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Research Article

Multisensor Fault Identification Scheme Based on Decentralized Sliding Mode Observers Applied to Reconfigurable Manipulators

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This paper concerns with a fault identification scheme in a class of nonlinear interconnected systems. The decentralized sliding mode observer is recruited for the investigation of position sensor fault or velocity sensor fault. First, a decentralized neural network controller is proposed for the system under fault-free state. The diffeomorphism theory is utilized to construct a nonlinear transformation for subsystem structure. A simple filter is implemented to convert the sensor fault into pseudo-actuator fault scenario. The decentralized sliding mode observer is then presented for multisensor fault identification of reconfigurable manipulators based on Lyapunov stable theory. Finally, two 2-DOF reconfigurable manipulators with different configurations are employed to verify the effectiveness of the proposed scheme in numerical simulation. The results demonstrate that one joint's fault does not affect other joints and the sensor fault can be identified precisely by the proposed decentralized sliding mode observer.

1. Introduction

Reconfigurable manipulators as a kind of nonlinear interconnected systems are widely investigated in recent years due to their potential applications, that is, space exploration, smart manufacturing, high risk operations, battle field, and so forth. However, faults will inevitably occur in the actuators, sensors, and other units after long time workings. Direct maintenance is difficult as well. A developing and undetected fault may lead to an abortion in the entire workspace. What is worse, this failure is sometimes even harmful to humans; thus higher safety and reliability are demanded. Hence, fault diagnosis and tolerant control have become an urgent problem.

In general, three strategies were carried out to achieve the aim at fault detection and identification. Based on model analysis schemes, Alwi et al. [1] proposed sliding mode observers to overcome the limitation that the linear observer schemes cannot be employed for sensor fault reconstruction. da Silva et al. [2] presented an expert system that uses a combination of object-oriented modeling, rules, and semantic networks to deal with the most common sensor faults. Du et al. [3] obtained the fault information by estimating the outputs of the actuators and comparing them with the corresponding prescribed control inputs and then developed a fault-tolerant control by choosing a safe-park point. Brambilla et al. [4] adopted a second order sliding mode approach to design the input laws of the observers to establish satisfactory stability properties of the observation error and reduce the chattering effect. Filasová and Krokavec [5] gave the solution of observer gain by using LMI and modified the optimal estimator parameters in the standard estimator structure. Based on the information processing, Zhang et al. [6] presented a fault feature extraction method combined wavelet analysis with neural network. Subrahmanya and Shin [7] considered three kinds of states in a generic system model no matter whether the states could be measured or not and proposed a framework based on the dynamic neural networks for data-based process monitoring, fault detection, and diagnostics of nonlinear systems with partial state measurement. van Eykeren et al. [8] introduced a form of analytical redundancy by using an adaptive extended Kalman filter to improve the fault detection performance and compared the state reconstruction with the measurements. Heredia and Ollero [9] accomplished a sensor fault detection system by evaluating any significant change, which was estimated by using an observer. Mhaskar et al. [10] proposed a fault detection and isolation filter, then redesigned controller for MIMO nonlinear system. Another strategy is based on the knowledge discovery. Zhang et al. [11] made the fault isolation decision for sensor bias fault based on the adaptive threshold, which is obtained by the corresponding isolation estimators. Heredia et al. [12] considered five different types of sensor failures, but they cannot be distinguished from the noise if errors are relatively too small. Mehranbod et al. [13] presented Bayesian belief network based sensor fault detection and identification scheme. Izumikawa et al. [14] proposed control system that estimates a strain gauge sensor signal based on the reaction force observer and detects the fault by monitoring the estimation error. Chenglin et al. [15] investigated a sensor fault diagnosis by chaos particle swarm optimization algorithm and support vector machine.

This paper conducts a novel multisensor fault detection protocol based on decentralized sliding mode observer for the nonlinear interconnected system. Under the fault-free state, decentralized neural networks were utilized to approximate or compensate the unknown term and interconnection term among the subsystems. Nonlinear transformation is constructed by diffeomorphism theory, then a simple filter is brought out to transform the sensor fault into pseudo-actuator fault scenario, and a decentralized sliding mode observer is derived based on Lyapunov stability theory so as to identify the multisensor fault function precisely in real time. Finally, the simulation results of two 2-DOF reconfigurable manipulators with different configurations are presented to demonstrate the effectiveness of the proposed scheme. The approach of this paper fits into the framework of decentralized control, which is also the main contribution. The same control law and parameters are implemented to all the subsystems. The focus of this paper is on the issue of the decentralized control algorithm which is independent of the fault information and other subsystems. In other words, a joint sensor failure will not affect others' under fault-free state.

2. Problem Description

The general fault-free dynamic model of nonlinear interconnected subsystem S_i can be presented by the following state equation:

$$S_i : \begin{cases} \dot{x}_i = A_i x_i + B_i \left[f_i \left(q_i, \dot{q}_i \right) + g_i \left(q_i \right) u_i + h_i \left(q, \dot{q}, \ddot{q} \right) \right] \\ y_i = C_i x_i, \end{cases} \tag{1}$$

where x_i is the state vector of subsystem S_i, and y_i is the output of subsystem S_i.

For the subsystem with multisensor fault (position sensor and velocity sensor), the faulty dynamic model can be expressed as

$$S_{if} : \begin{cases} \dot{x}_i = A_i x_i + B_i \left[f_i \left(q_i, \dot{q}_i \right) + g_i \left(q_i \right) u_i + h_i \left(q, \dot{q}, \ddot{q} \right) \right] \\ y_i = C_i x_i + D_i f_{si}, \end{cases} \tag{2}$$

where the initial $x_{i0} = x_i(0)$, the sensor fault distribution matrix is D_i and the fault function f_{si} that expressed as $D_i = \left[\begin{smallmatrix} 1 & 0 \\ 0 & 1 \end{smallmatrix} \right]$, $f_{si} = \left[\begin{smallmatrix} f_{si1} \\ f_{si2} \end{smallmatrix} \right]$, and $\| f_{si}(t) \| \le \rho_i(t)$, where $\rho_i(t)$ is a continuous function.

Assumption 1. $f_{si}(t)$ is an unknown function under the satisfaction of Table 1 and defined when $t \in R^+$.

The control object is to design a decentralized neural network controller for (1) to make the outputs of overall system follow desired trajectories, then design decentralized sliding mode observer to detect whether the whole system in failure or not, and identify the sensor fault when it occurs.

