

Fault diagnosis for nonlinear aircraft based on control-induced redundancy

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retour sur innovation

Outline

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- Related work

- Objectives

- Principles

Illustration

- Aeronautical case study

- FDI algorithm description

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- Simulation set-up

- Robustness

Summary and future work

Nonlinear Fault Detection and Isolation - related work

Fault Detection and Isolation of actuator faults for Nonlinear control-affine systems

Differential-geometric approach (De Persis & Isidori)

Transformation of coordinates to design nonlinear residual filters sensitive to faults and decoupled from disturbances.

Differential-algebraic approach (Diop, Bokor, Shumsky...)

Transformation of the system into a set of differential polynomials, functions of inputs, outputs and their successive derivatives. Use elimination theory to extract fault information.

Inversion-based FDI (Edelmayer, Szigeti...)

Left-inverse computation to obtain dynamical model with faults as outputs and original inputs, outputs and their successive derivatives as inputs.

Objectives

Known drawbacks of these nonlinear methods

- Design of coordinate transforms, tuning of inner parameters
- Successive time derivatives of noisy and disturbed measurements
- Integration of dynamical filters

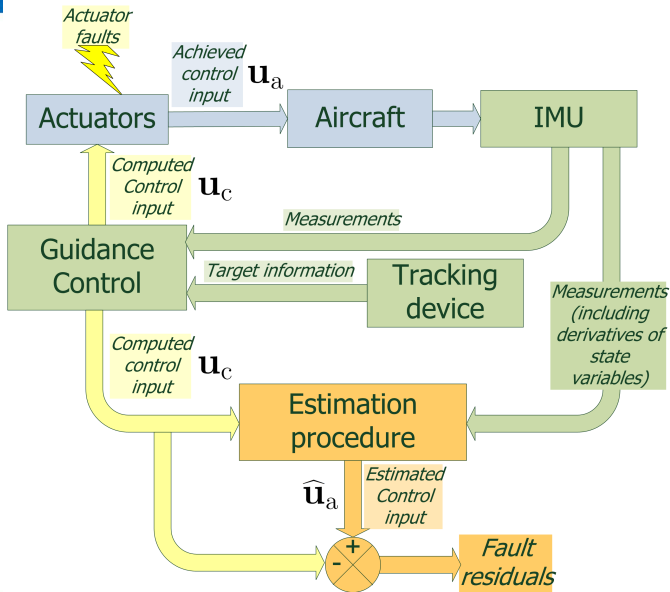
Objectives of present work

- Avoid numerical differentiation of measured variables
- Avoid dynamical integration, to reduce computational cost
- Assess robustness to model and measurement uncertainty

New approach

- Take advantage of systems involving *measured* state derivatives (e.g., autonomous vehicles equipped with IMUs)
- Design a completely nonlinear actuator fault diagnosis method

Principles of the approach



6-DOF aeronautical model

- State vector : $\mathbf{x} = [\zeta, \mathbf{v}_b, \boldsymbol{\Theta}, \boldsymbol{\omega}]^T$, ζ position in inertial frame, \mathbf{v}_b speed in body frame, $\boldsymbol{\Theta}$ orientation, $\boldsymbol{\omega}$ angular velocity
- Input vector : $\mathbf{u} = [\delta_l, \delta_m, \delta_n, \eta]^T$, rudders $\delta_{(\cdot)}$ and propulsion η
- Measurements : $\mathbf{y} = [\mathbf{a}_b, \boldsymbol{\omega}]^T$, acceleration in body frame \mathbf{a}_b

