Review of Methodologies for Aircraft Sensors Fault Detection and Correction

Omar Hazbon Alvarez[1], Luis B. Gutierrez Zea[1], Cees Bil [2], Marcello Napolitano [3], Mario L. Fravolini[4]

[1] *Universidad Pontificia Bolivariana, School of Aeronautical Engineering, Circular 1 # 70-01, 050031, Medellin, Colombia.*
[2] *RMIT University, School of Engineering, PO Box 71, Bundoora, VIC 3083, Australia.*
[3] *West Virginia University, School of Mechanical and Aerospace Engineering, PO Box 6106, Morgantown, WV, 26506, USA.*
[4]*University of Perugia, Department of Engineering, Via G. Duranti N8 93,06125, Perugia, Italy.*

Abstract

The air data system is responsible for estimating vital flight parameters for correct and safe operation of aircraft. One of the main components in this system is the Pitot tube sensor which is responsible for measuring the total pressure and in conjunction with the static pressure port estimates parameters like altitude, air speed, vertical speed and Mach number. The Pitot tube is prone to failure because of external adverse atmospheric conditions. The current research aims to develop a solution to the aircraft loss of control caused by an unreliable airspeed indication by introducing the concept of a digital twin that estimates flight parameters based on simulation and monitors actual flight parameters.

Keywords: Aircraft digital twin, unreliable air speed, air data system failure, loss of control.

Introduction

The Air Data System (ADS) plays a vital role in. aircraft operation. The information provided by this device is used by the pilot and other aircraft subsystems for maneuvering and navigating within safe performance boundaries. There is a history of aircraft accidents caused by the failure of one of the ADS sensor, the Pitot tube, for example Air France flight 447 in June 2009, Saratov Airlines flight 6W703 and Lion Air flight 610 in 2018. Table 1 shows a list of some selected non-military aircraft accidents caused by suspected Pitot tube failure since 1973 [1-15].

The Pitot-static system is responsible for airspeed estimation. Under certain atmospheric conditions the sensor can become covered and blocked with ice, dirt or even ground protection devices, and as a result, the computed airspeed become erratic and unreliable. This affects air safety as pilots may not be able to identify the failure and become confused due to unreliable and conflicting warnings. In unmanned air vehicles the situation is also critical because the autopilot is receiving erratic information from the ADS system causing a total loss of control.

Aircraft manufacturers have implemented sensor redundancy with a voting scheme to detect and isolate faulty air data sensor signals, however under certain atmospheric circumstances all sensors fail at the same time, which is called common mode failures. Airbus equipped the A320, A330 and A340 with a Backup Speed Scale (BUSS) were a theoretical airspeed is estimated from pitch and thrust tables, however the system failed on Air France 447 [16]. Airbus is planning to incorporate an extra airspeed estimation sensor based on engine nacelle pressure on the A350 [17]. On the other hand, Boeing's approach to this problem was to equip the 787 Dreamliner with an airspeed estimation calculated from angle of attack and inertial data which they call "Synthetic Air Speed", however this system failed on Jetstar flight JQ 07 [18].

The goal of this research is to develop an air data system tolerant to the ADS Pitot-static sensor failure by means of the analytical estimation of the airspeed, using information from other airborne sensors and supported by a high-fidelity aircraft dynamic model called digital twin as illustrated in figure 1.

Table 1. Some non-military aircraft accidents caused by Pitot tube Failure or ADS sensors since 1973.

Date	Model	Aircraft Damage	Cause	Passengers and Crew	Casualties / Injured
January 30 1973	DC-9-21	Aircraft total Loss	Ice in Pitot tubes	33	0
December 01 1974	Boeing 727 - 251	Aircraft total Loss	Ice in Pitot tubes	3	3
July 28 1984	Learjet 25B	Aircraft total Loss	Pitot tube covers not removed	3	0
May 21 1986	Tupolev 154B-2	Aircraft total Loss	Ice on Pitot tubes	176	0
March 02 1994	MD-82	Structural damage	Ice on Pitot tubes	116	0
February 06 1996	Boeing 757 - 225	Aircraft total loss	Dust or insect debris blocking Pitot tubes orifices	189	189
October 02 1996	Boeing 757-23A	Aircraft total loss	Adhesive tape blocking ADS static port orifice	70	70
October 10 1997	DC-9-32	Aircraft total loss	Ice on Pitot tubes	74	74
April 7 1999	Boeing 737 4Q8	Aircraft total loss	Ice on Pitot tubes	6	6
October 17 1999	MD-11F	Aircraft total loss	Ice blocking Pitot tube drain orifices	2	0
June 3 2006	Dornier 328Jet-300	Aircraft total loss	Obstruction of Pitot tube orifices	8	0
June 01 2009	Airbus A330 - 202	Aircraft total loss	Obstruction of Pitot tube orifices	228	228
Feb 11 2018	Antonov 148	Aircraft total loss	Ice on Pitot Tubes	71	71
Oct 29 2018	Boeing 737	Aircraft total loss	ADS Failure	189	189

Fig. 1: Aircraft digital twin concept.