3. Controller and Observer Design

At first, introduce the concept of Lie algebra and transforms the joint sensor fault into pseudo-actuator fault scenario [16]. Hence, for the subsystem (1),

$$\begin{aligned} \dot{z}_{i1} &= \frac{\partial x_{i1}}{\partial x_i} x_{i2} = L_{x_{i2}} x_{i2} = z_{i2}, \\ \dot{z}_{i2} &= \frac{\partial z_{i2}}{\partial x_i} \left(f_i \left(q_i, \dot{q}_i \right) + g_i \left(q_i \right) u_i + h_i \left(q, \dot{q}, \ddot{q} \right) \right) \\ &= L^2_{f_i(q_i,\dot{q}_i)+g_i(q_i)u_i+h_i(q,\dot{q},\ddot{q})} z_{i2} \\ &= f_i \left(q_i, \dot{q}_i \right) + g_i \left(q_i \right) u_i + h_i \left(q, \dot{q}, \ddot{q} \right). \end{aligned} \tag{3}$$

And in general, the equations above can be expressed as

$$\dot{z}_i = A_i z_i + B_i \left[f_i \left(q_i, \dot{q}_i \right) + g \left(q_i \right) u_i + h_i \left(q, \dot{q}, \ddot{q} \right) \right]. \tag{4}$$

3.1. Decentralized Neural Network Controller Design. Neural network could be utilized to approximate any nonlinear function in any accuracy with parameters modification. In this section, decentralized neural networks controller is designed for (1) under fault-free state.

Assumption 2. The desired trajectories y_{ir}, $\dot{y}_{ir}$, and $\ddot{y}_{ir}$ are bounded.

Use the RBF neural networks to approximate the unknown term $f_i(q_i, \dot{q}_i)$ and uncertainty term $g(q_i)$ as follows:

$$\begin{aligned} f_i \left(q_i, \dot{q}_i, W_{if} \right) &= W_{if}^T \Phi_{if} \left(q_i, \dot{q}_i \right) + \varepsilon_{if}, \quad \left\| \varepsilon_{if} \right\| \le \varepsilon_1, \\ g_i \left(q_i, W_{ig} \right) &= W_{ig}^T \Phi_{ig} \left(q_i \right) + \varepsilon_{ig}, \quad \left\| \varepsilon_{ig} \right\| \le \varepsilon_2, \end{aligned} \tag{5}$$

where the W_{if} and W_{ig} are the ideal neural network weights, $\Phi_{i\cdot}(\cdot)$ is the neural network basis function, and ε_{if} and ε_{ig} are the neural network approximation errors; ε_1 and ε_2 are known constants.

Define $\widehat{W}_{if}$ and $\widehat{W}_{ig}$ as the estimations of W_{if} and W_{ig}, respectively. $\widehat{f}_i(q_i, \dot{q}_i, W_{if})$ is estimation value of $f_i(q_i, \dot{q}_i)$, and $\widehat{g}_i(q_i, \widehat{W}_{ig})$ is estimation value of $g_i(q_i)$. $\widehat{f}_i(q_i, \dot{q}_i, W_{if})$ and $\widehat{g}_i(q_i, \widehat{W}_{ig})$ can be expressed as

$$\begin{aligned} \widehat{f}_i \left(q_i, \dot{q}_i, \widehat{W}_{if} \right) &= \widehat{W}_{if}^T \widehat{\Phi}_{if} \left(q_i, \dot{q}_i \right), \\ \widehat{g}_i \left(q_i, \widehat{W}_{ig} \right) &= \widehat{W}_{ig}^T \widehat{\Phi}_{ig} \left(q_i \right). \end{aligned} \tag{6}$$

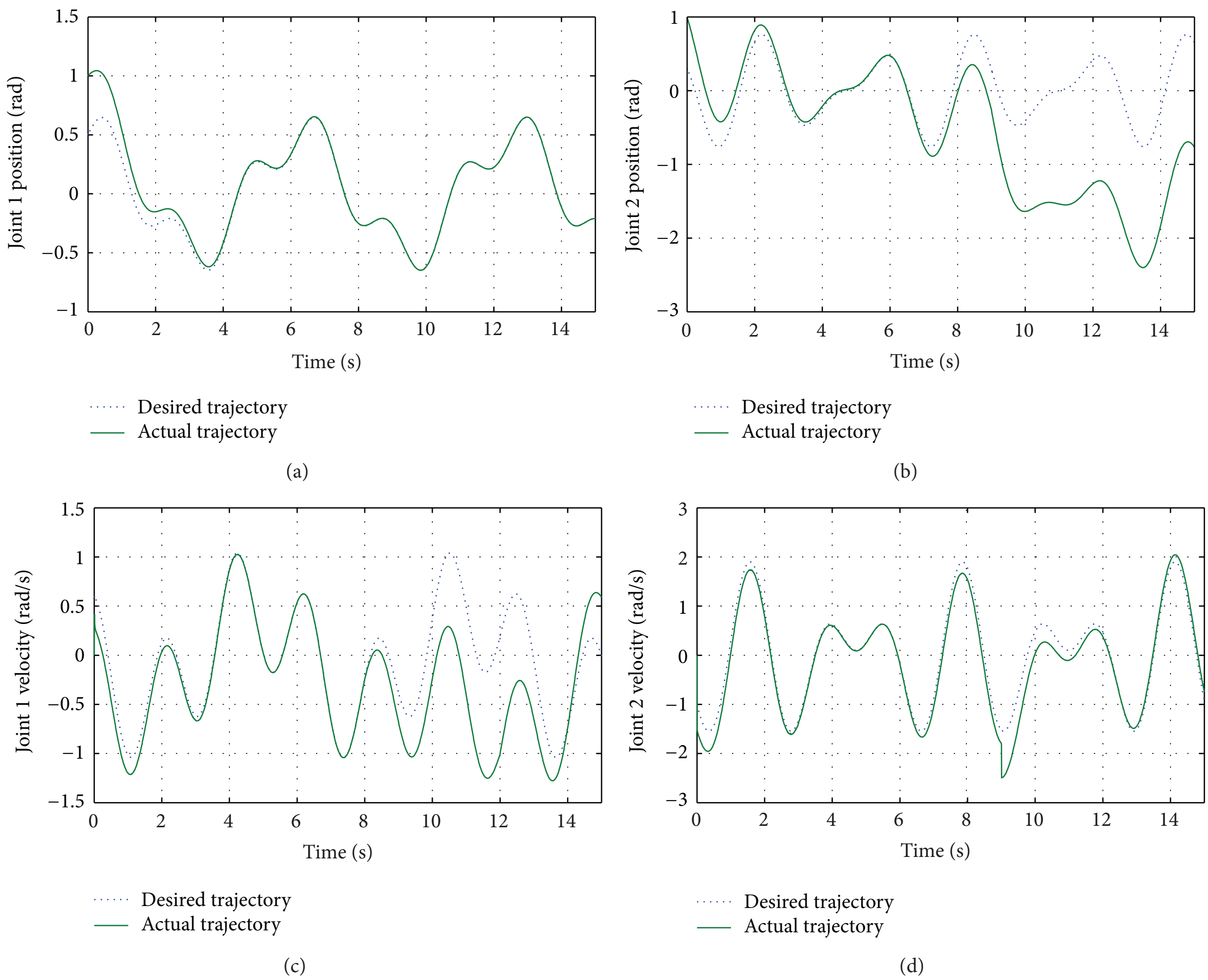


Figure 1: Tracking performance of configuration *a*.

