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Motion Control of a Hydraulic Manipulator with Adaptive Nonlinear Model Compensation and Comparative Experiments

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Abstract: Hydraulic manipulators play an irreplaceable role in many heavy-duty applications. Currently, there are stronger demands for the hydraulic manipulator to achieve high precision, as well as high force/power. However, due to the inherent nonlinearities of its high-order dynamics, the precision of the manipulator has been a common weakness compared with electrically driven ones. Thus, in this paper, a nonlinear adaptive robust control method for the hydraulic manipulator is proposed. To make the controller more applicable to practical engineering projects, this study tried to control each joint independently instead of directly based on the complicated multi-degree high-order dynamics, while guaranteeing the control precision by the adaptive nonlinear model compensation, as well as a robust feedback design. The closed-loop control performance was theoretically verified. Besides, several sets of comparative motion tracking experiments were conducted, and the proposed closed-loop system achieved high precision under different trajectories and postures.

Keywords: adaptive robust control; hydraulic manipulator; motion control; backstepping



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1. Introduction

Due to its higher power-to-weight ratio and fast response, the hydraulic manipulator is widely used as the main actuator in oil and gas production, civil engineering industries [1], military applications [2], and aerospace [3]. However, faced with various tasks and potentially extreme environments, it is inevitably difficult for open-loop control to achieve high precision, which includes slow dynamic response, low control accuracy, and the lack of fine work ability. The demand for closed-loop control of hydraulic manipulators with high precision is increasing [4–6]. The high-performance tracking of the given reference trajectory is always the basis [7–9].

However, there are numerous problems in the high-precision motion control of hydraulic manipulators. Compared with the electrically driven manipulator analyzed in [10], the hydraulic manipulator has a special mechanism configuration, as its rotary motion is driven by the linear motion of the hydraulic cylinder. This special mechanism configuration will result in a nonlinear relationship between the joint angle and the length of the hydraulic cylinder, as well as the joint torque and the hydraulic cylinder force. Besides, the dynamics of hydraulic systems are also highly nonlinear [11,12]. Excluding the nonlinearity, there are numerous uncertainties in the system, which can be divided into parametric uncertainties and uncertain nonlinearities [13]. Examples of the parametric uncertainties include rotational inertia, the coefficient of friction, and the hydraulic bulk modulus, which are imprecise or time-varying [14,15]. The uncertain nonlinearities refer to some physical factors whose nonlinear functions are unknown and cannot be accurately modeled, such as the external disturbance and internal oil leakage [16,17]. In addition to the aforementioned

dynamics of the manipulator, the chamber pressure dynamics and spool dynamics, which will undoubtedly lead to a higher order of the dynamics model [18,19], cannot be ignored. Above all, if the coupling dynamics is taken into account, it will be a high-order multi-input multi-output (MIMO) nonlinear system with various uncertainties. These characteristics undoubtedly exacerbate the difficulty of the controller design and make the parameter tuning more complex. What is more, the uncertainties may give rise to the significant performance degradation or instability of the controlled system designed on the nominal model [20,21].

Faced with the above difficulties, there are many related research works in the past few decades. Model-based control has been widely considered, and one of its prerequisites is that the parameters in the dynamics model should be completely known. Therefore, there are many related research works on parameter adaptation. Approximation-based control methods such as neural adaptation have been used to learn the robot dynamic model [22,23], which proves the uniformly ultimate boundedness of the tracking errors. In addition to the goal of parameter boundedness, there are some research works that are more concerned with the rate of convergence of the parameters, whose identification algorithm shows accurate and fast convergence [24,25]. In the motion control of the hydraulic manipulator, the identification of the system dynamics' parameters is also important. Considering the influence of the dynamics' parameters and the difficulty of identification, some parameters are selected in the controller, which are dealt with by the projection adaptation law to reduce the motion tracking error. On the other hand, the coupling dynamics of the hydraulic manipulator was also studied by Mattila and Koivumäki [26,27], who proposed a decoupling scheme called virtual decomposition control (VDC). Challenged by the parametric uncertainties and uncertain nonlinearities, the modeling and compensation control of the hydraulic manipulator were considered comprehensively. With the idea of VDC, the hybrid force/motion controller was designed, and the high-performance control and robustness of the controller were verified by the experiments. This method is feasible, but extremely dependent on the high-precision dynamics model, and the complexity of the controller design is greatly increased. Moreover, the physical model in real scenarios tends to deviate from the nominal model. These possible deviations will make the feedforward compensation of the controller suffer from certain discrepancies, which may lead to a decrease in the accuracy of the model compensation. Furthermore, control precision might be reduced due to the inaccurate tuning of numerous parameters in the coupling dynamics.

Nonetheless, in the industrial or commercial application of hydraulic manipulators, PID or state feedback controllers are the most widely used, including all kinds of controllers derived from PID [4]. For example, in the remote control robot for a fusion reactor, Han et al. [28] combined PID with an optimization algorithm to realize the fast tuning of the controller parameters. Kim and Lee [29] added the switching action of sliding mode control (SMC) to the PID controller, which was matched by a double-integral sliding surface (DISS), and carried out the experimental verification on the hydraulic manipulator. In the application of agricultural seedling transplanting technology, Jin et al. [30] proposed a control strategy based on fuzzy PID, which can adjust the PID parameters online and overcomes the disadvantages of nonlinearity and low control accuracy partly in the hydraulic seedling-picking-up system. However, generally speaking, the output of the PID controller basically depends on the tracking error, which cannot effectively compensate the model. Even though many teams have made some improvements on the basis of PID, its accuracy in model compensation is still limited. More importantly, it is difficult to ensure the robust stability of the controller in theory.

The above literature shows two common control strategies for the hydraulic manipulator, i.e., controlling each joint independently and directly based on its coupling dynamics. The former one is popular in engineering practice due to its simplicity, but the frequently used PID-based controller has difficulty achieving high performance. Within the current research, the latter one has been studied and can achieve better performance. However, the coupling dynamics will dramatically increase the complexity of the controller design,

which might not be a good solution for applications. Moreover, the performance of such a strategy highly relies on the accurate model compensation of the coupling dynamics, but numerous parameters, as well as the parametric uncertainties make it more challenging. In this paper, we tried to control each joint independently to avoid the complexities brought by the coupling dynamics. The nonlinear adaptive robust motion controller was designed, where both the parametric uncertainties and the nonlinearities were addressed properly and a high tracking precision was achieved. The contribution of this paper can be expressed by the following two aspects:

- The projection adaptation law was designed to deal with the parametric uncertainties and the uncertain nonlinearities, which aimed to obtain more accurate feedforward compensation. The nonlinear robust feedback and the linear stabilizing feedback were designed to overcome the external interference and the perturbation of the dynamics' parameters. The backstepping strategy was considered to deal with the high-order dynamic characteristics of the hydraulic systems;
- The motion of the hydraulic manipulator was realized by controlling each joint independently. The nonlinear adaptive robust controller was designed to deal with the parametric uncertainties and the nonlinearities. In theory, the guaranteed transient tracking performance can be achieved, as well as the asymptotic tracking under four conditions. A series of comparative experiments was carried out to test the control performance under different working conditions. In the comparative experiments, when tracking different reference trajectories under different moments of inertia, high-precision control can always be achieved by the proposed control design.

The rest of the paper is organized as follows. The dynamic model of the swing joint of the hydraulic manipulator is established in Section 2. The adaptive robust control method is adopted in Section 3. The comparative experiments to illustrate the effectiveness of the controller are given in Section 4, and conclusions are drawn in Section 5.

2. Dynamic Models and Problem Formulation

2.1. System Modeling

The hydraulic manipulator considered in this study is shown in Figure 1, where there are 4-DOFs, all driven by hydraulic cylinders. Following the standard DH definition, the axis of each joint is defined in Figure 1. In this paper, the swing joint of the manipulator was to be controlled, aiming at high-precision rotation about the Z_0 axis. The physical details of the swing joint are further shown in the enlarged plot in Figure 1, where x_L denotes the total length of the swing cylinder and q is the intersection angle between axes X_1 and X_0 .

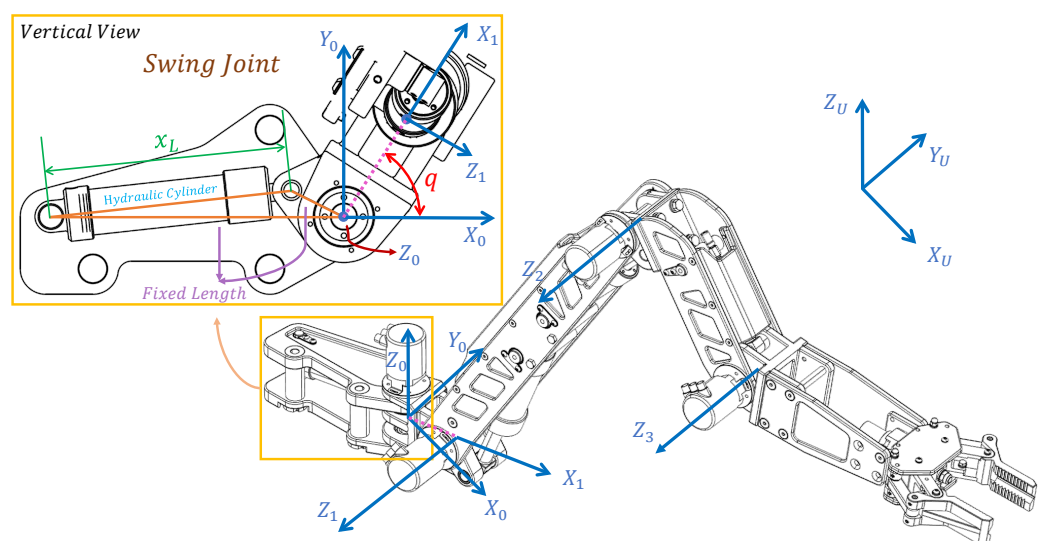


Figure 1. Schematic diagram of the mechanical arm structure.

