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Parameter Estimation for Fault Diagnosis in Nonlinear Systems by ANFIS

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Abstract

This paper presents a fault diagnosis approach to detect and estimate components faults in satellite's attitude control systems (ACSs). The proposed solution provides a framework to detect, isolate, and estimate various faults in system components, using Adaptive Fuzzy Inference Systems Parameter Estimators (ANFISPEs) that are designed and based on parameterizations related to each class of fault. Each ANFISPE estimates the corresponding unknown Fault Parameter (FP) that is further used for fault detection, isolation and identification purposes. Simulation results reveal the effectiveness of the developed FDI scheme of an ACSs actuators of a 3-axis stabilized satellite even in presence of disturbances.

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Open access under [CC BY-NC-ND license](http://creativecommons.org/licenses/by-nc-nd/3.0/).*Keywords:* ANFIS, Fault Diagnosis, Nonlinear System, Parameters Estimation;

1. Introduction

Fault detection and isolation (FDI) of dynamical systems is used to assure system reliability and safety. FDI has obtained more and more attention in many areas such as nuclear systems, process control, and aerospace. The high reliability required in processes has created the necessity of early failures detection and diagnosis. In addition, the use of autonomous systems with minimum human interferences, inflates the importance of systematic FDI. Faults lead to the degradation of the process or to its performance, because of changes in physical characteristics. Existing FDI approaches are generally separated into

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model-based and model-free approaches. Model-based approaches are based on the mathematical model of the process. Such approaches include different methods as parameters estimation, state observation or parity equations. Model-free approaches are divided into approaches based on statistical analysis, expert systems, and neural networks. Many literatures have attempted to develop hybrid methods that combine both qualitative and quantitative methods [1]. This work presents a contribution on this way. It describes an innovative method that uses ANFIS estimators and includes it in a hybrid diagnosis system for failure detection.

The failures in the ACS of spacecraft can be caused by malfunctions in components, actuators, and sensors due to unexpected interference or gradual aging of system components. These failures could result in higher energy consumption, loss of control and equipment operating problems. With increasing emphasis placed these days on energy efficiency and equipment reliability, there is a need for the development of robust FDI tools that are capable of detecting and isolating any sensor, actuator or system component faults, so that remedial actions and recovery procedures could be taken as soon as possible [2].

In the present paper, a fault diagnosis approach to detect and estimate components faults ACSs is presented. The proposed solution provides a framework to detect, isolate, and estimate various faults in system components, using Adaptive Fuzzy Inference Systems Parameter Estimators (ANFISPEs). The reminder of the current paper is organized as follows: Section 2 reviews the principle scheme of hybrid fault diagnosis system. Section 3 highlights dynamic modeling of the reaction wheel actuators. Section 4 discusses simulation results. Conclusions are drawn in Section 5.

2. Hybrid Fault Diagnosis System using ANFIS Parameters Estimator

The proposed scheme for FDI, illustrated in the figure 1, is structured in 3 parts. The first part is composed of ANFIS parameter estimator’s bank that evaluate specific parameters according to input measurements and command signals. These parameters change when faulty behaviors occur. The second part is composed of nonlinear faulty models that work out the estimated output according to the parameter evaluation. The third part is an usual FDI block that detects and isolates faults.

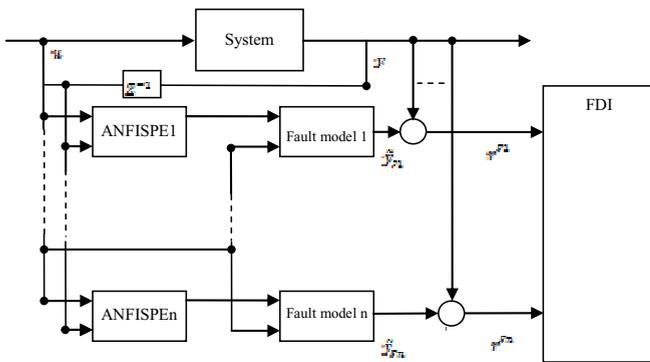


Fig.1 : FDI with ANFISPE

2.1. Faulty model design

In this section, we describe the nonlinear faulty system. It is modeled by the state space equation (1)

$$\begin{cases} \dot{x} = f(x, u, p) + d \\ y = h(x) \end{cases} \quad (1)$$

where x is the state vector, f is the state function, h is the output function and d represents the system disturbances that are assumed to be a bounded signal.

