An Algorithm for Instrument Fault Detection in Inertial Sensors of a Satellite Launcher Vehicle Control System

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Abstract. This work intends to show an algorithm for instrument fault detection in inertial sensors of a satellite launcher vehicle (SLV) control system. The study is based mainly in the aspect of fault diagnosis and in the results obtained for this type of control system. In case of unstable systems, such as satellite launcher vehicles and high performance aircrafts, the failure of a sensor can be catastrophic if the control system has no degree of redundancy, physical or analytical. Due to this characteristic, it is very important for these vehicles to have a redundant flight control system with the ability to diagnose faults in sensors as quickly as possible, to reconfigure the use of the remaining sensors or even the control law. Although many systems achieve fault tolerance by using hardware redundancy, there are several problems associated with this approach such as: cost, space, weight and complexity of the control system. Besides, it has been observed that redundant sensors tend to have similar life expectancies, so it is likely that when one sensor fails the other sensors of the redundant ensemble will fail soon. There are even situations in which it is not possible to use hardware redundancy; so, in this case, it is better to use the analytical redundancy approach to design control systems tolerant to failures in inertial systems. The Instrument Fault Detection (IFD) scheme of this work uses the approach of analytical redundancy of Patton (1989) for the longitudinal motion control system of a satellite launcher vehicle, Oliva (1998), in order to present others cases and simulation results.

Keywords. *Sensor Diagnosis, Fault Detection, Analytical Redundancy.*

1. Introduction

In case of unstable systems, such as satellite launcher vehicles and high performance aircrafts, the failure of a sensor can be catastrophic if the control system has no degree of redundancy, physical or analytical. Due to this characteristic, it is very important for these vehicles to have a redundant control system with the ability to diagnose faults in sensors as quickly as possible, to reconfigure the use of the remaining sensors or even the control law. In fault tolerant systems there are several problems associated to the hardware redundancy, such as: cost, space, weight and the physical complexity of the control system. Besides, it has been observed that identical redundant sensors tend to have similar life expectancy, so, it is likely that the event that cause one sensor to fail will probably cause faults in others redundant sensors. There are even situations where it is not possible to use hardware redundancy, so in this case it is necessary to use the approach of analytical redundancy.

2. Basic Concepts

2.1. Fault

Fault can be defined as a malfunction of any component of a system, causing since a loss of performance up to a total stop of its functions. According to Patton (1989), the faults can be divided in:

- **Sudden Fault:** fault that suddenly occurs and persists in a component.
- **Incipient Fault:** fault that develops slowly at a component.

The early detection of an incipient fault can help to avoid a total fault of the plant or even catastrophes, which could result in loss of significant amount of material or serious personal injury.
So, it is desired to have a **fault tolerant system**, that is, a system that can continue to do its task, even when there are hardware faults or software errors. But the implementation of such system is not easy to do.

According to the generally accepted terminology (Gertler, 1988), the fault detection and diagnostic consist of the following tasks:

- **Fault Detection**: detection that something is wrong in the system. Special emphasis is laid upon incipient, or developing, faults rather than step faults because incipient faults are harder to detect.
- **Fault Isolation**: determination of the fault origin.
- **Fault Identification**: determination of the size of the fault.

2.2. Model-Based Structure

If uncertainties about the model or unmeasured inputs to the process are structured, i.e., it is known how they enter at the system dynamics; this information can be incorporated into the model. In the linear case, if model uncertainties are supposed structured, according to Frisk (1996), the model can be represented by:

$$\begin{aligned}\dot{\mathbf{x}}(t) &= \mathbf{A}\,\mathbf{x}(t) + \mathbf{B}[\mathbf{u}(t) + \mathbf{f}_a(t)] + \mathbf{H}\,\mathbf{f}_\mathbf{c}(t) + \mathbf{E}\,\mathbf{d}(t)\\ \mathbf{y}(t) &= \mathbf{f}_\mathbf{sm}[\mathbf{C}\,\mathbf{x}(t) + \mathbf{D}\,\mathbf{u}(t)] + \mathbf{f}_\mathbf{sa}(t)\end{aligned} \tag{1}$$

Where $f_a(t)$ denotes actuator faults, $f_c(t)$ is the component faults, $f_{sa}(t)$ is the additive measurement sensor faults, $f_{sm}(t)$ is the multiplicative measurement sensors faults, d(t) is the disturbances acting upon the system, H is the distribution matrix for components faults and E is the distribution matrix for disturbances acting upon the system.

This work is based on fault identification and how to get this type of information from a control system. It will show a model with inclusion of an instrument fault detection (IFD) using an approach of analytical redundancy in a flight longitudinal control system of a satellite launcher vehicle. To do it, it was adopted the work developed by Oliva (1998), to design a simulation system to evaluate the results in the case of simple fault at one sensor.

2.3. Mathematical Model

The mathematical model used to be studied is the longitudinal motion of a satellite launcher vehicle (SLV), shown in Oliva (1998). In order to facilitate the description of the equations, the terms that indicate function of t will be omitted; and bold letters will identify the matrices and vectors.

According to McLean (1990), the matrix **A,** the vector **B**, the state vector of the longitudinal motion **x** and the control vector **u** from Eq. (1), are represented by:

$$\begin{aligned}\mathbf{A} &= \begin{bmatrix} Z_w & Z_q + U_0 & -g \\ M_w & M_q & 0 \\ 0 & 1 & 0 \end{bmatrix}\\ \mathbf{B}^T &= [Z_{\beta z} \quad M_{\beta z} \quad 0]\\ \mathbf{x}^T &= [w \quad q \quad \theta]\\ \mathbf{u} &= \beta_Z\end{aligned} \tag{2}$$

Where Z_w, Z_q, M_w, M_q, $Z_{\beta z}$ and $M_{\beta z}$ denotes the aerodynamic derivatives of the satellite launcher vehicle, obtained from wind tunnel tests, U_0 is the linear velocity of the vehicle, g is the local gravity acceleration, w is the linear velocity along the z-body axis called normal velocity, q is the angular velocity of pitch, i.e., the angular velocity around the y-body axis, θ is the pitch attitude and β_Z is the pitch control deflection.

