LEARNING BAYESIAN NETWORKS FOR FAULT DETECTION: APPLICATION TO THE 747 LONGITUDINAL MOTION

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Abstract. *The correct detection of a fault can save worthy resources or even prevent the destruction of key equipment, but, mainly, the correct detection of a single fault can save lives, as, for example, in the case of spaceships, aircraft and nuclear plants. In this work a new fault detection method, based on the learning of a Bayesian network, is applied to the longitudinal motion of the 747 aircraft. A linearized model of the 747 flying under the control of an autopilot and subjected to gusts of wind is used and faults at the altitude sensor are simulated. Such faults, if not detected, could make the autopilot lower the flight level causing a collision. A Bayesian network is learned from data collected from the aircraft flying under normal conditions and is used in the fault detection. The simulation results comparing the correct fault detection ratio, the false alarm ratio and the average time of detection of the proposed method and of the Luenberger observer residue approach show a clear advantage of the application of proposed method.*

Keywords: *Fault Detection, Bayesian Networks, Machine Learning, Aircraft Longitudinal Motion*

1. Introduction

The prompt detection of faults in dynamic systems is essential to prevent further deterioration of the system, which could lead to dangerous operating conditions and even physical breakdown, putting in risk worthy resources, key equipment and even human life.

An adequate fault detection (FD) scheme can save astronauts in a spaceship or in a space station. It can save the crew, the passengers and the equipment of a space shuttle or an aircraft (Chen, Patton and Liu, 1994). It can save nuclear power plant (Santoso et al, 1999) workers and neighbors or just the driver and the passengers of a car or bus (Capriglione, Liguori and Pietrosanto, 2004).

Specifically in airspace a non detected fault could lead to disastrous consequences. A single fault could cost an entire space station, a spaceship, an aircraft or a rocket. Sometimes only significant material investments are lost, but in the worst case, the crew and the passengers could also die and the craft or the debris of a space station or a rocket could fall over a highly populated area making many victims. The application example used in this work illustrate such a possibility, where a fault in the altitude sensor of a 747 aircraft under autopilot control could make the airplane go down and crash if not detected on time.

The growing demands for fault tolerance, cost efficiency, reliability and security, not only in aerospace, allied with the increasing complexity of the systems stimulated the development in the area of Fault Detection (FD) and during the last three decades a number of approaches concerned with fault detection and diagnosis have been reported. Some of the effort in this area can be seen from the survey papers by Angeli and Chatzinikolau (2004), Fenton, McGinnity and Maguire (2001), Venkatasubramanian et al (2003a), Venkatasubramanian et al (2003b), and Venkatasubramanian et al (2003c).

2. Related work

The early FD methods were based on physical redundancy, where redundant sensors were placed in the system and the value measured by the sensors were compared for fault detection, but this approach cannot be used in many systems due to space and cost limitations, such as in spaceships where space and weight limitations are critical.

Many approaches for FD are based on analytical redundancy (Capriglione, Liguori and Pietrosanto, 2004), (Patton, Frank and Clark, 1989), (Persin et al, 2002), (Simani, Fantuzzi, and Beghelli, 2000), where an analytical model of the system is used to generate the redundant signals instead of redundant hardware. Such signals are then compared with the measurement from the sensors. The Luenberger observer is one of the analytical models that can be used to generate the redundant signals and in many cases the observer and the residue evaluation can be implemented within the control algorithm, so no extra space is needed to implement the analytical redundancy.

There are also FD methods based on the training of artificial neural networks (Jakubek and Strasser, 2002), (Sorsa, Koivo, and Koivisto,1991) and on manually constructed Bayesian networks (Chien, Chen and Lin, 2002), (Lerner et al, 2000), (Santoso et al, 1999), but these methods rely on the existence of an extensive fault database or on the existence of a deep knowledge of the possible faults and their probability distribution. So in critical and complex systems where few or no data about past faults are available, such as in the aerospace area, these methods are of restricted use.

3. Background

Bayesian networks are directed acyclic graphs in which the nodes represent variables and the arcs express the probability dependences between the linked variables (Pearl, 1998). A Bayesian network is a powerful knowledge representation and reasoning tool under conditions of uncertainty (Cheng, Bell, and Liu, 1997).

