Received January 31, 2018, accepted March 7, 2018, date of publication March 19, 2018, date of current version April 18, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2817257

Robust Component Fault Diagnostic Observer Design for Underactuated Surface Vessels Using Moving Horizon Optimization

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This work was supported in part by the National Natural Science Foundation of China under Grant 51379044 and in part by the Fundamental Research Funds for the Central Universities under Grant HEUCF0418.

ABSTRACT For the consideration of improving the safety and reliability for underactuated surface vessel, the design scheme of a robust component fault detection (FD) is investigated in this paper. The main idea is to formulate the observer design as the H_-/H_∞problem of satisfying the disturbance attenuation and optimizing the fault detectability. The sufficient conditions for performance indexes are derived in the formulation of linear matrix inequality. Considering the remarkable fact that the actual system states are not involved in the iteration process for the parameters optimization, based on the moving horizon optimization strategy, the robust component FD design approach is proposed to achieve the improvements of FD performance and feasibility. The simulation results are given to demonstrate the effectiveness of the proposed approach.

INDEX TERMS Component fault, fault detection, H_-/H_∞, LMI, moving horizon optimization.

I. INTRODUCTION

In recent decades, with the urgent demands for good performance, safety and reliability, the control systems turn out to be much more complex, resulting to the higher possibility of the fault occurrence. In order to handle this case, a great deal of attention has been attracted for fault detection (FD) techniques from research and application domains [1]. The model-based FD approach is one of the widely used mainstream methods, and its main concept is to use the system model for the software implementation instead of the traditional hardware redundancy, in order to reduce the diagnostic cost and additional faults caused by the redundant hardware and improve the fault detectability [2]. The model-based fault diagnosis has an intimate relationship with the modern control theory, then rapids developments of computer techniques and control theory can make the model-based fault diagnosis technique accepted as a power tool to solve fault diagnosis problems. Among the existing model-based FD methods, the observer-based method has received much attention such as widely used unknown observer [3] and sliding mode observer [4], [5]. Using this kind of observer-based fault diagnosis method, the residual generator can then be designed to generate the residual signal to evaluate whether there exist faults in the control system.

The robustness of the FD system is different from the normal robust control, as it contains two parts: robustness to external disturbances with bounded energy and sensitivity to detected faults [6]. It is noteworthy modern systems are consisted of mechanical system and control system. The former is used to detect the possible faults, and the latter is used to control the system with the consideration of actuators and sensors. Thus, the system dynamics can be affected by different kinds of faults, such as the actuator fault and sensor fault. For the simplicity, only the component fault is considered in this paper, and then the actuator output can be considered as the component input. The component fault can be represented as the case when some condition changes in the system rendering the dynamic relation invalid, such as a leak in a water tank of USV [7], [8]. Furthermore, there is always the coupling between disturbances and faults in the actual control systems. Thus, an optimal trade-off between robustness and sensitivity has to be done to measure the performance of the FD system. In order to improve the robustness to unknown inputs with external disturbances and sensitivity to detected faults, many feasible performance indexes have been proposed based on the robust control theory, such as mixed H_-/H_∞ and H_-, H_∞. The sufficient conditions have also been derived in the linear matrix inequality (LMI) formulation in many published papers [9]–[11]. Although some particular systems, such as fuzzy system, dissipative system and piecewise affine systems [12]–[14], have been studied and well developed, few investigate the FD problem related to the USV system.

Nowadays, most marine surface vessels are only equipped with the propeller and rudder. The three degrees of freedom movement consisting of horizontal position and heading angle is controlled by the longitudinal propulsion of the propeller and steering moment of the rudder. As the number of controlled variables is more than the control actuators, this kind of control system is a typical underactuated system [15]. Due to the theoretical and practical necessities, the marine surface vessels have been researched for years, and achievements of different aspects (guidance and control, robust control and path following) have been reached [16]–[18]. However, the researches on the FD system for autonomous and intelligent USV starts late, due to the simple vessel construction and low maintenance cost after failure. With the increasing complexity of the vessel system and severe shipwreck accidents caused by faults, many institutions and scholars have been attracted and devoted to this research filed, and achievements have been reached in the aspect of the motion control [19], [20]. From another aspect of the fault diagnose, instead of the regular maintenance, it is necessary to monitor the vessel states during the operation in order to take measures after the failure occurrence as quickly as possible, so as to prevent more serious consequences. This approach also has advantages of avoiding unnecessary maintenance cost, enhancing the vessel reliability and increasing the crew safety. Driven by the increasing needs for FD in this field, it has become an application subject in the systematic FD methods. In a summary, the objective of FD for USV is to determine the location and occurrence time of the fault. As is known, USVs operate in the sophisticated environment and are affected with unknown external disturbances. It remains to be the difficulty of enhancing robustness to disturbances and sensitivity to faults. Nowadays, with the developments of computer technology and artificial intelligence, some achievements have been made in the field of DF for vessels, such as the fault tree method, neural network and expert system method [21]–[23]. Although some techniques has already been applied in reality, above methods are all data-driven based without the intimate relationship between fault diagnosis and modern control theory of model-based fault diagnosis, and various information about faults are necessary for the fault confirmation and correspondence between measured signals and detectable faults.

