

Lecture Notes in Networks and Systems 752

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# Intelligent Systems and Networks

Selected Articles from ICISN 2023,  
Vietnam



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Editors

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# Robust Adaptive Control for Industrial Robots Using Sliding Mode Control and RBF Neural Network

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**Abstract.** This paper presents a method of synthesizing a robust adaptive control system for the industrial robot with six degrees of freedom. We describe the mathematical model of the robot in the form of nonlinear state equations that consider variable parameters and unmeasurable external disturbance. Uncertainty components in the dynamic robot model are identified based on adaptive control and the RBF neural network. We create a signal vector from the identification results to compensate for these components. The control law is built based on sliding mode control in which the chattering phenomenon is reduced to a minimum because the influence of the uncertainty components has been eliminated. The article's proposed control system is adaptable, robust, anti-interference, and ensures good control quality.

**Keywords:** Industrial robot · Adaptive control · Sliding mode control

## 1 Introduction

Nowadays, robots are widely used in industrial fields to perform simple to complex and repetitive operations to replace manual processes. In order to meet the increasing requirements of actual production, improving the control quality of industrial robots is an important issue. Along with the development of automatic control theory, specific methods of synthesizing control systems for industrial robots have been proposed. In recent years, methods of adaptive control, sliding mode control, and neural networks (NNs) have been studied with many outstanding advantages. The adaptive control methods for industrial robots: model reference adaptive control applied to simple robot systems with a small number of degrees of freedom [1, 2]; adaptive inverse dynamics control based on the model-based nonlinear control method [3–5]; adaptive Li-Slotine control applied to robots with a model with an uncertain parameter in the form of a constant but with poor noise resistance [6–8]. Adaptive control methods based on NNs for robots in [9–12]. However, when designing adaptive laws for NNs, it is necessary to pay attention to the training method and the convergence speed of the algorithm. The sliding mode control method is applied to industrial robots without knowing the exact dynamic parameters

[13–16]. This control method is only effective when the upper bound of the uncertain component is known; in many cases, it cannot determine this limit directly. Besides, the main disadvantage of the sliding mode control method is the chattering phenomenon because the control signal generated from the sliding mode controller is a discontinuous function. Next, the paper proposed a method of synthesizing the sliding mode controller combined with the RBF NN for the industrial robot with six degrees of freedom (6-DOF). The proposed controller has high control quality, adaptability, robustness, good anti-interference, and minimal chattering phenomenon.

## 2 Mathematical Model of Industrial Robot

The dynamic model of a 6-DOF industrial robot is described by the equation [17]:

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q})[\dot{\mathbf{q}}\dot{\mathbf{q}}] + \mathbf{N}(\mathbf{q})[\dot{\mathbf{q}}^2] + \mathbf{g}(\mathbf{q}) = \boldsymbol{\tau}, \quad (1)$$

where  $\mathbf{M}(\mathbf{q}) \in \mathbb{R}^{6 \times 6}$  is the positive definite inertia matrix;  $\mathbf{C}(\mathbf{q}) \in \mathbb{R}^{6 \times 15}$  is the Coriolis torques;  $\mathbf{N}(\mathbf{q}) \in \mathbb{R}^{6 \times 6}$  is centrifugal torques;  $\mathbf{g}(\mathbf{q}) \in \mathbb{R}^6$  are the gravitational forces;  $\mathbf{q} \in \mathbb{R}^6$ ,  $\dot{\mathbf{q}} \in \mathbb{R}^6$ , and  $\ddot{\mathbf{q}} \in \mathbb{R}^6$  are vectors of the robot end effector's position, velocity, and acceleration;  $\boldsymbol{\tau} \in \mathbb{R}^6$  is the generalized joint force vector.

$$\mathbf{M}(\mathbf{q}) = \begin{bmatrix} m_{11} & m_{12} & \dots & m_{16} \\ \vdots & \vdots & \ddots & \vdots \\ m_{61} & m_{62} & \dots & m_{66} \end{bmatrix}; \quad (2)$$

$$\mathbf{C}(\mathbf{q}) = \begin{bmatrix} c_{112} & \dots & c_{116} & c_{123} & \dots & c_{156} \\ \vdots & \ddots & \dots & \vdots & \ddots & \vdots \\ c_{616} & \dots & c_{616} & c_{623} & \dots & c_{656} \end{bmatrix}; \quad (3)$$

$$\mathbf{N}(\mathbf{q}) = \begin{bmatrix} n_{11} & n_{12} & \dots & n_{16} \\ \vdots & \vdots & \ddots & \vdots \\ n_{61} & n_{62} & \dots & n_{66} \end{bmatrix}; \quad (4)$$