The use of the Bayesian networks have been increasing in many problem domain and in many kinds of applications (Matsuura, 2003), including but not limited to diagnosis and fault detection and diagnosis (Chien, Chen and Lin, 2002), (Lerner et al, 2000), (Mehranbod, 2002), (Santoso et al, 1999).

Since a Bayesian network constitutes a complete probabilistic model of the variables in a domain, the network contains the information needed to answer all probabilistic queries about these variables (Pearl, 1998). In particular it is possible to calculate the distribution probability of one variable given the values of all other variables in the domain (Matsuura, 2003).

A Bayesian network can be built from the knowledge of experts or learned from historical data, but the manual construction of a Bayesian network is not a simple task and may be of restricted use. On the other hand, in part due to the advances on computational power, the learning methods for Bayesian networks are becoming more popular and powerful (Cheng, Bell, and Liu, 1997), (Cooper and Herskovitz, 1992), (Koehler and Nassar, 2002).

The former fault detection methods that use Bayesian networks are based either on manually constructed Bayesian networks that assume a strong knowledge about the possible faults of the system (Lerner et al, 2000), (Mehranbod, 2002), on Bayesian networks learned from a faulty database or in a mixture of the two (Chien, Chen and Lin, 2002), (Santoso et al, 1999).

Hood and Ji (1997) proposed the use of Bayesian networks, learned from normal operation data only, for computer network fault detection, but the characteristics of a computer network and of a dynamic system are very different and the method of Hood and Ji (1997) cannot be direct applied to dynamic systems.

To the best knowledge of the authors no work using Bayesian networks, learned from normal operation data only, for fault detection on dynamic systems has been reported in the literature.

4. Proposed Method

The proposed fault detection method uses a learned Bayesian network to monitor a dynamic system. The nodes of the Bayesian network are the inputs and outputs of the system plus the state variables of a Luenberger observer and the generated residue. The structure (arcs) of the directed acyclic graph and the parameters (conditional probabilities) of the Bayesian network are learned from measures of the system operating under normal conditions, i.e., in the absence of faults.

For faster and simpler learning and inference the measured and estimated values are discretized. Continuous values should ideally be used, but the learning of a continuous or hybrid network and the inference process with continuous nodes would require considerably more computational resources without guarantying any improvement in the effectiveness of the Bayesian network. Some comparisons about using continuous and discretized variables in the learning process of Bayesian networks can be seen in Dougherty, Kohavi and Sahami (1995), Kohavi and Sahami (1996), Liu et al (2002), and in Ventura and Martinez (1995), none of them showing considerable differences in the effectiveness of the resulting Bayesian networks.

As the Bayesian network was learned from measures and estimates of the dynamic system operating under normal conditions, it is a probabilistic model of the system without faults. In the occurrence of a fault the probabilistic relations among the variables will be changed and the Bayesian network can be used to detect these changes.

At sampling times all the measurements of the system and the estimated states are taken and the Bayesian network is used to calculate the probability of occurrence of the value of each variable given the values of all other variables. The minimum probability calculated this way is considered as the probability of occurrence of this set of values. Under normal operational conditions the relationship among the variables are the same as in the learning data, so the probability of occurrence of each measured or estimated value and thus the probability of the entire set is expected to be significantly larger than zero. After a fault in the system the relations among the variables change and sets of values that normally would not be measured and estimated will be measured and estimated.

When the Bayesian network is used to calculate the probability of occurrence of these values and sets, a low or zero probability will be the result. Thus, a low probability of occurrence of a set, or a low probability of a value given the values of all other variables indicates the presence of a fault. Following this reasoning, when the probability of a set is equal or smaller than a pre-determined threshold probability (that should ideally be zero) a fault alarm is raised.

5. Aircraft Model and Simulations

For illustration, the proposed method is employed to monitor a 747 aircraft. More specifically, the target application is the longitudinal motion of a 747 aircraft flying at 12.000 m and 235 m/s (Bryson, 1993). The system was linearized and a 6th order linear state space model is derived and presented in Eq. (1).

$$\dot{x} = A.x + B.u + Bn.w \tag{1}$$

Where x is the 6x1 state vector, A the open-loop system dynamics matrix, u the 2x1 known input vector with the corresponding input distribution matrix B and the term $Bn.w$ characterizes a 2x1 unknown input (disturbance) vector w with known distribution matrix Bn acting directly onto the system dynamics.

