Contour control of biaxial motion system based on RBF neural network and disturbance observer

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Abstract
Friction is the main factor which degrades the control precisions of the servo system. In this paper, a cross coupled control method based on RBF neural network and disturbance observer is proposed for multi-axis servo system with LuGre friction, in order to implement high precision tracking and contouring control. Firstly, a feedback linearization controller is designed to realize the position stable tracking for single-axis motion; then, the disturbance observer is used to observe and compensate the friction. However, in practical application, the observation gain is difficult to select, and it is easy to cause observation error. In order to enhance the tracking accuracy and system robustness, the RBF neural network is introduced to approximate the disturbance observation error online. Finally, the cross coupled control is used to coordinate the motion between the axes to improve the contour accuracy. The simulation results show that the proposed method can effectively compensate the influence of friction on the system, has good tracking accuracy and high contour control precision.

Keywords
Feedback linearization controller, disturbance observer, RBF neural network, cross coupled controller

Introduction
Multi-axis servo system is widely used in precision machining and other manufacturing fields because of its high speed and high precision.¹ ² The main purpose of multi-axis linkage operation is to realize continuous control of tool or workpiece movement in turn or simultaneously in their respective coordinate system according to the command issued by the control system, so as to process parts with complex contour surface. The contour control of servo system is to move along the specified track as accurately as possible. When the specified trajectory is in multi-dimensional space, each feed axis of the system must coordinate to obtain the specified trajectory. Obviously, the contour accuracy of the system depends on the comprehensive motion accuracy of each axis. Different parameters of each axis and mismatching of dynamic characteristics may cause contour error. In the actual operation, any interference of each axis, especially the influence of friction, will affect the contour control performance.

Friction plays an important role in the servo control system, which limits the positioning accuracy of the system and even makes the system unable to run smoothly.³ ⁴ With the development of industrial equipment and technology, the traditional Coulomb friction model can no longer meet the requirements of high-

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precision control. Scholars began to study and put forward many friction models to describe the internal friction effect of servo, such as, Dahl friction model, Bristle friction model. On the basis of Dahl model and Bristle model, De Wit et al. proposed LuGre friction model which can more accurately describe the internal friction behavior of servo, and has been accepted by more and more scholars. In multi-axis servo motion system, LuGre friction model is introduced to describe the friction effect of servo motor, and friction compensation is needed in control algorithm. The design of friction compensation based on friction model often needs to identify the friction parameters, but it is difficult to obtain the dynamic LuGre friction parameters because the identification of internal friction parameters of servo is very complex. Based on non-friction model, adaptive control, neural network, and sliding mode control provide effective solutions for friction compensation. In addition, the disturbance observer can equivalent the difference between the actual object and the nominal model caused by external disturbances and model parameter changes to the control input, that is to observe the equivalent disturbance, and introduce equivalent compensation into the control to achieve complete control of the disturbance. Therefore, the disturbance observer can be used to observe and compensate the friction, which can effectively solve the problem of friction compensation. In this paper, the disturbance observer is introduced to estimate the friction, which is combined with feedback linearization to ensure the single-axis stable tracking. Then RBF neural network is introduced to approximate the disturbance observation error to further improve the single-axis tracking accuracy and system robustness.

In order to improve the contour accuracy, in addition to designing an effective single-axis servo tracking control algorithm, it is also necessary to deal with the coupling between the axes. The research shows that the cross coupled controller (CCC) is an effective way to improve the contour accuracy of the system. The core concept of the cross coupled controller is to establish a real-time contour error model according to the interpolator and the position information from each axis, and to find the optimal compensation method, and then feedback the correction signal to each axis to achieve the goal of multi-axis cooperative control.

The rest of this paper is organized as follows: Section 2 defines the permanent magnet linear synchronous servo motor (PMLSM model) and contour error estimation model. Section 3 describes the design of the proposed single-axis servo tracking control algorithm, which includes feedback linearization control, disturbance observer, and RBF neural network. Section 4 describes cross coupled control between two axes. Simulation and analysis are demonstrated in Section 5. Finally, the conclusions are remarked in Section 6.

