ROBUST ESTIMATION OF SENSORS AND ACTUATORS FAULTS DURING THE RE-ENTRY OF A REUSABLE LAUNCH VEHICLE

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The capability of a spacecraft to detect in time a fault and to identify or to isolate the failed functionality and component without ground diagnosis is one of the key features enabling automated space missions and/or safety critical space vehicle.

Today's spacecrafts or launchers rely mainly on hardware redundancy (associated to voting mechanisms) and consistency checks to perform autonomous failure detection of sensors. Failure detection of actuators is mainly based on rough detection of abnormal dynamics behaviour. However, a high level of hardware redundancy for the sole purpose of failure detection may be undesirable for cost, volume and mass reasons.

Beyond hardware redundancy, the fault detection may need to look at the plant output relative to a model-based estimate of that output. Such model-based methods raise the issue of modeling errors, that associated with tight detection threshold, may lead to a high false or missed alarm rate. In addition, environment perturbations can mask the effect of a given fault. Hence, the need of robust model-based fault estimation methods.

The controlled re-entry in Earth's atmosphere of a Re-usable Launch Vehicle (RLV) is one of the scenarios in which fast and robust fault detection is more relevant and challenging, as described in the following bullets:

– *Highly uncertain plant*: During re-entry the vehicle undergoes rapid changes in aerodynamic flight properties whose precise knowledge is not available. Also, there are also other major sources of uncertainty in the plant model, specially regarding mass, inertia and COG, critical for accurate control. Moreover, the atmosphere is another pernicious source of un-modelled perturbations.
– *Fast dynamics*: The re-entry flight envelope is very demanding. The total velocity of the vehicles varies from circa Mach 28

to Mach 1.5, whereas typical guidance profiles require for the vehicle to perform fast bank reversals from 70 to –70 degrees in short time intervals (around 30 seconds).

– *Coupled time varying plant*: The plant is controlled through the vehicle's attitude, inherently as a varying MIMO plant. The two main sources of coupling are the inertial and the aerodynamic coupling, which vary in relative importance during the re-entry.
– *Non-linear plant*: The angular motion of the re-entry vehicle constitutes a non-linear plant, in which the aerodynamic torques play an important role. They vary during the re-entry phase, yielding in practice a set of different non-linear plants.

This paper presents the application to the 6 DoF RLV re-entry problem of two well known model based robust estimation techniques: Stoustrup-Niemann [1] and Mangoubi [2]; It shall be noted that the implementation in the study of these two techniques did not reach a sufficient maturity level to yield conclusive detection results, only preliminary. Subsequent design iterations shall be carried-out.

On the other hand, the work performed has been highly beneficial for the identification of critical design issues and the derivation of lessons learnt to be taken into account in future design loops. These critical points and lessons learnt are explicitly addressed in the last chapter of the paper.

The filters have been designed and tuned using a RLV re-entry FDI test-bench. This test-bench includes detailed models of the environment (atmosphere and gravity) and the vehicle dynamics and kinematics, and the complete GNC loop making use of a state-of-the art Non-liner Dynamic Inversion (NDI) controller. It is used to perform a thorough performance assessment and benchmarking of the synthesized fault estimation filters.

1. Scenario Characterisation

1.1. RLV Re-entry Scenario

The study is based on a RLV Earth re-entry scenario. The RLV is based on the geometrical and dynamical features of a HL-20/X-38 vehicle class, comprising two-flaps and two rudders, independently driven by four Electro-Mechanical Actuators (EMA)

The RLV carries the following set of sensors and actuators:

– Inertial Measurement Unit (IMU)
– Flush Air Data Sensing System (FADS)
– Reaction Control System (RCS)
– Aerodynamic Control Surfaces (EMAs)

The RLV re-entry can be divided into five phases according to the availability of the on-board sensors and actuators. A re-entry reference trajectory (see Figure 1) was generated using a guidance algorithm (STS+) based on available reference profiles in terms of angle of attach vs. energy and drag acceleration vs. energy.

