NEAR REAL-TIME AUTONOMOUS HEALTH MONITORING OF ACTUATORS: FAULT DETECTION AND RECONFIGURATION

Sanjay Jayaram (UCF/Aximetric Inc) – sanjay@aximetric.com
Roger W. Johnson (UCF) – rjohnson@mail.ucf.edu
Guru Prasad (Aximetric Inc) – guru@aximetric.com

Abstract
This paper is concerned with the Near Real-time Autonomous Health Monitoring of autonomous satellites and autonomous unmanned ground vehicles. The dynamics of such unmanned systems is uncertain due to factors such as high non-linearity, consideration of higher modal frequencies, high dimensionality, multiple inputs and outputs, operational constraints, as well as unexpected failures of sensors and/or actuators. Hence a systematic framework of developing a high fidelity, dynamic model of the structural system needs to be understood. The fault detection mechanism that will be an integrated part of an autonomous health monitoring system comprises the detection of abnormalities in the sensors and/or actuators and correcting these detected faults (if possible). Applying the robust control law and the robust measures that are capable of detecting and recovering/replacing the actuators rectifies the actuator faults. The fault tolerant concept applied to the sensors will be in the form of an Extended Kalman Filter (EKF). The EKF is going to weigh the information coming from multiple sensors (redundant sensors used to measure the same information) and automatically identify the faulty sensors and weigh the best estimate from the remaining sensors. Specifically, this paper addresses the difficulties currently encountered by the autonomous vehicles. The insertion of this unique concept enhances the intelligence of the vehicle, reduces the cost, increases the safety and reliability to improve the global performance of the overall system.

Introduction

Present and future space missions will use flexible, lightweight, multi-body structural space systems. Such systems are expected to have significant flexibility in the structural members. The flexible multi-body systems are likely to be highly non-linear with time varying structural parameters with a great extent of inaccuracies and uncertainties in the mathematical model. Furthermore, it calls for the ultimate pursuit of a higher degree of autonomous operation, possibly in real-time. Hence, to meet the demanding performances that have to be achieved, highly sophisticated controllers like a Non-linear Robust Control needs to be designed.

Since space structures need to be operated for a long duration of time without frequent telecommunication from the ground station, a Real-time Model-Based Autonomous Health Monitoring approach will be a promising and viable tool for the present and future space missions.

Real-time Autonomous Health Monitoring is increasingly becoming a popular and accepted method for determining and monitoring the overall health of the structure. The analysis used here for health monitoring is to detect any abnormalities in the system parameters by developing a high fidelity dynamic model of the nominal system and comparing the measurements taken from sensors from the actual system. The testing consists of determining system parameters (i.e., natural frequencies, damping and stiffness constants, mode shapes etc.) of the flexible structural system from its response to a known excitation. Practically, the kind of external disturbance or excitation in space environments are highly unpredictable, hence robust methods are proposed to compensate for these uncertainties.

This paper concerns the accomplishment of near real-time autonomous health monitoring of a flexible lightweight structure using a high fidelity, dynamic model-based simulation and developing a fault tolerant robust control mechanism for its control.

Technical Objectives

This paper develops an integrated control framework that enables autonomy, monitoring, diagnosis, and fault-recovery and self-healing execution at two levels of control. Specifically, the proposed new control scheme addresses the technical difficulties currently encountered in the designs of autonomous management systems. Processes and components in the system must be controlled continuously, and their health has to be monitored in the presence of dynamic variations. Typically, control and monitoring are done conventionally using standard off-the-shelf control/sensor modules. The problems arising in monitoring dynamic states needs to be resolved. While advanced controls (such as nonlinear robust control, adaptive control, etc.) are ideal candidates in the design of an autonomous system operating in an unknown and changing environment, space-bound computers, at this time, have very limited computational power in analyzing all data in real-time and synthesizing all control signals. To overcome the above two major obstacles, a proposed intelligent control framework is discussed that can achieve the technical objectives of Robustness, Fault Tolerance, Autonomy and self-reconfiguration and Intelligence. Hence, the proposed intelligent control system will reduce the cost, enhance reliability, and increase safety, so that future space systems and vehicles can operate in an uncertain environment.

System Description

The block diagram of the system considered in this paper is shown in Figure 1. The system consists of a set of actuators that drive the plant being considered. The system and actuator output are monitored. The measured signals of sensors will pass through a Kalman filter (or Extended Kalman Filter) [5, 6]. The filtered signals will then be sent to the conventional control block for real-time execution after passing through fault detection module and a robust control module. In the fault detection module, the health of the actuators are monitored using robust measures so that fault identification can be done in the presence of significant uncertainties. Meantime, the same module also monitors performance of the system. When system performance is less than desired, the diagnostic algorithm will invoke the nonlinear robust control that is capable of guaranteeing performance. When a fault is detected, the nonlinear estimation is activated so that control action can be synthesized after excluding the feedback from the faulty actuator.