Following the above definition, the swing motion dynamics of the manipulator can be described as:

$$J\ddot{q} = \frac{\partial x_L}{\partial q} F_L - D_f \dot{q} - fs(\dot{q}) + D_1 \quad (1)$$

where J is the moment of inertia, $\partial x_L / \partial q$ comes from the transition from linear motion to rotation, D_f is the viscous friction coefficient, f is the Coulomb friction coefficient, and D_1 represents the lumped modeling error, including the unmodeled dynamic friction and external disturbance. In order to describe the switching function $\text{sgn}(\bullet)$ and make it apply to the design of the controller, $\text{sgn}(\bullet)$ is approximated as a smoothing function $s(\bullet)$. F_L is the load force generated by the hydraulic cylinder, which is expressed as:

$$F_L = p_1 A_1 - p_2 A_2 \quad (2)$$

in which A_1 and A_2 are the head and rod end ram areas of the cylinder and p_1 and p_2 represent the pressure in each compressible chamber, whose dynamics can be further expressed as:

$$\begin{aligned} \frac{V_1}{\beta_e} \dot{p}_1 &= -A_1 \frac{\partial x_L}{\partial q} \dot{q} + Q_1 + D_{21} \\ \frac{V_2}{\beta_e} \dot{p}_2 &= A_2 \frac{\partial x_L}{\partial q} \dot{q} - Q_2 + D_{22} \end{aligned} \quad (3)$$

where $V_1 = V_{h1} + A_1 x$ and $V_2 = V_{h2} - A_2 x$ are the total compressible volumes of the head and rod ends, respectively, with x being the displacement of the hydraulic cylinder. $V_{h1} = A_p l_{1p}$ and $V_{h2} = A_p l_{2p} + x_{max} A_2$ are the initial compressible volumes when $x = 0$, where x_{max} is the cylinder's total length, l_{1p} and l_{2p} are the length of the pipelines connecting the valve block with the cylinder, with A_p representing the pipeline's area. β_e is the effective bulk modulus, which is relatively stable and known. Q_1 and Q_2 are the flow into the head-end chamber and out of the rod-end chamber, respectively. D_{21} and D_{22} denote the lumped modeling errors.

Combining (2) and (3), the dynamics of the swing cylinder force can be further given as:

$$\begin{aligned} \dot{F}_L &= \dot{p}_1 A_1 - \dot{p}_2 A_2 \\ &= -\left(\frac{A_1^2}{V_1} + \frac{A_2^2}{V_2}\right) \frac{\partial x}{\partial q} \beta_e \dot{q} + Q_L \beta_e + \frac{A_1}{V_1} \beta_e D_{21} + \frac{A_2}{V_2} \beta_e D_{22} \end{aligned} \quad (4)$$

where $Q_L = (A_1/V_1)Q_1 + (A_2/V_2)Q_2$ is defined as the valve control flow.

A four-way proportional valve was used to control the swing cylinder. Since the dynamics between the valve spool voltage and valve spool displacement is usually much faster than the actuation system dynamics, it can be neglected in the control design, as done in other existing studies [31,32]. Thus, the following static mapping can be used to describe the relationship between valve spool voltage U_v and flow Q_L controlled by the valve:

$$\begin{aligned} U_v &= \frac{Q_L / K_v}{(A_1/V_1)k_{q1}\sqrt{\Delta P_1} + (A_2/V_2)k_{q2}\sqrt{\Delta P_2}} \\ \Delta P_1 &= \begin{cases} p_s - p_1, & U \geq 0 \\ p_1 - p_r, & U < 0 \end{cases}, \quad \Delta P_2 = \begin{cases} p_2 - p_r, & U \geq 0 \\ p_s - p_2, & U < 0 \end{cases} \end{aligned} \quad (5)$$

in which k_{q1} and k_{q2} are the flow gain coefficients of the proportional valve, p_s is the supply pressure of the fluid, p_r is the reference pressure, and K_v is the linearized valve flow gain.

In (1) and (3), though the lumped modeling error is unknown and time-varying, it can be split into the nominal value with slow variation and the bounded deviation value, which changes rapidly [16], i.e., D_i in (1) and (3) can be further denoted by:

$$\begin{aligned} D_1 &= D_{1n} + \Delta D_1 \\ D_{21} &= D_{21n} + \Delta D_{21} \\ D_{22} &= D_{22n} + \Delta D_{22} \end{aligned} \quad (6)$$

with D_{1n} , D_{21n} , and D_{22n} representing nominal value and ΔD_1 , ΔD_{21} , and ΔD_{22} representing the deviation amount.

2.2. Model Parameterization

Define a set of parameters $\theta \in R^{7 \times 1}$. Furthermore, the state-space form of this model can be expressed as:

$$\begin{aligned} \ddot{q} &= \theta_1 \frac{\partial x}{\partial q} F_L - \theta_2 \dot{q} - \theta_3 s + \theta_4 + \Delta D_F \\ \dot{F}_L &= -A\theta_5 + \theta_5 Q_L + B\theta_6 + C\theta_7 + \Delta D_Q \end{aligned} \quad (7)$$

Due to some parameters, such as $\partial x / \partial q$, A_i and $V_i, i = 1, 2$ are computable with precision, and $A = (A_1^2 / V_1 + A_2^2 / V_2)(\partial x / \partial q)\dot{q}$, $B = A_1 / V_1$, $C = A_2 / V_2$ are used to replace them for simplification. $\Delta D_F = \Delta D_1 / J$, as well as $\Delta D_Q = (A_1 / V_1)\beta_e \Delta D_{21} + (A_2 / V_2)\beta_e \Delta D_{22}$ are uncomputable parts. In particular, θ is defined as:

$$\begin{aligned} \theta &= [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7]^T \\ &= \left[\frac{1}{J}, \frac{1}{J} D_f, \frac{1}{J} f, \frac{1}{J} D_{1n}, \beta_e, \beta_e D_{21n}, \beta_e D_{22n} \right]^T \end{aligned} \quad (8)$$

Although there are many parameters θ_i and lumped modeling errors ΔD_F , as well as ΔD_Q suffering from uncertainties in practice, as a matter of fact, the parametric uncertainties and the modeling errors are bounded by certain boundaries. Naturally, the following practical assumptions can be made:

$$\begin{aligned} \theta_i &\in \Omega_{\theta_i} \triangleq \{\theta_i : \theta_{imin} \leq \theta_i \leq \theta_{imax}\}, \quad i = 1, 2, \dots, 7 \\ \Delta D_F &\in \Omega_{D_F} \triangleq \{\Delta D_F : |\Delta D_F| \leq \delta_F\} \\ \Delta D_Q &\in \Omega_{D_Q} \triangleq \{\Delta D_Q : |\Delta D_Q| \leq \delta_Q\} \end{aligned} \quad (9)$$

with δ_F and δ_Q being known functions.

For convenience, the following symbols are used in this paper to represent some particular meanings: $\hat{\bullet}$ represents the estimate of $\bullet$, while $\tilde{\bullet} = \hat{\bullet} - \bullet$ is the error of estimation.

2.3. Control Objective

The control objective can be stated as follows: given a third-order differentiable reference motion trajectory $q_d(t)$, the primary target is to compute a valve spool voltage so that the swing angle q can track $q_d(t)$ as accurately as possible, in spite of heterogeneous model uncertainty.

3. Adaptive Robust Motion Controller Design

In this section, the controller's structure is shown as in Figure 2, which includes the adaptive nonlinear model compensation, as well as the robust feedback design, and the specific meaning of each module is described in detail later.

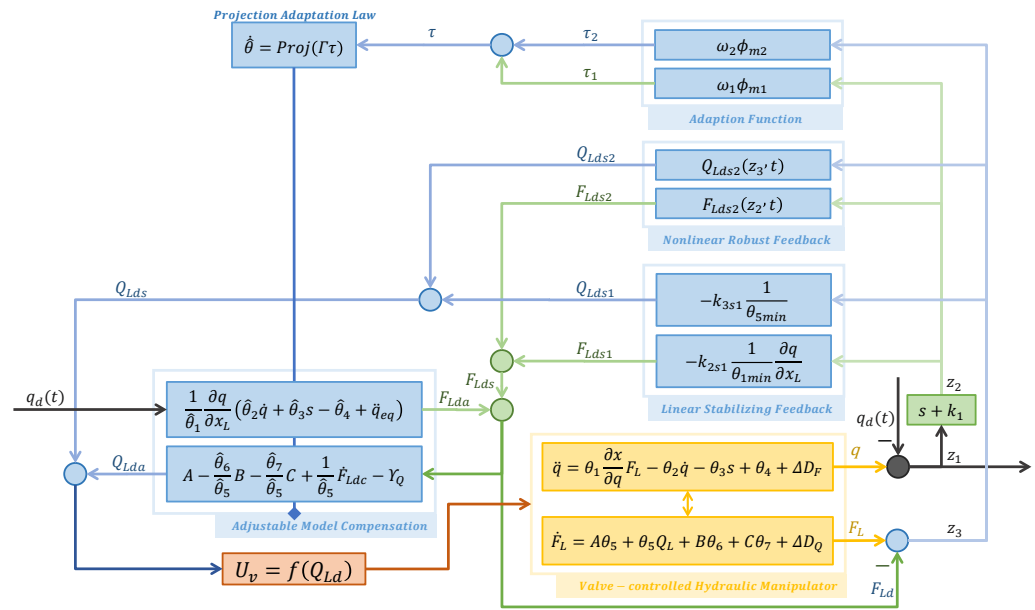


Figure 2. The structure of the ARC controller.