Following the work of Iserman [3], system component faults are reflected in the physical system parameters degeneration. Hence faults occurrence is represented by changes in the fault parameter vector p of the system. When the system is healthy, p takes the nominal value of the physical parameters. In faulty cases, the value of p depends on the way that the faults disturb the system. We assume in this paper that faults affect the physical parameters in additive form. The faulty model given by equation (1) is used to transform the problem of nonlinear fault diagnosis in an on-line nonlinear parameter estimation problem, for which unknown fault parameters are estimated using system inputs and measurements.

2.2. Fault detection and diagnosis with ANFISPEs

The proposed fault detection scheme is achieved by first estimating the fault parameter vector using system input-output measurements. For fault isolation, we propose to use a bank of parameter estimators where each estimator is designed for a single parameter fault as described below. Consider the general parameter fault model given in equation (1) with n fault parameters (length of system). We extract n single parameter model from the model (1). The bank of n parameter estimators is designed on each separate fault model given by equation (2), where the i th parameter estimator will essentially estimate the i th fault parameter.

$$\begin{cases} \dot{x} = f(x, u, p^i) + d \\ y = h(x) \end{cases} \quad i = 1, n \quad (2)$$

For nonlinear systems, the parameter estimation is commonly achieved though the Extended Kalman Filter (EKF) [4] used as a standard technique for recursive estimation. Such method suffers from suboptimal performance and sometimes model divergence due to errors introduced by first-order approximation of the nonlinear dynamics.

To overcome this limitation in estimating the parameters of a nonlinear system with disturbances, we integrate the ANFIS with the nonlinear dynamical model of the system. The estimation of parameters is then based on a minimization of instantaneous output estimation error. The choice of ANFIS is motivated by their good approximation properties for nonlinear systems.

The bank of ANFISPEs is composed of two subsystems; the nonlinear faults models given by (2) employed for state estimation and the ANFISPE used for adaptively approximate the nonlinear fault parameter estimation function. Therefore, at each time instant, each ANFISPE in the bank should perform two calculations. The first one is the estimation of the p^i element in the faulty parameter vector, that represent the estimation of i th fault parameter using the previous instant value of inputs-outputs measurements. The second calculation, is the state estimation based on the fault parameter estimation using the model (3) where \hat{x}^i is the state estimation using the i th FP estimation (\hat{p}^i) in the proposed bank and h is the measurement function. This bank of states estimation will be employed for the generation of the residues signal vector, used for the fault isolation.

$$\begin{cases} \dot{\tilde{x}} = f(\tilde{x}, u, p^i) + d \\ \tilde{y} = h(\tilde{x}) \end{cases} \quad i = 1, ..n \quad (3)$$

To formulate the isolation procedure, the residual vectors shall be introduced as:

$$r^i = y - \tilde{y}^i \quad i = 1, ..n \quad (4)$$

When a fault is occurred, the estimation of each ANFISPE bloc diverges from the correspondent parameter's nominal value and we can't decide which parameter is infected from the bank of ANFISPEs.

To solve this problem, the proposed method is based on the injection of each estimate parameter into the system's mathematical model (hybrid) and then we compare their states estimation with the system measurement. Thereafter, we compose the signature table to assume the fault isolation step. From the obtained combinations, we can decide the fault locate, with the condition that only one fault is occurred.

