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Fault Detection and Isolation Applied to a Ship Propulsion Benchmark

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Abstract:
Abstract: This paper describes a fault detection and isolation (FDI) scheme performed on the benchmark problem of a ship propulsion system. The model used for the ship propulsion system is nonlinear, for which two types of additive sensor faults, an additive incipient fault, and a multiplicative parametric fault are simulated. The estimation of the fault severity is accomplished by using an adaptive two-stage extended Kalman filter. A set of statistical detection variables is formed from the residuals of the bias and measurement estimates of the filter. These variables are then used in a threshold based hypothesis test to declare the occurrence of a fault and through a binary logic filter to identify the fault type. The simulation results showed that the developed fault detection and isolation scheme fulfilled some of the benchmark requirements reasonably well in the face of some prescribed perturbations in the model and disturbances of external signals.

Keywords:
Keywords: Fault detection and isolation, nonlinear adaptive two-stage Kalman filter, ship propulsion benchmark.

1. INTRODUCTION

The ship propulsion benchmark (Izadi-Zamanabadi and Blanke, 1999) is a complicated and realistic test bed for fault diagnosis and fault-tolerant control. It presents a realistic simulation environment of a ship propulsion system under faults, disturbances and random noises. In the benchmark, not only additive abrupt faults are present, a multiplicative fault and an incipient fault are considered as well. Since the publication of the benchmark, several approaches have been developed to solve the benchmark problem from fault diagnosis and/or fault-tolerant control aspects. Blanke *et al.* (1998) designed an adaptive, nonlinear observer for fault estimation of engine related faults in shaft speed sensor and engine gain. Research results from several groups were summarized in a book chapter (Izadi-Zamanabadi *et al.*, 2000). Edwards and Spurgeon (2000) extended their results by using a dedicated sliding mode observer for fault detection on the benchmark. A sensor fault masking scheme of the benchmark is proposed in (Wu *et al.*, 2006). A fault-tolerant control scheme has been developed in (Bonivento *et al.*, 2003).

In this paper, all faults entering the system are manipulated into additive random biases to the nonlinear ship propulsion system model. This enables us to approach fault diagnosis as a model based bias estimation problem. In this regard the utility of an earlier solution to a linear problem obtained by the authors (Wu *et al.*, 2000) is expanded to solve the nonlinear benchmark problem. This estimator is further developed into a two-stage adaptive extended Kalman filter (EKF). Beyond monitoring the operation of a system, on-line diagnosis also provides basis for decisions on fault accommodation. Therefore, it is important that diagnostic outcomes are tested for their statistical significance before a drastic action is taken, such as the reconfiguration of a control law. These tests are part of an FDI (fault detection and isolation) process. In this work, a set of statistically significant detection variables is constructed out of a set of selected residuals of the two-stage adaptive EKF. Some of the residuals represent the estimated fault magnitudes. Others are measurement residuals from which the interested sensor faults are directly observed. A fault occurrence is reported whenever a detection variable exceeds a set of threshold levels. The selection of the thresholds for these detection variables is dictated by the attempt to achieve not only a low probability of missed detection and a low probability of false alarm, but also a low probability of false isolation as well. Immediately following the declaration of a fault occurrence is a least squares linear regression analysis that confirms whether the detected fault is of an incipient or of an abrupt type, which is then followed by a fault isolation logic. The isolation logic depends on a highly compressed knowledge base obtained via extensive off-line analysis.

The paper is organized as follows. In Section 2, the ship propulsion benchmark model and fault scenario are briefly described. An adaptive nonlinear two-stage Kalman filter is presented in Section 3 which is based on the previous works in (Wu *et al.*, 2000). The developed filter can effectively estimate both state and fault parameters that undergo both abrupt and slow (incipient) changes. In Section 4, our fault detection and isolation approaches are presented. The simulation results for the benchmark test scenarios are reported in Section 5. Section 6 gives a brief overall evaluation on our approach to solving the benchmark problem.

2. THE SHIP PROPULSION MODEL

2.1 Brief Description of the Benchmark Model

The main subsystems of the benchmark system are: (1) propeller pitch angle control loop; (2) governor; (3) diesel engine; (4) propeller characteristics; (5) ship speed dynamics and (6) coordinated control level. For more detail of the benchmark model, please refer to (Izadi-Zamanabadi and Blanke, 1999).

Propeller pitch angle control system The pitch angle control system model is described by the following equations.

$$\begin{aligned} \theta_m &= \theta + \nu_\theta + \Delta\theta, \\ u_{\dot\theta} &= k_t(\theta_{ref} - \theta_m), \\ \dot\theta &= \max(\dot\theta_{\min}, \min(u_{\dot\theta}, \dot\theta_{\max})) + \Delta\dot\theta_{inc}, \\ \theta &= \max(\theta_{\min}, \min(\theta, \theta_{\max})), \end{aligned} \tag{1}$$

where θ_m is the measured pitch angle, $\dot\theta_{\min}$ and $\dot\theta_{\max}$ are the rate limits, and $\theta_{\min}$ and $\theta_{\max}$ are the limits for propeller blade travel, $\Delta\theta$ denotes the pitch sensor fault, $\Delta\dot\theta_{inc}$ the incipient leakage fault due to the leak in the hydraulic system, and ν_θ is the measurement noise of θ.

