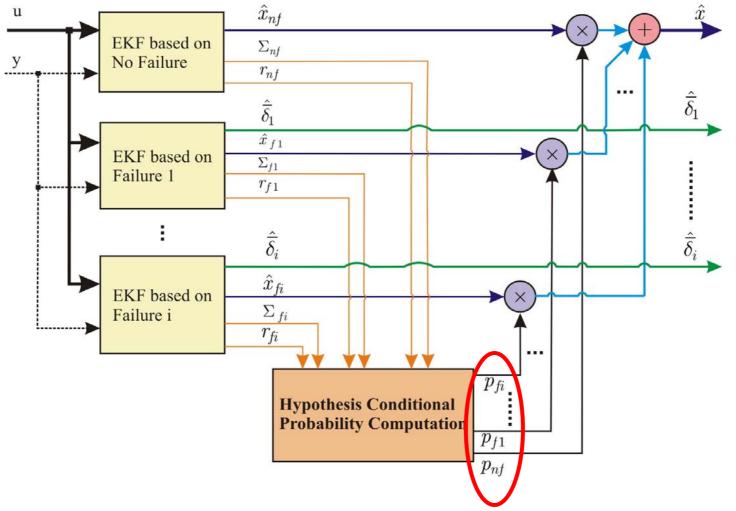
Discrete control input matrix for the no-fault filter $G_{k,NF} = G_{NF}(k).T_s$

3. C. EMMAE–FDI Design Example (actuator 1 filter matrices)



$$F_{\delta_{a1}}(k) = \begin{bmatrix} \frac{I_{zz}Sb^2C_{L3}}{2D_{1}V_{T}}\overline{q} - \frac{N_{1}}{D_{1}}q & \frac{-N_{1}}{D_{1}}p + \frac{N_{2}}{D_{1}}r & \frac{(I_{zz}C_{L4} - I_{xz}C_{N3})Sb^{2}}{2D_{1}V_{T}}\overline{q} + \frac{N_{2}}{D_{1}}q & 0 & \frac{Sb[I_{zz}C_{L2} - I_{xz}C_{N2}]}{D_{1}}\overline{q} & \frac{SbI_{xz}C_{La_{1}}}{D_{1}}\overline{q} \\ \frac{I_{xx} - I_{zz}}{I_{yy}}r - \frac{2I_{zx}}{I_{yy}}r & \frac{S\overline{c}^{2}C_{M4}}{2V_{T}I_{yy}}\overline{q} & -\frac{I_{xx} - I_{zz}}{I_{yy}}p - \frac{2I_{xz}}{I_{yy}}r & \frac{S\overline{c}C_{M3}}{I_{yy}}\overline{q} & 0 & \frac{S\overline{c}C_{Ma}}{I_{yy}}\overline{q} \\ \frac{-I_{xz}Sb^{2}C_{L3}}{2D_{1}V_{T}}\overline{q} + \frac{N_{3}}{D_{1}}q & \frac{N_{3}}{D_{1}}p + \frac{N_{1}}{D_{1}}r & \frac{(-I_{xz}C_{L4} + I_{xx}C_{N3})Sb^{2}}{2D_{1}V_{T}}\overline{q} + \frac{N_{1}}{D_{1}}q & 0 & \frac{Sb[I_{xx}C_{N2} - I_{xz}C_{L2}]}{D_{1}}\overline{q} & \frac{-SbI_{xx}C_{La_{1}}}{D_{1}}\overline{q} \\ 0 & 1 & 0 & \frac{\rho V_{T}SC_{Z2}}{2m} & 0 & 0 \\ 0 & 0 & -1 & 0 & \frac{\rho V_{T}SC_{Y1}}{2m} & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}_{z_{1}(k|k)}$$

3.C. EMMAE–FDI Design Example (fault isolation process)



For fault isolation, we observe the fault probabilities during the fault sequence

3.C. EMMAE–FDI Design Example (fault isolation process)

The sequence of the last measurement vectors is defined as

 $Y_k = \{ y[k], y[k-1], ..., y[0] \}$

Computation of the fault-scenario probability:

$$p_{i}[k] = p[(\theta = \theta_{i}) | Y_{k}] = \frac{p[(y = y_{k}) | (\theta = \theta_{i}, Y_{k-1})] p_{i}[k-1]}{\sum_{j=0}^{N} p[(y = y_{k}) | (\theta = \theta_{j}, Y_{k-1})] p_{j}[k-1]}$$