**System model description and analysis**

The permanent magnet linear synchronous serve motor (PMLSM) is widely used in CNC machine tools because of its high thrust, fast response, and high reliability. Compared with the traditional rotating motor, the linear motor can directly drive the load without the intermediate transmission link, which greatly improves the efficiency. In this paper, a two-axis motion platform driven by two PMLSM with LuGre friction is chosen as the control object.

**PMLSM model**

The mechanical motion equation of PMLSM is

\[
F_e = K_f i_q = M \dot{v} + B \dot{v} + F
\]

where, \(F_e\) is the electromagnetic thrust, \(K_f\) is the electromagnetic thrust coefficient. \(M\) is the total mass of the mover and the load, \(B\) is viscous friction coefficient, \(v\) and \(\dot{v}\) are the speed and acceleration of the motor mover respectively. \(F\) is disturbance, friction is the biggest disturbance in servo motion system. Therefore, the influence of friction is mainly considered in this paper.

Selecting motor position \(q\) and speed \(v\) as system state variables, PMLSM state equation can be written as:

\[
\begin{align*}
\dot{q} &= v \\
\dot{v} &= \frac{b}{M} \dot{q} + \frac{K_f}{M} u + F 
\end{align*}
\]

\(u = i_q\) is motor control input. PMLSM system model can be represented by second-order differential equations.

\[
\ddot{q} = -\frac{B}{M} \dot{q} + \frac{K_f}{M} u + F
\]

**LuGre friction model**

LuGre friction model can describe most of the static and dynamic characteristics observed in practice, and can accurately describe the friction phenomenon in multi-axis motion system. LuGre friction model uses the average offset of elastic bristles between two contact surfaces to characterize the dynamic behavior of friction. In practical application, the surfaces of two contact objects are uneven in micro state. LuGre friction model regards irregular surfaces as elastic bristles with random distribution. When the contact surfaces
move relative to each other under the action of tangential force, the surface bristles will deform like springs. The average deformation of the contact surface bristles is related to the relative velocity. The higher the speed is, the greater the average deformation of the bristles is, and the friction force will also increase.

LuGre model is described as:  

\[ F = \sigma_0 z + \sigma_1 \dot{z} + \alpha \dot{\theta} \]  

(4)

in which, \( \dot{\theta} \) is relative motion speed of contact surface, \( \sigma_0, \sigma_1, \) and \( \alpha \) are rigidity coefficient, damping coefficient, and viscous friction coefficient respectively. \( z \) is the average deformation of the surface bristles, and satisfies the following relationship:

\[ \dot{z} = \dot{\theta} - \frac{\sigma_0 \dot{\theta}}{g(\theta)} z \]  

(5)

\[ g(\theta) = F_c + (F_s - F_c) e^{-\left(\frac{\theta}{\theta_t}\right)^2} + \alpha \dot{\theta} \]  

(6)

in which, \( g(\theta) \) indicates different friction effects.\( F_c, F_s \) are coulomb frication coefficient and static friction coefficient, \( V_s \) is Striebeck switching speed.

**Contour error estimation**

Any disturbance or parameter mismatch of each axis may affect the contour error. Taking the two-axis linkage system as the research object, the contour error estimation model\(^{17}\) is shown in Figure 1.

![Figure 1. Contour error estimation model.](image)

where, \( R \) refers to the reference position of any working point, \( P \) refers to the actual operation point at the moment, \( e \) is the tracking error, which refers to the distance between the actual position and the reference position, and \( e_x, e_y \) is tracking error component on the \( x, y \) axis. \( e \) refers to contour error, which indicates the minimum distance between the actual position and the contour trajectory. \( \hat{e} \) is the estimated contour error, \( t \) refers to the normalized tangent vector, and \( n \) refers to the normalized normal vector.

