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Analytical fault tolerant navigation system for an aerospace launch vehicle using sliding mode observer

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Abstract. Aerospace Launch Vehicles (ALV) are generally designed with high reliability to operate in complete security through fault avoidance practices. However, in spite of such precaution, fault occurring is inevitable. Hence, there is a requirement for on-board fault recovery without significant degradation in the ALV performance. The present study develops an advanced fault recovery strategy to improve the reliability of an Aerospace Launch Vehicle (ALV) navigation system. The proposed strategy contains fault detection features and can reconfigure the system against common faults in the ALV navigation system. For this purpose, fault recovery system is constructed to detect and reconfigure normal navigation faults based on the sliding mode observer (SMO) theory. In the face of pitch channel sensor failure, the original gyro faults are reconstructed using SMO theory and by correcting the faulty measurement, the pitch-rate gyroscope output is constructed to provide fault tolerant navigation solution. The novel aspect of the paper is employing SMO as an online tuning of analytical fault recovery solution against unforeseen variations due to its hardware/software property. In this regard, a nonlinear model of the ALV is simulated using specific navigation failures and the results verified the feasibility of the proposed system. Simulation results and sensitivity analysis show that the proposed techniques can produce more effective estimation results than those of the previous techniques, against sensor failures.

Keywords: sliding mode observer; fault detection and isolation; aerospace launch vehicle

1. Introduction

ALV's used to place artificial satellites and space stations into Earth orbit. The stringent requirement for accurate positioning of the payloads in the desired orbit, even under adverse conditions, calls for the design of an FDI unit of such vehicles. The fault is caused by any malfunction in the navigation system that may lead to an unacceptable overall system performance. The gyroscopic operational unit is rarely faulty and therefore it is suitable that a fault occurrence should be detected and isolated so that the system is self-reconfigured in order to provide full performance. Therefore, the navigation system must be able to reconfigure itself in order to provide full performance in the presence of one or more component failures (Marzat, Piet-Lahanier *et al.* 2012).

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A traditional approach for fault diagnosis is a hardware-based method in which a particular variable is measured using multiple sensors. Several problems that hardware redundancy based fault diagnosis encounters are the extra equipment, cost, and additional space required for accommodating the redundant equipment. Analytical redundancy is a different approach compared with the hardware redundancy. A wide range of analytical redundancy fault diagnosis approaches can be broadly divided into model-based techniques, knowledge-based methodologies, and signal-based techniques Parity space, parameter estimation and the observer-based approach are commonly used for methods for model based residual generation (Kadlec, Gabrys *et al.* 2009), The observer fault detection is more populated than other model based methods due to its simplicity and compatibility with the control theories such as robust control, adaptive control, or intelligence control methods. The basic idea behind the use of the observer for fault detection is measurements by utilizing some types of the observer, and then constructing the residual by properly weighted output estimation error. The residual is then examined for the likelihood of faults by using a fixed threshold (Hwang, Kim *et al*. 2010). When the system is subject to unknown disturbances and uncertainty, their effects have to be decoupled from the residual signals to avoid false alarms. This problem is well known in the field of FDI as robust fault diagnosis (Jayakumar and Das 2010), H_∞ Observer (Falcoz, Henry *et al*. 2010) is applied for detecting the failure in the actuator and sensor of the European Atmospheric Reentry Vehicles (HL-20). Using H_∞ setting, a robust residual-based scheme is developed for the diagnosis of faults on the vehicle wing flap actuators. The faulty situation is selected by a prior analysis to determine those for which the remaining healthy control effectors are able to maintain the vehicle around its center of gravity. Finally, some performance indicators including detection time, required on board computational effort, and CPU time consumption are assessed and discussed. The Monte Carlo results are quite encouraging, illustrating clearly the effectiveness of the proposed techniques and suggesting that this solution could be considered as a viable candidate for the future Reentry Vehicle program. Although the development of H_∞ techniques can be considered today as a mature field of research within the academic community, their application to the real aerospace world has remained very limited (Zolghadri 2013), sliding mode techniques are well-known for their robustness properties against external perturbations and uncertainties. The sliding mode observer can force the output estimation error to converge to zero in finite time (as opposed to the linear observer which only converges asymptotically), while the observer states converge asymptotically to the system states (Li, Gao *et al*. 2014). During the sliding motion, the equivalent output error injection (the analogue to the equivalent control) contains information about the unknown signals, and by suitably scaling the equivalent output error injection, an accurate estimate of the unknown signals can be obtained. Therefore, by modelling faults as unknown signals, sliding mode observers can also be used to reconstruct faults. There are few sliding mode techniques which have already been considered for ALV. Shtessel *et al*. (2014) presented a multiple time scaled time-varying sliding mode observer for reusable launch vehicle attitude control.