With known θ_{imin} and θ_{imax} , $i = 1, 2, \dots, 7$ mentioned in (9), the discontinuous projection $Proj_{\hat{\theta}}(\bullet)$ is used to update the parameters online:

$$\dot{\hat{\theta}} = Proj_{\hat{\theta}}(\Gamma\tau) \quad (10)$$

in which Γ is a symmetrical positive determined gain matrix and τ is an adaption multinomial, which needs to be specific while designing the controller. $Proj_{\hat{\theta}}(\bullet) = [Proj_{\hat{\theta}_1}(\bullet_1), \dots, Proj_{\hat{\theta}_7}(\bullet_7)]^T$, and $Proj_{\hat{\theta}_i}(\bullet_i)$ can be defined as:

$$Proj_{\hat{\theta}_i}(\bullet_i) = \begin{cases} 0, & \text{if } \hat{\theta}_i = \theta_{imax} \text{ and } \bullet_i > 0 \\ 0, & \text{if } \hat{\theta}_i = \theta_{imin} \text{ and } \bullet_i < 0 \\ \bullet_i, & \text{otherwise} \end{cases} \quad (11)$$

Obviously, as long as the mapping relation meets (10), for any τ , the following conditions can be satisfied:

$$\begin{aligned} (i) \quad & \hat{\theta} \in \Omega_{\theta} \triangleq \{\hat{\theta} : \theta_{min} \leq \hat{\theta} \leq \theta_{max}\} \\ (ii) \quad & \tilde{\theta}^T (\Gamma^{-1} Proj_{\hat{\theta}}(\Gamma\tau) - \tau) \leq 0, \quad \forall \tau \end{aligned} \quad (12)$$

In the following, the recursive backstepping ARC design is used, which aims to synthesize a valve-controlled voltage signal to realize accurate tracking of the swing motion.

3.1. Step 1

To represent the control target of the swing motion, the output tracking error $z_1 = q - q_d$ is defined. Then, we define a switching-function-like quantity as:

$$z_2 = \dot{z}_1 + k_1 z_1 = \dot{q} - \dot{q}_{eq}, \quad \dot{q}_{eq} \triangleq \dot{q}_d - k_1 \dot{z}_1 \quad (13)$$

with $k_1 > 0$ being a customized constant and $q_d(t)$ being a known reference motion trajectory. The transfer function between z_1 and z_2 expressed as $G(s) = (Z_1(s)/Z_2(s)) = 1/(s + k_1)$ is stable, which means the equivalent conditions for z_1 converging to a small value is to let z_2 converge to a small value. Therefore, the subsequent target is to converge z_2 to the minimum, while guaranteeing sufficient transient performance.

Noticing (7), $\dot{z}_2$ can be further expressed as:

$$\begin{aligned} \dot{z}_2 &= \ddot{q} - \ddot{q}_{eq}, \quad \ddot{q}_{eq} \triangleq \ddot{q}_d - k_1 \dot{z}_1 \\ &= \theta_1 \frac{\partial x}{\partial q} F_L - \theta_2 \dot{q} - \theta_3 s + \theta_4 + \Delta D_F - \ddot{q}_{eq} \end{aligned} \quad (14)$$

In this step, it is F_L that is the virtual control input. Therefore, following the design approach shown in Figure 2, the proposed control law F_{Ld} for F_L is given by:

$$\begin{aligned} F_{Ld} &= F_{Lda} + F_{Lds} \\ F_{Lda} &= \frac{1}{\hat{\theta}_1} \frac{\partial q}{\partial x_L} (\hat{\theta}_2 \dot{q} + \hat{\theta}_3 s - \hat{\theta}_4 + \ddot{q}_{eq}) \\ F_{Lds} &= F_{Lds1} + F_{Lds2} \\ F_{Lds1} &= -k_{2s1} \frac{1}{\theta_{1min}} \frac{\partial q}{\partial x_L} z_2, \quad k_{2s1} \geq k_2 + g_{m1} \|\Gamma \phi_{m1}\|^2 \omega_1 \omega_2 \\ \tau_1 &= \omega_1 \phi_{m1} z_2 \end{aligned} \quad (15)$$

in which the virtual control law F_{Ld} contains the adaptive model compensation F_{Lda} and the robust control law F_{Lds} , $\Gamma > 0$ is the adaption rate matrix mentioned in (10) with $\omega_1 > 0$ and $\omega_2 > 0$ being the weighting coefficients, g_{m1} is a coefficient that satisfies $g_{m1} > 1/(2d_m)$ with d_m being a positive constant, τ_1 is a part of the adaption function, and F_{Lds2} is chosen to satisfy the following robust performance conditions as:

$$\begin{aligned} (i) \quad & z_2 F_{Lds2} \leq 0 \\ (ii) \quad & z_2 (\theta_1 \frac{\partial x_L}{\partial q} F_{Lds2} - \phi_{m1}^T \tilde{\theta} + \Delta D_F) \leq \varepsilon_1 \end{aligned} \quad (16)$$

with ε_1 being a design parameter.

Since the output pressure F_L is not a directly controllable physical quantity, additional definitions about the deviation between F_L and F_{Ld} as $z_3 = F_L - F_{Ld}$ are necessary. So far, substituting (15) into (14), the error dynamics' form of z_2 can be expressed as:

$$\dot{z}_2 = -k_{2s1} \frac{\theta_1}{\theta_{1min}} z_2 + (\theta_1 \frac{\partial x_L}{\partial q} F_{Lds2} - \phi_{m1}^T \tilde{\theta} + \Delta D_F) + \theta_1 \frac{\partial x_L}{\partial q} z_3 \quad (17)$$

where ϕ_{m1} is defined as:

$$\phi_{m1} = [\frac{\partial x_L}{\partial q} F_{Lda}, -\dot{q}, -s, 1, 0, 0, 0]^T \quad (18)$$

3.2. Step 2

The purpose of this step is to design an appropriate control law such that it makes z_3 small or converge to zero and synthesize the control signals U_v as the valve spool voltage. $z_3 = F_L - F_{Ld}$. According to the third expression in (7), $\dot{z}_3$ can be further expressed as:

$$\begin{aligned} \dot{z}_3 &= \dot{F}_L - \dot{F}_{Ld} \\ &= -A\theta_5 + Q_L\theta_5 + B\theta_6 + C\theta_7 + \Delta D_Q - \dot{F}_{Ld} \end{aligned} \quad (19)$$

where $\dot{F}_{Ld}$ can be divided into the computable part $\dot{F}_{Ldc}$ and the uncomputable part $\dot{F}_{Ldu}$, which can be represented as:

$$\begin{aligned}\dot{F}_{Ld} &= \dot{F}_{Ldc} + \dot{F}_{Ldu} \\ \dot{F}_{Ldc} &= \frac{\partial F_{Ld}}{\partial q} \dot{q} + \frac{\partial F_{Ld}}{\partial \dot{q}} \ddot{q} + \frac{\partial F_{Ld}}{\partial t} \\ \dot{F}_{Ldu} &= \frac{\partial F_{Ld}}{\partial \hat{q}} (\ddot{q} - \ddot{\hat{q}}) + \frac{\partial F_{Ld}}{\partial \hat{\theta}} \dot{\hat{\theta}}\end{aligned}\quad (20)$$

with $\hat{q} = \hat{\theta}_1 \frac{\partial x_L}{\partial \dot{q}} F_L - \hat{\theta}_2 \dot{q} - \hat{\theta}_3 s + \hat{\theta}_4$ being the estimate of $\ddot{q}$. In (20), $\dot{F}_{Ldc}$ is able to be restrained by an adaptive robust control law, but $\dot{F}_{Ldu}$ is unknown, which has to be processed by the linear stabilizing feedback approach.