Governor The following equations describe the dynamics of the governor.

$$\begin{aligned} n_m &= n + \nu_n + \Delta n, \\ \dot Y_{PI} &= \tfrac{k_r}{\tau_i}[(n_{ref} - n_m) + \tau_i \tfrac{d(n_{ref}-n_m)}{dt}], \\ Y_{PIb} &= \min(\max(Y_{PI}, Y_{lb}), Y_{ub}), \\ Y_{\max} &= \begin{cases} 1 & \text{if } n_m \ge 0.8 n_{\max,a} \\ \dfrac{1.5}{n_{\max,a}} n - 0.2 & \text{if } 0.4 n_{\max,a} < n_m < 0.8 n_{\max,a} \\ 0.4 & \text{if } n_m \le 0.4 n_{\max,a}, \end{cases} \\ Y &= \max(0, \min(Y_{PIb}, Y_{\max})), \\ Y_m &= \min(\max(Y + \nu_Y, Y_{lb}), Y_{ub}), \end{aligned} \tag{2}$$

where Y_m is the measured fuel index, Δn denotes the shaft speed fault, Y_{lb} and Y_{ub} are the lower and the upper limits for fuel index, k_r is the governor gain, and τ_i is the time constant in the controller of the governor. $Y_{\max}$ is the limitation on the fuel index.

Diesel engine dynamics The diesel engine dynamics includes two parts. The first part describes the relation between generated torque and the fuel index, which is given by

$$\dot Q_{eng} = \frac{1}{\tau_c}[(1 + \Delta k_y) k_y Y_m - Q_{eng}]. \tag{3}$$

The second part describes the relation between the applied torques and the shaft speed, which is given by

$$I_m \dot n = Q_{eng} - Q_{prop} - Q_f. \tag{4}$$

In Eqs. (3) and (4) Q_{eng} is the torque developed by the diesel engine, Q_{prop} is the developed torque from the propeller dynamics, Q_f is the unknown friction torque, k_y is the gain constant of the diesel engine, Δk_y denotes the percentage gain reduction of k_y, τ_c is the time constant.

Propeller characteristics The propeller characteristics are presented in the benchmark by two tables of real data. The first table characterizes the developed propeller torque Q_{prop}, and the second table characterizes the produced propeller thrust T_{prop}. In the benchmark simulation, Q_{prop} and T_{prop} are calculated by the interpolation of the two tables of real data measured under sea operation. They are highly nonlinear functions of pitch angle θ, shaft speed n, and ship speed U. The nonlinearities can be approximated by the following bilinear relations

$$Q_{prop} = Q_0 |n| n + Q_{|n|n} |\theta| |n| n + Q_{|n|V_a} \theta |n| V_a, \tag{5}$$
$$T_{prop} = T_{|n|n} \theta |n| n + T_{|n|V_a} |n| V_a, \tag{6}$$

where $T_{|n|n}, T_{|n|V_a}, Q_{|n|n}$ and $Q_{|n|V_a}$ are complex functions of the pitch angle θ. V_a is the advance speed. The relation between the advance speed and the ship speed U can be described by wake fraction number w in the following equation.

$$V_a = (1 - w)U. \tag{7}$$

Ship speed dynamics The following nonlinear differential equations describe the ship speed dynamics:

$$m\dot U = (1 - t_T) T_{prop} - R_U - T_{ext}, \tag{8}$$
$$U_m = U + \nu_U, \tag{9}$$

where the hull resistance R_U describes the resistance of the ship in the water, which is also given by a table of real data. The magnitude of hull resistance is dependent on the velocity of the ship and its loading condition. ν_U is the measurement noise of the ship speed; m is the mass of the ship.

Equations (1)-(9) constitute the basic model that will be used for the diagnosis purpose in this paper.

2.2 Discrete nonlinear state-space model

The benchmark ship propulsion system model can be described in the following state-space form

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \mathbf{f}[\mathbf{x}(t), \mathbf{u}(t), \mathbf{b}(t), \mathbf{d}(t)] + \Gamma(t)\mathbf{w}^x(t), \\ \mathbf{z}(t) &= \mathbf{h}[\mathbf{x}(t), \mathbf{b}(t)] + \mathbf{v}(t), \end{aligned} \tag{10}$$

where $\mathbf{x} = [\boldsymbol\theta \;\; n \;\; U \;\; Q_{eng}]^T$ is the state vector, $\mathbf{u} = [\boldsymbol\theta_{ref} \;\; Y_m]^T$ is the control input vector, $\mathbf{z} = [\boldsymbol\theta_m \;\; n_m \;\; U_m]^T$ is the measurement vector, $\mathbf{b} = [\Delta\theta \;\; \Delta n \;\; \Delta\dot\theta_{inc} \;\; \Delta k_y]^T$ is the fault parameter vector, and $\mathbf{d} = [Q_f \;\; T_{ext}]^T$ is the unknown disturbances vector. The system and measurement noise vectors are: $\mathbf{w}^x = [\nu_\theta \;\; 0 \;\; 0 \;\; 0]^T$, and $\mathbf{v} = [\nu_\theta \;\; \nu_n \;\; \nu_U]^T$.