$$\mathbf{g}(\mathbf{q}) = [g_1, g_2, \dots, g_6]^T. \quad (5)$$

The symbols  $[\dot{\mathbf{q}}^2]$  and  $[\dot{\mathbf{q}}\dot{\mathbf{q}}]$  are given by:

$$[\dot{\mathbf{q}}^2] = [\dot{q}_1^2, \dot{q}_2^2, \dots, \dot{q}_6^2]^T; \quad (6)$$

$$[\dot{\mathbf{q}}\dot{\mathbf{q}}] = [\dot{q}_1\dot{q}_2, \dot{q}_1\dot{q}_3, \dots, \dot{q}_1\dot{q}_6, \dot{q}_2\dot{q}_3, \dots, \dot{q}_5\dot{q}_6]^T. \quad (7)$$

Due to the invertibility of matrix  $\mathbf{M}(\mathbf{q})$ , we rewrite Eq. (1) as follows:

$$\ddot{\mathbf{q}} = \mathbf{M}^{-1}(-\mathbf{C}[\dot{\mathbf{q}}\dot{\mathbf{q}}] - \mathbf{N}[\dot{\mathbf{q}}^2] - \mathbf{g}) + \mathbf{M}^{-1}\boldsymbol{\tau}. \quad (8)$$

To facilitate the design process later, we set:  $\mathbf{x} = [x_1, x_2, \dots, x_{12}]^T$ ,  $x_1 = q_1$ ,  $x_2 = \dot{q}_1$ ,  $\dots$ ,  $x_{11} = q_6$ ,  $x_{12} = \dot{q}_6$ ;  $\mathbf{u} = [u_1, u_2, \dots, u_6]^T = [\tau_1, \tau_2, \dots, \tau_6]^T$ . Equation (8) is rewritten as:

$$\dot{\mathbf{x}} = \Psi(\mathbf{x}, \mathbf{u}). \quad (9)$$

We perform Taylor expansion (9) at the origin equilibrium point  $(\mathbf{x}_0, \mathbf{u}_0)$ , we have:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} + \mathbf{f}(\mathbf{x}), \quad (10)$$

where  $\mathbf{A} \in \mathbb{R}^{12 \times 12}$ ,  $\mathbf{B} \in \mathbb{R}^{12 \times 6}$  are Jacobian matrices:

$$\mathbf{A} = \left. \frac{\partial \Psi}{\partial \mathbf{x}} \right|_{(\mathbf{x}_0, \mathbf{u}_0)}; \quad \mathbf{B} = \left. \frac{\partial \Psi}{\partial \mathbf{u}} \right|_{(\mathbf{x}_0, \mathbf{u}_0)}; \quad (11)$$

and  $\mathbf{f}(\mathbf{x}) \in \mathbb{R}^{12}$  is a higher order terms of the Taylor series expansion and unknown nonlinear smooth function vectors. In fact, it is difficult to accurately determine the parameters of the robot due to the complexity of determining the values of mass, torque, geometrical dimensions, and operating mode. Therefore, the robot's parameters can change unpredictably over a wide range. In many cases, the robot is often affected by unmeasurable external disturbances. So the Eq. (11) can be rewritten as:

$$\dot{\mathbf{x}} = [\mathbf{A} + \Delta\mathbf{A}]\mathbf{x} + [\mathbf{B} + \Delta\mathbf{B}]\mathbf{u} + \mathbf{f}(\mathbf{x}) + \mathbf{d}(t), \quad (12)$$

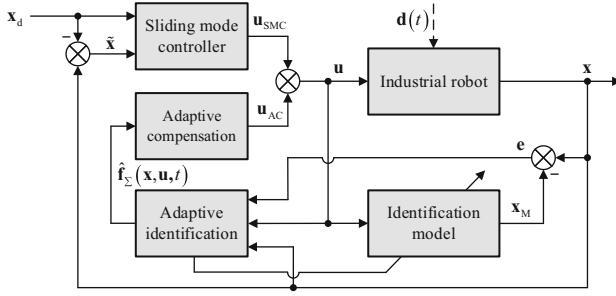
where  $\mathbf{A}$ ,  $\mathbf{B}$  are known matrices;  $\Delta\mathbf{A}$ ,  $\Delta\mathbf{B}$  are time-varying matrices;  $\mathbf{d}(t) \in \mathbb{R}^{12}$  is the vector of unmeasured external disturbances and bounded.