For (19), Q_L is considered as the virtual control input of the dynamics equation. In order for F_L to track F_{Ld} synthesized in Step 1 as closely as possible, imitating (15), the control function Q_{Ld} for Q_L is synthesized as:

$$\begin{aligned}Q_{Ld} &= Q_{Lda} + Q_{Lds} \\ Q_{Lda} &= A - \frac{\hat{\theta}_6}{\hat{\theta}_5} B - \frac{\hat{\theta}_7}{\hat{\theta}_5} C + \frac{1}{\hat{\theta}_5} \dot{F}_{Ldc} - Y_Q \\ Q_{Lds} &= Q_{Lds1} + Q_{Lds2} \\ Q_{Lds1} &= -k_{3s1} \frac{1}{\theta_{5min}} z_3, \quad k_{3s1} \geq k_3 + d_m \left\| \frac{\partial F_{Ld}}{\partial \hat{\theta}} \right\|^2 + g_{m2} \|\Gamma \phi_{m2}\|^2 \omega_2^2 \\ \tau_2 &= \omega_2 \phi_{m2} z_3\end{aligned}\quad (21)$$

where $Y_Q = (\hat{\theta}_1/\hat{\theta}_5)(\omega_1/\omega_2)(\partial x_L/\partial q)z_2$ is the backstepping compensation item, which is used to eliminate the additional items generated in (17). $g_{m2} > 1/(2d_m)$ is the same as g_{m1} . τ_2 is the other part of the adaption function, as mentioned in (15), and Q_{Lds2} is the nonlinear robust feedback term, which satisfies the following robust performance conditions:

$$\begin{aligned}(i) \quad & z_3 Q_{Lds2} \leq 0 \\ (ii) \quad & z_3 (\theta_5 Q_{Lds2} - \phi_{m2}^T \tilde{\theta} + \frac{\partial F_{Ld}}{\partial \dot{q}} \Delta D_F + \Delta D_Q) \leq \varepsilon_2\end{aligned}\quad (22)$$

with ε_2 being a design parameter.

Ignoring the fast dynamics from U_v to Q_L and substituting Q_{Ld} in (21) into Q_L in (19), the error dynamics' form of z_3 can be expressed as:

$$\dot{z}_3 = -k_{3s1} \frac{\theta_5}{\theta_{5min}} z_3 + (\theta_5 Q_{Lds2} - \phi_{m2}^T \tilde{\theta} + \frac{\partial F_{Ld}}{\partial \dot{q}} \Delta D_F + \Delta D_Q) - \frac{\partial F_{Ld}}{\partial \hat{\theta}} \dot{\hat{\theta}} - \frac{\omega_1}{\omega_2} \frac{\partial x_L}{\partial q} \theta_1 z_2 \quad (23)$$

where ϕ_{m2} is defined as:

$$\phi_{m2} = [\frac{\partial x_L}{\partial q} (\frac{\omega_1}{\omega_2} z_2 - \frac{\partial F_{Ld}}{\partial \dot{q}} F_L), \frac{\partial F_{Ld}}{\partial \dot{q}} \dot{q}, \frac{\partial F_{Ld}}{\partial \dot{q}} s, -\frac{\partial F_{Ld}}{\partial \dot{q}}, Q_{Lda} - A, B, C]^T \quad (24)$$

In addition, for the online estimation of unknown parameter set θ , the adaption function τ mentioned in (10) is synthesized by:

$$\tau = \tau_1 + \tau_2 = \omega_1 \phi_{m1} z_2 + \omega_2 \phi_{m2} z_3 \quad (25)$$

By the discontinuous projection type adaption law in (11), the influence of parameter uncertainty will be reduced.

Up to now, the ARC design process is over, but in order to obtain the final control output, the calculation about the valve spool voltage is necessary. Noticing (5), the valve control signals U_v can be calculated finally as:

$$U_v = \frac{Q_{Ld}/K_v}{(A_1/V_1)k_{q1}\sqrt{\Delta P_1} + (A_2/V_2)k_{q2}\sqrt{\Delta P_2}} \quad (26)$$

With the adaptive robust control law (15), as well as (21), and the projection type adaptation law (10) with adaptation function (25) for θ defined in (8), the following conclusions can be drawn.

Theorem 1. *The output tracking error is a bounded quantity with guaranteed transient performance and accuracy quantified by:*

$$V(t) \leq \exp(-\lambda t)V(0) + \frac{\varepsilon}{\lambda}[1 - \exp(-\lambda t)] \quad (27)$$

with $V = (1/2)\omega_1 z_2^2 + (1/2)\omega_2 z_3^2$, $\lambda = 2 \times \min\{k_2, k_3\}$, $\varepsilon = \omega_1 \varepsilon_1 + \omega_2 \varepsilon_2$. It is worth noting that the physical quantity of ω_1 and ω_2 in V is obviously intended to balance the huge difference in order of magnitude between z_2 and z_3 due to their different dimensions. Furthermore, they will be used to adjust the proportion of the feedback and feedforward quantities in the inverse calculation of the voltage U_v .

Proof of Theorem 1. Noticing the error dynamics of $\dot{z}_2$ in (17) and $\dot{z}_3$ in (23), $\dot{V}$ can be expressed as:

$$\begin{aligned} \dot{V} &= \omega_1 z_2 \dot{z}_2 + \omega_2 z_3 \dot{z}_3 \\ &= \omega_1 z_2 \left[-k_{2s1} \frac{\theta_1}{\theta_{1min}} z_2 + \left(\theta_1 \frac{\partial x_L}{\partial q} F_{Lds2} - \phi_{m1}^T \tilde{\theta} + \Delta D_F \right) + \theta_1 \frac{\partial x_L}{\partial q} z_3 \right] \\ &\quad + \omega_2 z_3 \left[-k_{3s1} \frac{\theta_5}{\theta_{5min}} z_3 + \left(\theta_5 Q_{Lds2} - \phi_{m2}^T \tilde{\theta} + \frac{\partial F_{Ld}}{\partial \dot{q}} \Delta D_F + \Delta D_Q \right) \right] \\ &\quad - \omega_2 z_3 \left(\frac{\partial F_{Ld}}{\partial \hat{\theta}} \dot{\hat{\theta}} + \frac{\omega_1}{\omega_2} \frac{\partial x_L}{\partial q} \theta_1 z_2 \right) \\ &= -k_{2s1} \frac{\theta_1}{\theta_{1min}} \omega_1 z_2^2 - k_{3s1} \frac{\theta_5}{\theta_{5min}} \omega_2 z_3^2 - \omega_2 z_3 \frac{\partial F_{Ld}}{\partial \hat{\theta}} \dot{\hat{\theta}} \\ &\quad + \omega_1 z_2 \left(\theta_1 \frac{\partial x_L}{\partial q} F_{Lds2} - \phi_{m1}^T \tilde{\theta} + \Delta D_F \right) \\ &\quad + \omega_2 z_3 \left(\theta_5 Q_{Lds2} - \phi_{m2}^T \tilde{\theta} + \frac{\partial F_{Ld}}{\partial \dot{q}} \Delta D_F + \Delta D_Q \right) \end{aligned} \quad (28)$$

In view of the adaption law (10) and the triangle inequality $\sqrt{2(x^2 + y^2)} \geq (x + y)$, the inequation can be obtained as:

$$\begin{aligned} \|\dot{\hat{\theta}}\|^2 &= \|\text{Proj}_{\hat{\theta}}(\Gamma(\omega_1 \phi_{m1} z_2 + \omega_2 \phi_{m2} z_3))\|^2 \\ &\leq \|\Gamma(\omega_1 \phi_{m1} z_2 + \omega_2 \phi_{m2} z_3)\|^2 \\ &\leq 2\|\Gamma \phi_{m1}\|^2 \omega_1^2 z_2^2 + 2\|\Gamma \phi_{m2}\|^2 \omega_2^2 z_3^2 \end{aligned} \quad (29)$$

Due to the setting that $g_{m1} \geq 1/(2d_m)$, as well as $g_{m2} \geq 1/(2d_m)$ and the fact that $(x + y) \geq 2\sqrt{xy}$, the following inequation can be drawn:

$$\begin{aligned} -z_3 \frac{\partial F_{Ld}}{\partial \hat{\theta}} \dot{\hat{\theta}} &\leq \left| z_3 \frac{\partial F_{Ld}}{\partial \hat{\theta}} \dot{\hat{\theta}} \right| \\ &\leq d_m \left\| \frac{\partial F_{Ld}}{\partial \hat{\theta}} \right\|^2 z_3^2 + \frac{1}{4d_m} \|\dot{\hat{\theta}}\|^2 \\ &\leq d_m \left\| \frac{\partial F_{Ld}}{\partial \hat{\theta}} \right\|^2 z_3^2 + g_{m1} \|\Gamma \phi_{m1}\|^2 \omega_1^2 z_2^2 + g_{m2} \|\Gamma \phi_{m2}\|^2 \omega_2^2 z_3^2 \end{aligned} \quad (30)$$

Then, substituting (30) into (28) and reviewing the conditions in (15) and (21), the derivative of $V(t)$ in (28) can be further denoted by:

$$\begin{aligned} \dot{V} &\leq -k_{2s1} \omega_1 z_2^2 + g_{m1} \|\Gamma \phi_{m1}\|^2 \omega_1^2 \omega_2 z_2^2 \\ &\quad - k_{3s1} \omega_2 z_3^2 + d_m \left\| \frac{\partial F_{Ld}}{\partial \hat{\theta}} \right\|^2 \omega_2 z_3^2 + g_{m2} \|\Gamma \phi_{m2}\|^2 \omega_2^3 z_3^2 \\ &\quad + \omega_1 z_2 (\theta_1 \frac{\partial x_L}{\partial q} F_{Lds2} - \phi_{m1}^T \tilde{\theta} + \Delta D_F) \\ &\quad + \omega_2 z_3 (\theta_5 Q_{Lds2} - \phi_{m2}^T \tilde{\theta} + \frac{\partial F_{Ld}}{\partial \dot{q}} \Delta D_F + \Delta D_Q) \\ &\leq -k_2 \omega_1 z_2^2 - k_3 \omega_2 z_3^2 + \omega_1 z_2 (\theta_1 \frac{\partial x_L}{\partial q} F_{Lds2} - \phi_{m1}^T \tilde{\theta} + \Delta D_F) \\ &\quad + \omega_2 z_3 (\theta_5 Q_{Lds2} - \phi_{m2}^T \tilde{\theta} + \frac{\partial F_{Ld}}{\partial \dot{q}} \Delta D_F + \Delta D_Q) \end{aligned} \quad (31)$$