The nonlinear functions in (10) are

$$\mathbf{f}[.] = \begin{bmatrix} \max(\dot\theta_{\min}, \min\{k_t[\theta_{ref} - (\theta + \nu_\theta + \Delta\theta)], \dot\theta_{\max}\}) + \Delta\dot\theta_{inc} \\ \dfrac{1}{I_m}[Q_{eng} - Q_{prop} - Q_f] \\ \dfrac{1}{m}[(1 - t_T)T_{prop} - R_U - T_{ext}] \\ \dfrac{1}{\tau_c}[(1 + \Delta k_y)k_y Y_m - Q_{eng}] \end{bmatrix}$$

and

$$\mathbf{h}[\mathbf{x}(t), \mathbf{b}(t)] = \begin{bmatrix} \theta + \nu_\theta + \Delta\theta \\ n + \nu_n + \Delta n \\ U + \nu_U \end{bmatrix}. \tag{11}$$

It can be seen that only pitch angle fault, $\Delta\theta$, and shaft speed fault, Δn, can be directly observed. The incipient fault, $\Delta\dot\theta_{inc}$, and multiplicative fault, Δk_y, are not directly observed.

By using the Euler approximation with sample period T, where $T = 1$ *sec*, the discretized version of the above nonlinear state-space model is

$$\begin{bmatrix} \theta(k^+) \\ n(k^+) \\ U(k^+) \\ Q_{eng}(k^+) \end{bmatrix} = \begin{bmatrix} (1-k_t)\theta(k) \\ n(k) + \frac{T}{I_m} Q_{eng}[\mathbf{x}(k),k] - \frac{T}{I_m} Q_{prop}[\mathbf{x}(k),k] \\ U(k) + \frac{(1-t_T)T}{m} T_{prop}[\mathbf{x}(k),k] - \frac{T}{m} R_U[\mathbf{x}(k),k] \\ (1-\frac{T}{\tau_c}) Q_{eng}[\mathbf{x}(k),k] \end{bmatrix} \tag{12}$$

$$+ \begin{bmatrix} k_t & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & \frac{T}{\tau_c} k_y \end{bmatrix} \begin{bmatrix} \theta_{ref}(k) \\ Y_m(k) \end{bmatrix} + \begin{bmatrix} -k_t & 0 & T & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{k_y T}{\tau_c} Y_m(k) \end{bmatrix} \begin{bmatrix} \Delta\theta(k) \\ \Delta n(k) \\ \Delta\dot{\theta}_{inc}(k) \\ \Delta k_y(k) \end{bmatrix}$$

$$+ \begin{bmatrix} 0 & 0 \\ -\frac{T}{I_m} & 0 \\ 0 & -\frac{T}{m} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} Q_f(k) \\ T_{ext}(k) \end{bmatrix} + \begin{bmatrix} -k_t T & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \nu_\theta(k) \\ 0 \\ 0 \\ 0 \end{bmatrix},$$

$$\begin{bmatrix} \theta_m(k^+) \\ n_m(k^+) \\ U_m(k^+) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \theta(k^+) \\ n(k^+) \\ U(k^+) \\ Q_{eng}(k^+) \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta\theta(k^+) \\ \Delta n(k^+) \\ \Delta\dot{\theta}_{inc}(k^+) \\ \Delta k_y(k^+) \end{bmatrix} + \begin{bmatrix} \nu_\theta(k^+) \\ \nu_n(k^+) \\ \nu_U(k^+) \end{bmatrix}$$

or a more compact vector form, where $k+1$ is denoted by k^+ for simplicity.

$$\begin{aligned} \mathbf{x}(k^+) &= \mathbf{f}(\mathbf{x},k) + G(k)\mathbf{u}(k) + B_1(k)\mathbf{b}(k) + D(k)\mathbf{d}(k) + \Gamma(k)\mathbf{w}^x(k) \\ \mathbf{z}(k^+) &= \mathbf{h}(\mathbf{x},k^+) + B_2(k^+)\mathbf{b}(k^+) + \mathbf{v}(k^+). \end{aligned} \tag{13}$$

3. AN ADAPTIVE TWO-STAGE EXTENDED KALMAN FILTERING ALGORITHM

In this section, a nonlinear adaptive two-stage Kalman filter is presented. This filter is the extended version of a linear two-stage adaptive Kalman filter developed in (Wu *et al.*, 2000) for estimating the amount of actuator effectiveness reduction.

