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Research Article

Parameter Identification and Control Algorithm of Electrohydraulic Servo System for Robotic Excavator Based on Improved Hammerstein Model

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In view of the nonlinearity and time-varying characteristics of the electrohydraulic servo system of the robotic excavator, a nonlinear adaptive identification and control algorithm based on improved Hammerstein model is proposed. The Hammerstein algorithm model can approximate the nonlinear system with enough precision, but for the time-varying systems is not satisfactory. In order to compensate for the influence of time-varying factors, the fuzzy control module is designed to adaptively update the forgetting factor. The experimental results show that the improved Hammerstein model error is about 40.11% less than the classical Hammerstein model error. This proves that the improved Hammerstein model is feasible and effective to describe the electrohydraulic servo system of the robotic excavator.

1. Introduction

In order to continuously improve the operation efficiency and operation quality of excavator, and to expand the application areas of the excavator, autonomous operation has become an important research direction [1, 2]. A key problem of the excavator's autonomous operation is how to establish the scientific effective model of the electrohydraulic servo system and improve the trajectory tracking accuracy of the robotic excavator [3, 4]. Due to the existence of dead zone, saturation, nonlinear friction, and the nonsymmetry of hydraulic cylinder, the electrohydraulic servo system has strong nonlinear and time-varying characteristics [5–8]. Traditionally, the mechanism modeling method [9] and the linear identification algorithm [10] are used to establish the mathematical model of the nonlinear system. In the modeling process, the mechanism modeling method makes some assumptions and simplifies the system, resulting in a certain error between the established model and the actual system. The linear model identification algorithm establishes the model of the approximation system according to the input and output data, but the model cannot describe the nonlinear characteristics such as friction and dead zone.

Many researchers have done a lot of works in this field. Tri et al. [11] proposed and designed an adaptive control algorithm based on a modified backstepping algorithm with the iterative learning scheme for the trajectory control of an electrohydraulic actuator; experimental results showed that the proposed controller can provide excellent tracking response. Yung et al. [12] designed a controller based on a proportional feedback, a disturbance compensator, and a relay controller for a hydraulic cylinder in mobile hydraulics applications; the controller shows its robustness to different lowering velocities by comparing with a PI controller. Guo et al. [13] carried out a study on the nonlinear cascade trajectory tracking control for an electrohydraulic system using the sliding mode control and the backstepping technique, and the stability of the controller was proved based on Lyapunov theory. Both the simulation and experimental results proved the excellent tracking performance of proposed approaches. Boaventura et al. [14] conducted an investigation on impedance control for a hydraulic robot actuator, many relevant aspects regarding the control algorithm were presented, and the experiment showed that tracking capabilities of the system were improved. Yao et al. [15] carried out a study on high-accuracy tracking control for hydraulic actuators, an improved LuGre friction model was derived, and then, an adaptive backstepping controller was proposed. Experimental results showed the controller can not only achieve the excellent asymptotic tracking performance but also ensure the robustness. Besides, the hybrid synchronization problem of chaotic systems was also investigated [16–19]. From all the research studies above, we can find that many valuable results have been obtained in the research field of hydraulic servo system. However, existing studies focused on the nonlinear characteristics, and little research on the time-varying characteristics has been done.

According to the strong nonlinear and time-varying characteristics of the electrohydraulic servo system, an adaptive identification algorithm based on the Hammerstein model is proposed. Hammerstein model [20, 21] consists of static nonlinear module and dynamic linear module. Its linear module is described by discrete autoregressive model, and nonlinear module is described by piecewise polynomial basis function. The Hammerstein model can effectively describe the nonlinear system, and the output error is significantly smaller than the linear identification algorithm. However, when the algorithm is used for nonlinear systems with time-varying parameters, the identification results are not satisfactory. Therefore, on the basis of the Hammerstein nonlinear identification algorithm, the limited memory method is introduced, fuzzy control module is designed, and the forgetting factor is adaptively adjusted by the fuzzy algorithm. The identified model can be updated in real time to better approximate the actual system.