When the value of \( ||e|| \) is small enough, \( e \) can use \( \hat{e} \) to calculate the approximate value of the contour error. Define \( t = [t_x \ t_y]^T, \ n = \alpha_1 t + \alpha_2 e = [n_x \ n_y]^T \), the relationship between \( t \) and \( n \) satisfies the following formula:

\[ t \cdot n = 0 \]  

(7)

Based on formula (7) and the definition of \( n \), it is concluded that

\[ \alpha_1 = -\alpha_2 \cdot \langle e, t \rangle \]  

(8)

From formulae (7) and (8), and according to the properties of vector and inner product, get

\[ \hat{e} = ||\hat{e}|| \cdot n = \langle n, e \rangle \cdot n \]  

(11)

According to Figure 1, \( \hat{e} \) is the inner product of \( e \) and \( n \). Thus, the estimated contour error vector is obtained as

\[ \hat{e} = \langle n, e \rangle \cdot n \]  

(13)

**Design of single-axis servo tracking control algorithm**

PMLSM can generate electromagnetic thrust in the linear direction, which saves a lot of intermediate transmission links. However, in the actual operation, due to the absence of any buffering process, the control difficulty is increased when it is affected by nonlinear uncertainties such as load disturbance and friction.

The single-axis tracking control target is to effectively suppress the uncertainty of the system through the action of the controller when it is affected by the uncertainties such as friction, so that the position of the mover can track the desired trajectory. In order to improve single-axis motion accuracy, the block
The diagram of single-axis PMLSM servo control system proposed in this paper is shown in Figure 2. The control algorithm includes feedback linearization control, disturbance observer, and RBF neural network. The feedback linearization is used to track the position to ensure the stability of the system, the disturbance observer is used to observe and compensate the influence of friction, and the RBF neural network is used to compensate the observation error of the disturbance observer.

**Feedback linearization control (FLC)**

The purpose of feedback linearization is to transform the mathematical model of the nonlinear system into a simple linear model, and compensate the nonlinear part of it, so that the linear control method can be used conveniently. Compared with the approximate linearization, the feedback linearization is not limited to the vicinity of the equilibrium point and can be effectively controlled in a wide range. For the PMLSM servo system, the feedback linearization control method is used to linearize the system, and the drive system moves toward the direction of eliminating the error, so that the position of the mover can track the desired trajectory and ensure the global stability.

Define tracking error \( e = q_d - q \), \( \dot{e} = \dot{q}_d - \dot{q} \), in which, \( e, \dot{e} \) is position error and velocity error.

It is assumed that the parameters of the servo system are known and the uncertainties such as friction can be measured, the feedback linearization control law is

\[
u_{FLC} = \frac{M}{K_f} \left( \ddot{q}_d + \frac{B}{M} \dot{q} - F + k_2 \dot{e} + k_1 e \right)
\]

in which, \( k_1, k_2 \) is the controller gain.

By introducing equation (3) into equation (14), and obtain

\[
\ddot{q} = -\frac{B}{M} \ddot{q} + \left( \ddot{q}_d + \frac{B}{M} \dot{q} - F + k_2 \dot{e} + k_1 e \right) + F
\]

The following relation is derived

\[
\ddot{e} + k_2 \dot{e} + k_1 e = 0
\]

By selecting the appropriate controller gain \( k_1, k_2 \), the error can converge to zero, that is, the state of PMLSM control system can track the desired trajectory gradually. However, friction is common in servo system, which shows strong nonlinearity at low speed, which will worsen the control of servo system and make it difficult for single axis to achieve high precision tracking. In order to ensure the stability of the system, a disturbance observer is used to estimate the friction, the feedback linearization controller can be written as

\[
u_{FLC} = \frac{M}{K_f} \left( \ddot{q}_d + \frac{B}{M} \dot{q} - \hat{F} + k_2 \dot{e} + k_1 e \right)
\]

where, \( \hat{F} \) is the estimated value of \( F \).