Consider a bias augmented nonlinear discrete time model of the form

$$\begin{aligned} \mathbf{x}(k^+) &= \mathbf{f}(\mathbf{x}(k)) + G(k)\mathbf{u}(k) + B_1(k)\mathbf{b}(k) + \mathbf{w}^x(k), \\ \mathbf{b}(k^+) &= \mathbf{b}(k) + \mathbf{w}^b(k), \\ \mathbf{y}(k^+) &= \mathbf{h}(\mathbf{x}(k^+)) + B_2(k^+)\mathbf{b}(k^+) + \mathbf{v}(k^+). \end{aligned} \tag{14}$$

where $\mathbf{x}(k) \in R^n$, $\mathbf{b}(k) \in R^q$, $\mathbf{u}(k) \in R^l$ and $\mathbf{y}(k^+) \in R^m$ are the state, bias, control input and output variables, respectively. $\mathbf{w}^x(k)$, $\mathbf{w}^b(k)$ and $\mathbf{v}(k^+)$ denote the white noise sequences of uncorrelated Gaussian random vectors with zero means and covariance matrices $Q^x(k) > 0$, $Q^b(k) > 0$ and $R(k^+) > 0$, respectively. The initial state $\mathbf{x}(0)$ and bias $\mathbf{b}(0)$ are specified as random Gaussian vectors with mean $\bar{\mathbf{x}}_0$ and covariance $\tilde{P}_0^x$, and mean $\bar{\mathbf{b}}_0$ and covariance P_0^b, respectively. The initial state $\mathbf{x}(0)$ and bias $\mathbf{b}(0)$ are assumed to be uncorrelated with the noise processes $\mathbf{w}^x(k)$, $\mathbf{w}^b(k)$, and $\mathbf{v}(k^+)$.

Following the derivation of a two-stage Kalman filter algorithm (Keller and Darouach, 1997) and the extended Kalman filter, the two-stage extended Kalman filter for system (14) can be obtained and given as follows.

Bias-free state estimator.

$$\tilde{\mathbf{x}}(k^+|k) = \mathbf{f}[\tilde{\mathbf{x}}(k|k)] + G(k)\mathbf{u}(k) + [M(k) - V(k^+|k)]\hat{\mathbf{b}}(k|k), \tag{15}$$

$$\begin{aligned} \tilde{P}^x(k^+|k) &= F[\tilde{\mathbf{x}}(k|k),k]\tilde{P}^x(k|k)F^T[\tilde{\mathbf{x}}(k|k),k] + Q^x(k) \\ &\quad + M(k)P^b(k|k)M^T(k) - V(k^+|k)P^b(k^+|k)V^T(k^+|k), \end{aligned} \tag{16}$$

$$\tilde{\mathbf{x}}(k^+|k^+) = \tilde{\mathbf{x}}(k^+|k) + \tilde{K}^x(k^+)[\mathbf{y}(k^+) - \mathbf{h}(\tilde{\mathbf{x}}(k^+|k))], \tag{17}$$

$$\tilde{K}^x(k^+) = \tilde{P}^x(k^+|k)H^T(k^+)[H(k^+)\tilde{P}^x(k^+|k)H^T(k^+) + R(k^+)]^{-1},$$

$$\tilde{P}^x(k^+|k^+) = [I - \tilde{K}^x(k^+)H(k^+))\tilde{P}^x(k^+|k), \tag{18}$$

where the filter residual vector and its covariance are given as

$$\tilde{\mathbf{r}}(k^+) = \mathbf{y}(k^+) - \mathbf{h}(\tilde{\mathbf{x}}(k^+|k)), \tag{19}$$

$$\tilde{S}(k^+) = H(k^+)\tilde{P}^x(k^+|k)H^T(k^+) + R(k^+). \tag{20}$$

The Jacobians in the Taylor series expansion for nonlinear functions $\mathbf{f}$ and $\mathbf{h}$ are

$$F[\tilde{\mathbf{x}}(k|k),k] = \left.\frac{\partial \mathbf{f}}{\partial \mathbf{x}}\right|_{\mathbf{x}=\tilde{\mathbf{x}}(k|k)}, \quad H(k^+) = \left.\frac{\partial \mathbf{h}}{\partial \mathbf{x}}\right|_{\mathbf{x}=\tilde{\mathbf{x}}(k^+|k)}.$$

Bias estimator.

$$\hat{\mathbf{b}}(k^+|k) = \hat{\mathbf{b}}(k|k), \tag{21}$$

$$P^b(k^+|k) = P^b(k|k) + Q^b(k), \tag{22}$$

$$\hat{\mathbf{b}}(k^+|k^+) = \hat{\mathbf{b}}(k^+|k) + K^b(k^+)[\tilde{\mathbf{r}}(k^+) - N(k^+|k)\hat{\mathbf{b}}(k|k)], \tag{23}$$

$$\begin{aligned} K^b(k^+) &= P^b(k^+|k)N^T(k^+|k)[N(k^+|k)P^b(k^+|k)N^T(k^+|k) \\ &\quad + \tilde{S}(k^+)]^{-1} \end{aligned} \tag{24}$$

$$P^b(k^+|k^+) = [I - K^b(k^+)N(k^+|k)]P^b(k^+|k). \tag{25}$$

Coupling equations.