Table 1: Sensor fault type.

Fault type	f_{si1}	f_{si2}
Fault-free	0	0
Position sensor fault	$\neq 0$	0
Velocity sensor fault	0	$\neq 0$
Position and velocity sensor fault	$\neq 0$	$\neq 0$

Define the estimation errors as $\widetilde{W}_{if} = W_{if} - \widehat{W}_{if}$ and $\widetilde{W}_{ig} = W_{ig} - \widehat{W}_{ig}$. Therefore

$$\begin{aligned} & f_i\left(q_i, \dot{q}_i, W_{if}\right) - \hat{f}_i\left(q_i, \dot{q}_i, \widehat{W}_{if}\right) \\ & \quad = \widetilde{W}_{if}^T \widehat{\Phi}_{if}\left(q_i, \dot{q}_i\right) + W_{if}^T \widetilde{\Phi}_{if}\left(q_i, \dot{q}_i\right) + \varepsilon_{if}, \\ & g_i\left(q_i, W_{ig}\right) - \hat{g}_i\left(q_i, \widehat{W}_{ig}\right) \\ & \quad = \widetilde{W}_{ig}^T \widehat{\Phi}_{ig}\left(q_i\right) + W_{ig}^T \widetilde{\Phi}_{ig}\left(q_i\right) + \varepsilon_{ig}, \end{aligned} \tag{7}$$

where the neural output error with Gaussian activation $\Phi(\cdot)$ is given by

$$\begin{aligned} \widetilde{\Phi}_{if}\left(q_i, \dot{q}_i\right) &= \Phi_{if}\left(q_i, \dot{q}_i\right) - \widehat{\Phi}_{if}\left(q_i, \dot{q}_i\right), \\ \widetilde{\Phi}_{ig}\left(q_i\right) &= \Phi_{ig}\left(q_i\right) - \widehat{\Phi}_{ig}\left(q_i\right). \end{aligned} \tag{8}$$

Next, the neural network expressed as (9) is proposed to compensate the interconnection term

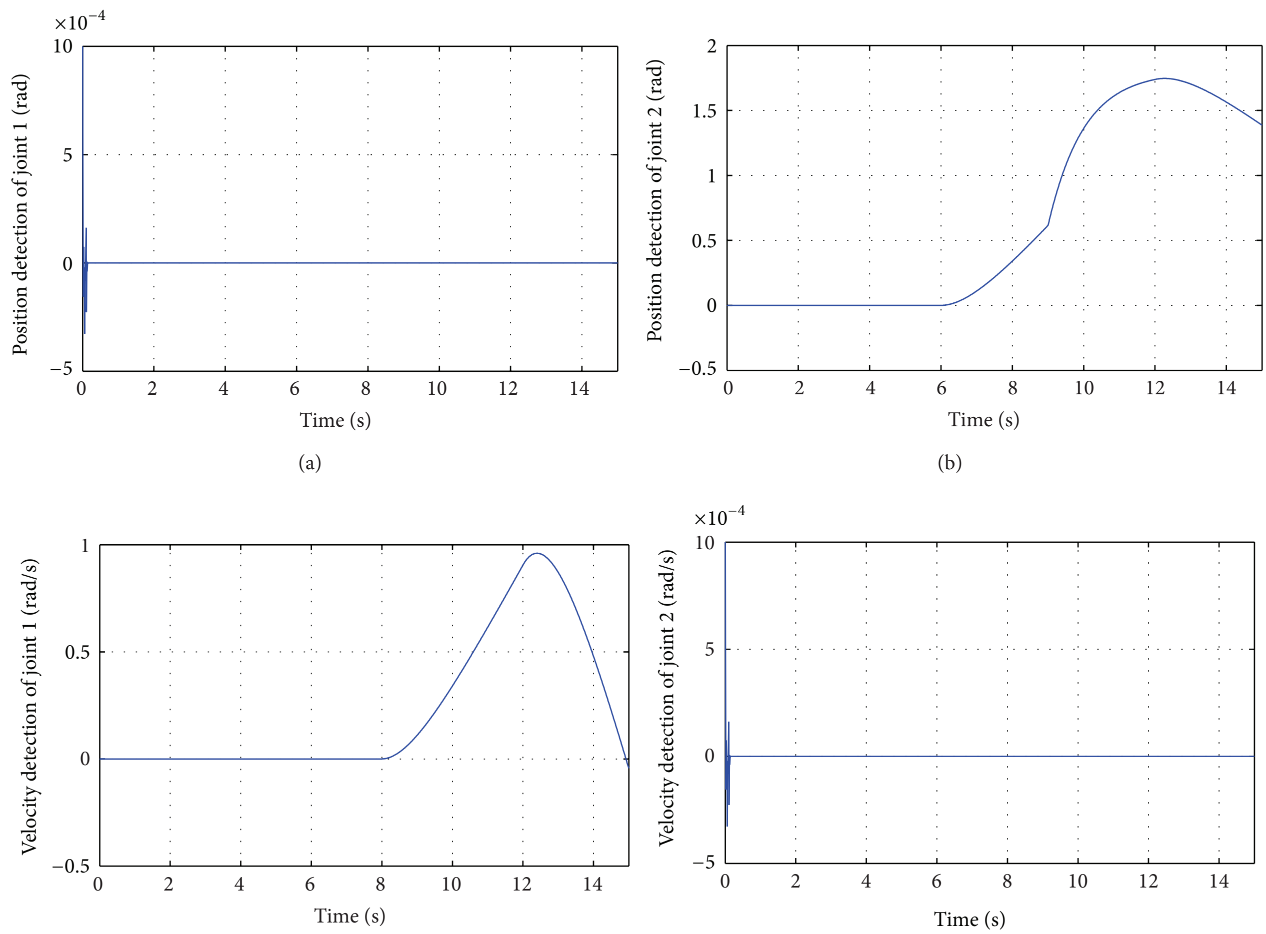
$$\hat{p}_i\left(\left|e_i^T P_i B_i\right|, \widehat{W}_{ip}\right) = \widehat{W}_{ip}^T \widehat{\Phi}_{ip}\left(\left|e_i^T P_i B_i\right|\right), \tag{9}$$

where $\widehat{W}_{ip}^T$ is the estimation of W_{ip}^T, and the weight estimation error is $\widetilde{W}_{ip}^T = W_{ip}^T - \widehat{W}_{ip}^T$.