### 3 Synthesis of the Robust Adaptive Control Law

To synthesize the controller for industrial robots with Eq. (12) tracking the desired trajectory, we propose the control signal as follows:

$$\mathbf{u} = \mathbf{u}_{AC} + \mathbf{u}_{SMC}, \quad (13)$$

where  $\mathbf{u}_{AC}$  is a control law for the adaptive compensation of uncertain components  $\mathbf{f}_{\Sigma}(\mathbf{x}, \mathbf{u}, t) = \Delta\mathbf{A}\mathbf{x} + \Delta\mathbf{B}\mathbf{u} + \mathbf{f}(\mathbf{x}) + \mathbf{d}(t)$ ;  $\mathbf{u}_{SMC}$  is the sliding mode control law to the robot tracking the desired trajectory  $\mathbf{x}_d$ . The block diagram of the control system for the 6-DOF industrial robot is shown in Fig. 1.



**Fig. 1.** The block diagram of the control system for the 6-DOF industrial robot.

### 3.1 Algorithm for Identification of Uncertain Parameters

Without loss of generality, we set:  $\mathbf{f}^*(\mathbf{x}) = \Delta\mathbf{A}\mathbf{x} + \mathbf{f}(\mathbf{x})$  and substitute into (12), we have:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + [\mathbf{B} + \Delta\mathbf{B}]\mathbf{u} + \mathbf{f}^*(\mathbf{x}) + \mathbf{d}(t). \quad (14)$$

The identification model for uncertain parameters in (14) is as follows:

$$\dot{\mathbf{x}}_M = \mathbf{A}\mathbf{x}_M + [\mathbf{B} + \Delta\hat{\mathbf{B}}]\mathbf{u} + \hat{\mathbf{f}}^*(\mathbf{x}) + \hat{\mathbf{d}}(t), \quad (15)$$

where  $\mathbf{x}_M$  is state vector of the model;  $\Delta\hat{\mathbf{B}}$  is the estimated matrix of  $\Delta\mathbf{B}$ ;  $\hat{\mathbf{f}}^*(\mathbf{x})$  is the estimated vector of  $\mathbf{f}^*(\mathbf{x})$ ;  $\hat{\mathbf{d}}(t)$  is the estimated vector of  $\mathbf{d}(t)$ .

From (14) and (15), we have:

$$\dot{\mathbf{e}} = \mathbf{A}\mathbf{e} + [\Delta\tilde{\mathbf{B}}]\mathbf{u} + \tilde{\mathbf{f}}^*(\mathbf{x}) + \tilde{\mathbf{d}}(t), \quad (16)$$

where:

$$\mathbf{e} = \mathbf{x} - \mathbf{x}_M; \quad (17)$$

$$\Delta\tilde{\mathbf{B}} = \Delta\mathbf{B} - \Delta\hat{\mathbf{B}}; \quad (18)$$

$$\tilde{\mathbf{f}}^*(\mathbf{x}) = \mathbf{f}^*(\mathbf{x}) - \hat{\mathbf{f}}^*(\mathbf{x}) \quad (19)$$

$$\tilde{\mathbf{d}}(t) = \mathbf{d}(t) - \hat{\mathbf{d}}(t). \quad (20)$$

With  $\mathbf{f}^*(\mathbf{x})$  is a smooth function vector, by using a RBF NN for the approximation [18]. The elements of  $\mathbf{f}^*(\mathbf{x})$  can be written:

$$f_i^*(\mathbf{x}) = \sum_{j=1}^L w_{ij}^* \phi_{ij}(\mathbf{x}) + \varepsilon_i; \quad (21)$$

$i = \overline{1, 12}; j = \overline{1, L}$ , where  $L$  is number of basis function with a large enough number to guarantee the error  $|\varepsilon_i| < \varepsilon_i^M$ ,  $w_{ij}^* = \text{const}$  is the ideal weights. The basis functions:

$$\phi_{ij}(\mathbf{x}) = \exp\left(\|\mathbf{x} - \mathbf{c}_{ij}\|^2 / 2\sigma_{ij}^2\right), \quad (22)$$

where  $\mathbf{c}_{ij}$  are the position of the center of the basis functions  $\phi_{ij}(\mathbf{x})$ , and  $\sigma_{ij}$  are the standard deviation of the basis functions. The evaluation vector  $\hat{\mathbf{f}}^*(\mathbf{x})$ :

$$\hat{f}_i^*(X) = \sum_{j=1}^L \hat{w}_{ij} \phi_{ij}(\mathbf{x}). \quad (23)$$

The approximation of the RBF NN is made by adjusting  $\hat{w}_{ij}$  against  $w_{ij}^*$ :