Looking back at the techniques and sufficient theoretical conditions of the model-based FD approach, the optimal trade-off between robustness and sensitivity has been done for the performance measurement without actual system states involved [24]. The actual states at each time contains the past information on internal dynamics, controls and external disturbances. In order to improve performance and enhance the feasibility, a scheme of moving horizon optimization is then introduced to automatically trade-off the performance and sufficient constrained conditions by adjusting the performance specification. With the online optimization updated by the actual states, the system performance can be further improved. Moving horizon optimization is one of the featured strategies in model predictive control, and it is widely used in the process industries by performing an optimization of the plant variables updated online and returning results for further real-time control systems at the next time. Furthermore, it can explicitly take account of system constraints in advance [25], [26]. Proceedings from the above papers, the main focus of this article is to design the FD system for USV affected by unknown bounded disturbances and sensor faults. Based on the designed residual generator, the optimal observer gain can be obtained by the maximization of H_- norm and the minimization of H_∞ norm. On this basis, moving horizon optimization is first introduced to involve the actual system states and make another optimal solution at the next time, so as to achieve better performance and feasibility.

The paper is organized as follows. After the introduction, the problem to be addressed is given in Section II. In Section III, the design scheme of the diagnostic observer-based FD approach is presented. The moving horizon optimization of the error system is proposed in Section IV. The simulation results are given to demonstrate the efficiency of the proposed approach in Section V, followed by the conclusion part in Section VI.

II. PROBLEM STATEMENT

In this section, the linear time time invariant dynamic system is formulated for the investigation of the DF design problem for USV. In the first place, the vessel dynamics need to be studied. Referring to the literature [15], one of the most widely used dynamics with four degrees of freedom (surge u, sway v, roll p and yaw$r$) is formulated as:

$$\begin{cases} m(\dot{u} - vr - X_G r^2 + Z_G pr) = X \\ m(\dot{v} + ur + X_G \dot{r} - Z_G \dot{p}) = Y \\ I_{XX}\dot{p} - I_{XZ}\dot{r} - mZ_G(\dot{v} + ur) = K - mgGM_T\phi \\ I_{ZZ}\dot{r} - I_{XZ}\dot{p} + mZ_G(\dot{v} + ur) = N \end{cases} \tag{1}$$

where m is the ship mass, I_{XX} and I_{XZ} denote the coupled moments of inertia between x, x and x, z axes. X_G and Z_G are the locations of the gravity center in the x-axis and z-axis, respectively. p is the roll velocity, and ϕ is the roll angle. GM_T denotes the metacentric height. The hydrodynamic forces X, Y and moments K, N are usually the third order Taylor series polynomials, and the explicit expressions in detail can be referred in [27].

The model (1) is one of most comprehensive ship models accessible in the open literature, and it covers wide operation conditions with the ability of capturing the ship basic characteristics. However, due to the nonlinearity, strong couplings and uncertainties, it is difficult to design the controller directly. With the assumptions that the surge velocity is constant without the consideration of surge dynamics, after the linearization at the equilibrium point, the nonlinear model (1) can be generally described by:

$$\begin{cases}\dot{x} = Ax + Bu \\ y = Cx + Du\end{cases} \tag{2}$$

$$A = \begin{bmatrix} a_{11} & a_{12} & 0 & a_{13} & a_{14} \\ a_{21} & a_{22} & 0 & a_{23} & a_{24} \\ 0 & 1 & 0 & 0 & 0 \\ a_{31} & a_{32} & 0 & a_{33} & a_{34} \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}, \quad B = \begin{bmatrix} b_1 \\ b_2 \\ 0 \\ b_3 \\ 0 \end{bmatrix} \tag{3}$$

where $x = [x_1, x_2, x_3, x_4, x_5]^T = [v, r, \psi, p, \phi]^T$ is defined as the state vector, $u = \delta$ is the rudder angle served as the system input, and y is the measurement output. A and B are the state matrix and input matrix, respectively. The coefficients $a_{ij}(i = 1, 2, 3, j = 1, 2, 3, 4)$ and $b_i(i = 1, 2, 3)$ are constants, obtained by the experiment and computational fluid dynamics (CFD) software [15]. Note that, the motion states of USVs are composed of the motions of the low and high frequencies. As the motion of the high frequency can only result to a slight movement of the vessel system with the position relatively unchanged, only the motion of the low frequency is considered.

The operation environment of the vessel is sophisticated with external disturbances, and the vessel is affected by some possible faults. In terms of possible faults in this paper, it is assumed that system sensors work efficiently and the actuator (rudder) is of fault-free condition, such that only the effect of component fault is modeled [7], [28]. Thus, considering the disturbances and component faults, the model (2) can be extended to the formulation as:

$$\begin{cases}\dot{x} = Ax + Bu + B_d d + B_f f \\ y = Cx + Du\end{cases} \tag{4}$$

where d denotes the unknown disturbances, and f denotes the all possible additive faults to be detected. $B_f f$ represents the component fault, which is used to indicate the effects of the system condition changes on rendering invalid dynamic relations. As only the component fault is considered in this paper, the actuator fault and sensor fault are unmodeled here. Without the loss of generality, d and f are assumed to be L_2 norm bounded. The L_2 norm is defined as $\|d\|_2 = \left[\sum_{k=0}^{\infty} d^T(k)d(k)\right]^{1/2}$ and $\|f\|_2 = \left[\sum_{k=0}^{\infty} f^T(k)f(k)\right]^{1/2}$. In order to facilitate the fault detectability for the observer-based FD approach, the condition that (A, C) is detectable is used throughout the paper [29].

On the basis of the formulated model (4) for USV with the consideration of the disturbances and faults, the objective of this paper can be simply described as constructing a robust DF system which has the best robustness and sensitivity to disturbances and faults.

