RBF Network Adaptive Control of SCARA Robot Based on Fuzzy Compensation

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Abstract. Facing the requirements of high-precision control of SCARA robot systems in assembly and handling, RBF network adaptive control method based on fuzzy compensated SCARA robots is proposed. First, a SCARA robot dynamics model is established and theoretically analyzed based on Newton's Euler equations. Second, the RBF network is used to approximate the ideal nominal model. Then, the fuzzy compensator is used to modify the friction, disturbance, load of the system and other external factors to compensate; finally, MATLAB/Simulink software was used to simulate the effect of SCARA robot system with and without fuzzy compensator. Experimental research shows that the control accuracy of SCARA robot joints with fuzzy compensators has been improved by 43.42%, 67.47% and 65.41%, respectively. The research results can provide some guidance for the precise assembly and handling of SCARA robots in production.

1. Introduction

The SCARA robot is a kind of robot that selective compliance assembly and approximate cylinder workspace [1]. It has three rotating joints and one moving joint, which is most suitable for plane positioning and vertical assembly. Therefore, it is widely used in sorting, assembly and palletizing work in the plastics industry, automotive industry, electronics industry and other industries [1-2]. In industrial production operations, SCARA robots have higher requirements for high-speed and high-precision characteristics. Thus, SCARA robots must have accurate control algorithms.

In recent years, the high-performance control algorithm of industrial robot has become a research hotspot. At present, non-model-based (PID algorithm, etc.) is generally used in control algorithms for industrial robot applications, but it has been proven in practice that this method has certain limitations in high-speed, high-precision, and large-load applications [3-4]. In order to improve the accuracy and response speed of robot control algorithms, scholars at home and abroad have carried out research on control algorithm including neural network control [5], fuzzy control, iterative learning control [6], inversion control [7], sliding mode control [8] robust control [9]. Among them, the RBF (radial basis function) network is applied to a certain extent in production practice because it does not need to
consider the mathematical model of the system and the characteristics of fast learning speed. For example, Kumar N [10] used RBF network to weaken the chattering of deburring manipulator in sliding mode control; Wang Hong et al.[11] proposed RBF network adaptive control of six axis manipulator based on sliding mode compensation; To some extent, the above two compensation strategies improve the robustness of the robot, but there is a tracking effect with average accuracy. Li Min et al. [12] compensated LuGre dynamic friction term in robot based on Fuzzy RBF neural network; Li Xin [13] proposed the adaptive control of manipulator modeling error compensation based on RBF; They compensate the unknown disturbance of the system, improve the tracking effect of the robot, but reduce the robustness of the robot system; Vu Thi Yen[14] proposed to solve the robot system's uncertainty and disturbance through adaptive sliding mode control of the manipulator trajectory tracking, but its tracking accuracy effect is average. Qiu Zhi-cheng [15] proposed the vibration control of a rotating flexible articulated beam based on an adaptive RBF fuzzy neural network, which achieved rapid suppression of system jitter, but the accuracy tracking effect for nonlinear interference was average.

Based on the literature [16], this paper proposes RBF adaptive control method based on fuzzy compensation in the application of SCARA robots. First, based on Newton's Euler equations, a SCARA robot dynamics model is established and theoretically analyzed. Second, the RBF network is used to approximate the ideal nominal model. Then, the fuzzy compensator is used to modify the friction, disturbance and load of the system. And other external factors to compensate; finally, MATLAB/Simulink software was used to simulate the effect of SCARA robot system with and without fuzzy compensator. The validity of this method is verified in experiments, which can provide certain guidance for the accurate assembly and handling of SCARA robots in production.

2. Dynamic modeling and analysis of SCARA robot based on Newton's Euler equation

2.1. SCARA Robot Dynamics Modeling

At present, the servo motor drives the reducer, and then drives the robot arm movement is the mechanical structure form of the series joint robot, the same with the SCARA robot. This article uses SCARA robots to verify the effectiveness of fuzzy compensation-based RBF network adaptive control algorithms in improving the control performance of robot systems and the accuracy of trajectory tracking control.

