IN-FLIGHT MONITORING OF CRITICAL SENSORS

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Abstract

The paper describes a method for the in-flight monitoring of sensors in aircraft using analytical redundancy. The redundant quantities are estimated with the help of a nonlinear Luenberger-observer. Comparing the estimated with the measured data, residuals are generated. The analysis of these residuals in a nonlinear, multistage bank of filters leads to a number of criteria, which enable a threshold logic to decide whether a sensor has failed or not. The method is applied to critical airdata sensors of the in-flight simulator ATTAS of the DLR. Some results for the response of the system to failures will be shown. Because the failure detection works with simple algorithms, the method is fast, flexible and easy to implement.

Introduction

Because of the increasing automation in aircraft systems, the reliability of the sensor-systems used becomes more and more important. The probability that one sensor failure leads to a safety-critical situation in flight must be less than 10^{-9} per flight hour [1]. Since the probability for a single sensor failure can be up to 10^{-4} per flight hour, the given reliability demands can only be achieved through redundancy.

Redundancy

The necessary redundancy can be achieved by tripling the sensor hardware (parallel or physical redundancy), but this approach increases also the costs and the weight of the sensor system. Another problem is that the tripled sensors are often used under the same or similar environmental conditions. In this case, the failure probabilities of those sensors are not statistically independent anymore, which leads to less safety. Both disadvantages can be avoided, if the redundancy is generated analytically.

In the analytical redundancy concept, the redundant sensor signals are evaluated through the mathematical model of the aircraft from other measured quantities. With the help of the difference between the calculated and the measured signal (residual) it can be decided, whether the corresponding sensor failed or not. The failure detection is done in two steps:

1. Generation of the residuals
2. Analysis of the residuals

Without any sensor failure in the ideal case the residual is zero. But because of model errors and disturbances with effect on the process there will be a deviation also in the faultless case. To come to a correct decision in sensor failure detection, the residual evaluation must be able to distinguish between the disturbance effects and the true sensor failures.

Sensor Failure Detection Tasks

In aircraft usually not only one sensor needs to be monitored, but multiple sensors are combined in a multi sensor system. Then, the sensor failure detection is devided into three tasks [2], which can be carried out together or separately, depending on the concept:

1. Failure detection
2. Failure isolation
3. Failure diagnosis

For each practical sensor failure detecting system, the first two tasks are obligatory. Although the third task is optional, it is often a useful addition. In the proposed scheme the second task is carried out by analyzing a residual for each sensor signal. In this case the failed sensor is immediately localized after detection.

Airlog

In the investigated case the failure detection algorithm is applied to the airlog of the research aircraft ATTAS (Advanced Technology

Testing Aircraft System) of the DLR. The airlog is used to measure angle of attack, angle of sideslip, and true airspeed (Figure 1).

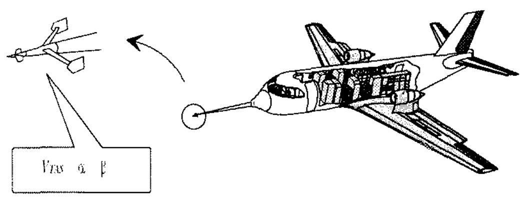


Fig 1: Research Aircraft ATTAS, Airlog

The airlog, a cardanic suspended vane with an impeller, is mounted on a noseboom of 4 m length. This sensor is critical, i) because the measured signals are of utmost importance for control and identification [3] and ii) it is mounted outside the cabin, where it is exposed to influence of the environment and therefore susceptible to faults (icing, mechanical damage, induced oscillations) above the average. For this reasons, it is advisable to apply an inflight monitoring in this case.

Generation of the Residuals

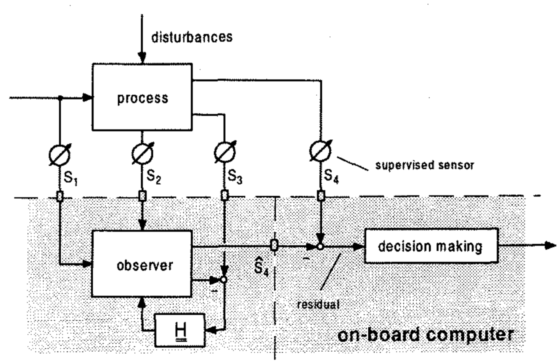
The residuals are generated by calculating the difference between estimated and measured signals. For the estimations a nonlinear Luenberger-observer is used [4]. An observer is an algorithm, which, similar to a simulation, calculates state and output variables from the input variables and a mathematical model of the process. In contrast to the simulation the estimated output variables are compared with the corresponding measurements and the differences (output errors) are fed back. The feedback matrix works like a controller and changes the state variables until the output error becomes small. In this way the observer is able to generate correct state and output variables in the presence of wrong initial conditions. The feedback matrix is constant and is provided by the user in that way that the system is stable.