Nonlinear aircraft model

$$\begin{cases} \mathbf{a}_b = \dot{\mathbf{v}}_b + \boldsymbol{\omega} \times \mathbf{v}_b = m^{-1} [\mathbf{f}_{\text{aero}}(\mathbf{x}, \mathbf{u}) + \mathbf{f}_g(\mathbf{x})] & \text{force equation} \\ \dot{\boldsymbol{\omega}} = \mathbf{I}^{-1} [\mathbf{m}_{\text{aero}}(\mathbf{x}, \mathbf{u}) - (\boldsymbol{\omega} \times \mathbf{I} \boldsymbol{\omega})] & \text{momentum equation} \\ \dot{\zeta} = \mathbf{R}_{bi}(\mathbf{x}) \mathbf{v}_b & \text{coordinate transform} \\ \dot{\boldsymbol{\Theta}} = \mathbf{R}_{\Theta}(\mathbf{x}) \boldsymbol{\omega} & \text{angular dynamics} \end{cases}$$

6-DOF aeronautical model

- State vector : $\mathbf{x} = [\zeta, \mathbf{v}_b, \boldsymbol{\Theta}, \boldsymbol{\omega}]^T$, position in inertial frame ζ , speed in body frame \mathbf{v}_b , orientation $\boldsymbol{\Theta}$, angular velocity $\boldsymbol{\omega}$
- Input vector : $\mathbf{u} = [\delta_l, \delta_m, \delta_n, \eta]^T$, rudders $\delta_{(.)}$ and propulsion η
- Measurements : $\mathbf{y} = [\mathbf{a}_b, \boldsymbol{\omega}]^T$, **acceleration in body frame \mathbf{a}_b**

Nonlinear aircraft model

$$\begin{cases} \mathbf{a}_b = \dot{\mathbf{v}}_b + \boldsymbol{\omega} \times \mathbf{v}_b = m^{-1} [\mathbf{f}_{\text{aero}}(\mathbf{x}, \mathbf{u}) + \mathbf{f}_g(\mathbf{x})] & \text{force equation} \\ \dot{\boldsymbol{\omega}} = \mathbf{I}^{-1} [\mathbf{m}_{\text{aero}}(\mathbf{x}, \mathbf{u}) - (\boldsymbol{\omega} \times \mathbf{I} \boldsymbol{\omega})] & \text{momentum equation} \\ \dot{\zeta} = \mathbf{R}_{bi}(\mathbf{x}) \mathbf{v}_b & \text{coordinate transform} \\ \dot{\boldsymbol{\Theta}} = \mathbf{R}_{\Theta}(\mathbf{x}) \boldsymbol{\omega} & \text{angular dynamics} \end{cases}$$

Starting point: force equation involves control inputs and only measured or estimated state variables and their *measured* derivatives

Preliminary step

- Extract force equation, $\mathbf{a}_b = m^{-1} [\mathbf{f}_{\text{aero}}(\mathbf{x}, \mathbf{u}) + \mathbf{f}_g(\mathbf{x})]$

$$\left\{ \begin{array}{l} a_{bx} = -\frac{Qs_{\text{ref}}}{M} [c_{x0} + c_{xa}\alpha + c_{x\delta_m}\delta_l + c_{x\delta_m}\delta_m + c_{x\delta_n}\delta_n] \\ \quad + \frac{1}{m} [f_{\text{min}} + (f_{\text{max}} - f_{\text{min}})\eta] \\ a_{by} = \frac{Qs_{\text{ref}}}{m} [c_{y0} + c_{yb}\beta + c_{y\delta_l}\delta_l + c_{y\delta_n}\delta_n] \\ a_{bz} = \frac{Qs_{\text{ref}}}{m} [c_{z0} + c_{za}\alpha + c_{z\delta_m}\delta_m] \end{array} \right.$$

- Rewrite model (linear in \mathbf{u} due to small-angle assumption) as

$$\begin{bmatrix} f_1 \\ f_2 \\ f_3 \end{bmatrix} = \begin{bmatrix} g_{11} & g_{12} & g_{13} & g_{14} \\ g_{21} & 0 & g_{23} & 0 \\ 0 & g_{32} & 0 & 0 \end{bmatrix} \begin{bmatrix} \delta_l \\ \delta_m \\ \delta_n \\ \eta \end{bmatrix}$$

where f_i and g_{ij} ($i = 1, 2, 3, j = 1, 2, 3, 4$) are nonlinear functions of \mathbf{y} , derived from above equations