3. Dynamic Modeling of Reaction Wheel Actuators

To judge the performance of this fault diagnosis scheme, we consider the problem of detection, isolation and estimation of faults in Reaction Wheel actuators components, in a satellites Attitude Control System (ACS). Developing an accurate and efficient fault diagnosis in reaction wheel components become a challenging problem due to the inherent nonlinearity of reaction wheel and satellite attitude dynamics and presence of disturbances exerting on satellite body. The selection of the reaction wheel platform is motivated by stringent requirements on satellites to operate autonomously in presence of faults in sensors, actuators and components. Moreover, the large number of reported publications [5, 6, 7] on this topic over the recent years provides further evidence of the importance of the application. To assess the performance of our proposed FDI scheme in a near-realistic environment, we use the MATLAB-Simulink tools to develop an accurate simulation model of a 3-axis stabilized satellite. The simulation model consists of the well-known nonlinear satellite attitude dynamics, a high fidelity nonlinear model of the reaction wheel [8] and decentralized PID controllers that stabilize the closed-loop system so that the control input signals and the state vector remain bounded prior to and after the occurrence of a fault. Furthermore, nonlinear Euler transformations are applied to transform the satellite angular velocities to Euler angle rates, namely roll, pitch, and yaw. The high-fidelity model of a reaction wheel (RW) incorporates all the nonlinearities as well as internal disturbances that are present in a real RW actuator [8]. The closed-form nonlinear state-space representation of a reaction wheel model may be expressed as follows:

$$\begin{bmatrix} \dot{I}_m \\ \dot{\omega} \end{bmatrix} = \begin{bmatrix} G_d \omega_d [\psi_1(I_{bus}, \omega) - \psi_3(\omega)] - \omega_d I_m \\ \frac{1}{j} [K_t I_m (1 + B\phi_1(\omega, t)) - \tau_c \psi_2(\omega) - \tau_v \omega + C\phi_2(\omega, t)] \end{bmatrix} + \begin{bmatrix} G_d \omega_d \\ 0 \end{bmatrix} V_{com} \quad (5)$$

Where I_m (the current) and ω (the angular velocity) are the measured states of Reaction Wheel, V_{Com} is the input command voltage signal of RW, generated by the PID controller in the closed-loop attitude control system. Ψ_1, Ψ_2, Ψ_3 are nonlinear functions modeling EMF torque limiting, coulomb friction, and speed limiter subsystems, respectively. I_{bus} a highly nonlinear function of states and the bus voltage V_{bus} , and ϕ_1, ϕ_2 are representing torque ripple and cogging respectively. The objective is to detect, isolate and estimate the severity of possible faults in RW components using Reaction wheel signals. Thus, measurements of RW current and angular velocity together with the wheel command voltage comprise the input vector of the ANFISPE. Our objective is to detect, isolate and estimate the faults in two components of reaction wheel, bus voltage V_{bus} , and motor gain, k_t , both have been identified as major sources of faulty behavior in reaction wheels. It should be accentuated. The corresponding faulty behavior can be represented as an additional signal in the form of a single-parameter fault model for each physical parameter (single fault case) given in the following equation [8].

4. Simulation Results

The simulations have been performed by using nonlinear models of the reaction wheel and the attitude dynamics of a 3-axis stabilized satellite. The closed-loop satellite attitude control system was stabilized

using three decentralized PID controllers. The simulation data are obtained from the closed-loop ACS of satellite simulation, with a run-time of 2000s. Many reference steps are commanded to the satellite in the Pitch channel. The satellite body is under a random torque disturbance action with the maximum norm of 10⁻⁴ N·m. The nonlinear model in the healthy mode ($k_t = 0.029$, $V_{bus} = 24V$, the parameters of the reaction wheel are adopted from Bialke [6] for the ITHACO’s standard type ‘A’ reaction wheels. In this paper, we suppose that the system submit to a series of intermittent faults with different severities injected in motor gain, k_t , over different time intervals. The following equation represents the motor gain behavior:

$$k_t = \begin{cases} k_t & 0 \leq t < 0380 \\ k_t + 0.007 & 0380 \leq t < 0770 \\ k_t - 0.015 & 0770 \leq t < 1690 \\ k_t - 0.007 & 1690 \leq t < 2000 \end{cases} \quad (6)$$

The results of our simulation are depicted in Figure 3 more specifically, it show a very close match between the effective and the estimated motor gain. A good estimation of the RW current and angular velocity is shown in the figure 4 (a) and (b), respectively. We note the significant impact of the introduced motor gain faults on the reaction wheel states. Therefore, a structural change occurs in the system. Such structural change can be also observed in the behavioral change of the RW current signal. It can be observed that in presence of faults in motor gain, differ his nominal value and converges fast to its true values, It should also be emphasized that even though there is a structural change in RW due to presence of the fault, our proposed scheme is still able to isolate the injected fault and accurately estimate its severity. In figure 5a and 5b, the divergence in the estimation of V_{bus} produces a wrong estimation of angular velocity and motor current observed from the V_{bus} faulty model ANFISPE Estimator, and we can isolate the fault after the construction of the signature table from the figure 4a,b and 5a,b.