Considering the robust performance conditions (ii) in (16) and (22), one can obtains:

$$\begin{aligned} \dot{V} &\leq -k_2 \omega_1 z_2^2 - k_3 \omega_2 z_3^2 + \omega_1 \varepsilon_1 + \omega_2 \varepsilon_2 \\ &\leq -\lambda V + \varepsilon \end{aligned} \quad (32)$$

which proves (27). $\square$

Theorem 2. After a finite time t_0 , if the model uncertainties are due to parametric uncertainties only, which means $\Delta D_F = 0$ and $\Delta D_Q = 0$, the swing angle q can track the target trajectory $q_d(t)$ asymptotically, i.e., $z_1 \rightarrow 0$ as $t \rightarrow \infty$ for any positive gain k_i , $i = 1, 2, 3$ and ε_j , $j = 1, 2$.

Proof of Theorem 2. To prove Theorem 2, $V_\theta = V + (1/2)\tilde{\theta}^T \Gamma^{-1} \tilde{\theta}$ is defined. Because the results of $\phi_i^T \tilde{\theta}$, $i = 1, 2$ are both unidimensional, it is obvious that $\phi_i^T \tilde{\theta} = \tilde{\theta}^T \phi_i$, $i = 1, 2$. Noticing the definition that $\tilde{\theta} = \hat{\theta} - \theta$, $\dot{\tilde{\theta}} = \dot{\hat{\theta}}$ can be deduced. Considering $\Delta D_F = \Delta D_Q = 0$ and the robust performance conditions (i) in (16) and (22) and drawing on the conclusion of (32), with the equations shown in (10) and (25), $\dot{V}_\theta$ can be presented as:

$$\begin{aligned} \dot{V}_\theta &\leq -k_2 \omega_1 z_2^2 - k_3 \omega_2 z_3^2 + \tilde{\theta}^T \Gamma^{-1} (\dot{\tilde{\theta}} - \Gamma \tau) \\ &\quad + \theta_1 \omega_1 \frac{\partial x_L}{\partial q} z_2 F_{Lds2} + \theta_5 \omega_2 z_3 Q_{Lds2} \\ &\leq -k_2 \omega_1 z_2^2 - k_3 \omega_2 z_3^2 + \tilde{\theta}^T (\Gamma^{-1} \text{Proj}_{\hat{\theta}}(\Gamma \tau) - \tau) \\ &\leq -k_2 \omega_1 z_2^2 - k_3 \omega_2 z_3^2 \end{aligned} \quad (33)$$

Therefore, $z_i \in L_2$, $i = 1, 2$ and $\dot{z}_i$, $i = 1, 2$ are bounded. By Barbalat's lemma, it is easy to know $z_2 \rightarrow 0$ as $t \rightarrow \infty$. As mentioned in (13), one can obtain $z_1 \rightarrow 0$ as $t \rightarrow \infty$, which proves Theorem 2. $\square$

4. Comparative Experiments

Several sets of comparative experiments were conducted on the hydraulic manipulator shown in Figure 1. In order to make the experiments more practical, the swing joint should track different kinds of trajectories, while the other joints should be fixed at different angles. Thus, the performance of the proposed method, e.g., tracking precision and robustness to parameter variation, can be verified comprehensively. In addition, common control strategies in this field were applied to conduct the same tracking tasks for comparison.

4.1. Experiment Setup

In order to verify the effectiveness of the ARC strategy, the manipulator driven by the single-rod hydraulic cylinders mentioned in Section 2.1 was used as the controlled object, whose four hydraulic cylinders were controlled by a high-performance proportional valve (4WRPEH6). The 16 bit pressure sensors (KS-Eiz-B16D-MV-530) manufactured by GEFRA Company with a resolution of approximately 1.5 Pa were installed in each chamber of the cylinder. The effective measurement resolution of the swing angle by the 16 bit angle sensor was about 9×10^{-5} rad. The angular velocity cannot be measured by this kind of angle sensor, so the angular velocity $\dot{q}$ needed in the controller design was obtained by the first-order differential method.

All analog measurement signals (the joint angles q , forward and return chamber pressures p_1 and p_2 , and pump-supplied pressures p_s) were fed back to Compact RIO via a plugged 16 bit A/D and D/A board. The calculation process of the control signal relied on LabVIEW software, and the final output was the valve spool voltage U_v . The working frequency of all controllers was set at 1 kHz.

4.2. System Identification and Controller Parameter Setting

In parameter identification and state estimation, a large number of papers (such as [33,34]) have proposed good identification methods. However, the core goal of the control method in this paper was precise motion control, so precise parameters were not necessary. In this experiment, the off-line least-squares method combined with differential filtering was used to obtain approximate values of the adaptive parameters. The identified parameters were used as the initial adaptive values of the controller.

The input voltage of the system was set as a sinusoidal superposition signal, which aimed at exciting the dynamic characteristics of the system and collecting the required data, such as $\dot{q}$, F_L , $\partial x_L / \partial q$, and so on. Considering (1), define $\psi = [\ddot{q}_f, \dot{q}_f, s(\dot{q})_f]^T$, $\Theta = [J, D_f, f]^T$, and $\eta = (\partial x_L / \partial q) F_L$. Through the s-function of MATLAB/Simulink, the filtered value $\bullet_f$ with the matched initial condition can be presented as follows:

$$\bullet_f = \frac{w_n^2}{s^2 + 2\omega_n \xi s + w_n^2} \bullet \quad (34)$$

with $\omega_n = 50$ and $\xi = 0.707$. In particular, the angular velocity $\dot{q}_f$ is calculated as $\mathcal{V}(s) = (w_n^2) / (s^2 + 2\omega_n \xi s + w_n^2) s Q(s)$, where $\mathcal{V}(s)$ is the Laplace transform of $\dot{q}_f$ and $Q(s)$ is the Laplace transform of q . The angular acceleration is calculated as $\Omega(s) = (w_n^2) / (s^2 + 2\omega_n \xi s + w_n^2) s^2 Q(s)$, where $\Omega(s)$ is the Laplace transform of $\ddot{q}_f$. Note that, when obtaining the angular velocity and angular acceleration online for the controller, ω_n was set to 300, whose bandwidth was high enough that the values could be usable. By off-line ordinary least squares, Θ can be obtained as:

$$\Theta = (\psi \cdot \psi^T)^{-1} \psi \eta_f = \left[\frac{4}{5}, 55, 9 \right]^T \quad (35)$$

Thus, $[5/4, 275/4, 45/4, 0, 1.5 \times 10^9, 0, 0]^T$ is used as the initial value for θ in (8), with $\Gamma = \text{diag}\{2 \times 10^{-9}, 2 \times 10^{-5}, 2 \times 10^{-6}, 4 \times 10^{-6}, 0, 2, 2\}$ being the gain for θ . Other main control parameters in ARC were set as $k_1 = 80$, $k_{2s1} = k_{3s1} = 60$ and $(\omega_1 / \omega_2) = 1.05 \times 10^7$.

Besides ARC, three controllers (DRC, PID, and feedforward PID) were tested for comparison. Deterministic robust control (DRC) is the same as ARC, but without parameter adaptation, i.e., $\Gamma = [0]_{7 \times 7}$. PID is the traditional linear control method. Feedforward PID is the controller widely used in industrial control. The parameter adjustment process of PID or feedforward PID must take into account the control effect under different trajectories and postures of the manipulator. Thus, for a particular posture and trajectory, it may be counterproductive to obtain higher accuracy through more limiting parameters. Through tuning, a group of reasonable values as found, which resulted in a good control effect. $K_{p1} = 0.013$, $T_{i1} = 1.2$ s, $T_{d1} = 0.03$ s were set for the PID controller, with $U_{PID} = K_{p1}(z_1 + (1/T_{i1}) \int_0^t z_1 dt + T_{d1}\dot{z}_1)$. $K_{p2} = 0.005$, $T_{i2} = 2.4$ s, $T_{d2} = 0.006$ s, and $K_f = 0.0012$ were set for the feedforward PID controller, with $Q_{FFPID} = K_f\dot{q}_d + K_{p2}(z_1 + (1/T_{i2}) \int_0^t z_1 dt + T_{d2}\dot{z}_1)$ replacing the Q_{Ld} in (21). All parameters set for the above four controllers in the experiments were fixed.

4.3. Comparative Experimental Results

There were two postures set to change the motion parameters of the manipulator. One was Posture A, as in Figure 3 (left), and the other was Posture B, as in Figure 3 (right).