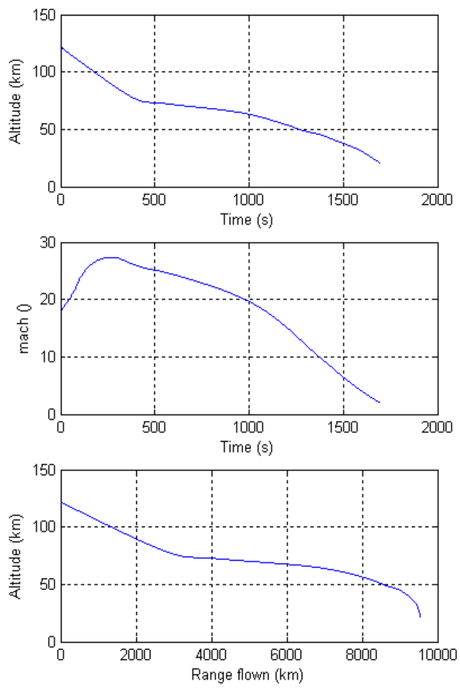

Fig.1 RLV re-entry trajectory

1.2. Faults definition

The following two fault modes have been considered:

– *One sensor fault* on the upper part of the trajectory where navigation plays a lead role in the sense that an early detection of a sensor degradation is crucial to enable a successful recovery decision. Specifically this will correspond to an IMU fault in Phase I of the re-entry affecting the misalignment of the gyroscope angular velocity components.

– *One actuator fault* on the lower part of the trajectory where bank reversal manoeuvres are more frequent and demanding. Specifically this will correspond to an flap aerodynamic surface EMA failure due to reduced dynamical response in phase V-a of the re-entry.

1.3. Attitude controller

To complete the system it is necessary to close the loop with a suitable controller. The implemented controller is based on the Nonlinear Dynamic Inversion (NDI) technique [3], suitable for all the re-entry phases.

Figure 2 shows the performance of the NDI controller in the lower part of the atmosphere in the presence of uncertainties.

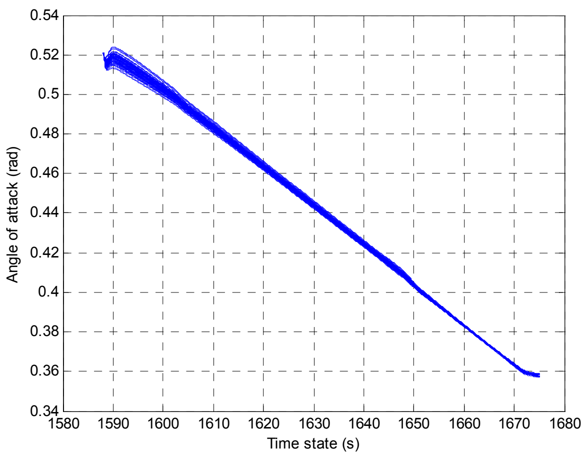

Fig. 2 Monte Carlo run (500 simulations) of controlled angle of attack (left), under parametric uncertainties

2. FDI problem formulation

2.1. FDI problem formulation

The FDI problem considered in the study is shown in Figure 3. The plant inputs (u) are the moments commanded by the control system to the RCS and the deflections commanded to the vehicle aero-surfaces. The output (y) is composed by the measured spacecraft angular velocity, spacecraft acceleration and the measured angle of attack (AoA) and sideslip.

The output of the FDI shall be the estimation of the faults (f) entering the plant and a fault detection signal (f_d). The plant disturbances (d) are applicable noises on each of the spacecraft subsystems plus the environment perturbations.

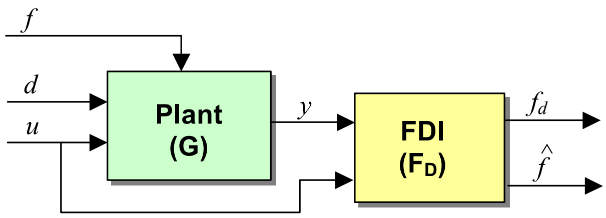

Fig. 3 FDI problem layout and components

2.2. System modelling

The re-entry scenario under study accounts both rotational and translational dynamics, being the vehicle controlled in attitude over a reference trajectory.

The equations of motion are formulated under the assumptions that the aero-elasticity of the RLV vehicle is neglected; the translational and rotational motion are coupled and that the RCS actuation system produces pure moments without translational forces.

The aerodynamics of the re-entry vehicle is formulated on the basis of two major aspects: the aerodynamic database and the aerodynamic forces and moments. The former, namely the aerodynamic coefficients, are needed to undertake the calculation of the later.

The IMU is modelled considering biases, noises, scale factors and misalignments, while a performance model of the FADS including noise was used.

