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Multilayer Neuroadaptive Output Feedback Control of Hydraulic Manipulators with Disturbance Compensation

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Abstract

In this study, a novel multilayer neuroadaptive output feedback controller is proposed for n -degree-of-freedom (n -DOF) serial hydraulic manipulators. This approach utilizes measurable position signals only while introducing a multilayer neuroadaptive observer to estimate modeling uncertainties and unknown states simultaneously. Notably, this controller can compensate for both endogenous uncertainties and exogenous disturbances simultaneously. Simulation results validate the feasibility and effectiveness of the developed controller, confirming its practical potential for hydraulic manipulator applications.

Keywords: hydraulic manipulator; output feedback control; multilayer neural networks; disturbance observer

MSC: 68T07; 93B52; 93C10; 93C40; 93C73; 93D21

1. Introduction

Compared to state feedback control, output feedback control (OFC) only relies on the measurable system output information [1]. In practical systems, not all system states are directly measurable. This limitation underscores the significance of designing controllers based on output feedback [2]. OFC not only addresses the challenge of unmeasurable state variables but also reduces costs by minimizing sensor usage [3,4]. Practical systems often exhibit complex, known nonlinearities as well as numerous unknown factors [5]. These complexities make the design of high-performance OFCs considerably more demanding. However, designing effective OFCs is full of significant challenges.

Hydraulic manipulators have garnered significant research attention owing to their superior payload capacity. Existing control approaches for hydraulic manipulators include adaptive and robust control [6–9], sliding mode control [10,11], and so on. To address exogenous disturbances, filter [12,13] or observer-based control techniques [14–16] have been developed. Moreover, disturbance observer-based adaptive output regulation approach has been proposed in [17]. Notably, fuzzy control [18–21] and neural networks [22,23] play an important role in dealing with endogenous disturbances. Therefore, it is of great research significance to simultaneously handle endogenous and exogenous disturbances in hydraulic robotic arm systems under output feedback conditions. It is worth noting that none of the above methods can handle mismatched disturbances under the output feedback condition.

To enhance the control performance of nonlinear systems, an extended state observer (ESO) based feedback controller is proposed in [24] assuming the existence of external disturbances in the system. By employing the ESO to estimate unknown states, this method



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can be extended to the output feedback condition. In [25], the authors have discussed the capabilities of ESO for estimating uncertainties existing in nonlinear systems. They first discussed the scope of the disturbances that could be observed by the ESO with bounded observing errors were given. They have analyzed the observing errors for several typical disturbances. In [26], the authors have study the disturbance compensation problem of nonlinear systems including multiple-input multiple-output systems with external disturbances. A nonlinear disturbance observer observer is designed to solve the problem that systems face large disturbances. Additionally, due to the existence of the unknown system nonlinear dynamics, neural networks (NNs) are introduced to approximate them. Then, through the combination of adaptive backstepping technology and disturbance compensation technology, a command filtered neuroadaptive control algorithm has been proposed, which introduces the filter to avoid the complicated derivation process of the virtual control function. However, none of the above methods can handle mismatched perturbations.

Inspired by this, we will propose a multilayer neuroadaptive OFC algorithm for hydraulic manipulators. Significantly, the design concepts of the ESO [24,25] and the nonlinear disturbance observer [26,27] will be incorporated to simultaneously estimate the matched and mismatched disturbances. Meanwhile, multilayer neural networks (MNN) [28–30] will be combined to estimate endogenous uncertainties. Although many works (adaptive/robust/fuzzy methods) have been proposed, how to reject the modeling uncertainties including matched and mismatched disturbances simultaneously in output feedback condition still hasn't been resolved. Overall, the major highlights of the proposed algorithm are as follows:

- (1) Only the output state will be utilized. This significantly reduces the sensor requirements, thereby simplifying the system architecture and lowering the implementation costs.
- (2) Matched and mismatched as well as endogenous and exogenous disturbances can be simultaneously compensated.
- (3) The “explosion of complexity” can be avoided since the filter-based backstepping control design method is employed.

Nomenclature: $\hat{\bullet}$ is the estimate of $\bullet$ with $\tilde{\bullet} = \bullet - \hat{\bullet}$ being the estimation error. $\bullet_{\min}$ and $\bullet_{\max}$ are the minimum and maximum values of $\bullet$, respectively. $\text{tr}(\bullet)$ is the trace of matrix $\bullet$. $\min\{\bullet\}$ is the minimum value of $\bullet$. $\kappa_{\max}(\bullet)$ is the maximum eigenvalue of $\bullet$. The subscripts i and j of variables denote $i = 1, 2, 3$ and $j = 1, 2$, respectively. Additionally, $r = 1, 2, \dots, n$ and $p = 2, 3, \dots, n - 1$ with n being the DOF of the system.

2. Problem Description

This paper investigates the motion control problems of n -DOF serial hydraulic manipulators. Notably, the joints of a hydraulic manipulator can be driven by hydraulic cylinders or hydraulic motors. Figure 1a illustrates that all joints are driven by hydraulic cylinders while Figure 1b describes that all joints are driven by hydraulic motors. However, the situation of joint motion driven by a mixture of hydraulic motors and hydraulic cylinders is not illustrated here.

The rigid-body dynamics of n -DOF serial hydraulic manipulators is given by [5]:

$$J(q)\ddot{q} + V_c(q, \dot{q})\dot{q} + G(q) + F_f(\dot{q}) + F_e(q, \dot{q}) + f_d(t) = T_c \quad (1)$$

where $q(t) \in \mathbb{R}^n$, $J(q) \in \mathbb{R}^{n \times n}$ and $V_c(q, \dot{q}) \in \mathbb{R}^{n \times n}$ are the joint angular displacement, the nominal inertial matrix and the centripetal-Coriolis matrix, respectively; $G(q) \in \mathbb{R}^n$ and $F_f(\dot{q}) \in \mathbb{R}^n$ are the gravity vector and the nonlinear friction vector, respectively; $F_e(q, \dot{q}) \in \mathbb{R}^n$ and $f_d(t) \in \mathbb{R}^n$ are the uncertainty related to system states and the time-varying disturbance, respectively; $T_c \in \mathbb{R}^n$ is the control torque which can be expressed as:

$$\begin{aligned}
 T_c &= W_L(A_a P_a - A_b P_b) \\
 W_L &= \text{diag}\{W_{L1}, W_{L2}, \dots, W_{Ln}\}, \quad y_L(q) = \text{diag}\{y_{L1}, y_{L2}, \dots, y_{Ln}\} \\
 W_{Lr} &= \begin{cases} \frac{\partial y_{Lr}(q_r)}{\partial q_r}, & \text{if the actuator is a hydraulic cylinder} \\ 1 & \text{if the actuator is a hydraulic motor} \end{cases}
 \end{aligned} \quad (2)$$

in which y_{Lr} is the displacement of a hydraulic actuator; $A_a \in \mathbb{R}^{n \times n}$ and $A_b \in \mathbb{R}^{n \times n}$ are the effective areas or displacements of hydraulic actuators; $P_a \in \mathbb{R}^n$ and $P_b \in \mathbb{R}^n$ are the actuator chamber pressures.

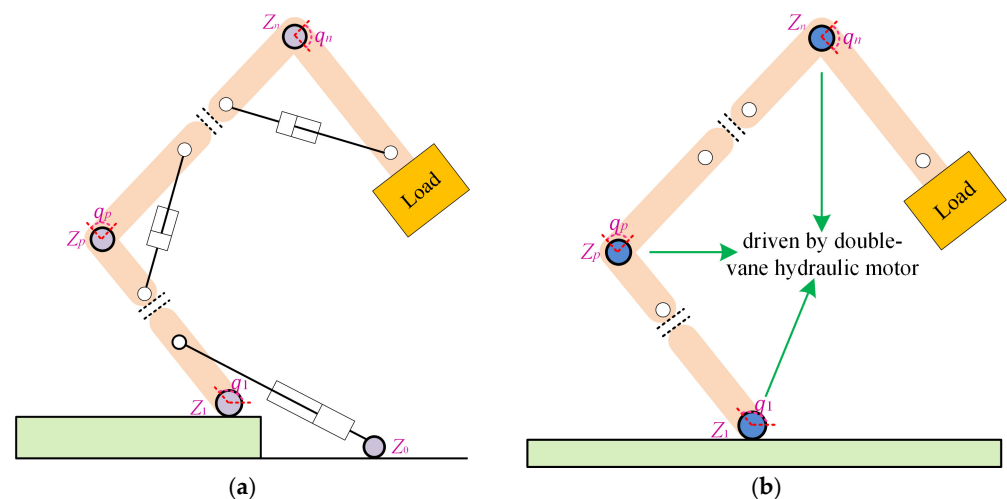


Figure 1. The structures of n -DOF serial hydraulic manipulators. (a) The manipulators driven by hydraulic cylinders; (b) The manipulators driven by hydraulic motors.