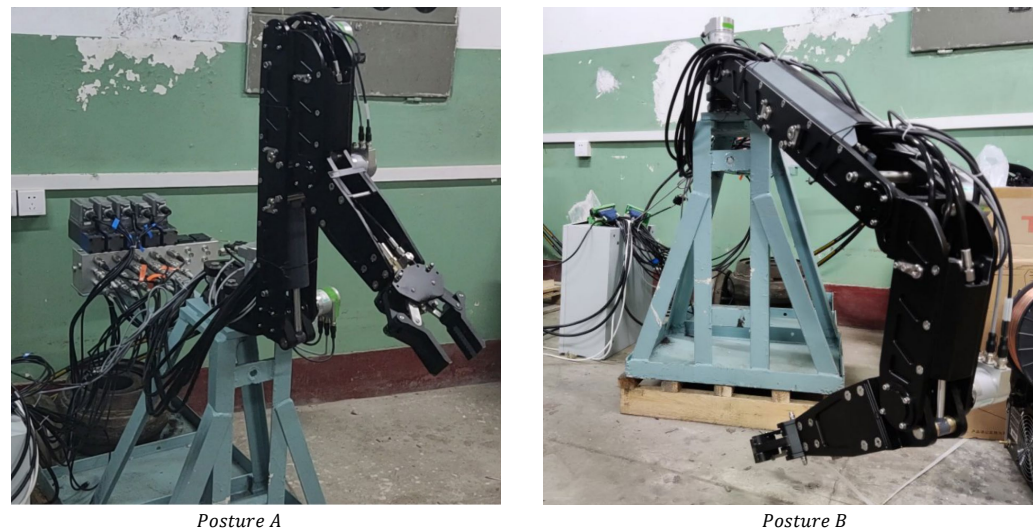


Figure 3. Two postures of the manipulator in the experiments.

In the first group of experiments, a smoothed point-to-point S-curve (the first plot in Figure 4, which is called the P2P trajectory later) was used as the reference trajectory, whose motion parameters were set a the maximum motion angle $\Delta q_d = 1.4$ rad, maximum angular velocity $v_{max} = 0.35$ rad/s, and maximum angular acceleration $a_{max} = 0.35$ rad/s². The test results of four controllers are shown in Figures 4 and 5. *Set 1* means the manipulator in Posture A tracking the P2P trajectory, and *Set 2* means the manipulator in Posture B tracking the P2P trajectory, whose clear and concise description of the experimental set is shown as Table 1. Note that the scales used for each figure in (4) to (7) were different for a clearer visual presentation.

Table 1. Table of the experimental sets' differentiation descriptions.

Label	Reference Trajectory	Manipulator Posture
Set 1	P2P Trajectory	Posture A
Set 2	P2P Trajectory	Posture B
Set 3	Sinusoidal Trajectory	Posture A
Set 4	Sinusoidal Trajectory	Posture B

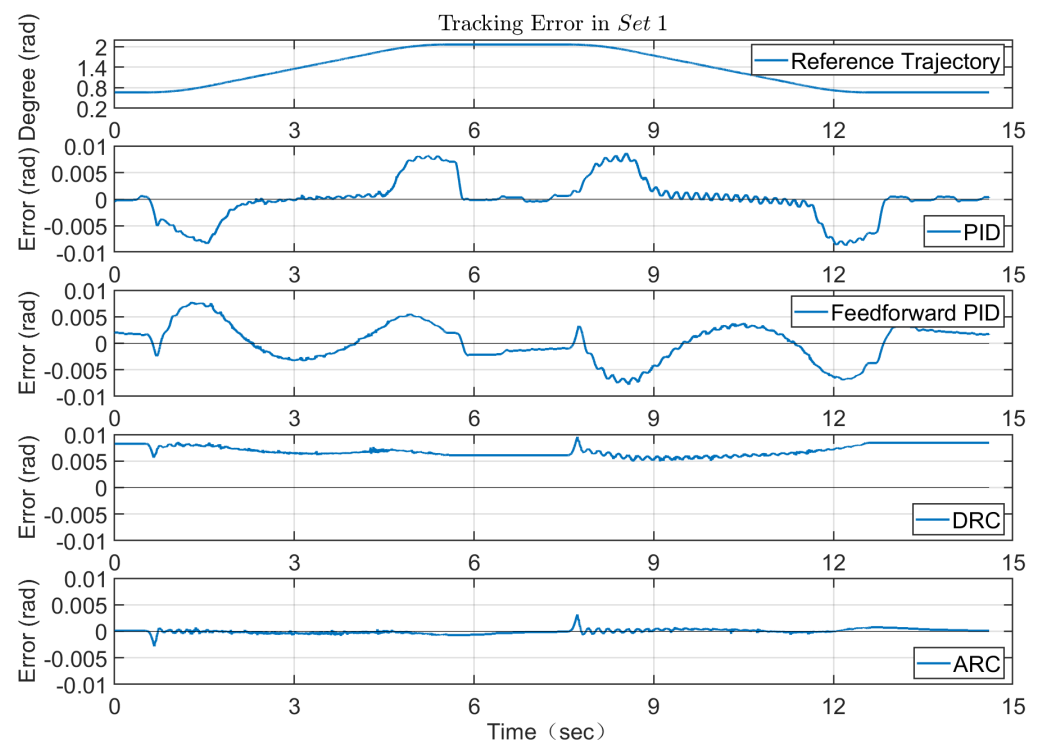


Figure 4. Point-to-point trajectory tracking error comparison diagram with Posture A.

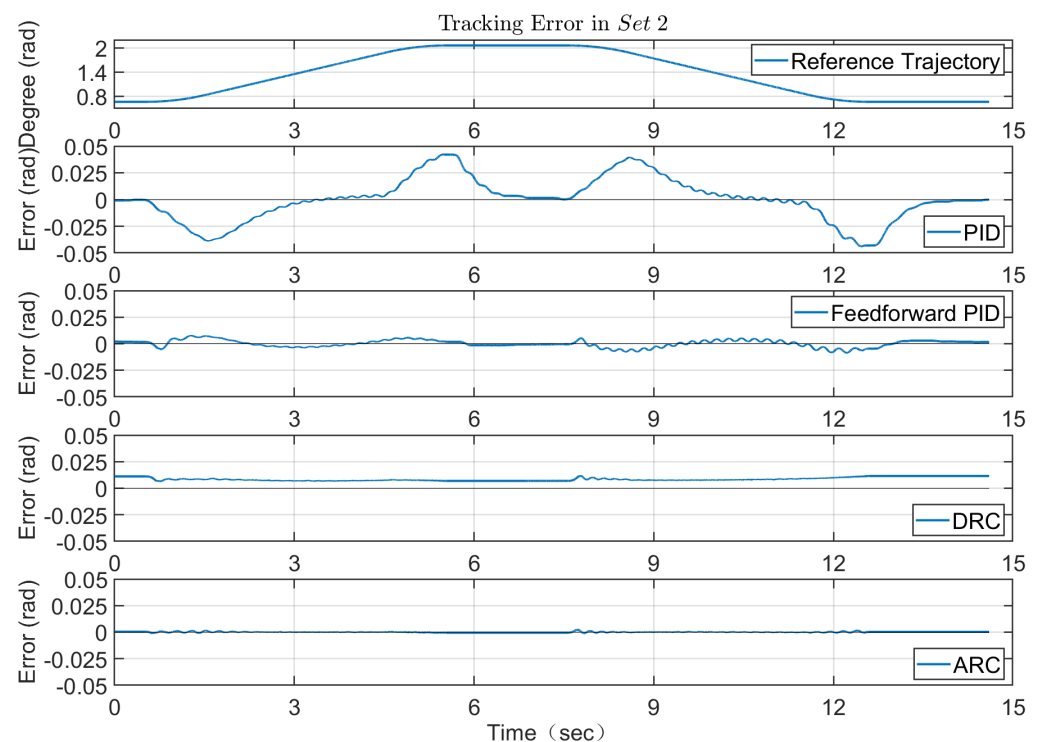


Figure 5. Point-to-point trajectory tracking error comparison diagram with Posture B.

For the horizontal comparison of the four kinds of controllers, the tracking error curves of the four controllers in Figures 4–7 are all fixed in the same coordinate range, while the ARC's amplified tracking error curve is placed separately later. It can be found that no matter whether in *Set 1* or *Set 2*, PID could not deal with the aggressive acceleration, and there was an obvious persistent hysteresis. Compared with PID, feedforward PID had a certain improvement in angle tracking. The control effect in DRC still had a slight

offset compared with ARC, which was caused by unmodeled errors and inaccurate initial parameter values, while ARC's control effect was superior to the other three controllers in both experiments.

The tracking tests of the sinusoidal trajectory (the first plot in Figure 6) were also added to the experiment, and the results are shown in Figures 6 and 7. The trajectory's amplitude $A_d = 0.7$ rad and period $T_d = 6$ s. *Set 3* means the manipulator in Posture A tracking the sinusoidal trajectory. *Set 4* means the manipulator in Posture B tracking the sinusoidal trajectory.