**Disturbance observer (DOB)**

Feedback linearization design is based on ideal model control, which requires high accuracy of the controlled plant model. When the nonlinear system model has uncertain friction phenomenon, it is difficult to ensure the robustness of the system. Therefore, the disturbance observer is introduced to observe and compensate the friction, which is combined with the feedback linearization controller to eliminate the influence of friction on the system and improve the robustness.

Rewrite formula (3) as

\[
F = \ddot{q} + \frac{B}{M} \dot{q} - \frac{K_f}{M} u
\]

Disturbance observer is design as

\[
\dot{\hat{F}} = L(F - \hat{F}) = -L\hat{F} + LF = -L\hat{F} + L \left( \ddot{q} + \frac{B}{M} \dot{q} - \frac{K_f}{M} u \right)
\]
In practical engineering, it is difficult to measure the acceleration signal \( \ddot{q} \), which makes it difficult to realize the observer. The next step is to reduce the order of acceleration signal.

Define auxiliary vector

\[
z = \ddot{F} - L\dddot{q}
\]

(20)

Substituting equation (19) into the derivative of equation (20), and get

\[
\dot{z} = \ddot{F} - L\dddot{q} = -L\dddot{F} + L\left(\dddot{q} + \frac{B}{M} \dddot{q} - \frac{K_f}{M}u\right) - L\dddot{q}
\]

\[
= -L(\dddot{F} - L\dddot{q}) - L(\dddot{q} - \frac{B}{M} \dddot{q} + \frac{K_f}{M}u)
\]

\[
= -Lz - L(\dddot{q} - \frac{B}{M} \dddot{q} + \frac{K_f}{M}u)
\]

(21)

To sum up, the nonlinear disturbance observer is designed as

\[
\begin{cases}
\dot{z} = -Lz - L(\dddot{q} - \frac{B}{M} \dddot{q} + \frac{K_f}{M}u) \\
\ddot{F} = z + L\dddot{q}
\end{cases}
\]

(22)

Define observer error as

\[
e_{DOB} = F - \ddot{F}
\]

(23)

Since the friction model is constant or step change, it can be described by differential equation as \( \dddot{F} = 0 \). The derivative of observation error is obtained as

\[
\dot{e}_{DOB} = \ddot{F} - \dddot{F} = -\dddot{z} - L\dddot{q}
\]

(24)

Substituting equation (21) into the above formula, and get

\[
\dot{e}_{DOB} = Lz + L(\dddot{q} - \frac{B}{M} \dddot{q} + \frac{K_f}{M}u) - L\dddot{q} = L(z + \dddot{q}) - L\dddot{q}
\]

\[
= -Lz - L(\dddot{q} - \frac{B}{M} \dddot{q} + \frac{K_f}{M}u)
\]

(25)

Substituting equations (18) and (22) into equation (25), then

\[
\dot{e}_{DOB} = L\dddot{F} - LF = -L(F - \ddot{F}) = -Le_{DOB}
\]

(26)

Get

\[
\dot{e}_{DOB} + Le_{DOB} = 0
\]

(27)

So, the observer is globally asymptotically stable.

\[\ldots\]

\textbf{RBF neural network}

In the above control methods, the selection of \( L \) value is very important. If \( L \) value is not selected properly, it is easy to cause large observation error. In order to improve the control performance and enhance the robustness of the system, the RBF neural network is combined with disturbance observer, in which, \( \text{RBF} \) neural network is used to approximate the observation error \( e_{DOB} \) with its arbitrary approximation function.

\[
u_{RBF} = e_{DOB} = F - \ddot{F}
\]

(28)

Get

\[F = \dddot{F} + u_{RBF}
\]

(29)

Substituting the above equation into equation (17), the new control law is obtained as follows

\[
u_{FLC} = M \frac{K_f}{K_f} \left( \dddot{q}_d - \frac{B}{M} \dddot{q} - \dddot{F} - u_{RBF} + k_2 \dddot{e} + k_1 e \right)
\]