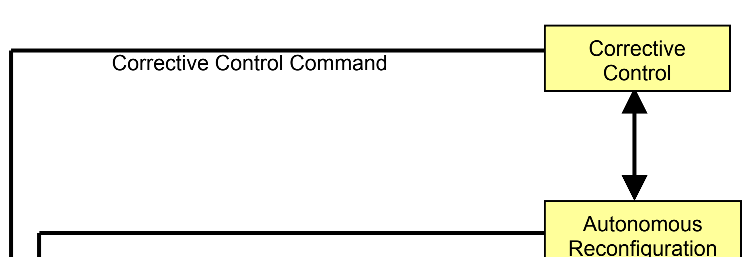

Figure 1: System Block Diagram

Kalman Filter Based Sensor Fault Detection

Real-time health monitoring of a dynamic system depends on accurate identification of the system parameters from the on-board sensors and actuators. In the case of a satellite that is flying in the Low Earth Orbit (LEO), the number of good passes that the satellite will have over the ground station is very few (around three to four passes in a day) and each good pass above the ground station would last for less than eight minutes (horizon to horizon). Hence, for each and every good pass, the data collected from various instruments on-board the satellite is transmitted to the ground station and various computations needs to be done in real-time, fast and accurately. For this reason, parallel processing Extended Kalman filter is the best candidate to compute the best estimate of the system parameters.

Extended Kalman Filter

To develop the statistical recursive algorithm for the Extended Kalman Filter, the general form of the dynamic equations of motion developed in the previous chapter will be used. Initially, the generalized second order differential equations are converted to first order differential equations using the state space analysis.

The Extended Kalman filter is an extension of Kalman filter from linear system to the more general case described by the nonlinear stochastic differential equation

$$\dot{\mathbf{X}}(t) = \mathbf{f}(\mathbf{X}(t),t) + \mathbf{w}(t)$$

The vector **f** is a nonlinear function of the state and **w***(t)* is zero mean gaussian noise having spectral density matrix **Q**(t). The nonlinear measurement has the form

$$\mathbf{Z}_k = \mathbf{h}_k(\mathbf{X}(t_k)) + \mathbf{v}_k \quad k = 1,2,...$$

Where h_k depends upon both the index *k* and the state at each sampling time, and v_k is a white random sequence of zero mean gaussian random variables with associated covariance matrices R_k. This constitutes a class of estimation problems for nonlinear systems having continuous dynamics and discrete-time measurements. Here we took the same assumption and notation as standard Kalman filter. The derivation procedure of EKF is as same as Kalman Filter, except to know that in order to get the methods of computing the mean and covariance matrix which don't depend upon knowing $P(X,t)$, we need to expand f in a Taylor series about the known vector $X(t)$, if we select to expand f about the current estimate $X_{e,k}$, then we can get the EKF formula as follows:

Measurement update phase

$$\mathbf{X}_{e,k} = \mathbf{X}^-_{e,k} + \mathbf{K}_k(\mathbf{Z}_k - \mathbf{h}_k(\mathbf{X}^-_{e,k}))$$
$$\mathbf{P}_k = (\mathbf{I} - \mathbf{K}_k\mathbf{H}_k(\mathbf{X}^-_{e,k}))\mathbf{P}^-_k$$
$$\mathbf{K}_k = \mathbf{P}^-_k\mathbf{H}^T_k(\mathbf{X}^-_{e,k})[\mathbf{H}_k(\mathbf{X}^-_{e,k})\mathbf{P}^-_k\mathbf{H}^T_k(\mathbf{X}^-_{e,k}) + \mathbf{R}_k]^{-1}$$

Time update phase (project ahead)

$$\mathbf{X}^-_{e,k+1} = {}_{t_k}^{t_{k+1}}\mathbf{f}(\mathbf{X}_{e,k}(t),t)$$
$$\mathbf{P}^-_{k+1} = \int_{t_k}^{t_{k+1}} \mathbf{F}(\mathbf{X}_{e,k}(t),t)\mathbf{P}(t) + \mathbf{P}(t)\mathbf{F}^T(\mathbf{X}_{e,k}(t),t) + \mathbf{Q}(t)dt$$

And the definitions

$$\mathbf{H}_k(\mathbf{X}^-{}_{e,k}(t),t) = \frac{\partial \mathbf{h}_k(\mathbf{X}(t),t)}{\partial \mathbf{X}(t)}\Big|_{\mathbf{X}(t)=\mathbf{X}^-{}_{e,k}(t)}$$
$$\mathbf{F}(\mathbf{X}_{e,k}(t),t) = \frac{\partial \mathbf{f}(\mathbf{X}(t),t)}{\partial \mathbf{X}(t)}\Big|_{\mathbf{X}(t)=\mathbf{X}_{e,k}(t)}$$

The above equations are the EKF formula for nonlinear continuous system with discrete time measurement.