$$M(k) = F[\tilde{\mathbf{x}}(k|k),k]V(k|k) + B_1(k), \tag{26}$$

$$V(k^+|k) = M(k)P^b(k|k)[P^b(k^+|k)]^{-1}, \tag{27}$$

$$N(k^+|k) = H(k^+)V(k^+|k) + B_2(k^+), \tag{28}$$

$$V(k^+|k^+) = V(k^+|k) - \tilde{K}^x(k^+)N(k^+|k). \tag{29}$$

Compensated state and error covariance estimates.

$$\hat{\mathbf{x}}(k^+|k^+) = \tilde{\mathbf{x}}(k^+|k^+) + V(k^+|k^+)\hat{\mathbf{b}}(k^+|k^+), \tag{30}$$

$$P(k^+|k^+) = \tilde{P}^x(k^+|k^+) + V(k^+|k^+)P^b(k^+|k^+)V^T(k^+|k^+) \tag{31}$$

To make the two-stage filter algorithm more responsive to the changes of bias parameters which model the faults, forgetting factors are introduced into the bias covariance equation (22)

$$P^b(k^+|k) = \sum_{i=1}^{p} \frac{\alpha_i(k|k)}{\lambda_i(k)} e_i(k)e_i^T(k) + Q^b(k), 0 < \lambda_i(k) \le 1. \tag{32}$$

The forgetting factor $\lambda_i(k)$ can be chosen as a decreasing function of the amount of information received in the direction $e_i(k)$. Since eigenvalue $\alpha_i(k|k)$ of $P^b(k|k)$ is a measure of the uncertainty in the direction of $e_i(k)$, a choice of forgetting factor $\lambda_i(k)$ can be

$$\lambda_i(k) = \begin{cases} 1, & \alpha_i(k|k) > \alpha_{\max}; \\ \alpha_i(k|k)\left[\alpha_{\min} + \frac{\alpha_{\max} - \alpha_{\min}}{\alpha_{\max}}\alpha_i(k|k)\right]^{-1}, & \alpha_i(k|k) \le \alpha_{\max}. \end{cases}$$

4. FAULT DETECTION AND ISOLATION SCHEME

4.1 Fault Detection

Detection based on statistical hypothesis test The statistical test process is divided into two phases. The first phase determines the statistical quantities of the normal operation, such as mean values and variances. The second phase determines the statistical quantities of the abnormal operation. By defining an appropriate statistical detection variable to accentuate the deviation in the statistical quantities from their normal values, the detection of a change can be achieved.

Phase I. Under the assumption that selected residuals vector from the estimated fault parameters and the residuals from the output estimates obey a Gaussian distribution at normal (no–fault) condition, we can define

$$\hat{\boldsymbol{\gamma}}(k) \sim \mathcal{N}(\bar{\boldsymbol{\mu}}_{\boldsymbol{\gamma}^0}, \boldsymbol{\sigma}^2_{\boldsymbol{\gamma}^0}), \tag{33}$$

where $\hat{\boldsymbol{\gamma}}(k) \in R^p$ denotes the chosen residuals vector from the estimated fault parameters and the measurement residuals of the filter. $\bar{\boldsymbol{\mu}}_{\boldsymbol{\gamma}^0}$ denotes the mean value of $\hat{\boldsymbol{\gamma}}(k)$, $\boldsymbol{\sigma}^2_{\hat{\boldsymbol{\gamma}}^0}$ denotes the associated variance. Then, these values can be determined based on the knowledge of statistical characteristics of system noises and parameters. When the no–fault mean and variance are not known, they can be estimated, for $i = 1, ..., p$, $k = 1, ..., N_1$, using

$$\bar{\mu}_{\hat{\gamma}_i^0}(k) = \frac{1}{k}\sum_{j=1}^{k} \hat{\gamma}_i(j), \tag{34}$$

$$\sigma^2_{\hat{\gamma}_i^0}(k) = \frac{1}{k-1}\sum_{j=1}^{k}[\hat{\gamma}_i(j) - \bar{\mu}_{\hat{\gamma}_i^0}(k)]^2, \tag{35}$$

Sample size N_1 is chosen to ensure a sufficient accuracy in the statistics.

Phase II. Define the following moving data window based statistical quantities

$$\bar{\mu}_{\hat{\gamma}_i}(k) = \frac{1}{N_2}\sum_{j=k-N_2+1}^{k} \hat{\gamma}_i(j) \tag{36}$$

$$\sigma^2_{\hat{\gamma}_i I}(k) = \frac{1}{N_2-1}\sum_{j=k-N_2+1}^{k} [\hat{\gamma}_i(j) - \bar{\mu}_{\hat{\gamma}_i^0}]^2 \tag{37}$$

$$\sigma^2_{\hat{\gamma}_i II}(k) = \frac{1}{N_2-1}\sum_{j=k-N_2+1}^{k} [\hat{\gamma}_i(j) - \bar{\mu}_{\hat{\gamma}_i}(k)]^2. \tag{38}$$

Then, a fault in the system corresponding to the ith residual is declared at time k if the following detection variable

$$d_i(k) = \frac{\sigma^2_{\hat{\gamma}_i I}(k)}{\sigma^2_{\hat{\gamma}_i^0}(k)} - \ln\frac{\sigma^2_{\hat{\gamma}_i II}(k)}{\sigma^2_{\hat{\gamma}_i^0}(k)} - 1,\ i = 1, ..., p, \tag{39}$$

exceeds a predetermined threshold ε_i. It is a common practice that a declaration is cautiously made after a threshold has been exceeded consistently for some M_D consecutive time steps. We have following hypothesis test.

$$d_i(k) \underset{H_0}{\overset{H_i}{\gtrless}} \varepsilon_i, \tag{40}$$

where $H_0 = \{i\text{th residual no fault indication}\}$, $H_i = \{i\text{th residual fault indication}\}$.