The rest of the paper is organized as follows. In Section 2, the mathematical model of the electrohydraulic servo system is established by using the mechanism modeling method, and the nonlinearity and time-varying characteristics of the system are analyzed. In Section 3, the Hammerstein model structure is presented, and the identification algorithm of the electrohydraulic servo system based on the Hammerstein algorithm is developed. In Section 4, the forgetting factor is introduced, and the fuzzy control model is established to tune the forgetting factor in real time. In Section 5, the experimental setup and experimental procedure are explained, and the experimental results are discussed. In Section 6, conclusions are presented in the final section.

2. Model Analysis of Electrohydraulic Servo System

The electrohydraulic servo system of the robotic excavator is mainly composed of pilot electrohydraulic proportional valve, valve-controlled asymmetric hydraulic cylinder, sensor, and control system, etc. The system model can be represented by the dynamic equation of electrohydraulic proportional valve, flow equation of spool valve, the flow continuity equation of hydraulic cylinder, the hydraulic cylinder, and the load force balance equation.

The electrohydraulic proportional valve is a conversion unit between the electric signal and the hydraulic output, and the corresponding pressure output is related to the input signal, which is used to move the spool of the multiway directional valve. This can be expressed by the first-order linear differential equations:

$$\tau_v \dot{x}_v + x_v = K_1 u, \tag{1}$$

where x_v is the main spool displacement, τ_v is the time constant, K_1 is the gain of the electrohydraulic proportional valve, and u is the system input.

The movement of the robotic excavator's working device can be simplified as the valve control asymmetric hydraulic cylinder system. The pressure fluid and load can be seen as a mass-spring-damped oscillation system. The system schematic diagram is shown in Figure 1. A_1 and A_2 are the effective areas of the cylinder chambers; p_1 and p_2 are the pressures in cylinder chambers; q_1 and q_2 are inlet flow and return flow; p_s and p_0 are system pressure and return pressure; y is the cylinder piston displacement; m is the equivalent mass of the piston and workload; B_p is the viscous damping coefficient; K is the load elasticity coefficient; F_L is the disturbance force.

Take the forward movement of the hydraulic cylinder as an example to establish the mathematic model of the valve-controlled cylinder system. The load pressure equation of the hydraulic cylinder in steady state is as follows:

$$p_L = \frac{F}{A_1} = p_1 - np_2, \tag{2}$$

where p_L is the load pressure; $n = A_2/A_1$ is the effective area ratio.

The flow of the directional valve is related to the pressure of inlet and outlet and the speed of the piston. The flow calculation formula of the directional valve is as follows:

$$\begin{cases} q_1 = C_d \omega x_v \sqrt{\dfrac{2}{\rho}\left(P_S - P_1\right)} = A_1 \dfrac{\mathrm{d}y}{\mathrm{d}t}, \\ q_2 = C_d \omega x_v \sqrt{\dfrac{2}{\rho} P_2} = A_2 \dfrac{\mathrm{d}y}{\mathrm{d}t}, \end{cases} \tag{3}$$

where C_d is the flow coefficient, ω is the area gradient of the valve, and ρ is the liquid density.

According to equations (2) and (3), the load flow equation of the spool valve can be obtained:

$$q_L = q_1 = C_d \omega x_v \sqrt{\frac{2\left(P_S - P_L\right)}{\rho\left(1 + n^3\right)}}. \tag{4}$$

Its linearized expression is as follows:

$$q_L = K_q x_v - K_c p_L, \tag{5}$$

where K_q is the flow gain and K_c is the pressure-flow gain.

Ignoring the influence of the pipeline on the hydraulic system, and assuming that the pressure in the working

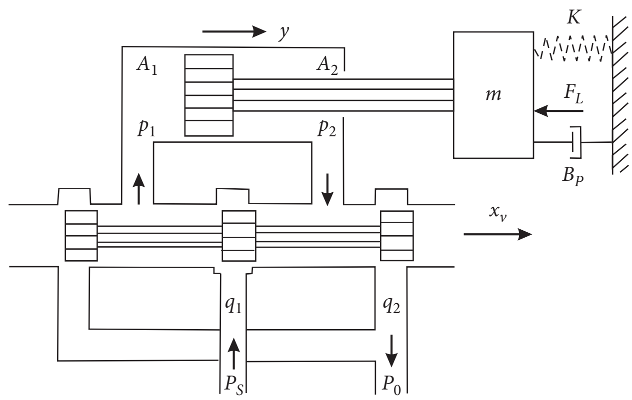

Figure 1: Schematic diagram of servo hydraulic cylinder system.