Sensor Fault Detection and Isolation

The technique developed for isolating faulty sensor measurement is to use a bank of Kalman filters (or Extended Kalman filters). The critical parameters of the system are sensed by on-board sensors (critical parameters like Roll, Pitch and Yaw angles and angular rates). Each set of sensors and redundant sensors monitoring the same parameters is assigned to a different Kalman filter (see Figure 2) for processing the data. Each Kalman filter will compute the best estimate of the states and computes the covariance values. The covariance values are the indication of the standard deviation of each sensor measuring the state (covariance is inversely proportional to the standard deviation). The higher the covariance values, the lower the standard deviation of the sensor, hence, more weight is given to the information collected by that sensor. By this method, we can always get the best estimate of the state variable (or critical parameter) of the system. During the weighing process, the Kalman filter automatically rejects the information from the sensors with the higher standard deviation, thus isolating the faulty sensor measurement contribution during the computation of the best estimate of the state.

The identification of faulty sensor(s) is accomplished by analyzing the profile of the covariance values computed by the Kalman filter process. The covariance values are inversely proportional to the standard deviation of the sensor, the smaller standard deviation; therefore more weight is given to that sensor. The sensor with the least covariance value will have the largest standard deviation. It is to be understood that we are observing the trend of the covariance values before making the conclusion that the sensor is faulty. A Model-based Simulation procedure (discussed later) will be used to demonstrate this concept.

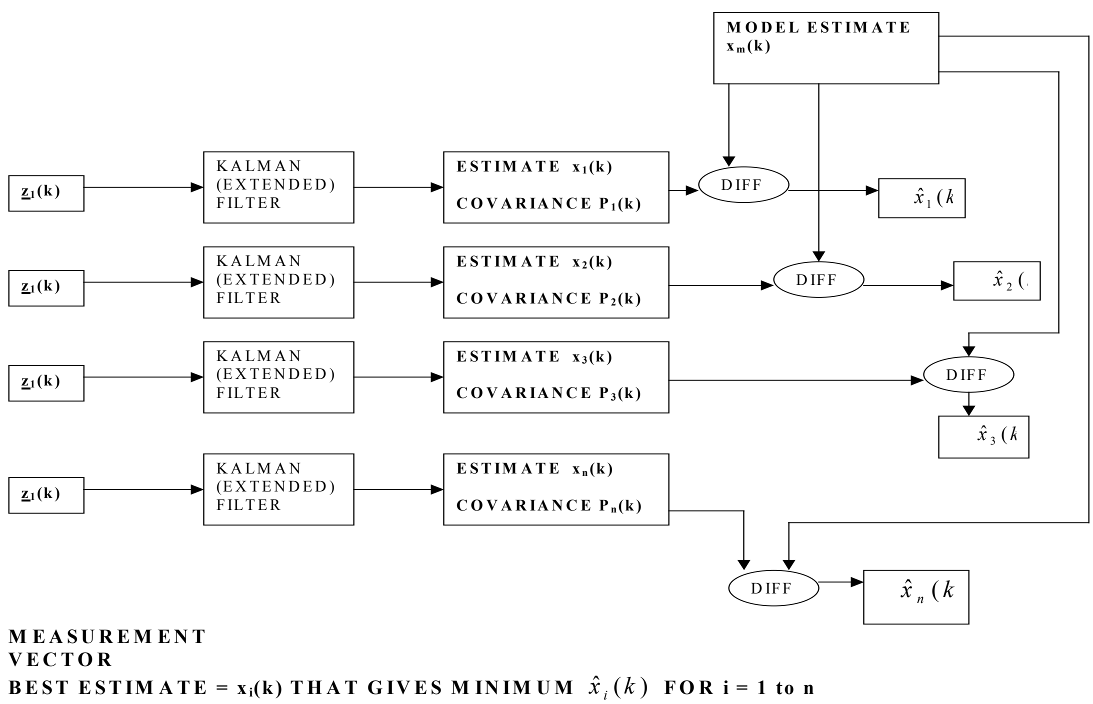

Figure 2: Model-based Sensor Fault Detection and Isolation

To detect and isolate the faulty sensor, we need to define the dynamic threshold for sensor parameter values. The Mean Square Error Threshold developed here depends on the error between the Kalman filter estimated value and the model value. This error is squared and multiplied by the standard deviation of the sensor. The standard deviation defined here is dynamic, meaning, it depends on the specific covariance value of a particular sensor. The covariance value is the weighing factor of the sensor. Higher the weighing value, more likely the contribution from that sensor will be towards the computation of the best estimate. The inverse of the covariance value will be the standard deviation of the sensor.