(30)

RBF network has attracted much attention because of its good generalization ability, simple network structure, and avoiding unnecessary and lengthy computation. RBF neural network can approach any nonlinear function with a compact set and arbitrary precision. It has three layers: input layer, hidden layer, and output layer. The structure of RBF network is shown in Figure 3 in which, \( x \in [x_i] \) represents input of RBF neural network, \( \phi \in [\phi_j]^T \) represents the hidden layer output, \( \phi_j \) represents the output of the \( j \)th neuron.

\[
\phi_j = \exp \left( -\frac{||x-c||^2}{2\sigma^2} \right)
\]

(31)

in which, \( c = [c_i] = \begin{bmatrix} c_{i1} & \cdots & c_{im} \\ \vdots & \cdots & \vdots \\ c_{nj} & \cdots & c_{nm} \end{bmatrix} \) is the coordinate vector of the central point of the Gaussian basis function of the \( j \)th neuron in the hidden layer.,
The weight of RBF network is
\[
\omega = [\omega_1, \ldots, \omega_m]^T
\]  
(32)

Then the output of RBF neural network is
\[
u_{RBF} = \omega^T \phi = \omega_1 \phi_1 + \omega_2 \phi_2 + \cdots + \omega_m \phi_m
\]  
(33)

### Two-axis cross coupled control

For the multi-axis motion control system, in addition to ensuring the tracking accuracy of the single-axis, the contour accuracy of the coupling of the two axes should be considered. Next, we use the cross coupled controller proposed by Koren and Lo\(^\text{18}\) for contour control, so as to improve the contour accuracy. The structure of the cross-coupled control is shown in Figure 4.

in which, \(e\) is contour error, \(c_x\) and \(c_y\) are the contour error distribution gain of the cross coupled controller. After being processed by cross coupled controller, the contour error compensation value is distributed to each servo axis. \(P_x\) and \(P_y\) are two axis PMLSM servo system.

In this section, PID controller is used as cross coupled controller. PID control has the advantages of small amount of calculation and good real-time performance. Through the action of PID cross coupled controller, the control precision of two axis contour is effectively improved.

The PID cross-coupled controller output is:
\[
u_{CCC} = K_p e + K_i \sum e + K_d \dot{e}
\]  
(34)

### Simulation and analysis

The two-axis motion platform driven by PMLSM with friction is used as the control object to verify the effectiveness of the proposed control method. Motor simulation parameters are shown in Table 1.

Feedback linearization control, disturbance observer, and RBF neural network is used for single-axis trajectory tracking control, and PID cross coupled controller is used to coordinate motion control between the axes. In which, position error \(e\) and its derivative \(\dot{e}\) are used as the input of RBF neural network. Define \(s = e + \Lambda e\), and choose the weight adjustment rate of neural network is \(\dot{\omega} = -\gamma \omega \|s\|\), \(\gamma\) is an adaptive parameter.

Controller simulation parameters are shown in Table 2.

A Heart-shape curve is selected as reference contour for simulation, which expressed as follows:
\[
\begin{align*}
x_d &= 2 \sin(t) - \sin(2t)(\text{mm}) \\
y_d &= 2 \cos(t) - \cos(2t)(\text{mm})
\end{align*}
\]

The effect of single-axis trajectory tracking and friction compensation are shown in Figure 5.