4.2 Fault Isolation

Once a fault has been detected by using above detection rule, the fault type (i.e. pitch angle fault, shaft speed fault, leakage incipient fault or gain parameter fault), fault location and the time for fault isolation have to be determined by an appropriate isolation method. Further, the fault size need also be determined. The demand for the determination of the fault size is the task of fault diagnosis. Even thought the estimation of fault size is not required in the benchmark, however, the proposed approach in this paper can actually provide the estimation of fault sizes which are represented by bias parameters in the two-stage filter algorithm. This is an additional advantage of the proposed FDI approach.

As pointed in Isermann (1997), fault isolation (or diagnosis) is based on the observed analytical and heuristic symptoms and the heuristic knowledge of the process system. Generally speaking, currently developed fault diagnosis approach can be roughly classified into analytical- and heuristic-based methods. Among these approaches, classification method is a popular analytical based approach. On the other hand, automatic fault diagnosis can be viewed as a sequential process involving two steps: the *symptom extraction* and the actual *diagnosis* task. Due to the analytical feature of the benchmark, a classification based fault isolation approach is proposed in this section for isolating four types of faults included in the benchmark.

To reliably detect and isolate the faults in the benchmark, the statistical quantities in (40) can be used as the fault symptom. By giving a set of predetermined thresholds $\varepsilon_j, j = 1, ..., p$, a set of fault symptom vectors for different faults can be described as

$$F_i = [F_{i1}\ \ F_{i2}\ ...\ F_{ip}],\quad i = 1, ..., q \tag{41}$$

where $q(= 4)$ denotes the number of fault type considered. F_{ij} is assumed to be binary (i.e., $F_{ij} \in [0, 1]$) to express the faults as either "happened" or "not happened", i.e.

$$F_{ij} = \begin{cases} 1 & d_j > \varepsilon_j \\ 0 & d_j \le \varepsilon_j \end{cases},\quad i = 1, ..., q,\ j = 1, ..., p \tag{42}$$

They may also represent gradual measures for the size of faults $F_{ij} \in [0, ..., 1]$ to use fuzzy-based approach. Based on these fault symptoms, by designing a set of fault isolation logic, different faults can be isolated according to the different fault indications. However, the fault isolation is obtained under the situations of the predetermined detection thresholds and the particular fault scenario. Any changes due to variations in system parameters, noises or disturbances, the time differences of each of statistical quantity in the fault symptom vector surpassing its threshold will lead to the changes of fault symptom vector. This leads to the obtained on-line fault symptom vector may be different with the designed (or called as reference) symptom vector. Therefore, a systematic approach to handle such an uncertainty need to be developed. By exploiting the idea of classification (pattern recognition) approach, following algorithm can be developed by defining

$$\triangle_i = \|F_{test} \oplus F_{ref,i}\|,\quad i = 1, ..., q \tag{43}$$

where $\triangle_i$ represents the Hamming distance between test fault symptom vector, F_{test}, and each of reference fault symptom vector, $F_{ref,i}$. The smaller the value of $\triangle_i$, the smaller the distance between the two fault symptom patterns, the larger the possibility that the test fault symptom vector belongs to the reference fault or normal symptom. Thus, the diagnosis task becomes into finding

$$i_{\min} = \arg_{i\in(1,q)}\{\min(\triangle_i)\} \quad i = 1, ..., q \tag{44}$$

Once $i_{\min}$ is determined, then the nearest neighboring reference fault symptom vector has been identified and the best guess for the test fault symptom vector F_{test} is $F_{i_{\min}}$. In the case if more than one $\triangle_i$ are identified as minimum distance, the final fault decision have to be made by combining the heuristic knowledge about the faulty system by using some decision logic. Similarly as the detection of a fault, to declare a fault type, the indicator, $i_{\min}$, should hold the same value in M_I consecutive time constants to get reliable isolation.

5. FAULT DETECTION AND ISOLATION RESULTS FOR THE BENCHMARK

The diagnostic method discussed in the previous section is used in the ship benchmark problem, and the results are presented here.

In the benchmark, the given scenario includes a total of six faults which occur sequentially. To obtain a relatively simple nonlinear state-space model for diagnosis, some saturation limits on pitch angle are omitted. To assess the effect of these simplifications, another set of simulation data is generated, which relaxes the saturation limits on pitch angle and fuel index by a factor of 10. At the same time, the magnitude of shaft speed n is increased from the given number 13 to 18 at the time Δn_{high} is present (i.e., the magnitude of Δn_{high} is changed from original 0.5 to 5.5). This fault scenario is named as S2 while the original fault scenario is name as S1.

