IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received April 9, 2020, accepted April 24, 2020, date of publication April 29, 2020, date of current version May 19, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2991188

Sensor Fault Diagnosis and Fault Tolerant Control for Forklift Based on Sliding Mode Theory

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This work was supported in part by the National Natural Science Foundation of China under Grant 51577046, and in part by Hefei Banyitong Science and Technology Development Company Ltd.

ABSTRACT For the forklift equipped with electrical sensors, a fault tolerant control (FTC) strategy is proposed. First, considering the uncertainty of forklift cargo and the external output disturbance, the equivalent sensor fault model of forklift is constructed. Then, a sliding mode observer (SMO) with adaptive regulation law is proposed to solve the problem that some fault reconstruction methods demand the upper bound of faults. Based on the fault value reconstructed by SMO, a sliding mode fault-tolerant controller is designed. It can realize active FTC of typical sensor faults of forklift in the presence of uncertainties and output disturbance. Finally, experiment is given to verify the effectiveness of the proposed FTC strategy.

INDEX TERMS Forklift, sensor fault diagnosis, multi-sensor fault reconstruction, fault tolerant control.

I. INTRODUCTION

With the rapid development of forklift, a growing number of electronic components have been adopted. It improves the flexibility of control system, but impairs the robustness because the reliability of electronic components is generally lower than that of traditional mechanical and hydraulic components [1]. The electronic components are likely to fail without warning and a small malfunction could be passed down and amplified to result in a fatal systematic failure [2], [3]. Generally, sensor faults will bring more serious consequences than actuator faults or some other failures because incorrect signals obtained from sensors will drive the control system to lose control [4], [5]. Therefore, there is an urgent demand for fault-tolerant control (FTC) strategy to ensure the reliable operation of modern vehicles in the presence of sensor faults.

In recent years, several methods for sensor fault diagnosis and FTC have been proposed. In [6], an approach of active fault-tolerant control based on signal reconfiguration is proposed for the fault of missile attitude control systems caused by failed inertial sensors. A fault-tolerant control strategy for the longitudinal dynamics of an autonomous vehicle is presented to detect potential failures of the vehicle's speed sensor and then to keep the vehicle in a safe state [7]. Reference [8] proposes a fault detection and isolation strategy for torque safety of automobile which is caused by the pedal mechanical stiction fault and pedal sensor faults. The aforementioned references could achieve the desired performances, but they are proposed for the specific sensor faults in the system. On the other side, as a forklift, the changing of load should also be taken into consideration. It means that it is necessary to design FTC controller in case of the system model uncertainty and disturbances.

Sliding mode observer (SMO) is always regarded as an effective robust control strategy [9], [10]. It holds the superiorities of fast response, excellent transient performance, and insensitiveness to perturbations and disturbances. Enlightened by these, SMO was extended to be utilized for FTC purposes. In [11], an improved second-order SMO is designed to cope with the fault reconstruction problem for autonomous underwater vehicle (AUV) subject to ocean current disturbance and modelling uncertainty. Wang Y.Y. et.al present a fault-tolerant tracking control strategy for Takagi–Sugeno fuzzy model-based nonlinear systems. It combines integral sliding mode control with adaptive control technique and has been applied to the dynamic positioning control of unmanned marine vehicles [12]. To solve the fault-tolerant control problem of Markov jump systems (MJS) with *Itô* stochastic process and output disturbances, a proportional-derivative SMO and an observer-based controller are designed and synthesized in [13].

The associate editor coordinating the review of this manuscript and approving it for publication was Sing Kiong Nguang.

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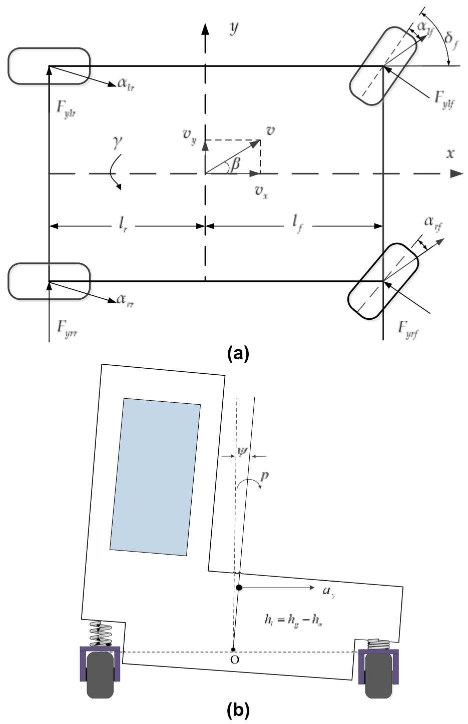

FIGURE 1. Dynamic model of forklift.

Motivated by above discussions, a FTC method is proposed to cope with the key sensor faults of forklift. It can be divided into two parts. One is the SMO with adaptive regulation law which reconstructs the fault value of sensors. Another is the FTC controller. Based on the fault value produced by the SMO, it can realize fault-tolerant control of uncertain linear system of forklift with output disturbances.

The rest of this paper is organized as follows. In Section 2, a fault model of forklift is established. In Section 3, the sliding mode FTC system is demonstrated. Experimental results are discussed in Section 4 and the conclusion is presented in Section 5.

II. FAULT MODEL OF FORKLIFT

This paper takes an electric forklift with front wheel steering as an example, and its dynamics model is shown in Figure 1. It can be simplified as: roll motion around X-axis, lateral motion along Y-axis and yaw motion around Z-axis. The frame origin is at the original vehicle center of mass, with the X-axis along the longitudinal vehicle direction pointing forward, the Y-axis pointing to the left vehicle side, and the Z-axis pointing upward. Assuming that the cornering characteristics of wheels are in linear range and the effect of load transfer caused by forklift motion on the wheel is neglected.