chamber of the hydraulic cylinder is equal everywhere, the flow continuity equation of the hydraulic cylinder is as follows [22]:

$$\begin{cases} q_1 = C_{ip}(p_1 - p_2) + C_{ep}p_1 + \dfrac{V_1}{\beta_e}\dfrac{\mathrm{d}p_1}{\mathrm{d}t} + \dfrac{\mathrm{d}V_1}{\mathrm{d}t}, \\ \\ q_2 = C_{ip}(p_1 - p_2) - C_{ep}p_2 - \dfrac{V_2}{\beta_e}\dfrac{\mathrm{d}p_2}{\mathrm{d}t} - \dfrac{\mathrm{d}V_2}{\mathrm{d}t}, \end{cases} \tag{6}$$

where $V_1 = V_{01} + A_1 y$ and $V_2 = V_{02} - A_2 y$; V_{01} and V_{02} are the initial volumes of the hydraulic cylinder; C_{ip} and C_{ep} are internal leakage and external leakage coefficients; β_e is liquid bulk elastic modulus.

At this point, the calculation formula of load pressure is as follows:

$$q_L = q_1 = A_1\frac{\mathrm{d}y}{\mathrm{d}t} + C_{ip}(P_1 - P_2) + C_{ep}P_1\frac{V_1}{\beta_e}\frac{\mathrm{d}p_1}{\mathrm{d}t}. \tag{7}$$

From equation (3) and equation (6), the load pressure equation can be obtained:

$$q_L = C_{iL}P_L + C_{es}P_s + \frac{V_t}{4\beta_e}\frac{\mathrm{d}p_L}{\mathrm{d}t} + A_1\frac{\mathrm{d}y}{\mathrm{d}t}, \tag{8}$$

where V_t is the equivalent volume, $V_t = 4V_1/1 + n^3$, and $V_1 = LA_1/2$, L is the total stroke of the hydraulic cylinder piston; $C_{iL} = ((n^2 + 1)C_{ip} + C_{ep})/1 + n^3$ is equivalent leakage coefficient; $C_{es} = (n^3(C_{ep} + C_{ip}) - n^2C_{ip})/1 + n^3$ is additional leakage coefficient.

The load force of the hydraulic cylinder includes inertial force, viscous damping force, elastic force, and random load force. According to Newton's second law, the force equilibrium equation can be obtained:

$$A_1P_1 - A_2P_2 = A_1P_L = m\frac{\mathrm{d}^2y}{\mathrm{d}t} + B_p\frac{\mathrm{d}y}{\mathrm{d}t} + Ky + F_L. \tag{9}$$

The piston displacement of the hydraulic cylinder under the action of the system input u and the external load force F_L can be obtained based on the above equations:

$$Y = \frac{\left(K_1K_q/\tau_v s + 1\right)U - C_{es}P_sA_1 - \left(K_C + C_{iL} + \left(V_t/4\beta_e\right)s\right)F_L}{\left(K_C + C_{iL} + \left(V_t/4\beta_e\right)s\right)\left(ms^2 + B_ps + K\right) + A_1^2 s}. \tag{10}$$

It can be seen from the transfer function of the electrohydraulic servo system that some parameters are difficult to be calculated. Due to the nonlinear factors such as dead zone, saturation, and friction, the system has strong nonlinear and time-varying characteristics; at the same time, the linear terms are cross-coupled with the nonlinear terms. If the parameters of the electrohydraulic servo system are identified directly, several state variables need to be measured, in addition to increasing the test cost; the measurement noise is also introduced to produce larger identification error. Therefore, it is necessary to design an identification algorithm which can accurately describe the nonlinear and time-varying characteristics of the system.

3. Nonlinear Identification Algorithm Based on Hammerstein

The Hammerstein algorithm model describes the nonlinear system by the combination of static nonlinear module and dynamic linear module, and its system structure diagram is shown in Figure 2, where $u(k)$, $x(k)$, $v(k)$, and $y(k)$ are identification input, intermediate state, noise sequence, and system output, respectively. $N(\cdot)$ and $L(z)$ are nonlinear module and linear module. The linear and nonlinear characteristics are distinguished by the intermediate state $x(k)$, which can be used to decouple the linear and nonlinear models. The Hammerstein algorithm only requires the input and output data, which can effectively reduce the measurement noise and improve the identification precision [23].