3. C. EMMAE–FDI Design Example (fault isolation process)

$$p[(y = y[k]) | (\theta = \theta_i, Y_{k-1})] = \lambda_i [k] e^{-\frac{r_i[k]^T \sum_i^{-1} r_i[k]}{2}}$$

$$density of probability: f(r_i | (\theta = \theta_i, Y_{k-1}))$$

$$\lambda_i [k] = \frac{1}{(2\pi)^{m/2} |\sum_i [k]|^{1/2}} \int_{0.35}^{0.4} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = y_k | (\theta = \theta_i, Y_{k-1}))} \int_{0.45}^{0.45} e^{-\frac{y}{9}(y = \theta_i, Y_{k-1})} \int_{$$

 $r_i[k]$

3.D. FDI simulation results

Conditions of simulations $\sigma_{p,q,r} = 5 \text{deg/s} = 0.0873 \text{rad/s}$ $\sigma_{\alpha,\beta} = 2 \text{deg} = 0.0349 \text{rad}$ $\sigma_{V_T} = 1 \text{m/s}$

 $\Sigma_{p,q,r} = 0.0076 \text{rad}^2/\text{s}^2$ $\Sigma_{\alpha,\beta} = 0.0012 \text{rad}^2$

The EKF process noise covariance matrix and sensor noise covariance matrix

$$R_w = 0.002 \ diag(I_5)$$

 $R_v = diag(0.1I_3, 0.02I_2)$

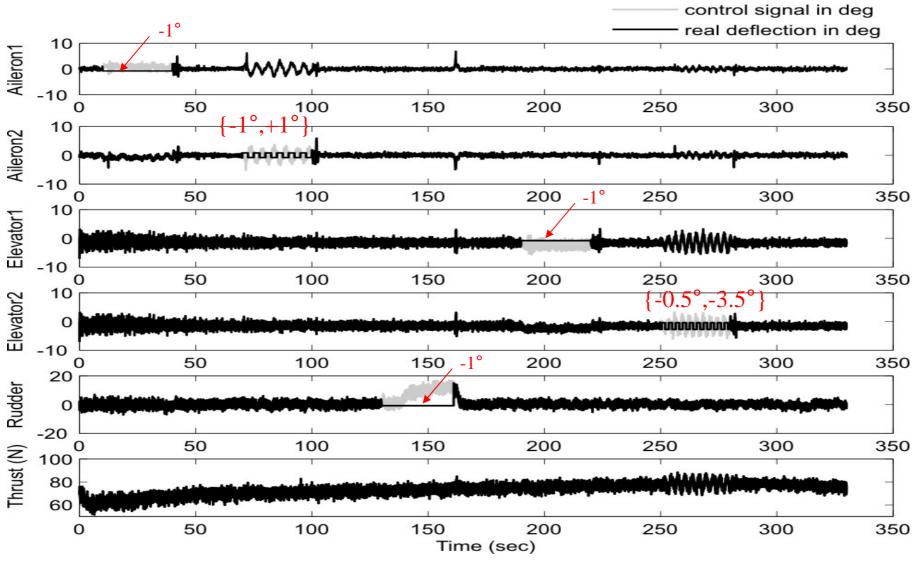
The aircraft flies constant speed, constant altitude and horizontal. No wind.

(conditions of least excitation possible of the system, most difficult conditions for the FDI system)