Assumption 3. The interconnection term $h_i(q, \dot{q}, \ddot{q})$ is bounded by

$$\left|h_i\left(q, \dot{q}, \ddot{q}\right)\right| \leq \sum_{j=1}^{n} d_{ij} E_j, \tag{10}$$

where $d_{ij} \geq 0$, $E_j = 1 + |e_j^T P_j B_j| + |e_j^T P_j B_j|^2$, and $P_i(|e_i^T P_i B_i|) = n \max_{ij}\{d_{ij}\} E_j$ is defined.



(a) (b) (c) (d)

FIGURE 2: Observe errors of multisensor fault for configuration a.

Define approximation error

$$w_{i1} = W_{if}^T \widetilde{\Phi}_{if}(q_i,\dot{q}_i) + W_{ig}^T \widetilde{\Phi}_{ig}(q_i) u_i + \varepsilon_{if} + \varepsilon_{ig} u_i,$$
$$w_{i2} = p_i\left(\left|e_i^T P_i B_i\right|\right) - W_{ip}^T \widehat{\Phi}_{ip}\left(\left|e_i^T P_i B_i\right|\right), \tag{11}$$
$$w_i = \left|w_{i1}\right| + \left|w_{i2}\right|.$$

The decentralized controller is designed as

$$u_i = -\frac{1}{\widehat{g}_i(q_i,\widehat{w}_{ig})}\left[\widehat{f}_i(q_i,\dot{q}_i,\widehat{w}_{if}) + \operatorname{sgn}\left(e_i^T P_i B_i\right)\widehat{p}_i \times \left(\left|e_i^T P_i B_i\right|, \widehat{w}_{ip}\right) - \ddot{y}_{ir}\right]. \tag{12}$$

With the adaptive update laws as

$$\dot{\widehat{W}}_{if} = \Gamma_{if} e_j^T P_j B_j \widehat{\Phi}_{if}(q_i,\dot{q}_i),$$
$$\dot{\widehat{W}}_{ig} = \Gamma_{ig} e_j^T P_j B_j \widehat{\Phi}_{ig}(q_i) u_i, \tag{13}$$
$$\dot{\widehat{W}}_{ip} = \Gamma_{ip}\left|e_j^T P_j B_j\right| \widehat{\Phi}_{ip}\left(\left|e_j^T P_j B_j\right|\right),$$

where Γ_{if}, Γ_{ig}, and Γ_{ip} are positive constants.

3.2. Decentralized Sliding Mode Observer Design. This section will give the detail design processing of decentralized sliding mode observer for nonlinear interconnected system to identify the precise fault functions.

Introduce a simple filter as

$$\dot{z}_{ai} = A_{ai} z_{ai} + B_{ai} y_i. \tag{14}$$

Then

$$\dot{z}_{ai} = A_{ai} z_{ai} + B_{ai} y_i = A_{ai} z_{ai} + B_{ai}\left(C_i x_i + D_i f_{si}\right) \tag{15}$$

with $z_{ai} = \left[\begin{smallmatrix} z_{ai1} \\ z_{ai2}\end{smallmatrix}\right]$, $A_{ai} = \left[\begin{smallmatrix} -1 & 0 \\ 0 & -1\end{smallmatrix}\right]$, $B_{ai} = \left[\begin{smallmatrix} 1 & 0 \\ 0 & 1\end{smallmatrix}\right]$. Thus the extended subsystem dynamics should be

$$\overline{S}_{if}: \begin{cases} \dot{z}_i = A_i z_i + B_i\left[f_i(q_i,\dot{q}_i) + g_i(q_i) u_i + h_i(q,\dot{q},\ddot{q})\right], \\ \dot{z}_{ai} = A_{ai} z_{ai} + B_{ai}\left(C_i x_i + D_i f_{si}\right), \\ y_a = z_{ai}. \end{cases} \tag{16}$$

