Command Filtering Control of Non-Strict Feedback Stochastic Nonlinear Systems with Time-Varying All-State Constraints and Dead-Zone Input

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***Abstract*—This paper proposes an adaptive fuzzy command filtering control (CFC) approach for non-strict feedback stochastic nonlinear systems with time-varying all-state constraints and dead-zone inputs. A novel barrier Lyapunov function (BLF) is employed to handle time-varying constraints on all states. The nonlinear dead-zone input is decomposed into a linear part and a bounded disturbance component, simplifying the control design. A fuzzy logic system (FLS) approximates unknown system nonlinearities, while a second-order fast command filter resolves the "complexity explosion" issue, compensating filtering errors regardless of initial conditions. By integrating backstepping and stochastic stability theory, the designed adaptive command filter controller guarantees that all closed-loop signals are semi-globally uniformly ultimately bounded (SGUUB) in probability, and all states remain within prescribed dynamic constraints. Moreover, the tracking error converges to a small neighborhood near zero. Simulation results confirm the effectiveness and robustness of the proposed scheme.**

***Index Terms*—Time-varying all-state constraint, dead-zone input, fuzzy adaptive control, command filter**

I. Introduction

With the increasing complexity of modern industrial systems, control strategies for stochastic nonlinear systems have become a prominent area in control science research. Non-strict feedback stochastic nonlinear systems represent a particular structure commonly encountered in scenarios such as robot trajectory tracking, power system stabilization, and aircraft attitude control [1–3]. Unlike strict feedback systems, the nonlinear functions in these systems depend not only on the current subsystem states but also exhibit dynamic coupling with subsequent subsystems. This coupling makes traditional recursive design methods like backstepping ineffective due to the absence of explicit analytic derivatives for virtual control variables. Moreover, random disturbances—including white noise, colored noise, and parameter jumps—further complicate stability analysis. Although these disturbances are typically characterized by Itô stochastic differential equations, a theoretical gap remains between mean-square boundedness and practical probabilistic constraints.

To address the challenges posed by non-strict feedback structures, researchers have primarily proposed two methodologies. One is approximation techniques based on fuzzy logic or neural networks [4, 5]. The other involves filtering approaches such as dynamic surface control (DSC) or CFC [6, 7]. The former employs fuzzy rule bases or radial basis function neural networks (RBFNN) to approximate unknown nonlinearities. For example, the adaptive fuzzy control method introduced by Tong et al. utilizes Lyapunov stability theory for online adjustment of fuzzy parameters, successfully achieving state tracking in non-strict feedback systems [8]. The latter strategy incorporates low-pass filters to avoid differentiating virtual control variables, thus preventing the "explosion of complexity" found in traditional backstepping. Notably, the DSC framework proposed by Zhou et al. significantly mitigates filter-induced delays through error compensation mechanisms [9]. Although both DSC and CFC utilize low-pass filters to circumvent complexity explosion, CFC holds two main advantages. First, DSC typically relies on fixed bandwidth filters, whose phase lag can lead to cumulative tracking errors, posing stability risks in non-strict feedback systems. In contrast, CFC dynamically corrects filtered outputs via auxiliary error compensation, substantially reducing steady-state errors resulting from filter-induced delays. Second, CFC effectively coordinates multiple constraints—including all-state constraints, input saturation, and prescribed performance—whereas DSC requires separate modules for each constraint, increasing overall complexity. Reference [10] explores adaptive fuzzy finite-time CFC for stochastic

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nonlinear systems with unknown dead-zone constraints and unmodeled dynamics. Similarly, Reference [11] examines finite-time adaptive constrained control for stochastic flexible-joint robot (FJR) systems. By designing nonlinear transformation functions dependent only on system outputs, the challenges posed by asymmetric time-varying output constraints are effectively handled, simplifying stability analyses and relaxing initial condition restrictions.