The pressure dynamics of the hydraulic actuators can be expressed as:

$$\begin{aligned}
 \dot{P}_a &= \frac{\beta_{ef}}{V_a(q)} (Q_a - A_a W_L \dot{q} - C_{tl} P_{ab}) + Q_{e1}(q, \dot{q}, P_a, P_b) + Q_{d1}(t) \\
 \dot{P}_b &= \frac{\beta_{ef}}{V_b(q)} (A_b W_L \dot{q} - Q_b + C_{tl} P_{ab}) + Q_{e2}(q, \dot{q}, P_a, P_b) + Q_{d2}(t)
 \end{aligned} \quad (3)$$

where β_{ef} is the effective bulk modulus of hydraulic oil; $V_a(q) = V_{a0} + A_a y_L(q)$ and $V_b(q) = V_{b0} - A_b y_L(q)$ are the volumes of the two chambers of a hydraulic actuator with V_{a0} and V_{b0} being the initial volumes; Q_a and Q_b are the flow rates of the two chambers; C_{tl} is the leakage coefficient of a hydraulic actuator; $P_{ab} = P_a - P_b$ is the pressure difference between the two chambers; $Q_{e1}(q, \dot{q}, P_a, P_b) \in \mathbb{R}^n$ and $Q_{e2}(q, \dot{q}, P_a, P_b) \in \mathbb{R}^n$ are the unknown dynamics; $Q_{d1}(t) \in \mathbb{R}^n$ and $Q_{d2}(t) \in \mathbb{R}^n$ are external disturbances.

The flows are described as follows:

$$Q_a = K_a u - 2K_c P_a, \quad Q_b = K_b u + 2K_c P_b \quad (4)$$

where $u \in \mathbb{R}^n$ is the input voltage; $K_a \in \mathbb{R}^{n \times n}$ and $K_b \in \mathbb{R}^{n \times n}$ are the total flow gains; $K_c \in \mathbb{R}^{n \times n}$ is a flow-pressure coefficient matrix.

Define $\psi = [\psi_1^T, \psi_2^T, \psi_3^T]^T \triangleq [q^T, \dot{q}^T, A_a P_a^T - A_b P_b^T]^T$, we have

$$\begin{aligned}
 \dot{\psi}_1 &= \psi_2 \\
 \dot{\psi}_2 &= \psi_3 + \chi_2(\psi_1, \psi_2) + \Delta_2(t, \psi_1, \psi_2, \psi_3) \\
 \dot{\psi}_3 &= R_u u + \chi_3(\psi_1, \psi_2) + \Delta_3(t, \psi_1, \psi_2, P_a, P_b)
 \end{aligned} \quad (5)$$

where

$$\begin{aligned}
\Delta_2(t, \psi_1, \psi_2, \psi_3) &= J^{-1}(\psi_1)[W_L \psi_3 - f_d(t)] - \psi_3 \\
\chi_2(\psi_1, \psi_2) &= J^{-1}(\psi_1) \left[-V_c(\psi_1, \psi_2) \psi_2 - G(\psi_1) - F_f(\psi_2) - F_e(\psi_1, \psi_2) \right] \\
R_u &= \left[\frac{K_a A_a}{V_a(\psi_1)} + \frac{K_b A_b}{V_b(\psi_1)} \right] \beta_{ef}, \quad \chi_3(\psi_1, \psi_2) = - \left[\frac{A_a^2}{V_a(\psi_1)} + \frac{A_b^2}{V_b(\psi_1)} \right] \beta_{ef} W_L \psi_2 \\
\Delta_3(t, \psi_1, \psi_2, P_a, P_b) &= -2\beta_{ef} K_c \left[\frac{A_a P_a}{V_a(\psi_1)} - \frac{A_b P_b}{V_b(\psi_1)} \right] - \left[\frac{A_a}{V_a(\psi_1)} + \frac{A_b}{V_b(\psi_1)} \right] C_{tl} \beta_{ef} P_{ab} \\
&\quad + A_a Q_{e1}(\psi_1, \psi_2, P_a, P_b) - A_b Q_{e2}(\psi_1, \psi_2, P_a, P_b) + A_a Q_{d1}(t) - A_b Q_{d2}(t)
\end{aligned} \tag{6}$$

Control objective: For the n -DOF serial hydraulic manipulator system, a multilayer neuroadaptive OFC algorithm will be designed to meet the following requirements:

- (1) It can compensate for all model uncertainties in system (5).
- (2) It can make ψ_1 track the desired trajectory ψ_{1d} as closely as possible.
- (3) It can ensure that all signals in system (5) are bounded.

Assumption 1. Only $q(t)$ can be measured.

Assumption 2. $\psi_{1d}(t)$ and its first-order time derivative are bounded.

Assumption 3. The unknown dynamics $\chi_2(\psi_1, \psi_2)$ and $\chi_3(\psi_1, \psi_2)$ are first-order continuously differentiable.

Assumption 4. $\Delta_2(t, \psi_1, \psi_2, \psi_3)$ and $\Delta_3(t, \psi_1, \psi_2, P_a, P_b)$ as well as their first-order time derivatives are bounded.

3. Multilayer Neuroadaptive OFC Algorithm Design

3.1. Multilayer Neural Networks

Based on Assumption 3, we can express $\chi_j(\psi_1, \psi_2)$ through the MNN as [28]:

$$\chi_j(\psi_1, \psi_2) = E_j^T \gamma_j(F_j^T \beta_j) + \tau_j(\beta_j) \tag{7}$$

where $E_j \in R^{x_{j1}+1}$ and $F_j \in R^{(x_{j1}+1) \times x_{j2}}$ are the bounded constant ideal weight matrices of the neural networks with x_{j1} and x_{j2} being the number of neurons; $\beta_j \triangleq [1, \psi_1^T, \psi_2^T]^T$ and $\gamma_j(\bullet)$ are inputs and activation functions, respectively; $\tau_j(\bullet)$ are the reconstruction errors.

Noticing (7), $\chi_j(\psi_1, \psi_2)$ can be approximated by:

$$\hat{\chi}_j(\psi_1, \psi_2) = \hat{E}_j^T \gamma_j(\hat{F}_j^T \beta_j) \tag{8}$$

3.2. Multilayer Neuroadaptive State/Uncertainty Observer Design

Firstly, we extend $\tau_2(\beta_2) + \Delta_2(t, \psi_1, \psi_2, \psi_3)$ and $\tau_3(\beta_3) + \Delta_3(t, \psi_1, \psi_2, P_a, P_b)$ as new states ψ_{d2} and ψ_{d3} , respectively. Thus, (5) can be arranged as

$$\begin{cases} \dot{\psi}_1 = \psi_2 \\ \dot{\psi}_2 = \psi_3 + E_2^T \gamma_2(F_2^T \hat{\beta}_2) + \psi_{d2} + W_2(\beta_2, \hat{\beta}_2) \\ \dot{\psi}_3 = R_u u + E_3^T \gamma_3(F_3^T \hat{\beta}_3) + \psi_{d3} + W_3(\beta_3, \hat{\beta}_3) \\ \dot{\psi}_{d3} = \Delta_4(t) \end{cases} \tag{9}$$

where $W_j(\beta_j, \hat{\beta}_j) \triangleq E_j^T \gamma_j(F_j^T \beta_j) - E_j^T \gamma_j(F_j^T \hat{\beta}_j)$.