The parameters values used in **A** and **B** are showed in Tab. (1).

Table 1 – Parameters used for the vehicle dynamics model.

Parameter	Value
Z_w [s^{-2}]	-0,0968
Z_q [s^{-2}]	0,1631
M_w [$m^{-1}s^{-1}$]	0,0096
M_q [s^{-1}]	0,0568
$Z_{\beta z}$ [m s^{-2}]	19,3761
$M_{\beta z}$ [s^{-2}]	7,2769
U_0 [m s^{-1}]	544,46
g [m s^{-2}]	9,7886

2.3.1. Longitudinal Control System

The control system was designed with the purpose that the model follows the reference sign θ_{ref} (reference pitch attitude) and settle the remaining state variables. Therefore, the control system will require three sensors to operate adequately, that is, sensors for w (normal velocity), q (pitch angular velocity) and θ (pitch attitude).

The following model represents the longitudinal control system designed:

$$\begin{bmatrix} \dot{w} \\ \dot{q} \\ \dot{\theta} \\ \dot{e}_\theta \end{bmatrix} = \begin{bmatrix} Z_w & Z_q + U_0 & -g & 0 \\ M_w & M_q & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & -1 & 0 \end{bmatrix} * \begin{bmatrix} w \\ q \\ \theta \\ e_\theta \end{bmatrix} + \begin{bmatrix} Z_{\beta z} \\ M_{\beta z} \\ 0 \\ 0 \end{bmatrix} * \beta_z + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} * \theta_{ref} \qquad (3)$$

$$\mathbf{y} = \mathbf{C}\,\mathbf{x} + \mathbf{D}\,\mathbf{u}$$

with **C** = **I** and **D** = **0**.

The state variable "e_θ" is the pitch attitude error integral and it was included to keep the steady state error near zero. The control system was designed by the LQR method as described in Rinaski (1982). The control law, the new state vector and the vector with the feedback gains are given below and the gains for this control law are given on Tab. (2).

$$\beta_z = -\mathbf{G}_1\,\mathbf{x} - G_0\,\theta_{ref} \qquad (4)$$

$$\mathbf{x}^T = [w \quad q \quad \theta \quad \text{and}_\theta] \qquad (5)$$

$$\mathbf{G_1} = [G_w \quad G_q \quad G_\theta \quad G_{e\theta}] \qquad (6)$$

Table 2 – Control law gains

Gain	Value
G_w [m^{-1}]	0,0013
G_q [s]	1,4551
G_θ [rad]	3,2581
$G_{e\theta}$ [rad]	-3,1623
G_0 [rad]	-3,2570

2.4. DOS Structure Observers

To design an analytical redundancy, it is necessary to include observers into the control law, to implement an alternative control law, that is, an observer based control law.

The method used to design the observers can be found in Chen (1984). The observer dynamics and the estimated state are given, respectively, by:

$$\dot{\hat{\mathbf{x}}} = \mathbf{F}\,\hat{\mathbf{x}} + \mathbf{G}\,\mathbf{y} + \mathbf{H}\beta_z \qquad (7)$$

$$\hat{\mathbf{y}} = \mathbf{N}\,\hat{\mathbf{x}} + \mathbf{M}\,\mathbf{y} + \mathbf{L}\,\beta_Z \qquad (8)$$

Where $\hat{\mathbf{x}}$ denotes a 2x1 vector of the state variables of the observer based on the sensor measures, **y** is a vector with the sensor measures, **F** is a 2x2 matrix that define the observer dynamics, obtained from the design of a robust observer, according to Doyle and Stein (1989), **G** is a 2x1 vector that define the contribution of the measures supplied by the sensor, obtained to get {**F**, **G**} controllable, **H** is a 2x1 vector that define the contribution of the control signal that is applied to the plant, obtained through the relation **H** = **T B**, where the matrix **T** is obtained through the Lyapunov equation **TA** – **FT** = **GC,** $\hat{\mathbf{y}}$ is the 2x1 vector of the estimated state based on sensor measures, **M** is the 2x1 vector that weight the contribution of the sensor measures, **N** is the 2x2 matrix that weight the contribution of the observer state variable and **L** is the 2x1 vector that weight the contribution of the input signal. In this case, **L = 0**.

According to this method, the composed matrix [**M N**] is obtained from: [**M N**] = $\mathbf{P}^{-1}$, where $\mathbf{P}^T$ = [**C T**]. For the model represented by Eq. (1), it is necessary to get one observer and one estimator for each state shown at Eq. (2). By this way, it is added the following indices to identify the measures used by each observer dynamic and by each state estimated:

- w – measures supplied by the normal velocity sensor;
- q – measures supplied by the pitch sensor angular velocity;
- θ – measures supplied by the pitch attitude sensor, and

m/s – estimated state for the sensor “m” obtained from the measures of the sensor “s”, considering that “m ≠ s”.

From Eq. (8) it is possible to get three vectors of the estimated state, of reduced order, designed for the system, where the observer/estimator “s” has the measure supplied by the sensor “s” and the actuation command “β_z” as inputs and the estimated state vector for the remain sensors as outputs, represented by:

$$\hat{\mathbf{y}}_s = [\hat{y}_{m/s}] \tag{9}$$

The parameters values used in this case study, according to Oliva (1998), are shown at Tab. (3).

Table 3 - Parameters values for matrices and vectors of the observers/estimators models.