$$\tilde{w}_{ij} = w_{ij}^* - \hat{w}_{ij}. \quad (24)$$

The identification process will converge if  $\mathbf{e} \rightarrow 0$  which means that (16) is stable. For Eqs. (16), the Lyapunov function is selected as follows:

$$V = \mathbf{e}^T \mathbf{P} \mathbf{e} + \sum_{i=1}^{12} \sum_{j=1}^6 \Delta \tilde{b}_{ij}^2 + \sum_{i=1}^{12} \sum_{j=1}^L \tilde{w}_{ij}^2 + \sum_{i=1}^{12} \tilde{d}_i^2, \quad (25)$$

where  $\mathbf{P}$  is a positive definite symmetric matrix. Take the derivative of both sides (25):

$$\dot{V} = \dot{\mathbf{e}}^T \mathbf{P} \mathbf{e} + \mathbf{e}^T \mathbf{P} \dot{\mathbf{e}} + 2 \sum_{i=1}^{12} \sum_{j=1}^6 \Delta \dot{\tilde{b}}_{ij} \Delta \tilde{b}_{ij} + 2 \sum_{i=1}^{12} \sum_{j=1}^L \dot{\tilde{w}}_{ij} \tilde{w}_{ij} + 2 \sum_{i=1}^{12} \dot{\tilde{d}}_i \tilde{d}_i. \quad (26)$$

Substitute (16) into (26):

$$\begin{aligned} \dot{V} = & \mathbf{e}^T \left( \mathbf{A}^T \mathbf{P} + \mathbf{P} \mathbf{A} \right) \mathbf{e} + 2 \mathbf{u}^T \Delta \tilde{\mathbf{B}}^T \mathbf{P} \mathbf{e} + 2 \mathbf{e}^T \mathbf{P} \tilde{\mathbf{f}}^*(\mathbf{x}) + 2 \mathbf{e}^T \mathbf{P} \tilde{\mathbf{d}}(t) + \\ & + 2 \sum_{i=1}^{12} \sum_{j=1}^6 \Delta \dot{\tilde{b}}_{ij} \Delta \tilde{b}_{ij} + 2 \sum_{i=1}^{12} \sum_{j=1}^L \dot{\tilde{w}}_{ij} \tilde{w}_{ij} + 2 \sum_{i=1}^{12} \dot{\tilde{d}}_i \tilde{d}_i. \end{aligned} \quad (27)$$

For (16) to be stable, from (27) to with draw the condition to  $\dot{V} < 0$ :

$$\mathbf{e}^T \left( \mathbf{A}^T \mathbf{P} + \mathbf{P} \mathbf{A} \right) \mathbf{e} + 2 \mathbf{e}^T \mathbf{P} \varepsilon < 0; \quad (28)$$

$$2 \mathbf{u}^T \Delta \tilde{\mathbf{B}}^T \mathbf{P} \mathbf{e} + 2 \sum_{i=1}^{12} \sum_{j=1}^6 \Delta \dot{\tilde{b}}_{ij} \Delta \tilde{b}_{ij} = 0; \quad (29)$$

$$2 \mathbf{e}^T \mathbf{P} \tilde{\mathbf{f}}^*(\mathbf{x}) + 2 \sum_{i=1}^{12} \sum_{j=1}^L \dot{\tilde{w}}_{ij} \tilde{w}_{ij} = 0; \quad (30)$$

$$2\mathbf{e}^T P \tilde{\mathbf{d}}(t) + 2 \sum_{i=1}^{12} \dot{\tilde{d}}_i \tilde{d}_i = 0. \quad (31)$$

Transform the inequality (28):

$$\mathbf{e}^T (\mathbf{A}^T \mathbf{P} + \mathbf{P} \mathbf{A}) \mathbf{e} + 2\mathbf{e}^T \mathbf{P} \boldsymbol{\varepsilon} = -\mathbf{e}^T \mathbf{Q} \mathbf{e} + 2 \sum_{i=1}^{12} \varepsilon_i \bar{\mathbf{P}}_i \mathbf{e} < 0, \quad (32)$$

where  $\mathbf{Q} = -(\mathbf{A}^T \mathbf{P} + \mathbf{P} \mathbf{A})$ , suppose that  $\mathbf{A}$  is Hurwitz matrix;  $\bar{\mathbf{P}}_i$  is the  $i$ -th row of the matrix  $\mathbf{P}$ . Using inequality transformations [19] for (32), we have:

$$\|\mathbf{e}\| > 2 \sum_{i=1}^{12} \varepsilon_i \|\bar{\mathbf{P}}_i\| / r_{\min}(\mathbf{Q}); \quad r_{\min}(\mathbf{Q}) \text{ is the smallest eigenvalue of the matrix } \mathbf{Q}. \quad (33)$$