According to (9) and introducing $\zeta_2 = \psi_{d2} - \rho_2 \psi_2$, a novel multilayer neuroadaptive state/uncertainty observer can be designed as:

$$\begin{cases} \dot{\hat{\psi}}_1 = \hat{\psi}_2 + 4\omega_o(\psi_1 - \hat{\psi}_1) \\ \dot{\hat{\psi}}_2 = \hat{\psi}_3 + \hat{E}_2^T \gamma_2 (\hat{F}_2^T \hat{\beta}_2) + \hat{\psi}_{d2} + 6\omega_o^2(\psi_1 - \hat{\psi}_1) \\ \dot{\hat{\psi}}_3 = R_u u + \hat{E}_3^T \gamma_3 (\hat{F}_3^T \hat{\beta}_3) + \hat{\psi}_{d3} + 4\omega_o^3(\psi_1 - \hat{\psi}_1) \\ \dot{\hat{\psi}}_{d3} = \omega_o^4(\psi_1 - \hat{\psi}_1) \\ \dot{\hat{\psi}}_{d2} = \hat{\zeta}_2 + \rho_2 \hat{\psi}_2 \\ \dot{\hat{\zeta}}_2 = -\rho_2 [\hat{\psi}_3 + \hat{E}_2^T \gamma_2 (\hat{F}_2^T \hat{\beta}_2) + \hat{\zeta}_2 + \rho_2 \hat{\psi}_2] \end{cases} \quad (10)$$

where ω_o and ρ_2 are positive diagonal gains.

By introducing a state vector $\varepsilon_o = [\varepsilon_{o1}^T, \varepsilon_{o2}^T, \varepsilon_{o3}^T, \varepsilon_{o4}^T]^T \triangleq [\tilde{\Psi}_1^T, \tilde{\Psi}_2^T/\omega_o, \tilde{\Psi}_3^T/\omega_o^2, \tilde{\Psi}_{d3}^T/\omega_o^3]^T$, we have:

$$\begin{aligned} \dot{\varepsilon}_o &= \sum_{j=2}^3 B_j \frac{\tilde{E}_j^T \gamma_j (\hat{F}_j^T \hat{\beta}_j) + \hat{E}_j^T \gamma_j' (\hat{F}_j^T \hat{\beta}_j) \tilde{F}_j^T \hat{\beta}_j + G_j + W_j(\beta_j, \hat{\beta}_j)}{\omega_o^{j-1}} \\ &\quad + \omega_o \Phi_o \varepsilon_o + B_2 \frac{\tilde{\zeta}_2 + \rho_2 \omega_o \varepsilon_{o2}}{\omega_o} + B_4 \frac{\Delta_4(t)}{\omega_o^3} \end{aligned} \quad (11)$$

$$\begin{aligned} \dot{\tilde{\zeta}}_2 &= \dot{\psi}_{d2} - \rho_2 [\omega_o^2 \varepsilon_{o3} + E_2^T \gamma_2 (F_2^T \hat{\beta}_2) - \hat{E}_2^T \gamma_2 (\hat{F}_2^T \hat{\beta}_2)] \\ &\quad - \rho_2 [\tilde{\zeta}_2 + \rho_2 \omega_o \varepsilon_{o2} + W_2(\beta_2, \hat{\beta}_2)] \end{aligned} \quad (12)$$

where

$$\Phi_o = \begin{bmatrix} -4 & 1 & 0 & 0 \\ -6 & 0 & 1 & 0 \\ -4 & 0 & 0 & 1 \\ -1 & 0 & 0 & 0 \end{bmatrix}, B_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, B_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, B_4 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \quad (13)$$

$$G_j \triangleq \tilde{E}_j^T \gamma_j' (\hat{F}_j^T \hat{\beta}_j) \tilde{F}_j^T \hat{\beta}_j + E_j^T O_j (\tilde{F}_j^T \hat{\beta}_j)^2 \quad (14)$$

Notably, the matrix C_o meets $\Phi_o^T C_o + C_o \Phi_o = -I$ [31].

3.3. Controller Design

Firstly, we define a set of error variables [32] as:

$$\begin{cases} \zeta_1 = \psi_1 - \psi_{1d} \\ \zeta_2 = \psi_2 - \delta_1^c \\ \zeta_3 = \psi_3 - \delta_2^c \end{cases}, \begin{cases} \tilde{\zeta}_1 = \zeta_1 - \alpha_1 \\ \tilde{\zeta}_2 = \zeta_2 - \alpha_2 \\ \tilde{\zeta}_3 = \zeta_3 - \alpha_3 \end{cases} \quad (15)$$

where δ_{j-1}^c are the filtered values of the virtual control laws δ_{j-1} ; and α_i are generated through an auxiliary system which will be introduced to remove the filtering errors.

Significantly, a set of filters is constructed as [29]:

$$\begin{aligned} \dot{\delta}_{j-1}^c &= \delta_{j-1}^{dc} + 2w_{c(j-1)} (\delta_{j-1} - \delta_{j-1}^c) \\ \dot{\delta}_{j-1}^{dc} &= w_{c(j-1)}^2 (\delta_{j-1} - \delta_{j-1}^c) \end{aligned} \quad (16)$$

in which $w_{c(j-1)}$ are positive gains and δ_{j-1}^{dc} are the filtered values of $\dot{\delta}_{j-1}$.

Define $\varepsilon_{c(j-1)} = [\varepsilon_{c(j-1)1}^T, \varepsilon_{c(j-1)2}^T]^T = [\delta_{j-1} - \delta_{j-1}^c, (\delta_{j-1}^{dd} - \delta_{j-1}^{dc})/w_{c(j-1)}]^T$, we have:

$$\dot{\varepsilon}_{c(j-1)} = w_{c(j-1)} \Phi_c \varepsilon_{c(j-1)} + B_c \frac{\delta_{j-1}^{dd}}{w_{c(j-1)}} \quad (17)$$

where δ_{j-1}^{dd} are the second-order derivatives of δ_{j-1} , $B_c = [0, 1]^T$ and $\Phi_c = [-2, 1; -1, 0]$ [31].

Moreover, the auxiliary system is designed as [32]:

$$\begin{aligned}\dot{\alpha}_1 &= -g_1\alpha_1 + \alpha_2 + (\delta_1^c - \delta_1) \\ \dot{\alpha}_2 &= -g_2\alpha_2 + \alpha_3 + (\delta_2^c - \delta_2) \\ \dot{\alpha}_3 &= -g_3\alpha_3\end{aligned}\quad (18)$$

where g_i are positive gains.

Step 1:

Differentiating ζ_1 along Equations (5), (15) and (18) obtains

$$\dot{\zeta}_1 = \delta_1 + \zeta_2 - \dot{\psi}_{1d} + g_1\alpha_1 \quad (19)$$

Based on Equation (19), δ_1 can be designed as:

$$\delta_1 = -g_1\zeta_1 + \dot{\psi}_{1d} \quad (20)$$

Thus, Equation (19) can be rearranged as:

$$\dot{\zeta}_1 = -g_1\zeta_1 + \zeta_2 \quad (21)$$

Step 2:

Differentiating ζ_2 along Equations (5), (15) and (18) obtains:

$$\dot{\zeta}_2 = \delta_2 + \zeta_3 + E_2^T \gamma_2 (\hat{F}_2^T \hat{\beta}_2) + \psi_{d2} + W_2(\beta_2, \hat{\beta}_2) - \dot{\delta}_1^c + g_2\alpha_2 \quad (22)$$

Therefore, δ_2 can be designed as:

$$\delta_2 = -g_2\zeta_2 - \hat{E}_2^T \gamma_2 (\hat{F}_2^T \hat{\beta}_2) - \hat{\psi}_{d2} + \dot{\delta}_1^c - \zeta_1 \quad (23)$$