In this paper, SMO based fault detection techniques have been applied for detecting faults in gyroscopes for the longitudinal motion of ALVs. To achieve this objective, the first stage of ALV is considered here. The misalignment of the thrust and center of gravity along the pitch and yaw channels are considered as disturbances. The residual between gyro rates (pitch rate) and estimated rates of the observer provides a measure for detecting the gyro fault. When a fault occurs, the fault diagnosis algorithm will generate and transmit an alarm signal to the control system. In the second part, the sliding mode theory is applied for a fault tolerance unit of ALV. For this purpose, when the failure in the gyroscope is detected by the fault detection subsystem, gyro output is filtered by the reconstructive fault unit in order to modify the faulty output.

The generation of the reconstructive fault signal for modifying faulty signal is considered using SMO theory suggested by Edwards (Hamayun, Edwards *et al*. 2010).

The structure of the paper is as follows: Section 2 describes the ALV equations of motion. The possible faults in the Gyroscope are considered in Section 3.The designing of SMO is covered in Section 4. The results of the nonlinear simulation are presented in Section 5.

2. Description of the ALV equations of motion

The dynamic model of six degree-of-freedom (DOF) equations of motion for an ALV can be written as follows (Roshanian, Saleh *et al*. 2007)

$$\begin{cases} P_x + R_x + G_x = m(\dot{U} + qW - rV), \\ P_y + R_y + G_y = m(\dot{V} + rU - pW), \\ P_z + R_z + G_z = m(\dot{W} + pV - qU), \\ M_{R_x} + M_{P_x} = I_x \dot{p} + (I_z - I_y)qr \\ M_{R_y} + M_{P_y} = I_y \dot{q} + (I_x - I_z)pr, \\ M_{R_z} + M_{P_z} = I_z \dot{r} + (I_y - I_x)pq \end{cases} \tag{1}$$

Where P_x, P_y, P_z, R_x, R_y, R_z, G_x, G_y, G_z are projections of thrust, aerodynamic and gravity forces; $M_{P_x}, M_{P_y}, M_{P_z}, M_{A_x}, M_{A_y}, M_{A_z}$ are the torques due to thrust and aerodynamic forces; I_x, I_y, I_z are the moments of inertia; m is the vehicle mass; U,V,W are the ALV velocity components, and p,q,r are the components of the ALV angular velocity vector. In Eq. (1), the Coriolis force, the variation force and the force described by members which develop due to system relative motion in respect to a vehicle body mass center are small in comparison with all other forces and can be neglected (Roshanian, Saleh *et al*. 2007),

In this paper, the SMO is applied for linear equations of the ALV. The linear equations of motion of the ALV are as follows

$$\begin{cases} \dot{v}_z = Z_{vz}.v_z + Z_q.q + Z_\theta.\theta + Z_{\delta_e}.\delta_e \\ \dot{v}_y = Z_V.v_y + Z_r.r + Z_\theta.\theta + Z_{\delta_r}.\delta_r \\ \dot{q} = M_{VZ}.v_z + M_q.q + M_{\delta_e}.\delta_e \\ \dot{r} = M_{VY}.v_y + M_y.r + M_{\delta_r}.\delta_r \\ \dot{p} = M_p.p - M_{\delta_e}.\delta_e \end{cases} \tag{2}$$

