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Implementation of real-time moving horizon estimation for robust air data sensor fault diagnosis in the RECONFIGURE benchmark ⋆

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Abstract: This paper presents robust fault diagnosis and estimation for the calibrated airspeed and angle-of-attack sensor faults in the RECONFIGURE benchmark. We adopt a low-order longitudinal model augmented with wind dynamics. In order to enhance sensitivity to faults in the presence of winds, we propose a constrained residual generator by formulating a constrained moving horizon estimation problem and exploiting the bounds of winds. The moving horizon estimation problem requires solving a nonlinear program in real time, which is challenging for flight control computers. This challenge is addressed by adopting an efficient structure-exploiting algorithm within a real-time iteration scheme. Specific approximations and simplifications are performed to enable the implementation of the algorithm using the Airbus graphical symbol library for industrial validation and verification. The simulation tests on the RECONFIGURE benchmark over different flight points and maneuvers show the efficacy of the proposed approach.

Keywords: Fault detection and isolation, moving horizon estimation, real-time computation.

1. INTRODUCTION

In aircraft applications, the industrial state-of-the-art for sensor fault detection and isolation (FDI) relies on triplex hardware redundancy, and performs a majority voting scheme to compute a consolidated value by discarding any failed sources (Goupil et al., 2015). This scheme works well if only one sensor source becomes faulty, but it would be inadequate to address simultaneous multiple sensor faults within the triplex redundancy. As currently investigated in the RECONFIGURE project (Goupil et al., 2015), one possibility to extend guidance and control functionalities for future aircraft could be the incorporation of analytical redundancy to detect, isolate, and estimate sensor faults without adding new redundant sensors.

A crucial issue with the analytical redundancy based FDI technique in aircraft applications is how to simultaneously maintain its robustness to wind disturbances and optimize its fault sensitivity (Marzat et al., 2012). In Eykeren and Chu (2014); Hansen and Blanke (2014), an extended Kalman filter based FDI method was proposed based on the assumption of constant winds. Without any limiting assumption about wind dynamics, the disturbance decoupling method based on differential geometry was used in Castaldi et al. (2014) to perfectly decouple the wind effect in the generated residual signal. A similar geometric FDI method was also discussed in Vanek et al. (2011) to deal with multiplicative model uncertainties in an aircraft example. In Marcos et al. (2005), a robust H_∞ FDI filter was proposed to estimate the fault signal while attenuating the disturbance effect for a transport aircraft. A sliding mode linear parameter varying fault reconstruction scheme was applied in Alwi and Edwards (2014) to yaw rate sensor faults with extensive industrial validation and verification (V&V). A combination of the nullspace based residual generator and the signal-based method were validated in Ossmann and Joos (2016) for the angle-of-attack (AOA) sensor faults in the RECONFIGURE project.

In our previous work (Wan et al., 2016), we have proposed a constrained residual generator to enhance fault sensitivity for simultaneous AOA and calibrated airspeed (VCAS) sensor fault diagnosis in the presence of winds. The constrained residual generator is formulated as a constrained moving horizon estimation (MHE) problem which requires solving a nonlinear program in real time. Compared to conventional unconstrained residual generators, the incorporation of constraints in residual generation further improves fault sensitivity without sacrificing disturbance robustness. Other relevant aircraft FDI methods related to the above mentioned robustness issue include, but not limited to,

This paper presents our continued efforts in implementing our MHE based FDI method proposed in the above reference for real-time computation on flight control computers (FCCs). This is a challenging task because computationally intensive nonlinear programming has to be solved within a short sampling interval. Furthermore, for industrial V&V, the proposed method needs to be implemented using the Airbus graphical symbol library SAO (Briere and Traverse, 1993; Fernández et al., 2015). This SAO library includes a significantly limited set of

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mathematical operation blocks, e.g., no single block for matrix manipulations, thus making the implementation of advanced computationally intensive algorithms even more difficult. Our algorithm implementation adopts a real-time iteration scheme with interior-point (IP) sequential quadratic programming (SQP) strategies. It ensures fixed computational cost per sample by limiting the number of iterations and admitting suboptimal solutions. Specific approximations and simplifications are taken to speed up computation. This implementation has been successfully tested in a number of scenarios using the high-fidelity non-linear RECONFIGURE benchmark. Its real-time applicability is preliminarily confirmed by Airbus, although future work is needed to further reduce its computational cost.

2. BENCHMARK PROBLEM

One of the objectives in the RECONFIGURE project is to exploit analytical redundancy to address simultaneous multiple AOA and VCAS sensor faults, which cannot be easily handled by the conventional triplex monitoring technique. The purpose is to detect and isolate any faulty AOA and VCAS sensors, and at the same time, to provide reliable estimation of AOA and VCAS. Table 1 lists eight benchmark scenarios considered in this paper. They include 4 different maneuvers, and cover 8 flight points at different combinations of low or high altitudes and speeds. Horizontal and vertical winds are present in all the considered scenarios. The fault types include oscillation, jamming, runaway, bias, and non-return to zero (NRZ). Examples of these fault signal profiles can be found in Goupil et al. (2015). In all the listed fault cases, faults occur simultaneously in two of the three redundant sensors of AOA or VCAS.