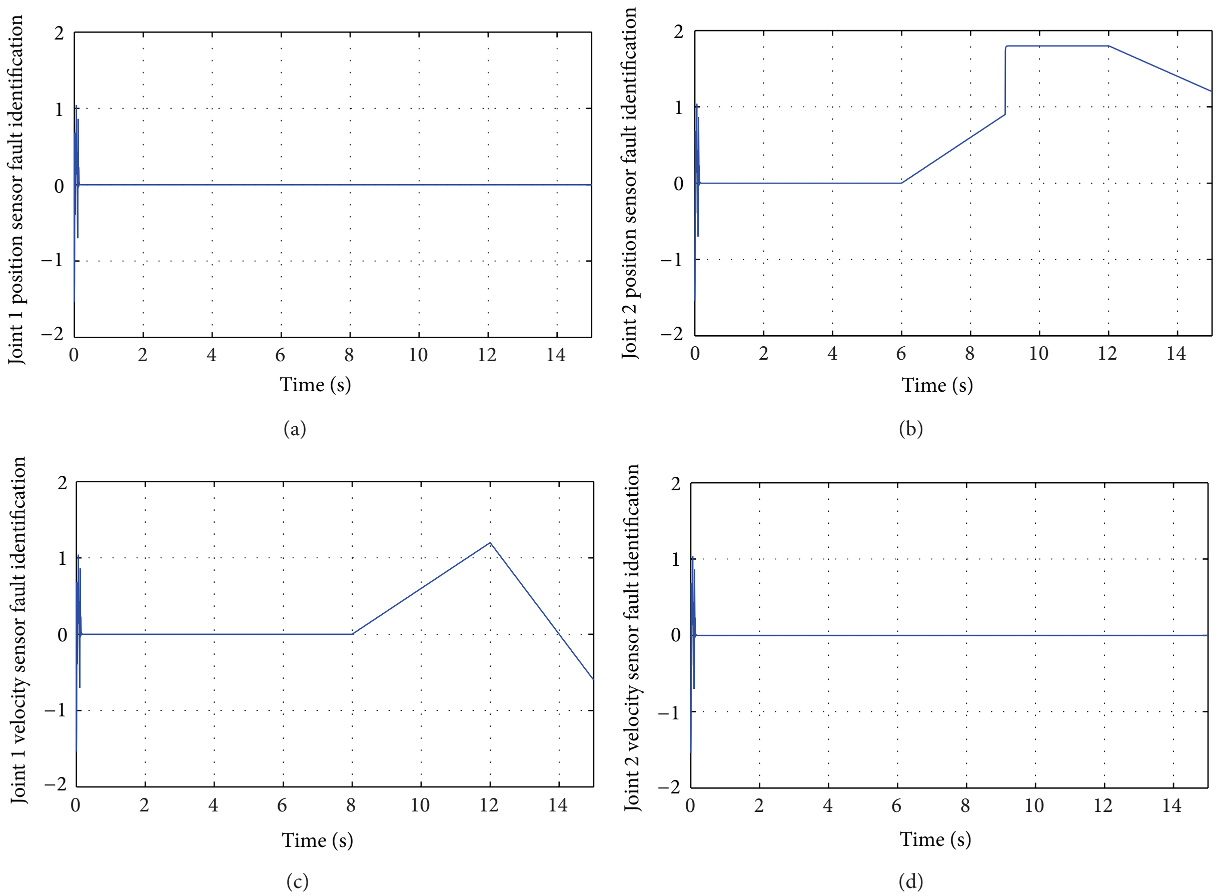


FIGURE 3: Multisensor fault identification of configuration a.

According to (16), the decentralized sliding mode observer should be designed as

$$\widehat{S}_{if}:\begin{cases}\widehat{z}_i = A_i\widehat{z}_i \\ \qquad + B_i\left[\widehat{f}_i(q_i,\dot{q}_i) + \widehat{g}_i(q_i)u_i + \widehat{p}_i\left(\left|e_i^T P_i B_i\right|, \widehat{W}_{ip}\right)\right], \\ \widehat{z}_{ai} = A_{ai}z_{ai} + B_{ai}(C_i x_i + v_i), \\ \widehat{y}_a = z_{ai},\end{cases} \tag{17}$$

where

$$v_i = -k_i\frac{y_a - \widehat{y}_a}{\left\|y_a - \widehat{y}_a\right\|}. \tag{18}$$

$\widehat{f}_i(q_i,\dot{q}_i)$, $\widehat{g}_i(q_i)$, and $\widehat{p}_i(|e_i^T P_i B_i|, \widehat{W}_{ip})$ should be estimated by neural networks.

3.3. Stability Analysis. Let

$$\begin{aligned} e_i &= z_i - \widehat{z}_i, \\ e_{ai} &= z_{ai} - \widehat{z}_{ai}. \end{aligned} \tag{19}$$

Thus

$$\begin{aligned} \dot{e}_i &= \dot{z}_i - \dot{\widehat{z}}_i, \\ \dot{e}_{ai} &= \dot{z}_{ai} - \dot{\widehat{z}}_{ai}. \end{aligned} \tag{20}$$

The error state space function can be expressed as

$$\dot{e}_i = A_i e_i + B_i\left[f_i - \widehat{f}_i + (g_i - \widehat{g}_i)u_i + h_i - \widehat{p}_i\right], \tag{21}$$

$$\dot{e}_{ai} = A_{ai}e_{ai} + B_{ai}(C_i e_i + D_i f_{si} - v_i). \tag{22}$$

Choose the Lyapunov candidate as

$$\begin{aligned} V_i &= e_i^T P_i e_i + \widetilde{W}_{if}^T\Gamma_{if}^{-1}\widetilde{W}_{if} \\ &\quad + \widetilde{W}_{ig}^T\Gamma_{ig}^{-1}\widetilde{W}_{ig} + \widetilde{W}_{ip}^T\Gamma_{ip}^{-1}\widetilde{W}_{ip}. \end{aligned} \tag{23}$$

By simple computing, its time derivative is

$$\begin{aligned} \dot{V}_i &= \dot{e}_i^T P_i e_i + e_i^T P_i \dot{e}_i - \widetilde{W}_{if}^T\Gamma_{if}^{-1}\dot{\widehat{W}}_{if} \\ &\quad - \widetilde{W}_{ig}^T\Gamma_{ig}^{-1}\dot{\widehat{W}}_{ig} - \widetilde{W}_{ip}^T\Gamma_{ip}^{-1}\dot{\widehat{W}}_{ip} \\ &\le e_i^T\left(A_i^T P_i + P_i A_i\right)e_i \\ &\quad + \frac{1}{\varepsilon_i}\left(e_i^T P_i B_i\right)^T e_i^T P_i B_i + \varepsilon_i^2 w_i^2. \end{aligned} \tag{24}$$

