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Double-model adaptive fault detection and diagnosis applied to real flight data

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ABSTRACT

The existing multiple model-based estimation algorithms for Fault Detection and Diagnosis (FDD) require the design of a model set, which contains a number of models matching different fault scenarios. To cope with partial faults or simultaneous faults, the model set can be even larger. A large model set makes the computational load intensive and can lead to performance deterioration of the algorithms. In this paper, a novel Double-Model Adaptive Estimation (DMAE) approach for output FDD is proposed, which reduces the number of models to only two, even for the FDD of partial and simultaneous output faults. Two Selective-Reinitialization (SR) algorithms are proposed which can both guarantee the FDD performance of the DMAE. The performance is tested using a simulated aircraft model with the objective of Air Data Sensors (ADS) FDD. Another contribution is that the ADS FDD using real flight data is addressed. Issues related to the FDD using real flight test data are identified. The proposed approaches are validated using real flight data of the Cessna Citation II aircraft, which verified their effectiveness in practice.

1. Introduction

Presently, Fault Detection and Diagnosis (FDD) is important to achieve fault-tolerance (Patton, 1997). For flight control systems, sensor or actuator faults may cause serious problems. Thus, quick detection and isolation of these faults is highly desirable (Goupil, 2011). During the last few decades, many approaches have been proposed for aircraft actuator and sensor Fault Detection and Isolation (FDI) (Chen & Patton, 1999; Isermann, 2005; Marzat, Piet-Lahanier, Damongeot, & Walter, 2012). Some recent advances and trends can be found in Zolghadri (2012) and Goupil (2011). One recent European project, Advanced Fault Diagnosis for Sustainable Flight Guidance and Control (ADDSAFE), aims to develop FDI methods for aircraft flight control systems (Goupil & Marcos, 2014). Within this project, a number of model-based FDI methods were tested and evaluated, refer to Varga and Ossmann (2014), Van Eykeren and Chu (2014), Henry, Cieslak, Zolghadri, and Efimov (2014), Alwi and Edwards (2014), Chen, Patton, and Goupil (2012), Vanek, Edelmayer, Szabó, and Bokor (2014), Hecker and Pfifer (2014) and Marcos (2012). However, few of these papers (Van Eykeren & Chu, 2014) consider the FDD of the Air Data Sensors (ADS). The ADS measure the air data information which is critical to the pilot and to the flight control system. They are usually mounted to the outside of the fuselage. Therefore, they can be affected by the environment in which the aircraft is flying. Faults of the ADS are contributing factors which have led to several aircraft accidents. For civil aircraft, the final report of the Air France Flight 447 accident stated that erroneous airspeed measurements from the pitot probes were a contributing factor (Lombaerts, 2010). An example for military aircraft is the cause of the crash of a B-2 Bomber; it was found that moisture in the port transducer units caused a large bias to the ADS (Lombaerts, 2010). These are only two examples of recent air disasters caused by failures of the ADS system. Therefore, the FDD of the ADS is important. Recently, Freeman, Seiler, and Balas (2013) model the faults of the ADS using the physical air data relationships and experimental wind tunnel data. The present paper deals with the detection and diagnosis of the ADS faults.

One of the most effective approaches for the FDD is the multiple-model-based approach (Zhang & Li, 1998). The basic idea of performing FDD using the multiple-model (MM) approach is: a

Abbreviation: ADDSAFE, advanced fault diagnosis for sustainable flight guidance and control; ADS, air data sensors; DMAE, double-model adaptive estimation; DMAE-NSR, double-model adaptive estimation-no selective reinitialization; FDD, fault detection and diagnosis; FDI, fault detection and isolation; GPS, global positioning systems; IMM, interacting multiple-model; IMU, inertial measurement unit; MM, multiple-model; MMAE, multiple-model adaptive estimation; SRMMAE, selective-reinitialization multiple-model adaptive estimation; SR, selective-reinitialization; UKF, unscented Kalman filter

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Nomenclature

A_x, A_y, A_z	linear accelerations along the body axis, m/s^2
p, q, r	roll, pitch and yaw rate along the body axis, rad/s
V_t	true airspeed, m/s
α, β	angle of attack, sideslip angle, rad
γ	innovation of the filter
ϕ, θ, ψ	roll, pitch and yaw angles along the body axis, rad
a, a_i	fault scenarios and the ith fault scenario
$\hat{x}$, P	state estimate and covariance of state estimation error
p_t, $\hat{x}_t$, P_t	model probability, state estimate and covariance of state estimate error of all the elemental filters
p_{nf}, $\hat{x}_{nf}$, P_{nf}	model probability, state estimate and covariance of state estimate error of the no-fault filter
p_{af}, $\hat{x}_{af}$, P_{af}	model probability, state estimate and covariance of state estimate error of the fault filter
f_o	output fault
f_V, f_α, f_β	faults in the velocity sensor, angle of attack sensor and angle of sideslip sensors
p_i	model probability of the ith elemental filter
$\hat{f}_i$, $\overline{f}_i$	fault estimation and the probability-weighted fault estimation of the ith elemental filter
$\hat{f}_{o,i}$, $\overline{f}_{o,i}$	estimation and probability-weighted estimation of the output fault of the ith elemental filter
p_m, T_o	threshold for detecting a fault and isolating the output faults, respectively
i_{max}	index of the model with the maximum model probability
n, b, l, m	dimension of the state, input, output and output faults respectively