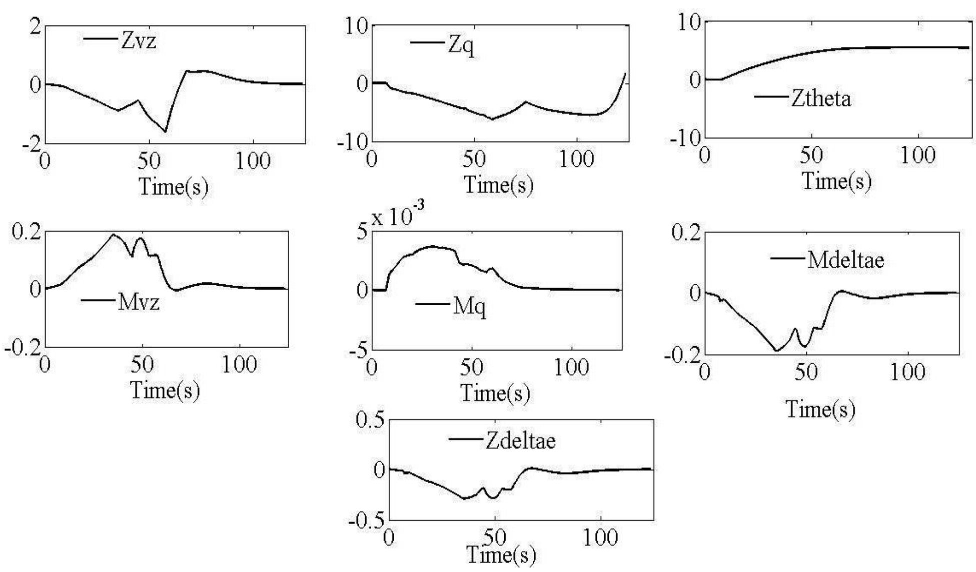

Fig. 1 Variation in dynamic coefficients of Pitch channel

Where Z's and M's are dynamic coefficients and δ_e, δ_r, δ_a, are control deflections in pitch, yaw and roll channels respectively.

Variation in dynamic coefficients of pitch transfer function and Yaw transfer function (Z, M) are given in Fig. 1 (Roshanian, Saleh *et al*. 2007).

The equation for Pitch channel can be written as follows

$$\begin{cases} \dot{v}_z = Z_{v_z}.v_z + Z_q.q + Z_\theta.\theta + Z_{\delta_e}.\delta_e \\ \dot{q} = M_{v_Z}.v_z + M_q.q + M_{\delta_e}.\delta_e \end{cases} \tag{3}$$

By defining the state variable as following: $x_1=\theta, x_2 = \dot{\theta}, x_3 = v_z, x_4 = \dot{v}_z$, the state equations can be written by following equations

$$\begin{cases} \dot{X} = A(t).X + B(t).\delta_e, \\ Y = C.X \end{cases}$$

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & M_q & M_{v_Z} & 0 \\ 0 & 0 & 0 & 1 \\ Z_\theta & Z_q & Z_{v_Z} & 0 \end{bmatrix} B = \begin{bmatrix} 0 \\ M_{\delta_e} \\ 0 \\ Z_{\delta_e} \end{bmatrix} \quad C = \begin{bmatrix} 0 & 1 & 0 & 0 \end{bmatrix} \tag{4}$$

The servo dynamics describing the thrust vector deflection is

$$[TF]_{servo} = \frac{\delta}{\delta_c} = \frac{1}{0.1s+1} \tag{5}$$

With a rate limit of $\left|\frac{d}{dt}\delta\right| < 25\,\mathrm{deg/sec}$. Reference signals of the control system is reference pitch rate, hence, rate Gyro is used for measuring the obtained pitch rate which is described as follows

$$[TF]_{Gyro} = \frac{(80\pi)^2}{s^2 + 40\pi s + (80\pi)^2} \tag{6}$$

3. Gyroscope faults classification

The Gyroscopes are basically the output interface of ALV to the external world and convey information about ALV's behavior. Gyroscopes serve the following two major purposes:

A. To establish an inertial reference coordinate frame

B. To measure the angular rotation of the ALV about reference axes.

Therefore, gyro faults may cause substantial performance degradation of all decision-making in an ALV that depends on data integrity for making decisions.