Due to the asymmetric characteristics of friction in the electrohydraulic servo system, the nonlinear part of the Hammerstein algorithm is represented by piecewise polynomial function [24], and the input and output relationship of the nonlinear part is as follows:

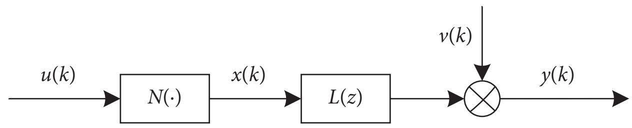

Figure 2: Hammerstein system identification structure.

$$x(k)=\begin{cases} f(u(k))=\sum_{k=1}^{r} f_k u^k(k), & u(k)\geq 0,\\ g(u(k))=\sum_{k=1}^{r} g_k u^k(k), & u(k)<0, \end{cases} \tag{11}$$

where f_k and g_k are nonlinear coefficients and r is the order of the polynomial.

The linear part of the Hammerstein model is represented by a discrete autoregressive model, namely:

$$A\left(z^{-1}\right)y(k)=z^{-n_k}B\left(z^{-1}\right)x(k)+v(k), \tag{12}$$

where $A(z^{-1})=1+a_1z^{-1}+a_2z^{-2}+\cdots+a_{n_a}z^{-n_a}$; $B(z^{-1})=b_0+b_1z^{-1}+b_2z^{-2}+\cdots+b_{n_b}z^{-n_b}$; n_k is system delay; $a_i\,(i=1,2,\cdots,n_a)$ and $b_j\,(j=0,1,\cdots,n_b)$ are linear coefficients.

Take the case of $u(k)>0$. Substituting equation (11) into equation (12), the least square format based on the Hammerstein model can be simplified as follows:

$$y(k)=\phi^T(k)\theta+v(k). \tag{13}$$

The autoregressive variable $\phi(k)$ and the estimated parameter vector θ are as follows:

$$\begin{aligned}\phi(k)&=(-y(k-1),\ldots,-y(k-n_a),u(k-n_k),\\&\quad\ldots,u(k-n_k-n_b),\ldots,u^r(k-n_k),\ldots,u^r(k-n_k-n_b));\\ \theta&=\left(a_1,\ldots,a_{n_a},C_{10},\ldots,C_{1n_b},C_{20},\ldots,C_{(r-1)n_b},C_{r0},\ldots,C_{rn_b}\right)^T;\end{aligned} \tag{14}$$

where $C_{ij}=f_ib_j$.

The estimated value of θ can be obtained by the least square method:

$$\widehat{\theta}=\left(\Phi^T\Phi\right)^{-1}\Phi^TY, \tag{15}$$

where $Y=[y(1),y(2),\ldots,y(N)]^T$ and $\Phi=[\phi^T(1),\phi^T(2),\ldots,\phi^T(N)]$.

Using the normalization method, and let $f_1=1$. The following equation can be obtained:

$$\begin{bmatrix} C_{10} & C_{11} & \cdots & C_{1n_b}\\ C_{20} & C_{21} & \cdots & C_{2n_b}\\ \vdots & \vdots & & \vdots\\ C_{r0} & C_{r1} & \cdots & C_{rn_b}\end{bmatrix}=\begin{bmatrix} b_0 & b_1 & \cdots & b_{n_b}\\ f_2b_0 & f_2b_1 & \cdots & f_2b_{n_b}\\ \vdots & \vdots & & \vdots\\ f_rb_0 & f_rb_1 & \cdots & f_rb_{n_b}\end{bmatrix}. \tag{16}$$

After matrix transformation, the expression of f_k is as follows:

$$f_k=\frac{\sum_{j=0}^{n_b}C_{1j}C_{kj}}{\sum_{j=0}^{n_b}C_{1j}^2},\quad (j=0,1,\ldots,n_b;k=0,1,\ldots,r). \tag{17}$$

According to equation (16), the intermediate variable $x(k)$ can be calculated in the iterative process.