Moreover, Equation (22) can be reorganized as:

$$\begin{aligned}\dot{\zeta}_2 &= -g_2\zeta_2 + \zeta_3 - \zeta_1 + g_2\omega_o\varepsilon_{o2} + \tilde{E}_2^T \gamma_2 (\hat{F}_2^T \hat{\beta}_2) + G_2 \\ &+ \hat{E}_2^T \gamma_2' (\hat{F}_2^T \hat{\beta}_2) \tilde{F}_2^T \hat{\beta}_2 + W_2(\beta_2, \hat{\beta}_2) + \tilde{\zeta}_2 + \rho_2\omega_o\varepsilon_{o2}\end{aligned}\quad (24)$$

Step 3:

Differentiating ζ_3 along Equations (5), (15) and (18) obtains

$$\dot{\zeta}_3 = R_u u + E_3^T \gamma_3 (\hat{F}_3^T \hat{\beta}_3) + \psi_{d3} + W_3(\beta_3, \hat{\beta}_3) - \dot{\delta}_2^c + g_3\alpha_3 \quad (25)$$

Based on Equation (25), u can be designed as:

$$u = \left[-g_3\zeta_3 - \hat{E}_3^T \gamma_3 (\hat{F}_3^T \hat{\beta}_3) - \hat{\psi}_{d3} + \dot{\delta}_2^c - \hat{\zeta}_2 \right] / R_u \quad (26)$$

Substituting Equation (26) into Equation (25) yields:

$$\begin{aligned}\dot{\zeta}_3 &= -g_3\zeta_3 - \zeta_2 + \omega_o\varepsilon_{o2} + g_3\omega_o^2\varepsilon_{o3} + \tilde{E}_3^T \gamma_3 (\hat{F}_3^T \hat{\beta}_3) \\ &+ \hat{E}_3^T \gamma_3' (\hat{F}_3^T \hat{\beta}_3) \tilde{F}_3^T \hat{\beta}_3 + G_3 + W_3(\beta_3, \hat{\beta}_3) + \omega_o^3\varepsilon_{o4}\end{aligned}\quad (27)$$

3.4. Main Results

Theorem 1. With the neuroadaptive laws updated as:

$$\begin{aligned}\dot{\hat{E}}_j &\triangleq \text{Proj} \left\{ \Gamma_j \left[\eta_j \gamma_j (\hat{F}_j^T \hat{\beta}_j) \hat{\zeta}_j + \mu_{oj} f_j(\varepsilon_{o1}) \frac{\gamma_j (\hat{F}_j^T \hat{\beta}_j)}{\omega_o^{j-1}} - \theta_j \hat{E}_j \right] \right\} \\ \dot{\hat{F}}_j &\triangleq \text{Proj} \left\{ v_j \left[\eta_j \hat{\beta}_j \hat{E}_j^T \gamma_j' (\hat{F}_j^T \hat{\beta}_j) \hat{\zeta}_j + \mu_{oj} f_j(\varepsilon_{o1}) \frac{\hat{\beta}_j \hat{E}_j^T \gamma_j' (\hat{F}_j^T \hat{\beta}_j)}{\omega_o^{j-1}} - \vartheta_j \hat{F}_j \right] \right\}\end{aligned}\quad (28)$$

where $\Gamma_j > \mathbf{0}$ and $v_j > \mathbf{0}$ are diagonal adaptation rate matrices, η_j , μ_{oj} , θ_j and ϑ_j are positive constants, $\text{Proj}(\bullet)$ is a continuous projection mapping operator, and $f_j(\varepsilon_{o1})$ represent the computable

parts of $\varepsilon_0^T C_0 B_j$. By choosing the design parameters reasonably, the resulting OFC algorithm can guarantee the boundedness of the whole closed-loop signals.

Proof. See Appendix A. $\square$

4. Application Example

To validate the proposed algorithm, a 2-DOF serial hydraulic robotic arm, which is shown in Figure 2, is considered as [5]:

$$\underbrace{\begin{bmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{bmatrix}}_{J(q)} \underbrace{\begin{bmatrix} \ddot{q}_1 \\ \ddot{q}_2 \end{bmatrix}}_{\ddot{q}} + 24 \underbrace{\begin{bmatrix} \tanh(0.82\dot{q}_1) - \tanh(0.42\dot{q}_1) \\ \tanh(0.82\dot{q}_2) - \tanh(0.42\dot{q}_2) \end{bmatrix} + \tanh(0.87\dot{q}_1) + \dot{q}_1}_{F_f(\dot{q})} + \underbrace{\begin{bmatrix} G_1 \\ G_2 \end{bmatrix}}_{G(q)} \quad (29)$$

$$+ \underbrace{\begin{bmatrix} V_{c11} & V_{c12} \\ V_{c21} & V_{c22} \end{bmatrix}}_{V_c(q,\dot{q})} \ddot{q} + \underbrace{\begin{bmatrix} 156 \sin(t) \\ 156 \sin(t) \end{bmatrix}}_{f_d(t)} + \underbrace{\begin{bmatrix} 0.52q_1\dot{q}_1 + 2.15\dot{q}_1 \cos(q_2) + 1.51\dot{q}_2 \cos(q_2) \\ 0.51q_2\dot{q}_2 + 2q_2 + 1.5\dot{q}_2 \end{bmatrix}}_{F_e(q,\dot{q})} = \underbrace{\begin{bmatrix} T_{c1} \\ T_{c2} \end{bmatrix}}_{T_c}$$

where

$$\begin{aligned} J_{11} &= J_{I1} + J_{m1}S_{c1}^2 + J_{m2}S_1^2 + J_L S_1^2 + J_{I2} + J_{m2}S_{c2}^2 \\ &\quad + J_L S_2^2 + 2(J_2 S_1 S_{c2} + J_L S_1 S_2) \cos(q_2) \\ J_{12} &= J_{I2} + J_{m2}S_{c2}^2 + J_L S_2^2 + (J_2 S_1 S_{c2} + J_L S_1 S_2) \cos(q_2) \\ J_{21} &= J_{12}, J_{22} = J_{I2} + J_{m2}S_{c2}^2 + J_L S_2^2 \\ V_{c11} &= -(J_{m2}S_1 S_{c2} + J_L S_1 S_2) \dot{q}_2 \sin(q_2) \\ V_{c12} &= -(J_{m2}S_1 S_{c2} + J_L S_1 S_2) (\dot{q}_2 - \dot{q}_1) \sin(q_2) \\ V_{c21} &= (J_{m2}S_1 S_{c2} \dot{q}_1 - J_L S_1 S_2 \dot{q}_2) \sin(q_2), V_{c22} = 0 \\ G_1 &= (J_{m1}S_{c1} + J_{m2}S_1 + J_L S_1)g \cos(q_1) \\ &\quad + (J_{m2}S_{c2} + J_L S_2)g \cos(q_1 + q_2) \\ G_2 &= (J_{m2}S_{c2} + J_L S_2)g \cos(q_1 + q_2) \end{aligned} \quad (30)$$

in which the meanings of q_j , J_{mj} , J_L , S_j , S_{cj} , g and J_{Ij} can be found in [5].

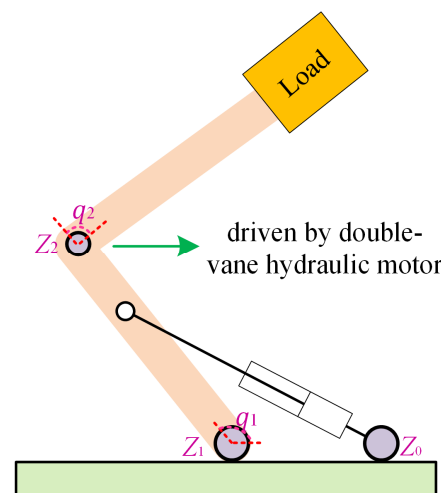


Figure 2. The 2-DOF serial hydraulic robotic arm.

