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Experimental interval models for the robust Fault Detection of Aircraft Air Data Sensors

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ABSTRACT

In this paper data-based approaches for a robust Fault Detection (FD) of the Air Data Sensors (ADS) including airspeed angles of attack and sideslip are proposed. Experimental Interval Models (IMs) have been considered for coping with modeling uncertainty and for providing interval estimations of the ADS signals. Specifically, a nonlinear-in-the-parameter Neural Network model has been introduced to characterize the nominal nonlinear response in the different phase of the flight, while model uncertainty is captured by an additional additive contribution provided by a linear in the parameters IM. The FD is achieved by verifying whether the measured ADS signals fall within time-varying bounds predicted by the nonlinear + IM. The IM identification has been formalized as a Linear Matrix Inequality (LMI) problem using as cost function the mean amplitude of the prediction interval and, as optimization variables, the amplitudes of the uncertain parameters of the model. The model identification was based on multi flight experimental data of a P92 Tecnam aircraft. The proposed method is compared with conventional FD schemes with fixed thresholds. Extensive validation tests have been conducted by injecting artificially additive hard and incipient failures on the ADS. The FD scheme has shown to be remarkably robust in all phases of the flight in terms of low false alarm rates while maintaining desirable detectability to faults.

1. Introduction

Failure Detection (FD) of sensors of flight control systems is a critical topic from an aviation safety point of view. This is confirmed by the strict requirements mandated by the FAA for aircraft instrumentation and, specifically, for the suite of sensors typically installed on civilian aircraft. Particularly critical is the FD for sensors whose measurements are used in real-time in the control laws of the aircraft closed-loop dynamics. In this scenario the FD system is required to be, at the same time, fast and robust to false failure detections. Clearly, Air Data Sensors (ADS) belong to this critical category. ADS are installed externally, either on the fuselage or on the wings. Therefore, unlike all the other sensors installed inside the fuselage, they are sensitive to atmospheric and weather conditions. Specifically, under particular combinations of humidity and temperature, they can be vulnerable to formation of ice crystals leading to obstructions in the different orifices of the sensor. Unfortunately, this condition is among the leading causes of sensors malfunctioning. In fact, in aviation safety literature (Belcastro & Foster, 2010) a relevant number of flight accidents has been attributed to ADS failures, such as in the cases of the crashes of the Air France Flight 447 (Final Report on the accident on 1st June 2009, 2012) and the Aero Peru Boeing 757 (Mc Kenna, 1996) just to cite a few.

To date the reliability of aircraft sensors is achieved through classic Hardware Redundancy (HR) (Dubrova, 2013). HR is based on the installation of multiple sensors and actuators along with a simple voting logic to detect, isolate, and exclude the faulty device (Edwards, Lombaerts, & Smaili, 2010; Goupil, 2011). Obviously HR implies an increase in the complexity of the on-board instrumentation, whose cost and weight is standard for large civilian aircraft. However, for UAVs and small aircraft, where the weight, power consumption, dimensions, costs, and system complexity are important design requirements, FD based on Analytical Redundancy (AR) approaches (Frank, 1990) is a particularly attractive alternative.

AR is in general achieved through the use of a mathematical model that provides in real time a fault free estimation of a possibly faulty measurement. This estimate is used to derive a diagnostic signal

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(residual) as the difference between the actual (possibly faulty) measurement and the estimation provided by the model. Failure Detection (FD) is then achieved by comparing the residual with a detection threshold that depends on the desired probability of False Alarms (FA). Today, AR-based fault diagnosis is a mature research area whose main research directions can be categorized as state-observers (or state estimators), parity-equations, and parameter estimation. Excellent readings on these topics can be found in Basseville (1988), Gertler (1998), Isermann (1984), Patton, Frank, and Clark (2000) and Simani, Fantuzzi, and Patton (2003).

In recent years many researchers have applied model based AR methods to the FD of air data sensors, in most cases using Extended Kalman Filters (EKF). The EFKs are based on mathematical models derived from the aircraft dynamic and kinematic equations, as shown in Castaldi, Mimmo, and Simani (2014), Fravolini, Brunori, Campa, Napolitano, and Cava (2009), Freeman, Seiler, and Balas (2013), Hansen and Blanke (2014), Lu, Van Eykeren, Van Kampen, De Visser, and Chu (2015), Rhudy et al. (2015), and Van Eykeren and Chu (2014).

Even more recently, a different approach has been adopted, featuring a data-driven methodology for the design of a fault detection scheme for the aircraft airspeed velocity sensor (Fravolini, Del Core, Papa, Valigi, & Napolitano, 2017), where system modeling and identification approaches (Ding, 2014; Simani et al., 2003) are used to derive experimental models directly from measured input–output data.

Regardless of the approach, the performance of the FD system is strictly related to the level of modeling uncertainty which is quantified as the discrepancy (difference) between the response of the actual system and the estimation provided by the model.

The presence of the modeling uncertainty essentially implies that in fault free conditions the residual signal is not zero. Therefore, the FD scheme must be robust against uncertainties where the robustness of the scheme is defined as the degree of sensitivity to faults compared to the sensitivity to uncertainty (Puig, 2010).