4. Adaptive Dynamic Identification Based on Fuzzy Algorithm

Due to the time-varying characteristics of the electrohydraulic servo system, the problem of model mismatch may occur over the long run, which requires the system model has to be frequently updated. At the same time, it is necessary to consider the phenomenon of "data saturation" in the update process, that is, the impact of new data on parameter estimation becomes weaker and weaker over time. When the system is highly variable, the Hammerstein model will not be able to quickly track the changes in the system, causing the identification to fail. Therefore, the "forgetting factor" is introduced to solve the problem of data saturation.

According to the limited memory recursive least square algorithm [25], the following equation can be obtained:

$$\widehat{\theta}(k)=\widehat{\theta}(k-1)+K(k)\left[y(k)-\phi^T(k)\widehat{\theta}(k-1)\right], \tag{18}$$

$$P(k)=\frac{1}{\lambda}\left[1-K(k)\phi^T(k)\right]P(k-1), \tag{19}$$

$$K(k)=\frac{P(k-1)\phi(k)}{\lambda+\phi^T(k)P(k-1)\phi(k)}, \tag{20}$$

where $P(k)=(\Phi^T\Phi)^{-1}$.

The forgetting factor λ is the weight of the old data in the identification process. The bigger the forgetting factor λ, the smaller the influence of the new data on the identification results. The smaller the forgetting factor λ, the greater the impact of the new data on the identification results. Therefore, in order to solve the problem of model mismatch, when the system changes slowly, it can adopt the larger forgetting factor λ to reduce the influence of the sensor's interference error on the model; when the system changes rapidly, it should adopt the smaller forgetting factor λ to make the model match the system more quickly.

In order to adapt to this change and obtain the optimal forgetting factor in real time, a fuzzy controller [26, 27] is designed to update the forgetting factor. The input of the controller is the displacement error e and the error variation Δe. Let the fuzzy universes of the error e and error variation Δe be $[-3,+3]$, and their lingual variables are {NB, NM, NS, ZO, PS, PM, PB} = $\{-3,-2,-1,0,1,2,3\}$. The output of the controller is forgetting factor and its lingual variables are {VS, MS, S, B, MB, VB} =$\{0.75, 0.80, 0.85, 0.90, 0.95, 1.0\}$.

The linear function can adjust the factors to reduce the error rapidly. The curve function is relatively smooth and is conducive to the stability of control. The membership function of fuzzy controller is designed based on the advantages of above two functions. When the error is large, the speed of adjustment is mainly considered and the trigonometric membership function is adopted; when the error is small, the stationarity is considered mainly and the curve membership function is adopted. The curve membership function is shown in Figure 3, and the corresponding fuzzy control rules are shown in Table 1.

The methods of defuzzification include weighted average method, maximum membership function method, and gravity method. According to the advantages and disadvantages of these methods, the gravity method is chosen for defuzzification, its calculation formula is as follows:

$$\lambda^* = \frac{\sum(\mu(x)^* p)}{\sum \mu(x)}, \tag{21}$$

where λ^* is the updated value of forgetting factor λ.

The overall control structure and data flow of the electrohydraulic servo system of the robotic excavator are shown in Figure 4. In the figure, y_r is the desired displacement and y is the actual displacement.

In summary, the steps of adaptive identification and control for robotic excavator based on Hammerstein are as follows:

Step 1: according to the mechanism characteristics of the electrohydraulic servo system of the robotic excavator, set the values of n_a, n_b, and n_k

Step 2: set the values of $\hat{\theta}(0)$, $P(0)$, and forgetting factor λ

Step 3: offline identification; calculate the nonlinear module coefficients of the Hammerstein model

Step 4: collect the experimental data of the electrohydraulic servo system of the robotic excavator

Step 5: update the forgetting factor by fuzzy control algorithm

Step 6: update the linear module coefficients of the Hammerstein model

Step 7: calculate the next output $u(k+1)$ of the controller

Step 8: return to Step 4 and continue the loop

5. Experimental Analysis

The experimental prototype of the robotic excavator is developed from the existing backhoe mountain excavator, which is composed of backhoe mountain excavator, sensor control system, and the 3D laser radar. The working device of the robotic excavator is composed of boom, arm, telescopic arm, and bucket in series, as shown in Figure 5. Each joint is driven by servo hydraulic cylinder, and the displacement of the piston rod is measured by using the cable type of absolute encoder, as shown in Figure 6.

