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Title page

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ORIGINAL ARTICLE

Parameter Adaptive Sliding Mode Trajectory Tracking Strategy with Initial Value Identification for the Swing in a Hydraulic Construction Robot

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Abstract: A novel trajectory tracking strategy is developed for a double actuated swing in a hydraulic construction robot. Specifically, a nonlinear hydraulic dynamics model of a double actuated swing is established, and a robust adaptive control strategy is designed to enhance the trajectory tracking performance. When an object is grabbed and unloaded, the inertia of a swing considerably changes, and the performance of the estimation algorithm is generally inadequate. Thus, it is necessary to establish an algorithm to identify the initial value of the moment of inertia of the object. To this end, this paper proposes a novel initial value identification algorithm based on a two-DOF robot gravity force identification method combined with computer vision information. The performance of the identification algorithm is enhanced. Simulations and experiments are performed to verify the effect of the novel control scheme.

Keywords: hydraulic servo; robust adaptive control; sliding mode; computer vision; construction robot

1 Introduction

Due to the risks associated with the presence of operating errors and dynamic changes in the environment,

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the development of fully automated systems for robotic construction machines or construction robots is limited, although automatic control can help achieve a high precision and efficiency for many kinds of machines [1,2]. To promote the operation of robotic construction machines, it is necessary to enhance the environmental perception and implement intelligent assistance with automatic control for novice operators [3-5]. By optimizing the proportional integral derivative (PID) controller, Feng [6] proposed an improved ant colony optimization algorithm (IACO) to increase the tracking accuracy of hydraulic systems. Moreover [7], a robust controller was designed using the μ -synthesis method to ensure the stability and performance of a hydraulic excavator.

Zhao et al. developed a construction robot system with physical human–robot interaction (PHRI), which could perform tasks in earthquake disaster sites [8,9]. In such systems, as the end effector operation may be dangerous to the operator, a novel force strategy associated with a master–slave control schematic is usually adopted.

Most engineering robot systems are actuated through hydraulic servo systems that suffer from disturbances and uncertainties. To attain high-performance trajectory tracking control in uncertain nonlinear systems, the robust adaptive control method [10] has been widely used

because of its flexibility and robustness. For example [11], a fuzzy logic controller was designed to track the trajectory of an industrial robot with 2 degrees of freedom. Three particle swarm optimization algorithms with different cost functions were used to optimize the controller parameters. The fuzzy logic in the algorithm decreased the complexity of mathematical modelling, which is commonly a complex and time-consuming process. However, owing to the lack of comprehensive analyses, the algorithm lacked generality in multiple situations, even though satisfactory results were obtained in the specific experiments. Among such strategies, adaptive sliding mode control is a valuable control method [13,14].

Adaptive sliding mode control is a new control strategy for nonlinear systems. This method combines the advantages of adaptive control and sliding mode control by introducing adaptive estimation into the sliding mode controller. According to the information uncertainty determined using the adaptive controller, the sliding mode controller can be adjusted to decrease the system uncertainty and conservativeness of the sliding mode control. In this manner, the system can maintain the robustness of sliding mode control to external disturbances and unmodelled dynamics, and the adaptive control strategy can help overcome the limitations of sliding mode control [15-18]. To suppress the motion disturbance of the actuator, a nonlinear robust dual-loop control scheme was proposed [19]. In addition to considering the motion disturbance of the actuator, the nonlinear characteristics and friction problems of the EHLS were considered. Furthermore, a continuous control set model predictive speed control (CCS-MPSC) based on the fast terminal cost index (FTCI) was proposed [20] to enhance the system tracking performance.