In addition to these issues, actuator dead-zone inputs and time-varying all-state constraints jointly exacerbate control performance degradation risks [12–14]. Dead-zone characteristics cause abrupt discontinuities in control signals near zero, leading to cumulative steady-state errors. Simultaneously, dynamic full-state constraints demand controllers with enhanced adaptability to varying boundaries, making traditional fixed-barrier methods insufficient. Existing studies primarily tackle these problems through two pathways [15–17]: one involves feedforward compensation based on inverse dead-zone models—such as the adaptive compensator by Wang et al., which dynamically compensates asymmetric dead-zones by online estimation of dead-zone parameters [18]; the other transforms state constraints into dynamic inequality constraints using time-varying barrier Lyapunov functions (TV-BLF). For example, Ye et al.'s adaptive controller couples TV-BLF with stochastic stability theory, effectively bounding state constraint violations below a predefined probability threshold [19]. Nevertheless, current methods still exhibit three critical limitations. First, many dead-zone compensation schemes assume known or symmetric dead-zone parameters, which contrasts with real-world asymmetric, time-varying dead-zone characteristics, thereby diminishing compensation accuracy. Second, existing TV-BLF methods largely target deterministic systems, inadequately addressing probabilistic constraint violations induced by stochastic disturbances, such as sensor noise or abrupt loads. Lastly, the coupling between non-strict feedback structures, dead-zone inputs, and dynamic constraints currently lacks a unified theoretical framework, often compromising dynamic response speeds for stability, failing to satisfy high-precision real-time control requirements.

Motivated by the above challenges, this paper investigates a class of non-strict feedback stochastic nonlinear systems with uncertain dead-zone inputs and time-varying all-state constraints, and proposes an adaptive command filtering control approach. Simulation results demonstrate that all signals in the closed-loop system achieve semi-global uniform ultimate boundedness in probability, while strictly adhering to the specified time-varying constraints. Additionally, the system output effectively tracks a given reference signal, with tracking errors converging into a small neighborhood around zero. The primary contributions of this work are summarized as follows:

(1) A novel barrier Lyapunov function (BLF) is designed to guarantee adherence of all system states to time-varying constraints. By decomposing the unknown dead-zone input into a linear component and a bounded disturbance, the interference from its nonlinear nature on controller design is effectively addressed, enabling robust control under asymmetric unknown dead-zone inputs.

(2) A second-order fast command filter is introduced to eliminate the complexity explosion issue. The filter-induced error is compensated through auxiliary error signals, significantly improving the overall control accuracy and disturbance rejection capabilities.

The remainder of this paper is structured as follows. Section 2 describes the system model and preliminary results; Section 3 and 4 present the controller design and stability analysis; Section 5 provides simulation verification; and Section 6 concludes the paper.

II. System Modeling and Preliminaries

A. System description

Consider the following stochastic nonlinear system with non-strict feedback:

$$\begin{cases} \mathrm{d}x_1 = (x_2 + f_1(x) + d_1(x))\,\mathrm{d}t + h_1^{\mathrm{T}}(x_1)\mathrm{d}\omega, \\ \mathrm{d}x_i = (x_{i+1} + f_i(x) + d_i(x))\,\mathrm{d}t + h_i^{\mathrm{T}}(\bar{x}_i)\mathrm{d}\omega, \\ \mathrm{d}x_n = (u(v) + f_n(x) + d_n(x))\,\mathrm{d}t + h_n^{\mathrm{T}}(\bar{x}_n)\mathrm{d}\omega, \\ \quad y = x_1, \quad i = 2, \cdots, n-1. \end{cases} \tag{1}$$

where $u \in \mathbb{R}$ and $y \in \mathbb{R}$ are the control input and output, respectively. x_i is the state of the stochastic nonlinear system subject to the time-varying state constraint $-k_{i1}(t) < x_i < k_{i2}(t)$, where $k_{i1}(t), k_{i2}(t)$ are known smooth positive functions. The functions $f_i(\cdot) : \mathbb{R}^n \to \mathbb{R}$ and $h_i(\cdot) : \mathbb{R}^i \to \mathbb{R}^r$ $(i = 1, 2, \ldots, n)$ are unknown smooth functions. $d_i(\cdot) : \mathbb{R}^n \to \mathbb{R}$ represents an unknown bounded disturbance. Let $\bar{x}_i = [x_1, x_2, \ldots, x_i]^{\mathrm{T}} \in \mathbb{R}^i$, and $x = [x_1, x_2, \ldots, x_n]^{\mathrm{T}} \in \mathbb{R}^n$. The process $w(t)$ denotes a standard r-dimensional independent Wiener process defined on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$, where Ω is the sample space, $\mathcal{F}$ is a σ-algebra, and $\mathbb{P}$ is the probability measure.