The dynamic model of forklift is given as [14]

$$\begin{cases} I_x\dot{p} - I_{xz}\dot{\gamma} = M_s g h_l \psi - K_\psi \psi - C_\psi p + M_s h_l v_x(\dot{\beta} + \gamma) \\ M v_x(\dot{\beta} + \gamma) - M_s h_l \dot{p} = F_{ylf} + F_{yrf} + F_{ylr} + F_{yrr} \\ I_z\dot{\gamma} - I_{xz}\dot{p} = -l_r(F_{ylf} + F_{yrf}) + l_f(F_{ylr} + F_{yrr}) \\ F_y = k\alpha \end{cases} \tag{1}$$

where M is the total mass of the vehicle, M_s is the sprung mass of the vehicle, h_l is the distance between the original center of the forklift and the roll center, l_f is the distance between center of gravity and the center line of the front axle, l_r is the distance between center of gravity and the center line of the rear axle, δ_f is the steering angle of the front wheel, β is the sideslip angle, γ is the yaw rate about the z axis. v_x and v_y are the longitudinal and lateral velocities at the center of gravity of vehicle, ψ is the body roll angle, p is the roll velocity, K_ψ is the total roll rate, C_ψ is the roll damping, I_x and I_z are the moment of inertia around x-axis and z-axis respectively, I_{xz} is the product of I_x and I_z, k_1 and k_2 are the front and rear tire cornering stiffness, respectively. Additionally, F_{yli} and F_{yri}, respectively, denotes the left and right lateral tire forces, and i represents front and rear. α, which is directly proportional to F $(F_{ylf}, F_{ylr}, F_{yrf}, F_{yrr} F_{yri})$, denotes the sideslip angle of tire. The state space of forklift can be derived as follows by considering $x(t) = [\omega_r, \beta, \psi, p]^T$ as the state vectors and $u(t) = \delta_f$ as the input vector:

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

where

$$A = M_1^{-1}M_2, B = M_1^{-1}M_3, C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$$M_1 = \begin{bmatrix} 0 & Mv_x & 0 & -M_s h_l \\ I_z & 0 & 0 & -I_{xz} \\ -I_{xz} & -M_s h_l v_x & 0 & I_x \\ 0 & 0 & 1 & 0 \end{bmatrix}, M_3 = \begin{bmatrix} k_1 \\ k_1 a \\ 0 \\ 0 \end{bmatrix},$$

$$M_2 = \begin{bmatrix} \frac{-k_1 a + k_2 b}{v_x} - Mv_x & -k_1 - k_2 & (k_1 R_f + k_2 R_r) & 0 \\ -\frac{k_1 a^2 + k_2 b^2}{v_x} & -ak_1 + bk_2 & (k_1 a R_f - k_2 b R_r) & 0 \\ M_s h_l v_x & 0 & -(K_\psi - M_s g h_l) & -C_\psi \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

In the SBW system, the sensor faults include gain fault, stuck fault and constant deviation fault. Yaw rate sensor, roll rate sensor and front wheel angle sensor are considered in this manuscript. When the i^{th} sensor occur faults, its output is

$$Y_{if} = \Delta_i Y_i + a_i \tag{3}$$

where Y_i and Y_{if} represent the true output and fault output respectively. Δ_i reflects the fault degree when sensor occurs the gain fault. a_i represents the value of stuck fault and constant deviation fault.

Assume that the sensor occur faults as follows:

1) Yaw rate sensor fault: $Y_{if} = \Delta_i Y_i (\Delta_i \in (0, 1))$. It means that the sensor occurs gain fault.

2) Roll rate sensor fault: $Y_{if} = a_i$. It means that the sensor occurs stuck fault.

3) Front wheel angle sensor fault: $Y_{if} = Y_i + \begin{cases} a_i, t_1 \leq t < t_2 \\ a_j, t_3 \leq t < t_4 \end{cases}$. It means that the sensor occurs constant deviation fault intermittently.

The fault output is summarized as follows

$$Y_f = \begin{bmatrix} Y_{1f} \\ Y_{2f} \\ Y_{3f} \end{bmatrix} = \begin{bmatrix} \Delta_1 Y_1 + a_1 \\ \Delta_2 Y_2 + a_2 \\ \Delta_3 Y_3 + a_3 \end{bmatrix} = \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} + \begin{bmatrix} (\Delta_1 - 1) Y_1 \\ -Y_2 + a_2 \\ a_3 \end{bmatrix} \tag{4}$$

Considering the uncertainty of cargo and the external output disturbance, the equivalent sensor fault model of forklift can be defined as

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + H\theta(t) + Ff_s \end{cases} \tag{5}$$

where $x(t) \in R^n$ denotes the unmeasurable state vector, $u(t) \in R^l$ denotes the measurable input vector, $y(t) \in R^m$ denotes the measurable output vector, $\theta(t)$ denotes the external uncertainties and nonlinear term, $f_s \in R^m$ denotes the sensor fault, H denotes the known external interference matrix, F denotes the known distribution matrix of sensor fault, A, B, and C are known constant matrices.

Assume that multiple sensor faults, the number of which is at most m, may occur at any time, the model can be described as:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y_1(t) = C_1 x(t) + H_1 \theta(t) + F_1 f_{s1} \\ \qquad \vdots \\ y_m(t) = C_m x(t) + H_m \theta(t) + F_m f_{sm} \end{cases} \tag{6}$$

The above sensor faults model can be simplified into the following equation (7), and it can be divided into multiple single sensor fault modules for the fault detection. When multiple sensors fail at the same time, the faults of the corresponding parts can be detected to realize fault detection and reconstruction.