Matrix/ Vector	Normal Velocity Parameters	Matrix/ Vector	Pitch Angle Velocity Parameters	Matrix/ Vector	Pitch Attitude Parameters
F_w	-20.0000 0.00000 0.00000 -0.12240	F_q	-20.0000 0.00000 0.00000 -0.12240	F_q	-20.0000 0.00000 0.00000 -0.12240
G_w	1 1	G_q	1 1	G_q	1 1
H_w	-9.08226 7.58401e2	H_q	3.67157e-1 -1.37869e-5	H_q	-1.83578e-2 1.12638e-4
M_w	1.69922e-1 7.39270	M_q	2.08708e3 -2.60643e1	M_q	5.97643e2 2.00824e1
N_w	-3.35822 -3.49628e-2 -1.46352e2 -1.94151	N_q	-4.13121e4 -3.84312e0 5.16582e2 7.85226e0	N_q	-1.05594e3 -7.64903e1 -3.96390e2 -3.68747e-2

2.5. Decision Functions

The decision functions will allow us to detect the faulty sensor, helping in deciding how to reconfigure the control law. To design the decision functions it was adopted the method shown at Chapter 2 of Patton (1989) for a DOS structure. For this structure, the residue is considered as been the module of the difference between the measures supplied by the sensors and the respective estimated values. The decision function, adopted in Oliva (1998), is the product of two residues, as showed by Eqs. (10), (11) and (12):

$$\left.\begin{array}{l} f_{\hat{q}/w} = |q - \hat{y}_{q/w}| \\ f_{\hat{\theta}/w} = |\theta - \hat{y}_{\theta/w}| \end{array}\right\} \quad \eta_w = f_{\hat{q}/w} . f_{\hat{\theta}/w} \tag{10}$$

$$\left.\begin{array}{l} f_{\hat{w}/q} = |w - \hat{y}_{w/q}| \\ f_{\hat{\theta}/q} = |\theta - \hat{y}_{\theta/q}| \end{array}\right\} \quad \eta_q = f_{\hat{w}/q} . f_{\hat{\theta}/q} \tag{11}$$

$$\left.\begin{array}{l} f_{\hat{w}/\theta} = |w - \hat{y}_{w/\theta}| \\ f_{\hat{q}/\theta} = |q - \hat{y}_{q/\theta}| \end{array}\right\} \quad \eta_\theta = f_{\hat{w}/\theta} . f_{\hat{q}/\theta} \tag{12}$$

The values supplied by the decision functions η_w, η_q and η_θ can be used in the decision logic to detect which sensor has failed. According to the cases analyzed by Oliva (1998) for step input, the following thresholds were used in order to detect the fault:

- Fault at the sensor w: $\eta_w > 150$
- Fault at the sensor q: $\eta_q > 2$
- Fault at the sensor θ: $\eta_\theta > 0.5$

We use these thresholds in another case study, where the system has to follow a random reference signal with uniform distribution between -0,25rad and 0,25rad with sample time of 2,5s. This sample time value was chosen to be smaller than the plant stabilization time for a step input. By this way, we can guarantee that the plant state variables will always be varying and we can evaluate the performance of the system for fault detection, false alarm and alarm loss. We limited the simulation time in 50s, and use the integration method “ODE5 – Dormand-Prince” from MATLAB, with constant integration step of 10ms. To compare the results between the simulations, the seed of the random signal generator for input signal was kept constant.

In Fig. (1) we can see the response of the system and the respective decision function to the case where the fault occurs during the time interval of 4s up to 34s of the simulation. The fault type is the maximum value at pitch angle sensor, that is, the pitch angle sensor begins to supply a constant value of 0,349rad (20^o), considered the maximum value that the sensor could supply. The system IFD proposed has a very good performance to detect the fault, but it has a very high alarm loss rate.