Figure 5(a) to (d) show the position tracking and tracking error of the two axes respectively. Figure 5(e) and (f) show the LuGre friction and its observation of two axis. The simulation results show that the \(x, y\) two axes have good trajectory tracking performance, the actual output can accurately track the reference trajectory, and the tracking error is basically zero. By using the observer, the LuGre friction can be observed and

### Table 1. PMLSM model parameters.

| Parameters | Unit | \(x\) axis | \(y\) axis |
|-----------|------|------------|------------|
| \(M\)    | kg   | 5.8        | 5.8        |
| \(B\)    | s/m  | 244        | 244        |
| \(K_f\)  | N/A  | 10.9       | 10.9       |
| \(s_0\)  | N/m/rad | 260 | 200 |
| \(s_1\)  | N/m/rad | 2.5 | 2.8 |
| \(\alpha\) | N m/s/rad | 0.02 | 0.05 |
| \(F_c\)  | N    | 0.28        | 0.3        |
| \(f_c\)  | N    | 0.34        | 0.5        |
| \(V_s\)  | rad/s | 0.01        | 0.02       |

### Table 2. Controller parameters.

| Parameters | Value |
|-----------|-------|
| \(k_1\)  | 5     | 15    |
| \(k_2\)  | 20    | 50    |
| \(L\)    | 15    | 20    |
| \(c\)    | 0.6   | 0.6   |
| \(b\)    | 3     | 3     |
| \(\Lambda\) | 5    | 8     |
| \(\gamma\) | 100  | 60    |

\[ x \]

\[ y \]
compensated well, and the influence of friction on the system is effectively eliminated.

For disturbance observer, it is difficult to select the observation gain. Usually a larger observation gain is selected to improve the observation accuracy, but it is easy to cause system instability. Taking x axis friction observation as an example, the influence of observer gain variation on friction compensation effect is shown in Figure 6.

Figure 5. Simulation effect of single-axis trajectory tracking and friction compensation: (a) x axis trajectory tracking, (b) x axis tracking error, (c) y axis trajectory tracking, (d) y axis tracking error, (e) x axis LuGre friction and its observation, and (f) y axis LuGre friction and its observation.
Beside, RBF neural network is introduced to approximate the disturbance observation error, which can further improve control performance. The approximation effect of RBF neural network is shown in Figure 7.

On the basis of ensuring the single-axis tracking performance, PID cross coupled control ($K_p = 0.1$, $K_i = 2$, $K_d = 0.2$) is adopted to improve the contour tracking accuracy. The contour tracking simulation results are shown in Figure 8.

Figure 8(a) and (b) are heart-shaped input and output, Figure 8(c) is the contour error. Figure 8(d) shows the real-time change of cross coupled gain. The simulation results of contour tracking show that the output can track the reference input contour very well, the contour error is close to zero, and the system has very high contour tracking accuracy.

In order to better verify the effectiveness of the proposed control algorithm, the proposed control algorithm (FLC + RBFDOB) is compared with the feedback linearization (FLC), feedback linearization, and disturbance observer (FLC + DOB) respectively. The comparison results are shown in Figure 9.

Among them, Figure 9(a) and (b) respectively show the $x$, $y$ axis tracking error under the action of three control algorithms. It can be seen that the tracking error is most obvious under the action of simple feedback linearization controller, especially the tracking error of the $x$ axis is divergent. After the action of disturbance observer, the tracking error decreases
obviously and the control performance is improved. Simulation comparison results show that the system has the best tracking performance and minimum error under the action of the proposed FLC + RBFDOB. Figure 9(c) shows the contour error under the action of three control algorithms. It can also be seen that the contour error performance under the combined action of FLC, DOB, and RBFNN adopted in this paper is the optimal, and the contour error is almost zero, which realizes high-precision control.

The maximum value, average value of tracking error, and contour error under the action of the three control methods are shown in Table 3.

### Conclusions

For two axis permanent magnet linear servo motor contour motion control system, it is easy to be affected by friction disturbance, which reduces the single-axis tracking accuracy, a friction compensation control algorithm is proposed. The control algorithm consists of feedback linearization controller, disturbance observer, and RBF neural network. The feedback linearization is used for position tracking control, the disturbance observer is used to observe and compensate the friction, and the RBF neural network is used to approximate the disturbance observation error to further improve the tracking accuracy and robustness of the system. Then, in order to solve the problem of contour error caused by different parameters and dynamic mismatching between two axes, PID cross coupled control is used to coordinate control between axes, so as to improve the contour control accuracy.