Although sliding mode control is highly robust, it is based on the precise mathematical model of the object [21-24]. The "rough" mathematical model of the system must be predicted before the system sliding mode surface parameters and controller parameters can be determined. For nonlinear systems, the dynamics of the nonlinear

function of the system must be identified before designing the sliding mode controller. The method of robot parameter identification to obtain accurate model parameters is of significance in the design of robot controllers including sliding mode controllers. To address the uncertain load disturbances of a hydraulic Stewart manipulator, sliding mode control based on the discontinuous projection adaptive law was developed to enhance the tracking performance [25-27]. J. B Cao et al. used neural networks to adjust the switching gain online and realize system identification and parameter prediction. Moreover, the authors designed a neural network sliding mode controller for hybrid electric vehicles [28]. Using the Szász–Mirakyan operator as the basic function and by adjusting the polynomial coefficients through the adaptive law determined through stability analyses, a robust adaptive controller was designed to enhance the impedance control of a robot manipulator [29]. Other common methods to enhance the estimation performance include the use of neuro-fuzzy model auxiliary filters and time-varying parameters [30-34].

A satisfactory trajectory tracking controller must ensure that a robot can perform precise trajectory tracking. To this end, the dynamic characteristics of the robot must be considered [35-38]. To design the controller for a swing when a robot carries an object and increase the trajectory tracking accuracy, it is necessary to design a robust adaptive controller to address the uncertainty of the parameters. For a hydraulic cylinder system, the load equivalent mass is the most important element in controller design. However, for a swing, because the load mass is large and changes in real time according to the working conditions, the equivalent mass cannot be accurately obtained. Nevertheless, it can be assumed that the load does not change during the carrying process. Based on the inverse dynamic analysis of the robot arm and boom cylinders, the initial value of the equivalent mass can be obtained through system identification [39]. Subsequently, relatively accurate initial values of the controller parameters can be obtained, and the convergence and trajectory tracking accuracy of the controller can be enhanced. These aspects are the focus of

this article.

The paper is organized as follows: The background and related research are described in Section 1. Section 2 presents the system overview of the teleoperation system and problem description. Section 3 describes the sliding mode adaptive robust controller for the swing. The method to identify the system initial value is described in Section 4. The simulation experiment is described in Section 5. Section 6 describes the experiment performed to compare the performance of three controllers carrying objects between two points.

2 System and Problem Description

2.1 System description

The proposed teleoperation system consists of two parts: a pair of hydraulic PHRIs as the master and an engineering robot reconstructed from a hydraulic excavator as the slave, as shown in Figure 1. Moreover, the system includes a control PC for each part.

Figure 1 Teleoperation system

The four asymmetric hydraulic cylinders are driven by servo valves. The working pressure can be measured using pressure sensors installed in the rod and rod-less cavities of the hydraulic cylinder. The displacement of the working device can be determined using a displacement sensor installed outside the hydraulic cylinder.

The system uses cameras for monitoring. However, considering the limitations of the camera viewing angle and clarity, a 3D vision device is used to construct a virtual scene and the work object. The general shape of the object can be determined through the 3D camera, although the volume and shape cannot be accurately identified due to the low camera resolution.

Figure 2 shows the actuation system of the swing. The double-cylinder actuated swing occupies a small space

and does not need to drive the heavy chassis. The production cost of the structure increases because of the use of the double cylinders. However, because multi-point transmission and effective force transmission can be realized by the hydraulic system, this design exhibits a low energy consumption and compact structure.

Figure 2 Swing DOF in the construction robot

2.2 Problem description

The moment of inertia parameter of the swing varies considerably when the work object is carried and unloaded. However, the parameter has a constant value during one procedure. This article designs a sliding adaptive robust trajectory tracking controller for the swing of a hydraulic construction robot. However, the strategy suffers from a low convergence speed when the moment of inertia parameter varies. Therefore, a moment of inertia identification algorithm is used.

The main problem can be divided into the following subproblems.

① According to the dynamic characteristics of the robot, the gravity compensation algorithm is used to determine the weight of the object according to the information provided by the arm and boom force sensors. The shape and size information of the working object is obtained through computer vision. These data points are combined with the weight information to determine the inertia of the object relative to the swing.

