IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received January 29, 2021, accepted February 10, 2021, date of publication February 22, 2021, date of current version March 2, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3060739

Learning-Based Neural Adaptive Anti-Coupling Control for a Class of Robots Under Input and Structural Coupled Uncertainties

JUNLONG NIU[1], XIANSHENG QIN[1], AND ZHENG WANG[2,3,4]

[1]School of Mechanical Engineering, Northwestern Polytechnical University, Xi'an 710072, China
[2]Research Center for Unmanned System Strategy Development, Northwestern Polytechnical University, Xi'an 710072, China
[3]Unmanned System Research Institute, Northwestern Polytechnical University, Xi'an 710072, China
[4]National Key Laboratory of Aerospace Flight Dynamics, Northwestern Polytechnical University, Xi'an 710072, China

Corresponding author: Zheng Wang (wz_nwpu@126.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 11772256, Grant 51275413, and Grant 5167051687; in part by the Key Research and Development Program in Shaanxi Province of China under Grant 2016KTZDGY4-03, and in part by the Natural Science Basic Research Plan in Shaanxi Province of China under Grant 2017JM5050.

ABSTRACT This paper investigates the learning - based adaptive anti-coupling control issue for the robots under input and structural coupled uncertainties. In this paper, the input and structural coupled uncertainties are modeled and transformed into a system state related term, an internal state related term and a system input related term. With the aid of the actual exponential input-state stability and the dynamic auxiliary signal, the internal state related uncertainties can be suppressed. By utilizing the properties of the robot dynamics and several special nonlinear functions, the system state related uncertainties can be handled. Moreover, to overcome the system input related uncertainties, an indirect control law and the adaptive boundary estimation law have been designed. To simplify the control structure, the neural networks have been introduced as online approximators. Finally, a novel learning-based intelligent adaptive anti-coupling control structure has been established for the robots. The simulation results revealed the satisfactory control performance of the proposed anti-coupling control algorithm.

INDEX TERMS Adaptive control, adaptive algorithm, uncertain systems, nonlinear dynamical systems, robot control.

I. INTRODUCTION

In the past decades, the methodologies and techniques of robots have been the focus of studying and fruitful results have been reported in this category. Generally speaking, the robots can be mainly divided into wheeled, tracked, legged, crawling and hybrid robots according to their moving modes. The robots possess expansive application prospects in several fields, such as aerospace, national defense and military, space exploration, emergency and disaster relief, medical service, warehouse logistics, and so on. Since the legged robots possess notable advantages in terrain adaptability, motion flexibility and obstacle-crossing capability, many researchers have carried out the research upon the legged robots, including the biped robots [1]–[8], quadruped robots [9]–[16] and hexapod robots [17]–[25]. The research of the bionic robots can be found in [26], [27], imitating the exquisite structure, external shape, motion principle and behavioral way of living beings in nature. The research of the underwater robots can be found in [28]–[30], involving the experiment platform, the simulation analysis and the control techniques. For the space robots, the research results can be found in [31], [32] and the references therein. In the corresponding techniques, the control technique play an important role for completing all kinds of complex tasks and guaranteeing the desired performance.

In recent years, to satisfy the increasing requirements of control tasks, the advanced control methods have been the research hotspot [73]–[75]. For the control problem of the nonlinear systems, researchers have proposed many advanced control methods, such as H_∞ control [33], [34], sliding mode control (SMC) [35]–[41], adaptive control [42], [43], active disturbance rejection control (ADRC) [44], [45], disturbance observer-based control (DOBC) [46]–[49]. SMC can effectively suppress matching interference or uncertainty,

The associate editor coordinating the review of this manuscript and approving it for publication was Min Wang.

and has become an important control method for uncertain systems [50]–[52]. Aiming at the uncertain systems with a relative order of 1, literature [53] proposed a second-order sliding mode method, ensuring the robustness of the system and can reduce chattering. Literature [54]–[56] proposed the Lyapunov method for analyzing the characteristics of the super-twist algorithm. Based on this idea, literature [57] further proposed a multi-variable super-twisted sliding mode control method. Literature [58] proposed a smooth second-order sliding mode control law, and proved the convergence of the closed-loop uncertain system using the homogeneous theorem. By introducing dynamic gain, literature [41] proposed an adaptive smooth second-order SMC scheme.

In actual control systems, the disturbances and uncertainties are unavoidable, and may reduce control accuracy or cause instability [46], [59], [60]. In recent years, the control methods based on disturbance estimation and compensation have also been extensively studied [46], [60]. Literature [61] introduced a disturbance observation device into the traditional proportional-derivative control structure, and improved the attitude stabilization and tracking control accuracy of the flexible spacecraft. Literature [62] developed a variable gain sliding mode disturbance observer, which can effectively estimate the time-varying disturbance signals without superabundant prior information. Literature [63] proposed a stochastic disturbance observer, which can effectively suppress the stochastic disturbances existing in the control system. Literature reviews [46] the control methods based on disturbance observers. In actual engineering applications, the disturbance and uncertainties factors usually possess multiple sources. In order to solve this problem, literature constructed [64] a composite hierarchical anti-disturbance control (CHADC) structure. Based on this idea, literature [65] explored a combined adaptive disturbance control method for the nonlinear systems with multi-source disturbance and time-varying unknown parameters. For the Markov jump system under the influence of multi-source disturbances, literature [66] proposed an effective composite anti-disturbance control strategy, which enables the system to achieve effective stabilization under the influence of unknown nonlinearities and multi-source disturbances. By introducing fuzzy adaptive update law in the DOBC framework, literature [67] proposed an intelligent anti-disturbance control scheme. To handle the mismatched uncertainties, literature [37] proposed an integral SMC method by using a disturbance observer, and designed the memory and memoryless type sliding mode surfaces. To overcome the multi-source mismatched disturbances, the literature [68] introduced the composite hierarchical anti-disturbance strategy into the backstepping control framework, which can realize the precise control of the high-order disturbed systems. Nevertheless, there are few control results have been obtained for the nonlinear system suffering dynamic coupling uncertainties. For the robots suffering from the dynamic coupling, it is difficult to apply the reported anti-disturbance control methods to achieve precise control. Furthermore, if the internal dynamics of coupled uncertainties are related to the system states and the system inputs, the control system are suffering from the input and structural coupled uncertainties, and the existing anti-disturbance control methods are difficult to achieve the desired control effect. As far as the authors know, the adaptive anti-coupling control for the robots under input and structural coupled uncertainties has never been investigated.

In this paper, we consider the adaptive anti-coupling control problem for the robots under input and structural coupled uncertainties. Firstly, the input and structural coupled uncertainties are modeled and transformed into a system state related term, an internal state related term and a system input related term, and by using the actual exponential input-state stability as well as a dynamic auxiliary signal, the internal state related uncertainties can be suppressed. Secondly, by taking full advantage of the properties of the dynamic characteristics of the robots and using several special nonlinear functions, the system state related uncertainties can be handled. Moreover, to overcome the system input related uncertainties, an indirect control law and the adaptive boundary estimation law have been designed. To simplify the control structure, the neural networks have been introduced as online approximators. Finally, a novel learning-based intelligent adaptive anti-coupling control structure has been established for the robots. The proposed control algorithm possess the following features:

- As far as the authors know, it is the first anti-coupling control structure for the robots suffering from the input and structural coupled uncertainties.
- The proposed anti-coupling algorithm can be extended to a wide category of practical engineering systems with coupled uncertainties.
- By introducing the neural networks, the control structure has been simplified and the control complexity can be reduced.

II. THE ROBOT MODEL WITH INPUT AND STRUCTURAL COUPLED UNCERTAINTIES

Assuming that the robot is composed of rigid parts and rigid connections, without considering the flexibility of the robotic arm and the liquid sloshing, the kinematics and dynamics model of robot system can be established as

$$H(q)\ddot{q} + C(q, \dot{q})\dot{q} = \tau(t) \tag{1}$$

where $q(t) \in \mathbb{R}^n$ denotes the states of the robot, $H(q) \in \mathbb{R}^{n\times n}$ is the inertia matrix, $C(q, \dot{q}) \in \mathbb{R}^{n\times n}$ is the nonlinear term including centrifugal force and coriolis force, $\tau(t) \in \mathbb{R}^n$ is the control torque exerted on the base and joints.

Define $w = \dot{q}$, then the kinematics dynamic model of the robot system can be given by

$$\begin{aligned} \dot{q}(t) &= w(t) \\ \dot{w}(t) &= -H^{-1}(q)C(q, w)w + H^{-1}(q)\tau(t) \end{aligned} \tag{2}$$

In practical, the influence of coupling uncertainty is hard to avoid. Coupling uncertainties include the coupling between channels of the control system and the coupling between system state and input signals. Ignoring the coupling uncertainty may induce the instability of the closed-loop system. Define $\chi(q(t), w(t), \tau(t), \eta(t)) \in \mathbb{R}^n$ as the coupling uncertainty, which is affected by the system state and input signal, and there is an unmodeled state $\eta(t) \in \mathbb{R}^p$ inside it. The dynamic characteristics of $\eta(t)$ can be expressed as

$$\dot{\eta}(t) = f_\eta(\eta(t), q(t), w(t), \tau(t)) \tag{3}$$

Considering the coupling uncertainty and external disturbances, the kinematics dynamic model of the robot system can be established as

$$\begin{aligned} \dot{q}(t) &= w(t) \\ \dot{w}(t) &= -H^{-1}(q)C(q, w)w + H^{-1}(q)\tau(t) + H^{-1}(q)d(t) \\ &\quad + H^{-1}(q)\chi(q(t), w(t), \tau(t), \eta(t)) \end{aligned} \tag{4}$$

Define

$$\begin{aligned} x_1(t) &= q(t), x_2(t) = w(t) \\ x(t) &= \left[x_1^T(t), x_2^T(t)\right]^T \\ f(x(t)) &= -H^{-1}(q)C(q, w)w \\ g(x(t)) &= H^{-1}(q), u(t) = \tau(t) \end{aligned} \tag{5}$$

It is easy to know that the uncertain nonlinear differential equation (4) is equivalent to

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= f(x(t)) + g(x(t)) \begin{bmatrix} u(t) + d(t) \\ +\chi(x(t), u(t), \eta(t)) \end{bmatrix} \\ \dot{\eta}(t) &= f_\eta(\eta(t), x(t), u(t)) \end{aligned} \tag{6}$$

Define the desired signal as $y_d(t)$, the inner loop tracking error as $e_1(t) = x_1(t) - y_d(t)$, and the outer loop tracking error as $e_2(t) = x_2(t) - x_{2c}(t)$, where $x_{2c}(t)$ is the inner loop virtual control signal. Therefore, combined with equation (6), equation (7) can be obtained to describe the dynamic features of the tracking error:

$$\begin{aligned} \dot{e}_1(t) &= x_{2c}(t) + e_2(t) - \dot{y}_d(t) \\ \dot{e}_2(t) &= f(x(t)) - \dot{x}_{2c}(t) \\ &\quad + g(x(t)) \begin{bmatrix} u(t) + d(t) \\ + \chi(x(t), u(t), \eta(t)) \end{bmatrix} \\ \dot{\eta}(t) &= f_\eta(\eta(t), x(t), u(t)) \end{aligned} \tag{7}$$

The objective of this paper is to design an adaptive anti-coupling control signal to ensure the stability of the robot dynamics equation (7) under the input and structural coupled uncertainties.