Moreover, we define $\psi_1 = [\psi_{11}, \psi_{12}]^T$, $\psi_2 = [\psi_{21}, \psi_{22}]^T$, $\psi_3 = [\psi_{31}, \psi_{32}]^T$, $\psi_{1d} = [\psi_{11d}, \psi_{12d}]^T$, $\chi_2 = [\chi_{21}, \chi_{22}]^T$, $\chi_3 = [\chi_{31}, \chi_{32}]^T$, $\psi_{d2} = [\psi_{d21}, \psi_{d22}]^T$ and $\psi_{d3} = [\psi_{d31}, \psi_{d32}]^T$. The specification of the hydraulic cylinder is 45/28-300. Additionally, other system parameters are provided in Table 1. Specifically, L_{11} is the length between Z_1 and the connection point of the rod, while L_{12} is the length between Z_0 and Z_1 .

Table 1. System parameters.

Variable (Unit)	Value	Variable (Unit)	Value
J_{m1} (kg)	15	L_{11} (m)	0.4
J_{m2} (kg)	12	L_{12} (m)	0.35
J_{I1} (kg·m ²)	3.4	B_{ef} (Pa)	1.268×10^9
J_{I2} (kg·m ²)	1.9	A_{a2} (m ³ /rad)	1.12×10^{-4}
J_L (kg)	25	A_{b2} (m ³ /rad)	1.12×10^{-4}
S_{c1} (m)	0.3	C_H (m ³ /s/Pa)	diag{ 2.85×10^{-12} , 2.85×10^{-12} }
S_{c2} (m)	0.2	K_a (m ³ /s/V)	diag{ 1.0×10^{-4} , 1.2×10^{-4} }
S_1 (m)	0.55	K_b (m ³ /s/V)	diag{ 1.0×10^{-4} , 1.2×10^{-4} }
S_2 (m)	0.35	K_c (m ³ /s/Pa)	diag{ 1.65×10^{-11} , 1.6×10^{-11} }

The initial positions of Link 1 and Link 2 are given as 88° and 12° , respectively. Moreover, $Q_{e1}(q, \dot{q}, P_a, P_b) = [1.1 \times 10^4 q_1 \dot{q}_1 + 6.1 \times 10^{-8} (P_{a1} - P_{b1})^2, 1.2 \times 10^4 q_2 \dot{q}_2 + 6.2 \times 10^{-8} (P_{a2} - P_{b2})^2]$, $Q_{e2}(q, \dot{q}, P_a, P_b) = [8.01 \times 10^4 q_1 \dot{q}_1 + 1.1 \times 10^{-8} (P_{a1} - P_{b1})^2, 8.02 \times 10^4 q_2 \dot{q}_2 + 1.2 \times 10^{-8} (P_{a2} - P_{b2})^2]$, $Q_{d1}(t) = [1.01 \times 10^6 \sin(t), 1.02 \times 10^6 \sin(t)]^T$ and $Q_{d2}(t) = [8.01 \times 10^6 \sin(t), 8.02 \times 10^6 \sin(t)]^T$. Additionally, ψ_{1d} is set as $\psi_{1d} = [\psi_{11d}, \psi_{12d}]^T = [90 + 15 \sin(\pi t)(1 - e^{-0.5t})^\circ, -15 - 22 \cos(\pi t)(1 - e^{-0.5t})^\circ]^T$ and the parameters of the proposed controller are shown in Table 2.

Table 2. The controller parameters.

Parameter	Value	Parameter	Value
g_1	diag{500, 500}	Γ_2	diag{100, 100}
g_2	diag{200, 500}	Γ_3	diag{100, 100}
g_3	diag{300, 300}	θ_2	0.1
ω_o	diag{600, 600}	θ_3	0.1
ω_{c1}	diag{ 3.2×10^3 , 3.2×10^3 }	v_2	diag{ 1×10^5 , 1×10^5 }
ω_{c2}	diag{ 3.2×10^3 , 3.2×10^3 }	v_3	diag{ 1×10^5 , 1×10^5 }
η_2	1	θ_2	0.1
η_3	1	θ_3	0.1
μ_{o2}	1	ρ_2	diag{50, 50}
μ_{o3}	1		

The tracking performances of Link 1 and Link 2 are presented in Figures 3 and 4, respectively. As seen, the proposed algorithm obtains good tracking performance, with the tracking errors maintained at near-zero levels. This good performance not only confirms the effectiveness of the designed controller in handling system uncertainties but also highlights its superior compensation capability. The results provide strong validation for the robustness and high-precision tracking performance of the proposed control algorithm.

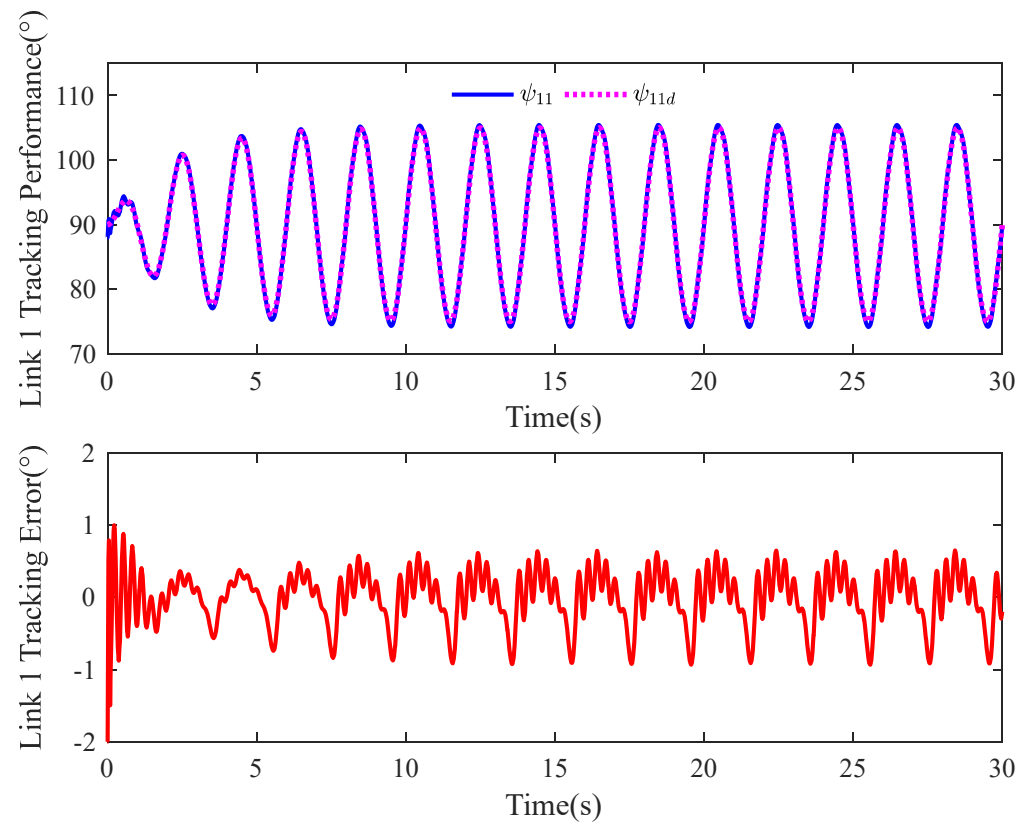


Figure 3. Tracking performance of Link 1.