III. ROBUST FAULT DETECTION SYSTEM DESIGN

In general, using an observer-based FD approach, the robust FD system is mainly composed of two parts: a residual generator and a residual evaluation function. Note that, the latter is a decision logic unit with a determined threshold.

A. THE RESIDUAL GENERATOR

In order to generate the residual signal, for our purpose, the Luenberger diagnostic observer adopted as the residual generator is given by [30]:

$$\begin{cases}\dot{\hat{x}} = A\hat{x} + Bu + L(y - \hat{y}) \\ \hat{y} = C\hat{x} + Du \\ r = E(y - \hat{y})\end{cases} \tag{5}$$

where $\hat{x}$ and $\hat{y}$ are the estimations of the state and output. r denotes the residual signal. L is the observer gain matrix which needs to be determined. E is the residual weighting matrix, and it is fixed as the identity matrix in order to facilitate the study. With the definition of the error state $e = x - \hat{x}$, after the simple mathematical manipulation between (4) and (5), the dynamics of the residual signal can be described as:

$$\begin{cases}\dot{e} = \bar{A}'e + B'_d d + B'_f f \\ r = y - \hat{y}\end{cases} \tag{6}$$

where $\bar{A}' = A - LC$. From the error dynamics (6), it can be seen that the dynamics of the residual dynamics are related to the disturbance d and the fault f. Therefore, the design problem of the observer-based DF can be described as finding the weighting matrix L, such that the generated residual signal r is the most robust to unknown disturbances and sensitive to the faults to be detected with $\bar{A}'$ asymptotically stable. Using the first order Eulerian discretization, the dynamics (6) can be formulated as:

$$\begin{cases}e(k+1) = \bar{A}e(k) + B_d d(k) + B_f f(k) \\ r(k) = Ce(k)\end{cases} \tag{7}$$

where $\bar{A} = \bar{A}'T + I$, $B_d = B'_d T$, and $B_f = B'_f T$. T is the sampling time, and I denotes the identify matrix with the appropriate dimension, which is 5 here.

In order to achieve the requirements for robustness and sensitivity, the widely used performance indexes H_∞ and H_- are adopted. The definitions are given by:

$$H_\infty \triangleq \|G_{rd}\|_\infty \leq \gamma \tag{8}$$

$$H_- \triangleq \|G_{rf}\|_- \geq \beta \tag{9}$$

where γ and β are two positive scalars. γ denotes the worst case criterion for the disturbance effect on the residual signal, and the smaller γ means the stronger robustness to restrain the unknown disturbances. Relatively, β denotes the worst case criterion for the sensitivity measurement from the fault to the residual signal, and the larger β leads to the better sensitivity of the residual generator and more interested faults to be detected or captured. G_{rd} and G_{rf} are the transfer functions from the disturbance d and fault f to the residual signal r, which are used to denote the effects of the residual signal on the disturbance and fault, respectively.

In the following, with the bounded real lemma, the robust DF design problem is solved by LMI formulation iteration. The robustness problem of the residual signal is firstly considered. The robust H_∞ performance can be formulated as finding a DF observer in the form of (5), such that the system (7) is asymptotically stable and the performance index (8) is satisfied for any non-zero d with fault-free condition $f = 0$.

Theorem 1: For the model (4) with the DF observer (5), if there exist matrices $P > 0$ and $\bar{L}$ such that the following condition hold:

$$\begin{bmatrix} \begin{bmatrix} A^TPA - P + C^TC \\ -C^T\bar{L}^TA - A^T\bar{L}C \end{bmatrix} & * & * \\ \bar{L}C & -P & \\ B_d^TPA - B_d^T\bar{L}C & & B_d^TPB_d - \gamma^2 I \end{bmatrix} \leq 0 \quad (10)$$

with $\bar{L} = PL$. Then the system (7) is stable and the H_∞ performance index $H_\infty \leq \gamma$ is satisfied. Note that the symbol $*$ indicates the corresponding symmetric elements.

Proof: With $f = 0$ and non-zero d, the system (7) can be described as: $e_d(k+1) = \bar{A}e_d(k) + B_d d(k)$ and $r_d(k) = Ce_d(k)$ with $\bar{A} = A - LC$. Then, the H_∞ performance index (8) can be equivalently described by $J_\infty^N = \sum_{k=0}^{N-1}\left[r_d^T(k)r_d(k) - \gamma^2 d^T(k)d(k)\right] \leq 0$ with an arbitrary positive integer N. Choose the Lyapunov function as $V(e_d(k)) = e_d^T(k)Pe_d(k)$, $P > 0$, and for non-zero d, the criterion J_∞^N can be rewritten as:

$$\sum_{k=0}^{N-1}\left[r_d^T(k)r_d(k) - \gamma^2 d^T(k)d(k) + \Delta V(k)\right] - V(k) \leq 0$$

where $\Delta V(k) = V(e_d(k+1)) - V(e_d(k)) = \begin{bmatrix} e_d^T(k) & d^T(k) \end{bmatrix} \begin{bmatrix} \bar{A}^TP\bar{A} - P & \bar{A}^TPB_d \\ * & B_d^TPB_d \end{bmatrix} \begin{bmatrix} e_d(k) \\ d(k) \end{bmatrix}$ denotes the increment of $V(k)$. After substituting $\Delta V(k)$ to J_∞^N, then the criterion J_∞^N can be formulated as:

$$J_\infty^N = \sum_{k=0}^{\infty}\begin{bmatrix} e_d^T(k) & d^T(k) \end{bmatrix} M \begin{bmatrix} e_d(k) \\ d(k) \end{bmatrix} - V(k) \leq 0$$

Hence, if $M = \begin{bmatrix} \bar{A}^TP\bar{A} - P & \bar{A}^TPB_d \\ * & B_d^TPB_d - \gamma^2 \end{bmatrix} + \begin{bmatrix} C^T \\ 0 \end{bmatrix}\begin{bmatrix} C & 0 \end{bmatrix}$, then J_∞^N can then be guaranteed. Using the Schur complement, it can be formulated as (10), and the proof is completed.