SCARA robot is composed of three rotating pairs and one moving pair, which ensures that it can move in three degrees of freedom and rotate around the vertical direction in its workspace. The D-H model of the SCARA robot is established according to the Craig method [17-18]. As shown in Figure 1. SCARA robot link parameters are shown in Table 1.

Figure 1. Schematic diagram of SCARA robot
Table 1. SCARA robot DH parameters

| i | $\alpha_{i-1}$ (°) | $a_{i-1}$ (mm) | $d_i$ | $\theta_i$ |
|---|-----------------|----------------|------|-----------|
| 1 | 0               | 500            | 0    | $q_1$     |
| 2 | -180            | 500            | 0    | $q_2$     |
| 3 | 0               | 0              | 0    | $q_3$     |
| 4 | 0               | 0              | 0    | $q_4$     |

The SCARA robot standard dynamic model is expressed as:

$$
D_{11} = \frac{1}{3} m_1 l_1^2 + \left(\frac{1}{3} l_1^2 + l_1^2 + l_2 \cos q_2\right) \times m_2 + \left(l_2^2 + l_1^2 + 2 l_1 l_2 \cos q_2\right) \times (m_3 + m_4) + \frac{1}{2} m_1 r^2
$$

$$
D_{12} = \frac{1}{3} m_2 l_2^2 + \frac{1}{2} m_2 l_1 l_2 \cos q_2 + m_3 l_3^2 + m_4 l_4^2 \cos q_2 + m_3 l_3^2 + m_4 l_4^2 \cos q_2 + \frac{1}{2} m_2 r^2
$$

$$
D_{14} = -\frac{1}{2} m_1 r^2
$$

$$
D_{21} = \frac{1}{3} m_2 l_2^2 + \frac{1}{2} m_2 l_1 l_2 \cos q_2 + m_3 l_3^2 + m_4 l_4^2 \cos q_2 + m_3 l_3^2 + m_4 l_4^2 \cos q_2 + \frac{1}{2} m_2 r^2
$$

$$
D_{22} = \frac{1}{3} m_2 l_2^2 + m_3 l_3^2 + m_4 l_4^2 + \frac{1}{3} m_2 r^2
$$

$$
D_{24} = -\frac{1}{2} m_2 r^2
$$

$$
D_{33} = m_3 + m_4
$$

$$
D_{41} = \frac{1}{2} m_4 r^2
$$

$$
D_{44} = \frac{1}{2} m_4 r^2
$$

In the formula.

$$
C_{11} = -2 \times \left(\frac{1}{2} m_2 + m_3 + m_4\right) l_1 l_2 \sin q_2 \times \dot{q}_2
$$