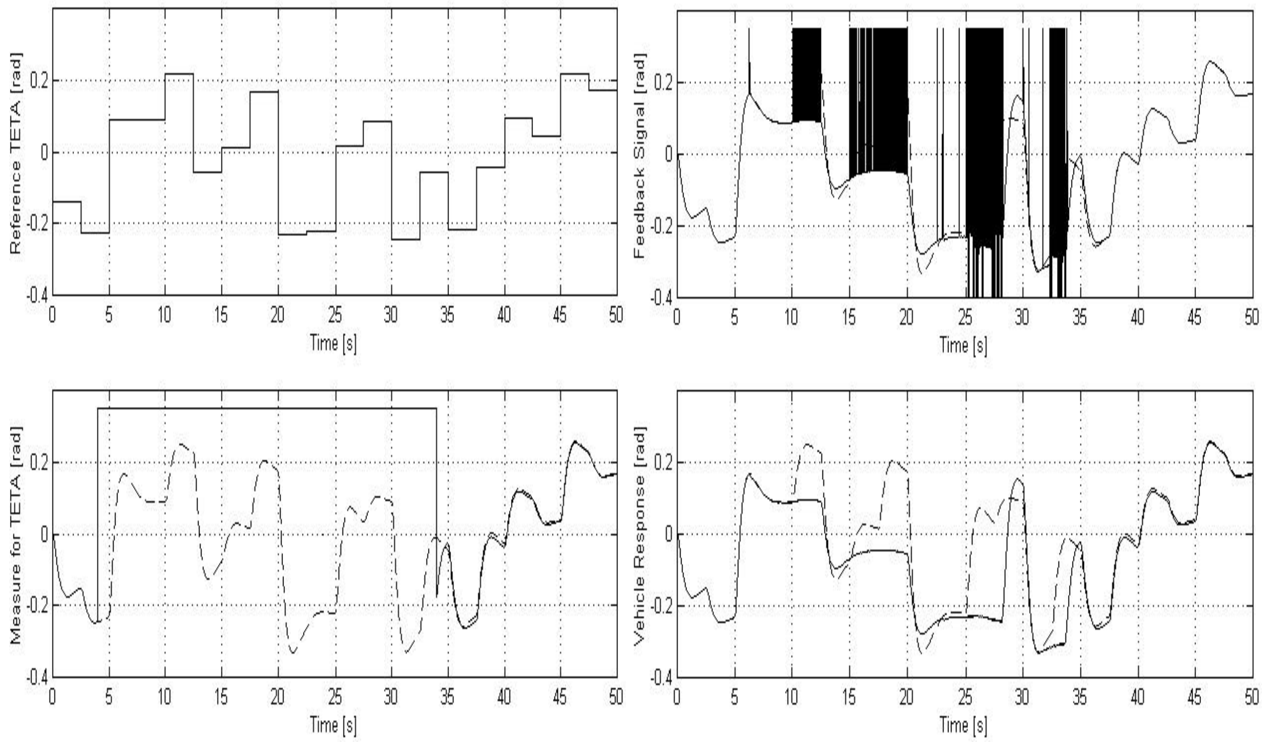

Figure 1 – System response for fault of type maximum value at pitch angle sensor.

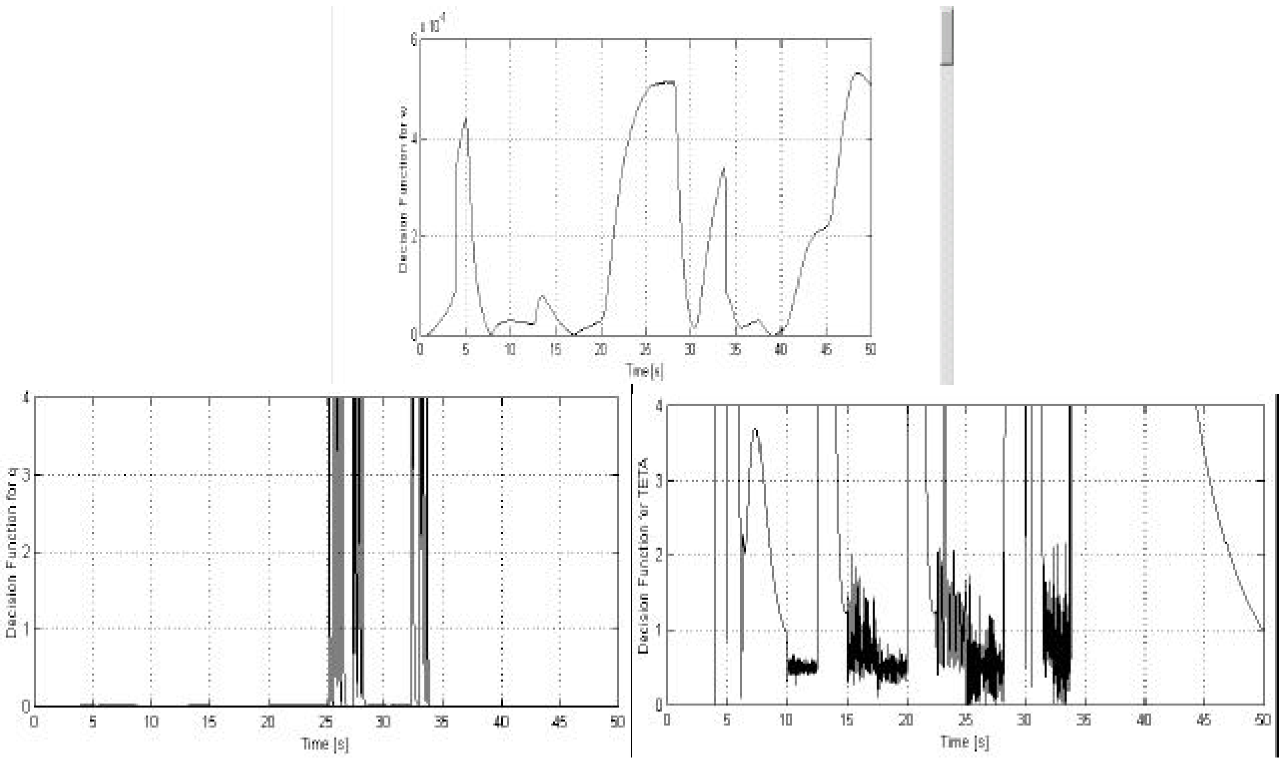

Figure 1b - Decision Function for fault of type maximum value at pitch angle sensor.

The transitions shown on attitude feedback signal graph are due the alarm loss, i.e., the system considers that the sensor measure is correct when in fact it is wrong. From the vehicle attitude graph we can evaluate and compare the vehicle attitude with the case when there is no fault (dotted line).

To get a better performance Oliva (1998) suggested adding a threshold for the derivative of the decision function to be tested. Here we used an approach slightly different: we added the differences between the derivatives of the measures and its respective estimated values to reduce the alarm loss rate of the decision function. By this way, adding the differences between the first and second derivatives of the measures and their respective estimated values, the decision functions become:

$$\eta_w = \left|q - \hat{y}_{q/w}\right| \left|\theta - \hat{y}_{\theta/w}\right| + \left|\dot{q} - \dot{\hat{y}}_{q/w}\right| \left|\dot{\theta} - \dot{\hat{y}}_{\theta/w}\right| + \left|\ddot{q} - \ddot{\hat{y}}_{q/w}\right| \left|\ddot{\theta} - \ddot{\hat{y}}_{\theta/w}\right| \quad (13)$$

$$\eta_q = \left|w - \hat{y}_{w/q}\right| \left|\theta - \hat{y}_{\theta/q}\right| + \left|\dot{w} - \dot{\hat{y}}_{w/q}\right| \left|\dot{\theta} - \dot{\hat{y}}_{\theta/q}\right| + \left|\ddot{w} - \ddot{\hat{y}}_{w/q}\right| \left|\ddot{\theta} - \ddot{\hat{y}}_{\theta/q}\right| \quad (14)$$

$$\eta_\theta = \left|w - \hat{y}_{w/\theta}\right| \left|q - \hat{y}_{q/\theta}\right| + \left|\dot{w} - \dot{\hat{y}}_{w/\theta}\right| \left|\dot{q} - \dot{\hat{y}}_{q/\theta}\right| + \left|\ddot{w} - \ddot{\hat{y}}_{w/\theta}\right| \left|\ddot{q} - \ddot{\hat{y}}_{q/\theta}\right| \quad (15)$$