Common Gyroscope failures include: (a) bias; (b) drift; (c) performance degradation (or loss of accuracy); (d) sensor freezing; and (e) calibration error. Fig. 2 schematically depicts the effect of the above faults on system measurements (Venkateswaran, Siva *et al*. 2002),

Moreover, the mathematical effect of various sensor faults on system measurements ($y(t)$) is as follows

$$y_i(t) = \begin{cases} x_i(t) & & \forall t \geq t_0 & \text{Normal} \\ x_i(t) + b_i & \dot{b}_i(t) = 0, b_i(t_F) \neq 0 & ----- & \text{Bias} \\ x_i(t) + b_i(t) & |b_i(t)| = c_i t,\ \ 0 < c_i << 0 & \forall t \geq t_{F_i} & \text{Drift} \\ x_i(t) + b_i(t) & |b_i(t)| \leq \bar{b}_i, \dot{b}_i(t) \in L^{\infty} & \forall t \geq t_{F_{i_0}} & \text{Loss Of Accuracy} \\ x_i(t_{Fi}) & & \forall t \geq t_{Fi} & \text{Freezing} \\ k_i(t) x_i(t) & 0 < \bar{k} \leq k_i(t) \leq 1 & \forall t \geq t_{Fi} & \text{Calibration} \end{cases} \tag{7}$$

Where $x(t)$ is the normal sensor output, t_{Fi} denotes the time of fault occurrence on the ith sensor and b_i denotes its accuracy coefficient such that $b_i \in \left[-\bar{b}_i, \bar{b}_i\right]$ where b_i>0. Furthermore, it is seen that $k_i \in [\bar{k}_i, 1]$, where $\bar{k}_i > 0$ denotes the minimum sensor effectiveness.

4. Fault diagnosis based on SMO

In this section, the fault detection by linear SMO is considered. Robust observers for fault detection are designed to prevent the occurrence of a "False Alarm" problem and preventing instability of the observer through fault occurrence.

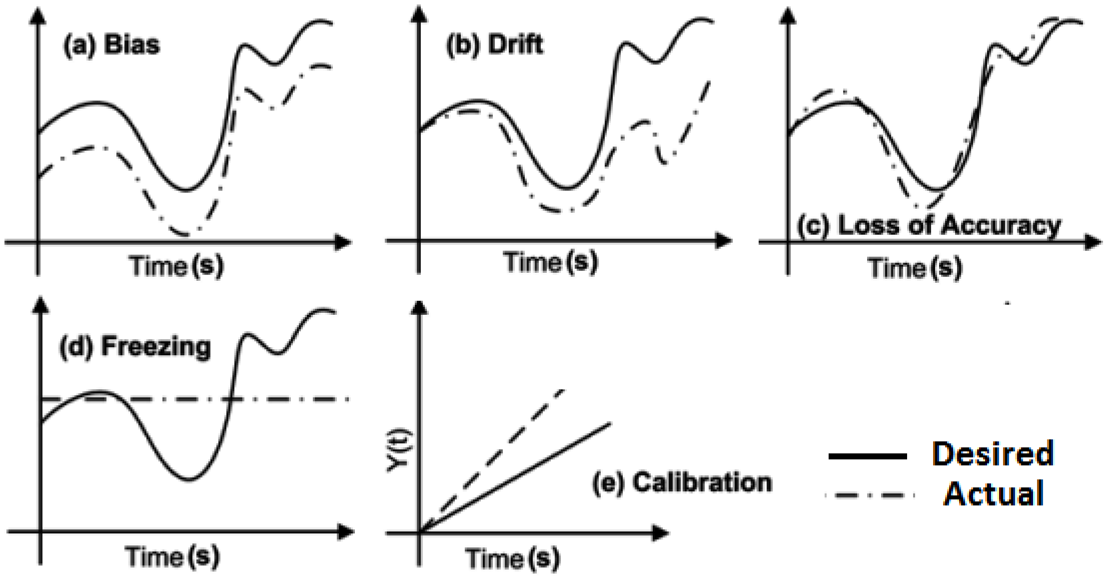

Fig. 2 Common sensor fault type (a) Bias fault;(b) Drift fault; (c) Loss of accuracy fault; (d) freezing fault; (e) Calibration fault

The linear ALV are used to design SMO due to the fact that a well-known and classical way to design a model-based FDI system is to use a linearized model of the plant to be supervised.