After the derivation of the sufficient condition to guarantee the robustH_∞ performance, the H_- index is considered to deal with the sensitivity problem of the residual signal r to fault f. Different from the H_∞ performance index, the robust H_- performance can be formulated as determining a DF observer in the form of (5), such that the system (7) is asymptotically stable and the performance index (9) is satisfied for any non-zero f with $d = 0$.

Theorem 2: For the model (4) with the DF observer (5), if there exist matrices $P > 0$ and $\bar{L}$ such that the following condition hold:

$$\begin{bmatrix} \begin{bmatrix} A^TPA - P - C^TC \\ -C^T\bar{L}^TA - A^T\bar{L}C \end{bmatrix} & * & * \\ \bar{L}C & -P & \\ B_f^TPA - B_f^T\bar{L}C & & B_f^TPB_f + \beta^2 I \end{bmatrix} \leq 0 \quad (11)$$

with $\bar{L} = PL$. Then the system (7) is stable and the H_- performance index $H_- \geq \beta$ is satisfied.

Proof: With $d = 0$ and non-zero f, the system (7) can be described as: $e_f(k+1) = \bar{A}e_f(k) + B_f f(k)$ and $r_f(k) = Ce_f(k)$ with $\bar{A} = A - LC$. Then, the H_- performance index (9) can be equivalently described by $J_-^N = \sum_{k=0}^{N-1}\left[r_f^T(k)r_f(k) - \beta^2 f^T(k)f(k)\right] \geq 0$ with an arbitrary positive integer N. Choose the Lyapunov function as $V(e_f(k)) = e_f^T(k)Pe_f(k)$, $P > 0$, and for non-zero f, the criterion J_-^N can be rewritten as:

$$\sum_{k=0}^{N-1}\left[r_f^T(k)r_f(k) - \beta^2 f^T(k)f(k) - \Delta V(k)\right] + V(k) \geq 0$$

where $\Delta V(k) = V(e_f(k+1)) - V(e_f(k)) = \begin{bmatrix} e_f^T(k) & f^T(k) \end{bmatrix} \begin{bmatrix} \bar{A}^TP\bar{A} - P & \bar{A}^TPB_f \\ * & B_f^TPB_f \end{bmatrix} \begin{bmatrix} e_f(k) \\ f(k) \end{bmatrix}$ denotes the increment of $V(k)$. After substituting $\Delta V(k)$ to J_-^N, then the criterion J_-^N can be formulated as:

$$J_-^N = \sum_{k=0}^{\infty}\begin{bmatrix} e_f^T(k) & f^T(k) \end{bmatrix} N \begin{bmatrix} e_f(k) \\ f(k) \end{bmatrix} + V(k) \geq 0$$

Hence, if $N = -\begin{bmatrix} \bar{A}^TP\bar{A} - P & \bar{A}^TPB_f \\ * & B_f^TPB_f + \beta^2 \end{bmatrix} + \begin{bmatrix} C^T \\ 0 \end{bmatrix}\begin{bmatrix} C & 0 \end{bmatrix} \geq 0$, then J_-^N can then be guaranteed. Using the Schur complement, it can be formulated as (11), and the proof is completed.

B. THE RESIDUAL EVALUATION FUNCTION

As the component faults to be detected are mixed with unknown inputs, it is absolutely necessary to make a distinguishment for the purpose of a robust DF system. The second component of the FD system is a fault evaluation function, which includes a decision logic unit and a threshold to be computed.

According to the specified system under consideration, different approaches can be adopted to achieve the fault evaluation. In this paper, one of the widely used approaches is adopted and the decision logic of the fault evaluation can be formulated as:

$$\begin{cases} J(r) > J_{th} \Rightarrow faulty \\ J(r) \leq J_{th} \Rightarrow fault - free \end{cases} \quad (12)$$

where J_r denotes the residual evaluator, which is generally a positive definite function of the residual signal. J_{th} denotes the threshold as the maximum influence of unknown input on the residual signal in the fault-free case, which means $f = 0$.

As the root mean square (RMS) evaluation function has the advantages of the strong application potential, reduced instantaneous unknown inputs and improved signal smoothness, RMS is used as the norm-based evaluation function to measure the average energy of a residual signal over a time period, which is defined as [7], [12]:

$$J(r) = \|r\|_{RMS} = \left[\frac{1}{T}\sum_{i=1}^{T}\|r(k+i)\|_2\right]^{1/2} \tag{13}$$

As the used evaluation function and decision logic are given, the threshold is ought to be determined. The threshold is the tolerant limit of unknown input to residual signal in the fault-free case, and is determined by:

$$J_{th} = J_{th,RMS} = \sup_{f=0, d\in L_2} \|r\|_{RMS} \tag{14}$$

where sup denotes the supremum. Note that, if the disturbance d is assumed to satisfy $\sum_{k=0}^{\infty}\|r(k+i)\|^2 \leq \alpha^2$, the constant threshold is determined as $J_{th} = \gamma\alpha T^{-1/2}$.