As the frequency bandwidth increases when we use the derivative differences and due to the fact that the system is subject to a sudden fault, we used a low pass filter in order to smooth the signal. In this case, considering the bandwidth of each sensor signal we included a 5 rad/s cutoff frequency low pass filter. So, we reduced the alarm loss rate in several conditions and kept approximately the same performance to detect the fault.

2.6. Decision Logic

Based on the nonlinear functions given by Eqs. (10), (11) and (12), it is possible design a decision logic. If, for instance, the pitch attitude sensor fails, the functions $f_{\hat{w}/\theta}$ and $f_{\hat{q}/\theta}$ will increase fast, so η_θ will increase much faster. This fact allows us to diagnose that the pitch attitude sensor has failed.

This consideration can also be applied on Eqs. (13), (14) and (15). Therefore, it is necessary to find an appropriate threshold value to define a fault condition, but we must consider that this value has also to prevent false alarm or alarm loss. The boundary value for the decision function is not easy to get because: it involves the entire vehicle flight conditions, which is very wide; the vehicle dynamic parameters are inaccurate and vary with time; the vehicle is subjected to unknown external disturbances; and can realize several kinds of maneuvers. We analyzed the following cases for a fault in one single sensor during the time range from 4s up to 15s: maximum value fault, zero value fault and last value fault. In Tab. (4) we can evaluate the boundary values of the decision functions, when we use and don't use the derivative differences to avoid the false alarm and the alarm loss.

Table 4 – Boundary values got for decision functions with use of derivatives.

Derivative	Sensor	Noise Levels without Fault	Noise Level Due to Sensor Fault			Boundary Values for the Decision Function
			w	q	θ	
No	w	0,0019	*3,1*	**0,50**	0,0045	0,50 a 3,1
	q	0,000057	0,20	*1,8*	**0,42**	0,42 a 1,8
	θ	0,00000023	0,0074	**0,014**	*0,00018*	- x -
1st Order	w	0,0019	*2.500*	**0,56**	0,20	0,56 a 2500
	q	0,00024	**0,48**	*22*	0,074	0,48 a 22
	θ	0,00000031	**0,018**	0,016	*0,0064*	- x -
1st Order and 2nd Order	w	0,0025	*9300*	1,3	**5,1**	5,1 a 9300
	q	0,0011	**2,5**	*22*	0,52	2,5 a 22
	θ	0,00000073	**0,093**	0,035	*0,097*	0,093 a 0,097

Note: - the bold values correspond to minimum value for the decision functions to indicate that the sensor is good. Thresholds below this value will cause the system to generate false alarm; and
- italic values correspond to maximum values for the decision functions. Thresholds greater than this value will cause the system to generate alarm loss.

At Tab. (4) it is easy to see that only by adding the second derivative in the decision function we can meet the condition that the upper limit will be greater than the lower limit for all sensors. To define the threshold to detect a fault it was assumed approximately the average value of the range for each sensor. Therefore, the following thresholds were adopted to detect the faults:

- Fault of the sensor w: $h_w > 4650$
- Fault of the sensor q: $h_q > 12$
- Fault of the sensor θ: $h_q > 0.095$

2.7. Control Laws

When the system is operating at normal mode, i.e., without fault, it will use the designed control law, given below:

$$\beta_z = -G_w * w \ - \ G_q * q \ - \ G_\theta * \theta \ - \ G_{e\theta} * \text{and}_\theta \ - \ G_0 * \theta_{ref} \tag{16}$$

After a fault in one of the sensors: w, q or θ, this control law shall be changed, respectively, to one of the following alternatives control laws, in accordance to the sensor that failed:

$$\beta_{zw} = -G_w * \hat{w}/\theta \ - \ G_q * q \ - \ G_\theta * \theta \ - \ G_{e\theta} * \text{and}_\theta \ - \ G_0 * \theta_{ref} \tag{17}$$

$$\beta_{zq} = -G_w * w \ - \ G_q * \hat{q}/\theta \ - \ G_\theta * \theta \ - \ G_{e\theta} * \text{and}_\theta \ - \ G_0 * \theta_{ref} \tag{18}$$

$$\beta_{z\theta} = -G_w * w \ - \ G_q * q \ - \ G_\theta * \hat{\theta}/q \ - \ G_{e\theta} * e_{\hat{\theta}/q} \ - \ G_0 * \theta_{ref} \tag{19}$$

Where, $e_{\hat{\theta}/q}$ is obtained from the estimated state given by: $\dot{e}_{\hat{\theta}/q} = \theta_{ref} - \hat{\theta}/q$

The control law can also operate with double fault, but this method is only applied for one single fault at a time. So, it is possible to define a logic of selection of what measure should be substituted, as shown in Tab. (5).

Table 5 – Logic of selection of the redundant signal.

Fault Detected			Selection of the Redundant Signal					
h_w	h_q	h_q	$\hat{w}/q$	$\hat{w}/q$	$\hat{q}/w$	$\hat{q}/q$	$\hat{q}/w$	$\hat{q}/q$
0	0	0						
0	0	1						1
0	1	0				1		
0	1	1			1		1	
1	0	0	1					
1	0	1	1					1
1	1	0		1		1		
1	1	1	*	*	*	*	*	*

Note: the cells with "*" are reserved when all sensors fail. In this case the system will need to use the redundant signal generated from an analytical model of the plant.