② To effectively suppress the uncertainties and disturbances, a sliding mode adaptive controller is designed for the hydraulic servo system of the swing. By combining the control strategy and initial value obtained by determining the moment of inertia, the parameter convergence and trajectory tracking

performance can be enhanced.

3. Sliding adaptive robust controller for the swing

3.1 Mathematical model of the hydraulic system

The dynamic model for the hydraulic system shown in Figure 2 is

$$F_1 l_1 \sin \theta_1 + F_2 l_2 \sin \theta_2 = m \ddot{\theta} + I \ddot{\theta} + m \ddot{\theta} + C \dot{\theta} \quad (1)$$

where m is the mass of the cylinder rod, I is the equivalent mass of the robotic arm and the cylinders, F_1 and F_2 denote the load forces of the cylinders, and C is the damping coefficient.

In this case,

$$(P_1 A_1 - P_2 A_2) l_1 \sin \theta_1 + (P_1 A_2 - P_2 A_1) l_2 \sin \theta_2 = m \ddot{\theta} + I \ddot{\theta} + m \ddot{\theta} + C \dot{\theta} \quad (2)$$

where A_1 and A_2 are the areas of the two sides of the piston, C is the coefficient of viscous friction, and P_1 and P_2 denote the pressures in the two chambers of the cylinder.

Figure 3 l_1 and l_2 when the object is carried

(kinematics model of the double actuated swing)

The kinematics of the swing during the carrying process are derived in the Supplementary file. The result calculated using the MATLAB program is shown in Figure 3. The lengths l_1 and l_2 are small and exhibit similar amplitudes when the swing DOF varies from the centre position to the 60° position.

$$A_1 l_1 \sin \theta_1 + A_2 l_2 \sin \theta_2 \approx A_2 l_1 \sin \theta_1 + A_1 l_2 \sin \theta_2 \approx A_s$$

$$\Delta l_1 \approx \Delta l_2 \approx y,$$

Subsequently, (2) can be expressed as

$$(P_1 - P_2) A_s = 2m \ddot{\theta} + I \ddot{\theta} + C \dot{\theta} \quad (3)$$

According to Eq. (3), considering leakage and compressibility, the dynamics of the cylinder oil flow can be expressed as [17]

$$V_1 P_1 / \beta_e = -A_s x_l + Q_1 - C_t (P_1 - P_2) \quad (4)$$

$$V_2 P_2 / \beta_e = A_s x_l - Q_2 + C_t (P_1 - P_2)$$

where C_t is the internal leakage coefficient, V_1 and V_2 denote the total fluid volumes of the hydraulic cylinders, β_e is the bulk modulus of the fluid, and Q_1 and Q_2 are the fluid flow rates of the cylinders. The displacement of the spool valve, x_v , is

$$\begin{aligned} Q_1 &= k_q x_v \sqrt{\Delta P_1} \\ Q_2 &= k_q x_v \sqrt{\Delta P_2} \end{aligned} \quad (5)$$

where k_q is the flow gain coefficient of the servo valve.

The state variables are defined as

$$\mathbf{x} = [x_1 \ x_2 \ x_3 \ x_4] = [y \ \dot{y} \ P_1 \ P_2] \quad (6)$$

The dynamics are expressed in a state-space form as

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= \frac{1}{M} [(x_3 - x_4) A_s - B x_2 - d] \\ \dot{x}_3 &= \frac{\beta_e}{V_0} (-A_s y + k_q k_a \sqrt{\Delta P_1} u - C_t (x_3 - x_4)) \\ \dot{x}_4 &= \frac{\beta_e}{V_0} (A_s y - k_q k_a \sqrt{\Delta P_2} u + C_t (x_3 - x_4)) \end{aligned} \quad (7)$$

where M is the equivalent load mass obtained from Eq. (3), V_0 is the total fluid volume of the two cylinders, and A_s is the total area of the cylinders.