$$
C_{12} = -\frac{1}{2} \left(m_2 + m_3 + m_4\right) l_1 l_2 \sin q_2
$$

$$
G_3 = -(m_3 + m_4) g
$$

Where: $\tau_1$, $\tau_2$, $\tau_3$ and $\tau_4$ are the control torques of robot joints 1, 2, 3 and 4 respectively; $m_1$, $m_2$, $m_3$, and $m_4$ are the masses of robot links 1, 2, 3 and 4 respectively; $l_1$ and $l_2$ are the lengths of links 1 and 2 respectively, $l_3 = l_2$; $q_1$, $q_2$, $q_3$ and $q_4$ are the corners of robot links 1, 2, 3 and 4 respectively; $r$ represents the vertical distance between the center of mass and the axis of rotation of the connecting rod 4; $g$ acceleration of gravity, $g = 9.8$. Considering that the 4th axis (rotating joint) motion has a certain amount of coupling effect in the same direction on the 3rd axis (moving joint), and the 4th axis motion has no effect on the horizontal positioning motion of SCARA robot [18], therefore, only the first three axes of the SCRAR robot are taken as the research object in the laboratory. Reference formula (1) the dynamic equation of the first three axes of SCARA robot is modified as follows:
\[
\begin{align*}
\tau_1 &= \left[7 - m_1 + \left(\frac{10}{3} + 3\cos q_2\right)m_2 + (2 + 2\cos q_2)m_3\right]l_1^2 \ddot{q}_1^2 + \left[\left(\frac{7}{3} + 3\cos q_2\right)m_2 + (1 + \cos q_2)m_3\right]l_2^2 \ddot{q}_2^2 \\
&\quad - \frac{3m_2 + 2m_3}{2} \sin q \int \left(\dot{q}_2^2 + \dot{q}_1^2 + \dot{q}_1^2\right) \\
\tau_2 &= \left(\frac{7}{3}m_2 + m_3\right)l_2^2 \ddot{q}_2^2 + \left[\left(\frac{7}{3} + 3\cos q_2\right)m_2 + (1 + \cos q_2)m_3\right]l_2^2 \ddot{q}_1^2 + \frac{3m_2 + 2m_3}{2} \sin q \int \ddot{q}_i^2 \\
\tau_3 &= m_3 \ddot{q}_3^2 - m_3 g
\end{align*}
\]

Considering the effects of gravity, friction, and unknown disturbances, according to the Lagrangian equation, the dynamic equation of the N-joint robot is expressed as:

\[
D(q)\ddot{q} + C(q, \dot{q}) \dot{q} + G(q) + F(q) = \tau + d
\]

Where: \((q, \dot{q}, \ddot{q}) \in \mathbb{R}^n\) represents the position, velocity and acceleration vector of the robot joint; \(D(q) \in \mathbb{R}^{n \times n}\) is the inertia matrix of the robot; \(C(q, \dot{q}) \in \mathbb{R}^n\) is centrifugal force and Coriolis force; \(G(q) \in \mathbb{R}^{n \times 1}\) is the gravity term; \(F(q) \in \mathbb{R}^n\) is the friction torque; \(\tau \in \mathbb{R}^{n \times 1}\) is the control torque, that is, the input torque of each joint of the robot; \(d \in \mathbb{R}^{n \times 1}\) is the uncertain disturbance.

In the design of the system controller, the dynamic model characteristics of the robot system are considered:

1. \(D(q) - 2C(q, \dot{q})\) is skew symmetric matrix, so it satisfies \(x^T(D(q) - 2C(q, \dot{q}))x = 0\); 
2. The inertia matrix \(D(q)\) is symmetric positive definite matrix, that is, there are positive numbers \(m_1\) and \(m_2\) to ensure \(m_1 I \leq D(q) \leq m_2 I\); 
3. The uncertain disturbance satisfies \(d \leq \tau, \tau \geq 0\).

### 2.2. Dynamics model analysis of SCARA robot

Assuming the ideal position of robot joint is \(q_d\), the actual position is \(q\), so the tracking error is \(e = q_d - q, \dot{e} = \dot{q}_d - \dot{q}\).

Supposing \(E(q, \dot{q}) = C(q, \dot{q}) \dot{q} + G(q) + F(q)\), then, \(\tau + d = D(q) \ddot{q} + E(q, \dot{q})\).

If the model implements precise modeling and \(d = 0\), the controller can be designed as:

\[
\tau = D(q) \ddot{q}_d - K \dot{e} - K \dot{e} + C(q, \dot{q}) \dot{q} + G(q) + F(q)
\]

The stable closed-loop system is \(\ddot{e} + K \dot{e} + K \dot{e} = 0\).