The initial threshold is defined for each sensor is defined as:

$$\mathrm{MSET} = (x(i)_{\mathrm{estimate}} - x_{\mathrm{model}})^2 (P(i)^{-1})$$

Where MSET – Mean Square Error Threshold

$P(i)^{-1}$ – inverse of the covariance value which will be the initial standard deviation of the sensor

Is set to be equal to 0.1 rad (for angular sensors) and 0.1 rad/sec for angular rate sensor)

$$(x_{\mathrm{estimate}} - x_{\mathrm{model}})$$

Simulation Results

The demonstration of the above methodology for isolating and identifying the faulty sensors performed very well during the simulation. Faulty measurements were intentionally induced into the sensor data to investigate the performance of the Kalman filter. The results showed that the faulty sensors were identified and the faulty measurements from those sensors were rejected during the computation of the best estimate. The faulty sensors identified during the simulation can either be replaced or permanently isolated. Figures 3, 4, 5 shows the simulation results, which was performed for three redundant sensors measuring the roll, pitch and yaw angles. Each sensor consisted of the simulated measurements, to which, random noise was added with a known mean and standard deviation. Those filtered measurement from the sensors that exceeded the threshold limit was automatically isolated and those filtered measurement that had the lease standard deviation was used to compute the best estimate.

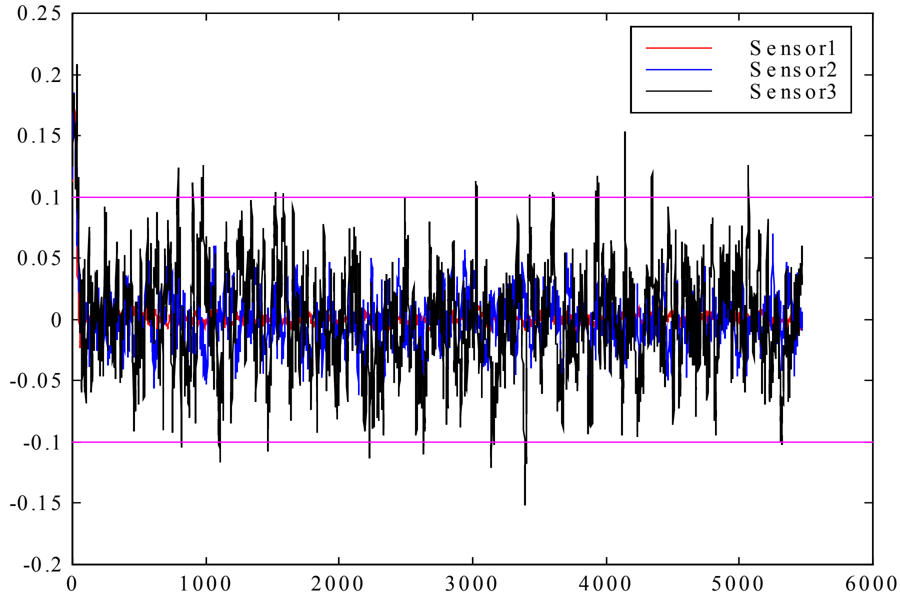

Figure 1: Sensor Measurements from three redundant sensors measuring roll angle. Sensor 1 gives the best estimate.