The time derivative of the second expression in (7) is

$$\dot{x}_2 = \frac{1}{M} [(x_3 - x_4) A_s - B x_2 - d] \quad (8)$$

In (8), the difference in the third and fourth terms is

$$\dot{x}_3 - \dot{x}_4 = \frac{V_1}{\beta_e} \left(-2A_s y + 2k_q k_a \sqrt{\Delta P_1} u - 2C_t (x_3 - x_4) \right) \quad (9)$$

Thus,

$$\begin{aligned} \ddot{x}_3 - \ddot{x}_4 = & \frac{-2A_s^2 x_1 \beta_e}{MV_0} + \frac{A_s k_q k_a (\sqrt{\Delta P_1} - \sqrt{\Delta P_2})}{MV_0} \beta_e u \\ & - \frac{2A_s \beta_e C_t}{MV_0} (x_3 - x_4) - \frac{B}{M} \dot{x}_2 - \frac{d}{M} \end{aligned} \quad (10)$$

3.2 Controller design

The following unknown parameter set is defined:

$$\begin{aligned} \sigma_1 &= \frac{-2\beta_e A_s^2}{MV_0}, \sigma_2 = \frac{-2\beta_e A_s C_t}{MV_0}, \sigma_3 = \frac{B}{M}, \sigma_4 = \frac{1}{M}, \\ \sigma_5 &= \frac{\beta_e}{MV_0} k_q k_a \end{aligned}$$

The state-space Eq. (10) is linearly parameterized as [40]

$$\begin{aligned} f &= \sigma_1 x_2 + \sigma_2 (x_3 - x_4) + \sigma_3 \dot{x}_2 + \sigma_4 \ddot{x}_2 \\ g &= \sigma_5 (\sqrt{\Delta P_1} + \sqrt{\Delta P_2}) \end{aligned} \quad (11)$$

Function f can be expressed as $f = \hat{f} + \Delta f$, where

$\hat{f}$ is the nominal part, and Δf is the uncertain part,

bounded as

$$|\Delta f(\mathbf{x}, t)| \leq F(\mathbf{x}, t) \quad (12)$$

$$\hat{f} = \hat{\sigma}_1 x_2 + \hat{\sigma}_2 (x_3 - x_4) + \hat{\sigma}_3 \dot{x}_2 + \hat{\sigma}_4 \ddot{x}_2 \quad (13)$$

where F is a known function.

The control gain g is confined to a certain constant range.

$$0 < \beta_{\min} < g < \beta_{\max}$$

The estimated value of g is

$$\hat{g} = \hat{\sigma}_5 (\sqrt{\Delta P_1} + \sqrt{\Delta P_2}) \quad (14)$$

The control objective is to ensure that x_L asymptotically tracks the desired trajectory x_{Ld} .

The tracking error is defined as

$$y_e = y - y_d \quad (15)$$

The sliding mode surface is defined as

$$s = \left(\frac{d}{dt} + \lambda \right)^2 y_e = \ddot{y}_e + 2\lambda \dot{y}_e + \lambda^2 y_e \quad (16)$$

Differentiating s with respect to t yields

$$\begin{aligned} \dot{s} &= \ddot{y}_e + 2\lambda \dot{y}_e + \lambda^2 y_e \\ &= f + gu - \ddot{y}_d + 2\lambda \dot{y}_d + \lambda^2 y_d \end{aligned} \quad (17)$$

The Lyapunov function candidate is defined as

$$V(s) = \frac{1}{2} s^2 \quad (18)$$

Thus,

$$\begin{aligned} \dot{V} = s \dot{s} &= s \left\{ \sigma_1 x_2 + \sigma_2 (x_3 - x_4) + \sigma_3 \dot{x}_2 + \sigma_4 \ddot{x}_2 \right. \\ & \left. + \left[\sigma_5 (\sqrt{\Delta P_1} + \sqrt{\Delta P_2}) \right] u - \ddot{y}_d + 2\lambda \dot{y}_d + \lambda^2 y_d \right\} \end{aligned} \quad (19)$$