IV. MOVING HORIZON OPTIMIZATION OF ERROR DYNAMICS

In some open literature, with the sufficient conditions for the performance indexes (8) and (9) derived in LMI formulations, one can use the performance index $\inf(\gamma/\beta)$ to obtain the relatively optimal parameters based on the trail-and-error method [12], [29]. However, the actual system states have not been considered in the iteration of optimization process. To tackle this case, the moving horizon optimization strategy is adopted to involve the actual states in the optimization process resulting to the performance improvement. Furthermore, the strategy has the ability to make the trade-off between the performance and condition satisfaction, such that the performance and feasibility can be further improved.

The robust DF design can be considered as a mixed H_-/H_∞ problem, and it can be reduced to a H_∞ model-matching problem. Referring to H_∞ control theory, if the performance index (8) is satisfied, the dissipation inequality can be obtained and formulated as:

$$\sum_{i=0}^{k-1}(\|r(i)\|^2 - \gamma^2\|d(i)\|^2) \leq V(e(0)) - V(e(k)) \tag{15}$$

where $V(e) = e^T Pe$.

With the bounded-energy disturbance d, the residual output can be assumed to be bounded satisfying $\sum_{i=0}^{\infty}\|r(i)\|^2 \leq \alpha^2$. Then, for the actual state e in the error dynamics (7), two state ellipsoids can be defined as:

$$\xi_1 = \{e \in \Re^n \,|V(e) \leq \lambda\} \tag{16}$$

$$\xi_2 = \{e \in \Re^n \,\big|V(e) + \alpha^2\gamma^2 \leq \lambda\} \tag{17}$$

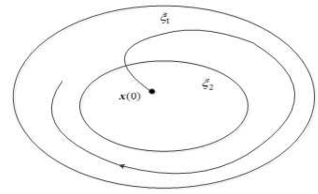


FIGURE 1. State invariant ellipsoids.

According to the literature [25], (17) is the sufficient condition for guaranteeing (16), illustrated in Fig. 1. It is equivalent to say that if $\lambda - \alpha^2\gamma^2 > 0$ and the initial state $e(0) \in \xi_2$ which is affected by the disturbance or fault, then the system state can be still constrained in the ellipsoid defined in (16), which means that $e(k) \in \xi_1, \forall k \geq 0$.

Using the Schur complement, the constraint (17) can be transferred to an LMI for fixed α, which is formulated as:

$$\begin{bmatrix} \lambda - \alpha^2\gamma^2 & e^T(k) \\ * & P_k^{-1} \end{bmatrix} \geq 0 \tag{18}$$

As the actual states contain the past information about system dynamics, disturbances and control inputs, the performance can be absolutely improved with the involvement of the actual states. In order to take advantages of the moving horizon optimization strategy, it can not be achieved with the simple implementation (18), due to the insufficient dissipation condition for error dynamics (7) [26]. In order to obtain the sufficient dissipation condition, the moving horizon strategy should be investigated. At the initial time $k = 0$, the control input is unchanged till the next time. Based on (15), there exists $\|r(0)\|^2 - \gamma_0^2\,\|d(0)\|^2 \leq e^T(0)P_0\,e(0) - e^T(1)P_0\,e(1)$ at time $k = 0$. The dissipation at the next time $k = 1$ formulated as $\|r(1)\|^2 - \gamma_1^2\,\|d(1)\|^2 \leq e^T(1)P_1\,e(1) - e^T(2)P_1\,e(2)$ needs to be investigated. If the dissipation at time $k = 1$ is assumed to hold, the inequality can be given by:

$$\sum_{i=0}^{1}(\|r(i)\|^2 - \max\{\gamma_0^2, \gamma_1^2\}\|d(i)\|^2) \leq e^T(0)P_0e(0) - [e^T(1)P_0e(1) - e^T(1)P_1e(1)] - e^T(2)P_1e(2) \tag{19}$$

Referring to (15), if the second item on the right of the inequality $[e^T(1)P_0e(1) - e^T(1)P_1e(1)] \geq 0$ is satisfied, the dissipation at time $k = 1$ can be ensured. Then, at the next time $k = 2$, the inequality with the similar formulation of (19) can be given by:

$$\begin{aligned}\sum_{i=0}^{2}(\|r(i)\|^2 &- \max\{\gamma_0^2, \gamma_1^2, \gamma_2^2\}\|d(i)\|^2) \\ &\leq e^T(0)P_0e(0) - [e^T(1)P_0e(1) - e^T(1)P_1e(1)] \\ &\quad - [e^T(2)P_1e(2) - e^T(2)P_2e(2)] - e^T(3)P_2e(3)\end{aligned} \tag{20}$$

Referring to (15), the dissipation of (20) can be guaranteed if the following condition holds:

$$\begin{aligned}e^T(0)P_0e(0) &- [e^T(1)P_0e(1) - e^T(1)P_1e(1)] \\ &- [e^T(2)P_1e(2) - e^T(2)P_2e(2)] \\ &- e^T(3)P_2e(3) \leq e^T(0)P_0e(0)\end{aligned} \tag{21}$$

From the dissipation conditions at the first two sampling periods, it can be concluded that at time k, if$p_k = p_{k-1} - [e^T(k)P_{k-1}e(k) - e^T(k)P_k e(k)] \leq p_0 = e^T(0)P_0\, e(0)$, the dissipation can be guaranteed. Given the recursion formulation, the notation p_k is defined as:

$$p_k = e^T(0)P_0 e(0) - \sum_{i=1}^{k}[e^T(i)P_{i-1}e(i) - e^T(i)P_i e(i)] \quad (22)$$

Theorem 3: For the error dynamics (7), the dissipation can be guaranteed if the following LMI hold:

$$\begin{bmatrix} p_0 - p_{k-1} + e^T(k)P_{k-1}e(k) & e^T(k) \\ * & P_k^{-1} \end{bmatrix} \geq 0 \quad (23)$$

where $p_0 = e^T(0)P_0\, e(0)$, p_{k-1} and P_{k-1} are all constants at time k.