Direct Residual Generation

- Estimate each control input as a function of measurements and other computed control inputs. For example, ,

$$\begin{cases} \hat{\delta}_{la} = \frac{f_2 - g_{23}\delta_{nc}}{g_{21}} \\ \hat{\delta}_{na} = \frac{f_2 - g_{21}\delta_{lc}}{g_{23}} \end{cases}$$

- Compare these estimates to corresponding computed inputs,

$$\begin{cases} r_{21} = \hat{\delta}_{la} - \delta_{lc} = \frac{f_2 - g_{23}\delta_{nc}}{g_{21}} - \delta_{lc} \\ r_{23} = \hat{\delta}_{na} - \delta_{nc} = \frac{f_2 - g_{21}\delta_{lc}}{g_{23}} - \delta_{nc} \end{cases}$$

- Example of sensitivity to faults. Inject expression of f_2 into residual

$$r_{21} = \frac{g_{21}\delta_{la} + g_{23}\delta_{na} - g_{23}\delta_{nc}}{g_{21}} - \delta_{lc} = (\delta_{la} - \delta_{lc}) + \frac{g_{23}}{g_{21}} (\delta_{na} - \delta_{nc})$$

→ Sensitivity to faults on δ_l and δ_n and possible identification on δ_l

Additional Residual Generation

Further combinations between equations

$$\text{Reminder : } \begin{bmatrix} f_1 \\ f_2 \\ f_3 \end{bmatrix} = \begin{bmatrix} g_{11} & g_{12} & g_{13} & g_{14} \\ g_{21} & 0 & g_{23} & 0 \\ 0 & g_{32} & 0 & 0 \end{bmatrix} \begin{bmatrix} \delta_l \\ \delta_m \\ \delta_n \\ \eta \end{bmatrix}$$

From 3rd line, $\hat{\delta}_{ma} = f_3/g_{32}$ can be used in other residuals, e.g.,

$$r_{11} = \frac{f_1 - g_{12}\delta_{mc} - g_{13}\delta_{nc} - g_{14}\eta_c}{g_{11}} - \delta_{lc}$$

to get

$$\tilde{r}_{11}^1 = \frac{f_1 - g_{12}\frac{f_3}{g_{32}} - g_{13}\delta_{nc} - g_{14}\eta_c}{g_{11}} - \delta_{lc}$$

This residual is now insensitive to faults affecting rudder δ_m

Additional Residual Generation

- From line 2, $\hat{\delta}_{1a}$ and $\hat{\delta}_{na}$ can be used similarly to get residuals that are insensitive to faults on either δ_l or δ_n .
- One step further: combine $\hat{\delta}_{1a}$ and $\hat{\delta}_{ma}$ to obtain residuals insensitive to faults on both actuators.
- Same kind of substitution possible with $\hat{\delta}_{ma}$ and $\hat{\delta}_{na}$.

Fault signature table – 27 residuals max with 8 different signatures

	r_{1i}	r_{21}/r_{23}	r_{32}	\tilde{r}_{1i}^1	\tilde{r}_{1i}^2	\tilde{r}_{1i}^3	\tilde{r}_{1i}^4	\tilde{r}_{1i}^5
δ_l	1	1	0	1	0	1	0	1
δ_m	1	0	1	0	1	1	0	0
δ_n	1	1	0	1	1	0	1	0
η	1	0	0	1	1	1	1	1

$(i = 1, 2, 3, 4)$

Full isolation possible, and partial identification

Simulation set-up

3 fault scenarios

- 1 Loss of 25% propulsion
- 2 Locking-in-place of δ_m then loss of 25% propulsion
- 3 Loss of 50% propulsion then locking of δ_m then locking of δ_n