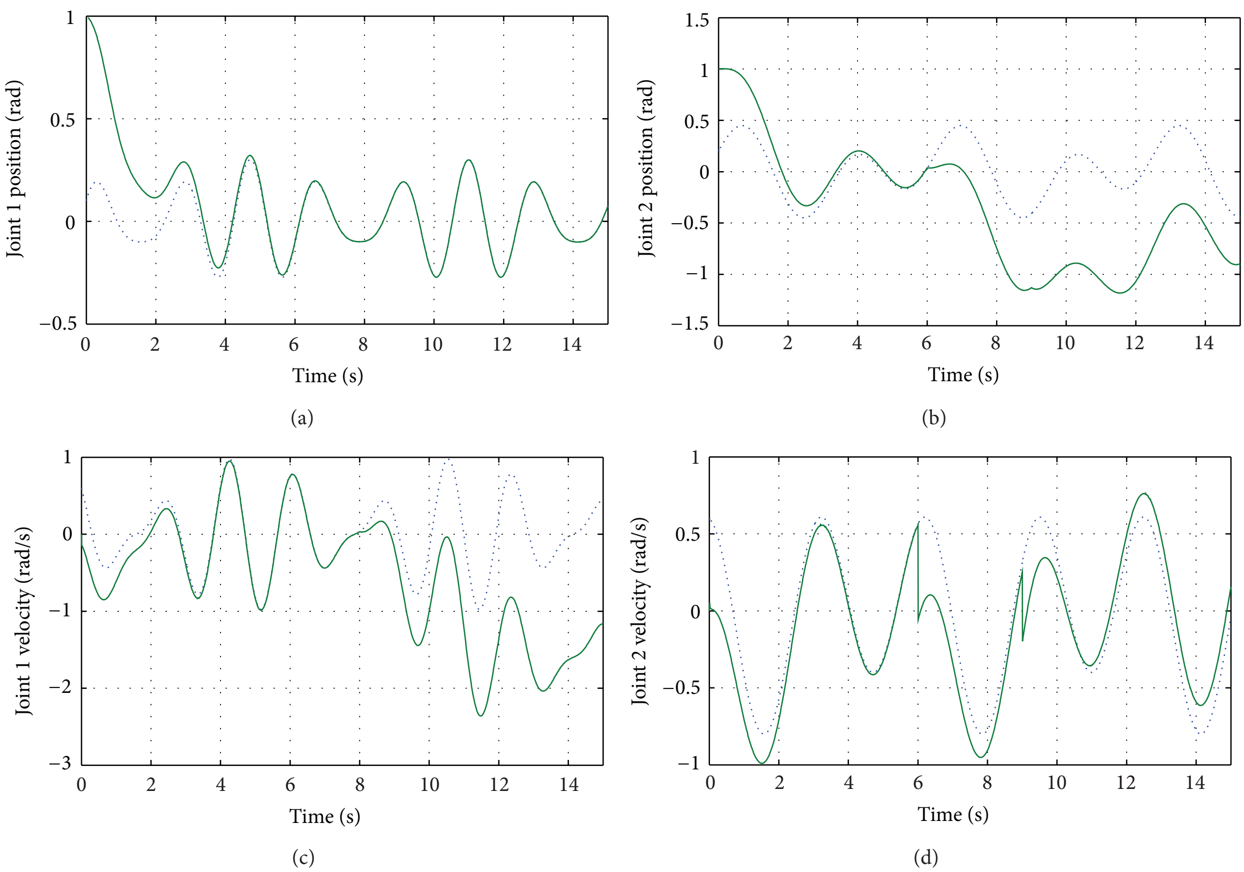


FIGURE 4: Tracking performance of configuration b.

Assumption 4. The Euclidean norm of estimation error satisfies $\|w_i\| \le L_i(u_i)\|e_i\|$.

According to Young's inequality and Racatti function below

$$A_i^T P_i + P_i A_i + \frac{1}{\varepsilon_i} P_i B_i B_i^T P_i + \varepsilon_i^2 L_i^2 (u_i) < 0 \tag{25}$$

the Lyapunov candidate is nonpositive definite, where ε_i is a positive constant

$$\begin{aligned} \dot{V}_i &\le e_i^T \left(A_i^T P_i + P_i A_i\right) e_i \\ &\quad + \frac{1}{\varepsilon_i} \left(e_i^T P_i B_i\right)^T e_i^T P_i B_i + \varepsilon_i^2 L_i^2 (u_i) e_i^2 \\ &= e_i^T \Bigg(A_i^T P_i + P_i A_i \\ &\quad + \frac{1}{\varepsilon_i} P_i B_i B_i^T P_i + \varepsilon_i^2 L_i^2 (u_i) \Bigg) e_i \le 0. \end{aligned} \tag{26}$$

Assumption 5. The subsystem observe error e_i is bounded as $\sup\{\|e_i\|\} \le b_i$.

Define the sliding mode surface as

$$s_i = \left\{ \operatorname{col}\left(e_i, e_{ai}\right) \mid e_{ai} = 0 \right\}. \tag{27}$$

And choose Lyapunov candidate for the sliding mode surface

$$V_{ai} = e_{ai}^T e_{ai}. \tag{28}$$

Hence

$$\begin{aligned} \dot{V}_{ai} &= \dot{e}_{ai}^T e_{ai} + e_{ai}^T \dot{e}_{ai} \\ &= -2\|e_{ai}\|^2 + 2e_{ai}^T \left(C_i e_i + D_i f_{si} - v_i\right) \\ &\le -2\|e_{ai}\|^2 + 2\|e_{ai}\| b_i + 2\|e_{ai}\| \rho_i - 2\|e_{ai}\| k_i \\ &= -2\|e_{ai}\|^2 + 2\|e_{ai}\| \left(b_i + \rho_i - k_i\right). \end{aligned} \tag{29}$$

Definition 6. The subsystem error (21) and (22) can reach the sliding mode surface (27), if k_i satisfies (30) with Assumption 5

$$k_i \ge b_i + \rho_i + \eta_i, \tag{30}$$

where $\eta_i > 0$ is a positive constant. Thus

$$\dot{V}_{ai} \le -2\|e_{ai}\|^2 - 2\|e_{ai}\| \eta_i < 0. \tag{31}$$

According to Barbalat Lemma and (26) and (31), decentralized sliding mode observer is asymptotic stable. From the analysis above, a sliding mode takes place in finite time and during the sliding motion