Proof: Based on the Schur complement, the LMI can be easily obtained from the recursion formulation after a simple manipulation based on (22).

Aiming at designing a robust FD observer to generate the residual signal, which has the best robustness to external disturbances and sensitivity to possible component faults, the mixed H_∞/H_- design approach integrated with moving horizon optimization strategy is proposed, and the optimization problem is defined as:

$$\min_{\bar{L},P} \frac{\gamma}{\beta}$$
$$s.t.\ (10),\ (11),\ (18)\ and\ (23) \quad (24)$$

The algorithm process for the proposed robust FD design scheme can be described as follows:

Step 1: Given the residual generator mode (7), set small constants $\Delta\gamma > 0$, $\Delta\beta > 0$, α, λ_0 and sufficient large value $J_{min,k}$.

Step 2: Calculate γ_{min} and β_{max} with (10) and (11) satisfied.

Step 3: At time k, set $\gamma_k = \gamma_{min}$. Solve (10) and (11), so that the value β_k is maximized for the matrices P_k and L_k.If $\frac{\gamma_k}{\beta_k} \leq J_{min,k}$, let $\frac{\gamma_k}{\beta_k} = J_{min,k}$, and save γ_k, β_k, P_k and L_k. If not feasible, go to *Step 4*.

Step 4: Let $\gamma_k = \gamma_k + \Delta\gamma$, repeat *Step 3* until $\gamma_k \geq 1$.

Step 5: Set $\beta_k = \beta_{max}$. Solve (10) and (11), so that the value γ_k is minimized for the matrices P_k and L_k. $\frac{\gamma_k}{\beta_k} \leq J_{min,k}$, let $\frac{\gamma_k}{\beta_k} = J_{min,k}$, and save γ_k, β_k, P_k and L_k. If not feasible, go to *Step 6*.

Step 6: Let $\beta_k = \beta_k - \Delta\beta$, repeat *Step 5* until $\beta_k \leq 0$.

Step 7: Set $\lambda_k = \lambda_0$. If (18) and (23) are satisfied, calculate the recursion for the next computation based on (22), then go to *Step 9*.

Step 8: Solve the LMI optimization (24). If it admits a solution, calculate P_k and L_k. If not feasible, increase λ_k, repeat *Step 8*.

Step 9: Go back to *Step 3* with $k \to k+1$.

V. SIMULATION RESULTS

In order to demonstrate the effectiveness of the proposed FD scheme, the numerical simulation has been done. The extended model (4) is considered with the following parameters [27], [31]:

$$A = \begin{bmatrix} -0.2276 & -2.7910 & 0 & -0.09211 & -0.1169 \\ -0.0009168 & -0.1068 & 0 & 0.009949 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0.002032 & -0.3058 & 0 & -0.1982 & -0.04486 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix},$$

$$B = \begin{bmatrix} -0.05699 \\ -0.002838 \\ 0 \\ 0.004081 \\ 0 \end{bmatrix},$$

$$B_d = \begin{bmatrix} 0.005 \\ -0.015 \\ 0.01 \\ 0.0050 \\ 0.0050 \end{bmatrix}, \quad D = 0,$$

$$B_f = \begin{bmatrix} 0.200 \\ -0.200 \\ 0.400 \\ 0.400 \\ 0.400 \end{bmatrix}, \quad C = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

The sampling time is set to be 0.2s, and the unknown input d of the system is assumed to be the white noise with bounded energy 0.01. As a result, the residual signals of system outputs with the fault-free case are shown in Fig. 2. r_1 and r_2 denote the residual signals of the yaw angle and roll angle, respectively.

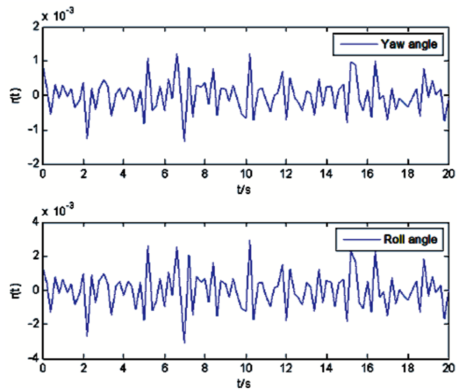


FIGURE 2. **Residual signals in the fault-free case.**

Referring to [12], [14],and [29], with some of generality, for the purpose of demonstrating the effectiveness of the proposed method, the simulated component fault signal is a pulse with the amplitude 0.1 from 5 to 10s. The residual signals with bounded disturbance and component fault to be detected are shown in Fig. 3. During the time interval from 0 to 20s, the disturbance d has less affection on the amplitude change of the residual signal, which illustrates the good robustness of the proposed FD system. Due to the simulated fault signal, a relatively apparent amplitude change occurs at 5s, and it

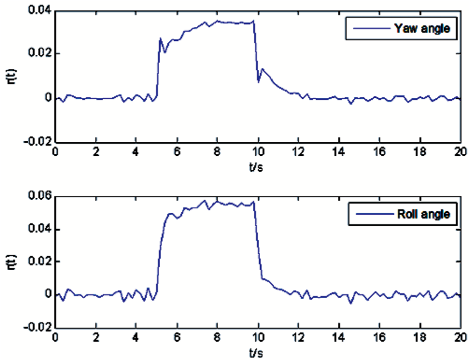


FIGURE 3. Residual signals with the simulated faults.

holds till 10s. This means the existence of a sort of abnormal conditions in the yaw angle and roll angle.