The matrices and vectors of the linearized model are given by Eq. (2).

$$A = \begin{bmatrix} -0.003 & 0.039 & 0 & -0.322 & 0 & 1 \\ -0.065 & -0.319 & 7.74 & 0 & 0 & -0.04 \\ 0.0201 & -0.101 & -0.429 & 0 & 0 & 0.598 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 7.74 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -0.25 \end{bmatrix}, B = \begin{bmatrix} 0.01 & 0 \\ -0.18 & 0 \\ -1.16 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0.25 \end{bmatrix},$$
$$Bn = \begin{bmatrix} -0.003 & 0.039 \\ -0.65 & -0.319 \\ 0.0201 & -0.101 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, x = \begin{bmatrix} i \\ j \\ q \\ \theta \\ h \\ t \end{bmatrix}, u = \begin{bmatrix} e \\ tc \end{bmatrix}, w = \begin{bmatrix} wi \\ wj \end{bmatrix} \tag{2}$$

where the components of the input vector u are the elevator command and the throttle command, the components of the disturbance vector w are gusts of wind in the x (head-tail) and z (up-down) directions, and the components of the state vector are the aircraft airspeed in the x and z directions, the angular velocity of the x-axis with relation to the horizontal line, the Euler angle between the x-axis and the horizontal line, the altitude and the real throttle. The angle θ and the directions of the axis and velocities are show in Fig 1.

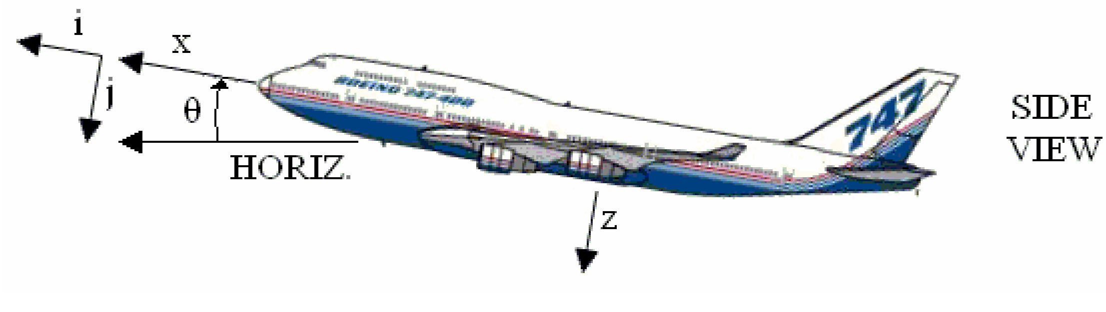


Figure 1. Nomenclature for aircraft longitudinal motions

The aircraft is controlled by state feedback with a stability augmentation system for altitude hold. The feedback gains of such autopilot are those determined by Bryson (1993).

The 747 has an inertial reference system, so good estimates of i, j, θ and q are available. We also assume that t can be estimated and that the only state variable measure from sensors is the altitude h. The altitude sensor was subject to an additive white Gaussian noise of zero mean and standard deviation of 0.1.

The estimates from the inertial reference system should also be used to the learning of the Bayesian network, but since an analytical redundancy scheme using a Luenberger observer was chosen for result comparison purposes, the estimates of the Luenberger observer were used in the Bayesian scheme. This way both methods were using the same information for the fault detection. The use of the inertial reference system estimates would improve the performance of the Bayesian method, thus making the comparison unfair.

The Luenberger observer was designed to use only the altitude sensor as system output, so the residue for the analytical redundancy scheme was the difference between the altitude sensor reading and the altitude estimated by the Luenberger observer. Figure 2 shows the Matlab/Simulink block diagram used to simulate the 747 aircraft and the sensor fault.