Thus, if simultaneously satisfied (29), (30), (31), (33) then  $\dot{V} < 0$  and (16) is stable. From (18), (29), notice that the parameter of the robot changes slowly, i.e.  $\Delta \dot{b}_{ij} \approx 0$ :

$$\Delta \dot{b}_{ij} = u_j \bar{\mathbf{P}}_i \mathbf{e}; \quad i = \overline{1, 12}; j = \overline{1, 6}. \quad (34)$$

From (19), (21), (23), (24) and (30), because of  $w_{ij}^* = \text{const}$  so  $\dot{w}_{ij}^* = 0$ :

$$\hat{f}_i^*(\mathbf{x}) = \sum_{j=1}^L \hat{w}_{ij} \phi_{ij}(\mathbf{x}); \quad \dot{\hat{w}}_{ij} = -\bar{\mathbf{P}}_i \mathbf{e} \phi_{ij}(\mathbf{x}); \quad i = \overline{1, 12}; \quad j = \overline{1, 6}. \quad (35)$$

From (20), (31), notice that external disturbances changes slowly so  $\dot{d}_i(t) \approx 0$ :

$$\dot{\hat{d}}_i = -\bar{\mathbf{P}}_i \mathbf{e}; \quad i = \overline{1, 12}. \quad (36)$$

The identification results from (34), (35), and (36) are used to synthesis the compensation control law  $\mathbf{u}_{AC}$ .

### 3.2 Algorithm for Compensation of Uncertain Parameters

We set:  $\mathbf{f}_{\Sigma}(\mathbf{x}, \mathbf{u}, t) = \Delta \mathbf{B} \mathbf{u} + \mathbf{f}^*(\mathbf{x}) + \mathbf{d}(t) = [f_{\Sigma 1}, f_{\Sigma 2}, \dots, f_{\Sigma 12}]^T$ , and substitute into (14):

$$\dot{\mathbf{x}} = \mathbf{A} \mathbf{x} + \mathbf{B} \mathbf{u} + \mathbf{I} \mathbf{f}_{\Sigma}(\mathbf{x}, \mathbf{u}, t), \quad (37)$$

where  $\mathbf{I} \in \mathbb{R}^{12 \times 12}$  matrix has elements  $I_{ij} = 1$  if  $i = j$  and  $f_{\Sigma i} \neq 0$ ;  $I_{ij} = 0$  if  $i \neq j$  and  $f_{\Sigma i} = 0$ ;  $i, j = \overline{1, 12}$ .

Substitute (13) into (37):

$$\dot{\mathbf{x}} = \mathbf{A} \mathbf{x} + \mathbf{B} \mathbf{u}_{SMC} + \mathbf{B} \mathbf{u}_{AC} + \mathbf{I} \mathbf{f}_{\Sigma}(\mathbf{x}, \mathbf{u}, t). \quad (38)$$



From (38),  $\mathbf{f}_\Sigma(\mathbf{x}, \mathbf{u}, t)$  will be compensated when:

$$\mathbf{B}\mathbf{u}_{AC} + \mathbf{I}\mathbf{f}_\Sigma(\mathbf{x}, \mathbf{u}, t) = 0. \quad (39)$$

To create a signal vector  $\mathbf{u}_{AC}$  satisfying (39), we choose:

$$\mathbf{u}_{AC} = -\mathbf{H}\mathbf{f}_\Sigma(\mathbf{x}, \mathbf{u}, t), \quad (40)$$

where  $\mathbf{H}$  is the gain matrix. From (34), (35), (36), replace  $\mathbf{f}_\Sigma(\mathbf{x}, \mathbf{u}, t)$  with  $\hat{\mathbf{f}}_\Sigma(\mathbf{x}, \mathbf{u}, t)$ :

$$\hat{\mathbf{f}}_\Sigma(\mathbf{x}, \mathbf{u}, t) = \Delta\mathbf{B}\mathbf{u} + \hat{\mathbf{f}}(\mathbf{x}) + \hat{\mathbf{d}}(t). \quad (41)$$

From (40) and (41), we have:

$$\mathbf{u}_{AC} = -\mathbf{H}\hat{\mathbf{f}}_\Sigma(\mathbf{x}, \mathbf{u}, t). \quad (42)$$