IMU uncertainty

Measurement of q is $\tilde{q} = k_q q + b_q + w_q$

k_q : scale factor, b_q : bias, w_q : Gaussian white noise

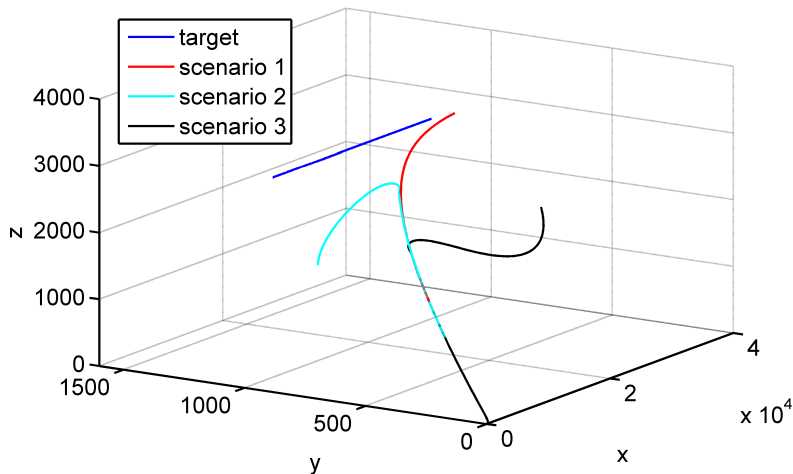
Delay of 2 time steps

Multiplicative model uncertainty

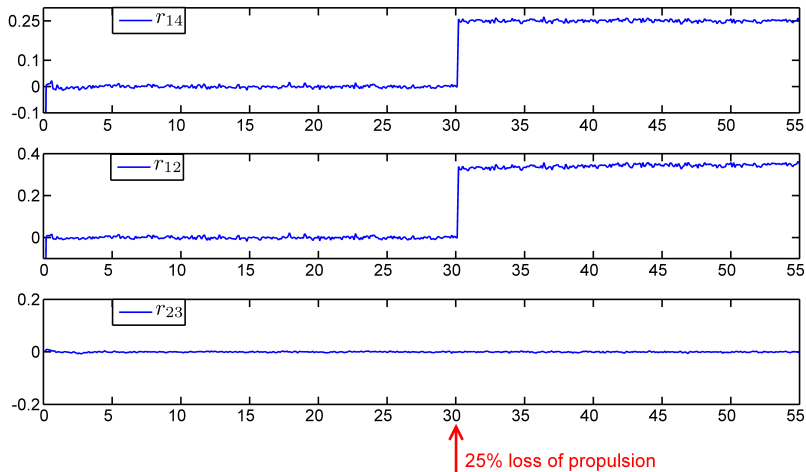
Each aerodynamic coefficient value is randomly chosen as either

$$c_{\text{sim}} = 0.95c_{\text{model}} \text{ or } c_{\text{sim}} = 1.05c_{\text{model}}$$