Subscripts

i, j	variable number
k	time step
ff	fault free
af	augmented fault

model set must be created that contains models corresponding to different fault conditions of the monitored system. In addition to fault models, the model set usually includes the nominal model. There are two principal stochastic architectures based on the MM approach (Marzat et al., 2012): the Multiple-Model Adaptive Estimation (MMAE) and the Interacting Multiple-Model (IMM). Both approaches require the design of a model set which represents or covers all possible system models at any time (Zhang & Li, 1998).

The MMAE (Eide & Maybeck, 1996; Magill, 1965; Maybeck, 1999; Ormsby, Raquet, & Maybeck, 2006) algorithm runs a bank of filters in parallel, termed “elemental filters”. Each filter is based on a model matching a particular fault mode of the system. If the set of models used by the MM approach does not change, it is referred to as a fixed model set. When coping with partial faults or simultaneous faults, one disadvantage of the MM approach based on a fixed model set is that the number of models needed to cover all expected failures can be large, making implementation of a single MM estimator impractical (Ru & Li, 2008) for real time FDD. In order to cope with this situation, Maybeck and his research team proposed a hierarchical structure (Maybeck, 1999) and a moving-bank MMAE algorithm (Maybeck & Hentz, 1985; Vasquez & Maybeck, 2004) to reduce the number of required filters online. The hierarchical MMAE is designed for the FDD of single- and dual-failure hypotheses. Although this approach runs $K+1$ (K is the number for single fault FDD) models online, $K(K+1)+1$ models have to be designed. When it is used for FDD of dual-failure scenarios, it is assumed that the second fault occurs two or more seconds later which allows enough time for the first fault to be detected before the second is inserted (Eide & Maybeck, 1996). In addition, it cannot cope with three or more simultaneous faults. The moving-bank MMAE is also designed to avoid the potentially large number of element filters needed for an MMAE bank. It uses less filters to identify the parameters related to the K basic element models. However, more than $K+1$ models are still required only for single FDD. Ducard and Geering (2008) proposed to augment the faults of the input as additional states, which reduces the number of the models to only $K+1$. More recently, Lu and van Kampen (2014) proposed to use Selective-Reinitialization (SR) algorithms to solve the problem when the output faults are augmented to reduce the size of the model set.

The IMM (Blom & Bar-Shalom, 1988; Li & Bar-shalom, 1996; Zhang & Li, 1998) is another multiple-model-based approach. Its difference from the MMAE lies in the fact that element filters in the IMM interact with each other, which leads to a better state estimation performance. Both the MMAE and the IMM display deteriorated performance in case where the model set does not contain a model corresponding to the true system (Hallouzi, Verhaegen, & Kanev, 2009). The model set can become very large when dealing with multiple faults. Li and Bar-shalom (1996) proposed a variable structure IMM with an adaptive model set. The expected-mode augmentation (Li & Jilkov, 2001) is used to adaptively change the model set. However, to cope with partial faults, an extra feature needs to be added to the IMM. Ru and Li (2008) used a maximum likelihood estimator to estimate the extent of the faults after the detection of a fault using the IMM. In addition, to cope with two or more simultaneous faults, the number of expected modes will increase which makes the model set larger.

The drawbacks of a large model set are as follows: firstly, it brings a high computational load which increases with the number of models. This is also the reason why many approaches were proposed to reduce the model set; secondly, a large model set could lead to models being similar to one another in terms of input–output behavior, which could lead to performance deterioration of the MM approaches (Hallouzi et al., 2009; Zhang & Li, 1998).

In this paper, a novel approach called DMAE is proposed for the output FDD. This approach reduces the number of the models in the model set to only two, regardless of K and whether there are partial faults or simultaneous output faults. The two models used in this approach are the no-fault model and the fault model. The states of the fault model are augmented by the K output fault scenarios rather than one fault scenario. Augmenting the output faults as states may lead to reconstructibility problems; this is solved by using the SR scheme. Two SR algorithms are proposed to guarantee the performance of the DMAE approach. The elemental filters are designed based on an Unscented Kalman Filter (UKF) (Julier & Uhlmann, 1997), which uses the direct nonlinear model without linearization and can achieve higher order accuracy. The performance of the two proposed double-model-based approaches is compared to the multiple-model-based approach as well as to each other. The example is the FDD of the ADS faults of a Cessna Citation II CE-500 aircraft model. In order to demonstrate the performance, different fault scenarios are considered, including a single fault and simultaneous faults, small faults and big faults, bias faults and drift faults.

A second contribution of this paper is the application of the proposed approach to the ADS FDD using real flight test data. It