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y_i(t) = C_i x(t) + H_i \theta(t) + F_i f_{si} \end{cases} \tag{7}$$

The following state variable z is defined as the first-order low-pass filtering output of the signal $y(t)$ [15]. The sensor fault is transformed as an actuator fault by the first-order low-pass filter.

$$\dot{z}_i = -A_{si} z_i + A_{si} y_i \tag{8}$$

where A_{si} is the stable matrix of appropriate dimensions. From equation (7) and (8), we can get

$$\begin{cases} \begin{bmatrix} \dot{x} \\ \dot{z}_i \end{bmatrix} = \begin{bmatrix} A & 0 \\ A_{si} C_i & -A_{si} \end{bmatrix} \begin{bmatrix} x \\ z_i \end{bmatrix} + \begin{bmatrix} B \\ A_{si} G_i \end{bmatrix} u \\ \qquad + \begin{bmatrix} 0 \\ A_{si} H_i \end{bmatrix} \theta(t) + \begin{bmatrix} 0 \\ A_{si} F_i \end{bmatrix} f_{si} \\ z_i = \begin{bmatrix} 0 & I_1 \end{bmatrix} \begin{bmatrix} x \\ z_i \end{bmatrix} \end{cases} \tag{9}$$

A new state variable and the corresponding matrix can be defined as

$$\bar{x}_i = \begin{bmatrix} x & z_i \end{bmatrix}^T, \bar{y}_i = z_i, \bar{A}_i = \begin{bmatrix} A & 0 \\ A_{si} C_i & -A_{si} \end{bmatrix},$$
$$\bar{B}_i = \begin{bmatrix} B \\ A_{si} G_i \end{bmatrix}, \bar{C}_i = \begin{bmatrix} 0 & I \end{bmatrix}, \bar{H}_i = \begin{bmatrix} 0 \\ A_{si} H_i \end{bmatrix}, \bar{F}_i = \begin{bmatrix} 0 \\ A_{si} F_i \end{bmatrix} \tag{10}$$

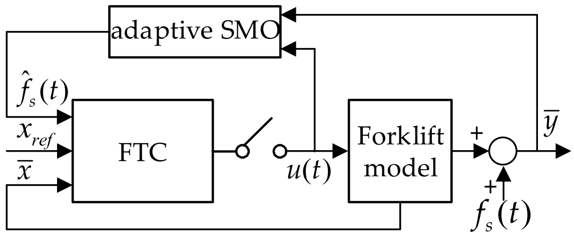

FIGURE 2. The structure of Forklift sensor FTC system based on adaptive SMO.

Substituting (10) into (8), we can get

$$\begin{cases} \dot{\bar{x}}_i(t) = \bar{A}_i \bar{x}_i(t) + \bar{B}_i u(t) + \bar{H}_i \theta(t) + \bar{F}_i f_{si} \\ \bar{y}_i(t) = \bar{C}_i \bar{x}_i(t) \end{cases} \tag{11}$$

From equation (11), through the introduction of state variables z, the sensor fault is converted into a pseudo-actuator fault. It forms an augmented state space system [16] and a single sensor fault model is constructed.

III. SLIDING MODE FTC SYSTEM

For the fault model of key sensors in the forklift stability control system, firstly, a fault reconstruction method of multiple sensors based on SMO is proposed. It separates the faults from external disturbances and achieves robust fault estimation. Then, a sliding mode fault-tolerant controller is designed by the state feedback design method based on the SMO. It can realize robust control in the presence of uncertainties and external output disturbances. Its purpose is to compensate sensor faults and realize active FTC for typical sensor faults of forklift. The structure of sliding mode FTC system [17], [18] is shown in Figure 2.

A. ADAPTIVE SMO DESIGN

According to the sensor fault model (11), the SMO with adaptive algorithm is described as

$$\begin{cases} \dot{\hat{\bar{x}}}_i(t) = \bar{A}_i \hat{\bar{x}}_i(t) + \bar{B} u(t) + L_i(\bar{y}_i - \hat{\bar{y}}_i) + \bar{F}_i v_i \\ \hat{\bar{y}}_i(t) = \bar{C}_i \hat{\bar{x}}_i(t) \end{cases} \tag{12}$$

where $\hat{\bar{x}}_i(t)$ is the state observation vector of $\bar{x}_i(t)$, L_i is the gain matrix of observer to be designed, $e_{yi} = \bar{y}_i - \hat{\bar{y}}_i$ is the output estimation error, v_i is the discontinuous sliding mode control input vector which is used to cut off the effect of fault f_{si} and its expression is

$$v_i = \begin{cases} \rho_i(t) \frac{D_i \bar{e}_{yi}}{\|D_i \bar{e}_{yi}\|} & \bar{e}_{yi} \neq 0 \\ 0 & \bar{e}_{yi} = 0 \end{cases} \tag{13}$$

where $\rho_i(t)$ denotes the adjustable gain parameter with the advantage of adaptive adjustment, it is designed by the corresponding adaptive algorithm without knowing the upper limit of unknown sensor fault. The adaptive algorithm is described as

$$\frac{d\rho_i(t)}{dt} = \eta_i \left\| D_i \bar{e}_{yi} \right\| \operatorname{sgn}(\left\| D_i \bar{e}_{yi} \right\| - \lambda_i), \quad i = 1, \cdots m \tag{14}$$

where $\rho_i(0) > 0$, $\eta_i < 2$, $0 < \lambda_i < 1$, $i = 1, \cdots m$.

From (14), when $\mathrm{sgn}(\|D_i\bar{e}_{yi}\| - \lambda_i) = 1$, the adjustable gain parameter $\rho_i(t)$ will increase and its rate is proportional to $\|D_i\bar{e}_{yi}\|$. Also, when $\mathrm{sgn}(\|D_i\bar{e}_{yi}\| - \lambda_i) = -1$, $\rho_i(t)$ will decrease. It means that once sliding mode motion occurs, which means $\|D_i\bar{e}_{yi}\|$ is close to zero, $\|D_i\bar{e}_{yi}\| \le \lambda_i$ when λ_i takes a minor constant. Then the adjustable gain parameter changes a little, which ensures that the sliding mode adjustable parameter is not too large, so that the chattering phenomenon caused by the excessive gain parameter can be weakened to some extent.

Lemma 1: The adaptive adjustment law of the adjustable gain parameter in (14) should observe the following condition: the upper limit of $\rho_i(t)$ is ρ_i^* and $\rho_i^* > \gamma_i$ [19].