Comparing the proposed control algorithm FLC + RBFDDB with the single FLC and FLC + DOB, it is found that the tracking error and contour error are very obvious under the action of FLC alone. After adding disturbance observer, the tracking error and contour error performance are significantly improved. It can be seen from error
comparison Table 3 that the average tracking error of the $x$ axis is reduced from 24.5 to 1.1, and the accuracy is improved by about 22 times; after adaptive approximation of disturbance observation error by RBF neural network, the performance is further improved. The average tracking error of $x$ axis is reduced from 1.1 to 0.0763, the accuracy is improved by about 14 times. Similarly, the $y$ axis tracking control and contour control have higher control performance under the proposed control algorithm.
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Data availability
The data used to support the findings of this study are included within the article.

References
1. Song DN, Ma JW, Zhong YG, et al. Definition and estimation of joint-space contour error based on generalized curve for five-axis contour following control. Precis Eng 2020; 65: 32–43.
2. Hendrawan YM, Simba KR and Uchiyama N. Iterative learning based trajectory generation for machine tool feed drive systems. Robot Comput Integr Manuf 2018; 51: 230–237.
3. Mashimo T, Ohishi K and Dohmeki H. High-speed positioning method for servomotor considering friction load torque. Electr Eng Jpn 2010; 157: 666–673.
4. Wang J, Ge SS and Lee TH. Adaptive friction compensation for servo mechanisms. Int J Syst Sci 2001; 32(4): 523–532.
5. De Wit CC, Olsson H, Aström KJ, et al. A new model for control of systems with friction. IEEE Trans Automat Contr 1995; 40(3): 419–425.
6. Chen Q, Shi HH and Sun MX. Echo state network based backstepping adaptive iterative learning control for strict-feedback systems: an error-tracking approach. IEEE Trans Cybern 2020; 50: 3009–3022.
7. Wang SB and Na J. Parameter estimation and adaptive control for servo mechanisms with friction compensation. IEEE Trans Industr Inform 2020; 16: 6816–6825.
8. Sun T, Pei H, Pan Y, et al. Neural network-based sliding mode adaptive control for robot manipulators. Neurocomputing 2011; 74: 2377–2384.
9. Xie WF. Sliding-mode-observer-based adaptive control for servo actuator with friction. IEEE Trans Ind Electron 2007; 54: 1517–1527.
10. Kang S, Yan H, Dong L, et al. Finite-time adaptive sliding mode force control for electro-hydraulic load simulator based on improved GMS friction model. Mech Syst Signal Process 2018; 102: 117–138.
11. Kim E. A fuzzy disturbance observer and its application to control. IEEE Trans Fuzzy Syst 2002; 10: 77–84.
12. Chen M and Ge SS. Direct adaptive neural control for a class of uncertain nonaffine nonlinear systems based on disturbance observer. IEEE Trans Cybern 2013; 43: 1213–1225.
13. Shih YT, Chen CS and Lee AC. A novel cross-coupling control design for Bi-axis motion. Int J Mach Tools Manuf 2002; 42: 1539–1548.
14. Wang W and Su LY. Application of CMAC-PID compound control in PMLSM servo system. Adv Mater Res 2012; 341–342: 780–784.
15. Song FZ, Liu Y, Xu JX, et al. Iterative learning identification and compensation of space-periodic disturbance in PMLSM systems with time delay. IEEE Trans Ind Electron 2018; 65: 7579–7589.
16. Yao J, Deng W and Jiao Z. Adaptive control of hydraulic actuators with LuGre model-based friction compensation. IEEE Trans Ind Electron 2015; 62: 6469–6477.
17. Yeh SS and Hsu PL. Estimation of the contour error vector for the cross-coupled control design. IEEE/ASME Trans Mechatron 2002; 7: 44–51.
18. Koren Y and Lo CC. Variable-gain cross-coupling controller for contouring. CIRP Ann Manuf Technol 1991; 40: 371–374.