The structure of electrohydraulic proportional position control system of the robotic excavator's working device is the same, which is mainly composed of the electrohydraulic pilot proportional pressure reducing valve, LUDV multiway valve, hydraulic cylinder, and the cable type absolute encoder used to measure the displacement of the hydraulic cylinder piston rod, as shown in Figure 6.

The DSP controller is connected with main control computer and encoder through CAN bus. The main control computer gives the target position of the piston rod of the hydraulic cylinder, and the controller collects the displacement of the piston rod as the feedback, takes the difference between the target position and the feedback as the input of the controller, and then sends the control amount to the driver. The driver generates the PWM signal PWM and changes the voltage of the electrohydraulic pilot proportional reducing valve by adjusting the duty ratio of the PWM signal value. Therefore, the input pressure of LUDV multiway valve can be controlled to control the flow of the hydraulic cylinder, and then the movement of the working device can be driven by the piston rod of the hydraulic cylinder.

In order to study the nonlinear dynamic characteristics of the electrohydraulic servo system of the robotic excavator, take the boom control system for example, and the combination of low amplitude sinusoidal signal is used as excitation signal (as shown in Figure 7(a)). The stable low-speed output signal of the boom is shown in Figure 7(b).

It can be seen from Figure 7(b) that when the excitation signal is near 0, the output remains almost constant due to dead zone characteristics; when the input is sinusoidal symmetric signal, the output shows a downward trend, which is that the response characteristic of the positive and negative direction is asymmetrical.

In order to verify the effectiveness of the adaptive Hammerstein nonlinear identification algorithm, the system model of the electrohydraulic servo system of the robotic excavator is identified by the classical Hammerstein nonlinear identification algorithm (CHNLIA) and adaptive Hammerstein nonlinear identification algorithm (AHNLIA), respectively, which is combined with the control algorithm to form the controller, and the control performance of two algorithms is compared by experiments.

Based on the hydraulic control theory, the linear module orders of the Hammerstein model structure are set to $n_a = 3$, $n_b = 1$, and $n_k = 1$; the polynomial order of the nonlinear module is set to $r = 3$. The basic universe of error e is $[-4, 4]$, and the basic universe of error variation Δe is $[-2, 2]$. Let $f_1 = 1.0$, based on the adaptive Hammerstein nonlinear identification algorithm, and the model parameters of the boom control system of the robotic excavator are obtained, as shown in Table 2.

For the same test data, the model parameters of the boom control system of the robotic excavator are identified by the classical Hammerstein nonlinear identification algorithm again. The identified system model is compared with the actual system, and servo tracking experiment is carried out. The experimental results of the two algorithms are shown in Figure 8.

It can be seen from Figure 8 that the adaptive Hammerstein nonlinear identification algorithm (AHNLIA) has

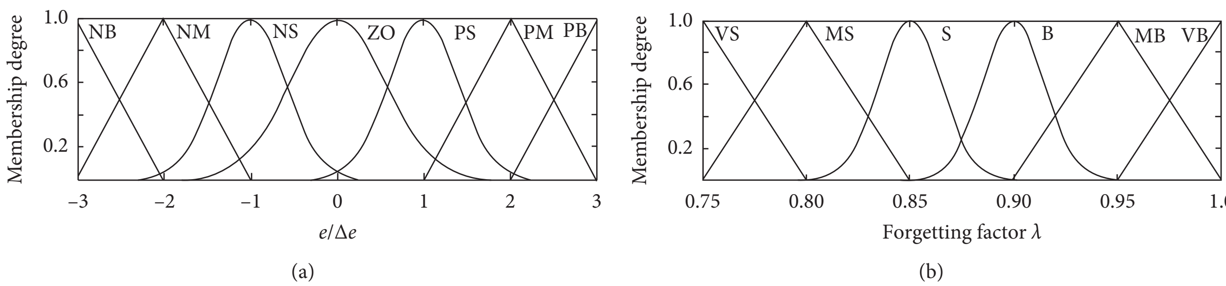

Figure 3: Input and output curves of the membership function.

Table 1: Fuzzy control rules.