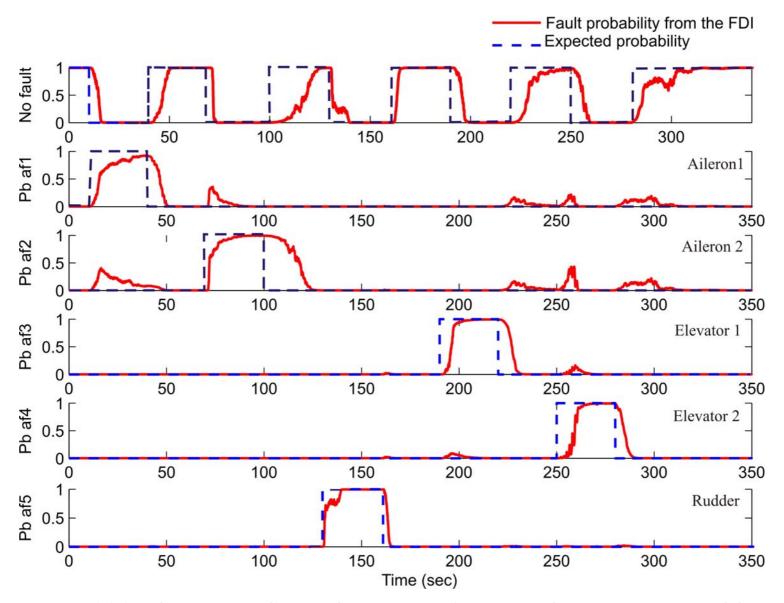
Faults/failures: very close to the trim conditions (more difficult for the FDI to detect the fault in noisy measurements)

Simulations with a nonlinear 6DOF model of an aircraft.