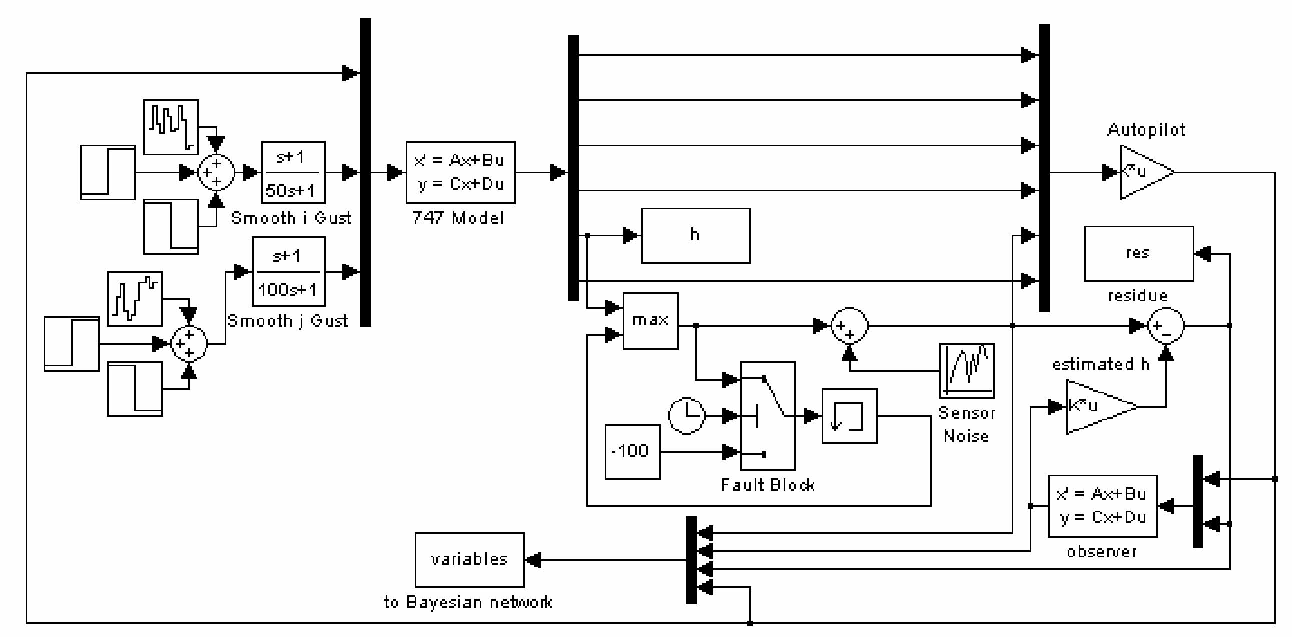
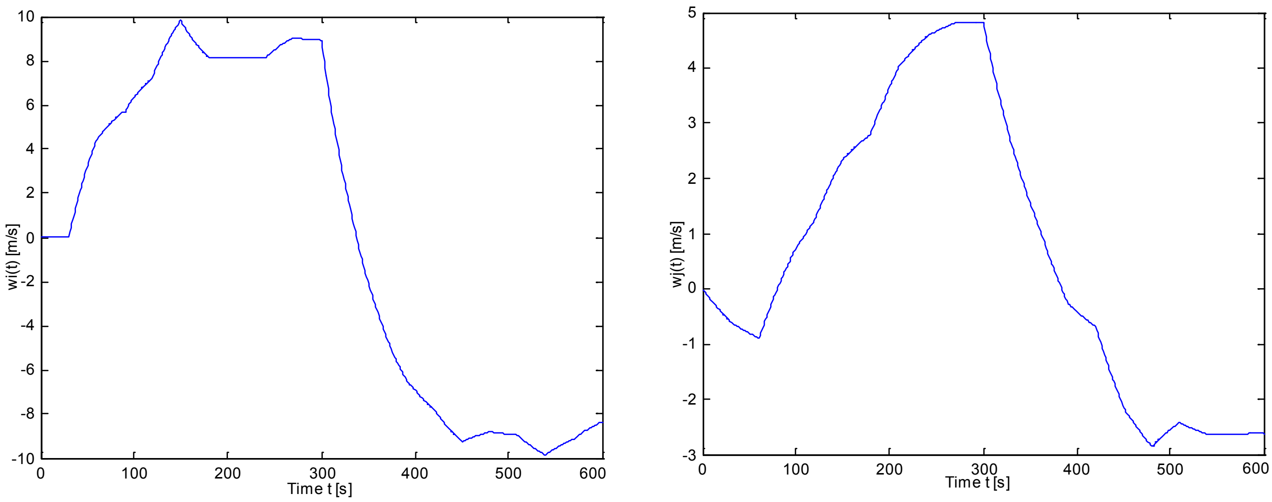


Figure 2. Block diagram for the simulation of the 747 model

Figure 3 presents the waveforms of typical gusts of wind used in the simulations. The head-tail gusts vary from -10 to +10 m/s, while the up-down gusts vary from -5 to 5 m/s.