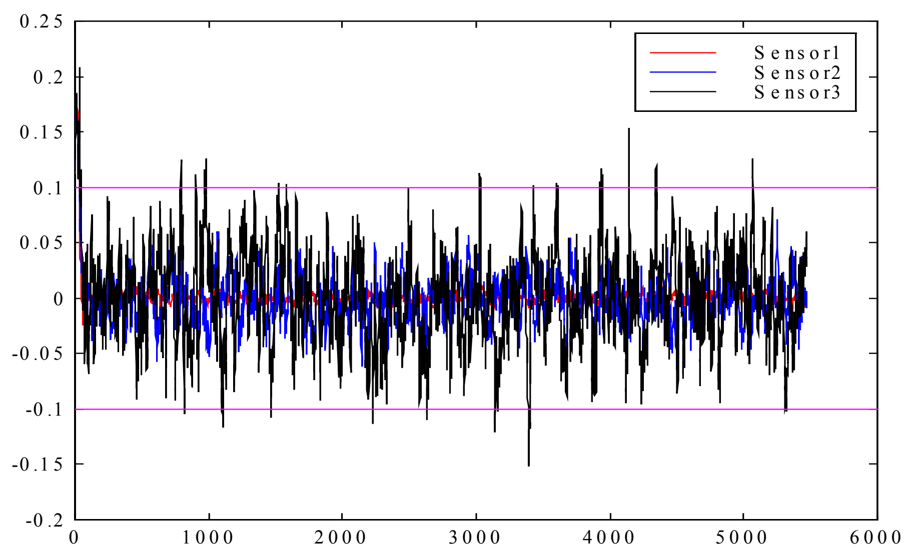

Figure 2: Sensor Measurements from three redundant sensors measuring pitch angle. Sensor 1 gives the best estimate

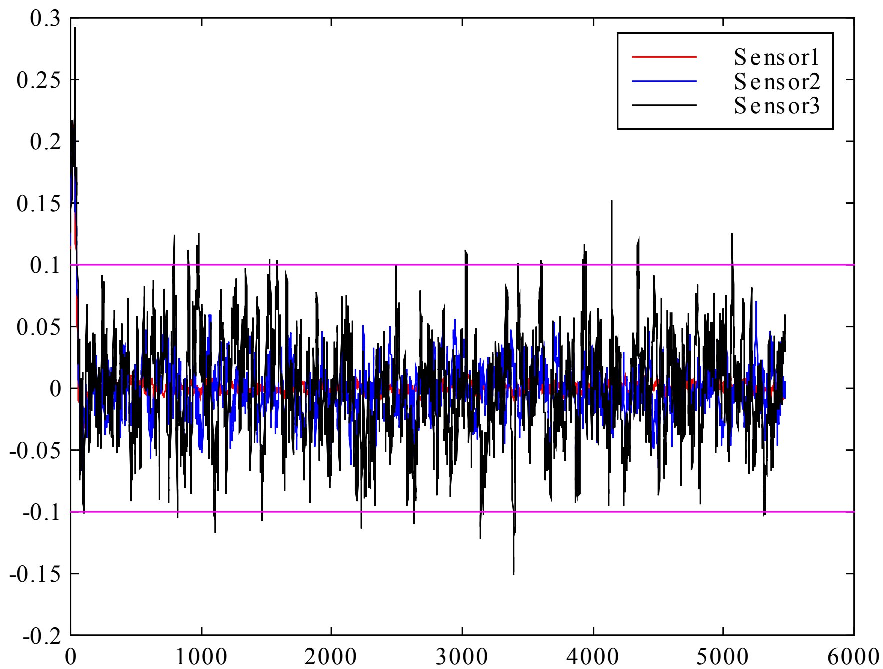

Figure 3: Sensor Measurements from three redundant sensors measuring yaw angle. Sensor 1 gives the best estimate

Model-based Actuator Fault Detection

The problem of devising a fault-tolerant robust control for the actuators is discussed here. Various possible failure scenarios of the actuators and/or the dynamic parameter ("system state variables") are considered, and robust fault tolerant measures are developed to identify stability-vulnerable failures. Based on the evaluation of the robust measures, the fault-tolerant robust control will switch itself to the redundant actuator and reconfigure the faulty actuator or in the case of dynamic parameter failure, a control measure is selected under the specific faulty conditions. The proposed scheme guarantees not only the desired performance under normal operations but also robust stability and best achievable performance when there is detected failure.

Fault diagnosis and fault tolerant (or reconfiguration) control has been primarily studied for linear and/or parameterizable systems. The proposed robust fault-detection measures and the robust control strategy is derived using the Lyapunov direct method. The proposed robust measures are to detect those faults that hinder the system performance and /or potentially de-stabilize the system.

Problem Formulation

The high fidelity, model of the non-linear system with the model of the actuator dynamics is incorporated into the simulation. Mathematically the non-linear dynamics are given by the following differential equations:

$$\dot{x} = f(x,t) + B(x,t)[\Delta f(x, v_x, t) + z] \text{ and } \dot{z} = g(z,t) + \Delta g(z, v_z, t) + u$$

where x(t) is the state of the system and z(t) is the state of the actuator and u(t) is the control to be designed and v(t) denotes the vector of unknowns/uncertainties, f(x,t), g(z,t) and B(x,t) are known parts of the system dynamics and $\Delta f(x,v_x,t)$ and $\Delta g(z,v_z,t)$ are uncertainties in the system dynamics and actuator dynamics respectively. Due to the presence of unknowns/uncertainties, a successful control must be robust. For the purpose of designing a fault tolerant control, potential failures of the actuators are considered. To this end, we are going to measure the output of the actuator and detect any failures in the actuators. If any failure is detected, the robust control should shift to the redundant actuator and recover the failed actuator (if possible).