4.1 Sliding mode observer theory

SMOs are very useful tools for many reasons such as reduced observation error dynamic, the possibility of step by step design, a finite time convergence for all the observable states and robustness against uncertainties of systems.

Consider a linear uncertain dynamic system described by

$$\begin{cases} \dot{x} = Ax + Bu + Gd(x,u,t) \\ y = Cx \end{cases} \tag{8}$$

Where $x \in R^n$ is the state, $u \in R^m$ is the control input, $y \in R^P$ is the output. The matrices A, B and C are of appropriate dimensions. It is assumed that $d(x,u,t)$ is unknown, but bounded, so that

$$\|d(x,u,t)\| \le \rho \qquad \forall x \in R^n, u \in R^m, t \ge 0 \tag{9}$$

Where $\| \;\|$ refers to the Euclidean norm. G is a full rank matrix in $R^{n \times q}$ $Gd(x,u,t)$ represents the system uncertainties or nonlinearities, namely the unknown input.

Furthermore, without the loss of generality, it can be assumed that the output distribution matrix can be written as

$$C = \left[C_1, C_2\right] \tag{10}$$

Where $C_1 \in R^{p\times(n-p)}, C_2 \in R^{p\times p}$ and det(C_2)=0. Consequently, the transformation is non-singular and with respect to this new coordinate system it can be seen that the new output distribution matrix can be written as

$$T = \begin{bmatrix} I_{n-p} & 0 \\ C_1 & C_2 \end{bmatrix}$$
$$CT^{-1} = \begin{bmatrix} 0 & I_p \end{bmatrix} \tag{11}$$

If the other system matrices are written as

$$TAT^{-1} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix},\ TB = \begin{bmatrix} B_1 \\ B_2 \end{bmatrix} \tag{12}$$

Then the nominal system can be written by following equations

$$\begin{cases} \dot{x}_1 = A_{11}x_1 + A_{12}y + B_1u \\ y = A_{21}x_1 + A_{22}y + B_2u \end{cases} \tag{13}$$

The corresponding SMO for the y subsystem is derived as

$$\dot{\hat{y}} = A_{22}\hat{y} + A_{21}\hat{x}_1 + B_2u + L_1 sign(y - \hat{y}) \tag{14}$$

Where $(\hat{x}_1, \hat{y}_1)$ are the estimation of (x_1,y_1), L_1 is a constant nonsingular feedback gain matrix, and sign(.) is the sign function. If the error between the estimates and the true states are written as $e_y = y - \hat{y}$ and $e_1 = x_1 - \hat{x}_1$, then the following error system is obtained

$$\dot{e}_1 = A_{11}e_1 - L_2L_1 sign(e_y) \tag{15}$$

It can be shown using singular perturbation theory that for a large enough L1, a sliding mode motion can be induced by the outputs' error state in (15), It follows that, after some finite time t_s, for all subsequent time, e_y=0 and $\dot{e}_y = 0$. For the second subsystem, the observer equation is

$$\dot{\hat{x}}_1 = A_{11}\hat{x}_1 + A_{12}y + B_1u + L_2L_1 sign(e_y) \tag{16}$$

Based on equivalent control system theory, the system is treated as a sliding mode if the magnitude of $L_1 sign(e_y)$ is changed by $(L_1 sign(e_y))_{equ}$ equivalent magnitude.

This magnitude can be calculated by subsystem by replacing e_y=0, $\dot{e}_y = 0$ equation has been changed to the following equation

$$\left(L_1 sign(e_y)\right)_{equ} = A_{21}e_1 \tag{17}$$

By replacing (18) into (16)

$$\dot{e}_1 = A_{11}e_1 - L_2 A_{21} e_1 = (A_{11} - L_2 A_{21})e_1 \tag{18}$$

The A_{11}, A_{21} expression is observable when A and C are observable. By choosing fine L_2 the estimation error e_1 is getting close to zero.