In order to achieve the control goal, the following assumptions, lemmas and properties are necessary:

Assumption 1: The coupling uncertainties are assumed to satisfy that

$$\chi(q(t), w(t), \tau(t), \eta(t)) \le \varphi_1(q(t), w(t)) + \varphi_2(\eta(t)) + p_\tau \tau(t) \tag{8}$$

where $\varphi_1(q(t), w(t))$, $\varphi_2(\eta(t))$ are unknown non-negative smooth functions. $p_\tau \in (-1, 1)$ is a constant. At the same time, it is assumed that the unmodeled dynamic $\eta(t)$ has actual exponential input-state stability. That is, there exists a Lyapunov function $V_\eta(\eta(t))$ that satisfies

$$\begin{aligned} \alpha_1(\eta(t)) \le V_\eta(\eta(t)) &\le \alpha_2(\eta(t)) \\ \frac{\partial V_\eta(\eta(t))}{\partial \eta(t)} f_\eta(\eta(t), q(t), w(t), \tau(t)) &\le -\gamma_3 V_\eta(\eta(t)) \\ &\quad + \rho(q(t), w(t)) + \gamma_4 \end{aligned} \tag{9}$$

where $\alpha_1(\eta(t))$, $\alpha_2(\eta(t))$ are K_∞ functions. γ_3, γ_4 are normal numbers. $\rho(q(t), w(t)) = q^T(t)q(t) + w^T(t)w(t)$.

Lemma 1 [69]: For any $\varepsilon > 0$, define set $\Omega_\varepsilon = \left\{x \middle| ||x|| < 0.2554\varepsilon\right\}$. Then, for any $x \notin \Omega_\varepsilon$, the following inequality holds:

$$1 - 16\tanh^2\left(\frac{x}{\varepsilon}\right) \le 0 \tag{10}$$

Lemma 2 [70]: Given any constant $\varepsilon > 0$ and vector $\xi \in \mathbb{R}^n$, the following inequity holds:

$$\|\xi\| < \frac{\xi^T\xi}{\sqrt{\xi^T\xi + \varepsilon^2}} + \varepsilon \tag{11}$$

Lemma 3 [71]: Let $f : \mathbb{R} \to \mathbb{R}$ represent any continuous differentiable function defined on $[0, \infty)$, and $\lim_{t\to\infty} f(t)$ exists and possesses upper bound. If its derived function is uniformly continuous, then $\lim_{t\to\infty} \dot{f}(t) = 0$.

Obviously, the concerned robots possess the following properties:

Property 1 [72]: $C(q, \dot{q})$ can be chosen so that $\dot{H} - 2C$ is an antisymmetric matrix, which is

$$x^T(\dot{H} - 2C)x = 0, \quad \forall x \in \mathbb{R}^n \tag{12}$$

Property 2 [72]: $H(q)$ is positive definite bounded, satisfying

$$h_1 I \le H(q) \le h_2 I \tag{13}$$

where $h_1, h_2 > 0$ are constants □.

Property 3 [72]: $H(q)$ is not singular, that is, there is $H^{-1}(q)$ □.

III. INTELLIGENT ADAPTIVE ANTI-COUPLING CONTROL STRUCTURE

In this section, a robust adaptive control scheme is given. Firstly, we introduce the dynamic signal $r(t)$, which is generated according to the following equation:

$$\dot{r}(t) = -\gamma_0 r(t) + \rho(x(t)), r(0) = r_0 \tag{14}$$

where $\gamma_0 \in (0, \gamma_3)$. The dynamic signal $r(t)$ has the following properties:

$$\begin{aligned} r(t) &\ge 0, \quad \forall t \ge 0 \\ V_\eta(\eta(t)) &\le r(t) + \varepsilon_r \end{aligned} \tag{15}$$

where $\varepsilon_r = V_\eta(\eta(0)) + \gamma_4/\gamma_3$. In view of the first equation of (7), design the virtual control signal of inner loop as follows

$$x_{2c}(t) = -k_0 \int_0^t e_1(\tau)d\tau - k_1 e_1(t) + \dot{y}_d(t) \tag{16}$$

where $k_0, k_1 > 0$ are the control gains. Simple analysis show that

$$\begin{aligned} & e_2^T(t)g(x(t))\chi(x(t), u(t), \eta(t)) \\ & \quad \le \left\| e_2^T(t)g(x(t)) \right\| (\varphi_1(x(t)) + \varphi_2(\eta(t)) + p_u u(t)) \end{aligned} \tag{17}$$

According to **Lemma 2**, it is easy to know

$$\begin{aligned} & \left\| e_2^T(t)g(x(t)) \right\| \varphi_1(x(t)) \\ & \quad \le e_2^T(t)g(x(t))\bar{\varphi}_1(e_2(t), x(t)) + \varepsilon_1 \\ & \left\| e_2^T(t)g(x(t)) \right\| \varphi_2(\eta(t)) \\ & \quad \le \left\| e_2^T(t)g(x(t)) \right\| \varphi_2 \circ \alpha_1^{-1}(2r(t)) \\ & \qquad + \left\| e_2^T(t)g(x(t)) \right\| \varphi_2 \circ \alpha_1^{-1}(2\varepsilon_r) \end{aligned} \tag{18}$$

where $\varepsilon_1 > 0$ is an constant,

$$\bar{\varphi}_1(e_2(t), x(t)) = \frac{\varphi_1(x(t))e_2^T(t)g(x(t))\varphi_1(x(t))}{\sqrt{\left[e_2^T(t)g(x(t))\varphi_1(x(t))\right]^2 + \varepsilon_1^2}} \tag{19}$$

Further, based on Young's inequality, we know that

$$\begin{aligned} & \left\| e_2^T(t)g(x(t)) \right\| \varphi_2(\eta(t)) \\ & \quad \le e_2^T(t)g(x(t))\bar{\varphi}_2(e_2(t), x(t), r(t)) \\ & \qquad + \varepsilon_2 + \frac{1}{4} e_2^T(t)g^T(x(t))g(x(t))e_2(t) + \varepsilon_3 \end{aligned} \tag{20}$$

where $\varepsilon_2 > 0$ is an constant,

$$\begin{aligned} & \bar{\varphi}_2(e_2(t), x(t), r(t)) \\ & \quad = \frac{\varphi_2 \circ \alpha_1^{-1}(2r(t))e_2^T(t)g(x(t))\varphi_2 \circ \alpha_1^{-1}(2r(t))}{\sqrt{\left[e_2^T(t)g(x(t))\varphi_2 \circ \alpha_1^{-1}(2r(t))\right]^2 + \varepsilon_2^2}} \\ & \varepsilon_3 = \left[\varphi_2 \circ \alpha_1^{-1}(2\varepsilon_r)\right]^2 \end{aligned} \tag{21}$$

Aiming at the dynamic equation of the outer-loop tracking error, a neural network is introduced to reduce the control complexity:

$$\begin{aligned} & \Theta^T \Phi(e_2(t), x(t), r(t)) + \varepsilon_\Theta \\ & \quad = \bar{\varphi}_1(e_2(t), x(t)) + \bar{\varphi}_2(e_2(t), x(t), r(t)) \end{aligned} \tag{22}$$

On the other hand, the control signal $u(t)$ can be designed to satisfy $e_2^T(t)g(x(t))u(t) < 0$, then the following inequality holds:

$$\begin{aligned} & e_2^T(t)g(x(t))u(t) + \left\| p_u e_2^T(t)g(x(t))u(t) \right\| \\ & \quad \le e_2^T(t)g(x(t))u(t) - \|p_u\| \, e_2^T(t)g(x(t))u(t) \\ & \quad \le (1 - \|p_u\|)e_2^T(t)g(x(t))u(t) \end{aligned} \tag{23}$$

Based on the above analysis, we design the nominal outer loop controller as

$$\begin{aligned} u_c(t) = g^{-1}(x(t)) & \begin{bmatrix} -k_2 e_2(t) - e_1(t) - f(x(t)) \\ -\varphi_\rho(x(t), e_2(t)) \\ -\hat{\Theta}^T \Phi(e_2(t), x(t), r(t)) + \dot{x}_{2c}(t) \end{bmatrix} \\ & - \hat{D}\varphi_d(x(t), e_2(t)) - \frac{1}{4} g(x(t))e_2(t) \end{aligned} \tag{24}$$

where $\varphi_d(x(t), e_2(t))$ is the function vector of $x(t)$ and $e_2(t)$, defined as

$$\varphi_d(x(t), e_2(t), \varepsilon_d) = \frac{g(x(t))e_2(t)}{\sqrt{e_2^T(t)g(x(t))g(x(t))e_2(t) + \varepsilon_d^2}} \tag{25}$$

where $\varepsilon_d > 0$ is any normal constant. $\varphi_\rho(x(t), e_2(t))$ will be explained later. Further, define $\vartheta = 1/inf_{t\ge0}[1 - \|p_u\|]$. The actual outer loop controller is designed as

$$u(t) = -\frac{\hat{\vartheta} u_c(t)[e_2^T(t)g(x(t))\hat{\vartheta} u_c(t)]}{\sqrt{\left[e_2^T(t)g(x(t))\hat{\vartheta} u_c(t)\right]^2 + \varepsilon_v^2}} \tag{26}$$

where $\hat{D}$, $\hat{\Theta}$, $\hat{\vartheta}$ is the estimated value of D, Θ, ϑ. $D = sup_{t\ge0}\|d(t) + \varepsilon_\Theta\|$. The adaptive law of $\hat{D}$, $\hat{\Theta}$, $\hat{\vartheta}$ is designed as

$$\begin{aligned} \dot{\hat{D}} &= \Gamma_D e_2^T(t)g(x(t))\varphi_d(x(t), e_2(t)) - \Gamma_D\lambda_D\hat{D} \\ \dot{\hat{\Theta}} &= \Gamma_\Theta \Phi(e_2(t), x(t), r(t))e_2^T(t) - \Gamma_\Theta\lambda_\Theta\hat{\Theta} \\ \dot{\hat{\vartheta}} &= -\Gamma_\vartheta e_2^T(t)g(x(t))u_c(t) - \Gamma_\vartheta\lambda_\vartheta\hat{\vartheta} \end{aligned} \tag{27}$$

where Γ_D, Γ_Θ, Γ_ϑ, λ_D, λ_Θ, λ_ϑ are all positive design parameters.