Define the state estimation error as:

$$\bar{e}_i = \bar{x}_i - \hat{\bar{x}}_i \tag{15}$$

By subtracting equation (12) from equation (11), when the i^{th}sensor fails, the deviation equation of the i^{th} observer is:

$$\dot{\bar{e}}_i = (\bar{A}_i - L_i\bar{C}_i)\bar{e}_i + \bar{H}_i\theta(t) + \bar{F}_i(f_{si} - v_i) \tag{16}$$

Theorem 1: Based on the above definitions, when the i^{th} sensor fails and the following conditions satisfy:

1) $\|\bar{e}_i\| > 2\|P_i\|\,\|\bar{H}_i\|\,\omega/\lambda_{\min}(Q_i)$

2) LMI: $\begin{bmatrix} (\bar{A}_i - L_i\bar{C}_i)^T P_i + P_i(\bar{A}_i - L_i\bar{C}_i) & 0 \\ 0 & -P_i \end{bmatrix} \le 0,$

the dynamic systems of state estimation error are asymptotically stable.

Proof: Consider the following Lyapunov function:

$$V(\bar{e}_i) = \bar{e}_i^T P\bar{e}_i + \frac{1}{2}(\rho_i - \rho_i^*)^2 \tag{17}$$

and its time derivative is calculated as follows:

$$\begin{aligned}
\dot{V}(\bar{e}_i) &= \bar{e}_i^T\left[(\bar{A}_i - L_i\bar{C}_i)^T P_i + P_i(\bar{A}_i - L_i\bar{C}_i)\right]\bar{e}_i \\
&\quad + 2\bar{e}_i^T P_i\bar{F}_i(f_{si} - v_i) + \dot{\rho}_i(\rho_i - \rho_i^*) + 2\bar{e}_i^T P_i\bar{H}_i\theta(t) \\
&= -\|\bar{e}_i\|\left[\lambda_{\min}(Q_i)\|\bar{e}_i\| - 2\|P_i\|\,\|\bar{H}_i\|\,\omega\right] \\
&\quad + 2\bar{e}_i^T P_i\bar{F}_i(f_{si} - v_i) + \eta_i(\rho_i - \rho_i^*)\|D_i\bar{e}_{yi}\| \\
&\quad \times \mathrm{sgn}(\|D_i\bar{e}_{yi}\| - \lambda_i) \\
&\le -\|\bar{e}_i\|\left[\lambda_{\min}(Q_i)\|\bar{e}_i\| - 2\|P_i\|\,\|\bar{H}_i\|\,\omega\right] \\
&\quad + \left(2\gamma_i - 2\rho_i + \eta_i(\rho_i - \rho_i^*)\right)\|D_i\bar{e}_{yi}\| \\
&= -\|\bar{e}_i\|\left[\lambda_{\min}(Q_i)\|\bar{e}_i\| - 2\|P_i\|\,\|\bar{H}_i\|\,\omega\right] \\
&\quad + \left(2\gamma_i - 2\rho_i + 2\rho_i^* - 2\rho_i^* + \eta_i(\rho_i - \rho_i^*)\right)\|D_i\bar{e}_{yi}\| \\
&= -\|\bar{e}_i\|\left[\lambda_{\min}(Q_i)\|\bar{e}_i\| - 2\|P_i\|\,\|\bar{H}_i\|\,\omega\right] \\
&\quad + \left[2(\gamma_i - \rho_i^*) - |\rho_i - \rho_i^*|(\eta_i - 2)\right]\|D_i\bar{e}_{yi}\|
\end{aligned}$$

Combine with the condition in Theorem 1, $\dot{V}(\bar{e}_i) < 0$ and $\|\bar{e}_i\|$ converges in the following domain:

$$U(\bar{e}_i) = \left\{\|\bar{e}_i\| \le 2\|P_i\|\,\|\bar{H}_i\|\,\omega/\lambda_{\min}(Q_i)\right\}$$

To reduce the chattering of the sliding mode motion, add an appropriate scalar and the sliding mode control input (13) can be adjusted to:

$$v_i = \begin{cases} \rho_i(t)\dfrac{D_i\bar{e}_{yi}}{\|D_i\bar{e}_{yi}\| + \delta_i} & \bar{e}_{yi} \ne 0 \\ 0 & \bar{e}_{yi} = 0 \end{cases} \tag{18}$$

where δ_i is a fully small positive constant. Thus, the value of the fault can be approximated as:

$$\hat{f}_{si}(t) \to \rho_i\left[(\bar{C}_i\bar{F}_i)^+(\bar{C}_i\bar{F}_i)\right]\frac{D_i\bar{e}_{yi}}{\|D_i\bar{e}_{yi}\| + \delta_i} - (\bar{C}_i\bar{F}_i)^+\bar{C}_i\bar{H}_i\theta(t) \tag{19}$$

B. FTC CONTROLLER DESIGN

Considering the model uncertainties, the sensor fault model of forklift is described as:

$$\begin{cases} \dot{\bar{x}}(t) = (\bar{A} + \Delta\bar{A})\,\bar{x}(t) + (\bar{B} + \Delta\bar{B})\,u(t) + \bar{H}\theta(t) + \bar{F}f_s \\ \bar{y}(t) = \bar{C}\bar{x}(t) \end{cases} \tag{20}$$

where $\Delta\bar{A}$ and $\Delta\bar{B}$ represent the uncertainty of the model, they can be expressed by

$$\begin{cases} \Delta\bar{A} = \sum_{i=1}^{N} a_i\bar{A}_i \\ \Delta\bar{B} = \sum_{i=1}^{N} b_i\bar{B}_i \end{cases}$$

where $\bar{A}_i$ and $\bar{B}_i$ are the known matrixes which have the same dimensions as $\Delta\bar{A}$ and$\Delta\bar{B}$, a_i and b_i are the corresponding scalar. Then the uncertainty of the model can be described as

$$\begin{aligned} W_1\omega_1(t) &= \Delta\bar{A}\bar{x}(t) + \Delta\bar{B}u(t) \\ &= [A_1, A_2, \cdots A_N, B_1, B_2, \cdots B_N]\begin{bmatrix} a_1\bar{x}(t) \\ a_2\bar{x}(t) \\ \vdots \\ a_N\bar{x}(t) \\ b_1u(t) \\ b_2u(t) \\ \vdots \\ b_Nu(t) \end{bmatrix} \end{aligned} \tag{21}$$

To simplify the design of matrix with model uncertainties and external disturbances, the external disturbances and model uncertainties can be integrated as

$$\bar{W}\omega(t) = W_1\omega_1(t) + \bar{H}\theta(t) \tag{22}$$

Substituting (22) into (20), it can be transformed to

$$\begin{cases} \dot{\bar{x}}(t) = \bar{A}\bar{x}(t) + \bar{B}u(t) + \bar{W}\omega(t) + \bar{F}f_s \\ \bar{y}(t) = \bar{C}\bar{x}(t) \end{cases} \tag{23}$$

The above process converts the model uncertainty to external disturbances, so that the model uncertain parameters and external disturbances can be uniformly processed to simplify the calculation.