$$\begin{aligned} e_{ai} &= 0, \\ \dot{e}_{ai} &= 0. \end{aligned} \tag{32}$$

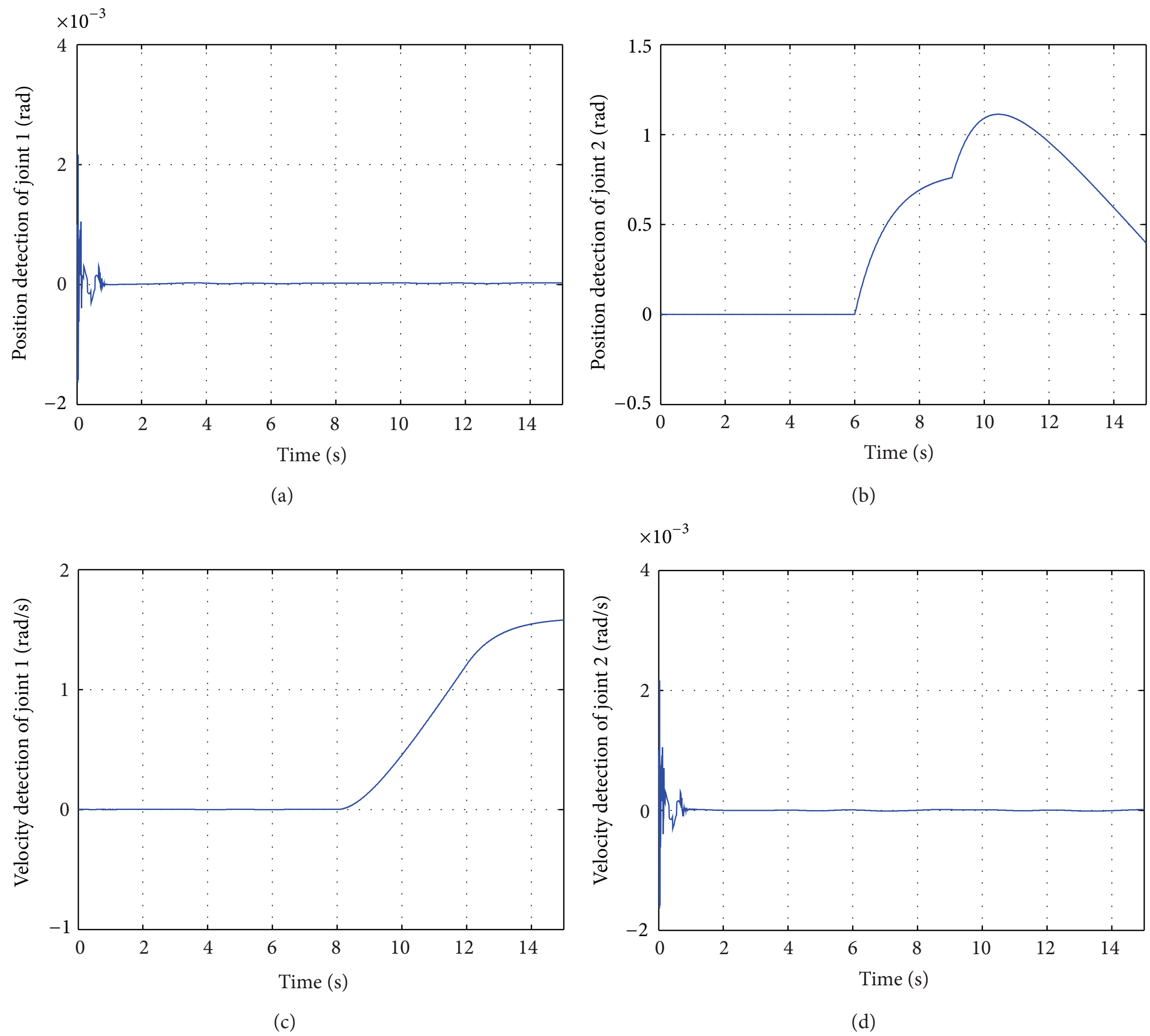


FIGURE 5: Observe errors of multisensor fault for configuration b.

And thus from (22),

$$C_i e_i + D_i f_{si} - v_{\text{ieq}} = 0, \tag{33}$$

where v_{ieq} is the equivalent output error injection which plays the same role as the equivalent control in sliding mode control. The equivalent output injection signal represents the average behavior of the discontinuous function v_i defined by (18), which is necessary to maintain an ideal sliding mode motion.

From (33), it follows that

$$f_{si} = D_i^{-1} \left(v_{\text{ieq}} - C_i e_i \right). \tag{34}$$

Now, it is required to recover the equivalent output error injection v_{ieq}. Considering the structure of v_i in (18), it follows that by choosing an appropriate positive constant scalar σ_i, v_{ieq} can be approximated to any accuracy by

$$v_{i\sigma} = k_i \frac{z_{ai} - \hat{z}_{ai}}{\left\| z_{ai} - \hat{z}_{ai} \right\| + \sigma_i}, \tag{35}$$

where k_i satisfies (30). Let

$$\hat{f}_{si} = D_i^{-1} v_{i\sigma}, \tag{36}$$

where $v_{i\sigma}$ is defined by (35). Then from (34) and (36),

$$f_{si} - \hat{f}_{si} = v_i - e_{\text{ieq}} - v_{i\sigma}, \tag{37}$$

where $\lim_{t\to\infty} e_i = 0$. Therefore, $\hat{f}_{si}$ defined by (36) is an identification for the sensor fault f_{si} since $\| v_{\text{ieq}} - v_{i\sigma} \|$ can be made arbitrarily small by choice of σ_i.

4. Simulation Results

Reconfigurable manipulators system presented as a kind of nonlinear interconnected system, which are employed to verify the effectiveness of the proposed decentralized sliding mode observer for multisensor fault identification.

The dynamic model of reconfigurable manipulators with n-DOF obtained by Newton-Euler is described as

