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A fault detection scheme for ship propulsion systems using randomized algorithm techniques

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ABSTRACT

This paper studies the fault detection problem in ship propulsion systems based on randomized algorithms. The nominal propulsion system model, model with uncertainties and model with additive and multiplicative faults are first addressed in the form of normalized left coprime factorization (LCF), respectively. The $\mathcal{K}$-gap metric is then introduced to measure how far the system deviates from the nominal operation. To reduce the conservatism in the norm-based threshold, a threshold setting law and the estimation of fault detection rate (FDR) are formulated on the probabilistic assumption of uncertain and faulty parameters. The simulation results on the ship propulsion system show that the randomized technique is an efficient solution to deal with the fault detection issues.

1. Introduction

The propulsion system is the most essential part in vessels, hence its fault detection is of great significance in the long-term safety operation and entire lifecycle management of ships. The benchmark work by Izadi-Zamanabadi and Blanke (1999) has established a complete framework of the fault detection system design for ship propulsion systems, since then numerous fault detection strategies have been published (Blanke, 2005; Blanke, Izadi-Zamanabadi, & Lootsma, 1998; Edwards & Spurgeon, 1999; Lootsma, Izadi-Zamanabadi, & Nijmeijer, 2001; Zhang, Wu, & Jiang, 2008). The main idea of these works is to construct a residual signal based on which a decision logic is formulated to indicate whether the system is in abnormal condition. The decision logic consists of an evaluation function and a threshold. Since the evaluation function is influenced not only by the faults but also by the parameter uncertainties and external disturbances, the threshold setting law will greatly influence the fault detection performance. A larger threshold means the smaller false alarm rate (FAR) but the poorer fault detectability, while a smaller threshold stands for the better fault detection rate (FDR) but the higher false alarm rate. In the norm-based framework, the maximal norm of the residual signal in fault free case is chosen as the threshold (Ding, 2008), which is rather conservative because the extreme situation, as the residual reaches the maximal value is rare in real operations.

In recent years, the randomized algorithm has been proposed to deal with uncertainties as an alternative method of the robust control theory. Most of the researches are aiming to design controllers by randomized algorithms to achieve some control performance in the probabilistic sense, such as in Calafiore, Dabbene, and Tempo (2011), controllers that guarantee the "probabilistic robust" performance are synthesized. Compared with the deterministic techniques, the probabilistic methods can significantly reduce the conservatism and computational burden though at the cost of small failure risks. In Ding, Zhang, Frank, and Ding (2003) and Zhang, Ding, Sader, and Noack (2005), the application of probabilistic robustness technique to the fault detection system design has been formulated for the first time. The utilizations of randomized algorithms in controller design and fault detection can be found in noisy MIMO uncertain systems (Ma, Sznaier, & Lagoa, 2007) and in UAVs (Capello, Quagliotti, & Tempo, 2013; Capello & Tempo, 2013; Lorefice, Pralio, & Tempo, 2009; Zhong, Zhang, Ding, & Zhou, 2017). As for the fault detection of ship propulsion systems, the norm-based threshold will lead to poor fault detection rates which is not coincident with the safety-critical requirements. In this paper, we use the well-established coprime factorization technique to model the propulsion system. The $\mathcal{K}$-gap is adopted as the measurement of system deviation. A fault detection strategy based on randomized algorithms to achieve better trade-off between FAR and FDR for the ship propulsion system is studied. The proposed method can significantly enhance the fault detection performance while keeping the false alarm rate below an accepted level.

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The paper is organized as follows. Section 2 gives a detailed description of the ship propulsion model with one engine and one propeller. Four kinds of fault scenarios are also included. In Section 3, the nominal system model, model with uncertain parameters, model with sensor and actuator faults are formulated by the normalized left coprime factorization, respectively. In Section 4, a novel method for fault detection of ship propulsion systems based on randomized algorithms is given. Both the threshold setting strategy and fault detection rate estimation scheme are included. Section 5 is the implementation and simulation on the ship propulsion system. The conclusion is addressed in Section 6.

2. Ship propulsion system model

2.1. Nonlinear model of ship propulsion system

The typical mechanical structure of a ship propulsion system consists of four main subsystems. They are diesel engine, reduction gearbox, transmission shaft and propeller. For low speed and heavy duty vessels, the diesel engine directly drives the propeller thus the reduction gearbox can be omitted. The screw propeller considered in this paper is the controllable pitch propeller (CPP), the pitch of which can be controlled to meet the requirements for ship speed. Ships can move backward or change speed while the diesel engines need not to change the rotation speed frequently.

$$\tau_c \dot{Q}_e = -Q_e + k_y Y \quad (1)$$

$$I_m \dot{n} = Q_e - Q_p - Q_f. \quad (2)$$

The driving torque Q_e generated by diesel engine is relevant with the fuel consumption Y. As Eq. (1) indicates, the diesel engine can be approximately modeled as a first-order inertial loop. k_y is the engine gain and τ_c is the time constant. I_m is the rotational inertia of shaft, Q_p is the resisting torque caused by propeller and Q_f is the unknown friction torque.

$$m\dot{V} = (1-\kappa)T_p - R_V - T_{ext} \quad (3)$$

$$R_V = \lambda V^2. \quad (4)$$

The above two equations are dynamics of hull. m is the total mass of the ship, T_p is the driving force generated by propeller and T_{ext} is the unknown disturbance caused by wind or waves. κ is the thrust deduction number which has a typical value in the interval [0.05 0.2]. The main drag force on passage is due to flow resistance R_V which can be approximately calculated as the quadratic function of ship speed V (Izadi-Zamanabadi & Blanke, 1999). λ is the empirical coefficient.