Fault Detection

The non-linear subsystem considered in this paper can be mathematically given by the following differential equations:

$$\dot{x} = f(x,t) + B(x,t)z \quad and \quad \dot{z} = g(z,t) + u$$

Fault diagnosis and fault tolerant control have been studied primarily on linear systems, but in the non-linear systems, the fault tolerant control is much more complicated and the presence of uncertainties in the systems makes the diagnosis more difficult. To overcome these difficulties, we derive the robust fault-detection measures to design robust control strategies using the Lyapunov direct method. When an actuator failure is detected, a Kalman Filter is used to compute the best estimate of the state. The Kalman Filter, in essence, is monitoring the redundant sensors and statistically setting the optimal gain based on the weighted average of the covariance matrix.

Robust Measures for Identifying Actuator Failure

The approach is to develop a stability/performance-based measure by which a faulty condition will be diagnosed if it causes stability problem or performance degradation. Specifically, the following criteria will be used:

$$L_m(z_m,t) \leq L_c(t) \text{ and } V_m(\hat{x},t) \leq V_c(t)$$

Where L(.) and V(.) are the Lyapunov functions. The $L_c(t)$ and $V_c(t)$ are defined by the differential equations:

$$\dot{L}_c = \frac{-1}{3}\gamma_6 \circ \gamma_5^{-1}(L_c) + 3^{\frac{1}{\beta}-1}\beta(1-\beta)^{\frac{1}{\beta}-1}(c_0 b_2 c_2)^{\frac{1}{\beta}} + 3^{\frac{\lambda}{1-\lambda}}(1-\lambda)\lambda^{\frac{\lambda}{1-\lambda}}[b_2(c_r + |u|)]^{\frac{\lambda}{1-\lambda}}$$

$$\dot{V}_c = \frac{-1}{3}\gamma_3 \circ \gamma_2^{-1}(V_c) + 3^{\frac{1}{\beta}-1}\beta(1-\beta)^{\frac{1}{\beta}-1}(c_0 b_1 c_1)^{\frac{1}{\beta}} + 3^{\frac{\lambda}{1-\lambda}}(1-\lambda)\lambda^{\frac{\lambda}{1-\lambda}}[b_2(c_r' + |z|)]^{\frac{\lambda}{1-\lambda}}$$

Simulation Example

To illustrate the fault tolerance robust control, the following dynamics of the satellite along with the actuator dynamics (a rate gyro) is considered:

$$\dot{\theta}_1 = \{(\frac{1}{I_y})[-3\omega_0^2(I_x - I_z)\sin\theta_1]\} - 6\theta_1 - 10\theta_2 \quad ; \quad \dot{\theta}_2 = -0.1\theta_2$$

$$\dot{\phi}_1 = \{(\frac{1}{I_x})[-4\omega_0^2(I_y - I_z)\sin\phi_1]\} - 6\phi_1 - 10\phi_2 + \frac{I_z}{I_x}\omega_0\psi_2 \quad ; \quad \dot{\phi}_2 = -0.5\phi_2$$

$$\dot{\psi}_1 = \{(\frac{1}{I_z})[-\omega_0^2(I_y - I_z)\sin\psi_1]\} - 6\psi_1 - 10\psi_2 + \omega_0\phi_2 \quad ; \quad \dot{\psi}_2 = -0.1\psi_2$$

In the cases we have considered, the output of the faulty actuator jumps from its current value to its maximum value and stays there indicating the worst type of fault for stability.
The uncertain dynamics are chosen to be
$\Delta f(x,v_x,t)=0.04\sin(\theta_1)+0.03\sin(2\theta_1)$,
$\Delta g(z,v_z,t)=0.0045\theta_2^2+0.01\cos(\theta_2)+c_r\sin(2\pi t)$.
Lyapunov functions are
$V(\theta_1,t) = 0.5[\theta_1^2 + \phi_1^2 + \psi_1^2]$ and
$L(\theta_2,t) = 0.5[\theta_2^2 + \phi_2^2 + \psi_2^2]$.
The design parameters that are extracted are
$b_1=2$, $b_2=2$, $c_0=0.06$, $c_r = 0.1$, $c_r' = 0$, $c_1=2$, $c_2=2$, $\lambda=0.5$, $\beta=0.25$, $\lambda_1=5$, $\lambda_2=2$, $\varepsilon_z=0.5$.
The robust controller parameters are $\varepsilon_r=0.8$, $\varepsilon_k=0.5$, $k_a=0.4$, $k_l=4$, $k_r=0$, $\tau=1$