(a) (b)

Figure 3. Typical gusts of wind (m/s). (a) *wi*, (b) *wj*. The horizontal axis corresponds to the discrete time index k.

In order to simulate a fault, the altitude measurement was held at a fixed value after positive gusts of wind in the *x* and *z* body axes. As positives gusts of wind make the aircraft go up, the sensor sticks at a positive value of altitude variation, informing the autopilot that the aircraft is always at an altitude higher than the desired altitude. Such a fault, if not detected in time could make the autopilot flight the aircraft below safe altitudes causing a collision.

The altitude variations measured by the altitude sensor, for the aircraft flying under normal conditions and with a sensor stuck at 300 seconds, are presented in Fig. 4.

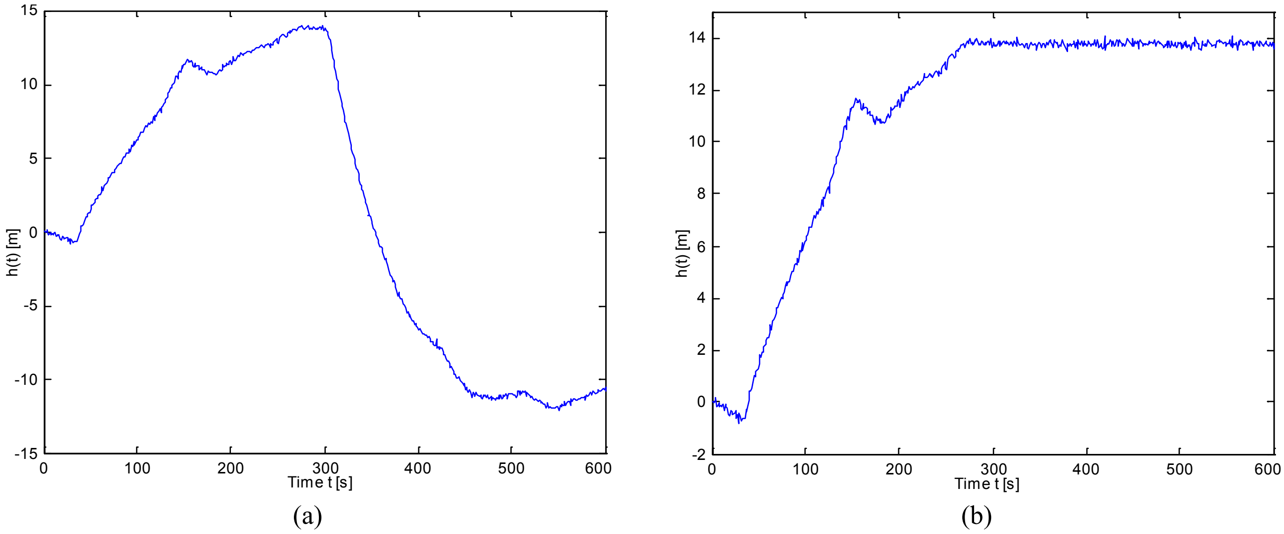


Figure 4. Sensor altitude variation (m). (a) Normal conditions, (b) Fault at 300s.

The real altitude for a sensor stuck at 300 seconds is shown in Fig. 5.

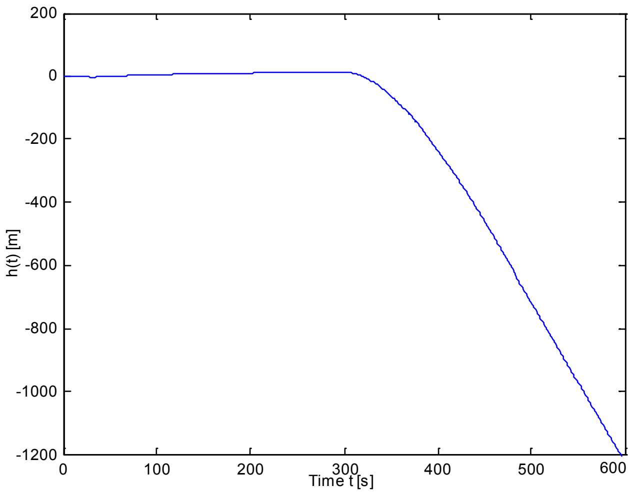


Figure 5. Real altitude variation (m) for a fault at 300s.