2.8. Fault Case Studies

In this study we will only consider faults in sensors, therefore, the faults $f_a(t)$ and $f_c(t)$ and the disturbance d(t), presented in Eq. (1), will be considered null.

One sensor can have several types of fault. The following types of fault were considered:

- **Zero:** when the sensor begins to supply only the value zero, that is, the sensor has an abrupt variation for the value zero;
- **Maximum Value:** when the sensor begins to supply only the maximum value in module, that is, the sensor has an abrupt variation for its maximum or minimum value;
- **Constant:** when the sensor begins to supply the last measure made before the fault occurs;
- **Offset Drift:** when the value of the offset alters the measure in function of the time; and
- **Scale Factor Drift:** when the scale factor of the sensor alters the measure in function of the time.

2.8.1. Response of the System without Fault

The complete model of the system with implementation of the IFD and fault simulator is presented in Fig. (2). The response of the system without activation of the fault mode is presented at Fig. (3a), where we have the input reference, the attitude measured, the attitude feedback and the vehicle attitude.

The graphs of η_w, η_q and η_θ are shown in Fig. (3b). It can be verified that their values are very small compared with the threshold adopted to detect a sensor fault, according to Tab. (4).

2.8.2. Fault of Type "Maximum Value"

This fault is simulated setting the maximum value adopted for the pitch attitude sensor (0,349066rad = 20^o). The fault was programmed to occur 4s after the beginning of the simulation and with duration of 30s. In Fig. (4a) we have the response of the system with IFD and reconfiguration of feedback signals for the control system. It can be noticed that the response with IFD was identical to the response of the system without fault. In the graph of measure we can compare the values supplied by the sensor (solid line) with the values that should be supplied in case of no fault (dotted line). In the graph of attitude of the vehicle we can see that we can not distinguish the dotted line, what indicates that the IFD system presented a good performance.

In Fig. (4b) we have the response of the decision function for the indication of the fault. The system detected the fault at the moment that it occurred and didn't presented fault loss. But it delays too much in leaving the fault state for the normal state. During this period we have an indication of false alarm, so it's necessary to design the observer/estimator, to have a faster response to its input signals, and the decision function, selecting the residues that have better performance to detect the respective sensor fault.

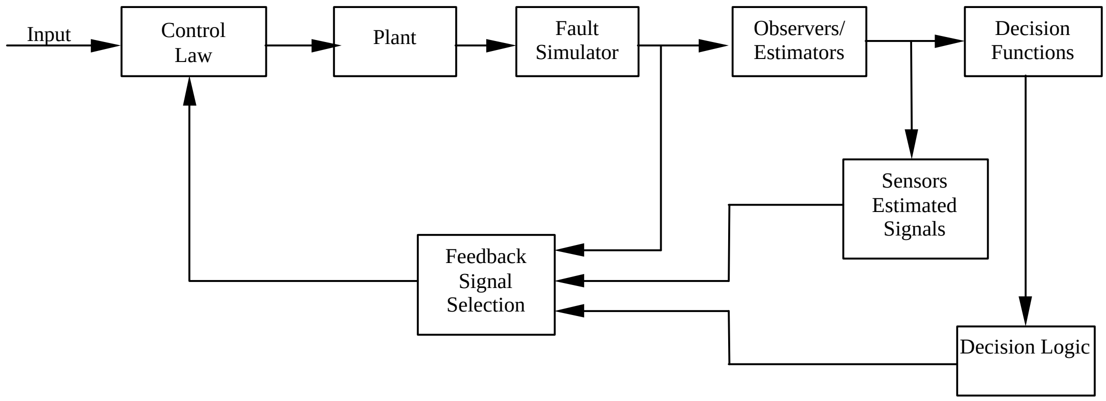

Figure 2 – Complete block model of the system.

2.9. Comments and Conclusion

The method presented here, with inclusion of the residue of the derivative differences between the real and estimated measures, presented a great improvement in the reduction of the alarm loss. But there still is the problem that the decision function delays too much to disable the fault indication. This problem probably can be solved through the improvement of the observers/estimators response time design, the selection the residues that have better performance to detect the respective sensor fault and the quality of the redundant signals.

It should also be taken into account in the observers/estimators design that they should operate in a plant where the initial conditions are not null, otherwise, it will cause a false alarm indication for all sensors.

This method of determination of the fault based on the product of two residues presents the advantage of being able to detect the beginning of abrupt faults quickly, but with the disadvantage that it doesn't have strong fault detectability (Frisk, 1996); so it is difficult to get the appropriate decision threshold along the fault time. As we have the multiplication of two sensor residues in the decision function, the influence of the faulty sensor also affects the decision function of good sensors, see Tab. (4); so it easily can cause false alarm or alarm loss indications. Another disadvantage of this method is that we have the product of two signals, generating a very wide frequency spectrum.

In the presented cases it is noticed that the system has a quick response to the faults of the type transition; it is slow to detect incipient faults; and it delays too much to leave the indication of fault state in cases of intermittent fault. The decision logic was elaborated to work with multiple faults, but this situation only will be able to be used after designing decision functions with strong detectability capacity, such that they allow detecting and isolating more than one fault simultaneously, and after designing an analytical model, when all sensors fail.