In the simulations performed, there is an actuator failure and depending upon the sequence of the failure, the proposed robust control law is energized. Thresholds can be placed on uncertainties to automatically detect whether actuator failures have been detected and/or corrected which in turn makes it possible for the fault tolerant control to restore its operation and ensure system performance. Figure (6) shows the actual states of the system and also of the actuator and the estimated states of the system as well as the actuator. Figure (7) is another plot that shows the fault detected in the actuator at 0.5 sec and the recovery made at 0.55 second. Finally Figure (8) shows the robust control acting at 0.5 second as soon as the actuator 1 fails and recovers it at 0.55 second. During that brief period of 0.05 second, the robust control shifts to actuator (2) from actuator (1) so that the overall system is still stable. In this simulation, all the actuators (roll, pitch and yaw) are designed to fail at the same time. The robust fault tolerant controller is applied to all the actuators at the same time and the reconfiguration to the redundant actuators occurs at 0.55 seconds on all the three axes. Simulation results for only one axis is shown here.

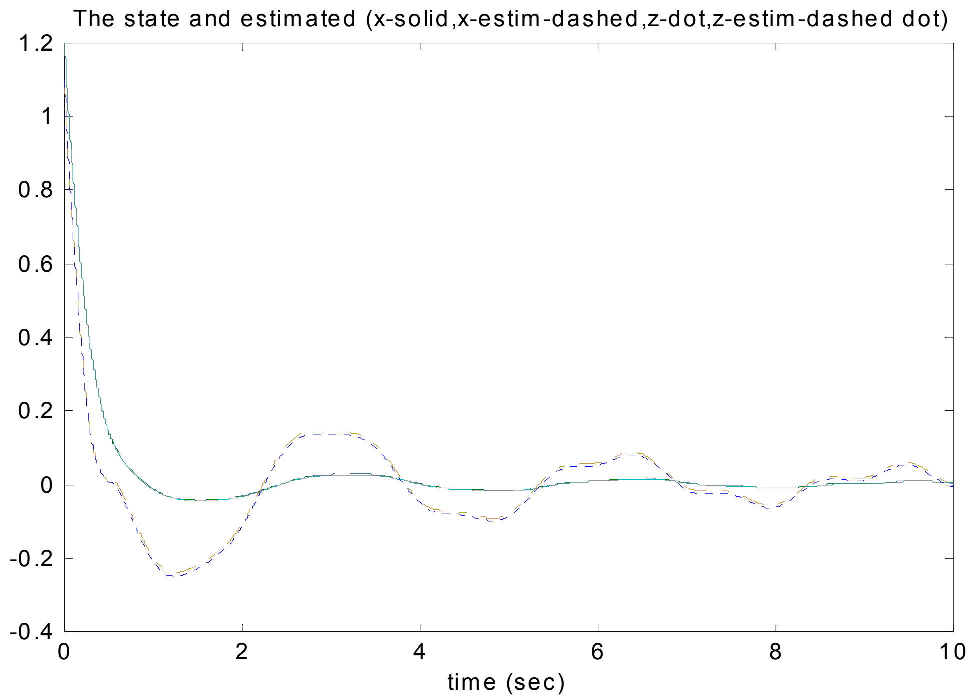

Fig (6): State Estimates $\hat{x}(t)$ and Z(t) (Pitch Axis)