3.D. EMMAE FDI simulation results

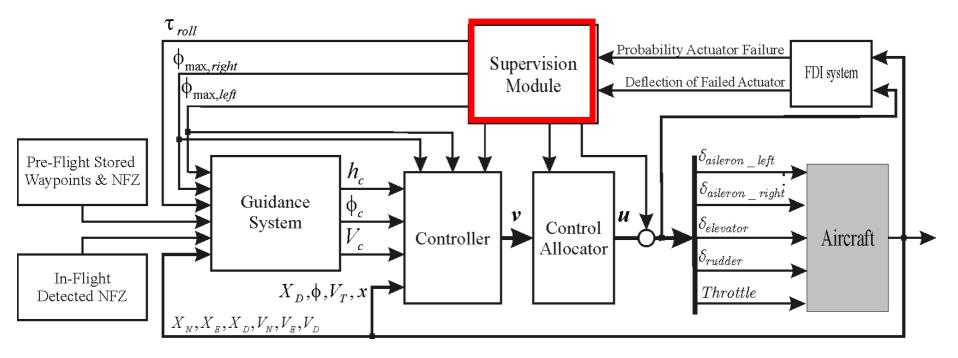


Control signals and actual actuator deflections

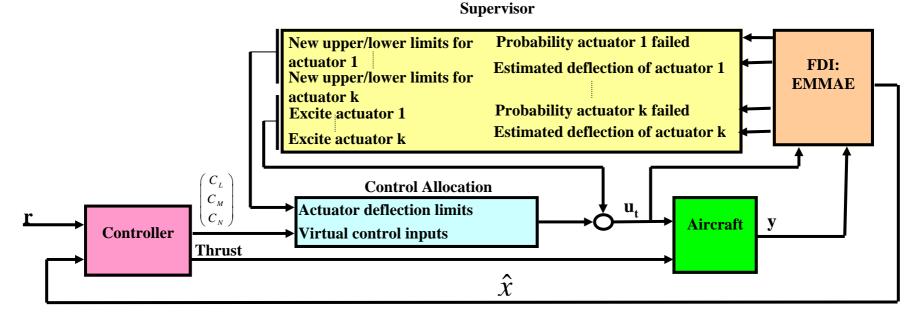


Probabilities from each filter of the EMMAE-FDI after a sequence of faults

4. Supervision Module



4. Supervision Module

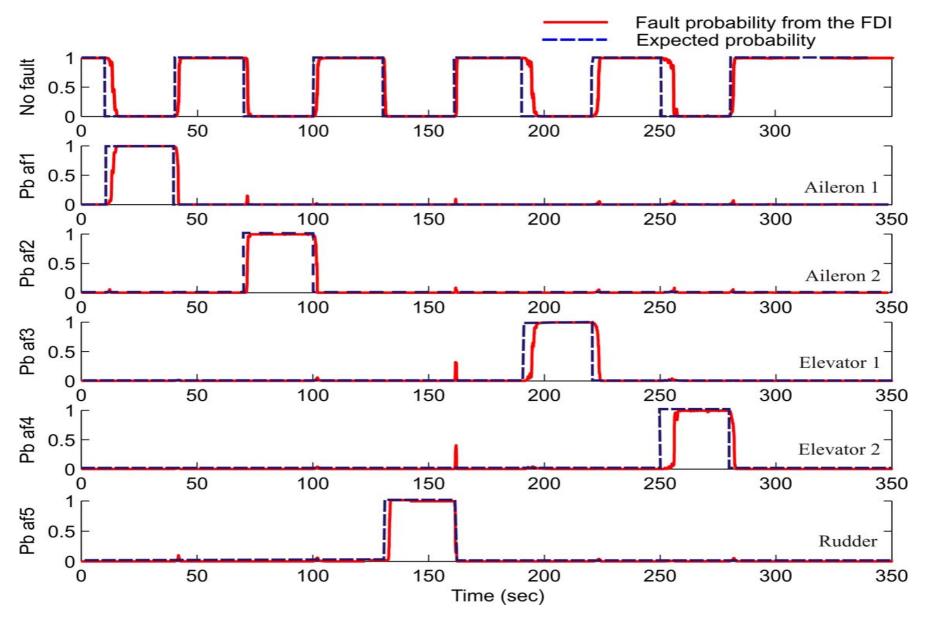


The supervision module:

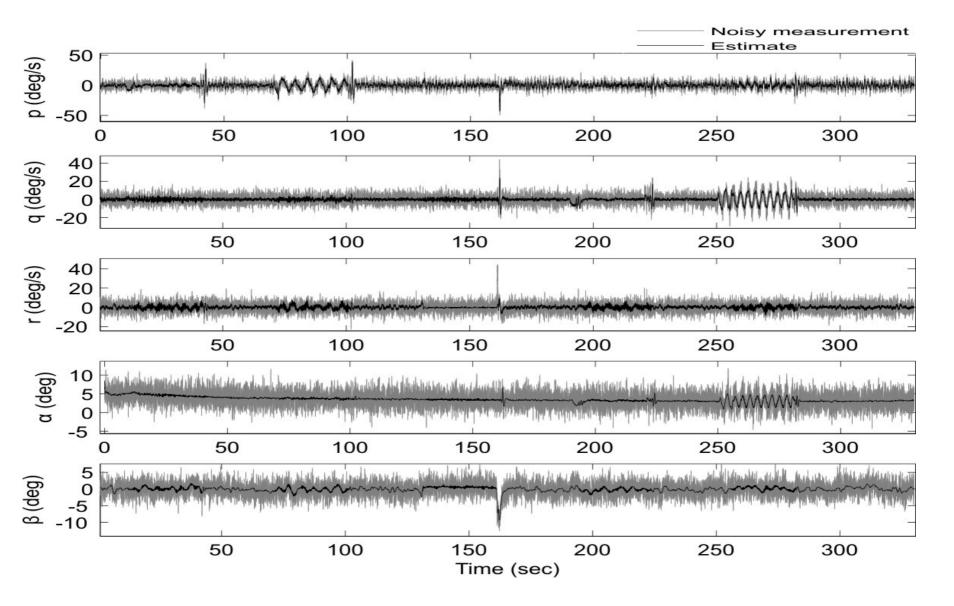
- monitors probabilities of an actuator failing,
- checks if one of these probabilities exceeds a threshold,
- generates an excitation signal and superimposes it to the input control signal of the corresponding actuator:

$$\delta_{ex_i}(t) = [1 + 3(1 - p_i(t))]\cos(2\pi f_i t) \text{ (deg)} \qquad f_i = 1Hz$$