To demonstrate the advantages of the proposed method, the comparison of the FD performance should be done. Based on the the corollary in [29], the performance indexes are optimized to be $\gamma_{min} = 0.0108$, $\beta_{max} = 0.0425$, and $L = \begin{bmatrix} -96.3173 & 30.2003 & 8.4620 & -26.3153 & -16.7852 \\ 82.8388 & -28.9349 & -0.1133 & 28.2566 & 20.3852 \end{bmatrix}^T$. Applying the corollary, the residual signals are given in Fig. 4. With the comparison of the two figures, it is easy to draw the conclusion that the proposed FD system is more sensitive to the fault variables, such that the fault detectability is improved.

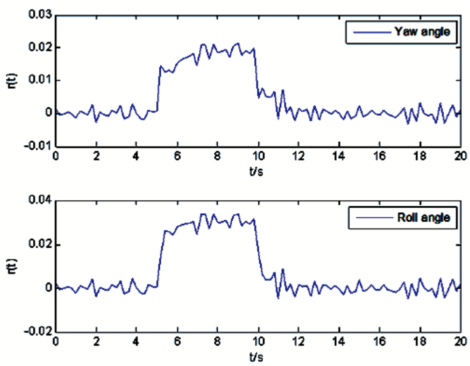


FIGURE 4. FD performance using the method in [29].

The residual evaluation function and threshold for r_1 are shown in Fig. 5. It can be seen that at 5.4s, the value of residual evaluation function is larger than corresponding threshold, and then the simulated fault signal is detected. Equivalently, after the existence of fault signal for 0.4s, the fault signal can be detected using the proposed FD approach, and then a fault alarm is delivered. Due to the similarity of r_2 and r_1, the residual evaluation function and threshold for r_2 are omitted here.

Thus, it can be concluded that for the system with unknown input and fault, the proposed robust FD approach in this paper can achieve the robustness to the external disturbance and the sensitivity to the fault signal to be detected.

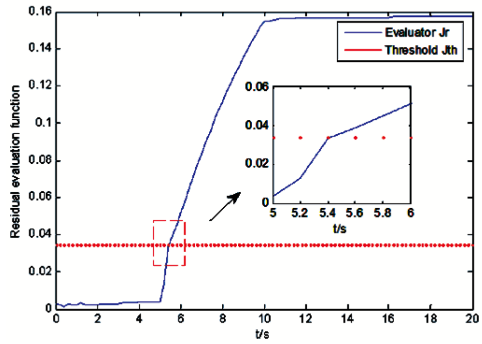


FIGURE 5. Residual evaluation and determined threshold.

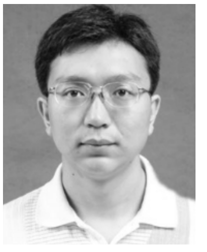
VI. CONCLUSION

In this paper, considering the system model for USV with bounded disturbances and component faults, the robust observer-based DF method is studied in order to improve the performance, safety and reliability. To tackle the FD observer design problem, the sufficient conditions are derived to guarantee the performance indexes using LMI formulation. The so-called moving horizon optimization is introduced to involve the actual states in the optimization process, such that it can be updated online with the real-time parameters leading to the improvements of performance and feasibility. The simulation is carried out in order to show the effectiveness of the proposed FD design scheme. Considering that the common Lyapunov matrix $P > 0$ is used in the sufficient conditions derived for guaranteeing different performance indexes throughout this paper with the consideration of component faults, the future work are focused on: (i) the multiple Lyapunov functions for less of conservatism, (ii) component faults compounded with sensor faults or actuator faults, (iii) and the compositions of the specific components in ships to make the simulated fault correspond to the real fault condition of marine surface vessels.

REFERENCES

[1] M. P. Frank, S. Ding, and B. Koppen-seliger, "Current developments in the theory of FDI," *J. Coastal Conservation*, vol. 4, no. 2, pp. 105–108, 1998.
[2] P. M. Frank, S. X. Ding, and T. Marcu, "Model-based fault diagnosis in technical processes," *Trans. Inst. Meas. Control*, vol. 22, no. 1, pp. 57–101, 2000.
[3] P. S. Teh and H. Trinh, "Design of unknown input functional observers for nonlinear systems with application to fault diagnosis," *J. Process Control*, vol. 23, no. 8, pp. 1169–1184, 2013.
[4] S. Yin, H. Gao, J. Qiu, and O. Kaynak, "Descriptor reduced-order sliding mode observers design for switched systems with sensor and actuator faults," *Automatica*, vol. 76, pp. 282–292, Feb. 2017.
[5] S. Yin, H. Yang, and O. Kaynak, "Sliding mode observer-based FTC for Markovian jump systems with actuator and sensor faults," *IEEE Trans. Autom. Control*, vol. 62, no. 7, pp. 3551–3558, Jul. 2017.
[6] J. Chen, R. J. Patton, and H. Zhang, "Design of unknown input observers and robust fault detection filters," *Int. J. Control*, vol. 63, no. 1, pp. 85–105, 1996.
[7] J. Chen and R. J. Patton, *Robust Model-Based Fault Diagnosis for Dynamic Systems*. New York, NY, USA: Springer, 1999.
[8] N. Meskin and K. Khorasani, "Actuator fault detection and isolation for a network of unmanned vehicles," *IEEE Trans. Autom. Control*, vol. 54, no. 4, pp. 835–840, Apr. 2009.