The stability of the control structure can be shown by the following theorem.

Theorem 1: Considering the closed-loop control system composed of the tracking error dynamic equation of the robot (7), the control law (26) and adaptive law (27). Then all signals are ultimately bounded during the whole control process, and the tracking error will converges to zero finally.

Proof: Define $\widetilde{D} = \hat{D} - D$, $\widetilde{\Theta} = \hat{\Theta} - \Theta$, $\widetilde{\vartheta} = \hat{\vartheta} - \vartheta$, $e_0(t) = \int_0^t e_1(s)ds$. By substituting equations (16) and (24) into equation (7), we can get that

$$\begin{aligned} \dot{e}_0(t) &= e_1(t) \\ \dot{e}_1(t) &= -k_0 e_0(t) - k_1 e_1(t) + e_2(t) \\ \dot{e}_2(t) &= -k_2 e_2(t) - e_1(t) \\ & \quad + g(x(t))\left[u(t) + d(t) + \chi(x(t), u(t), \eta(t))\right] \\ & \quad - \hat{\Theta}^T \Phi(e_2(t), x(t), r(t)) - g(x(t))u_c(t) \\ & \quad - \hat{D}g(x(t))\varphi_d(x(t), e_2(t)) \\ & \quad - \frac{1}{4} g^T(x(t))g(x(t))e_2(t) - \varphi_\rho(x(t), e_2(t)) \end{aligned} \tag{28}$$

The following Lyapunov function is selected

$$\begin{aligned} V &= V_1 + V_2, V_1 = \frac{1}{2} e_0^T(t)e_0(t) + \frac{1}{2} e_1^T(t)e_1(t) \\ V_2 &= \frac{1}{2} e_2^T(t)e_2(t) + \frac{1}{2} Tr(\widetilde{\Theta}^T \Gamma_\Theta^{-1} \widetilde{\Theta}) \\ & \quad + \frac{1}{2\Gamma_D}\widetilde{D}^2 + \frac{1}{2\vartheta\Gamma_\vartheta}\widetilde{\vartheta}^2 + \frac{r}{\Gamma_r} \end{aligned} \tag{29}$$

where $\Gamma_r > 0$ is a normal constant. By using equation (28), the derivative of V_1 can be easily obtained:

$$\dot{V}_1 = e_0^T(t)e_1(t) - k_0 e_1^T(t)e_0(t) - k_1 e_1^T(t)e_1(t) + e_1^T(t)e_2(t) \tag{30}$$

Define $\bar{e}_1 = \left[e_0^T(t), e_1^T(t)\right]^T$. Equation (30) can be rewritten as

$$\dot{V}_1 = -\bar{e}_1^T(t)Q\bar{e}_1(t) + e_1^T(t)e_2(t) \tag{31}$$

where

$$Q = \begin{bmatrix} 0 & -I_3 \\ k_0 I_3 & k_1 I_3 \end{bmatrix} \tag{32}$$

Similarly, using equation (28) and the dynamic equation (14) of the dynamic signal $r(t)$, the derivative of V_2 can be obtained as

$$\begin{aligned}\dot{V}_2 = &-k_2 e_2^T(t)e_2(t) - e_2^T(t)e_1(t) + e_2^T(t)g(x(t))u(t) \\ &+ e_2^T(t)g(x_1(t), x_2(t))dt - e_2^T(t)g(x(t))u_c(t) \\ &+ e_2^T(t)g(x(t))\chi(x(t), u(t), \eta(t)) \\ &- e_2^T(t)\hat{\Theta}^T\Phi(e_2(t), x(t), r(t)) \\ &- e_2^T(t)\hat{D}g(x(t))\varphi_d(x(t), e_2(t)) \\ &- \frac{1}{4}e_2^T(t)g^T(x(t))g(x(t))e_2(t) \\ &- e_2^T(t)\varphi_\rho(x(t), e_2(t)) + Tr(\widetilde{\Theta}^T\Gamma_\Theta^{-1}\dot{\hat{\Theta}}) \\ &+ \frac{1}{\Gamma_D}\widetilde{D}\dot{\hat{D}} + \frac{1}{\vartheta\Gamma_\vartheta}\widetilde{\vartheta}\dot{\hat{\vartheta}} - \frac{\gamma_0}{\Gamma_r}r(t) + \frac{\rho(x(t))}{\Gamma_r}\end{aligned} \tag{33}$$

For any vector $\xi \in \mathbb{R}^n$, define

$$Tanh(\xi(t)) = [\tanh\xi_1(t), \tanh\xi_2(t), \ldots, \tanh\xi_n(t)]^T \tag{34}$$

Then, it is easy to know that

$$\frac{\rho(x(t))}{\Gamma_r} = \frac{\rho(x(t))}{\Gamma_r}\left(1 - 16Tanh^T\left(\frac{e_2(t)}{\varepsilon_\rho}\right)Tanh\left(\frac{e_2(t)}{\varepsilon_\rho}\right)\right) + e_2^T(t)\varphi_\rho(x(t), e_2(t)) \tag{35}$$

where

$$\varphi_\rho(x(t), e_2(t)) = \frac{16e_2(t)\rho(x(t))}{\Gamma_r e_2^T(t)e_2(t)}Tanh^T\left(\frac{e_2(t)}{\varepsilon_\rho}\right)Tanh\left(\frac{e_2(t)}{\varepsilon_\rho}\right) \tag{36}$$

Note that $\varphi_\rho(x(t), e_2(t))$ is a non-singular function vector for $e_2(t)$. Hence, by combining with equation (33) we can get that

$$\begin{aligned}\dot{V}_2 = &-k_2 e_2^T(t)e_2(t) - e_2^T(t)e_1(t) + e_2^T(t)g(x(t))u(t) \\ &+ e_2^T(t)g(x_1(t), x_2(t))dt - e_2^T(t)g(x(t))u_c(t) \\ &+ e_2^T(t)g(x(t))\chi(x(t), u(t), \eta(t)) \\ &- e_2^T(t)\hat{\Theta}^T\Phi(e_2(t), x(t), r(t)) \\ &- e_2^T(t)\hat{D}g(x(t))\varphi_d(x(t), e_2(t)) \\ &- \frac{1}{4}e_2^T(t)g^T(x(t))g(x(t))e_2(t) \\ &+ \rho(x(t))\left(1 - 16\tanh^T\left(\frac{e_2(t)}{\varepsilon_\rho}\right)\tanh\left(\frac{e_2(t)}{\varepsilon_\rho}\right)\right)\Big/\Gamma_r \\ &+ Tr(\widetilde{\Theta}^T\Gamma_\Theta^{-1}\dot{\hat{\Theta}}) + \frac{1}{\Gamma_D}\widetilde{D}\dot{\hat{D}} + \frac{1}{\vartheta\Gamma_\vartheta}\widetilde{\vartheta}\dot{\hat{\vartheta}} - \frac{\gamma_0}{\Gamma_r}r(t)\end{aligned} \tag{37}$$

Then from equations (17)–(21), it can be known that

$$\begin{aligned}&e_2^T(t)g(x(t))\chi(x(t), u(t), \eta(t)) \\ &\quad\le e_2^T(t)g(x(t))\bar{\varphi}_1(e_2(t), x(t)) \\ &\qquad+ e_2^T(t)g(x(t))\bar{\varphi}_2(e_2(t), x(t), r(t)) \\ &\qquad+ \frac{1}{4}e_2^T(t)g^T(x(t))g(x(t))e_2(t) \\ &\qquad+ \|p_u\|\left\|e_2^T(t)g(x(t))u(t)\right\| + \sum_{i=1}^{3}\varepsilon_i\end{aligned} \tag{38}$$

By using the neural network approximate equation (22), we have

$$\begin{aligned}&e_2^T(t)g(x(t))\chi(x(t), u(t), \eta(t)) \\ &\quad\le e_2^T(t)g(x(t))(\Theta^T\Phi(e_2(t), x(t), r(t)) + \varepsilon_\Theta) \\ &\qquad+ \frac{1}{4}e_2^T(t)g^T(x(t))g(x(t))e_2(t) \\ &\qquad+ \|p_u\|\left\|e_2^T(t)g(x(t))u(t)\right\| + \sum_{i=1}^{3}\varepsilon_i\end{aligned} \tag{39}$$

Considering the value range of p_u and the form of $u(t)$, it is easy to know $e_2^T(t)g(x(t))u(t) < 0$. Therefore, equation (39) can be rewritten as

$$\begin{aligned}&e_2^T(t)g(x(t))\chi(x(t), u(t), \eta(t)) \\ &\quad\le e_2^T(t)g(x(t))(\Theta^T\Phi(e_2(t), x(t), r(t)) + \varepsilon_\Theta) \\ &\qquad+ \frac{1}{4}e_2^T(t)g^T(x(t))g(x(t))e_2(t) \\ &\qquad- \|p_u\|\, e_2^T(t)g(x(t))u(t) + \sum_{i=1}^{3}\varepsilon_i\end{aligned} \tag{40}$$