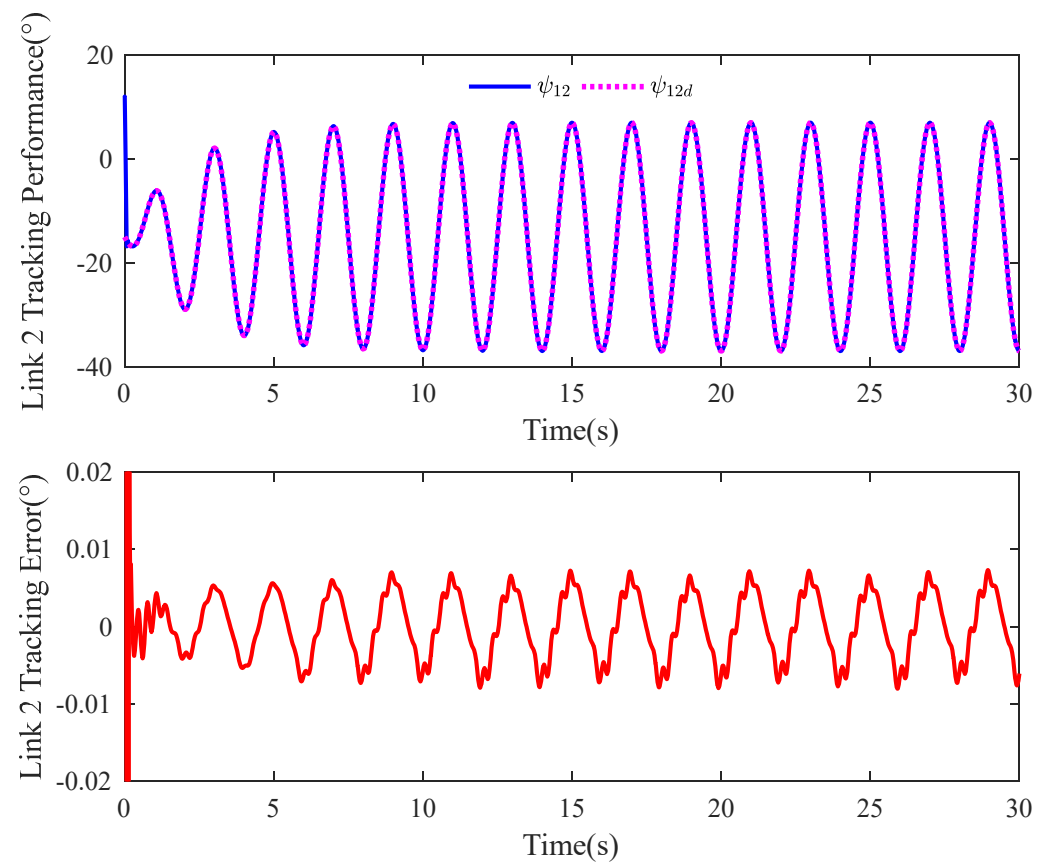


Figure 4. Tracking performance of Link 2.

Furthermore, Figures 5 and 6 show the state estimations for Link 1 and Link 2, respectively. As seen in Figures 5 and 6, the state estimations for both Links converge to their true values, which validates the rationality of the controller design based on these state estimations. This lays an important foundation for the feasibility of the algorithm.

The estimations for unknown functions in Link 1 and Link 2 are shown in Figures 7 and 8. The estimation curves show bounded oscillations around specific equilibrium values, indicating that the proposed method can effectively estimate the unknown functions within the system. Additionally, the estimations of external disturbances are shown in Figures 9 and 10, they indicate the approach also obtains accurate estimation performance. Notably, under the designed controller, the system obtains high-precision steady-state tracking performance while effectively compensating for both unknown dynamics and external disturbances. This comprehensive compensation capability guarantees robust and accurate tracking control.

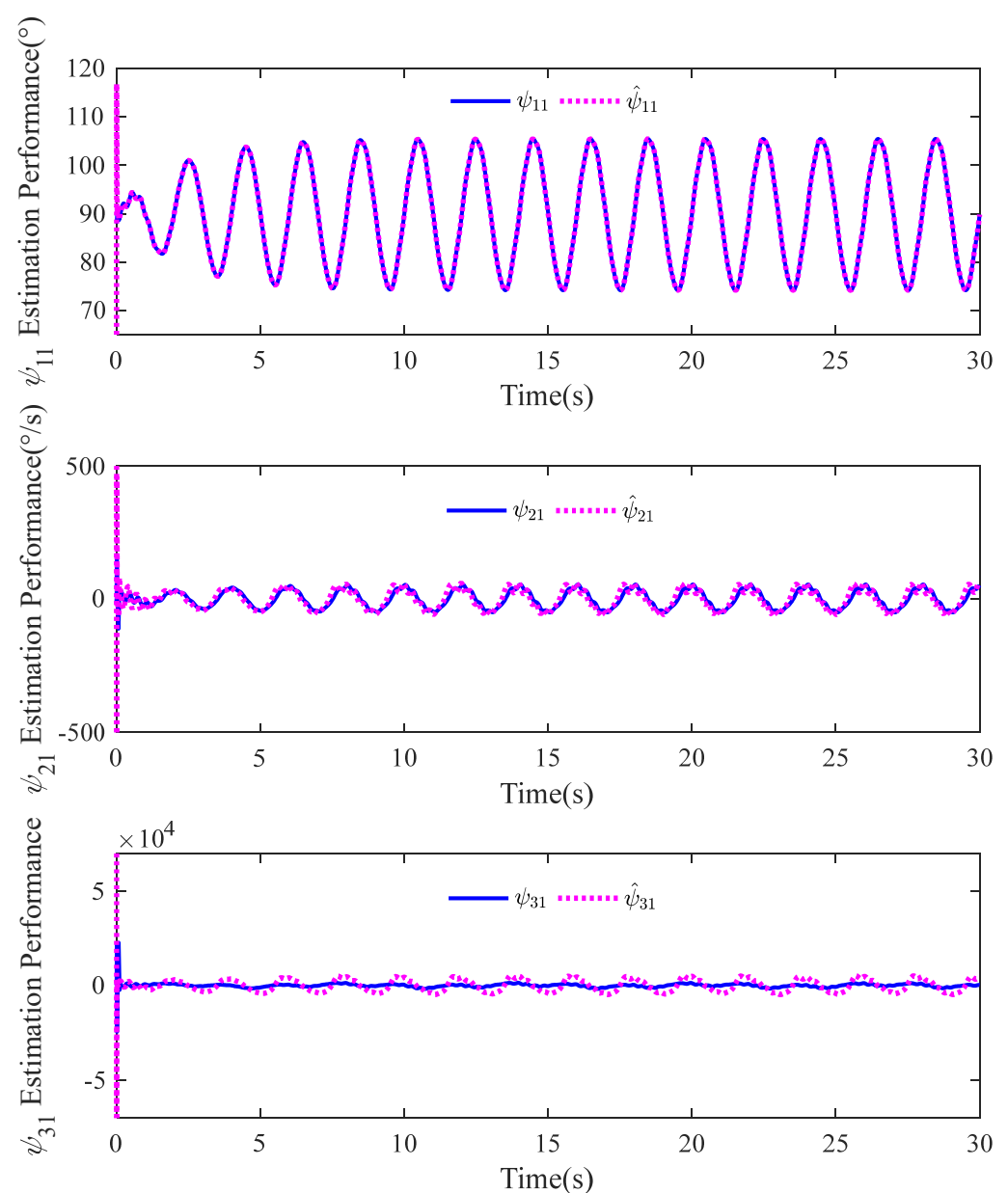


Figure 5. State estimations for Link 1.