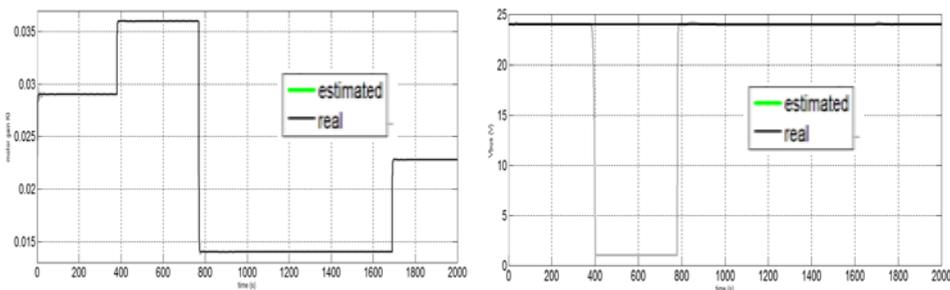


Fig. 3 k_t failures: (a) k_t estimation (b) V_{bus} estimation.

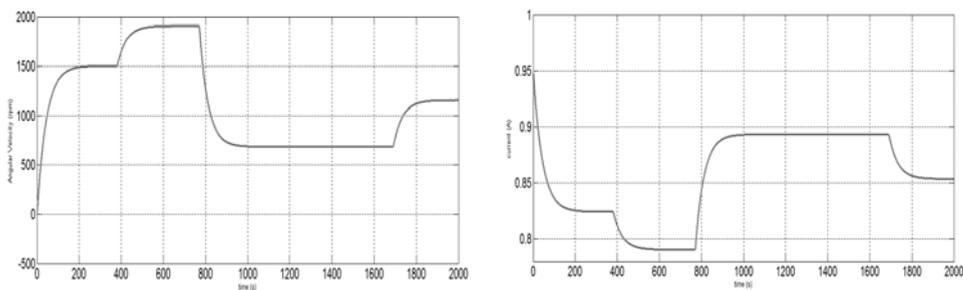


Fig. 4 k_t failures: (a) Angular velocity estimation (b) Current I_m estimation (k_t faulty model ANFISPE Estimator).

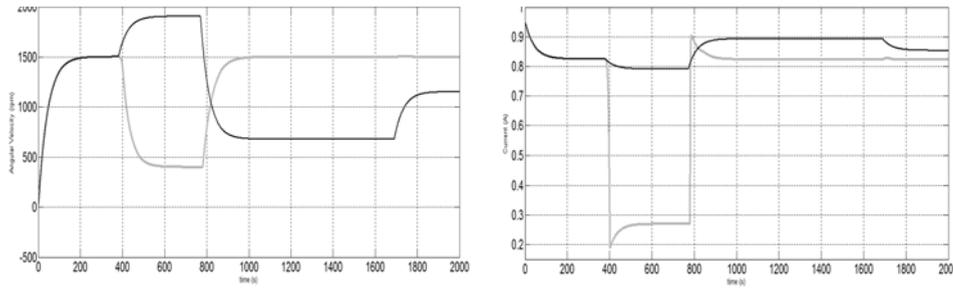


Fig. 5 kt failures: (a) Angular velocity estimation (b) Current I_m estimation (V_{bus} faulty model ANFISPE Estimator).

5. Conclusion

In this paper, a new hybrid solution based on the adaptive neural fuzzy inference system (ANFIS) is proposed and presented to achieve the objectives of fault detection, isolation in a satellite's ACS nonlinear system with the states measurement. This approach is based on two ANFIS parameter estimators where each fault parameter is representative of a specific kind of system component fault. Such method allows fault isolation with minimum residual signal processing. Simulation results show the effectiveness of this method in estimation of the effective value of physical parameters, of one type of component faults in reaction wheel actuators of a satellite's attitude control system. Consequently, in fault diagnosis and estimation of this component faults inferential physical parameters observer is a very effective tool to detect the malfunction of nonlinear satellite's ACS.

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