Substituting equation (40) into equation (37) yields

$$\begin{aligned}\dot{V}_2 \le &-k_2 e_2^T(t)e_2(t) - e_2^T(t)e_1(t) \\ &+ (1 - \|p_u\|)e_2^T(t)g(x(t))u(t) \\ &+ e_2^T(t)g(x_1(t), x_2(t))\,(dt + \varepsilon_\Theta) \\ &- e_2^T(t)\hat{\Theta}^T\Phi(e_2(t), x(t), r(t)) - e_2^T(t)g(x(t))u_c(t) \\ &- e_2^T(t)\hat{D}g(x(t))\varphi_d(x(t), e_2(t)) \\ &+ \rho(x(t))\left(1 - 16Tanh^T\left(\frac{e_2(t)}{\varepsilon_\rho}\right)Tanh\left(\frac{e_2(t)}{\varepsilon_\rho}\right)\right)\Big/\Gamma_r \\ &+ Tr(\widetilde{\Theta}^T\Gamma_\Theta^{-1}\dot{\hat{\Theta}}) + \frac{1}{\Gamma_D}\widetilde{D}\dot{\hat{D}} \\ &+ \frac{1}{\vartheta\Gamma_\vartheta}\widetilde{\vartheta}\dot{\hat{\vartheta}} - \frac{\gamma_0}{\Gamma_r}r(t) + \sum_{i=1}^{3}\varepsilon_i\end{aligned} \tag{41}$$

By using **Lemma 2**, we have

$$\begin{aligned}&e_2^T(t)g(x(t))\,(dt + \varepsilon_\Theta) - e_2^T(t)\hat{D}g(x(t))\varphi_d(x(t), e_2(t)) \\ &\quad\le D\left\|e_2^T(t)g(x(t))\right\| - e_2^T(t)\hat{D}g(x(t))\varphi_d(x(t), e_2(t)) \\ &\quad\le -\widetilde{D}e_2^T(t)g(x(t))\varphi_d(x(t), e_2(t)) + D\varepsilon_d\end{aligned} \tag{42}$$

On the other hand, with the aid of **Lemma 2** we can also obtain the following inequality

$$\begin{aligned}
&(1-\|p_u\|)e_2^T(t)g(x(t))u(t) - e_2^T(t)g(x(t))u_c(t) \\
&= \frac{1-\|p_u\|\,[e_2^T(t)\hat{\vartheta}g(x(t))u_c(t)]^2}{\sqrt{\left[e_2^T(t)\hat{\vartheta}g(x(t))u_c(t)\right]^2+\varepsilon_v^2}} - e_2^T(t)g(x(t))u_c(t) \\
&\leq -\frac{1}{\vartheta}\frac{[e_2^T(t)\hat{\vartheta}g(x(t))u_c(t)]^2}{\sqrt{\left[e_2^T(t)\hat{\vartheta}g(x(t))u_c(t)\right]^2+\varepsilon_v^2}} - e_2^T(t)g(x(t))u_c(t) \\
&\leq \frac{1}{\vartheta}\left(-\left\|e_2^T(t)\hat{\vartheta}g(x(t))u_c(t)\right\|+\varepsilon_v\right) - e_2^T(t)g(x(t))u_c(t) \\
&\leq \frac{1}{\vartheta}\left(\tilde{\vartheta}e_2^T(t)g(x(t))u_c(t)+\varepsilon_v\right)
\end{aligned} \tag{43}$$

Therefore, combining equations (41), (42) and (43), it can be concluded that

$$\begin{aligned}
\dot{V}_2 \leq& -k_2e_2^T(t)e_2(t) - e_2^T(t)e_1(t) \\
&- e_2^T(t)\tilde{\Theta}^T\Phi(e_2(t),x(t),r(t)) \\
&- \tilde{D}e_2^T(t)g(x(t))\varphi_d(x(t),e_2(t)) \\
&+ \frac{\tilde{\vartheta}}{\vartheta}e_2^T(t)g(x(t))u_c(t) + Tr(\tilde{\Theta}^T\Gamma_\Theta^{-1}\dot{\hat{\Theta}}) + \frac{1}{\Gamma_D}\tilde{D}\dot{\hat{D}} \\
&+ \rho(x(t))\left(1-16Tanh^T\left(\frac{e_2(t)}{\varepsilon_\rho}\right)Tanh\left(\frac{e_2(t)}{\varepsilon_\rho}\right)\right)\Big/\Gamma_r \\
&+ \frac{1}{\vartheta\Gamma_\vartheta}\tilde{\vartheta}\dot{\hat{\vartheta}} - \frac{\gamma_0}{\Gamma_r}r(t) + \sum_{i=1}^{3}\varepsilon_i + D\varepsilon_d + \frac{\varepsilon_v}{\vartheta}
\end{aligned} \tag{44}$$

Substituting the adaptive law equation (27) into equation (44), the following formula can be obtained:

$$\begin{aligned}
\dot{V}_2 \leq& -k_2e_2^T(t)e_2(t) - e_2^T(t)e_1(t) \\
&- \lambda_\Theta Tr(\tilde{\Theta}^T\hat{\Theta}) - \lambda_D\tilde{D}\hat{D} - \lambda_\vartheta\tilde{\vartheta}\hat{\vartheta} \\
&+ \rho(x(t))\left(1-16Tanh^T\left(\frac{e_2(t)}{\varepsilon_\rho}\right)Tanh\left(\frac{e_2(t)}{\varepsilon_\rho}\right)\right)\Big/\Gamma_r \\
&- \frac{\gamma_0}{\Gamma_r}r(t) + \sum_{i=1}^{3}\varepsilon_i + D\varepsilon_d + \frac{\varepsilon_v}{\vartheta}
\end{aligned} \tag{45}$$

Due to

$$\begin{aligned}
-2Tr(\tilde{\Theta}^T\hat{\Theta}) &\leq -Tr(\tilde{\Theta}^T\hat{\Theta}) + Tr(\tilde{\Theta}^T\hat{\Theta}) \\
-2\tilde{D}\hat{D} &\leq -\tilde{D}^2 + D^2,\ -2\tilde{\vartheta}\hat{\vartheta} \leq -\tilde{\vartheta}^2 + \vartheta^2
\end{aligned} \tag{46}$$

Equation (45) can be written as

$$\begin{aligned}
\dot{V}_2 \leq& -k_2e_2^T(t)e_2(t) - e_2^T(t)e_1(t) \\
&- \frac{\lambda_\Theta}{2}Tr(\tilde{\Theta}^T\tilde{\Theta}) - \frac{\lambda_D}{2}\tilde{D}^2 - \frac{\lambda_\vartheta}{2\vartheta}\tilde{\vartheta}^2 - \frac{\gamma_0}{\Gamma_r}r(t) \\
&+ \rho(x(t))\left(1-16\tanh^T\left(\frac{e_2(t)}{\varepsilon_\rho}\right)\tanh\left(\frac{e_2(t)}{\varepsilon_\rho}\right)\right)\Big/\Gamma_r \\
&+ \frac{\lambda_\Theta}{2}Tr(\Theta^T\Theta) + \frac{\lambda_D}{2}D^2 + \frac{\lambda_\vartheta}{2}\vartheta \\
&+ \sum_{i=1}^{3}\varepsilon_i + D\varepsilon_d + \frac{\varepsilon_v}{\vartheta}
\end{aligned} \tag{47}$$

Thus, by combining equations (31) and (47) we can get

$$\begin{aligned}
\dot{V} \leq& -\gamma V + \varepsilon_f \\
&+ \rho(x(t))\left(1-16\tanh^T\left(\frac{e_2(t)}{\varepsilon_\rho}\right)\tanh\left(\frac{e_2(t)}{\varepsilon_\rho}\right)\right)\Big/\Gamma_r
\end{aligned} \tag{48}$$

In equation (48),

$$\begin{aligned}
\gamma &= \min\left\{\begin{matrix}2\lambda_{\min}(Q),\ 2k_2,\ \lambda_{\min}(\Gamma_\Theta)\lambda_\Theta \\ \Gamma_D\lambda_D,\ \Gamma_\vartheta\lambda_\vartheta\end{matrix}\right\} \\
\varepsilon_f &= \sum_{i=1}^{3}\varepsilon_i + D\varepsilon_d + \frac{\varepsilon_v}{\vartheta} + \frac{\lambda_\Theta}{2}Tr\left(\Theta^T\Theta\right) + \frac{\lambda_D}{2}D^2 + \frac{\lambda_\vartheta}{2}\vartheta
\end{aligned} \tag{49}$$

Define the following compact set:

$$\begin{aligned}
\Omega_f &= \left\{x\in\mathbb{R}^n \middle| V(x)\leq\gamma_2/\gamma_1\right\} \\
\Omega_\rho &= \left\{x \middle| \|x\| < 0.2554\varepsilon\right\}
\end{aligned} \tag{50}$$

Based on **Lemma 2**, it is easy to know that if $e_2(t)\in\Omega_f\bigcap\Omega_\rho$, the solution of the closed-loop control system $e_0(t)$, $e_1(t)$, $e_2(t)$, $\tilde{D}(t)$, $\tilde{\Theta}(t)$, $\tilde{\vartheta}(t)$ are naturally bounded. If $e_2(t)\notin\Omega_f\bigcap\Omega_\rho$, $\dot{V}<0$ can be proved and $V(t)$ gradually decreases, and the solution will eventually converge to the set $\Omega_f\bigcap\Omega_\rho$. Furthermore, since $e_0(t)$ is bounded, according to **Lemma 3**, we know that when $t\to\infty$, $e_1(t)\to 0$, that is, the system tracking error gradually converges to 0. The proof is complete. □

Remark 1: There indeed exist differences between the proposed method and [60], [61], [67], [68]. Firstly, the concerned uncertainties are different. In this paper, the coupling uncertainty term is assumed to satisfy that $\chi(q(t),\omega(t),\tau(t),\eta(t))\leq\varphi_1(q(t),\omega(t))+\varphi_2(\eta(t))+p_\tau\tau(t)$. In other words, the uncertainties considered in this paper are related to the system states and the control inputs simultaneously. However, in [60], [61], [67], [68], the disturbances are supposed to be

$$\begin{aligned}
d(t) &= V\omega(t) \\
\dot{\omega}(t) &= W\omega(t) + H\delta(t)
\end{aligned}$$

which means that the disturbances are generated by the internal states of an exogenous system, rather than the system states and the control inputs. Moreover, the disturbances handled by [68] are mismatched. Therefore, it can be known that the concerned uncertainties are quite different. Secondly, the control structure of the proposed method and [60], [61], [67], [68] are different. In the proposed method, the nominal outer loop controller is designed as

$$\begin{aligned}
u_c(t) =& g^{-1}(x(t))\begin{bmatrix}-k_2e_2(t)-\varphi_\rho(x(t),e_2(t)) \\ -e_1(t)-f(x(t)) \\ -\hat{\Theta}^T\Phi(e_2(t),x(t),r(t)) \\ +\dot{x}_{2c}(t)\end{bmatrix} \\
&-\hat{D}\varphi_d\left(x(t),e_2(t)\right)-\frac{1}{4}g(x(t))e_2(t)
\end{aligned}$$