$\Delta e/e$	NB	NM	NS	ZO	PS	PM	PB
NB	VS	VS	MS	S	B	MB	MB
NM	VS	MS	S	B	MB	VB	B
NS	MS	S	B	MB	MB	VB	S
ZO	S	S	VB	VB	VB	S	MS
PS	S	B	MB	VB	B	S	MS
PM	S	MB	MB	MB	S	MS	VS
PB	MB	MB	VB	S	S	VS	VS

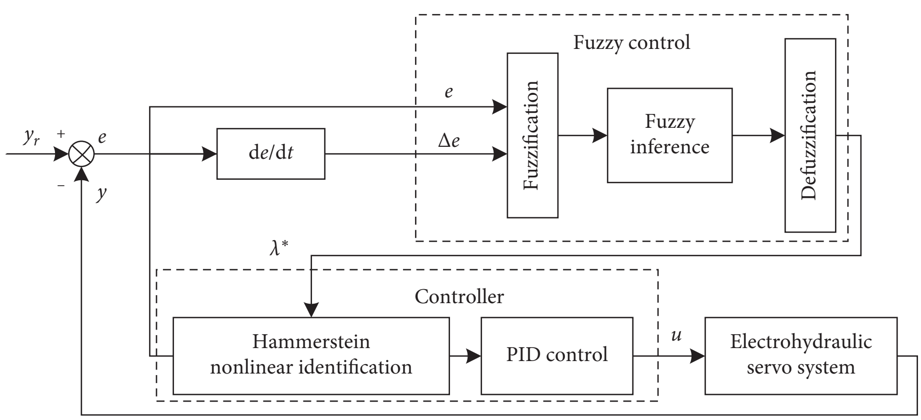

Figure 4: Structure diagram of controller.

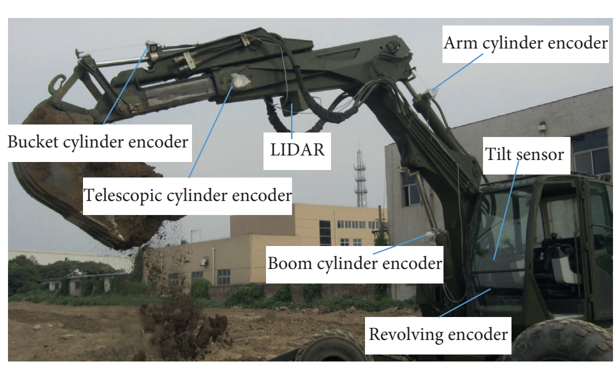

Figure 5: Experimental prototype of the robotic excavator.

better approximation accuracy than the classical Hammerstein nonlinear identification algorithm (CHNLIA). The calculated standard deviation of the CHNLIA is $\sigma_1 = 5.8921$, and the error of the identified model is obvious when the hydraulic cylinder changes its motion direction. The calculated standard deviation of the AHNLIA is $\sigma_2 = 3.5287$, the

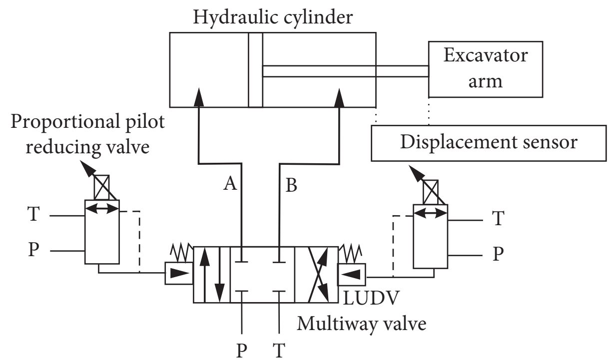

Figure 6: Electrohydraulic servo control system of the robotic excavator.