2.1 Modeling of longitudinal motions and wind dynamics

Since only longitudinal dynamics is investigated in this paper, the following model is adopted:

$$\begin{cases} \dot{\alpha}(t) = f\left(\alpha(t), \Theta(t)\right) + u_\alpha(t) \\ \dot{\mathbf{w}}(t) = \mathbf{u}_w(t) \\ \mathbf{y}(t) = h\left(\alpha(t), \mathbf{w}(t), \Theta(t)\right) \\ \mathbf{y}_m(t) = \mathbf{y}(t) + \mathbf{n}(t) \end{cases} \tag{1}$$

with the definitions $\Theta = [V_g\ \theta\ q\ n_x\ n_z\ z]^{\mathrm{T}}$, $\mathbf{w} = [W_x\ W_z]^{\mathrm{T}}$, $\mathbf{u}_w = [u_{w,x}\ u_{w,z}]^{\mathrm{T}}$, $\mathbf{y} = [\alpha\ V_z\ V_c]^{\mathrm{T}}$, and $\mathbf{n} = [n_\alpha\ n_{vz}\ n_{vc}]^{\mathrm{T}}$. The system outputs $\mathbf{y}(t)$ include AOA α, vertical speed V_z, and VCAS V_c. The output measurements $\mathbf{y}_m(t)$ are corrupted with white Gaussian measurement noises $\mathbf{n}(t)$. W_x and W_z represent horizontal and vertical wind speeds, respectively. The model parameter Θ consists of ground speed V_g, pitch angle θ, pitch rate q, horizontal load factor n_x, vertical load factor n_z, and altitude z, which are all measurable. The input noise u_α accounts for the model mismatch. The output equations in (1) for V_z and V_c are $V_z = h_{vz}(\alpha, \mathbf{w}, \Theta)$ and $V_c = h_{vc}(\alpha, \mathbf{w}, \Theta)$, respectively. For each redundant AOA sensor measurement $\alpha_m^{(i)}$ or VCAS sensor measurement $V_{c,m}^{(i)}$, $i = 1, 2, 3$, the latent sensor faults $f_\alpha^{(i)}$ and $f_{vc}^{(i)}$ are additive, i.e.,

$$\alpha_m^{(i)} = \alpha + f_\alpha^{(i)} + n_\alpha^{(i)},\ V_{c,m}^{(i)} = V_c + f_{vc}^{(i)} + n_{vc}^{(i)}.$$

The first-order integrating model in (1) is a simple yet powerful approximation of the wind dynamics. $u_{w,x}$ and $u_{w,z}$ represent horizontal and vertical wind accelerations.

The system model (1) is adopted due to several considerations: a) it avoids using other air data measurements which are considered as unreliable in the presence of AOA or VCAS sensor faults, and involves only inertial sensors; b) it includes no aerodynamic parameters, avoiding the issue of robustness to uncertain aerodynamic parameters; c) its low state dimensions are attractive for real-time computation. The readers are referred to Wan et al. (2016) for more details about the model (1).

3. FAULT-TOLERANT MOVING HORIZON ESTIMATION SCHEME

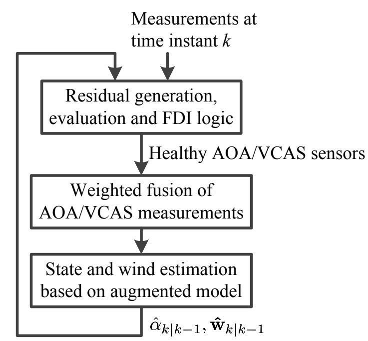

Fig. 1. Fault detection and isolation scheme

As depicted in Figure 1, our FDI scheme consists of three consecutive steps: a) isolating faulty AOA/VCAS sensors based on generated residual signals; b) fusing the healthy AOA and VCAS sensors into two weighted mean values; c) estimating states and winds. The residual signals for FDI are generated as the difference between the AOA/VCAS measurements $\{\alpha_{m,k}^{(i)}, V_{c,m,k}^{(i)}\}$ and their one-step-ahead predictions $\{\hat{\alpha}_{k|k-1}, \hat{V}_{c,k|k-1}\}$, i.e.,

$$r_{\alpha,k}^{(i)} = \alpha_{m,k}^{(i)} - \hat{\alpha}_{k|k-1},\ r_{vc,k}^{(i)} = V_{c,m,k}^{(i)} - \hat{V}_{c,k|k-1},\ i = 1, 2, 3.$$

Here, the index k denotes the samples at time instant t_k. The residual signals are evaluated by their root mean square (RMS) values over a sliding window:

$$J_{\star,k}^{(i)} = \sqrt{\frac{1}{N_{\mathrm{eval}}} \sum_{j=k-N_{\mathrm{eval}}+1}^{k} (r_{\star,j}^{(i)})^2} \tag{2}$$

where $\star$ represents "α" and "vc", N_{eval} is the length of residual evaluation window. With suitable threshold $J_{\star,\mathrm{th}}$, the ith AOA or VCAS sensor is concluded to be faulty if we have $J_{\star,k}^{(i)} > J_{\star,\mathrm{th}}$ for n_d times during the past time window $[k - N_{\mathrm{eval}} + 1, k]$, which allows a confirmation time for the detected fault.

The redundant AOA sensors identified as fault-free are fused into a weighted mean measurement α_m:

$$\begin{aligned} \alpha_{m,k} &= \sum_{i \in \{J_{\alpha,k}^{(i)} \le J_{\alpha,\mathrm{th}}\}} \beta_{\alpha,k}^{(i)} \alpha_{m,k}^{(i)}, \\ \beta_{\alpha,k}^{(i)} &= \frac{1}{\sum_{j \in \{J_{\alpha,k}^{(j)} \le J_{\alpha,\mathrm{th}}\}} \frac{1}{\left(J_{\alpha,k}^{(j)}\right)^2}} \frac{1}{\left(J_{\alpha,k}^{(i)}\right)^2}. \end{aligned} \tag{3}$$