Measurement Variables of the Process

To estimate the states and outputs the observer needs the inputs of the process. Here, the inputs are the control surface deflections and the thrust, which initiate the motion of the aircraft. As output, the observer estimates the angle of attack, angle of sideslip, and airspeed. These are substracted from the corresponding process variables to generate the residual (Figure 2).

For the feedback the translational accelerations, registered by the inertial measurement unit, are used. Because the observer is designed as a local observer and therefore estimates only the translational motion of the aircraft, the rotational quantities (attitude and angular rates), which are needed in the observer for the transformation of coordinates, have to be taken from the process.

With this arrangement the process variables, coming from the airlog, can be monitored. The other process variables, coming from the sensor groups S_1, S_2 and S_3, are supposed to be failure free.



S_1 input signals (control surface deflections, thrust, etc.)

S_2 non observed states (roll-, pitch- and yaw rates, attitude)

S_3 feedback signals (translational accelerations)

S_4 supervised sensor signals (V_{TAS}, α, β)

$\hat{S}_4$ estimated sensor signals

Fig 2: Sensor Signals in the Process

Experimental Flight Test Data from ATTAS

Figure 3 shows on the left side time histories, where measured airlog variables and the corresponding estimates from the observer are compared. On the right side, the differences between both are presented as residuals. The residuals are caused by model inaccuracies and disturbances, like gusts, turbulences or measurement noise. Because they are not caused by sensor failures and therefore belong to the failure free case, they have to be tolerated by the sensor failure detection scheme. To evaluate all consequences of these effects on the residuals, extensive flight data have to be analyzed.

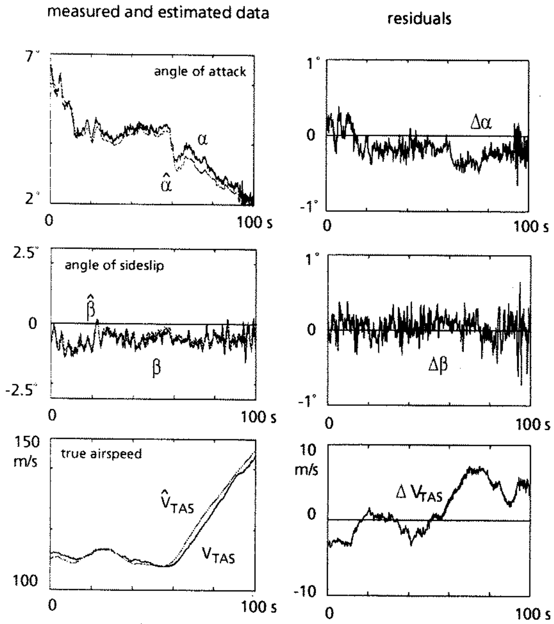


Fig 3: Flight Test Data

As one can see also, the three failure free residuals have different properties which are characteristic for each measurement variable. For example in the residual for V_{TAS} low frequency fluctuations and in the residual for β high frequency noise dominate, respectively. These differences in properties have to be taken into account when the parameters for the failure detection algorithm are set.

Analysis of Residuals

To distinguish between the failure free case and a failure, it is assumed, that failures in the sensor system have certain characteristic effects on the residual (e.g. sudden deviations like spikes or jumps, slowly accumulating deviations as drifts, constant deviations like offsets, and fluctuating deviations like noise or oscillations). The detection of a failure depends on the appearance of the residual. In this sense the detection algorithm is a kind of pattern recognition method. Its task is to extract characteristic criteria from the residual to achieve criteria, which can be used to decide whether a sensor has failed or not.

The analysis of one residual is done in two steps:

1. Extraction of criteria
2. Decision making

Bank of Parallel Filters

For the extraction of criteria in the first step a bank of parallel filters is used. The lowpass filters at the first stage can be realized in different ways: as gliding mean value or exponential filter. The time constants are set in such a way that strong, medium and weak filtering of the residual ($T_1 < T_2 < T_3$) is applied.

In the second stage the squares of the differences of every two neighbouring residuals are generated. The resulting signals are equivalent to a bandpass filtered residual. Altogether one can say that the residual is processed in a bank of parallel bandpass filters. Because of the different dynamics of the filters the residual is reduced in different spectral areas. The reason why bandpass filters are not used directly is that the lowpass filtered residuals are needed as criteria for the following decision making.

In the block diagram the square operation is depicted by a quadratic characteristic. Because the squaring not only causes a positive sign but also a stronger weighting of the higher amplitudes compared with the lower amplitudes, the squares of the differences are very sensitive to fast and strong variations of the residuals. So, they are also taken as criteria for failure detection.