The control input u is

$$\begin{aligned} u &= \frac{1}{\hat{g}} (\hat{u} - v) \\ \hat{u} &= -\hat{f} + \ddot{y}_d - 2\lambda \dot{y}_d - \lambda^2 y_d \\ v &= k \text{sat}\left(\frac{s}{\phi}\right) \end{aligned} \quad (20)$$

where f is the boundary layer, k is the control gain, and $\text{sat}(\Delta)$ is the saturation function, defined as

$$\text{sat}(\Delta) = \begin{cases} 1, & \Delta > 1, \\ \Delta, & |\Delta| < 1, \\ -1, & \Delta < -1, \end{cases} \quad (21)$$

To obtain the adaptation parameters, the following Lyapunov function is defined:

$$V_1(s) = \frac{1}{2} s^2 + \frac{1}{2} \sum_{i=1}^5 \gamma_i \hat{\sigma}_i^2 \quad (22)$$

where $\hat{\sigma}_i$ is the estimated value of σ_i .

The estimation error is

$$e_i = \sigma_i - \hat{\sigma}_i \quad (23)$$

The time derivative of V_1 is

$$\begin{aligned} \dot{V}_1 = s\dot{x} + \sum_{i=1}^5 \gamma_i \hat{\sigma}_i \dot{\sigma}_i = -\hat{\sigma}_1 [s\sigma_1 x_2 - \gamma_1 \sigma_1] + \\ \hat{\sigma}_2 [s(x_3 - x_4) - \gamma_2 \sigma_2] + \hat{\sigma}_3 (\dot{x}_2 - \gamma_3 \sigma_3) \\ + \hat{\sigma}_4 (sd + \gamma_4 \sigma_4) [\sigma_5 (\sqrt{\Delta P_1} + \sqrt{\Delta P_2})u - \gamma_5 \sigma_5] \\ - ks \text{sat}\left(\frac{s}{\phi}\right) + \sigma_4 \frac{ds}{dt} \end{aligned} \quad (24)$$

To ensure that $\dot{V}_1 < 0$, the adaptation laws are set as

$$\begin{aligned} \dot{\sigma}_1 &= \text{Proj}_{\hat{\sigma}_1} \left(-\frac{s\sigma_1 x_2}{\gamma_1} \right) \\ \dot{\sigma}_2 &= \text{Proj}_{\hat{\sigma}_2} \left(-\frac{s(x_3 - x_4)}{\gamma_2} \right) \\ \dot{\sigma}_3 &= \text{Proj}_{\hat{\sigma}_3} \left(\frac{\dot{\sigma}_3}{\gamma_3} \right) \\ \dot{\sigma}_4 &= \text{Proj}_{\hat{\sigma}_4} \left(-\frac{sd}{\gamma_4} \right) \\ \dot{\sigma}_5 &= \text{Proj}_{\hat{\sigma}_5} \left(\frac{\sigma_5 (\sqrt{\Delta P_1} + \sqrt{\Delta P_2})us}{\gamma_5} \right) \end{aligned} \quad (25)$$

Function $\text{Proj}()$ is a discontinuous projection, defined as

$$\text{Proj}_{\hat{\sigma}_i}(\bullet) = \begin{cases} 0 & \text{if } \hat{\sigma}_i = \sigma_{\max} \text{ and } \bullet > 0, \\ 0 & \text{if } \hat{\sigma}_i = \sigma_{\min} \text{ and } \bullet < 0, \\ \bullet & \text{otherwise} \end{cases} \quad (26)$$

For any adaptation function, the projection mapping ensures that

$$\hat{\sigma}_i \in \{ \hat{\sigma}_i : \sigma_{\min} \leq \hat{\sigma}_i \leq \sigma_{\max} \} \quad (27)$$

$$\hat{\sigma}_i [\gamma_i \text{proj}_{\hat{\sigma}_i}(\gamma_i^{-1} \Delta_i) - \Delta_i] \leq 0 \quad (28)$$

Controller (20) and adaptation laws (26) ensure that the tracking errors asymptotically converge to zero, i.e., $\|e(t)\| \rightarrow 0$ as time $t \rightarrow \infty$.