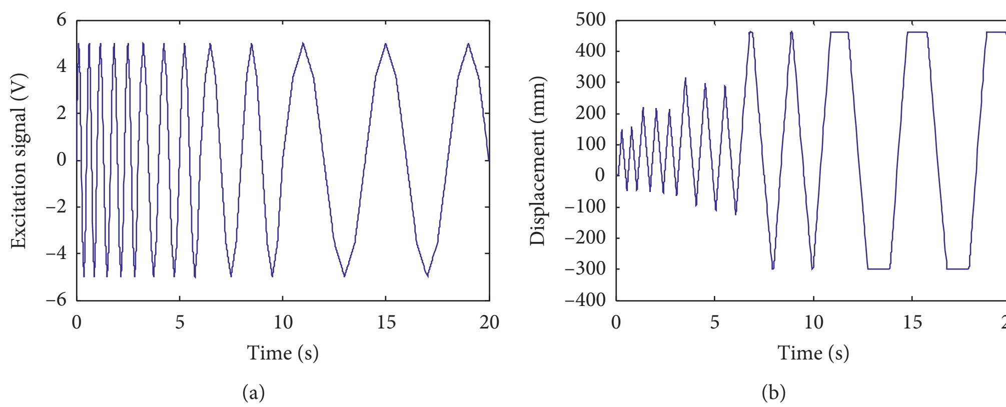

Figure 7: Input and output signal of the identification experiment. (a) Open-loop input and (b) output signal.

Table 2: Model parameters of the electrohydraulic servo system.

Name	Estimated value	Name	Estimated value
a_1	−0.9923	b_1	0.8375
a_2	0.0236	f_1	1.0
a_3	0.0042	f_2	0.0924
b_0	0.7237	f_3	−0.0133

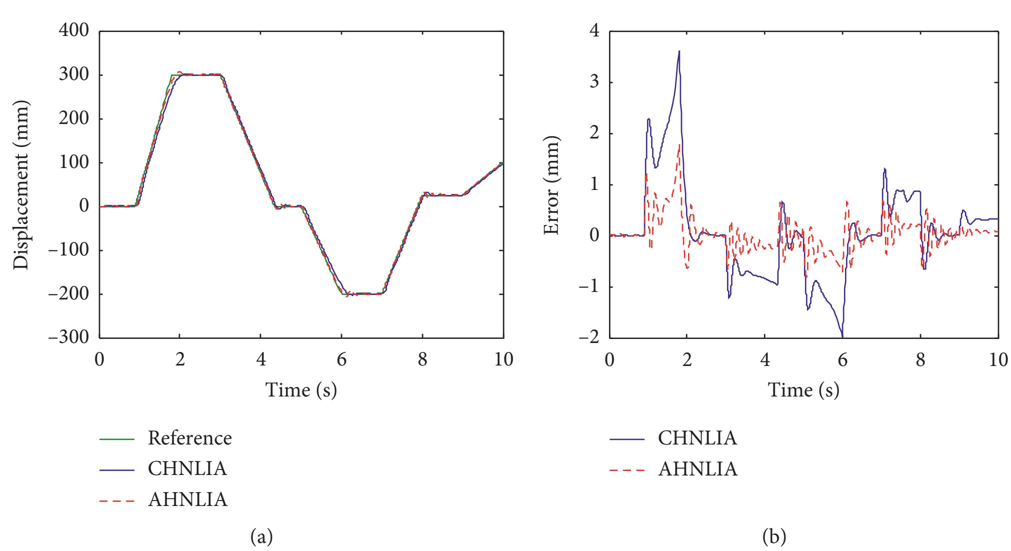

Figure 8: Comparison curves of output and output error. (a) Output comparison curve and (b) error comparison curve.

error of the algorithm fluctuates within a small range, and the hydraulic cylinder always stays near the designated position. It can be seen that the identification error of the AHNLIA is about 40.11% lower than that of the CHNLIA, and it can describe the dynamic characteristics of the electrohydraulic servo system of the robotic excavator more accurately.

6. Conclusion

On the basis of establishing the nonlinear model of the electrohydraulic servo system of the robotic excavator, the complex dynamic characteristics of the system are analyzed. Due to the nonlinear and time-varying characteristics of the electrohydraulic servo system, it is difficult to establish a precise mathematical model. The Hammerstein model with dynamic linear module and static nonlinear module is applied to describe the system; a forgetting factor is introduced to adjust the model, and the fuzzy control module is designed to adaptively update the forgetting factor. The identification results provide a reference model for the adaptive control of the robotic excavator, and the model predictive control can be used to track the predetermined trajectory accurately.

Experimental results show that the tracking accuracy of the adaptive Hammerstein nonlinear identification algorithm is improved significantly compared with the classical Hammerstein identification algorithm, which can describe the dynamic characteristics of the electrohydraulic servo system of the robotic excavator more accurately. The method provides a reference for the identification and control of other nonlinear time-varying systems in the industrial field.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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