To design a fault-tolerant controller for the corresponding model of fault system, make the following assumptions:

Hypothesis 1: (A, B) is controllable, (A, C) is observable and (A, F, C) remains unchanged.

Hypothesis 2: The faults have been reconstructed precisely. It means$\hat{f}_s(t) \to f_s(t)$.

The active FTC for the system (23) can be described as: when no fault occurs,$f_s(t) = 0$, there exists the appropriate state feedback control law to achieve asymptotic stability of the system. When faults occur, $f_s(t) \neq 0$, the control law $U(t)$ can be designed to achieve adjustment and control of faults.

Hypothesis 3: $(\bar{A}, \bar{C})$ is observable and there exists appropriate matrix L, D, K, positive definite matrix P and Q such that $(\bar{A} - L\bar{C})$remains stable, $P\bar{F} = \bar{C}^T D^T$, $P\bar{H} = \bar{C}^T K^T$ and $(\bar{A} - L\bar{C})^T P + P(\bar{A} - L\bar{C}) = -Q$.

Hypothesis 4: ΔA and ΔB are bounded matrices, there exists $\varsigma_1, \varpi_2 > 0$ such that $\begin{cases} \|\Delta A\| \leq \varpi \varsigma_1 \\ \|\Delta B\| \leq \varpi \varsigma_2 \end{cases}$.

Hypothesis 5: On the basis of hypothesis (4), $\omega(t)$ is a bounded function, then there exists $\omega_0 > 0$ such that $\|\omega(t)\| \leq \omega_0$.

Hypothesis 6: The upper bound of the adjustable gain parameter $\rho(t)$ satisfies $\rho^* \geq \|\bar{C}\bar{F}\|^{-1}\left(\left\|\tilde{\bar{F}}_{s2}\right\|\gamma + \left\|\tilde{\bar{W}}_2\right\|\omega_0 + \kappa\right)$, where κ is a positive scalar, γ is the upper bound of the norm of sensor faults $\|f_s\|$ and its value is unknown.

For the sensor fault model (23), the design of a sliding mode fault-tolerant controller is designed by the following steps.

1) CONTROLLER MODEL

On the basis of (23), consider the following reference model according to the law of sliding mode motion:

$$\dot{x}_s = A_s x_s + B_s r_s \tag{24}$$

where $x_s \in R^{6\times1}$ is the state parameter of the model, $r_s \in R^{1\times1}$ is the input vector of the model, A_s and B_s are matrices with appropriate dimensions and the model remains stable.

Define the state estimation error as:

$$e_s = \bar{x} - x_s \tag{25}$$

From (23) and (24), the dynamic equation of state tracking error system can be derived as

$$\dot{e}_s = A_s e_s + (\bar{A} - A_s)\bar{x} + \bar{B}u - B_s r_s + \bar{F}_s f_s + \bar{W}\omega(t) \tag{26}$$

2) CONSTRUCTION OF INTERGRAL SURFACE

The robustness of the system can be enhanced by designing the integral sliding surface. Construct the function of integral sliding surface as follows

$$\delta_s = S_s e_s - S_s e_s(0) - S_s \int_0^t \left(A_s - \bar{B}K\right) e_s dt \tag{27}$$

where $S_s \in R^{1\times6}$ is a constant matrix with full rank so that the square matrix $S_s\bar{B}$ is nonsingular. $K \in R^{1\times6}$ meets the following inequality conditions:

$$\max\left(Re\left[\lambda\left(A_s - \bar{B}K\right)\right]\right) < 0 \tag{28}$$

where $Re[\lambda(*)]$ is the real part of $\lambda(*)$, $\lambda(*)$ is the eigenvalue of matrix.

Correspondingly, the convergence property can be calculated as

$$\delta_s = 0 \rightarrow S_s e_s - S_s e_s(0) - S_s \int_0^t \left(A_s - \bar{B}K\right) e_s dt = 0 \tag{29}$$

and its derivative is

$$\dot{e}_s = \left(A_s - \bar{B}K\right) e_s \tag{30}$$

It means that the greater state estimation error e_s is, the faster the convergence speed is. And the speed can be controlled by changing the value of $A_s - \bar{B}K$.

3) SLIDING MODE FTC LAW DESIGN

On the basis of upper discussion, the sliding mode FTC law is defined as

$$U(t) = u(t) + U_s(t) \tag{31}$$

where $u(t)$ is the linear part of the sliding mode control law. It can ensure that the system performs ideal sliding mode motion on the sliding surface and according to equivalent control, it can be constructed as

$$u = -\left(S_s\bar{B}\right)^{-1}\left[S_s\bar{B}Ke_s + S_s\left(\bar{A} - A_s\right)\bar{x} - S_s B_s r_s\right] \tag{32}$$

As a non-linear part, U_s can generate the discontinuous signal which forces the system trajectory to reach and maintain on the predetermined sliding surface, thus ensure the robustness to external disturbances. Combining with $\hat{f}_s$ and the inherent robustness of sliding mode control, U_s can be constructed as

$$U_s = -\left(S_s\bar{B}\right)^{-1} \frac{\delta_s\left(\tau_f + \tau\right)}{\left(\|\delta_s\| + \sigma\right)} \left(\delta_s \neq 0\right) \tag{33}$$

where σ is a fully small positive constant. By using fault estimation $\hat{f}_s$ provided by SMO, the nonlinear gain τ_f, which handles with sensor faults in the system, can be constructed as

$$\tau_f \geq \left\|S_s\bar{F}\right\| \left\|\hat{f}_s\right\| \left\|\bar{G}_3^{-1}N_2\right\|^{-1} \left\|\tilde{\bar{F}}_{s2}\right\|^{-1} + \kappa_f \tag{34}$$

where κ_f is a known positive integer. By introducing nonlinear gain τ_f, the impact of unknown information in the fault reconstruction value can be processed online, which can improve the fault tolerance of the system to handle more complex fault information.