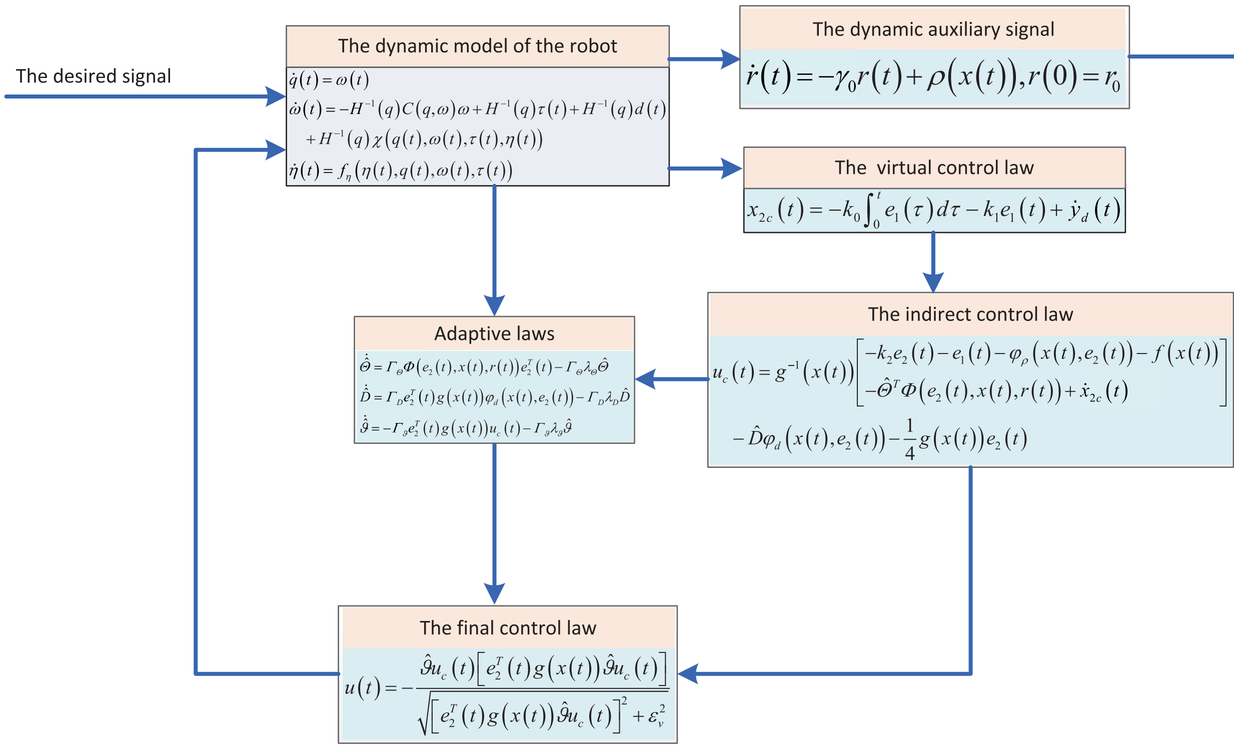

FIGURE 1. **The structure diagram of the proposed control laws.**

The actual outer loop controller is designed as

$$u(t) = -\frac{\hat{\vartheta} u_c(t)\left[e_2^T(t)\, g(x(t))\, \hat{\vartheta} u_c(t)\right]}{\sqrt{\left[e_2^T(t)\, g(x(t))\, \hat{\vartheta} u_c(t)\right]^2 + \varepsilon_v^2}}$$

Moreover, in this paper, the uncertainties are handled by using the adaptive laws. However, in [60], [61], [67], [68], the control laws is designed as $u(t) = Kx(t) - \theta^T \varphi(x) - \hat{d}(t)$, and the uncertainties are deal with by using the disturbance observer. Hence, it can be known that there indeed exist differences between the proposed method and [60], [61], [67], [68].

IV. SIMULATION STUDY

To reveal the effectiveness of the proposed intelligent adaptive anti-coupling control method for the robots under the influence of the input and structural coupling uncertainties, the tracking control experiment for the time-varying desired signal are considered in this section. Moreover, to show the advantages of the proposed NN-based adaptive control (NNAC) with coupling uncertainties compensation (CUC), the NNAC method without CUC and the conventional adaptive control method (AC) without CUC were considered for comparison.

Considering the robot with 2 degrees of freedom, it is easy to know that its inertia parameter matrix $H(q)$ can be formulated by:

$$H(q) = \begin{bmatrix} 2p_1c_1 + 2p_2c_2 + 2p_3c_{12} + p_4 + p_5 + p_6 & p_1c_1 + 2p_2c_2 + p_3c_{12} + p_4 + p_5 & p_2c_2 + p_3c_{12} + p_4 \\ p_1c_1 + 2p_2c_2 + p_3c_{12} + p_4 + p_5 & 2p_2c_2 + p_4 + p_5 & p_2c_2 + p_4 \\ p_2c_2 + p_3c_{12} + p_4 & p_2c_2 + p_4 & p_4 \end{bmatrix} \quad (51)$$

where $c_{ij} = cos\,[q(i) + q(j)]$

$$C = \begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix} \quad (52)$$

In equation (52),

$$\begin{aligned} C_{11} &= -p_1q_{2y}s_1 - p_2q_{2z}s_2 - p_3(q_{2y} + q_{2z})s_{12} \\ C_{12} &= -p_1(q_{2x} + q_{2y})s_1 - p_2q_{2z}s_2 - p_3(q_{2x}+q_{2y}+q_{2z})s_{12} \\ C_{13} &= -(q_{2x} + q_{2y} + q_{2z})(p_2s_1 - p_3s_{12}) \\ C_{21} &= p_1q_{2x}s_1 - p_2q_{2z}s_2 + p_3q_{2x}s_{12} \\ C_{22} &= -p_2q_{2z}s_2,\ C_{23} = -p_2(q_{2x} + q_{2y} + q_{2z})s_2 \\ C_{31} &= p_2(q_{2x} + q_{2y})s_2 + p_3q_{2x}s_{12} \\ C_{32} &= p_2(q_{2x} + q_{2y})s_2,\ C_{33} = 0 \\ s_{ijk} &= sin\,[q_1(i) + q_1(j) + q_1(k)] \end{aligned} \quad (53)$$

In the simulation, the inertia parameters of the robot are shown in **Table 1**. Simple calculation show that $p = col\,\{p_i\}$

TABLE 1. Inertia parameters of the robot.

Variable	Parameter value
Mass of base and each connecting rod	$m_0 = 570, m_1 = 12, m_2 = 18$
Moment of inertia of base and connecting rod	$J_0 = 50, J_1 = 0.8, J_2 = 1.6$
Length parameter between base and connecting rod	$B_0 = 0.45, L_1 = 1, L_{C1} = 0.45, L_{C2} = 0.45$

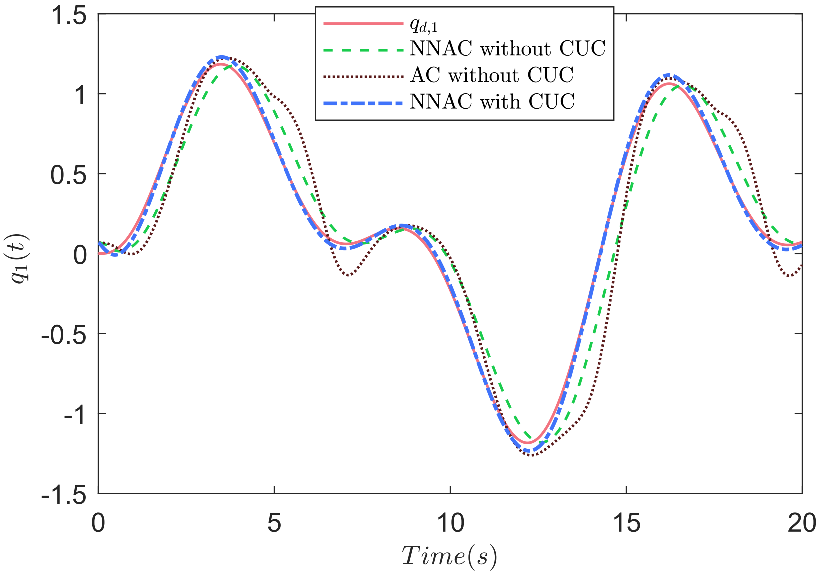

FIGURE 2. The tracking performance of the three control laws.

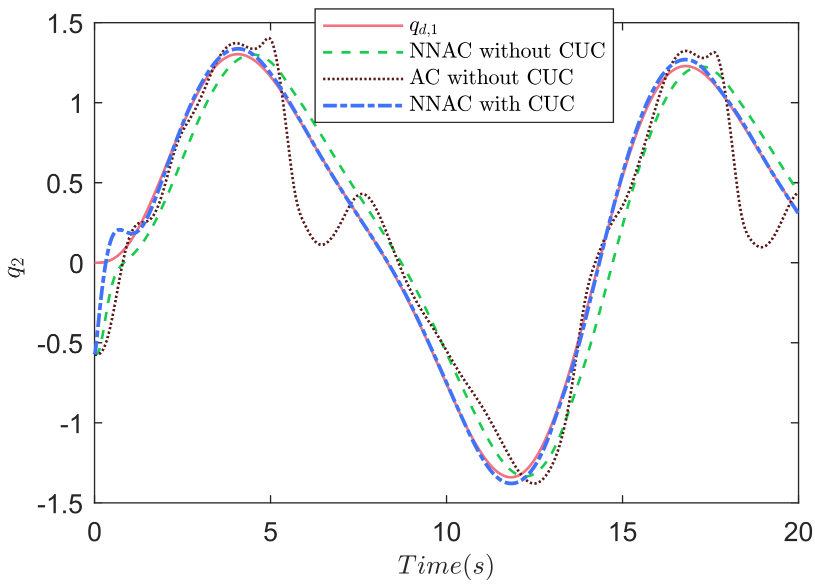

FIGURE 3. The tracking performance of the three control laws.