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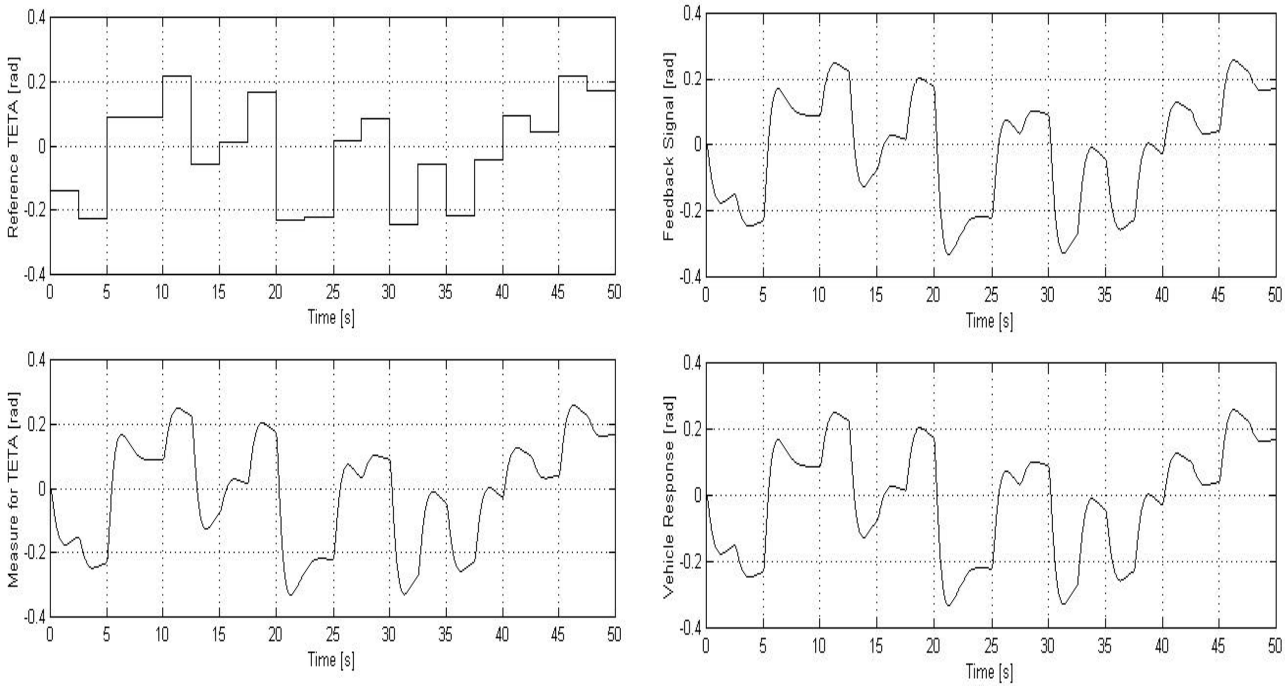

Figure 3a – Response of the system without fault.

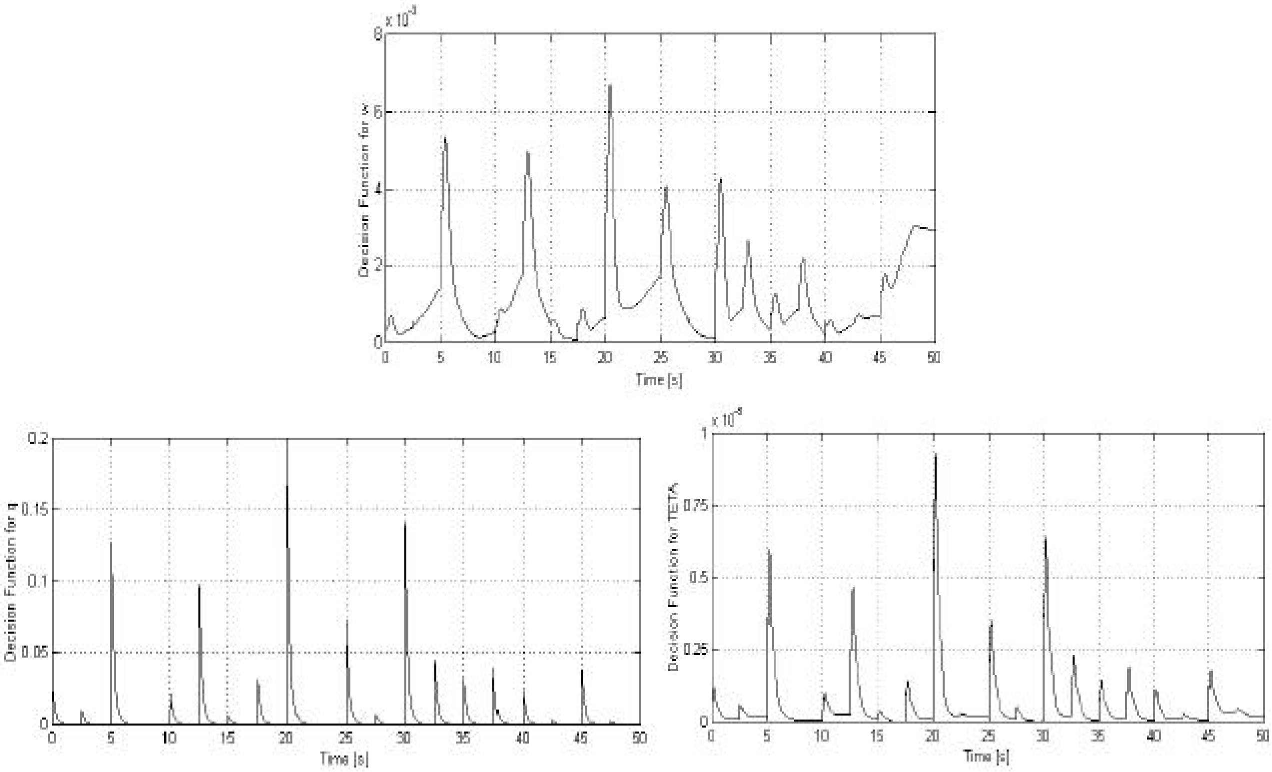

Figure 3b – Decision functions without fault.