The system is changed to the following expression by using T transformation

$$\begin{cases} \dot{x}_1 = A_{11}x_1 + A_{12}y + B_1 u + G_1 d \\ \dot{y} = A_{21}x_1 + A_{22}y + B_2 u + G_2 d \end{cases} \tag{19}$$

4.2 Reconstruction of the output fault via SMO theory

A different SMO for fault detection and isolation was suggested by Edwards (Alwi and Edwards 2014), The innovation of this approach is that the observer attempts to reconstruct the fault signals instead of detecting the presence of a fault through a residual signal (e_1) .

Edwards proposed an observer in order to maintain the sliding motion, even in the presence of faults, which are specified by analyzing the equivalent output injection signal obtain from the discontinuous injection signal required to maintain sliding motion. The equivalent injection signal is, therefore, not the injection signal applied to the observer but represents the effective injection signal required to maintain sliding motion. The equivalent injection signal can be freely obtained by appropriate filtering of the applied, usually discontinuous, injection signal implemented within the observer.

To explain the Fault tolerant approach, let consider a nominal linear system in presence of certain sensor fault as follows

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + f_0(t) \end{cases} \tag{20}$$

Where $A \in R^{n\times n}$, $B \in R^{n\times m}$, $C \in R^{n\times n}$, $D \in R^{n\times q}$ with $q \leq p < n$ and the matrices B,C and D are of full rank. The function $f_0(t)$ represented the sensor fault. It is assumed that the states of the system are unknown and only the signals $u(t)$ and $y(t)$ are available.

In this situation since $y(t)=Cx(t)+f_0(t)$ it follows that

$$e_y(t) = Ce(t) - f_0(t) \tag{21}$$

And the state estimation error is obtained by

$$\begin{cases} \dot{e}_1(t) = A_{11}e_1(t) + A_{12} f_0(t) \\ \dot{e}_y(t) = A_{21}e_1(t) + A^s 22 e_y(t) - \dot{f}_0(t) + A_{22} f_0(t) + v \end{cases} \tag{22}$$

Note that $f_0(t)$ and $\dot{f}_0(t)$ appear as output disturbances and thus, ρ in the equation must be chosen sufficiently large to maintain sliding in the presence of these disturbances .The provided sliding motion can be attained as follows

$$0 = A_{21}e_1 - \dot{f}_0(t) + A_{22} f_0(t) + v_{eq} \tag{23}$$

Thus, for slowly varying faults, provided the dynamics of the sliding motion are sufficiently fast ($\dot{f}_0(t)$ =0)

$$v_{eq} \approx -\left(A_{22} - A_{21}A_{11}^{-1}A_{12}\right)f_0 \tag{24}$$

And consequently, if $\left(A_{22} - A_{21}A_{11}^{-1}A_{12}\right)$ is non-singular, the fault signal can be obtained as follow

$$f_0 \approx -\left(A_{22} - A_{21}A_{11}^{-1}A_{12}\right)^{-1} v_{eq} \tag{25}$$

If $\left(A_{22} - A_{21}A_{11}^{-1}A_{12}\right)^{-1}$ is singular, proposed methods can still be made about certain fault channels depending on the precise nature of the rank deficiency (Alwi and Edwards 2014),

5. Fault tolerant sliding mode control

In this section, a fault tolerant control is proposed based on the sliding mode theory to accommodate the fault occurrence. The basic idea of the design is to add a reconstructive signal to gyroscope faulty signal to generate healthy gyroscope output. When a fault occurs, Eq. (20) becomes

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + f_0 = \bar{y} + f_0 \\ \dot{\hat{x}} = A\hat{x} + Bu + L(\bar{y} - \hat{y}) + Lf_0 \\ \hat{y} = C\hat{x} \end{cases} \tag{26}$$

Based on what was mentioned above, when a fault occurs, the output of the gyroscope is replaced by the reconstructive signal which is produced by SMO. Thus, Eq. (26) is changed by the following equation

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + f_0 = \bar{y} + f_0 - \tilde{f}_0 \\ \dot{\hat{x}} = A\hat{x} + Bu + L(\bar{y} - \hat{y}) + Lf_0 - L\tilde{f}_0 \\ \hat{y} = C\hat{x} \end{cases} \tag{27}$$