$$T_p = T_p(n,\theta) = \rho D^4 K_T n^2 \quad (5)$$

$$Q_p = Q_p(n,\theta) = \rho D^5 K_Q n^2. \quad (6)$$

As Eqs. (5)–(6) indicates, the force and torque generated by the controllable pitch propeller are complex functions of shaft speed and propeller pitch angle. ρ is the density of sea water. D is the diameter of propeller. K_T and K_Q are the non-dimensional propeller thrust and propeller torque coefficients. They are relevant with propeller's mechanism and can be obtained from real voyage tests. Referring to the benchmark paper (Izadi-Zamanabadi & Blanke, 1999), we have approximately obtained their functional relationship with respect to θ and n as

$$K_T = \alpha_1\theta + \alpha_2 J \quad (7)$$

$$K_Q = \beta_1\theta + \beta_2 J \quad (8)$$

where $\alpha_i, \beta_i, i = 1,2$ are constants determined by ship types. $J = \frac{2\pi(1-\mu)V}{nD}$ is the open water advance coefficient. μ is the wake fraction number which has a typical value between 0.1 and 0.4. It indicates the influence on advance speed caused by non-uniform shape of the water flow under the ship hull (Izadi-Zamanabadi & Blanke, 1999).

Table 1
Fault scenarios in ship propulsion systems.

Fault scenarios	Causes	Consequences
Engine gain fault	Less air/oil inlet	Drop of engine gain
Shaft speed sensor fault	EMI disturbance	Higher measurements
Pitch angle sensor fault	Broken wire/short circuit	Higher measurements
Hydraulic system fault	Hydraulic system leakage	Propeller pitch drifts

The component structure of ship propulsion system is illustrated in Fig. 1. Given a reference signal V_{ref}, the control objective is to make the ship speed V_m track its reference. As the ship speed is determined by both the rotation speed n and propeller pitch θ, the efficient optimizer takes V_{ref} as input and generates two optimal control signals Y and θ_{ref}. These two signals serve as the input of shaft speed control loop and propeller pitch control loop. In our study, the shaft speed is assumed to be an open control loop while the pitch controller is simplified as an integral feedback controller which has the form

$$\dot{\theta} = k_t(\theta_{ref} - \theta_m). \quad (9)$$

2.2. Fault scenarios

Four main fault scenarios in the above ship propulsion model are considered in this paper. They are diesel engine gain fault ΔB, shaft speed sensor fault Δn, pitch angle sensor fault $\Delta\theta$ and hydraulic system leakage $\Delta\dot{\theta}$. The causes and effects of these faults are listed in Table 1. All these faults must be detected in a short time since they would lead to abrupt changes in ship speed and even cause severe collision damage.

$x(t) = [\theta\ n\ V\ Q_e]^T$ is the state vector, $u(t) = [\theta_{ref}\ Y]^T$ is the input vector, $f(t) = [\Delta\dot{\theta}\ \Delta\theta\ \Delta n]^T$ is the additive fault, ΔB is the multiplicative fault, $y(t) = [\theta_m\ n_m\ V_m]^T$ is the measurement output. The nonlinear model of ship propulsion system is given as

$$\begin{aligned} \dot{x}(t) &= g(x(t)) + (B+\Delta B)u(t) + F_1 f(t) + D_1 d_1(t) \\ y(t) &= Cx(t) + F_2 f(t) + D_2 d_2(t) \end{aligned} \quad (10)$$

$$g(x(t)) = \begin{bmatrix} -k_t \\ \frac{1}{I_m}(Q_e - Q_p) \\ \frac{1}{m}((1-\kappa)T_p - R_V) \\ -\frac{1}{\tau_c}Q_e \end{bmatrix}.$$

2.3. Linearized model of ship propulsion system

This paper studies the integrated influence of faults and uncertain parameters on fault detection performance, thus the influence of disturbances is omitted. Select the steady working point as $x_0 = [\theta_0\ n_0\ V_0\ Q_{e0}]^T$, nonlinear model (10) can be linearized as

$$\begin{aligned} \dot{x}(t) &= A(\omega)x(t) + (B+\Delta B)u(t) + F_1 f(t) \\ y(t) &= Cx(t) + F_2 f(t) \end{aligned} \quad (11)$$

where $\omega = [\kappa\ \mu]^T$ denotes system uncertain parameters and $A(\omega)$ is the complex function matrix of ω. The linearized parameter matrix is given below.

$$A(\omega) = \begin{bmatrix} -k_t & 0 & 0 & 0 \\ -\frac{b_1 n_0^2}{I_m} & -\frac{2b_1\theta_0 n_0 + b_2 V_0}{I_m} & -\frac{b_2 n_0}{I_m} & \frac{k_y}{I_m \tau_c} \\ \frac{(1-\kappa)a_1 n_0^2}{m} & \frac{2(1-\kappa)a_1\theta_0 n_0 + (1-\kappa)a_2 V_0}{m} & \frac{(1-\kappa)a_2 n_0 - 2\lambda V_0}{m} & 0 \\ 0 & 0 & 0 & -\frac{1}{\tau_c} \end{bmatrix}$$

where

$$a_1 = \rho\alpha_1 D^4,\ a_2 = 2\pi\rho\alpha_2 D^3(1-\mu)$$

$$b_1 = \rho\beta_1 D^5, b_2 = 2\pi\rho\beta_2 D^4(1-\mu).$$