The nonlinear gain τ is used to deal with the effects of external disturbances. By using the boundary conditions, it can be designed as:

$$\tau \geq \left\|S_s\bar{W}\right\| \omega_0 + \kappa_\theta \tag{35}$$

where κ_θ is a known positive integer.

4) VERIFICATION OF SYSTEM STABILITY

Theorem 2: When the conditions of the state tracking error system (26) are satisfied, design the sliding mode surface according to (27) and FTC law according to (29)-(33), then the error system (26) is asymptotically stable.

Proof: Consider a candidate of the Lyapunov function as $V_s = \frac{1}{2}\delta_s^T\delta_s$ and its derivative is

$$\dot{V}_s = \delta_s^T\dot{\delta}_s \tag{36}$$

Substituting the time derivative of (27) into (29)-(31), we can get

$$\begin{aligned}\dot{\delta}_s &= S_s\dot{e}_s - S_s\left(A_s - \bar{B}K\right)e_s\\ &= S_s\left[A_se_s + \left(\bar{A} - A_s\right)\bar{x} + \bar{B}U - B_sr_s + \bar{F}\hat{f}_s + \bar{W}\omega(t)\right]\\ &\quad - S_sA_se_s + S_s\bar{B}Ke_s\\ &= -\tau\frac{\delta_s}{\|\delta_s\| + \sigma} - \tau_f\frac{\delta_s}{\|\delta_s\| + \sigma} + S_s\bar{F}\hat{f}_s + S_s\bar{W}\omega(t)\end{aligned} \tag{37}$$

Then (34) can be calculated as

$$\begin{aligned}\dot{V}_s &= \delta_s^T\left(-\tau\frac{\delta_s}{\|\delta_s\| + \sigma} - \tau_f\frac{\delta_s}{\|\delta_s\| + \sigma} + S_s\bar{F}\hat{f}_s + S_s\bar{W}\omega(t)\right)\\ &= -\tau\|\delta_s\| + \delta_s^TS_s\bar{W}\omega(t) - \tau_f\|\delta_s\| + \delta_s^TS_s\bar{F}\hat{f}_s\\ &\le -\tau\|\delta_s\| + \|S_s\|\left\|S_s\bar{W}\right\|\|\omega(t)\| - \tau_f\|\delta_s\|\\ &\quad + \|S_s\|\left\|S_s\bar{F}\right\|\left\|\hat{f}_s\right\|\\ &\le -\left(\left\|S_s\bar{W}\right\|\omega_0 + \kappa_\theta\right)\|\delta_s\| + \left\|S_s\bar{W}\right\|\omega_0\|\delta_s\|\\ &\quad - \left(\left\|S_s\bar{F}\right\|\left\|\bar{G}_3^{-1}N_2\right\|^{-1}\left\|\bar{F}_{s2}\right\|^{-1}\left\|\hat{f}_s\right\| + \kappa_f\right)\|\delta_s\|\\ &\quad + \left\|S_s\bar{F}\right\|\gamma\|\delta_s\|\\ &= -\left(\kappa_\theta + \kappa_f\right)\|\delta_s\| - \left\|S_s\bar{F}\right\|\left[\left\|\tilde{\bar{F}}_{s2}\right\|^{-1}\left\|\bar{G}_3^{-1}N_2\right\|^{-1}\left\|\hat{f}_s\right\| - \gamma\right]\\ &\quad \times\|\delta_s\| < 0\end{aligned} \tag{38}$$

From hypothesis 6 and (33),

$$\begin{aligned}\left\|\bar{G}_3^{-1}N_2\right\|^{-1}\left\|\tilde{\bar{F}}_{s2}\right\|^{-1}\left\|\hat{f}_s\right\| &= \left\|\bar{G}_3^{-1}N_2\right\|^{-1}\left\|\tilde{\bar{F}}_{s2}\right\|^{-1}\left\|\bar{G}_3^{-1}N_2\right\|\rho^*\\ &\ge \left\|\tilde{\bar{F}}_{s2}\right\|^{-1}\times\left[\left\|\tilde{\bar{F}}_{s2}\right\|\gamma + \left\|\tilde{\bar{W}}_2\right\|\omega_0 + \kappa\right] > \gamma\end{aligned} \tag{39}$$

then

$$\dot{V}_s \le -\left(\kappa_\theta + \kappa_f\right)\|\delta_s\| < 0 \tag{40}$$

In summary, under the sliding mode FTC law (29)-(33), V_s will decrease and stop changing when $\|\delta_s\| = 0$. Therefore, the systematic error will also be driven to zero and the error system will be asymptotically stable [20].

IV. EXPERIMENT RESULTS

The experimental forklift is TFC35 electric forklift with SBW system. The experiment is carried out in a warehouse with noise and 20% indoor relative humidity. The experiment environment is shown in Fig.3.

The external output is $\theta(t) = \sin(2t)$ and the uncertainty of system (ΔA and ΔB) is bounded matrix. There exists $\sigma_1, \varpi\sigma_2 > 0$ such that $\begin{cases}\|\Delta A\| \le \sigma_1\\ \|\Delta B\| \le \sigma_2\end{cases}$, $\varpi\sigma_1 = \sigma_2 = 0.1$.

FIGURE 3. Experimental forklift.

TABLE 1. Description of the faults.

Fault	Type of faults	FTC time
1	$T_f = 4s$, $\Delta_1 = 0.3$ (gain fault)	$T_r = 8s$
2	$T_f = 4s$, $a_2 = 0.04$ (stuck fault)	$T_r = 8s$
3	$T_f \in [4s, 10s]$, $T_f = 12s$, $a_{31} = 0.06$ and $a_{32} = 0.09$ (constant deviation fault intermittently)	$T_r = 8s$

According to (2), the state parameters of forklift are A, B, as shown at the bottom of the next page.