In the practical engineering application, the actual model of the object is difficult to achieve accurate modeling, that is, it cannot get accurate \(D(q), E(q, \dot{q})\), so only the nominal model of estimation can be established. If the nominal model \(D_0(q), E_0(q, \dot{q})\) replace \(D(q), E(q, \dot{q})\), the control law can be designed as:

\[
\ddot{e} + K \dot{e} + K \dot{e} = D_0^{-1}(\Delta D \ddot{q} + \Delta E + d)
\]

Where \(\Delta D = D_0 - D, \Delta E = E_0 - E\).
Namely, \[
\dot{\epsilon} = \begin{bmatrix} 0 & I \\ -K_\rho & -K_\omega \end{bmatrix} \epsilon + \begin{bmatrix} 0 \\ I \end{bmatrix} f,
\]
If \( A = \begin{bmatrix} 0 & I \\ -K_\rho & -K_\omega \end{bmatrix} 
B = \begin{bmatrix} 0 \\ I \end{bmatrix} \)

Take the inaccurate part of modeling as \( f = Dq^T (\Delta Dq + \Delta E + d) \), So

\[
\dot{x} = Ax + Bf
\]

It can be seen from equation (7) that the imprecise modeling will reduce the control performance of the system. Therefore, in this paper, firstly, RBF is used to approximate the nominal model, and then fuzzy compensator is used to compensate the unmodeled part.

3. Design of controller

3.1. RBF neural network

RBF network is a three-layer forward network, including input layer, hidden layer and output layer [4], it can speed up learning and avoid local minimum problems [5]. In order to ensure the accuracy of the robot model, RBF is used to approximate the nominal model.

In the structure of RBF network, as shown in Figure 2. \( x = [x_1, x_2, \cdots, x_n]^T \) is the input vector of the network, and the radial basis vector \( H = [h_1, h_2, \cdots, h_m]^T \) of RBF network is set, where Gaussian basis function is expressed as \( h_j = \exp \left( -\frac{\|x - c_j\|^2}{2b_j^2} \right), j = 1, 2, \cdots, m \). In the formula, the center vector \( c_j = [c_{j1}, c_{j2}, \cdots, c_{jm}] \) of the \( j \) th node of the network, and base width vector \( b_j = [b_{j1}, b_{j2}, \cdots, b_{jm}]^T \), \( b_j \) of the network represent the base width parameter of node \( j \). The weight vector of the network is expressed as \( w = [w_1, w_2, \cdots, w_m]^T \), so the output of RBF network is \( y_n(t) = w^T \cdot H \).

![Figure 2. RBF network structure](image)

Select the input of the main controller: \( \tau = D_i(q_i, \dot{q}_i) + E_i(q_i, \dot{q}_i), (i = 1, 2, \cdots, n) \). The input vectors of the network are \( q_i, \dot{q}_i, \cdots, q_j, \dot{q}_j, [q_i, \dot{q}_i], [q_j, \dot{q}_j] \cdots [q_i, \dot{q}_j] \). RBF network is used to approach \( D_i \) and \( E_i \) respectively, and the output is expressed as \( D_{i0} \) and \( E_{i0} \), So the control torque of the robot system is: \( \tau = D_{i0}(\dot{q}_i) + E_{i0}(q_i, \dot{q}_i) + D_{i0}(K_i \epsilon + K_i \dot{\epsilon}) \)
3.2. Fuzzy control

Considering the external factors such as friction, disturbance and load change in the actual operation, a control system structure based on fuzzy compensation is designed to improve the robustness of the system model, as shown in Figure 3.

![Control system diagram based on fuzzy compensation](image)

**Figure 3.** Control system diagram based on fuzzy compensation

For variable $x_i (i = 1, 2, \cdots, n)$, fuzzy sets $A_i^l (l = 1, 2, \cdots, p_i)$ are defined, and $p_i$ fuzzy rules are used to construct fuzzy system $\tilde{f}(x|\theta)$, and IF-THEN fuzzy rules are used to describe control knowledge:

**IF** $x_i$ is $A_i^l$ and...and $x_n$ is $A_n^{l_n}$ **THEN** $\tilde{f}$ is $B_i^{l_i}.$

Using a product inference engine, a single-valued fuzzier, and a central average defuzzifier, the output of the fuzzy system is

$$
\tilde{f}(x|\theta) = \frac{\sum_i \cdots \sum_i \prod_{i=1}^n \mu_{A_i^l}(x_i)}{\sum_i \cdots \sum_i \prod_{i=1}^n \mu_{A_i^l}(x_i)}
$$

Where $A_i^l(x_i)$ is a membership function of $x_i$. Let $\overrightarrow{\theta}$ be a free parameter and put it in function $\theta$.