The actual control input $u(v)$ affected by a saturated nonlinearity is defined as:

$$u = D(v) = \begin{cases} m_r(v - c_r), & v \geq c_r, \\ 0, & c_l < v < c_r, \\ m_l(v - c_l), & v \leq c_l, \end{cases} \tag{2}$$

where $u \in \mathbb{R}$ is the actual control signal affected by an uncertain dead-zone. $v \in \mathbb{R}$ is the virtual control input to be designed. $D(\cdot)$ is a piecewise function characterizing the uncertain dead-zone.

Equation (2) can be rewritten as:

$$u = D(v) = mv + d(v), \tag{3}$$

where m is the slope of the dead-zone and is piecewise constant, and $d(v)$ is the approximation error given by:

$$d(v) = \begin{cases} -mc_r, & v \geq c_r, \\ -mv, & c_l < v < c_r, \\ -mc_l, & v \leq c_l. \end{cases} \tag{4}$$

The control objective is to design a fuzzy adaptive control scheme based on a second-order fast command filter for a non-strict feedback stochastic nonlinear system with time-varying full-state constraints and dead-zone inputs. The proposed method aims to achieve the following:

(1) All signals of the closed-loop system are SGUUB in probability. Furthermore, the system states satisfy the prescribed time-varying constraints.

(2) The system output tracks a given reference signal, and the tracking error converges to a small neighborhood of zero. The proposed controller effectively compensates for the uncertainties introduced by the dead-zone nonlinearity.

B. Preparation knowledge

In order to facilitate the design of the controller, some necessary definitions and lemmas are introduced in this section. Meanwhile, relevant assumptions and remarks are also provided. First, consider the following stochastic nonlinear system:

$$dx = F(x)dt + G(x)d\omega, \tag{5}$$

where $x \in \mathbb{R}^n$ is the state variable of the system, ω is a standard Wiener process, and $F(\cdot) \in \mathbb{R}^n$, $G(\cdot) \in \mathbb{R}^{n\times r}$ satisfy the local *Lip.* condition. For any given scalar function $V(t,x)$, the stochastic differential of V is given by:

$$dV(t,x) = LV(t,x)dt + \frac{\partial V(t,x)}{\partial x} G d\omega. \tag{6}$$

Definition 1. *For any function $V(t,x) : \mathbb{R}^+ \times \mathbb{R}^n \to \mathbb{R}^+$, define the infinitesimal generator L as:*

$$LV = \frac{\partial V}{\partial x} F + \frac{1}{2}\mathrm{Tr}\left(G^{\mathrm{T}} \frac{\partial^2 V}{\partial x^2} G\right), \tag{7}$$

where $\mathrm{Tr}(\cdot)$ denotes the trace of a matrix.

Lemma 1. For the stochastic nonlinear system in (5), if there exists a positive definite, radially unbounded, and twice continuously differentiable Lyap. function $V(x) \in C^2$, then there exist $\mu_1, \mu_2 \in \mathcal{K}_\infty$ and constants $\alpha_0 > 0$, $\beta_0 > 0$ such that:

$$\begin{cases} \mu_1(\|x\|) \le V(x) \le \mu_2(\|x\|), \\ LV(x) \le -\alpha_0 V(x) + \beta_0. \end{cases} \tag{8}$$

Then for any $x_0 \in \mathbb{R}^n$, the system admits a unique solution, and the state is bounded in probability:

$$\mathbb{E}[V(x)] \le V(x_0)e^{-\alpha_0 t} + \frac{\beta_0}{\alpha_0}, \quad \forall t > t_0. \tag{9}$$

Lemma 2. For $\alpha, \beta \in \mathbb{R}$ and any positive constants μ, ν, ε, the following inequality holds:

$$|\alpha|^\mu |\beta|^\nu \le \frac{\mu}{\mu+\nu}\varepsilon|\alpha|^{\mu+\nu} + \frac{\nu}{\mu+\nu}\varepsilon^{-\mu/\nu}|\beta|^{\mu+\nu}. \tag{10}$$