In the third stage the squares of the differences are filtered by a gliding mean value filter. The width of the sliding window (time constant) is the same for all filters which are used at this stage. The criteria, which are created this way, correspond under certain conditions to the square effective value or the variance of the bandpass filtered residuals. By comparison among themselves one can decide which spectral regions dominate in the residual.

Use of Counters

Further criteria are generated by counters, which count discrete events, which occur, when a criterion exceeds a certain threshold. Counters are used if an accumulation of threshold excitations characterizes a special failure case. In the following three different counters will be described: duration counters, frequency counters and drift detectors.

The duration counters register the duration of a threshold excitation by incrementing their value by one each sample as long as the signal is beyond its threshold. The number of threshold crossings in an interval of time are registered by the frequency counters. Their values reflect the changeability of the residual. The implemented drift detectors supply hints about the monotony of the signal. For this purpose these counters work with variable thresholds, which are set each time step on the last value of the signal. If the next value is greater, then the counter is incremented, if it is less, the counter is decremented by 1. Because the residual contains stochastic noise, there is no strict monotony during more than a few samples. To recognize longer lasting drifts the drift counters must be applied to the lowpass filtered residuals.

The counter values refer to a window of constant width, which slides over the time history of the residual, and over some of the extracted criteria. Each time step the window is shifted one step forward and all new excitations or crossings of thresholds are added to the corresponding counter. To decrement the counter, the passing values are saved and substracted from the sum (counter value) when they leave the window on the other side. Here such a counter is named 'sliding counter'.

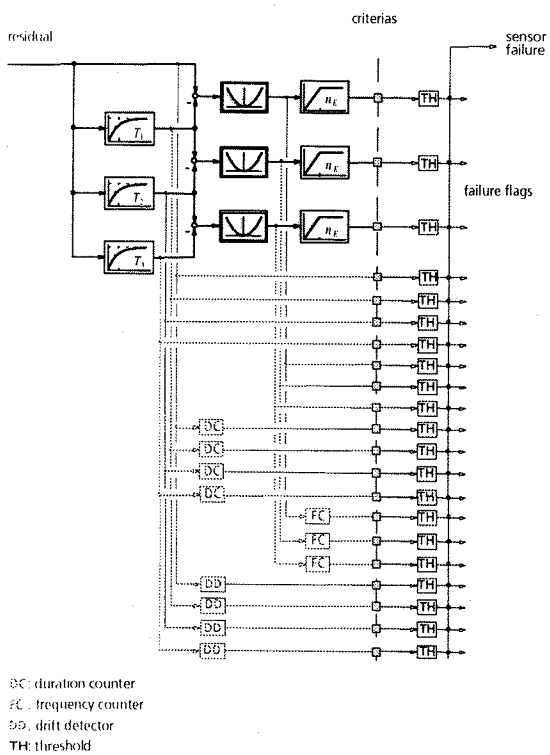


Fig 4: Analysis of the Residual

Decision Making via Threshold Logic

The digital character of the yes/no-decision for the detection of a failure requires a nonlinear threshold logic. The extracted criteria are supervised regarding the exceeding of certain limits. If one limit is exceeded, the corresponding failure flag is set. If criteria stay inside the tolerance area, the failure flags are zero. The overall failure flag, which is evaluated by logical-or-combination of all failure flags, shows if a failure has occurred at all.

Many parameters of the algorithm, like time-constants, thresholds, etc. can be set by the user. Therefore the algorithm is very flexible and can be adapted to very different characteristics of measurement signals or residuals. Also it is possible to locate the cause, if a wrong decision in failure detection has been made, and make corrections by modifying the parameters. Because the failure detection works with simple algorithms, the method is fast enough to run on low speed computers in real-time.

The failure detection is indeed very fast, because its algorithms consist of only a few operations to perform the filter and threshold calculations. On a PC (486/50 MHz) the analysis of a residual of 1000 samples lasted 6 sec (incl. initialization and harddisk operations), which means that the cycle time is less than 6 ms. So the failure detection is fast enough to run in real-time even on computers with less performance.

Examples

In the following passage two examples will be given to show, how the analysis of the residual leads to the detection of a sensor failure. First, the case of a spike in the residual will be demonstrated.

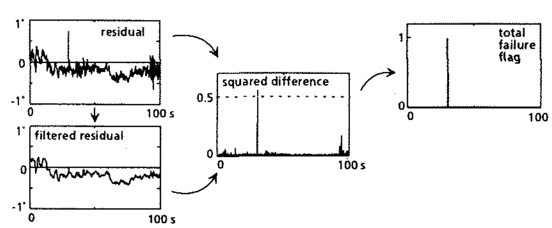


Fig 5: Detection of a Spike

A spike is a short (few samples) and strong deviation from the correct value. Spikes can be produced by a loose connection in the electric part of the measurement system. A characteristic of spike is the sudden appearance and disappearance. This leads to steep flanks in the residual. From the criteria especially the high frequency square-difference is suited. In the case shown (Figure 5) this criterion exceeds its threshold and sets the failure flag for a short moment to 1. The frequency counter counts two crossings, but it is not enough to exceed its own threshold. Other criteria are not involved in this situation.