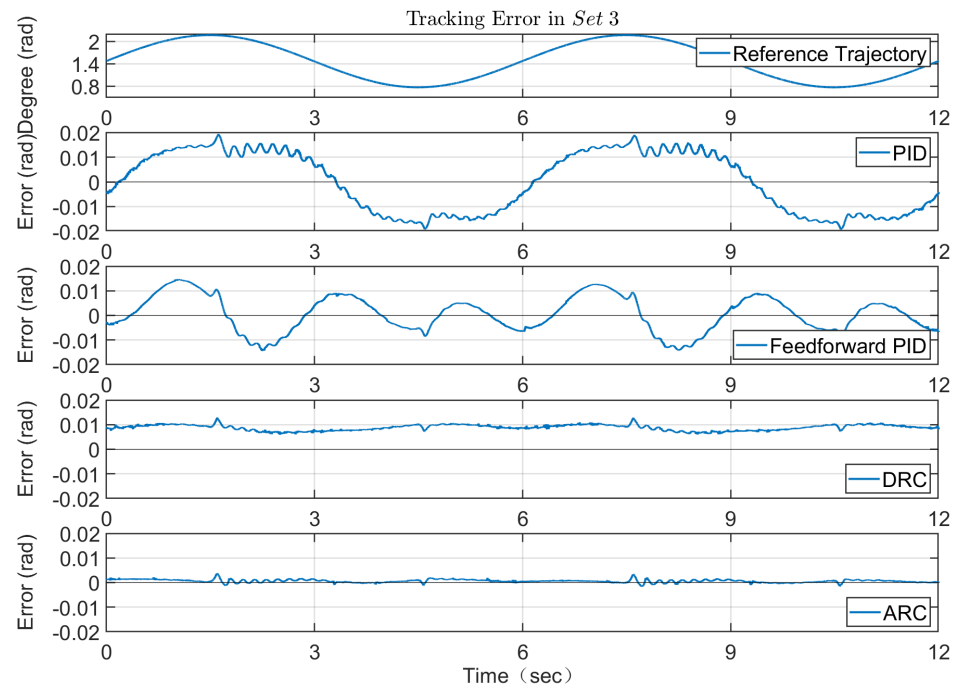


Figure 6. Sinusoidal trajectory tracking error comparison diagram with Posture A.

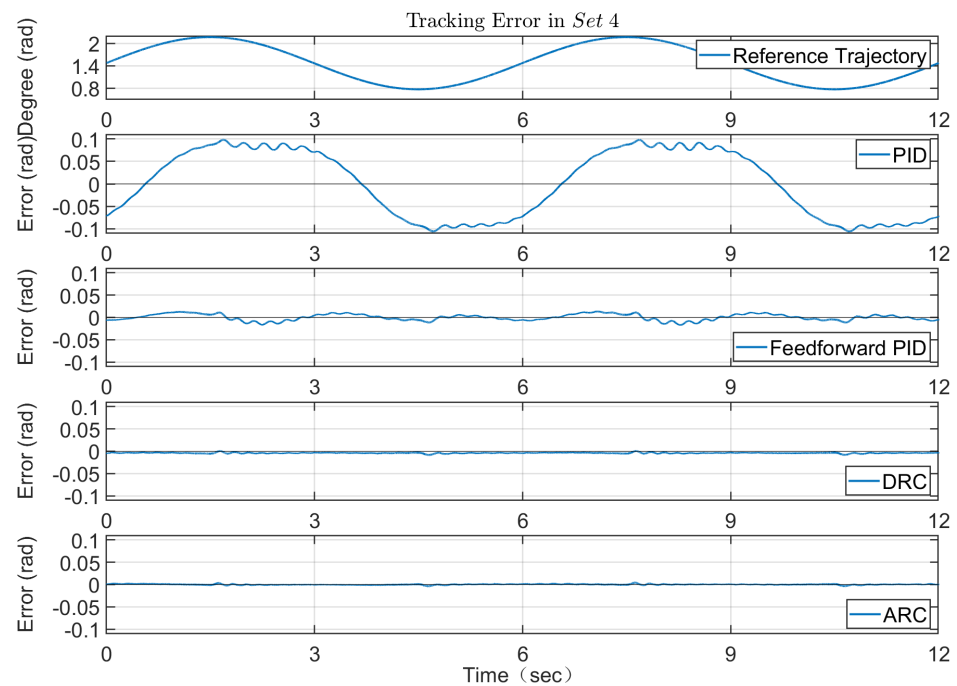


Figure 7. Sinusoidal trajectory tracking error comparison diagram with Posture B.

In sinusoidal tracking, the limitation of PID was further magnified, especially in *Set 4*. The tracking effect of feedforward PID for the period of acceleration changing dramatically was not ideal, and its maximum error was even similar to that of PID in *Set 3*. Generally, the performance of feedforward PID was even better than DRC in some conditions. Although DRC is composed of feedforward model compensation and robust feedback, it lacks an integration effect. In *Set 1* and *Set 3*, the tracking error in DRC was always greater than zero, while that of *Set 2* and *Set 4* was close to zero. On the one hand, this confirmed that the change of the posture of the manipulator significantly changed the state of the system, which could be approximated as the change of the momentum of inertia. On the other hand, this showed that the pre-set nominal model was more similar to the system when the manipulator was in “Posture B”. As a result, the nominal momentum of inertia in DRC was too large compared to its true value when the manipulator was in “Posture A”, which made $\hat{\theta}_i$ so small that the feedforward compensation F_{Lda} was inaccurate. In contrast, ARC with the integration effect could provide better control performance.

To better demonstrate the control effect of different controllers, the average $\mu(e)$, maximum $M(e)$, and standard deviation $\sigma(e)$ of the tracking errors were calculated and shown in Figures 8–10, where $\mu(e) = (\sum_1^n |e_i|)/n$, $M(e) = \max\{e_i\}$, and $\sigma(e) = (\sum_1^n (e_i - \mu)^2/n)^{-1/2}$ with $e = q - q_d$. Noting that the display of *Set 4* in PID is shown incompletely, its values were much higher than the others.

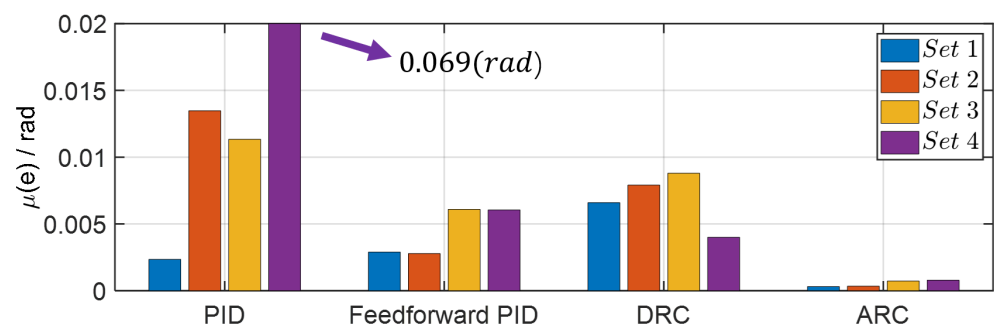


Figure 8. Average tracking error in 4 controllers.

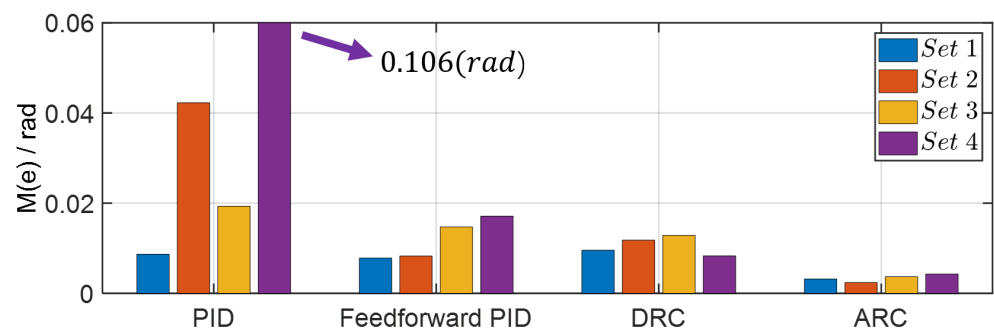


Figure 9. Maximum tracking error in 4 controllers.

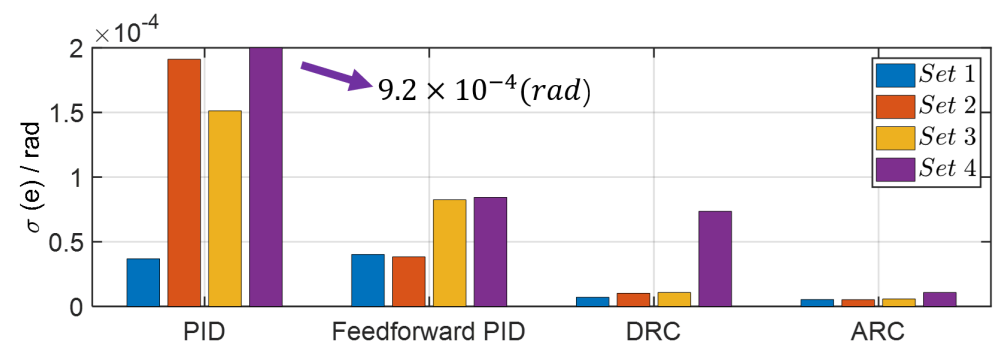


Figure 10. Standard deviation of tracking error in 4 controllers.

In the comparison of Figures 8–10, it can be found that PID was obviously influenced by the reference trajectory and the postures of the manipulator. Feedforward PID could largely resist the influence of the changes of the motion parameters. In terms of the average tracking error, the control effects of feedforward PID and DRC were similar, but DRC had a smaller standard deviation. The control effect of ARC was superior to the other three controllers in all aspects. The comparison between DRC and ARC illustrated the effectiveness of the parameter adaptation in (10).