Lemma 3. Let $f(X)$ be a continuous function on a compact set $\Psi_X \subseteq \mathbb{R}^n$. For any given constant $\varepsilon^* > 0$, there exists a fuzzy logic system $y(X) = W^{\mathrm{T}}\Phi(X)$ such that:

$$\sup_{X\in\Psi_X} \left| f(X) - W^{\mathrm{T}}\Phi(X) \right| < \varepsilon^*, \tag{11}$$

where $W = [w_1, w_2, \ldots, w_N]^{\mathrm{T}}$ is the weight vector and $\Phi(X) = [p_1(X), p_2(X), \ldots, p_N(X)]^{\mathrm{T}} / \sum_{i=1}^N p_i(X)$ is the basis function vector. $N > 1$ is the number of fuzzy rules, $p_i = \exp[-(x-\mu_i)^{\mathrm{T}}(x-\mu_i)/\gamma_i^2]$ is a Gaussian basis function, $\mu_i = [\mu_{i1}, \ldots, \mu_{in}]^{\mathrm{T}}$ is the center, and γ_i is the width of the i-th basis function.

Lemma 4. For any $x \in \mathbb{R}$ satisfying $|x| < k_b$, the following inequality holds:

$$\log\left(\frac{k_b^4}{k_b^4 - x^4}\right) \le \frac{x^4}{k_b^4 - x^4}. \tag{12}$$

Remark. *Let $e = k_b^4/(k_b^4 - x^4)$, then the inequality becomes $\log e \le e - 1$. Define $f(e) = \log e - e + 1$, then $f'(e) = 1/e - 1$. Since $f'(e) = 0$ at $e = 1$, $f'(e) > 0$ when $e < 1$, and $f'(e) < 0$ when $e > 1$, we conclude that $f(e)$ attains its maximum at $e = 1$ with $f(1) = 0$. Hence, the inequality holds for all $|x| < k_b$.*

Lemma 5. Define a second-order command filter as follows:

$$\begin{cases} \dot{w}_i = \zeta_{i,1}, \\ \zeta_{i,1} = -\zeta|w_i - \alpha_{i-1}|^{1/2}\mathrm{sign}(w_i - \alpha_{i-1}) + \zeta_{i,2}, \\ \dot{\zeta}_{i,2} = -\zeta_m \mathrm{sign}(\zeta_{i,2} - \zeta_{i,1}), \quad i = 1, 2, \ldots, n. \end{cases} \tag{13}$$

Remark. *Here, α_{i-1} is the virtual control rate (input), w_i is the command filter output. ζ, ζ_m are filter parameters. Initial conditions are $w_i(0) = \alpha_{i-1}(0)$ and $\zeta_{i,2}(0) = 0$. The command filter helps alleviate the explosion of complexity in backstepping designs and simplifies the controller design.*

Assumption II.1. *The desired trajectory x_d and its i-th derivative $x_d^{(i)}$ are assumed to be continuously differentiable and bounded.*

Assumption II.2. *The parameters of the dead-zone nonlinearity c_r, c_l, m_r, m_l are unknown but bounded. Their signs are known: $c_r > 0$, $c_l < 0$, $m_r > 0$, $m_l > 0$.*

Assumption II.3. *The disturbance functions $|d_i(x)| \le \bar{d}_i$, $i = 1, 2, \ldots, n$, where $\bar{d}_i$ are unknown positive constants.*

Remark. *Assumption 1 ensures boundedness and smoothness of the reference signal and its derivatives, which is realistic in engineering practice. Assumption 2 guarantees that the dead-zone parameters are bounded, which follows from the expression of $d(v)$ in (4). Assumption 3 ensures that system uncertainties are bounded, which is a common condition in robust control theory.*

III. Controller Design

In this section, we design an adaptive fuzzy controller. Based on the backstepping method and a command filter, the stochastic nonlinear system (1) with dead-zone input is ensured to satisfy time-varying full-state constraints. A second-order fast command filter is introduced to reduce the computational burden caused by recursive differentiation of virtual controls and improve control performance. Furthermore, to enhance control accuracy, a filter error compensation device is incorporated.

The following coordinate transformations are considered:

$$\begin{cases} w_1 = x_d, \\ z_i = x_i - w_i, \\ \xi_i = z_i - r_i, \quad i = 1, 2, \ldots, n. \end{cases} \tag{14}$$

where x_i is the state variable of the system, x_d is the given reference signal, z_i is the tracking error, w_i is the output of the command filter, and r_i is the error compensation signal of the command filter.