The RCS were modelled with a performance model in body axes, whereas the EMAs model account for a number of linear and non-linear effects, including delay, quantisation, second-order dynamics, rate limits, saturation and scale factors.

2.3. FDI plant

The original non-linear plant was linearised around selected relevant points in the reentry trajectory. This linearization has to take into account several issues, such as a simplification of the complete equations, linearization of the aerodynamic coefficients and avoidance of singular points (e.g. a change in the layers of the atmosphere model).

The resulting plant has 20 states, with 7 inputs (commands to RCS and EMAs) and 8 outputs (measured velocities and accelerations, plus AoA and sideslip)

The plant resulted observable, strictly speaking, but in practice, for the two scenarios, the ratio between the maximum and minimum singular values was very high. This was caused by ill-conditioning at both linearization points.

The validity of the plant was analyzed through residual analysis (residual, autocorrelation and cross-correlation plots) putting in evidence some non-modelled dynamics to be introduced in the FDI problem as dynamical uncertainties.

2.4. Uncertainties

Model uncertainty comes from different sources and requires different representations. We have identified two types of uncertainty in the plant model at hand: parametric and dynamic uncertainties.

Parametric uncertainties are associated to model parameters. In Table 1 we present a list of the parametric uncertainties considered in this study, including the subsystems they belong to.

There are two main sources of dynamics uncertainties in the plant model:

- Un-modelled dynamics and linearization uncertainty in the aerodynamic database. It has been represented as output dynamic uncertainty by a diagonal weighting matrix.
- Linearization uncertainty in several subsystems of the plant. This source of uncertainty has been represented as lumped uncertainty. The outcome is a rational transfer function weight matrix corresponding to a multiplicative uncertainty representation. Figure 4 show the frequency response of uncertainty for several points away from the linearization point.

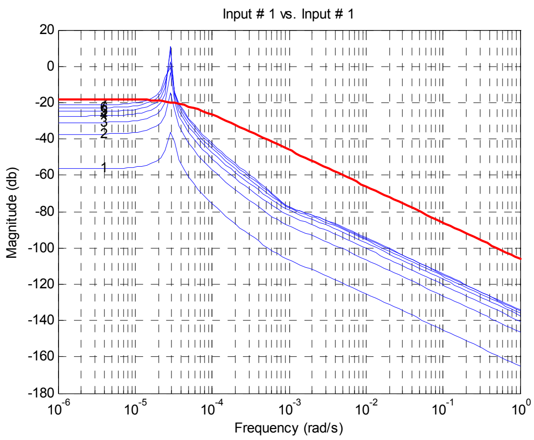

Fig. 4 Linearization uncertainty of the rotational dynamics during phase I

Table 1 Parametric uncertainties.

Subsystem	Parameter
Rotational dynamics	Moments of inertia Products of inertia
Translational dynamics	Mass
Gyroscopes	Scale factors Misalignments
EMA	Scale factor Dynamics parameters
FADS	Gas constant for air Adiabatic constant

4.Stoustrup-Niemann robust FDI method

The first robust FDI technique considered is the one developed by Stoustrup-Niemann. Through this method [1], the fault estimation problem can be formulated as a standard problem approach based on the standard formulation developed for robust control. This approach has been employed for a wide-set of problems and is valid for FDI design in systems with model (dynamic or unstructured) uncertainty, systems with parametric uncertainty and parametric faults and a class of non-linear systems. Important is to note that it is specially well suited for treating parametric and additive failures in a combined set-up.

4.1. Results for the sensor case

After a structural analysis of the plant [4] it was found that a part of measurement system could be de-coupled from the rest of the system, yielding a much more manageable reduced order model.

The implemented filter was only capable of detecting the fault in the first component of the angular rates (*p,q,r*), as the magnitude of the other faults were below noise level.

Figure 5 shows the fault estimate on *p* for several runs in the presence of uncertainties without the controller. The filter responses in all cases.