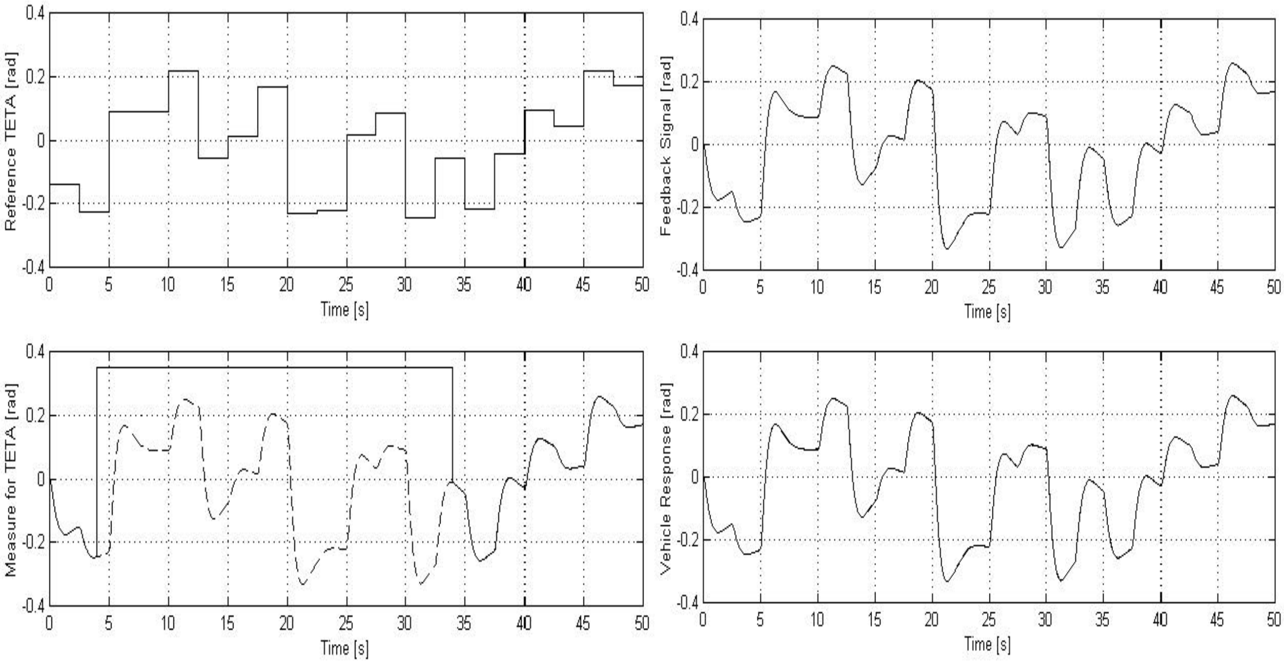

Figure 4a - Response of the system for the maximum value at pitch angle sensor.

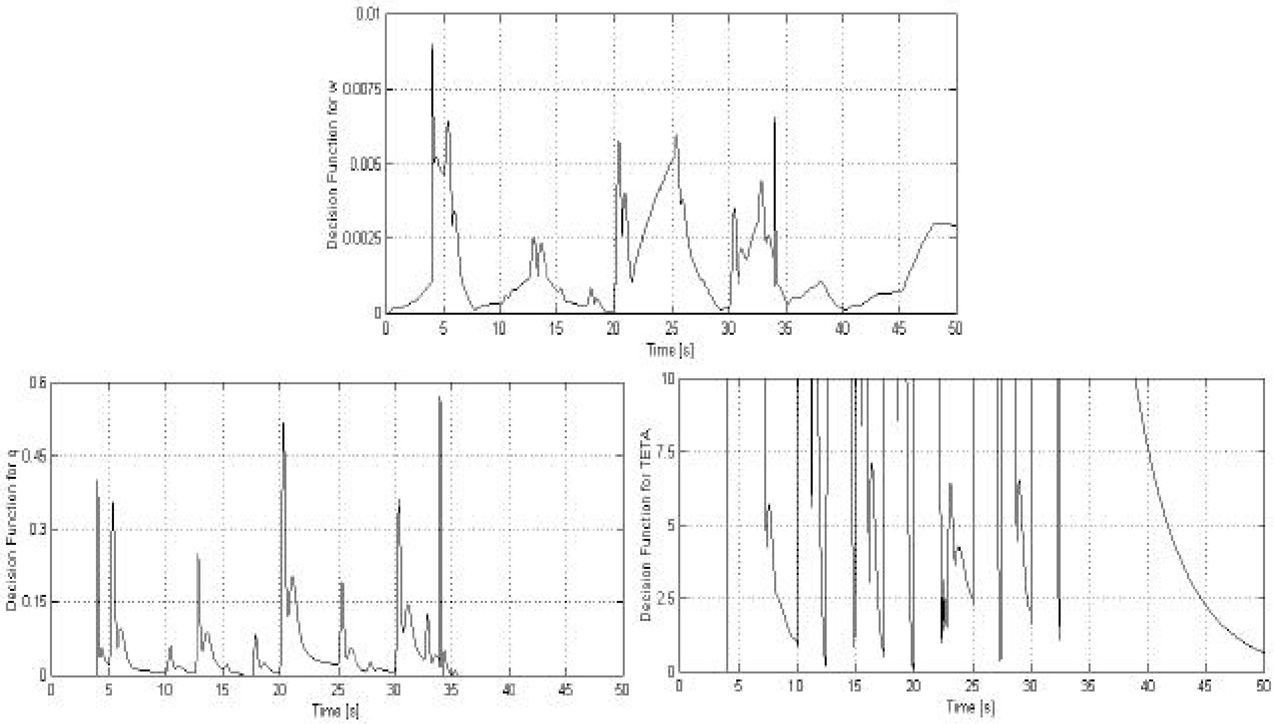

Figure 4b – Decision function for the maximum value at pitch angle sensor.