Where $\tilde{f}_0$ denotes the reconstructive fault signal. A design method to achieve L coefficients can be obtained by minimizing trace (P^{-1}) subject to the following inequalities:

$$PA + A^T P - C^T V^{-1} C + PWP < 0, \qquad P > 0$$

Where *W* and *V* are the symmetrical positive definite user-defined matrix. From the solution for *P* that is obtained by employing LMI approach (Alwi and Edwards 2014), the observer gain *L* can be directly calculated as:

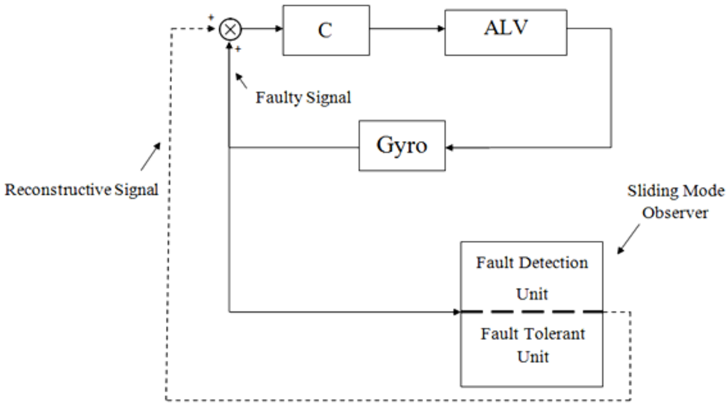

Fig. 3 Proposed fault tolerant scheme

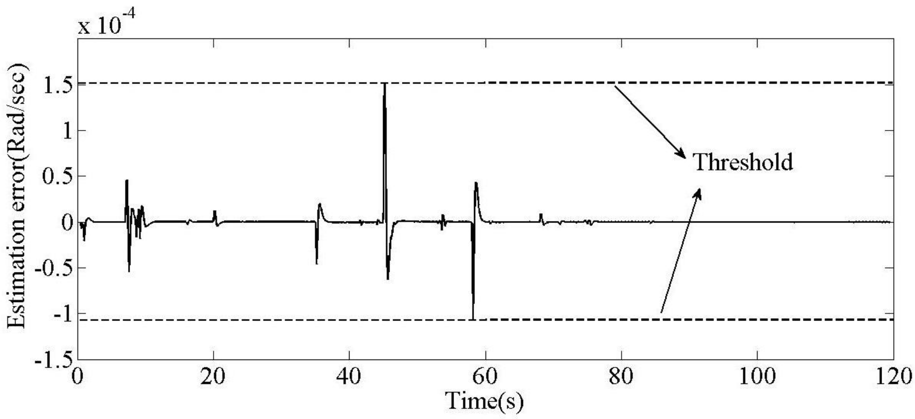

Fig. 4 The residual(estimation error) in a fault-free case obtained by SMO

$$L = P^{-1}C^T V$$

It is obvious that the fault signal effect will be decreased due to the exertion of the reconstructive signal .This proposed fault tolerant system is schematically described in Fig. 3.

6. Results and discussions

To evaluate the performance of the FDI strategy for ALV navigation proposed in this paper, simulations of a series of typical faults were performed using 6DOF simulation in MATLAB/Simulink. In the simulations, the US standard atmosphere and rotating elliptical models were used for the atmosphere and the earth models, respectively. The simulation was carried out in the presence of disturbances acting along the pitch and yaw channels. It is important to note that for all the following simulation cases, the function “sign” is approximated by a saturation function with a slow rate equal to 10^{-5}.

In this problem detection of the defined gyroscope fault, and evaluation of performance of fault