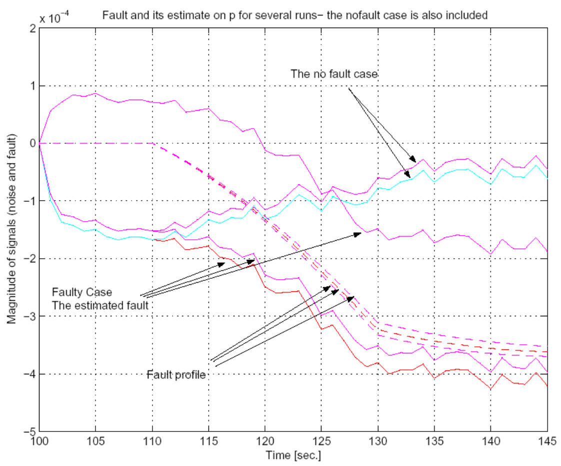

Fig. 5 Results of Stoustrup-Niemann method for fault on angular rate *p* without controller

It is relevant to note that the inclusion of the controller damps the fault and affects its detectability. Figure 6 shows the results for f_p with the inclusion of the NDI controller.

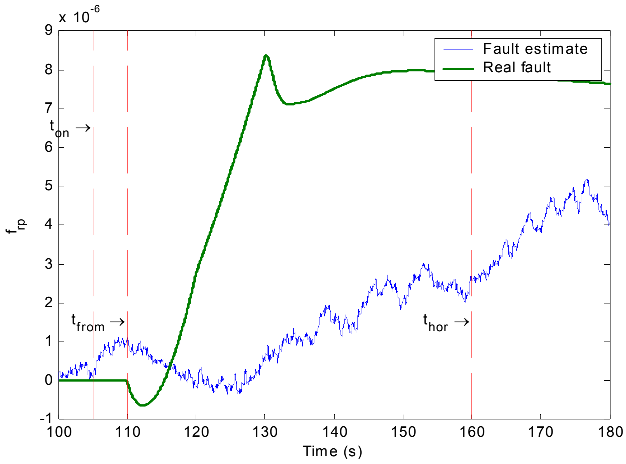

Fig. 6 Results of Stoustrup-Niemann method for fault on angular rate *p* misalignment with NDI controller

4.2. Results for the actuator case

Due to plant high ill-conditioning, a reduced order model with 8 states was obtained without loosing the dynamic properties of the plant. The fault is separated in three components. Figure 7 shows the results for the second component. Only partial results were obtained in open-loop. Moreover, results show that the filter requires a large time to detect the fault and that there is a bias in the estimated signal. Further tuning was identified as required.

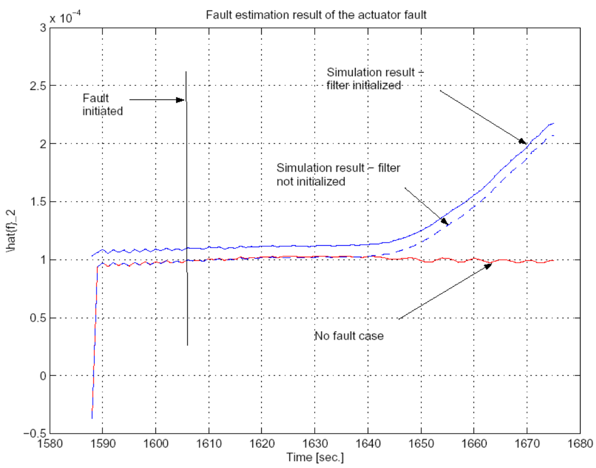

Fig. 7 Fault impact on the second fault component for the actuator fault scenario

5. Mangoubi robust FDI method

The second robust fault estimation method considered is the one developed by R.S. Mangoubi [2]. This method is robust to failure mode as well as noise and plant model uncertainties. It is based on min-max detection and isolation functions and makes use of a robust H-inf filter. The Mangoubi method has been originally derived for additive faults.

5.1. Results for the sensor case

As in the previous method, a reduced order model comprising the measurement system can be found, facilitating the design. Figure 8 show the results, without uncertainties, for the lumped fault f_Δ (encompassing a linear combination of f_p and f_q signals), in the presence of uncertainties. The estimation signal does not correspond directly with the fault but since it is quite different from the signal in the nominal case, it might be used for detection purposes.

The steady state error of the fault estimate in the uncertain system make it difficult to use the estimate directly for a fault detection, whereas in the nominal case, the fault estimate can be applied directly by selecting a suitable threshold.

5.2. Results of the actuator case

Since the Mangoubi method can only deal with additive faults, the parametric fault on the EMA needs to be converted first to an additive fault. Also a reduced order model with 9 states was obtained without loosing the dynamic properties of the plant.

Figure 9 shows the simulation results of the nominal fault estimator. It can be seen that it is possible to see a difference between the fault-free case and the faulty system, although very slowly. This divergence can be used to design a detection function. The spike at the beginning can be reduced by proper tuning the initial state vector.