In order to further illustrate the effectiveness of ARC for hydraulic manipulator model compensation, the feedforward compensation of ARC and feedforward PID is shown as Figures 11 and 12. In the two figures, the feedforward compensation of ARC was mainly calculated as Q_{Lda} , even though there was still a little feedback signal mixed in it. The feedforward signal of feedforward PID was mainly calculated as $K_f \dot{q}$.

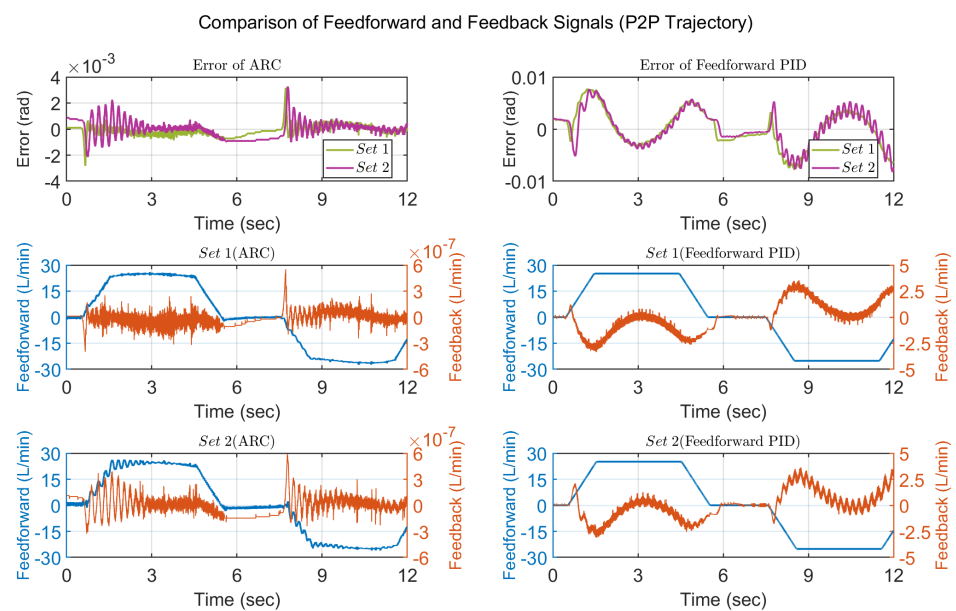


Figure 11. The comparison of feedforward and feedback between ARC and feedforward PID in the P2P trajectory.

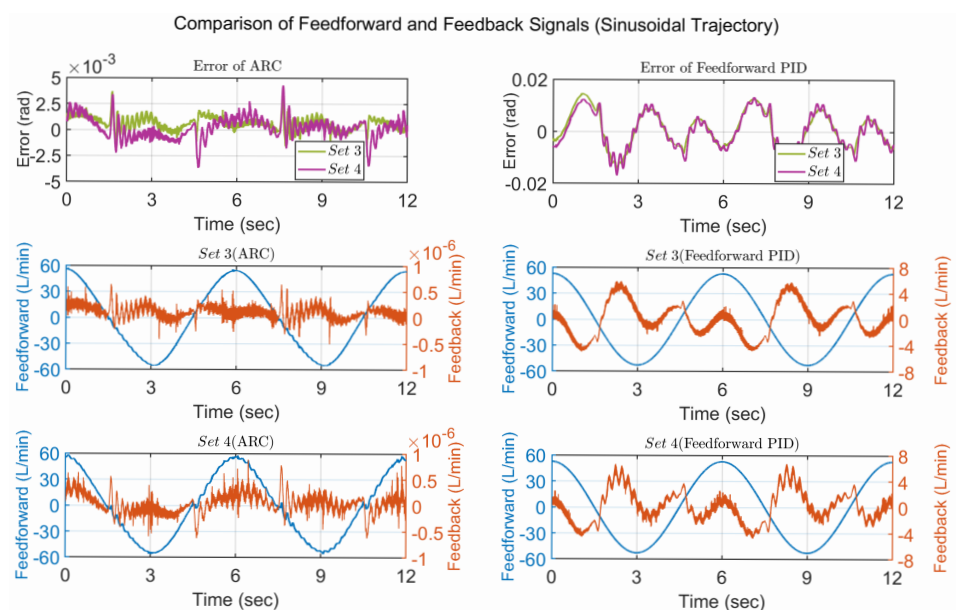


Figure 12. The comparison of feedforward and feedback between ARC and feedforward PID in the sinusoidal trajectory.

By comparing the two figures, it can be found that the two kinds of feedforward compensation were roughly the same in the trend and the order of magnitude. The feedforward compensation of the feedforward PID depends entirely on the velocity of the reference trajectory, which is determined by the design structure of the controller. Differently, based on the similar general trend, ARC has a more subtle adjustment of the feedforward compensation, and it is this adjusted value that is really needed in the control. The more accurate the feedforward model compensation is, the higher the control precision is. In any experimental set, the feedforward controls of ARC largely provided the necessary compensation, while guaranteeing that its feedback only needed to be kept at a small value, which showed indirectly that the model compensation of the ARC-controlled system was effective.

Figure 13 shows the vertical comparison of the tracking error of ARC when two different reference trajectories were given and the manipulator was set up in different postures. Throughout the experiment, the tracking error of ARC was always within 5×10^{-3} rad in the four cases. In addition, after large acceleration and deceleration, the tracking error could quickly return to the measurement noise level of 9×10^{-5} rad. It is worth noting that, whether tracking the P2P trajectory or the sinusoidal trajectory, when the hydraulic cylinder was about to start moving from the stopped state, the system would overshoot relatively more than in other processes, which will be the focus of our subsequent research.

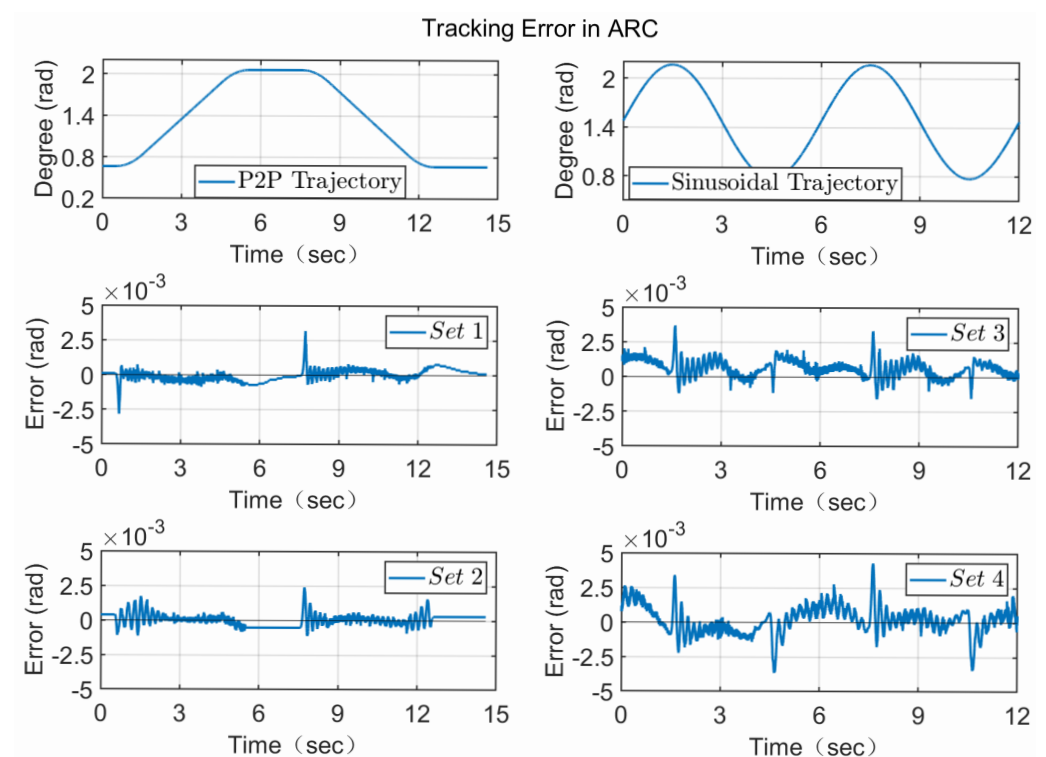


Figure 13. The tracking error comparison of ARC in different cases.

5. Conclusions

In this paper, the special mechanism configuration and high-order nonlinear dynamic characteristics of the hydraulic manipulator were fully considered, which included the parametric uncertainties and the uncertain nonlinearities. To make the control design more applicable to engineering practice, each joint was controlled independently, instead of directly based on its coupling dynamics, and the first swing joint was controlled as an example. Namely, the control precision was guaranteed by the adaptive nonlinear model compensation, as well as the robust feedback design, and the performance of the closed-loop control was strictly demonstrated. For the experiment, the changes of the

dynamics' parameters, which were caused by the changes of its posture, were compensated by the projection adaptation law, and the robust feedback term eliminated the effect of the external interference, which ensured that the error was in the same order of magnitude. Therefore, compared with PID and other traditional methods, the ARC controller achieved higher precision under the four conditions with different trajectories and postures. In the future, more degrees of freedom will be adopted for the control design of the hydraulic manipulator, and more attention will be paid to the dynamic characteristics during the start–stop state switch.

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