As can be seen from Fig. 5, if nothing is done, the aircraft would descend to dangerous altitudes in few minutes.

For the learning of the Bayesian network the model was simulated for 100 hours (600 simulations of 10 minutes) subjected to typical gusts of wind. The sample time was 1 second. For the monitoring process the model was simulated 100 times, each simulation lasting 600 seconds, with a fault happening at 300 seconds.

6. Results

The K2 learning algorithm (Cooper and Herskovitz, 1992) was used in this work due to its popularity and good results obtained when applied to the ALARM data set, a well-accepted benchmark to Bayesian learning algorithms (Koehler and Nassar, 2002).

The values of the estimated states *i* (x-axis velocity), *j* (z-axis velocity), *q* (angular velocity), θ (Euler angle), *h* (estimated altitude) and *t* (throttle) and of the measured variables *e* (elevator command), *tc* (throttle command), *h* (measured altitude) and *r* (residue, difference between the measured and the estimated altitude) sampled at a period of 1 second over 100 hours of simulation were stored and used in the learning of a Bayesian network with the K2 algorithm. The structure of the learned Bayesian network is presented in Fig. 6. The arcs indicate the existence of probability dependence from the variable in the tail to the variable in the arrowhead. Circle nodes are measurements from the system and square nodes are the estimated states.

The learned Bayesian network was then used to monitor the system and as already mentioned a Luenberger observer was also used to monitor the system for comparison purposes.

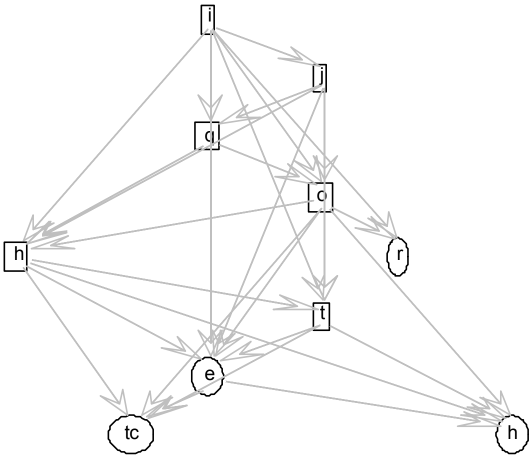


Figure 6. Structure of the learned Bayesian network.

To circumvent the threshold selection problem, which could make the results tendentious, for comparison purposes, the results are presented in Receiver Operating Characteristic (ROC) Curves. The ROC curve, which is defined as a plot of test sensitivity as the y coordinate versus the false positive rate (FPR) as the x coordinate, is an effective method of evaluating the performance of diagnostic tests (Park, Goo and Jo, 2004). For fault detection the sensitivity is the correct fault detection ratio and the FPR is the false alarm ratio.

One of the most popular measures associated with the ROC curve is the area under the ROC curve (AUC) (Park, Goo and Jo, 2004). The AUC is a measure of the overall performance of a diagnostic test and is interpreted as the average value of sensitivity for all possible values of specificity (1-FPR). The closer AUC is to one, the better the overall diagnostic performance of the test, and a test with an AUC value of one is one which is perfectly accurate.

The Bayesian network and the observer residue methods were used with different thresholds levels to monitor the 747 aircraft and the ROC curves for the Bayesian network and for the observer approach are shown in Fig. 7.