5.1 Fault Detection Results

To detect a fault as soon as possible, under the given constraints on false alarm, the detection threshold should be set as low as possible. Two sets of thresholds are given to demonstrate the effect with different threshold levels: $\boldsymbol{\varepsilon}_l = [6\ 120\ 7.2e^5\ 2.15e^6\ 1300]^T$ and $\boldsymbol{\varepsilon}_s = [6\ 120\ 5e^4\ 2.5e^5\ 1300]^T$. Note that the difference between $\boldsymbol{\varepsilon}_l$ and $\boldsymbol{\varepsilon}_s$ are due to ε_{b_θ} and ε_{b_n}. The length of the moving date window is chosen as 20 sample points.

Table 1 and Table 2 display the detection time for each fault with two sets of thresholds and two fault test scenarios.

Table 1. Fault detection time with the higher threshold set (sec.).

ε_l		d_{r_θ}	d_{r_n}	d_{b_θ}	d_{b_n}	$d_{b_{\dot\theta_{inc}}}$	ΔT_D
$\Delta\theta_{high}$	S1	183	186	189	207	182*	1
	S2	182+	185	188	207	182+	1
Δn_{high}	S1	-	689*	-	-	-	8
	S2	-	682+	-	-	685	1
$\Delta\dot\theta_{inc}$	S1	-	-	-	-	1052*	251
	S2	-	-	-	-	1052+	251
$\Delta\theta_{low}$	S1	1892*	1899	1902	-	1892*	1
	S2	1892+	1899	1902	-	1892+	1
Δn_{low}	S1	-	2642*	-	2663	2644	1
	S2	-	2642+	-	2662	2644	1
Δk_y	S1	-	3014*	-	3097	-	13
	S2	-	3014+	-	3483	-	13

The detection criterion given in (40) has been used to obtain these results. First, by comparing the results of the two test scenarios (S1 and S2), it can be seen that the effect of saturation limits on the pitch angle and fuel index is very small. Δn_{high} is an exception because its fault magnitudes are different in the two test scenarios. Secondly, by comparing the results in Table 1 and in Table 2, it is clear that different thresholds have resulted in different detection outcomes and different detection times. For example, for the higher threshold, Δn_{high} and $\Delta\dot\theta_{inc}$ faults are not detected from residual d_{b_n}. They are detected in Table 2 when a lower threshold is used. In Table 1 and 3, "*" and "+" denote the smallest detection time with respect to different detection variables for test scenario S1 and S2, respectively. The possible minimum detection delay for different scenarios and thresholds are shown in the last column in the tables. It is found that for the given fault test scenario, detection delay smaller than 2 sample periods ($\Delta T_D < 2T_s$) are achieved for $\Delta\theta_{high}$, $\Delta\theta_{low}$ and Δn_{low}, but not for Δn_{high}. The reason for no detection of Δn_{high} is the small fault magnitude. In fact the percentage of magnitude change due to fault occurrence for $\Delta\theta_{high}$, $\Delta\theta_{low}$, Δn_{high} and Δn_{low} faults are $75.75\%, 148.8\%, 4.0\%$ and 48.45%, respectively. It is seen that the relative magnitude of Δn_{high} is much smaller than that of the others. With an increase in the magnitude of Δn_{high} (S2), the requirement for detection delay is met. From the tables, the detection delay of $\Delta T_D < 5T_s$ for multiplicative fault is not met when the higher threshold is used, and is met when the lower threshold is used. From the Matlab/Simulink program provided for the benchmark, it seems that all faults occur 1 second later than the indicated times in Table 1.

Table 2. Fault detection time with the lower threshold set (sec.).

ε_l		d_{r_θ}	d_{r_n}	d_{b_θ}	d_{b_n}	$d_{b_{\dot\theta_{inc}}}$	ΔT_D
$\Delta\theta_{high}$	S1	183	186	184	199	182*	1
	S2	182+	185	183	198	182+	1
Δn_{high}	S1	-	689*	-	708	-	8
	S2	-	682+	700	696	685	1
$\Delta\dot\theta_{inc}$	S1	-	-	-	807*	1052	6
	S2	-	-	-	849+	1052	48
$\Delta\theta_{low}$	S1	1892*	1899	1893	1914	1892*	1
	S2	1892+	1899	1893	1916	1892+	1
Δn_{low}	S1	-	2642*	2649	2653	2644	1
	S2	-	2642+	2649	2652	2644	1
Δk_y	S1	-	3014*	3042	3019	-	13
	S2	-	3014+	3042	3015	-	13

5.2 Fault Isolation Results

In the benchmark, four types of faults were considered and simulated. The task of fault isolation is to design an appropriate isolation logic to distinguish among these 4 types of faults and the normal operation.