Introducing vector $\xi(x)$, then $\tilde{f}(x|\theta) = \theta^T \xi(x)$

Where $\xi(x)$ is $\prod_{i=1}^n p_i$ dimensional vector, and the $l_i, \cdots, l_n$ th element is

$$
\xi_{l_i, \cdots, l_n}(x) = \frac{\prod_{i=1}^n \mu_{A_i^l}(x_i)}{\sum_i \cdots \sum_i \prod_{i=1}^n \mu_{A_i^l}(x_i)}
$$

Suppose there is an ideal fuzzy system $\hat{f}(x|\theta^*)$
\[ f(x) = \hat{f}(x | \theta') + \varepsilon \] (9)

\[ \theta' = \arg \min_{\theta \in \mathbb{R}^{|\theta|}} \left\{ \sup_{x \in \mathbb{R}} \left| f(x | \theta) - \hat{f}(x | \theta') \right| \right\} \]

Among them, \( \theta' \) is a matrix of order \( n \times n \), which represents the optimal approximation of the parameter values of the fuzzy system to \( \hat{f}(x | \theta) \).

Then, formula (8) can be written as

\[ \dot{x} = Ax + B(\theta'^T \xi(x) + \varepsilon) \] (10)

3.3. Design of controller

Design the controller as

\[ \tau = D_0(q)(\dot{q}_d - K, \dot{q} - K, \varepsilon) + E_0(q, \dot{q}) - D_0(q) \hat{f}(x | \theta) \]

By substituting the above formula into the formula (5),

\[ D(q) \ddot{q} + C(q, \dot{q}) \dot{q} + F(q) = D_0(q)(\dot{q}_d - K, \dot{q} - K, \varepsilon) + E_0(q, \dot{q}) - D_0(q) \hat{f}(x | \theta) + d \] (11)

Using \( D(q) \ddot{q} + E(q, \dot{q}) \) to subtract two sides of the above formula, we can get\( \dot{\varepsilon} + K, \dot{\varepsilon} + K, \varepsilon = f(x) - \hat{f}(x | \theta) \)

In other words,

\[ \dot{x} = Ax + B \left( f(x) - \hat{f}(x | \theta) \right) \] (12)

Since, \( f(x) - \hat{f}(x | \theta) = f(x) - \hat{f}(x | \theta') + \hat{f}(x | \theta') - \hat{f}(x | \theta) = \varepsilon + \theta'^T \xi(x) - \theta'^T \hat{\xi}(x) = \varepsilon + \hat{\theta}' \hat{\xi}(x) \)

Where \( \hat{\theta} \) is the estimated value of \( \theta' \), \( \hat{f}(x | \theta) = \hat{\theta}' \hat{\xi}(x) \), \( \hat{\theta}' = \theta'^T - \hat{\theta}' \), so

\[ \dot{x} = Ax + B(\varepsilon + \hat{\theta}' \hat{\xi}(x)) \] (13)

3.4. Lyapunov stability analysis

Assuming the existence of symmetric positive definite matrices \( p \) and \( Q \), the following Lyapunov equations are satisfied.

\[ PA + A^T p = -Q \] (14)

Define Lyapunov function as
\[ V = \frac{1}{2} x^T P x + \frac{1}{2\gamma} \| \dot{\theta} \|^2 = \frac{1}{2} x^T P x + \frac{1}{2\gamma} \text{tr} \left( \dot{\theta}^T \dot{\theta} \right) \quad \gamma > 0 \] (15)