Substitute (42) into (39):

$$-\mathbf{B}\mathbf{H}\hat{\mathbf{f}}_\Sigma(\mathbf{x}, \mathbf{u}, t) + \mathbf{I}\mathbf{f}_\Sigma(\mathbf{x}, \mathbf{u}, t) = 0. \quad (43)$$

To satisfy (43), we must have:

$$\mathbf{B}\mathbf{H} = \mathbf{I}. \quad (44)$$

From (44), we choose  $\mathbf{H} = \mathbf{B}^+$ , where  $\mathbf{B}^+$  is the pseudo-inverse matrix of  $\mathbf{B}$ [19]. Thus, with (42), the uncertainty elements are compensated then (38) becomes:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}_{SMC}. \quad (45)$$

Next, the system (45) of the control law is built based on sliding mode control.

### 3.3 Synthesis of the Sliding Mode Control Law

The error vector between the state vector and the desired state vector  $\mathbf{x}_d$ :

$$\tilde{\mathbf{x}} = \mathbf{x} - \mathbf{x}_d \rightarrow \mathbf{x} = \tilde{\mathbf{x}} + \mathbf{x}_d. \quad (46)$$

Substitute (46) into (45):

$$\dot{\tilde{\mathbf{x}}} = \mathbf{A}\tilde{\mathbf{x}} + \mathbf{B}\mathbf{u}_{SMC} + \mathbf{A}\mathbf{x}_d - \dot{\mathbf{x}}_d. \quad (47)$$

For (47), the hyper sliding surface is chosen as follows [20]:

$$\mathbf{s} = \mathbf{\Omega}\tilde{\mathbf{x}}, \quad (48)$$

where  $\mathbf{s} = [s_1, s_2, \dots, s_6]^T$ ;  $\mathbf{\Omega} \in \mathbb{R}^{6 \times 12}$  is the parameter matrix of hyper sliding surface and choose  $\mathbf{\Omega}$  is Hurwitz matrix such that  $\det(\mathbf{\Omega}\mathbf{B}) \neq 0$ .

The control signal  $\mathbf{u}_{SMC}$  can be written by:

$$\mathbf{u}_{SMC} = \begin{cases} \mathbf{u}_{eq} & \text{if } \mathbf{s} = 0 \\ \mathbf{u}_N & \text{if } \mathbf{s} \neq 0 \end{cases}, \quad (49)$$

$\mathbf{u}_{eq}$  is the equivalent control signal that keeps the system (47) on the hyper sliding surface (48);  $\mathbf{u}_N$  is the control signal that moves the system (47) towards the hyper sliding surface (48). From (49), we can rewrite:

$$\mathbf{u}_{SMC} = \mathbf{u}_{eq} + \mathbf{u}_N. \quad (50)$$

$\mathbf{u}_{eq}$  is defined in [20]:

$$\mathbf{s} = \boldsymbol{\Omega} \tilde{\mathbf{x}} = 0. \quad (51)$$

From (47) and (51), the equivalent control signal can be defined as follows:

$$\mathbf{u}_{eq} = -[\boldsymbol{\Omega} \mathbf{B}]^{-1} [\boldsymbol{\Omega} \mathbf{A} \tilde{\mathbf{x}} + \boldsymbol{\Omega} \mathbf{A} \mathbf{x}_d - \boldsymbol{\Omega} \dot{\mathbf{x}}_d]. \quad (52)$$

Next, we define the control signal  $\mathbf{u}_N$ . For (48), the Lyapunov function selected by:

$$V = 1/2 \mathbf{s}^T \mathbf{s}. \quad (53)$$

Condition for the existence of slip mode can be written:

$$\dot{V} = \mathbf{s}^T \dot{\mathbf{s}} < 0. \quad (54)$$

From (47), (48), (50), (54), and attention to (52), we have:

$$\dot{V} = \mathbf{s}^T [\boldsymbol{\Omega} \mathbf{B} \mathbf{u}_N] < 0. \quad (55)$$

So to satisfy (54), from (55), we have:

$$\mathbf{u}_N = -[\boldsymbol{\Omega} \mathbf{B}]^{-1} \delta \text{sgn}(\mathbf{s}), \quad (56)$$

where  $\delta$  is a small positive coefficient. Substituting (52) and (56) into (50), we have:

$$\mathbf{u}_{SMC} = -[\boldsymbol{\Omega} \mathbf{B}]^{-1} [\boldsymbol{\Omega} \mathbf{A} \tilde{\mathbf{x}} + \boldsymbol{\Omega} \mathbf{A} \mathbf{x}_d - \boldsymbol{\Omega} \dot{\mathbf{x}}_d + \delta \text{sgn}(\mathbf{s})]. \quad (57)$$