Table 3. Fault knowledge base.

	d_{r_θ}	d_{r_n}	d_{b_θ}	d_{b_n}	$d_{b_{\dot\theta_{inc}}}$
$\Delta\theta$	1	1	1	1	1
Δn	0	1	0	1	1
$\Delta\dot\theta_{inc}$	0	0	0	1	1
Δk_y	0	1	0	1	0
normal	0	0	0	0	0

A set of detection thresholds $\boldsymbol{\varepsilon} = [6\ 120\ 7.2e^5\ 2.5e^5\ 1300]^T$ is determined heuristically based on Table 1 and Table 2, and the analysis performed thus far. Table 3 shows a set of pre-classified detection outcomes. In this case, the number of possible detection outcomes that have not been pre-classified is equal to $2^p - 5$. Unless these outcomes have all been determined as less likely or unlikely events by the designers, further analysis must be carried out to pre-classify the more likely outcomes among them. Based on Table 3, following fault isolation logic can be easily designed as:

Table. 4. fault isolation logic.

Isolation decision logic	Fault type
$(T_{11} \wedge T_{12} \wedge T_{13} \wedge T_{14} \wedge T_{15} = 1) \vee (T_{11} \wedge T_{13} = 1)$	$\Delta\theta$ fault
$(\bar{T}_{21} \wedge T_{22} \wedge \bar{T}_{23} \wedge T_{24} \wedge T_{25} = 1) \vee (\bar{T}_{21} \wedge T_{22} = 1)$	Δn fault
$(\bar{T}_{31} \wedge \bar{T}_{32} \wedge \bar{T}_{33} \wedge T_{34} \wedge T_{35} = 1) \vee (\bar{T}_{34} \wedge T_{35} = 1)$	$\Delta\dot{\theta}_{inc}$ fault
$(\bar{T}_{41} \wedge T_{42} \wedge \bar{T}_{43} \wedge T_{44} \wedge \bar{T}_{45} = 1) \vee (\bar{T}_{42} \wedge T_{44} = 1)$	Δk_y fault
$(\bar{T}_{51} \wedge \bar{T}_{52} \wedge \bar{T}_{53} \wedge \bar{T}_{54} \wedge \bar{T}_{55} = 1)$	Normal

In the table, $T_{ij}, i, j \in [1, 5]$ denotes the event of $F_{ij} = 1$ and $\bar{T}_{ij}$ the event of $F_{ij} = 0$. "$\wedge$" and "$\vee$" denote logic operation AND and OR, respectively. It is clear that the fault symptom vector will be probably different with above design of the reference fault symptom due to the changes in the design of threshold, the differences between the designed test fault scenario, noise and disturbance characteristics and their actual values. By using the approach presented by (43) and (44), a test fault symptom vector can be first classified into the designed fault pattern given in Table 4. Then, reliable fault isolation result can be obtained by using the fault isolation logic given in Table 4. However, as mentioned in the previous section, there exists the possibility in which more than one $\triangle_i$ are identified as minimum Hamming distance. In this case, the final fault decision have to be made by combining the heuristic knowledge about the faulty system or the special feature in Table 3. For example, in the case if $\triangle_1 = \triangle_2$, it denotes the possibility that either pitch angle or shaft speed was failed. To determine actual fault, we can find the fault type by further computing following minimum Hamming distance for test fault symptom vector

$$j = \arg\min_i \{\|F_{ref,i}\| - \|F_{test}\|\}, \quad i = 1, 2 \tag{45}$$

For the two test scenarios of the benchmark, Table 5 presents the simulation results of the isolation times, and the time delays of isolating each type of faults when M_I is set as 5, where M_I is the number of consecutive cycles in which the same isolation result remains before it is declared. $p = 5$ denotes the number of residuals for FDI.

Table 5. Detection time and time delay of fault isolation (sec.).

		$\Delta\theta_{high}$	$\Delta\theta_{low}$	Δn_{high}	Δn_{low}	$\Delta\dot{\theta}_{inc}$	Δk_y
S1	T_I	193	1906	712	2648	811	3023
	ΔT_I	12	15	31	7	10	22
S2	T_I	192	1906	689	2648	853	3019
	ΔT_I	11	15	8	11	52	18

6. CONCLUSION

In this paper, an adaptive two-stage extended Kalman filter and statistical hypothesis test based fault diagnosis approach to a ship propulsion benchmark problem has been presented and evaluated by the benchmark data. Simulation results on the benchmark data have shown that the proposed approach can effectively detect and isolate different types of faults specified in the benchmark in the presence of modeling errors and unknown disturbances. The detection time delay requirement has been met for both the abrupt and the incipient faults, but not for the multiplicative gain fault. It is observed that detection speed for abrupt faults benefits from the use of filtered measurement residuals, while both detection and isolation of incipient and multiplicative faults heavily rely on the direct estimates of these faults. The diagnosis results are presented only for two test scenarios in this paper. More test scenarios are desirable not only for more thorough evaluation of the diagnosis approach, but also for more complete information based on which the knowledge base is established for FDI. Due to the nonlinearity and short occurrence duration of abrupt faults, the estimation accuracy of the fault magnitudes is not ideal. A focused effort is needed to enhance the FDI performance for the multiplicative fault.

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