Therefore

\[ \dot{V} = \frac{1}{2} \left[ x^T P x^T x + \frac{1}{\gamma} \text{tr} \left( \dot{\theta}^T \dot{\theta} \right) \right] = \frac{1}{2} \left[ x^T P (A x + B (s + \dot{\theta} x)) + (A x + B (s + \dot{\theta} x))^T P x + \frac{1}{\gamma} \text{tr} \left( \dot{\theta}^T \dot{\theta} \right) \right] = \frac{1}{2} \left[ x^T (P A + A^T P) x + x^T P B \dot{\theta} \xi(x) + x^T P B \delta \xi(x) \right] + \frac{1}{\gamma} \text{tr} \left( \dot{\theta}^T \dot{\theta} \right) \] (16)

\[ \dot{\theta}^T = 2\gamma B^T P x^T \xi(x) \quad \dot{\theta} = 2\gamma \xi(x) x^T P B \] (17)

Substituting the above formula into formula (16), because \( \dot{\theta} = \ddot{\theta} \), then

\[ \dot{V} = -\frac{1}{2} x^T Q x + \dot{\theta}^T B^T P x \] (18)

From known \( \| \xi \| \leq \| e \| \) and \( \| B \| = 1 \), let \( \lambda_{\text{min}}(Q) \) be the minimum eigenvalue of matrix \( Q \), and \( \lambda_{\text{max}}(P) \) be the maximum eigenvalue of matrix \( P \), so,

\[ \dot{V} \leq -\frac{1}{2} \lambda_{\text{min}}(Q) \| x \|^2 + \| e \| \lambda_{\text{max}}(P) \| x \| = -\frac{1}{2} \| x \| (\lambda_{\text{min}}(Q) \| x \| - 2 \| e \| \lambda_{\text{max}}(P)) \] (19)

In order to ensure \( \dot{V} \leq 0 \), we need to satisfy \( \lambda_{\text{max}}(Q) \geq 2 \lambda_{\text{max}}(P) \| e \| \), that is,

The convergence radius of \( x \) needs to satisfy

\[ \| x \| \geq \frac{2 \lambda_{\text{max}}(P)}{\lambda_{\text{min}}(Q) \| e \|} \]

It can be seen from formula (19) that the larger the minimum value of \( Q \) eigenvalue is, the smaller the maximum value of matrix \( P \) eigenvalue is, and the smaller the error \( \| e \| \) of fuzzy compensator is, the smaller the convergence radius of \( x \) is, and the better the tracking effect of the system is.

4. SCARA robot simulation analysis

In order to compare the effects of the input, position tracking and estimation of model uncertainties of SCARA robot under RBF adaptive control and fuzzy compensation-based RBF adaptive control, it is planned to use MATLAB /SIMULINK to simulate the relevant data. It is assumed that the ideal
trajectory of each joint of the robot conforms to 
\[
\begin{align*}
q_{1\alpha} &= 1 + 0.2 \sin(0.5 \pi t) \\
q_{2\alpha} &= 1 - 0.2 \cos(0.5 \pi t) \\
q_{3\alpha} &= 1 + 0.2 \sin(0.5 \pi t)
\end{align*}
\]
and the initial value of the controlled object is 
\[
\begin{bmatrix}
q_0 \\
\dot{q}_0
\end{bmatrix}
= 
\begin{bmatrix}
1.0 & 8.1 \\
0.6 & 0.6
\end{bmatrix}^T.
\]

To ensure that the robot system is more stable, it must meet
\[
K_{\varepsilon} = 50 \text{eye(3)}
\]
overshoot. Therefore, the controller parameter is taken as 
\[
K_{\rho} = 50 \text{eye(3)}
\]
\[
Q = 100 \text{eye(6)}
\]

The values of the parameters of Gaussian basis function are \([-1 -0.5 0 0.5]\) and \(b_j = 0.3\) respectively, and the initial value of \(\hat{\theta}\) is 0.