Thus, the article has synthesized the sliding mode control law (57) for the industrial robot to follow the desired trajectory. Besides, when the adaptive recognition algorithm converges, the components of uncertainty change are compensated for, making the  $\mathbf{u}_{SMC}$  (57) independent of the uncertain components of the robot. Then we can choose the positive coefficient  $\delta$  with a small value, which means that chattering phenomenon in the sliding mode control law is reduced to a minimum.

Finally, the control signals (42) and (57) are used for (13), and the control laws of the industrial robot (1) have been synthesized successfully.

## 4 Results and Discussion

By choosing the values for the parameters of the 6-DOF PUMA 560 robot manipulator proposed in [17] which the dynamic model is described by the Eq. (1).

Perform Taylor series expansion of Eq. (9) at the origin equilibrium point  $(\mathbf{x}_0, \mathbf{u}_0) = (\mathbf{0}, \mathbf{0})$ . We have the matrices  $\mathbf{A} \in \mathbb{R}^{12 \times 12}$  and  $\mathbf{B} \in \mathbb{R}^{12 \times 6}$  (11) as follows:

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -0.74 & 0 & 0.17 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.71 & 0 & 0.46 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 6.93 & 0 & 5.32 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0.11 & 0 & 0.12 & 0 & 0 & 0 & 0.16 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix};$$

$$\mathbf{B} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0.254 & 0.003 & 0.029 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0.003 & 0.149 & -0.044 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0.029 & -0.044 & 0.876 & 0 & -0.006 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 4.98 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -0.006 & 0 & 5.55 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 5.26 \end{bmatrix}.$$

Assume the nonlinear function vector  $\mathbf{f}(\mathbf{x})$  and the external disturbance vector  $\mathbf{d}(t)$  in Eq. (12) have the form:

$$\mathbf{f}(\mathbf{x}) = \begin{bmatrix} 0 \\ \sin(x_2 + x_5) + 0.2 \sin(x_7 + x_6) + 0.5 \sin(x_9) \sin(x_{11}) \\ 0 \\ \sin(x_3) + \sin(0.5x_8) + \sin(x_8) \sin(x_3) + \sin(0.5x_8) + \sin(x_8) \\ 0 \\ \sin(0.2x_3) + \sin(x_5) + \sin(0.8x_7) + \sin(x_9) + \sin(0.5x_{10}) \\ 0 \\ \sin(x_3 + x_5) + \sin(x_7) + \sin(0.8x_9) + \sin(x_{12}) \\ 0 \\ \sin(0.8x_3) + \sin(x_5 + x_7) + \sin(x_9) + \sin(0.6x_{11}) \\ 0 \\ \sin(x_3 + 0.5x_5) + \sin(x_7) + \sin(0.6x_9) + \sin(0.9x_{12}) \end{bmatrix};$$

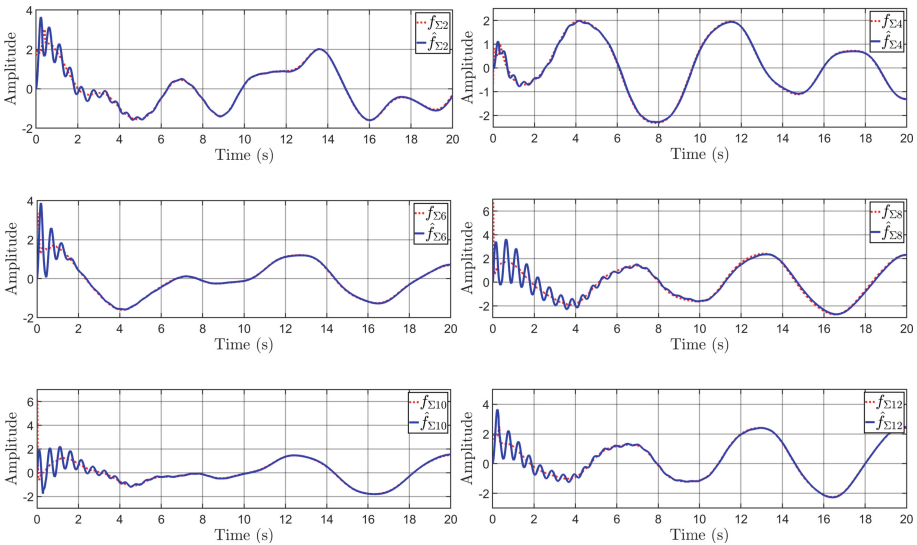
$$\mathbf{d}(t) = \begin{bmatrix} 0 \\ \sin(0.5t + \pi/2) \\ 0 \\ 0.8 \sin(0.6t) \\ 0 \\ 0.6 \sin(0.5t + \pi/3) \\ 0 \\ 0.7 \sin(0.8t + \pi/4) \\ 0 \\ 0.9 \sin(0.6t - \pi/3) \\ 0 \\ 0.5 \sin(0.7t) + 0.3 \end{bmatrix}.$$