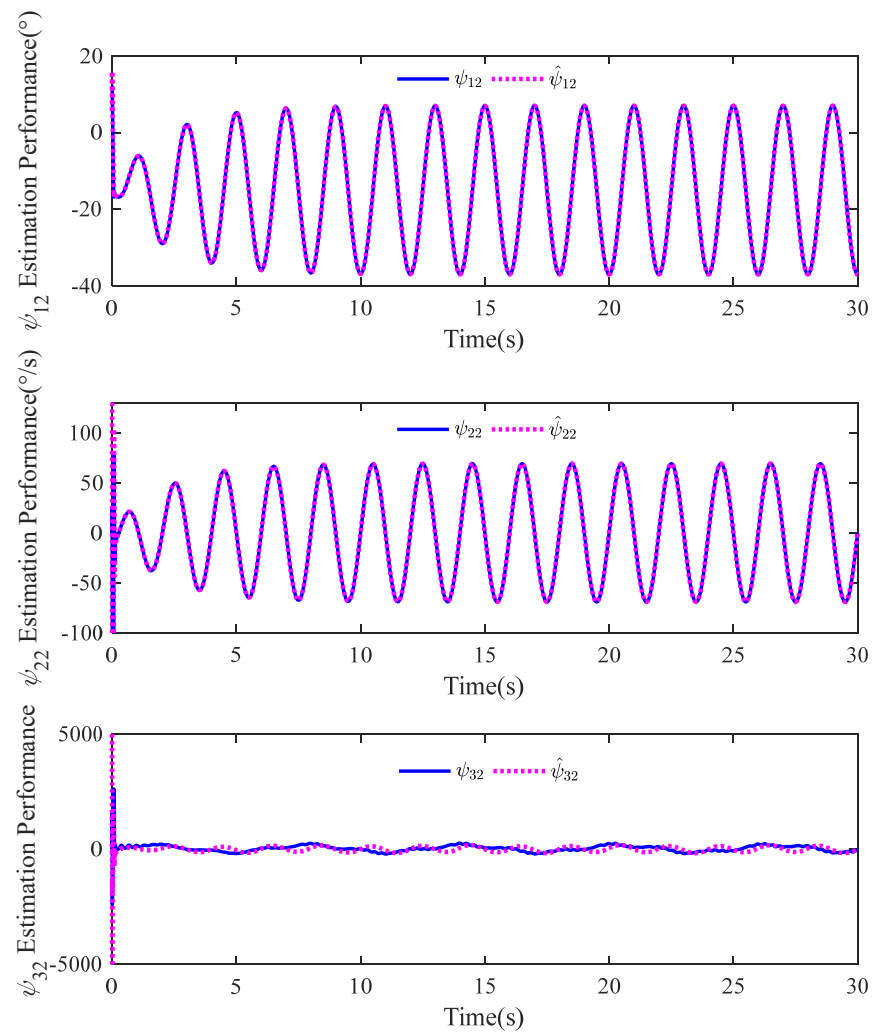


Figure 6. State estimations for Link 2.

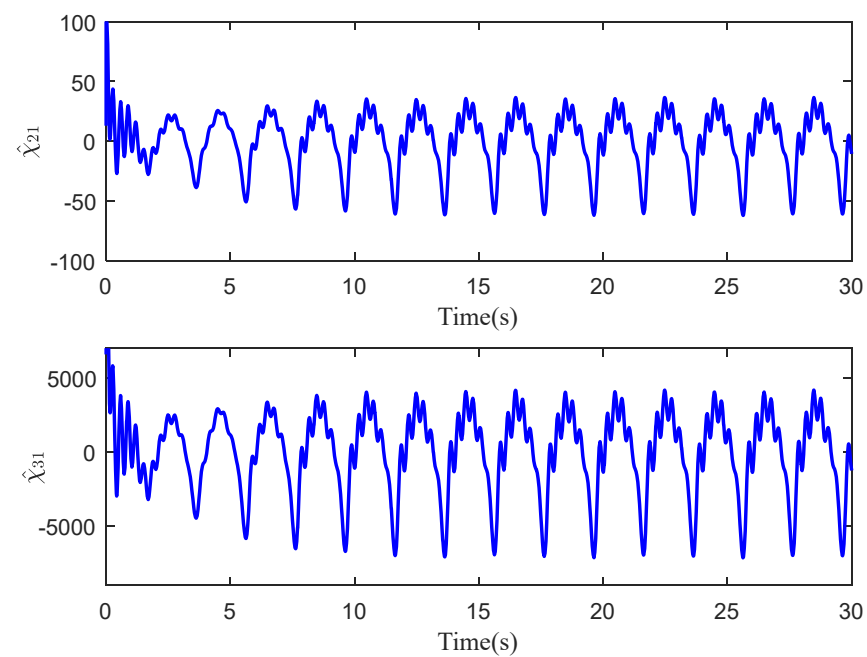


Figure 7. $\hat{\chi}_{21}$ and $\hat{\chi}_{31}$.

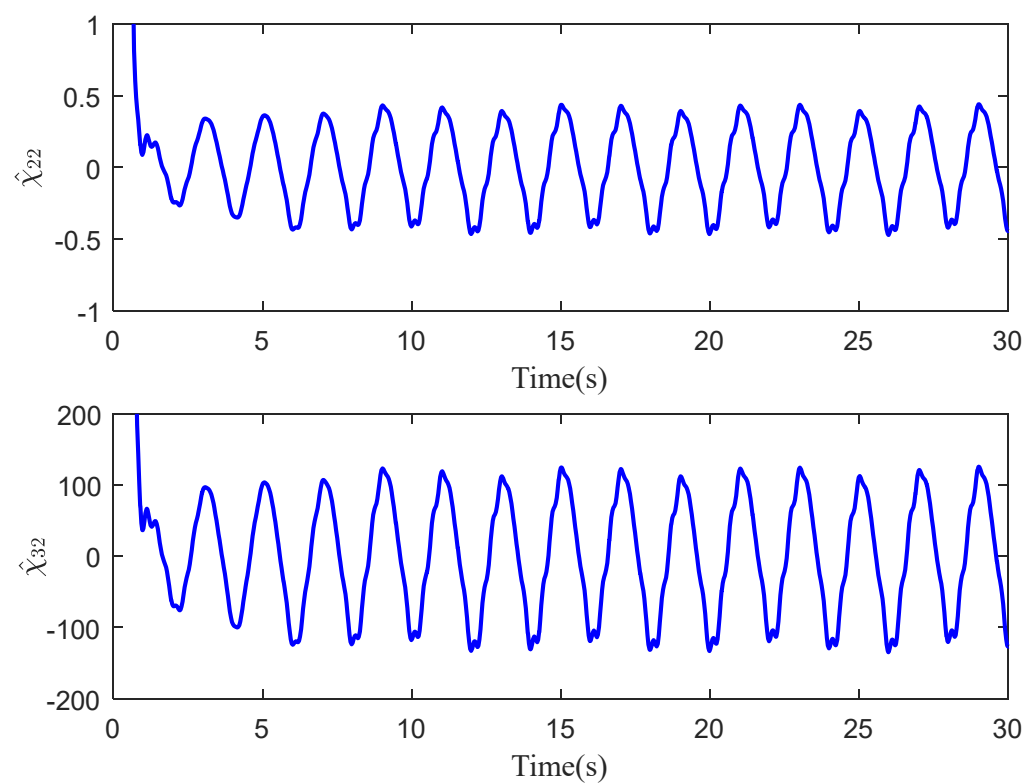


Figure 8. $\hat{\chi}_{22}$ and $\hat{\chi}_{32}$.

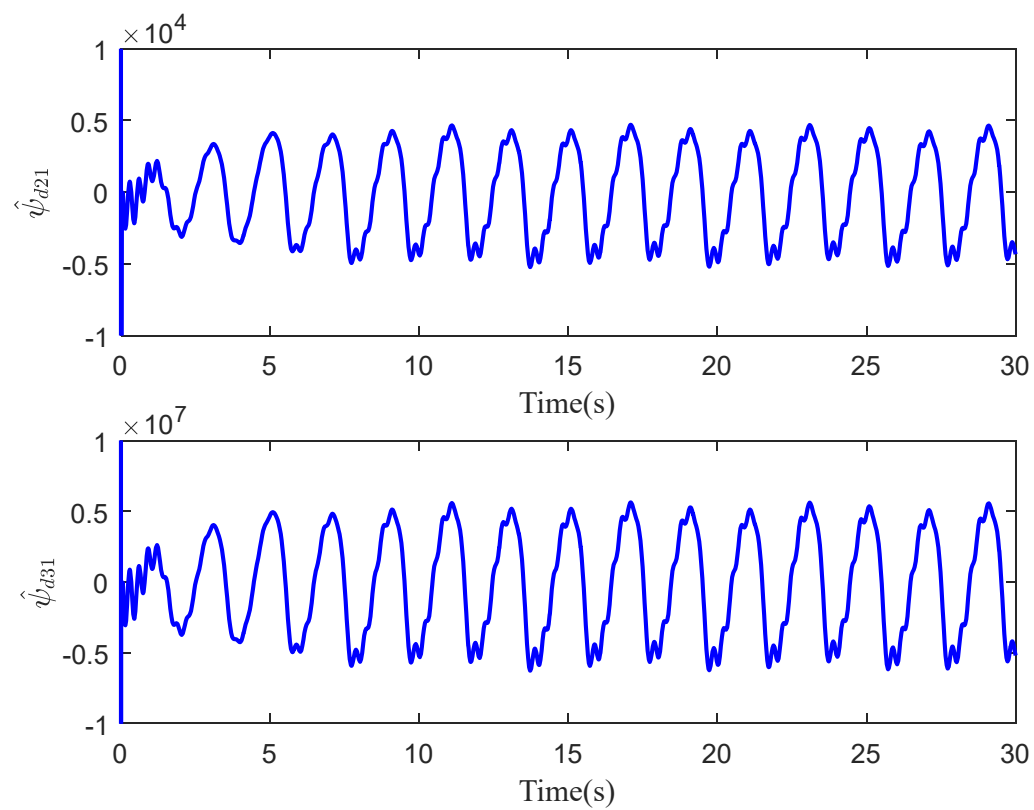


Figure 9. $\hat{\psi}_{d21}$ and $\hat{\psi}_{d31}$.