4. Identification of the moment of inertia

The swing DOF when an object is being carried pertains to a robot arm system with constant parameters that cannot be identified offline. As described in Section 3, the main parameters in (10) are dependent on the equivalent mass M . The equivalent mass M is composed of the mass of the swing hydraulic cylinder push rod and moment of inertia I . Therefore, I is determined as

$$I = I_a + I_b + I_o \quad (29)$$

where I_a is the moment of inertia of the arm and folk glove, and I_b is the moment of inertia of the linkage system with the swing and boom. I_a and I_b can be accurately obtained through offline identification. I_o is the moment of inertia of the object being carried, which varies in a large range and cannot be accurately calculated offline. A new method is proposed that combines the stereo vision system and hydraulic cylinder information of the boom and arm to obtain I_o .

The density and approximate shape and volume of the work object can be derived as

$$I_o = \int \rho V \quad (30)$$

However, the shape and volume obtained by the vision system are considerably different from those of the work object, and thus, the direct use of these parameters may lead to a low estimation accuracy. The force obtained by the force sensor is highly accurate. If the mass of the work object can be obtained considering the force of the arm and boom, the moment of inertia can be corrected to obtain more accurate moment of inertia parameters.

The dynamic model for a system composed of booms, arms and folkloves is [29]

$$\begin{bmatrix} \tau_b \\ \tau_a \end{bmatrix} = \begin{bmatrix} m_b l_{gb} C_b + m_a l_b & m_a l_{ga} C_a \\ 0 & m_a l_{ga} C_a \end{bmatrix} \begin{bmatrix} C\theta_b \\ C\theta_{ba} \end{bmatrix} \mathbf{g} \\ - \begin{bmatrix} m_b l_{gb} S_b & m_a l_{ga} S_a \\ 0 & m_a l_{ga} S_a \end{bmatrix} \begin{bmatrix} S\theta_b \\ S\theta_{ba} \end{bmatrix} \mathbf{g} \quad (31)$$

PID control (CPID), common sliding mode control (SM) and the proposed strategy, namely, sliding mode control with initial value (SMI), as shown in Figure 7, are used in the comparison experiments.

The schematics of the controllers are shown in the following figures.

Figure 5 Compound PID controller (CPID)

The CPID controller is shown in Figure 5. This system represents a practical controller in a linear system. The zero and pole points are optimized through the feedforward and feedback PID controller, and the PID parameters can be adjusted in conjunction with the Routh stability criterion.

Figure 6 Sliding mode controller (SM)

Figure 7 Sliding mode controller with initial value identification (SMI)

The sliding mode controller is shown in Figure 6. The input modules in Figures 4 and 5 function on the desired trajectory output, such as the position, velocity and acceleration. The trajectory is $y=\sin(\pi t)$.

Figure 8 SimMechanics plant

The plant built by SimMechanics (Figure 8) is applied in the simulation program. As shown in Figure 6, the load features can be adjusted by setting the mass and gravity centre. Considering the work scenario, the load parameter is a constant value after it is determined, and no disturbance force is applied. Only the commonly used friction force based on the LuGre model is introduced.

$$D = v_0 z + v_1 \frac{dz}{dt} + v_2 \phi \quad (44)$$

where z is the average deformation of the bristles, v_0 is the bristle stiffness coefficient, v_1 is the microdamping coefficient, and v_2 is the viscous coefficient.

The parameters adopted in the program are listed in Table I.