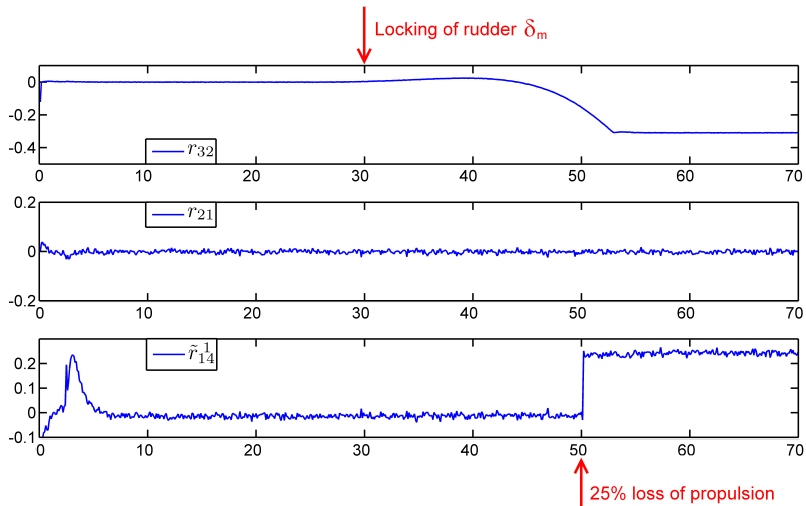
Trajectories



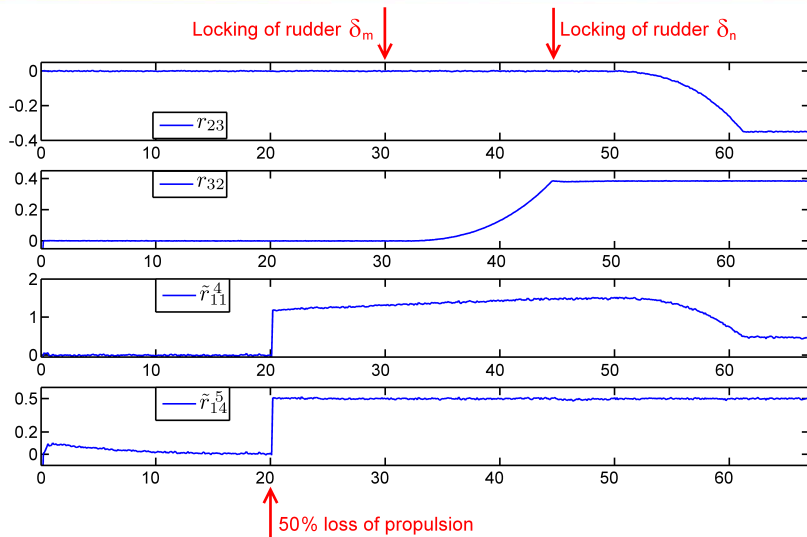
Selection of residuals - Scenario 1



Selection of residuals - Scenario 2



Selection of residuals - Scenario 3

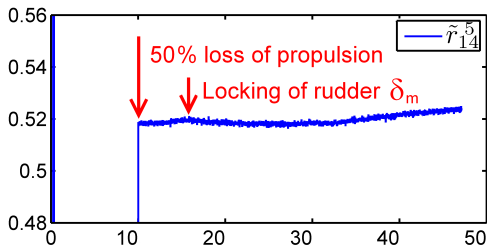


Robustness of the residuals

Model error $g_{12-\text{sim}} = g_{12-\text{model}} + \varepsilon$, ε small and bounded

$$\tilde{r}_{14}^5 = \frac{1}{g_{14}} \left[\left(g_{11} + \frac{g_{13}g_{21}}{g_{23}} \right) (\delta_{lc} - \delta_l) + \frac{g_{12}\delta_m}{g_{23}} - \frac{(g_{12} + \varepsilon)\delta_m}{g_{23}} + g_{13}(\delta_n - \delta_n) \right] + (\eta_c - \eta)$$

$$\tilde{r}_{14}^5 = (\eta_c - \eta) + \frac{g_{11}g_{23} + g_{13}g_{21}}{g_{14}g_{23}} (\delta_{lc} - \delta_l) + \frac{g_{12}}{g_{23}g_{14}} \varepsilon \delta_m$$



Summary and future work

Summary

- Nonlinear FDI scheme applied to a realistic aeronautical model
- Multiple faults detectable, isolable and identifiable
- Static residuals : hard-coding possible, no tuning required
- Acceptable robustness to model and measurement uncertainty
- Formal description of the procedure in our NOLCOS 2010 paper + MAPLE implementation providing residuals automatically

Future work

- Loosen sensitivity of the static residuals with a sliding window
- Automatic tuning of FDI approaches for systematic comparison