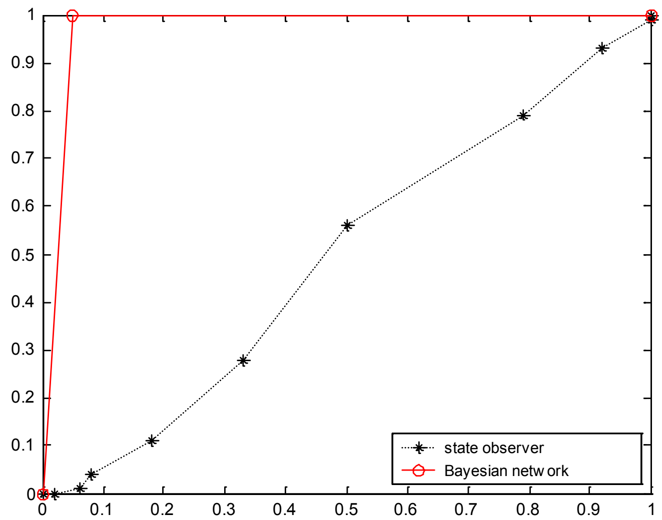


Figure 7. ROC curves

From the ROC curves in Fig. 7 it is possible to see a near perfect result for the Bayesian network and a very poor result for the Luenberger observer. A better result should be expected for the Luenberger observer, but the feedback in the state estimation dynamics obscures the effect of the fault, making the observer output track the value of the faulty sensor as it was the real output value. Therefore the absolute value of the residue, which guides the fault detection decision, does not rise after the fault, making this approach useless in this case. Fortunately, even with the state estimation feedback, the fault causes a large enough change in the relations of the variables to be detected by the Bayesian network.

Figure 8 shows the control signals for a typical simulation run without faults and for a fault at 300 s. The signal e(t) is the elevator command and tc(t) is the throttle command. It is important to note that the stuck sensor does not make the control signals vary much from the values without faults, this way the observer is able to track the wrong output signal closely, thus keeping the residue at low values.

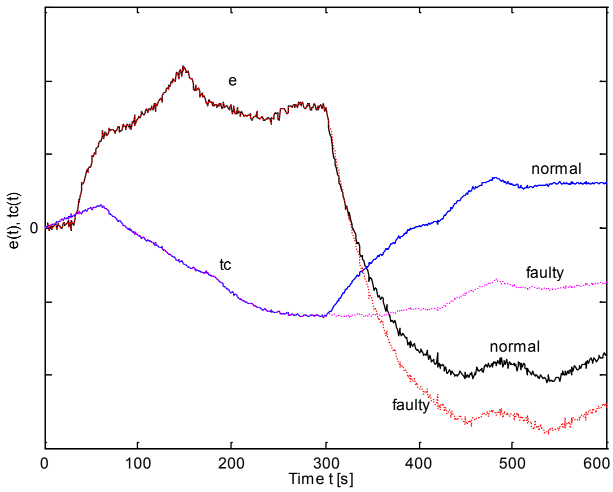


Figure 8. Control signals for normal operation conditions and for a fault at 300 s.

Table 1 summarizes the results obtained with the application of the two fault detection methods. Besides the greater AUC, the Bayesian approach was also able to detect the faults much faster than the observer. This promptness could also make the difference between safe recovery and crash. As shown in Tab. 1 and as can be seen on Fig. 5, 10 seconds after the fault, the aircraft altitude is still close to the desired value. In fact, due to the effects of the positive gusts of wind the aircraft altitude is even higher than desired (about 10 meters higher). Therefore, the detection delay of the Bayesian approach can be deemed acceptable. On the other hand, 129 seconds after a fault (average time needed for the observer to detect a fault) the aircraft is about 347 meters below the desired altitude, so even if both methods had similar AUC, the Bayesian method should still be preferred.

Table 1. Average results for the observer approach and for the Bayesian network.

	Observer	Bayesian network
AUC	0.49	0.98
Average Detection Delay	129.1 s	10.1 s
Altitude deviation at Detection Time	- 347 m	10 m

7. Concluding Remarks

The simulation results show a great potential of the proposed method. It was able to detect 100% of the simulated faults with about only 5% of false alarms, as could be seen in Fig. 7, and with an average detection delay of only 10 seconds. So, by using the proposed fault detection method, the pilot should have more than enough time to turn-off the autopilot and assume the control of the aircraft before it descends to dangerous altitudes.

In the other hand, the observer residue approach was not capable of distinguishing normal operation from the faulty condition, with an AUC near 50%. And even when the observer scheme detected a fault, the time needed to make the decision is not acceptable.

It is interesting to note that the performance of the Bayesian network approach should be enhanced if the inertial reference system was used instead of the estimates of the Luenberger observer and if more data were used in the learning process. Even data collected during the use of the Bayesian network to detect faults can be used to improve the learning process. Also, other learning algorithms and discretization methods like the one proposed by Matsuura (2003) could be used to try to improve the Bayesian network performance.

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