[9] I. M. Jaimoukha, Z. Li, and V. Papakos, "A matrix factorization solution to the H_{-}/H_{∞} fault detection problem," *Automatica*, vol. 42, no. 11, pp. 1907–1912, 2006.
[10] J. Liu, J. L. Wang, and G.-H. Yang, "An LMI approach to minimum sensitivity analysis with application to fault detection," *Automatica*, vol. 41, no. 11, pp. 1995–2004, Nov. 2005.
[11] H. Wang, J. Wang, J. Lam, and J. Liu, "Iterative LMI approach for robust fault detection observer design," in *Proc. IEEE Conf. Decision Control*, vol. 2. Dec. 2003, pp. 1974–1979.
[12] M. Chadli, A. Abdo, and S. X. Ding, "H_{-}/H_{∞} fault detection filter design for discrete-time Takagi-Sugeno fuzzy system," *Automatica*, vol. 49, no. 7, pp. 1996–2005, 2013.
[13] W. Chen, S. X. Ding, M. Abid, and A. Q. Khan, "Energy based fault detection for dissipative systems," in *Proc. Control Fault-Tolerant Syst.*, 2010, pp. 517–521.
[14] L. Li, S. X. Ding, K. Peng, J. Qiu, and Y. Yang, "An optimal fault detection approach for piecewise affine systems via diagnostic observers," *Automatica*, vol. 85, pp. 256–263, 2017.
[15] T. I. Fossen, *Guidance and Control of Ocean Vehicles*. Norway, U.K.: Wiley, 1994.
[16] X. Xiang, C. Yu, J. Zhang, Q. Zhang, and L. Lapierre, "Survey on fuzzy-logic-based guidance and control of marine surface vehicles and underwater vehicles," *Int. J. Fuzzy Syst.*, vol. 20, no. 2, pp. 572–586, 2018, doi: 10.1007/s40815-017-0401-3.2017.
[17] X. Xiang, C. Liu, H. Su, and Q. Zhang, "On decentralized adaptive full-order sliding mode control of multiple UAVs," *ISA Trans.*, vol. 71, pp. 196–205, Nov. 2017.
[18] X. Xiang, C. Yu, and Q. Zhang, "Robust fuzzy 3D path following for autonomous underwater vehicle subject to uncertainties," *Comput. Operat. Res.*, vol. 84, pp. 165–177, Aug. 2017.
[19] X. Xiang, C. Yu, and Q. Zhang, "On intelligent risk analysis and critical decision of underwater robotic vehicle," *Ocean Eng.*, vol. 140, pp. 453–465, Aug. 2017.
[20] X. Xiang, L. Lapierre, and B. Jouvencel, "Smooth transition of AUV motion control: From fully-actuated to under-actuated configuration," *Robot. Auto. Syst.*, vol. 67, pp. 14–22, May 2015.
[21] H.-J. Lee, B.-S. Ahn, and Y.-M. Park, "A fault diagnosis expert system for distribution substations," *IEEE Trans. Power Del.*, vol. 15, no. 1, pp. 92–97, Jan. 2000.
[22] Y. Guan, J. Zhao, P. Zhu, and T. Shi, "Fault tree analysis of fire and explosion accidents for dual fuel (diesel/natural gas) ship engine rooms," *J. Marine Sci. Appl.*, vol. 15, no. 3, pp. 331–335, 2016.
[23] R. Yu, R. Xiang, Z. W. Ke, S. W. Yao, and X. Wan, "Fault diagnosis of condenser in ship steam power system based on unsupervised learning neural network," *Appl. Mech. Mater.*, vols. 271–272, pp. 1568–1572, Mar. 2013.
[24] S. X. Ding, *Model Based Faults Diagnosis Techniques-Design Schemes, Algorithms and Tools*. Springer-Verlag, 2008.
[25] H. Chen and C. W. Scherer, "Disturbance attenuation with actuator constraints by moving horizon H_{∞} control," *IFAC Proc. Vols.*, vol. 37, no. 1, pp. 415–420, 2004.
[26] C. W. Scherer, H. Chen, and F. Allgower, "Disturbance attenuation with actuator constraints by hybrid state-feedback control," in *Proc. 41st IEEE Conf. Decision Control*, Dec. 2002, pp. 4134–4139.
[27] Z. Li, J. Sun, and S. R. Oh, "Path following for marine surface vessels with rudder and roll constraints: An MPC approach," in *Proc. Amer. Control Conf.*, 2009, pp. 3611–3616.
[28] J. Huang, Z. Jiang, and J. Zhao, "Component fault diagnosis for nonlinear systems," *J. Syst. Eng. Electron.*, vol. 27, no. 6, pp. 1283–1290, 2016.
[29] J. Guo, X. Huang, and Y. Cui, "Design and analysis of robust fault detection filter using LMI tools," *Comput. Math. Appl.*, vol. 57, nos. 11–12, pp. 1743–1747, 2009.
[30] L. Qin, X. He, and D. Zhou, "A fault estimation method based on robust residual generator," *J. Shanghai Jiaotong Univ.*, vol. 49, no. 6, pp. 768–774, 2015.
[31] T. Peng, W. Gui, and X. D. Steven, "An LMI based H_{-}/H_{∞} optimal design approach for fault detection observer," *J. Central South Univ. Technol. (Sci. Technol.)*, vol. 35, no. 4, pp. 628–631, 2004.



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