Table I Parameters in the simulation program

Parameter	Description	Value	Unit
A_s	Area of the piston	6.08×10^3	m^2
β_e	Bulk modulus of the fluid	690	MPa
w	Servo valve area gradient	0.008	m
P_s	Supply pressure	2	MPa
V_0	Total fluid volume	9.05×10^{-4}	m^3
C_t	Discharge coefficient of the cylinder	7×10^{-9}	$\text{m}^5/(\text{N} \cdot \text{s})$
k_q	Pressure gain	5.09×10^5	$\text{m}^4/\text{s}/\text{kg}$
k_a	Amplification gain	1.0	mA/V

In the simulation program, the real value of m_o is 2681 $\text{kg} \cdot \text{m}^2$, and the calculated values of the parameters are

$$\sigma = [-4547, -0.0113, 0.2984, 3.73 \times 10^{-4}, 14.48] \quad (45)$$

Figure 9 Trajectory tracking result

The initial parameter value is input to the adaptive parameter identification module by setting the parameters in the S function. To validate the performance of the initial value identification, the initial values of M and σ are set. In SM, the initial value of m_0 is set as the unloading moment of inertia, $723 \text{ kg}\cdot\text{m}^2$; thus, the initial values of σ are

$$\sigma = [-16861, -0.0417, 1.1065, 0.0014, 53.68] \quad (46)$$

In SMI, the initial value of m_0 is set as $2469 \text{ kg}\cdot\text{m}^2$; thus, the initial values of σ are

$$\sigma = [-4937.4, -0.0122, 0.3240, 4.05 \times 10^{-4}, 15.718] \quad (47)$$

The reference trajectory is $\theta_d = 60 \times \sin \pi t$ ($^\circ$).

According to the simulation experiment results shown in Figures 9 and 10, the CPID method has a certain effect. Because the CPID does not have the parameter estimation function, the initial and final tracking errors are similar. The trajectory tracking error of the SM controller is considerably smaller than the steady-state error of the CPID. However, due to parameter coupling [14], the parameters of the SM method cannot approach the target parameters, and thus, the performance of the controller is limited. The SMI trajectory tracking results in the later stage are the best among the three methods because of the superior parameter estimation performed through the

initial value. However, the parameter identification results are slightly different from the real values because of the limitations of the estimation algorithm.

Figure 10 Parameter identification result

6 Experiment

This section describes the moment of inertia identification experiment and validation experiment of SMI. The system setup and implementation issues are outlined in Section 6.1. The process and result of the identification experiment are described in Section 6.2, and the control effect verification experiment is described in Section 6.3.

6.1 Experiment setup and implementation issues

The experimental setup consists of the following hardware components.

- ① Construction robot reconstruction for the 10 T LiuGong excavator.
- ② Pointgrey Research Colour Digiclops, with three

Sony 1/3" progressive scan CCD cameras.

- ③ Rexroth Huade 4 WRE16-10 servo valve.
- ④ Druck PTX1400 pressure transmitters with an operating pressure range of 25 MPa.
- ⑤ Miran LVDT20 rod-type displacement sensor.
- ⑥ ADVANTECH PCI-1710UL Data acquisition card (DAQ) with 12-bit data acquisition and 100 kHz sampling rate.

For simplicity, the initial values are determined by offline experiments. The hardware of the control system consists of two PC-compatible computers that communicate through a local area network. All analogue measurement signals (cylinder position, chamber pressure, supply pressure and load force) are fed back to the slave PC through four plug-in DAQ cards.

6.2 Moment of inertia identification experiment

To test the effect of the vision information combined with the gravity recognition algorithm of moment of inertia, as described in Section 3.2, a three-dimensional vision and gravity compensation method was applied to grasp stone and wood specimens.

In the experiment, the object stone is grabbed by a folk glove at the centre position and 20 cm to the left. The position is manually measured to ensure accuracy. In another experiment, a wood object is grabbed.

The moment of inertia result is I_{sum} . According to Table II, the identification results and real results are different, especially in the case of wood objects, primarily owing to the irregular shape of the objects. The irregularity of the work object at the work site highlights the necessity of using the integrated adaptive algorithm and initial value identification algorithm.