$=$ [10.0035, 7.7841, 3.4628, 5.1357, 20.3174, 55.7713]. The unmodeled dynamics is supposed to be:

$$\dot{\eta}(t) = -3\eta(t) + q_1(t)q_2(t)q_3(t) + \dot{q}_1(t)\dot{q}_2(t)\dot{q}_3(t) \quad (54)$$

The following coupling uncertainty including both input and structural coupled uncertainties is considered:

$$\chi(q(t), w(t), \tau(t), \eta(t)) = 0.5q(t)sin(t) + \eta(t)(q(t) + \dot{q}(t)) - 0.2sin(\eta(t))\tau(t) \quad (55)$$

In the mathematical simulation, the initial value of the system state quantity is selected as $q(0) = [0.0675, -0.5738, 0.4536]^T$, $w(0) = [0, 0, 0]^T$, $\eta(0) = 1$. The expected signal is selected as a time-varying signal. Select the second-order transfer function as the pre-filter, and relevant parameters are selected as $\xi = 0.9$, $w_n = 3$. The dynamic auxiliary signal $r(t)$ is designed as

$$\dot{r}(t) = -5r(t) + q^T(t)q(t) + \dot{q}^T(t)\dot{q}(t), \quad r(0) = 2 \quad (56)$$

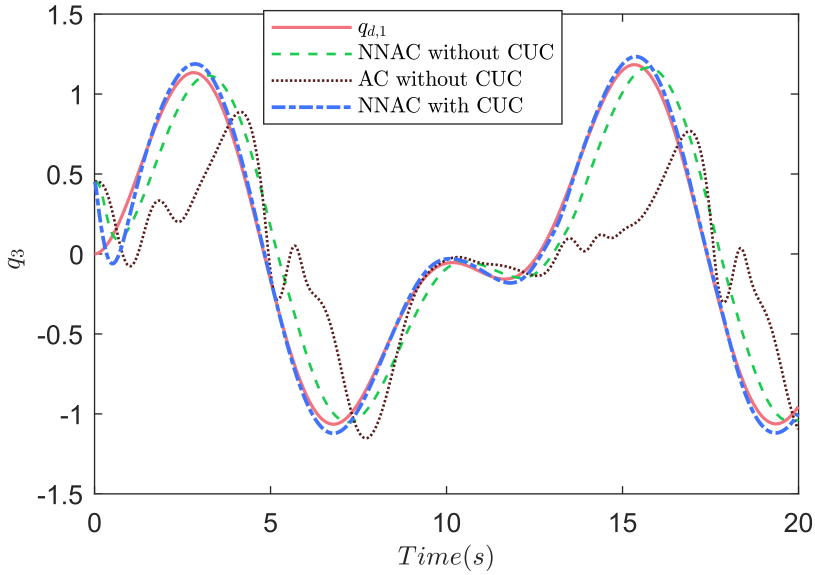

FIGURE 4. The tracking performance of the three control laws.

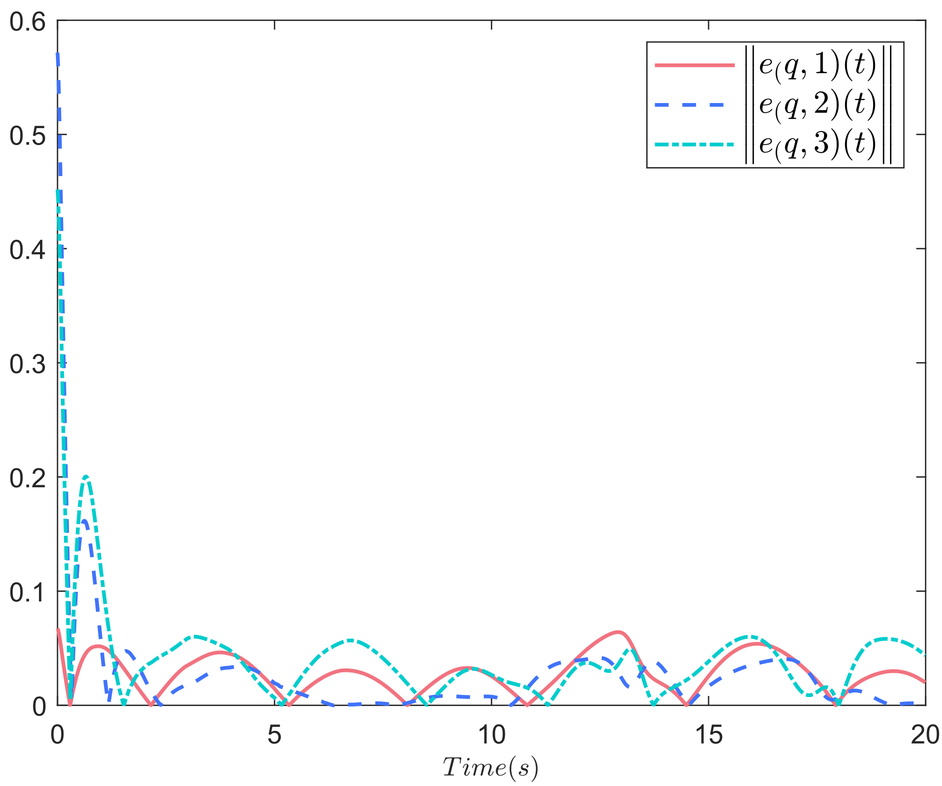

FIGURE 5. The norm of the tracking errors.

The control gains are selected as $k_0 = 3$, $k_1 = 6$, $k_2 = 6$. The initial value of adaptive parameters are designed as $\hat{\Theta}(0) = 0.01$, $\hat{\vartheta}(0) = 1.5$, $\hat{D}(0) = 0.002$. The gains of adaptive laws are chosen as $\Gamma_\Theta = 3$, $\Gamma_\vartheta = \Gamma_D = 2$. The other parameters of adaptive laws are selected as $\lambda_\Theta = 0.2$, $\lambda_\vartheta = 0.1$, $\lambda_D = 5$.

The tracking performance are shown in Fig.1–Fig.3. The norm variation trend of tracking error is shown in Fig.4. Fig.5 shows the trajectory of the adaptive parameters. Fig.6 displays the trajectories of the auxiliary signal $r(t)$ and the internal state $\eta(t)$. It is easy to know that for the time-varying desired signal, the method proposed in this paper can maintain accurate tracking, and the overshoot and tracking error can meet the requirements. Furthermore, the auxiliary signal, and adaptive parameters are all stable. It can be concluded that the proposed method can maintain fast tracking

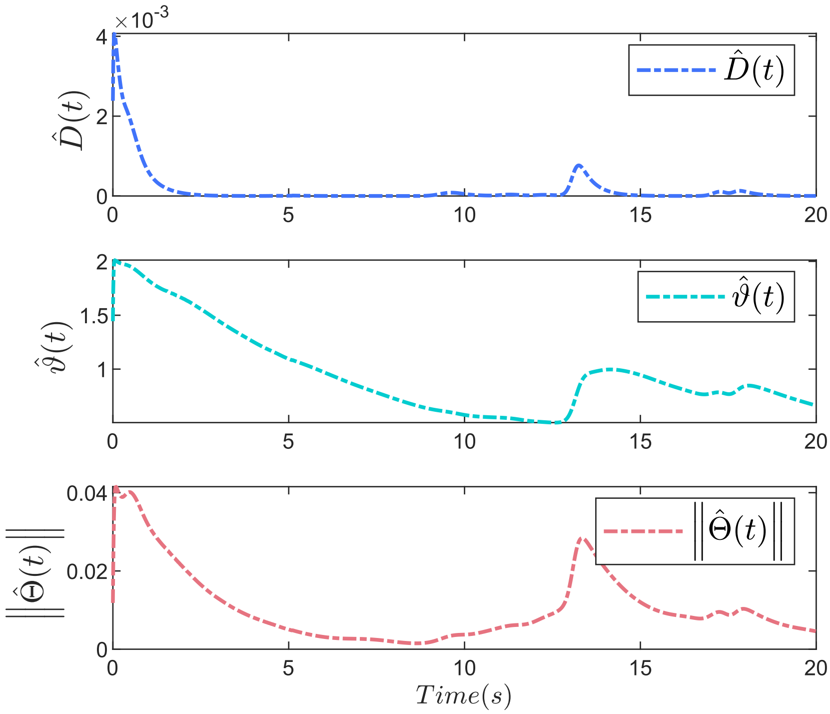

FIGURE 6. The adaptive terms.

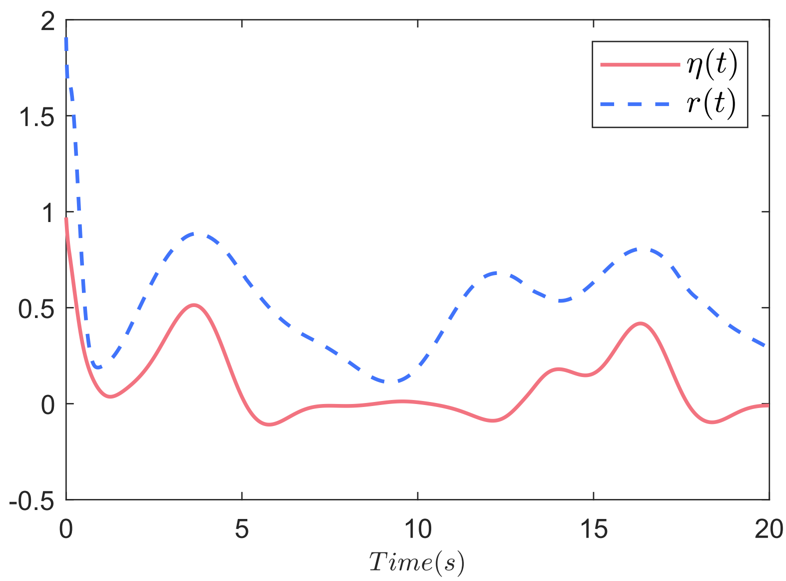

FIGURE 7. The trajectories of the auxiliary signal $r(t)$ and the internal state $\eta(t)$.

of time-varying signals, and possess advantages compared to the other two methods.