Current Pitot tube failure research

The airspeed sensor failure problem has been worked out by means of a Sensor failure detection identification and accommodation (SFDIA) task. SFDIA has been traditionally divided in two steps. The first step involves the detection of the sensor failure and identification (SFDI) of the sensor that is generating the unhealthy signal so the corrupted hardware can be isolated.

Accommodation (SFA), the second task, consist in the analytical estimation of the airspeed by means of a virtual sensor estimation and the statistical comparison of this value with the sensor (or sensors) signal so the healthy one can be selected and used by the flight control system.

Napolitano et al [19] used three approaches on the SFDI task based in fault detection filters. The first approach consist on a fixed failure detection threshold using a Cumulative Sum filter – CUSUM. The second approach is based on adaptive failure detection thresholds using a floating limiter. The third approach is based on a generalized Likelihood ratio test – GLRT. In either approaches, the difference between the sensor measurement and the analytically estimated value, so called the residual, is compared with the threshold and the failure will be identified when the residual exceeds a particular threshold value thus triggering failure detection. Recent research efforts are focused on minimizing the number of false alarms or undetected failures generated with the previous approaches by using the exponentially weighted moving averaged – EWMA filter which can detect small shifts in the mean and standard deviation of process variables [20]. The EWMA chart tracks the EWMA mean of all previous samples so that the most recent are weighted more heavily than the older ones, preventing that the faults in previous time steps affect the current residual. These fault tolerant techniques can be extended to as many sensors as needed in conjunction with a bank of residual monitors to isolate the faulty sensor.

The model-based airspeed estimation approach takes advantage of the well-known aircraft non-linear model [21, 22] and redundant measurements from the sensors onboard. The commonly used model state variables are the true airspeed, angle of attack, angle of sideslip, angular rates, Euler attitude angles and the aircraft position. The state control variables relies on the thrust force and the elevator, rudder and aileron deflections. The airspeed is implicit in all the twelve equations of the aircraft nonlinear model, however in Napolitano's cited research it is stated that the airspeed is strongly correlated with the angle of attack equation and it suffices for the estimation of the airspeed. This equation is expressed in a form that is suitable for parameter identification with a linear combination of unknown coefficients and known nonlinear functions of measured signals. The equation is evaluated at several instants on a time window to set up a linear systems of equations that is solved for the unknown equation coefficients by means of least squares and taking advantage of previously recorded flight test data. The online estimates of the airspeed at a particular time are based on the online solution of the quadratic equation were the unknown coefficients are substituted by the LS estimate and only the positive value of the airspeed is selected.

The model-independent virtual sensors are of great interest because the estimation method can be applied conveniently to any aircraft without information of the vehicle dynamics which most of the time is difficult to obtain. As stated by Napolitano et al [23], the first approach was done by the implementation of Kalman Filter estimators (extended - EKF and unscented - UKF). The second approach is by the implementation of artificial neural networks (Multi-Layer Perceptron - MLP and Extended Minimal Resource Allocating Network - EMRAN) [24]. These approaches were evaluated in terms of their performance (by means of mean and standard deviation) in the evaluation of the airspeed. The advantage of these methods is that it is not required and exact dynamic model of the aircraft were a large data depository containing the linear or non-linear relationships of the complete flight envelope of a commercial aircraft will be necessary. The previous methods use information from the other airborne sensors to estimate the airspeed, particularly the three axis accelerations and angular rates from the IMU, roll and pitch angle measurements from the vertical gyro and angle of attack and sideslip from the ADS.

The MLP ANN used on the estimation of the airspeed was selected by Napolitano [24] due to its flexibility for several applications, including function fitting and pattern recognition. The MLP was trained to learn the functional relationship between the airspeed and a set of correlated measurements provided by the other aircraft sensors.

The EMRAN [24] ANN architecture allows only the parameters of the most active neurons to be updated, while all the others are left unchanged. Essentially, the EMRAN algorithm allocates neurons in order to decrease the estimation error in regions of the state space where the mapping accuracy is poor. This strategy results in a significant reduction of the number of parameters to be updated online, thus reducing the computational burden, and therefore making this architecture particularly suitable for online applications.

Some other types ANNs had been used in aircraft airspeed estimation. Husain [25] used a fully connected cascade ANN for estimation arguing that it requires lower computational effort that MLP and EMRAN ANNs.