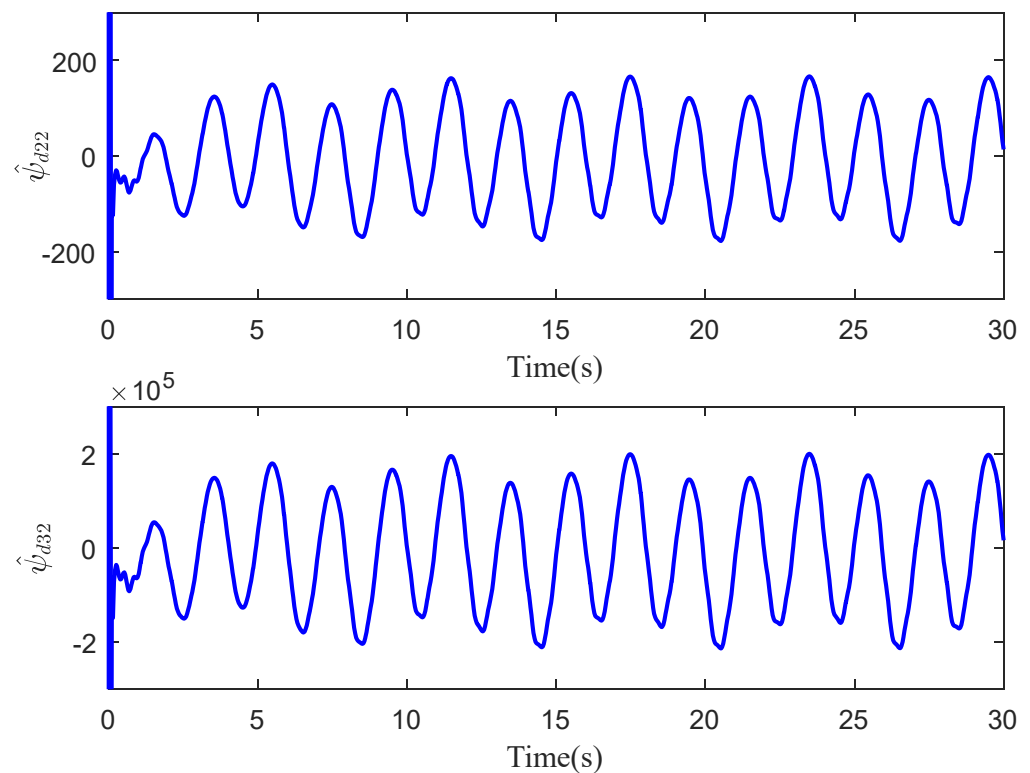


Figure 10. $\hat{\psi}_{d22}$ and $\hat{\psi}_{d32}$.

5. Considerations for Real-World Deployment

(1) Sensor Noise and Measurement Uncertainty

In real systems, sensor measurements are often corrupted by various noises. To enhance robustness, we will use signal preprocessing techniques to mitigate the impact of high-frequency noise.

(2) Actuator Saturation and Rate Limits

Physical actuators have inherent amplitude and rate saturation, which can lead to performance degradation. We will analyze the effect of saturation on the proposed scheme and suggest practical compensation strategies, such as anti-windup structures and reference governors, to preserve closed-loop stability under constrained actuation.

(3) Sampling and Communication Delays

Digital implementation introduces sampling delays, while networked control systems may suffer from varying communication latencies. The proposed algorithm will be extended to a discrete-time formulation with a bounded delay margin in future implementations.

6. Conclusions

This paper proposes a multilayer neuroadaptive OFC algorithm for n -DOF serial hydraulic robotic manipulator systems with modeling uncertainties. It provides theoretical support and a technical pathway for the engineering application of hydraulic manipulators with strong disturbances. Future research will focus on other advanced algorithms for hydraulic manipulators under complex working conditions.

The highlights of this paper are listed as follows:

- (1) Only output state will be utilized.
- (2) Matched and mismatched disturbances can be simultaneously compensated.

- (3) The “explosion of complexity” can be avoided.

Future research directions:

- (1) Data-Driven and Learning-Augmented Control

Using a nominal physics-based model as a prior to safely and efficiently train a reinforcement learning agent, aiming to optimize tracking performance and energy efficiency.

- (2) Hardware-in-the-Loop (HIL) and Co-Simulation Frameworks

Developing a HIL platform where the real-time controller interfaces with a hydraulic plant model. This allows for exhaustive testing of the control software under extreme conditions and fault scenarios without the risk of damaging physical hardware.

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Conflicts of Interest: There is no conflict of interest.

Appendix A

Define a function L_V as:

$$L_V = \frac{1}{2} \sum_{i=1}^3 \eta_i \tilde{\zeta}_i^2 + \frac{1}{2} \mu_o \varepsilon_o^T C_o \varepsilon_o + \frac{1}{2} \tilde{\zeta}_2^2 + \frac{1}{2} \sum_{j=2}^3 \varepsilon_{c(j-1)}^T C_c \varepsilon_{c(j-1)} + \frac{1}{2} \sum_{i=1}^3 \alpha_i^2 + \frac{1}{2} \sum_{j=2}^3 \text{tr}(\tilde{E}_j^T \Gamma_j^{-1} \tilde{E}_j) + \frac{1}{2} \sum_{j=2}^3 \text{tr}(\tilde{F}_j^T v_j^{-1} \tilde{F}_j) \quad (\text{A1})$$

Based on (11), (12), (17), (18), (21), (24), (27) and (28), one has

$$\dot{L}_V \leq - \sum_{i=1}^3 k_{\tilde{\zeta}_i} \tilde{\zeta}_i^2 - k_{\varepsilon_o} \|\varepsilon_o\|^2 - k_{\tilde{\zeta}_2} \tilde{\zeta}_2^2 - \sum_{j=2}^3 k_{\varepsilon_{c(j-1)}} \|\varepsilon_{c(j-1)}\|^2 - \sum_{i=1}^3 k_{\alpha_i} \alpha_i^2 - \sum_{j=2}^3 k_{\tilde{E}_j} \|\tilde{E}_j\|_F^2 - \sum_{j=2}^3 k_{\tilde{F}_j} \|\tilde{F}_j\|_F^2 + \Delta_L \quad (\text{A2})$$

where $k_{\tilde{\zeta}_i}$, k_{ε_o} , $k_{\tilde{\zeta}_2}$, $k_{\varepsilon_{c(j-1)}}$, k_{α_i} , $k_{\tilde{E}_j}$, $k_{\tilde{F}_j}$ and Δ_L are positive variables if the controller parameters are chosen appropriately.

Based on Equation (A2), we have

$$L_V(t) \leq L_V(0) e^{-k_V t} + \frac{\Delta_L}{k_V} \quad (\text{A3})$$

where $k_V = \min\{2k_{\tilde{\zeta}_i}/\eta_i, 2k_{\varepsilon_o}/(\mu_o \kappa_{\max}\{C_o\}), k_{\tilde{\zeta}_2}, 2k_{\varepsilon_{c(j-1)}}/\kappa_{\max}\{C_c\}, 2k_{\alpha_i}, 2k_{\tilde{E}_j}/\kappa_{\max}\{\Gamma_j^{-1}\}, 2k_{\tilde{F}_j}/\kappa_{\max}\{Y_j^{-1}\}\}$. Based on [33–37], Theorem 1 can be proved.

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