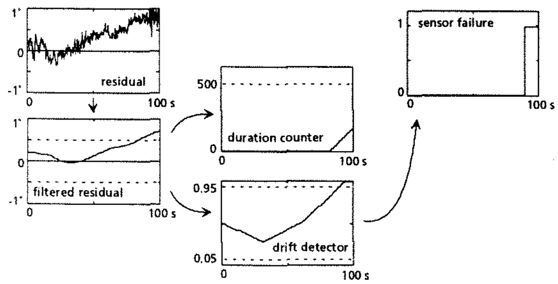


Fig 6: Detection of a Drift

Figure 6 shows a drift of 1°/min which is superimposed on the angle of attack residual. A drift is a slowly increasing, more or less monotone, deviation of the measured signal from the correct value. This can be the consequence of temperature variation or attrition. As one can see in the figure, the drift is recognized by the lowpass filtered residual, which increases monotonously for a certain time and causes the drift counter to exceed its threshold. Because of the slowly arising offset, the lowpass filtered residual exceeds its threshold and causes a incrementation of the corresponding duration counter. But because the time history ends already 20 sec after this event, the duration counter does not reach its own threshold.

The failure flags, which are derived from the criteria, can be used as a preliminary stage for a diagnosis, because they are activated in a characteristic combination depending on the failure. To fulfil a complete diagnosis, the relation between the residuals and their causes has to be found.

Flight Experiments

Presently the method will be applied in flight experiments. By the implementation of the failure detection algorithm in the research aircraft ATTAS the airlog can be observed and, if a failure occurs, the flight can be discontinued. Cancelling the flight in an early stage of the experiment, time and money can be saved.

If measurement data are used to feed flight controllers in a fly-by-wire system, in the case of a sensor failure there is a crucial need to react very fast and to switch off the failed sensor. In such a case it is either possible to turn over the control to the pilot (fail passive) or to replace the missing sensor information by its analytically redundant quantity in order to continue the automatically controlled flight (fail operate). This replacement of a lost sensor signal by an other signal is the reconfiguration of the measurement system.

To fulfill these tasks, the failure detection has to be very reliable in flight. The flight experiments are aimed at the following objectives:

- Implementation of software in on-board computer and real-time operation
- Identification of the effects of model errors and disturbances on the residual by analyzing flight data from flight in turbulent air and extreme flight maneuvers
- Determination of tolerances and thresholds for the failure free residual
- Minimization of false alarm rate
- Validation of failure detection algorithm by initializing artificial sensor failures

For the preparation of the flight experiments the ground simulation facility is a necessary and helpful tool. In the ground simulation the developed software can be tested under almost the same conditions as in the aircraft. With the help of the simulation the motion of the aircraft and the sensor inputs are calculated. In this environment it is also possible to simulate turbulences and sensor failures.

Conclusion

Since the airlog is a good example for a critical sensor, the discussed in-flight monitoring method is applied to the airlog of the research aircraft ATTAS of the DLR. The monitoring is done by analyzing the residual – this is the difference between estimated and measured sensor signal – with respect to sensor failures. For the estimation of the translational motion of the aircraft a nonlinear local Luenberger-observer is used. The analysis of the residual is done through a multi-stage bank of parallel filters, where several criteria are extracted. Further criteria are generated by thresholds. The decision, if a sensor failure is detected or not, is done with the help of a threshold logic.

The main advantages of the presented approach are speed, flexibility and transparency. Speed is a result of simple filter algorithms. This makes an operation of the failure detection possible even in situations with low computation power. The parameters, which can be set by the user, allow an adaptation to different residual properties. So the method is applicable to several sensor types. The way the residual is computed until a decision is made, is easy to comprehend. If false alarms are triggered because of unsuited parameters, the user can identify the reason and make adequate changes.

A disadvantage of the used observer scheme is that only some selected sensors can be monitored, while the others are assumed to be free of failures. If one of these fails, the observer is not able to make accurate estimations. So, the caused deviation in the residual may be interpreted as a failure in a working sensor, and a false alarm will be triggered.

For that reason DLR is working now on a method to monitor all important sensors, which are related by analytical redundancy, at a time. Also it is intended to extend the analysis by a diagnosis of the failure. This will be done by combination of different failure flags.

Literature

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