The identification experiment results are shown in Table II.

Table II Results of identification experiments

	Calculated value	Identified value
Stone (M)	2681	2670
Stone (L)	2690	2710
Wood (M)	1809	2087
Wood (L)	1824	2123

6.3 Carrying experiment

To validate the effect of the proposed control scheme in trajectory tracking, the following experiment is performed. Three controllers, CPID, SM and SMI, are used to grab a stone and apply a step desired displacement. These conditions are similar to real working conditions.

Using CPID, SM and SMI, the following processes are performed through automatic control methods:

- ① Grasp the object and lift it approximately 5 cm.
- ② Set the parameters of SM and SMI, according to (45) and (46), respectively.
- ③ Initiate data acquisition.
- ④ Use the step signal to move the swing to the left for 5 s at the desired speed of 0.02 m/s, release the folk glove, and allow the object to land freely.
- ⑤ Set the parameters (SM and SMI) to the unloaded initial value (45), and use the step signal to move the swing to the right for 5 s with a target speed of 0.02 m/s.

The evaluation indicators of the trajectory tracking results include the maximum error and root mean square error (RMSE).

The experimental process is similar to the real working conditions.

Figure 11 shows the velocity tracking result. Table III presents the trajectory tracking results. In the carrying process, the SM and SMI sliding mode algorithms are superior to the CPID due to the uncertainties related to the object. SM exhibits an inferior result owing to the convergence effect of the estimation algorithm. SMI combined with visual and gravity parameter identification exhibits an enhanced control performance.

Figure 11 Velocity tracking result

Table III Trajectory tracking result

Controller	Maximum error	RMSE
CPID	0.004	0.1083
SM	0.003	0.0530
SMI	0.0008	0.0183

This phenomenon occurs because the initial value is accurately set in advance. The SMI method thus exhibits a high accuracy at the initial moment. Due to the relatively brief period of the swing in each handling and unloading procedure, the working performance is mostly determined by the initial period, and SMI is thus a practical method.

Moreover, in the process of handling and unloading, due to the uncertainties associated with the object weight, it is challenging to obtain satisfactory results from the simple identification algorithm. The experimental results demonstrate the importance of the initial value identification method for all sliding mode strategies with adaptive parameter identification. In addition to trajectory tracking, this method can be used in other fields, such as energy-saving control.

7 Conclusion

This study focuses on the adaptive robust sliding mode control scheme for trajectory tracking of a swing with a double actuated hydraulic cylinder in a hydraulic construction robot.

A novel control scheme that obtains the initial value of the moment of inertia of swing through the robot gravity identification algorithm and stereo vision information is proposed. The scheme can be used to overcome the limitations associated with the low convergence speed of

the parameter identification algorithm and large change in the inertia caused by the change in the work object.

Simulation and online experiments are performed to validate the effect of the novel scheme. The simulation experiment demonstrates the superiority of the SM algorithm over the CPID algorithm and necessity of obtaining the initial value for the sliding mode algorithm in SMI. Online experiments indicate that the moment of inertia deviation obtained using Digiclops combined with the gravity identification method is more than 20%, indicating the necessity of using the parameter adaptive algorithm in the relevant strategy. Comparison experiments involving the grabbing of stones using SMI and SM show that the proposed SMI method is more accurate than the SM method and CPID control algorithm. This research can facilitate further work on robots and parameter estimation-based control.

8 Declaration

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Availability of data and materials

The datasets supporting the conclusions of this article are included within the article.

Authors' contributions

The author's contributions are as follows: Ding-Xuan Zhao and Jing-Wei Hou were in charge of the whole trial; Jing-Wei Hou wrote the manuscript; Zhu-Xin Zhang assisted with sampling and experiment analyses. All authors reviewed the manuscript.

Competing interests

The authors declare no competing financial interests.

Consent for publication

Not applicable

Ethics approval and consent to participate

Not applicable

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