7. Critical issues and lessons learnt

As anticipated in the introduction, the results obtained are preliminary and are not conclusive due to a set of critical issues. The identification of these critical issues plus the analysis of the shortcomings present in the approach followed, lead to the identification of a set of lessons learnt.

These lessons learnt have been classified into different groups based on the different stages of the FDI design process.

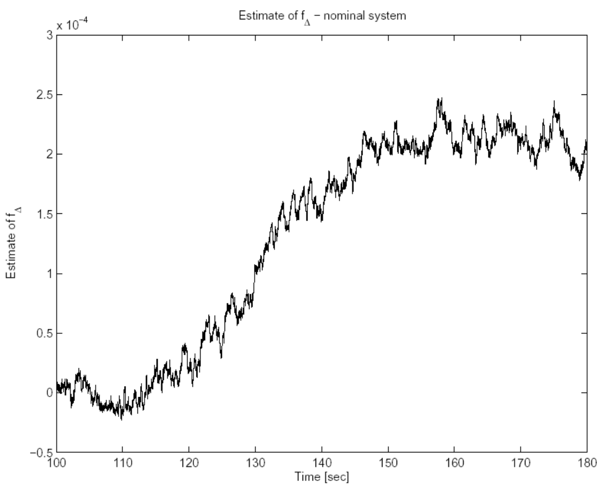

Fig. 8 Results with uncertain system in faulty case for f_Δ (a linear combination of f_p and f_q signals)

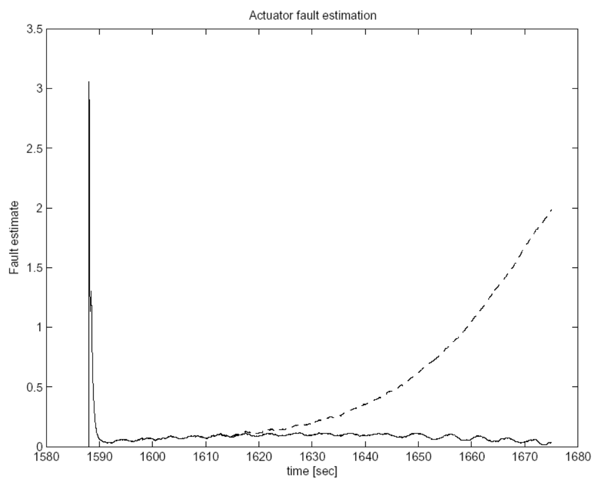

Fig. 9 Simulation of the actuator case for the nominal system. Solid line: fault free system; dashed line: with fault.

7.1 Requirements analysis

- The plant definition and fault selection will affect decisively the representativity and usefulness of the results. Enough effort must be put on their definition.
- The fault selection and FDI requirements must be refined and iterated as more insight is got during the whole process.

7.2 FDI problem assessment

- The definition of the faults shall not be decoupled from the plant dynamics, specially under closed loop control.
- It is very important to count with faults that are relevant, detectable and that allow for the system to take recovery action after their detection.

7.3 FDI plant modelling

- A structural analysis of the plant at early stages can provide much information for subsequent modelling and designing tasks. The higher the order of the plant is, the higher the order of the synthesised failure detection filter. Working with high order filters has many disadvantages or could even result unfeasible in practice
- The FDI plant modelling process shall be conducted on an iterative basis until the final reduced order LTI plant and the associated uncertainty representation have been validated and deemed suitable for FDI design.
- A correct formulation of the system uncertainty is crucial for robust FDI. If system uncertainty is underestimated, the robust performance of the filter will be compromised. On the other hand, if uncertainty is too large, it will mask failure effects.

7.4 FDI filter design

- The FDI design must be iterative but also incremental as for the FDI plant considered, beginning with simple models that allow the designed to get confident with plant behaviour and fault effects so that design problems can be promptly spotted.
- It should be taken into account that the inclusion of a controller changes the dynamics of the closed-loop system and therefore might affect the detectability of the faults.
- It is important to get as simple models description of the systems as possible without loosing relevant dynamics, because it will reduce the complexity of the residual generators/filters very much.
- Another issue is the complexity of the system vs. the complexity of the applied filter design method. Using very complex design methods, there will in general be an upper bound on the order of the system that can be handled in a proper and suitable way by the design algorithm

8. Acknowledgements

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