Position tracking (Figure 4-6.), speed tracking (Figure 7-9.), tracking error (Figure 10.), control input torque (Figure 11.), model uncertainty and its estimation curve (Figure 12-14.) of SCARA robot joints 1, 2 and 3 without fuzzy compensator.

![Figure 4. Position tracking of joint 1 without blur compensation](image)

![Figure 5. Position tracking of joint 2 without blur compensation](image)
Figure 6. Position tracking of joint 3 without blur compensation

Figure 7. Speed tracking of joint 1 without blur compensation

Figure 8. Speed tracking of joint 2 without blur compensation

Figure 9. Speed tracking of joint 3 without blur compensation
**Figure 10.** Position tracking error of the joint without blur Compensation

**Figure 11.** Control input torque of the joint without blur compensation

**Figure 12.** Uncertainty and estimation of joint 1 without blur compensation

**Figure 13.** Uncertainty and estimation of joint 2 without blur compensation
Figure 14. Uncertainty and estimation of joint 3 without blur compensation

Position tracking of SCARA robot joints 1, 2, and 3 (Figure 15-17.), speed tracking (Figure 18-20.), tracking error (Figure 21.), control input torque with fuzzy compensator (Figure 22.) and the model uncertainties and their estimates (Figure 23.-25.).

Figure 15. Position tracking of joint 1 with blur compensation

Figure 16. Position tracking of joint 2 with blur compensation
Figure 17. Position tracking of joint 3 with blur compensation

Figure 18. Speed tracking of joint 1 with blur Compensation

Figure 19. Speed tracking of joint 2 with blur compensation
Figure 20. Speed tracking of joint 3 with blur compensation

Figure 21. Position tracking error of joints with blur compensation

Figure 22. Control input torque with fuzzy compensation joints
Comparing the position tracking effect of joints before and after adding blur compensation (Figure 4. and Figure 15, Figure 5. and Figure 16, Figure 6. and Figure 17.), it can be found that the position tracking effect of joints with blur compensation is significantly better than without blur compensation; The speed tracking effect of joints with blur compensation is also excellent (Figure 7. and Figure 18, Figure 8. and Figure 19, Figure 9. and Figure 20.); comparing the uncertain terms of joints before and after adding blur compensation and their estimates, it is not difficult to find blur the compensation joint curve fitting effect is better (Figure 12. and Figure 23, Figure 13. and Figure 24, Figure 14. and Figure 25.); the control input torque curve of the joint is relatively smooth (Figure 11. and Figure 22.), and the robot system control output meets the requirements.

In order to visually compare the effects of the position tracking error of the robot joint before and after blur compensation, the root mean square (RMSE) calculation is used for the position tracking error, as shown in the table. Compared with the addition of blur compensation, the position tracking
accuracy of joints has been significantly improved before and after. The performance of joint 1 is 43.42%, joint 2 is 67.47%, and joint 3 is 65.41%.

| Joint | RMSE without fuzzy compensation | RMSE with fuzzy compensation | Improvement of tracking accuracy |
|-------|---------------------------------|-----------------------------|---------------------------------|
| Joint 1 | 0.001414                        | 0.0008                      | 43.42%                          |
| Joint 2 | 0.003418                        | 0.001112                    | 67.47%                          |
| Joint 3 | 0.006527                        | 0.002258                    | 65.41%                          |

5. Conclusion

For the SCARA robot control system, an adaptive control method of RBF network based on fuzzy compensation is proposed. First, the dynamic model of SCARA robot is established based on Newton's Euler equation, and the theoretical analysis of the dynamic model is performed. An ideal nominal model; then compensate for possible external factors such as friction, disturbance, and load changes through a fuzzy compensator; finally, apply this method to a SCARA robot, and find that it has a good control effect through simulation. The research results can provide some guidance for the precise assembly and handling of SCARA robots in production.

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