The external interference matrix is $H = \left[0.2\ 0.02\ 0\ 0.04\ 0.3\ 0\right]^T$, $F = C$, The parameters of SMO is set as $\rho_1(0) = \rho_2(0) = \rho_3(0) = \rho_4(0) = 10$, $\eta_1 = \eta_2 = \eta_3 = \eta_4 = -100$, $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0.5$. The parameters of sliding mode FTC law is set as $S_s = [\,0\ 0\ 0\ 1\ 1\ 1\,]$, $K = [\,-6\ 20\ 5\ 7\ -24\ 9\,]$.

In the case of yaw rate sensor, roll rate sensor and front wheel angle sensor occurring faults respectively, the types of faults are shown in TABLE 1 correspondingly [21]. In order to compare the results before and after FTC, the FTC introducing time is set to T_r.

Take the current of steering motor as the input. During experiment, input the step signal at 2s and return back the steering handle at 16s.

When yaw rate sensor, roll rate sensor and front wheel angle sensor occur the corresponding faults, the output is reconstructed according to (19). The experimental results are shown as follows.

In Fig.4, before the time of fault-occurring ($T_f = 4s$), there is no fault in yaw rate sensor and the output Y_{1f} is similar as the fault-free state. The fault output with uncertainty and

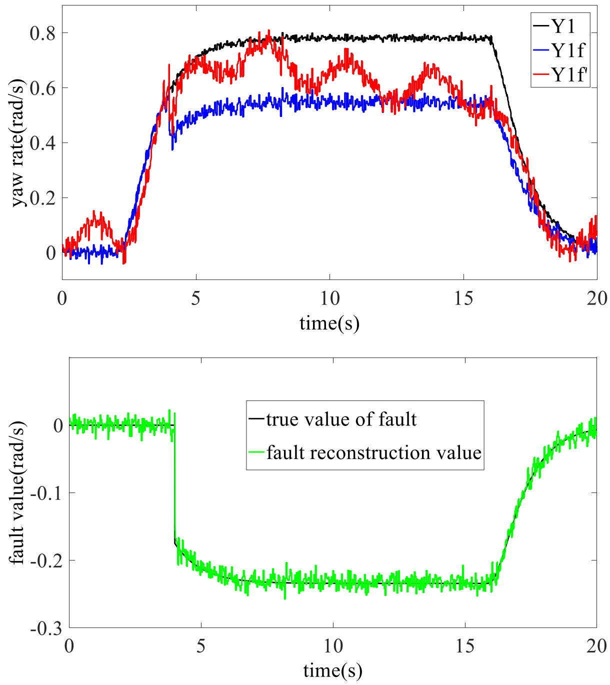

FIGURE 4. Yaw rate sensor output and fault reconstruction.

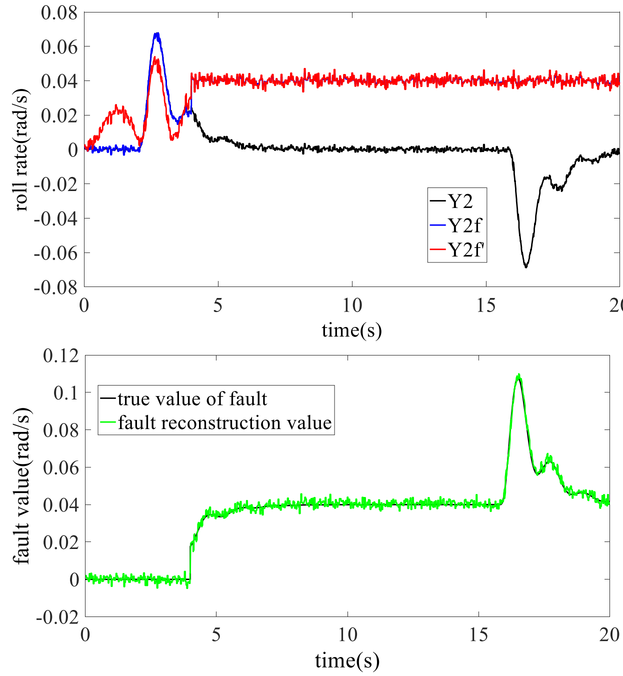

FIGURE 5. Roll rate sensor output and fault reconstruction.

interference ($Y_{1f'}$) differs considerably form Y_{1f} andY_1. The adaptive SMO can estimate the status of sensor accurately. After the fault, the adaptive SMO can estimate the output and fault value of sensor accurately in the case of fault type 1 and the fault reconstruction value is basically consistent with the true value of the fault. It will not be affected by uncertainty and external interference.

As is shown in Fig.5, Fig.6 and Fig.7, before and after roll rate sensor and the front wheel angle sensor occurring the faults of type 2, 3 respectively, the output with no uncertainty and disturbance is almost the same as the fault-free state. And the fault output with uncertainty and disturbance differs greatly from the fault-free state. But the adaptive SMO and the fault reconstruction system can track the fault signal and reconstruct fault value. The fault reconstruction value is also consistent with the true value of the fault.

The experiments of FTC are carried out with the fault conditions listed in Table 1. To verify the benefits of the developed method proposed in this manuscript, the regular sliding mode controller is also adopted to make a comparison and the control law is defined as $U(t) = u(t) = -\left(S_s\bar{B}\right)^{-1}\left[S_s\bar{B}Ke_s + S_s\left(\bar{A} - A_s\right)\bar{x} - S_sB_sr_s\right]$. When yaw rate sensor, roll rate sensor and front wheel angle sensor occur the faults respectively, the comparison results of each sensor are shown in Fig. 7-Fig. 9.