It is assumed that the parameters of the robot have a change of  $\Delta \mathbf{A} = 25\% \mathbf{A}$ ,  $\Delta \mathbf{B} = 25\% \mathbf{B}$ , and the desired trajectory for each articulation has the following form:

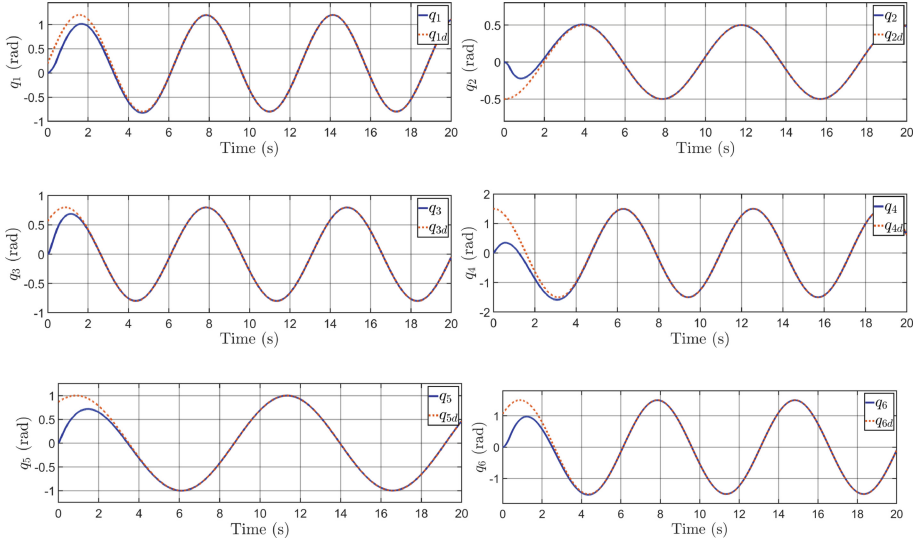
$$\begin{aligned} q_{1d} &= \sin(t) + 0.2; & q_{2d} &= 0.5 \sin(0.8t - \pi/2); & q_{3d} &= 0.8 \sin(0.9t + \pi/4); \\ q_{4d} &= 1.5 \sin(t + 3\pi/2); & q_{5d} &= \sin(0.6t + \pi/3); & q_{6d} &= 1.5 \sin(0.9t + \pi/4). \end{aligned}$$

Simulations were performed using Matlab software. The simulation results are shown in Fig. 2 and Fig. 3.

The results in Fig. 2 show that the robot's uncertainty components recognition algorithms (34), (35), and (36) have entirely converged. Next, with controller  $\mathbf{u}$  (13) where  $\mathbf{u}_{AC}$  (42) and  $\mathbf{u}_{SMC}$  (57), the robot's trajectory has tracking to the desired trajectory shown in Fig. 3. These simulation results once again prove the correctness and effectiveness of the proposed control law.



**Fig. 2.** The identification result of uncertainty vector  $\hat{\mathbf{f}}_{\Sigma}(\mathbf{x}, \mathbf{u}, t)$ .



**Fig. 3.** Trajectory tracking of the 6-DOF industrial robot.

## 5 Conclusion

This paper has synthesized the 6-DOF industrial robot control systems based on sliding control and RBF neural network. Robot's mathematical model is described as nonlinear state equations considering variable parameters and unmeasured external disturbance using the Taylor expansion method. We synthesized the identification rule of uncertain components in the robot model based on adaptive control theory and RBF neural network; building a mechanism to compensate for uncertain elements from the identification results ensures the system is invariant with these components. The sliding mode control law is synthesized with a chattering phenomenon reduced to a minimum and overcomes the limitations of the basic sliding mode control method [13–16]. Our control system has good controllability, adaptability, and robustness. Simulation results confirm the correctness and effectiveness of the proposed method.

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