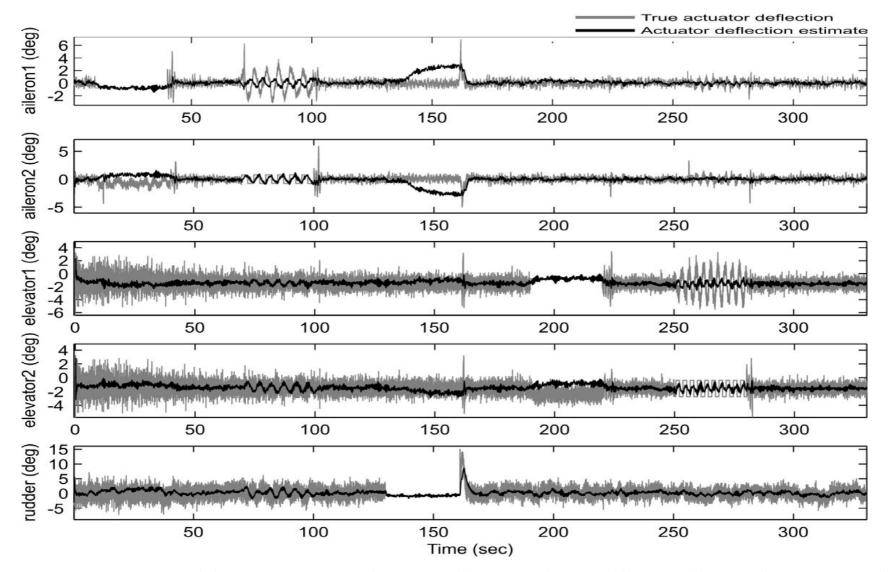
4. Supervision Module



Probabilities from each filter of the EMMAE-FDI after a sequence of faults (with the supervisor).



Comparison between noisy measurements and the probability weighted state estimate from the EMMAE method: despite large amount of sensor noise, the state estimate accurately tracks the true aircraft motion.



True actuator positions and associated estimates (a position estimate is only valid during the occurrence of a fault)

5. Conclusion on the EMMAE FDI System

The EMMAE algorithm has been combined with the supervision module that generates artificial excitation signals

- Nonlinear FDI technique, all operating points over the flight envelope can be handled.
- It provides fast and accurate fault detection and isolation with active fault search (even during low excitation of the aircraft).
- The estimation of the control surface deflection during a fault
 - Used to modify on-line the settings of a control allocator
 - no actuator position sensor is needed
- The state vector is also estimated

5. FDI System Extensions

Extensions to the method:

- Simultaneous faults
- Second filtering stage can be included to robustify the FDI system in the presence of severe wind gusts.

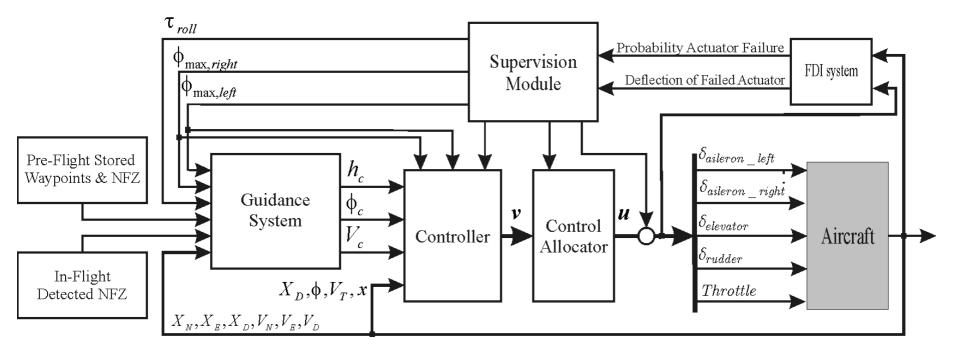
See papers:

G. Ducard, H. P. Geering, "Efficient Nonlinear Actuator Fault Detection and Isolation System for Unmanned Aircraft", *AIAA Journal of Guidance, Control, and Dynamics*. 31(1): 225-237, January-February 2008.

Ducard, G., Geering, H. P., "A Reconfigurable Flight Control System based on the EMMAE Method," *Proceedings of the 2006 American Control Conference,* Minneapolis, MN, June 2006, *pp. 5499-5504*. (Award for the Best Paper Presentation in the Session)

D. Rupp, G. Ducard, E. Shafai, H. P. Geering, "Extended Multiple Model Estimation for the Detection of Sensor and Actuator failures", *Proceedings of IEEE ECC-CDC 2005, Seville, pp. 3079-3084*

5. Conclusion





Fault-tolerant Flight Control and Guidance Systems

Practical Methods for Small Unmanned Aerial Vehicles



springer.com

Guillaume J. J. Ducard, ETH Zurich June 2009 http://www.springer.com/engineering/ mechanical+eng/book/978-1-84882-560-4

2009. XXII, 266 p. 151 illus. (Advances in Industrial Control) Hardcover

🖄 Springer

Advances in Industrial Control

AIC