As shown in Fig.7-Fig.9, the outputs of yaw rate sensor, roll rate sensor and front wheel angle sensor begin to vibrate from the fault time ($T_f = 4s$). And from FTC time ($T_r = 8s$), the sliding mode FTC methods are adopted for the fault system of forklift based on sensor signal reconstruction. We can observe that the methods can all make the system recover gradually after a short period of 1$\sim$3s.

$$A = \begin{bmatrix} -15.6271 & -24.3286 & -3.3306 & -0.2499 & 32.2186 & 0 \\ -3.1099 & -9.4608 & -2.9200 & -0.1695 & 6.4088 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ -11.6650 & -39.5987 & -35.2933 & -1.8246 & 31.1961 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ -3.3133 & -7.6675 & 0 & 0 & 7.6675 & -1.8041 \end{bmatrix}$$

$$B = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 98.8506 \end{bmatrix}, C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

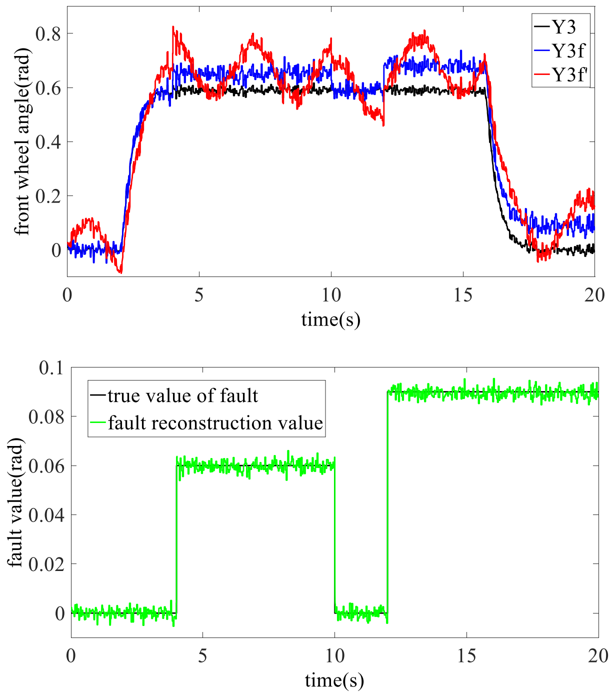

FIGURE 6. Front wheel angle sensor output and fault reconstruction.

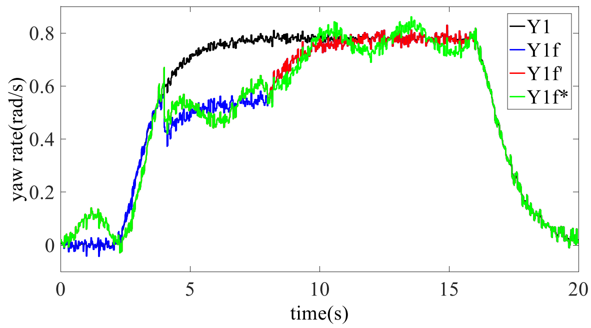

FIGURE 7. Yaw rate sensor tolerant control output.

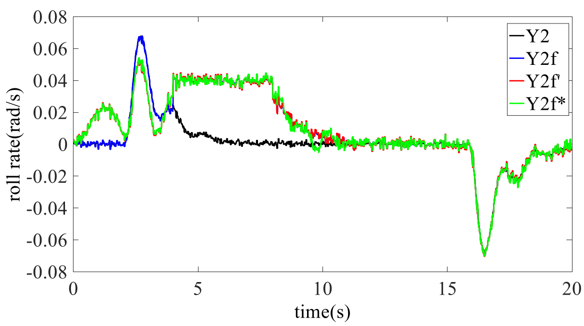

FIGURE 8. Roll rate sensor tolerant control output.

But the developed method ($Y3f'$) has a better performance than the regular method ($Y3f^*$). When there is output disturbance, the proposed method can suppress it and reduce the vibration. The outputs under the developed method with and without uncertainty and interference are both similar with the output in the fault-free state which can reflect the driving condition of the electric forklift.

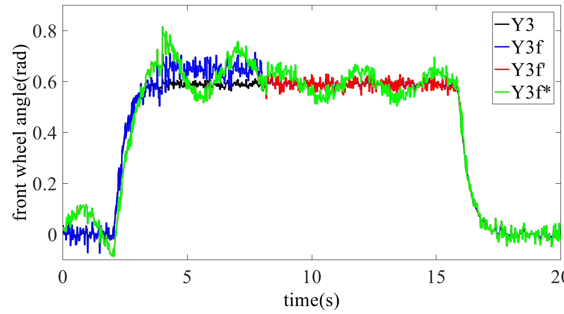

FIGURE 9. Front wheel angle sensor tolerant control output.

V. CONCLUSION

Forklift is one of the most widely used vehicles for short-distance transportation of cargo and its safety is very important. As electronic components have been used in modern forklift widely, the fault diagnosis, fault reconstruction and FTC technology are particularly important to ensure safety.

For the problem of multi-sensor fault detection and reconstruction of forklift, a SMO with adaptive regulation law is adopted to detect and reconstruct sensor faults. It can separate the fault from the external disturbance and realize robust fault estimation. Specifically, without knowing the upper bounds of the unknown fault, the adaptive algorithm can also make the observer effective. The comparison experiment between the real fault value and the reconstructed result shows that this method can achieve a good estimation of sensor fault.

Based on the SMO proposed, a sliding mode fault-tolerant controller is adopted to deal with key sensor faults of forklift system. It realizes the robust processing of system parameter uncertainties and external output disturbances, and can make the forklift return to normal.

Experiments on TFC35 SBW electric forklift show that the adaptive SMO can reconstruct sensor fault value effectively, and the sliding mode fault-tolerant controller designed is also effective when sensor faults occur. And the performance of each sensor in the fault system can gradually restore to the similar level as that of fault-free SBW forklift. But in this research, the FTC method relies on the fault model of forklift. To a certain extent, the sliding mode control strategy can overcome the influence of model uncertainty. In future research activities, we shall investigate FTC controller without knowing the complete information about the state of the forklift.

ACKNOWLEDGMENT

The authors thank senior engineer Junliang Guo, Zijian Fang, Pengfei Li, Xingzhi Fang, and Weilin Lv for their cooperation and helpful suggestions. They also thank graduate students Chenggong Sun, Junjie Huang, Xu Zhang, and Zhizheng Jiang in the same study room.

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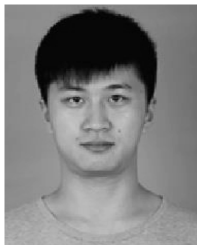

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