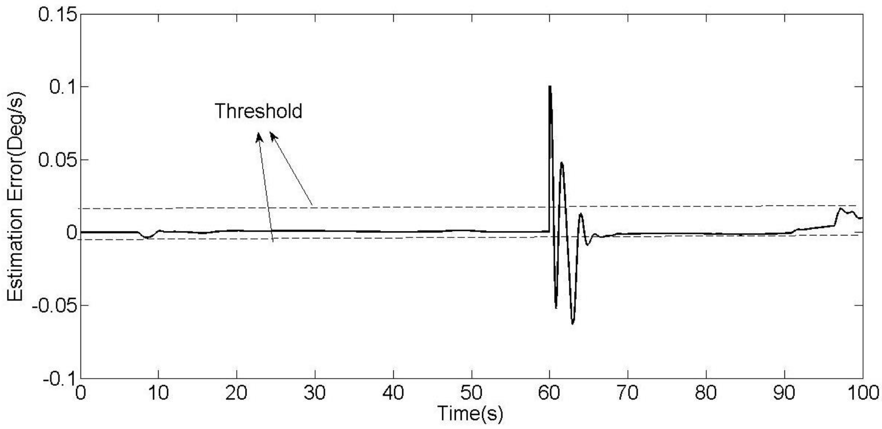

Fig. 5 Gyro fault detection in the presence of bias fault at t=60 s

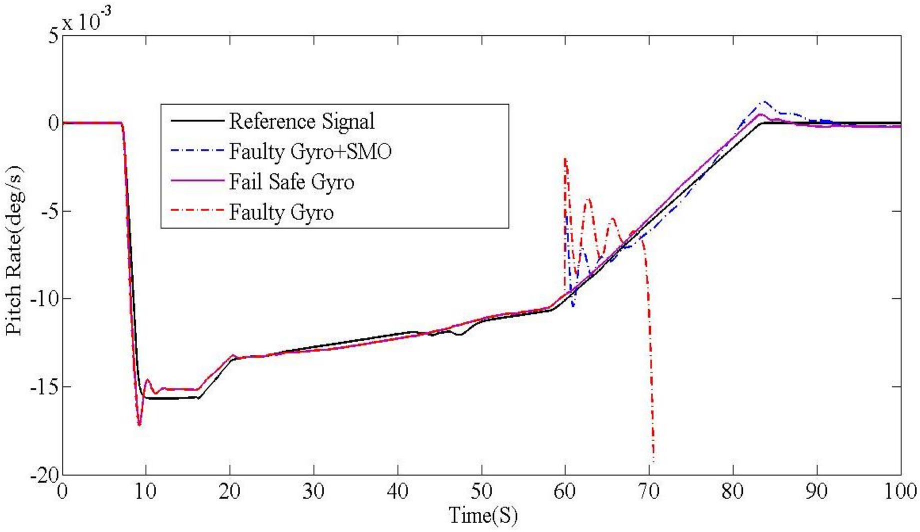

Fig. 6 Performance of the proposed fault recovery strategy at t=60 s

reconfiguration were examined. In this problem detection of the defined gyroscope fault, and evaluation of performance of fault reconfiguration were examined. Fig. 4 shows the estimation error of the proposed method. As seen, in the presence of disturbances, the estimation error (residual) is entirely bounded by the predefined threshold.

Fig. 5 illustrates the detection of Gyro bias fault (b_{60s}=0.2x_{60s}) which was described in section 3. As shown, the residual exceeded its corresponding threshold at t=60s and transmitted an alarm signal to the fault recovery system to accommodate the occurrence of a fault. Fig. 5 shows detection procedure for common faults has been successively done.

The simulation results of the fault recovery system for control deflection and pitch-rate angle based on the proposed soft sensor are shown in Fig. 6. Fig. 6 shows the effect of the proposed fault recovery system in the presence of bias faults, which are the strongest and most probable faults in a gyroscope. It can be seen that the abruption created in the control deflection at 60 s was tolerated by the proposed method. The abruption created in pitch-rate in the next 60 s was quickly tolerated by the proposed fault tolerance to correctly follow the pitch rate program in the presence of a predefined fault.

7. Conclusions

Fault detection and recovery are important operations for reliability analysis of ALVs. It is desirable that vehicle control systems detect and identify any fault occurring in the system. The control system must be able to reconfigure the vehicle navigation system in the presence of one or more component failures. This study employs SMO theory for detection and recovery of navigation failure in the ALV. The technique was applied for exclusive fault detection of the gyroscope for the launch vehicle. The observer design was carried out to make the rate residues triggered by gyro faults. In spite of the complexity of online detection of navigation fault, effective detection was accomplished using the SMO theory. Reconfiguring a predefined fault is successfully designed and numerically simulated by the proposed method.

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