The estimation methods described previously require time consuming tuning procedures that usually produce unreliable performance when validated with actual flight data. To overcome this problem current research effort is being conducted by Napolitano's team [20] based on a semiautomatic data driven approach to select model regressors and identify Nonlinear Autoregressive Exogenous – NARX input-output neural network prediction models. This approach provides online model adaption mechanisms to cope with time dependent and flight dependent levels of uncertainties. The drawback of the NARX estimation model is that being an autoregressive model, its prediction is influenced by the fault. Trying to unlink the estimation result from the fault the researcher's tried [26] a feed-forward non-autoregressive MLP NN modelled as follows which is able to provide a reliable multi-step ahead estimation independently of the occurrence of the fault.

The fault on the airspeed sensor is usually modeled by different authors like in Napolitano [23] as an additive bias. Two suddenly fault scenarios commonly used in fault detection and identification practice are usually implemented: a sudden bias (SB) failure and a slow ramp bias (SRB) failure. The residual signal used for the purpose of SFD is defined as the difference between the measured air speed from the ADS and the estimated airspeed. Theoretically the residual signal should approach to zero in the fault free condition scenario, but in the real world, due to modelling uncertainties and noise, the residual signal is different from zero. It is found in experiments that the raw residual signal has a significant autocorrelated length that is introduced mainly by uncertainties in the low frequency range. Since statistical detectors perform optimally when residual signals are completely uncorrelated, a whitening filter is usually designed to remove the residual signal correlation.

Proposed research

The proposed work estimates the airspeed using a combination of an Unscented Kalman Filter that implements an augmented model that works as a navigation filter able to predict wind velocity components to estimate airspeed, angle of attack, and angle of sideslip. The concept is to use information of all sensors available and give more weight to healthier sensor signals. The scheme should be capable of determine the degree of confidence of each sensor by using a statistical measure of the variation of the residual signals like the EWMA filter. Based on statistical measurements a mechanism is being developed to adjust the weight of each sensor in a proportional way and feedback the sensor autoregulation algorithm. The autoregulation will be carried out by automatically adjusting the estimation covariance of each sensor. This filter would be an extension of current filters used nowadays for INS-GNSS integration, including the wind model and the relative velocity equation, and using as sensors an IMU (gyroscopes and accelerometers), a magnetometer, a barometric altimeter (from static port), a GPS or RTK (to measure position and velocity respect to earth), a Pitot and the of angle of attack and sideslip vanes. The filter is implemented at a higher sample rate of 100Hz having the advantage of providing a healthy estimate of the variables even in the case of a Pitot tube failure or any of the air angle vanes, as long as the observability condition for the variable being measured is attained. This estimate can also be used as a feedback for the flight control system.

A second subsystem of the proposed scheme is the use of a supervised learning mechanism to train a Neural Network or Neuro Fuzzy structure (aircraft digital twin), of an additive model of aerodynamic and propulsion forces and moments, based on data provided by the Kalman Filter and direct measurements of aircraft controls (from flight test data). Once the digital twin is trained and accuracy achieved, it will be used to augment the UKF with some virtual measurements of aerodynamic net force and moment to improve the navigation solution of the UKF itself in case of a sensor failure. Figure 2 shows a schematic of the proposed approach. The system will first be tested in RMIT´s research flight simulator facility and later on the real aircraft so the reaction of the pilot can be assessed. It an improvement in the estimation accuracy is expected with the approach described above. A novelty will be provided by performing aircraft state estimation during the take-off and landing phases of flight.

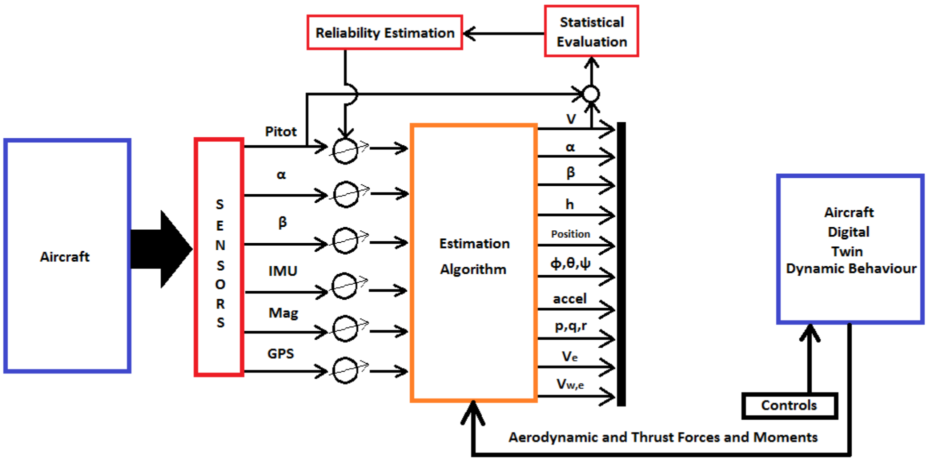

Fig. 2: Proposed airspeed estimation scheme.

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