Remark 2: The gain selection should satisfy the following rules:

1) The control gains and the adaptive gains should be positive constants;
2) Generally speaking, the control gains should satisfy that $1.5k_0 \leq k_1 \leq k_2$;
3) The adaptive damping parameters should satisfy that $\lambda_\Theta \leq 0.5\Gamma_\Theta$, $\lambda_\vartheta \leq 0.5\Gamma_\vartheta$, $\lambda_D \leq 2\Gamma_D$.

Based on the aforementioned rules, and through the adjustment and iteration on the basis of the simulation results, the design parameters can be finally selected.

V. CONCLUSION

In this paper, the adaptive anti-coupling control problem has been investigated for the robots subjected to input and structural coupled uncertainties. Firstly, the input and structural coupled uncertainties are modeled and transformed into three terms of uncertainties. Secondly, the dynamic auxiliary signal has been introduced and as a result the internal state related uncertainties have be suppressed. By utilizing the adaptive boundary estimation law and several special nonlinear functions, the system state related uncertainties and the system input related uncertainties can be handled. Furthermore, the neural networks are introduced to reduce the control complexity. The simulation results revealed the effeteness of the proposed anti-coupling control method. In the future, we will consider the stochastic anti-coupling control for the robots.

REFERENCES

[1] H.-O. Lim and A. Takanishi, "Biped walking robots created at waseda university: WL and WABIAN family," *Phil. Trans. Roy. Soc. A, Math., Phys. Eng. Sci.*, vol. 365, no. 1850, pp. 49–64, Jan. 2007.

[2] M. Hirose and K. Ogawa, "Honda humanoid robots development," *Phil. Trans. Roy. Soc. A, Math., Phys. Eng. Sci.*, vol. 365, no. 1850, pp. 11–19, Jan. 2007.

[3] G. Nelson, A. Saunders, N. Neville, B. Swilling, J. Bondaryk, D. Billings, C. Lee, R. Playter, and M. Raibert, "PETMAN: A humanoid robot for testing chemical protective clothing," *J. Robot. Soc. Jpn.*, vol. 30, no. 4, pp. 372–377, 2012.

[4] Z. Xia, L. Liu, J. Xiong, Q. Yi, and K. Chen, "Design aspects and development of humanoid robot THBIP-2," *Robotica*, vol. 26, no. 1, pp. 109–116, Jan. 2008.

[5] Z. Yu, Q. Huang, G. Ma, X. Chen, W. Zhang, J. Li, and J. Gao, "Design and development of the humanoid robot BHR-5," *Adv. Mech. Eng.*, vol. 6, Jan. 2014, Art. no. 852937.

[6] S. Kuindersma, R. Deits, M. Fallon, A. Valenzuela, H. Dai, F. Permenter, T. Koolen, P. Marion, and R. Tedrake, "Optimization-based locomotion planning, estimation, and control design for the atlas humanoid robot," *Auto. Robots*, vol. 40, no. 3, pp. 429–455, Mar. 2016.

[7] T. Yoshiike, M. Kuroda, R. Ujino, H. Kaneko, H. Higuchi, S. Iwasaki, Y. Kanemoto, M. Asatani, and T. Koshiishi, "Development of experimental legged robot for inspection and disaster response in plants," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Vancouver, BC, Canada, Sep. 2017, pp. 4869–4876.

[8] Q. Huang, T. Yang, W. Liao, W. Zhang, Z. Yu, X. Chen, and M. Ceccarelli, "Historical development of BHR humanoid robots," in *Proc. HMM IFToMM Symp. History Mach. Mech.*, vol. 37, B. Zhang and M. Ceccarelli, Eds. Cham, Switzerland: Springer, 2019, pp. 310–323.

[9] M. Raibert, K. Blankespoor, G. Nelson, and R. Playter, "BigDog, the rough-terrain quadruped robot," in *Proc. 17th IFAC World Congr.*, Seoul, South Korea, Jul. 2008, pp. 10822–10825.

[10] C. Semini, N. G. Tsagarakis, E. Guglielmino, M. Focchi, F. Cannella, and D. G. Caldwell, "Design of HyQ—A hydraulically and electrically actuated quadruped robot," *Proc. IMechE I, J. Syst. Control Eng.*, vol. 225, no. 6, pp. 831–849, Sep. 2011.

[11] X. Rong, Y. Li, J. Ruan, and B. Li, "Design and simulation for a hydraulic actuated quadruped robot," *J. Mech. Sci. Technol.*, vol. 26, no. 4, pp. 1171–1177, Apr. 2012.

[12] C. RunBin, C. YangZheng, L. Lin, W. Jian, and M. H. Xu, "Inverse kinematics of a new quadruped robot control method," *Int. J. Adv. Robotic Syst.*, vol. 10, no. 1, p. 46, Jan. 2013.

[13] L. Ding, "Key technology analysis of BigDog quadruped robot," *J. Mech. Eng.*, vol. 51, no. 7, pp. 1–23, Apr. 2015.

[14] M. Hutter, C. Gehring, D. Jud, A. Lauber, C. D. Bellicoso, V. Tsounis, J. Hwangbo, K. Bodie, P. Fankhauser, M. Bloesch, R. Diethelm, S. Bachmann, A. Melzer, and M. Hoepflinger, "ANYmal—A highly mobile and dynamic quadrupedal robot," in *Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst. (IROS)*, Daejeon, South Korea, Oct. 2016, pp. 38–44.

[15] R. Xiong, "Development of bionic legged robot," *Robot Tech. Appl.*, vol. 30, no. 2, pp. 29–36, Apr. 2017.

[16] G. Bledt, M. J. Powell, B. Katz, J. Di Carlo, P. M. Wensing, and S. Kim, "MIT cheetah 3: Design and control of a robust, dynamic quadruped robot," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Madrid, Spain, Oct. 2018, pp. 2245–2252.

[17] U. Saranli, M. Buehler, and D. E. Koditschek, "RHex: A simple and highly mobile hexapod robot," *Int. J. Robot. Res.*, vol. 20, no. 7, pp. 616–631, Jul. 2001.

[18] P. Gonzalez de Santos, J. A. Cobano, E. Garcia, J. Estremera, and M. A. Armada, "A six-legged robot-based system for humanitarian demining missions," *Mechatronics*, vol. 17, no. 8, pp. 417–430, Oct. 2007.

[19] K. C. Galloway, G. C. Haynes, B. D. Ilhan, A. M. Johnson, R. Knopf, G. A. Lynch, B. N. Plotnick, M. White, and D. E. Koditschek, "X-RHex: A highly mobile hexapedal robot for sensorimotor tasks," Dept. Elect. Syst. Eng., Univ. Pennsylvania, Philadelphia, PA, USA, Tech. Rep., Nov. 2010.

[20] Y.-C. Chou, W.-S. Yu, K.-J. Huang, and P.-C. Lin, "Bio-inspired step-climbing in a hexapod robot," *Bioinspir. Biomim.*, vol. 7, no. 3, pp. 1–19, Sep. 2012.

[21] A. Roennau, G. Heppner, M. Nowicki, and R. Dillmann, "LAURON V: A versatile six-legged walking robot with advanced maneuverability," in *Proc. IEEE/ASME Int. Conf. Adv. Intell. Mechatronics*, Besacon, France, Jul. 2014, pp. 82–87.

[22] H. Zhang, Y. Liu, J. Zhao, J. Chen, and J. Yan, "Development of a bionic hexapod robot for walking on unstructured terrain," *J. Bionic Eng.*, vol. 11, no. 2, pp. 176–187, Jun. 2014.

[23] A. Schneider, J. Paskarbeit, M. Schilling, and J. Schmitz, "HECTOR, a bio-inspired and compliant hexapod robot," in *Proc. 3rd Int. Conf. Biomim. Biohybrid Syst., Living Mach.*, Milan, Italy, Jul. 2014, pp. 427–429.

[24] Y. Zhao, X. Chai, F. Gao, and C. Qi, "Obstacle avoidance and motion planning scheme for a hexapod robot Octopus-III," *Robot. Auton. Syst.*, vol. 103, pp. 199–212, May 2018.

[25] B. D. Ilhan, A. M. Johnson, and D. E. Koditschek, "Autonomous legged hill ascent," *J. Field Robot.*, vol. 35, no. 5, pp. 802–832, Aug. 2018.

[26] G. Ma, "Research evolution on biorobotics," *Robot*, vol. 23, no. 5, pp. 463–466, Sep. 2001.

[27] A.-H. Ji, Z.-D. Dai, and L.-S. Zhou, "Research development of bio-inspired robotics," *Robot*, vol. 27, no. 3, pp. 284–288, May 2005.

[28] J. Yuh, "Design and control of autonomous underwater robots: A survey," *Auton. Robot.*, vol. 8, no. 1, pp. 7–24, Jan. 2000.

[29] A. K. Khalaji and R. Zahedifar, "Lyapunov-based formation control of underwater robots," *Robotica*, vol. 38, no. 6, pp. 1105–1122, Jun. 2020.

[30] Z. Wang, H. Dang, T. Wang, and B. Zhang, "Design and simulation analysis on underwater robots like reptiles," *J. Phys. Conf. Ser.*, vol. 1550, May 2020, Art. no. 022016.

[31] C. Wei, J. Luo, H. Dai, Z. Bian, and J. Yuan, "Learning-based adaptive prescribed performance control of postcapture space robot-target combination without inertia identifications," *Acta Astronaut.*, vol. 146, pp. 228–242, May 2018.

[32] C. Wei, J. Luo, H. Dai, and G. Duan, "Learning-based adaptive attitude control of spacecraft formation with guaranteed prescribed performance," *IEEE Trans. Cybern.*, vol. 49, no. 11, pp. 4004–4016, Nov. 2019.

[33] W. Kang, "Nonlinear H_∞ control and its application to rigid spacecraft," *IEEE Trans. Autom. Control*, vol. 40, no. 7, pp. 1281–1285, Jul. 1995.

[34] E. Lavretsky and K. A. Wise, "State feedback H_∞ optimal control," in *Robust and Adaptive Control*. London, U.K.: Springer-Verlag, 2013, pp. 73–96.

[35] Y. Feng, X. Yu, and F. Han, "On nonsingular terminal sliding-mode control of nonlinear systems," *Automatica*, vol. 49, no. 6, pp. 1715–1722, Jun. 2013.

[36] J. Song, Y. Niu, and Y. Zou, "Finite-time sliding mode control synthesis under explicit output constraint," *Automatica*, vol. 65, pp. 111–114, Mar. 2016.