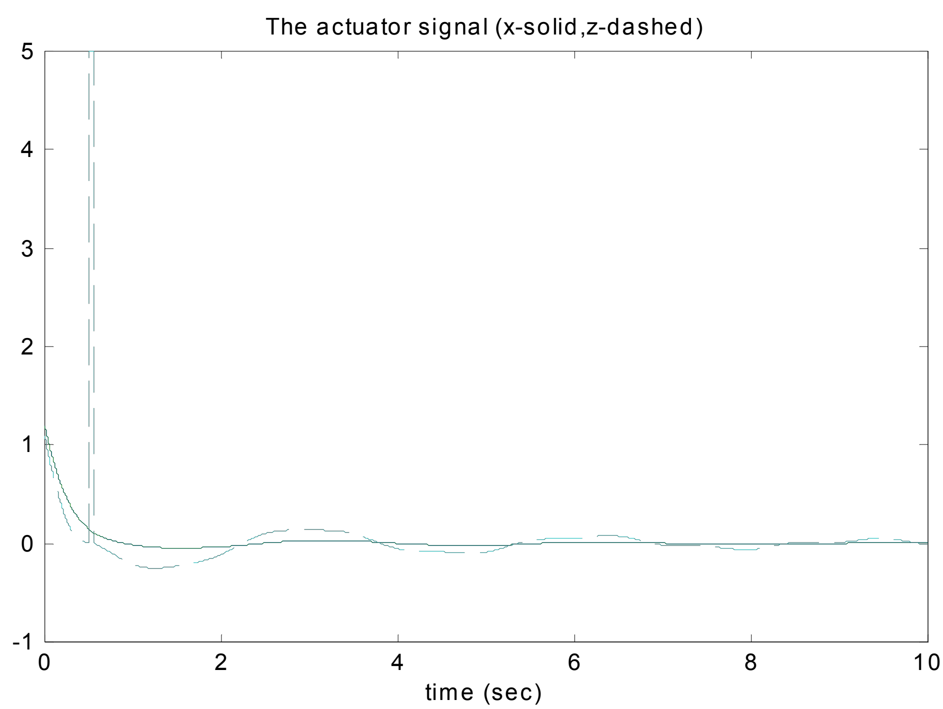

Fig. (7): Fault detected in actuator (1) at 0.5 sec, reconfigured to actuator (2) at 0.55 sec (Pitch Axis)

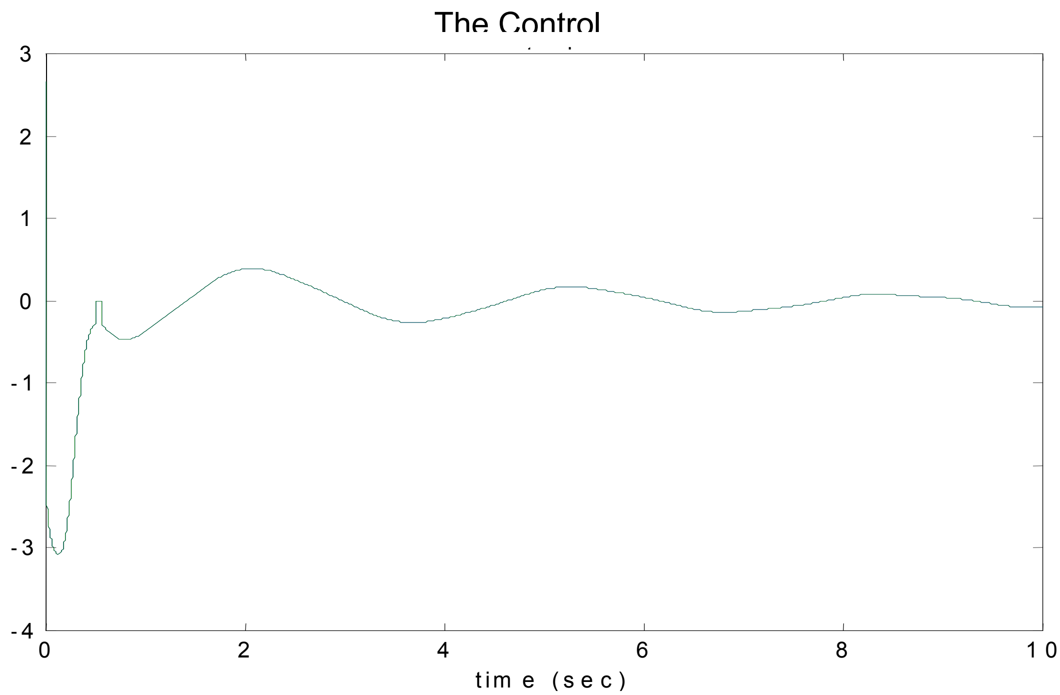

Fig (8): Fault tolerant robust control applied at 0.5 sec (Pitch Axis)

Conclusions

We have studied the application of fault tolerant robust control in non-linear systems with uncertainties. We may experience actuator failures in such systems and the proposed robust control is made fault tolerant by integrating robust controls that are designed under faulty conditions and have used robust algorithms capable of detecting faults. Also, the robust control has the capability to switch the actuator from the faulty one to the redundant actuator using these robust measures, robust control strategies and fault tolerant control; this control framework is therefore defined and synthesized using the Lyapunov's direct method. The fault tolerant concept is applied to the sensors by using a Kalman Filter. The Kalman filter weighs the information coming from multiple sensors and automatically weighs out faulty sensors and computes the best estimate from the remaining sensors.

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