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) = u, \tag{38}$$

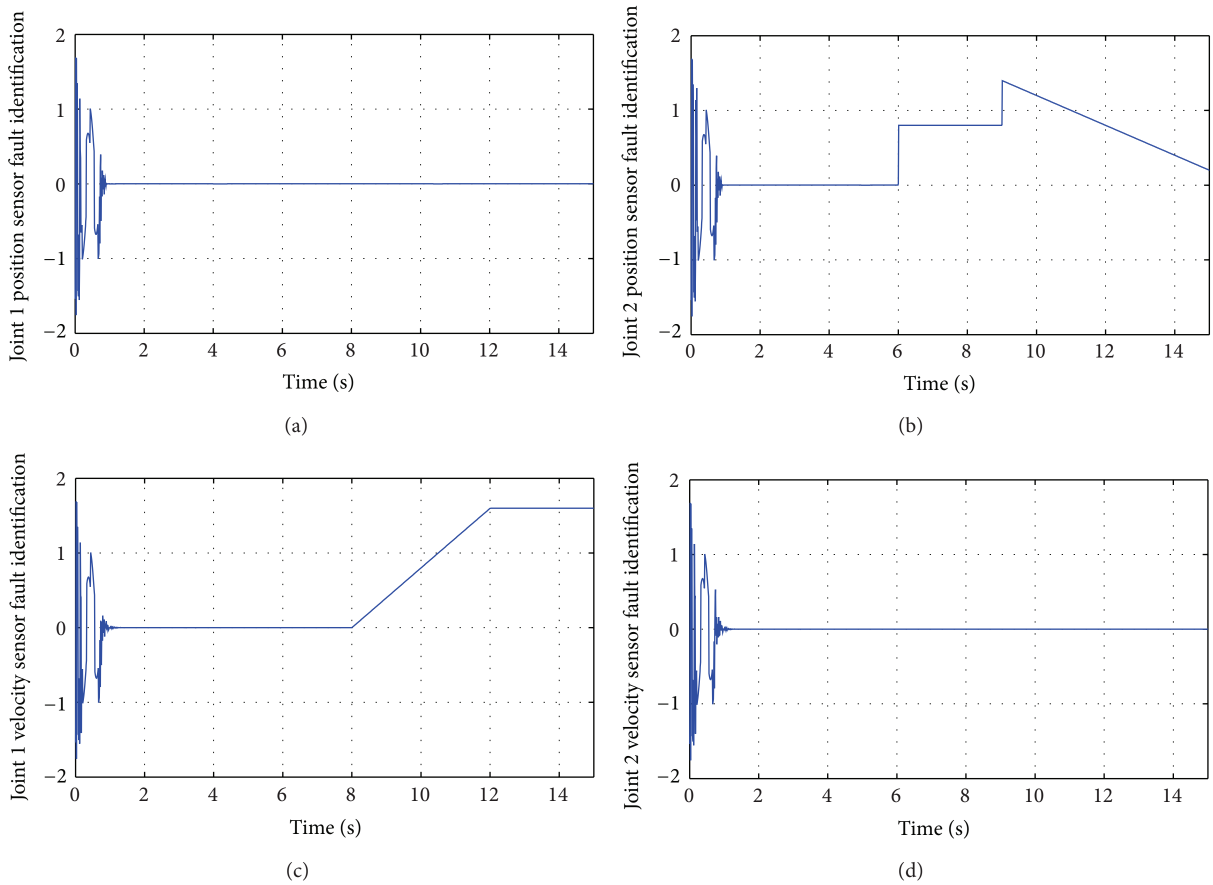


FIGURE 6: Multisensor fault identification of configuration b.

where $q \in R^n$ is the vector of joint displacements, $M(q) \in R^{n\times n}$ is the inertia matrix, $C(q,\dot{q}) \in R^n$ is the Coriolis and centripetal force, $G(q) \in R^n$ is the gravity term, and $u \in R^n$ is the applied joint torque.

For the development of decentralized control, each joint is considered as a subsystem of the entire manipulator system interconnected by coupling torque. By separating terms only depending on local variables $(q_i, \dot{q}_i, \ddot{q}_i)$ from those terms of other joint variables, each subsystem dynamical model can be formulated in joint space as

$$\begin{aligned} &M_i(q_i)\ddot{q}_i + C_i(q_i,\dot{q}_i)\dot{q}_i + G_i(q_i) + Z_i(q,\dot{q},\ddot{q}) = u_i, \\ &Z_i(q,\dot{q},\ddot{q}) \\ &\quad = \left\{ \sum_{j=1, j\neq i}^{n} M_{ij}(q)\ddot{q}_j + \left[M_{ii}(q) - M_i(q_i)\right]\ddot{q}_i \right\} \\ &\qquad + \left\{ \sum_{j=1, j\neq i}^{n} C_{ij}(q,\dot{q})\dot{q}_j + \left[C_{ii}(q,\dot{q}) - C_i(q_i,\dot{q}_i)\right]\dot{q}_i \right\} \\ &\qquad + \left[\overline{G}_i(q) - G_i(q_i)\right], \end{aligned} \tag{39}$$

where $q_i, \dot{q}_i, \ddot{q}_i, G_i(q)$, and u_i are the ith element of the vectors $q, \dot{q}, \ddot{q}, G(q)$, and u, respectively. $M_{ij}(q)$ and $C_{ij}(q,\dot{q})$ are the ijth element of the matrices $M(q)$ and $C(q,\dot{q})$, respectively.

Let

$$x_i = \begin{bmatrix} x_{i1} & x_{i2} \end{bmatrix}^T = \begin{bmatrix} q_i & \dot{q}_i \end{bmatrix}^T, \quad i = 1, 2, \ldots, n. \tag{40}$$

Each subsystem motion equation may be presented as (1), where

$$\begin{gathered} A_i = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \qquad B_i = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \qquad C_i = \begin{bmatrix} 1 & 0 \end{bmatrix}, \\ f_i(q_i,\dot{q}_i) = M_i^{-1}(q_i)\left[-C_i(q_i,\dot{q}_i)\dot{q}_i - G_i(q_i) - F_i(q_i,\dot{q}_i)\right] \\ g_i(q_i) = M_i^{-1}(q_i), \\ h_i(q,\dot{q},\ddot{q}) = -M_i^{-1}(q_i) Z_i(q,\dot{q},\ddot{q}). \end{gathered} \tag{41}$$

Now, consider 2-DOF reconfigurable manipulators with different configurations shown in [17], along with dynamic model and initial state, for numerical simulation. The nonlinear terms are compensated by neural networks with the parameters $\Gamma_{if} = \Gamma_{ig} = 0.0002$, $\Gamma_{ip} = 6000$, $\varepsilon_i = 0.0001$, $\sigma_i = 0.0003$, $k_i = 2$, $f = 0.01$.

Consider configuration a first and apply control law (12) to the reconfigurable manipulators working at fault-free state.

Next, fault signals are added to the position sensor of joint 2 at $t = 6$ s and velocity sensor of joint 1 at $t = 8$ s, respectively, in order to detect and identify the multisensor fault. From Figure 1, one can see that the actual trajectories can follow the desired trajectories at about $t = 5$ s, and the actual trajectories illustrate unstable performance after the faults occur.

In this case, an appropriate threshold is required to be established for multisensor fault detection which can be realized by decentralized sliding mode observer. When the fault signals added on, the observe errors for multisensors of each joint showed as Figure 2 should over the threshold. From the curves in Figure 2, one can obtain that the sensor fault can be detected online in real time when the faults occur. The following step is to use (35) to identify fault function. Figure 3 shows the results of identification with multisensor fault. One can see the identification chattering appears only at the beginning of the identification after a short time of the faults occurred; the proposed scheme could identify the fault function precisely which was verified by the actual identification curves.

To further test the effectiveness of the proposed scheme for multisensor fault detection and identification under different configurations, the same scheme is applied to the configuration b. The simulation results are shown as Figures 4, 5, and 6 that illustrate the proposed decentralized sliding mode observer can be applicable to different configurations of reconfigurable manipulator without any parameters modification.

5. Conclusion

A decentralized sliding mode observer based on multisensor fault detection and identification scheme for a class of nonlinear interconnected systems has been presented. The decentralized neural networks controller is applied to compensate the unknown term, uncertainty term, and interconnection term when the system is fault-free. In order to detect and identify the multisensor fault, a set of decentralized sliding mode observer has been established by introducing a simple filter which can transform the sensor fault into pseudo-actuator fault scenario with diffeomorphism theory. In this case, the control accuracy of other joints cannot be affected by the fault one due to decentralized control. The effectiveness of the proposed scheme is verified by the simulation results with different configurations without modifying any parameters.

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