[37] J. Zhang, X. Liu, Y. Xia, Z. Zuo, and Y. Wang, "Disturbance observer-based integral sliding-mode control for systems with mismatched disturbances," *IEEE Trans. Ind. Electron.*, vol. 63, no. 11, pp. 7040–7048, Nov. 2016.

[38] F. Li, L. Wu, P. Shi, and C.-C. Lim, "State estimation and sliding mode control for semi-Markovian jump systems with mismatched uncertainties," *Automatica*, vol. 51, pp. 385–393, Jan. 2015.

[39] J. Zhu, X. Yu, T. Zhang, Z. Cao, Y. Yang, and Y. Yi, "Sliding mode control of MIMO Markovian jump systems," *Automatica*, vol. 68, pp. 286–293, Jun. 2016.

[40] D. Ginoya, P. D. Shendge, and S. B. Phadke, "Sliding mode control for mismatched uncertain systems using an extended disturbance observer," *IEEE Trans. Ind. Electron.*, vol. 61, no. 4, pp. 1983–1992, Apr. 2014.

[41] Z. Wang, "Adaptive smooth second-order sliding mode control method with application to missile guidance," *Trans. Inst. Meas. Control*, vol. 39, no. 6, pp. 848–860, Jun. 2017.

[42] T. E. Gibson, Z. Qu, A. M. Annaswamy, and E. Lavretsky, "Adaptive output feedback based on closed-loop reference models," *IEEE Trans. Autom. Control*, vol. 60, no. 10, pp. 2728–2733, Oct. 2015.

[43] G. Tao, "Multivariable adaptive control: A survey," *Automatica*, vol. 50, no. 11, pp. 2737–2764, Nov. 2014.
[44] T. Jiang, C. Huang, and L. Guo, "Control of uncertain nonlinear systems based on observers and estimators," *Automatica*, vol. 59, pp. 35–47, Sep. 2015.
[45] B.-Z. Guo, "Active disturbance rejection control: From ODEs to PDEs," *IFAC-PapersOnLine*, vol. 49, no. 8, pp. 278–283, Jun. 2016.
[46] W.-H. Chen, J. Yang, L. Guo, and S. Li, "Disturbance-observer-based control and related methods—-An overview," *IEEE Trans. Ind. Electron.*, vol. 63, no. 2, pp. 1083–1095, Feb. 2016.
[47] S. Li, J. Yang, W.-H. Chen, and X. Chen, "Disturbance observer-based control," in *Disturbance Observer-Based Control: Methods and Applications*, 1st ed. Boca Raton, FL, USA: CRC Press, 2014, pp. 11–14.
[48] L. Guo and W.-H. Chen, "Disturbance attenuation and rejection for systems with nonlinearity via DOBC approach," *Int. J. Robust Nonlinear Control*, vol. 15, no. 3, pp. 109–125, Feb. 2005.
[49] W.-H. Chen, "Disturbance observer based control for nonlinear systems," *IEEE/ASME Trans. Mechatronics*, vol. 9, no. 4, pp. 706–710, Dec. 2004.
[50] V. I. Utkin, "Scope of the theory of sliding modes," in *Sliding Modes in Control and Optimization*. Berlin, Germany: Springer-Verlag, 1992, pp. 1–11.
[51] A. Levant, "Sliding order and sliding accuracy in sliding mode control," *Int. J. Control*, vol. 58, no. 6, pp. 1247–1263, Dec. 1993.
[52] J. Kochalummoottil, Y. B. Shtessel, J. A. Moreno, and L. Fridman, "Adaptive twist sliding mode control: A Lyapunov design," in *Proc. IEEE Conf. Decis. Control Eur. Control Conf. (CDC-ECC)*, Orlando, FL, USA, Dec. 2011, pp. 7623–7628.
[53] A. Levant, "Robust exact differentiation via sliding mode technique," *Automatica*, vol. 34, no. 3, pp. 379–384, Mar. 1998.
[54] J. A. Moreno and M. Osorio, "A Lyapunov approach to second-order sliding mode controllers and observers," in *Proc. 47th IEEE Conf. Decis. Control*, Cancun, Mexico, Dec. 2008, pp. 2856–2861.
[55] J. A. Moreno, "A linear framework for the robust stability analysis of a generalized super-twisting algorithm," in *Proc. 6th Int. Conf. Electr. Eng., Comput. Sci. Autom. Control (CCE)*, Toluca, Mexico, Jan. 2009, pp. 12–17.
[56] J. A. Moreno and M. Osorio, "Strict Lyapunov functions for the super-twisting algorithm," *IEEE Trans. Autom. Control*, vol. 57, no. 4, pp. 1035–1040, Apr. 2012.
[57] I. Nagesh and C. Edwards, "A multivariable super-twisting sliding mode approach," *Automatica*, vol. 50, no. 3, pp. 984–988, Mar. 2014.
[58] Y. B. Shtessel, I. A. Shkolnikov, and A. Levant, "Smooth second-order sliding modes: Missile guidance application," *Automatica*, vol. 43, no. 8, pp. 1470–1476, Aug. 2007.
[59] Z. Gao, "On the centrality of disturbance rejection in automatic control," *ISA Trans.*, vol. 53, no. 4, pp. 850–857, Jul. 2014.
[60] W.-H. Chen, K. Ohnishi, and L. Guo, "Advances in disturbance/uncertainty estimation and attenuation," *IEEE Trans. Ind. Electron.*, vol. 62, no. 9, pp. 5758–5762, Sep. 2015.
[61] H. Liu, L. Guo, and Y. Zhang, "An anti-disturbance PD control scheme for attitude control and stabilization of flexible spacecrafts," *Nonlinear Dyn.*, vol. 67, no. 3, pp. 2081–2088, Feb. 2012.
[62] Y.-S. Lu, "Sliding-mode disturbance observer with switching-gain adaptation and its application to optical disk drives," *IEEE Trans. Ind. Electron.*, vol. 56, no. 9, pp. 3743–3750, Sep. 2009.
[63] Y. Pan, "Stochastic disturbance observer-based adaptive anti-disturbance control for non-linear systems with stochastic non-harmonic multiple disturbances," *Trans. Inst. Meas. Control*, vol. 40, no. 10, pp. 3222–3231, Jun. 2018.
[64] L. Guo and S. Cao, "Anti-disturbance control theory for systems with multiple disturbances: A survey," *ISA Trans.*, vol. 53, no. 4, pp. 846–849, Jul. 2014.
[65] X. Wei, N. Chen, and W. Li, "Composite adaptive disturbance observer-based control for a class of nonlinear systems with multisource disturbance," *Int. J. Adapt. Control Signal Process.*, vol. 27, no. 3, pp. 199–208, Mar. 2013.
[66] X. Yao and L. Guo, "Composite anti-disturbance control for Markovian jump nonlinear systems via disturbance observer," *Automatica*, vol. 49, no. 8, pp. 2538–2545, Aug. 2013.
[67] X. Wei and N. Chen, "Composite hierarchical anti-disturbance control for nonlinear systems with DOBC and fuzzy control," *Int. J. Robust Nonlinear Control*, vol. 24, no. 2, pp. 362–373, Jan. 2014.
[68] H. Sun and L. Guo, "Composite adaptive disturbance observer based control and back-stepping method for nonlinear system with multiple mismatched disturbances," *J. Franklin Inst.*, vol. 351, no. 2, pp. 1027–1041, Feb. 2014.
[69] M. Wang, B. Chen, and P. Shi, "Adaptive neural control for a class of perturbed strict-feedback nonlinear time-delay systems," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 38, no. 3, pp. 721–730, Jun. 2008.
[70] X. Ning, Y. Zhang, and Z. Wang, "Robust adaptive control for a class of T-S fuzzy nonlinear systems with discontinuous multiple uncertainties and abruptly changing actuator faults," *Complexity*, vol. 2020, pp. 1–16, Dec. 2020.
[71] E. Lavretsky and K. A. Wise, *Robust and Adaptive Control*. London, U.K.: Springer, 2013, doi: 10.1007/978-1-4471-4396-3.
[72] A. Astolfi, R. Ortega, and A. Venkatraman, "A globally exponentially convergent immersion and invariance speed observer for mechanical systems with non-holonomic constraints," *Automatica*, vol. 46, no. 1, pp. 182–189, Jan. 2010.
[73] H. A. Hashim, "Systematic convergence of nonlinear stochastic estimators on the special orthogonal group SO(3)," *Int. J. Robust Nonlinear Control*, vol. 30, no. 10, pp. 3848–3870, Jul. 2020.
[74] H. A. Hashim, L. J. Brown, and K. Mcisaac, "Nonlinear stochastic attitude filters on the special orthogonal group 3: Ito and Stratonovich," *IEEE Trans. Syst Man Cybern. Syst.*, vol. 49, no. 9, pp. 1853–1865, Sep. 2018.
[75] H. A. Hashim and F. L. Lewis, "Nonlinear stochastic estimators on the special Euclidean group SE(3) using uncertain IMU and vision measurements," *IEEE Trans. Syst., Man, Cybern. Syst.*, early access, Mar. 23, 2020, 10.1109/TSMC.2020.2980184.

JUNLONG NIU received the B.E. degree in machine design, manufacturing and automation and the M.E. degree in machine manufacturing and automation from the Shaanxi University of Science and Technology, Xi'an, China, in 2009 and 2012, respectively. He is currently pursuing the Ph.D. degree in mechanical manufacturing and automation with Northwestern Polytechnical University, Xi'an. His current research interests include medical image processing, 3D model reconstruction, and robot bionic joint.

XIANSHENG QIN received the B.E., M.E., and Ph.D. degrees from Northwestern Polytechnical University, Xi'an, China, in 1983, 1986, and 1991, respectively. He is currently a Full Professor and a Ph.D. Supervisor with the School of Mechanical Engineering, Northwestern Polytechnical University. His research interests include computer numerical control systems, bionic and industrial robots, brain computer interface, computer vision, and product development and quality management.

ZHENG WANG received the B.E., M.E., and Ph.D. degrees from Northwestern Polytechnical University, Xi'an, China, in 2013, 2016, and 2020, respectively. He is currently an Associate Professor and a Master Supervisor with the Research Center for Unmanned System Strategy Development, Northwestern Polytechnical University. His current research interests include flight dynamics and control, intelligent decision, and autonomous control of the unmanned systems.