Modeling uncertainty is particularly relevant for the FD of the ADS. This is due to the fact that the outputs of the models depend on the aerodynamic behavior of the aircraft which changes significantly with flight conditions in addition to being affected by external loads such as atmospheric turbulence. The above factors make the development of accurate ADS models particularly challenging. This aspect became clearly evident when dealing with experimental flight data. In Lu et al. (2015) FD robustness was achieved through an 'ad-hoc' calibration of the sensors model while in Fravolini et al. (2017) through an on-line adaptation mechanism of the residual.

Therefore, in the context of Robust FD it is important not only to compute the nominal model but, even more critical, to correctly characterize its uncertainty bounds (Campi, Calafiore & Garatti, 2009). The classical approach for characterizing and assessing model uncertainty is to provide a probabilistic interval of confidence around the nominal prediction model that is derived from first principles or identified from input–output data. The probabilistic intervals of confidence depend on the assumptions on the uncertainty generation mechanism which, in practical applications, is very often unknown. Also, worst case approaches can be applied to characterize the uncertainty; however, in this case excessively conservative bounds are generally achieved (Chen, 2000).

In recent years different paradigms have been explored and developed to provide a more effective description of the uncertainty where only the boundedness of the noise and of the parametric uncertainty is assumed. The bounded error estimation paradigm (Milanese, Norton, Piet-Lahanier, & Walter, 1996) belongs to this category. The concept of a bounded error estimation idea has attracted a great deal of attention in the FD research community leading to the so-called set membership or Interval Model (IM) methods (Blesa, Puig, & Saludes, 2011; Fagarasan, Ploix, & Gentil, 2004; Sainz, Armengol, & Vehí, 2002). The idea of interval models has also been investigated in the area of fuzzy modeling where upper and lower membership functions along with weighting coefficients are employed to characterize the uncertainties in the so called interval type-2 fuzzy approach (Gao, Xiao, Liu, & Wang, 2018; Liu, Wu, Wang, & Wu, 2017).

In these methods the uncertainty in the parameters and noise is translated into an interval uncertainty in the IM model output that is bounded by time varying bounds that are computed by varying the uncertain parameters within their intervals. The presence of a fault is detected when the measured signal falls outside the modeling bounds, thus proving that the actual measurement is not compatible with the fault free IM. Within this framework is, therefore, important to correctly define the intervals associated with the modeling parameters in fault free conditions.

In this research effort robust model identification methods that infer the interval bounds directly from data were considered. Specifically, the class of models in linear (in the parameters) regression form was considered to build interval predictors of the uncertainty to be used for the robust FD of the air data sensors of Airspeed, Angle of Attack and Angle of Sideslip.

In particular an extension of the IM approaches proposed in Blesa et al. (2011), Blesa, Rotondo, Puig, and Nejjari (2014), Fagarasan et al. (2004) and Puig and Blesa (2013) has been introduced and adapted by applying the optimization based system identification technique ideas proposed in Campi et al. (2009) to estimate a nominal model and to restrict the uncertainty bounds for model parameters in order to guarantee that all the experimental data are included in the IM prediction interval. The main contributions of this paper are summarized below.

The first contribution is given by the interval model identification procedure. This is set up as a convex optimization problem whose decision variables are the amplitudes of the uncertainty intervals box and the cost function is the mean amplitude of the prediction intervals. The problem is formulated as a constrained Linear Matrix Inequality (LMI) optimization that can be efficiently solved using common convex optimization procedures. The proposed method represents a significant generalization of the state of the art IM identification procedures proposed, for instance, in Puig (2010) where the computation of the uncertainty is performed optimizing only a scalar free parameter λ to scale the dimensions of a predefined shape uncertainty box. The approach outlined in Puig (2010) has the great advantage of simplicity but, on the other side, could produce an excessively conservative interval box because the same value of λ is used to scale the uncertain box along all the directions in the same fashion even when the parameters have a significant difference in the relative ranges of variation. Instead, the proposed optimization method scales the uncertainty box components independently and, therefore, is able to produce a more tight approximation of the uncertainty domain. This last aspect has a direct impact on the FD performance since tight uncertain models allow the detection of small amplitude failures.

The second contribution is the experimental validation of the proposed approach using multiple batches of flight data of a P92 Tecnam aircraft ("Tecnam P92 webpage", 2017) that have been used to derive robust IM prediction modes for ADS sensors, thus showing that the procedure can be readily applied to a relevant real FD problem.

The third contribution is given by a detailed performance comparison between interval and conventional FD schemes. Toward this goal complete FD schemes based on linear and nonlinear regression models and fixed probabilistic detection thresholds were designed. Specifically the approach proposed in Fravolini et al. (2017) was applied to the same set of data.

The fourth contribution is that the proposed IM based robust FD scheme has been specifically designed and validated to operate throughout the entire flight including take-off, climb, level flight, descent, approach, and landing. This represents a significant improvement with respect to the most of the existing model based schemes for ADS sensors such as in Cho, Kim, Lee, and Kee (2011), Hansen and Blanke (2014), Lie and Gebre-Egziabher (2013) and Lu et al. (2015) where models and FD performance were evaluated only at a single level flight condition,