Step 1: According to the coordinate transformations in (14) and system (1), we have:

$$\begin{aligned} d\xi_1 &= dz_1 - \dot{r}_1 dt \\ &= (x_2 + f_1(x) + d_1(x) - \dot{x}_d - \dot{r}_1)\,dt + h_1^{\mathrm{T}} d\omega. \end{aligned} \tag{15}$$

Select the following Lyap. function:

$$V_1 = \frac{1}{4}\log\left(\frac{k_{b1}^4}{k_{b1}^4 - \xi_1^4}\right) + \frac{1}{2}r_1^2 + \frac{1}{2\gamma_1}\tilde{\theta}_1^2, \quad (16)$$

where $k_{b1}(t)$ is the upper bound function of $\xi_1(t)$ defined on the set $\Omega_{\xi_1} = \{\xi_1(t) \,|\, |\xi_1(t)| < k_{b1}(t)\}$, $\tilde{\theta}_1 = \theta_1 - \hat{\theta}_1$ is the parameter estimation error, and $\gamma_1 > 0$ is a design parameter.

By Definition 1 and Eq. (14), the infinitesimal operator of V_1 is given by:

$$\begin{aligned} LV_1 = &\frac{\xi_1^3}{k_{b1}^4 - \xi_1^4}\Big(\xi_2 + w_2 - \alpha_1 + \alpha_1 + r_2 + f_1 \\ &+ d_1 - \dot{x}_d - \dot{r}_1 + \frac{\xi_1 \dot{k}_{b1}}{k_{b1}}\Big) \\ &+ \frac{\xi_1^2(3k_{b1}^4 + \xi_1^4)}{2(k_{b1}^4 - \xi_1^4)^2}\|h_1\|^2 + r_1\dot{r}_1 - \frac{1}{\gamma_1}\tilde{\theta}_1\dot{\hat{\theta}}_1. \quad (17) \end{aligned}$$

According to Lemma 2 and Assumption 3, the following inequalities hold:

$$\frac{\xi_1^3\xi_2}{k_{b1}^4 - \xi_1^4} \le \frac{3}{4}\xi_1^4(k_{b1}^4 - \xi_1^4)^{-4/3} + \frac{1}{4}\xi_2^4, \quad (18)$$

$$\frac{\xi_1^3 d_1}{k_{b1}^4 - \xi_1^4} \le \frac{3}{4}\xi_1^4(k_{b1}^4 - \xi_1^4)^{-4/3} + \frac{1}{4}\bar{d}_1^4, \quad (19)$$

$$\frac{\xi_1^2(3k_{b1}^4 + \xi_1^4)}{2(k_{b1}^4 - \xi_1^4)^2}\|h_1\|^2 \le \frac{\xi_1^4(3k_{b1}^4 + \xi_1^4)^2\|h_1\|^4}{4l_1^2(k_{b1}^4 - \xi_1^4)^4} + \frac{1}{4}l_1^2. \quad (20)$$

Substituting Eqs. (18)–(20) into (17), we obtain:

$$\begin{aligned} LV_1 \le &\frac{\xi_1^3}{k_{b1}^4 - \xi_1^4}\Bigg(w_2 - \alpha_1 + \alpha_1 + r_2 - \dot{x}_d - \dot{r}_1 \\ &+ \frac{3}{2}\xi_1(k_{b1}^4 - \xi_1^4)^{-1/3} \\ &+ \frac{\xi_1(3k_{b1}^4 + \xi_1^4)^2}{4l_1}(k_{b1}^4 - \xi_1^4)^{-3}\|l_1\|^4 \\ &+ \frac{\xi_1\dot{k}_{b1}}{k_{b1}}\Bigg) + \frac{1}{4}\bar{d}_1^4 + \frac{1}{4}l_1^2 + r_1\dot{r}_1 \\ &- \frac{1}{\gamma_1}\tilde{\theta}_1\dot{\hat{\theta}}_1 + \frac{1}{4}\xi_2^4. \quad (21) \end{aligned}$$

As $f_1(\cdot)$ contains an unknown nonlinear term that cannot be directly canceled, we construct an unknown smooth function as:

$$\begin{aligned} \mathrm{T}_1(Z_1) = &f_1 + \frac{3}{2}\xi_1(k_{b1}^4 - \xi_1^4)^{-1/3} \\ &+ \frac{\xi_1(3k_{b1}^4 + \xi_1^4)^2}{4l_1}(k_{b1}^4 - \xi_1^4)^{-3}\|l_1\|^4, \end{aligned}$$

and approximate $\mathrm{T}_1(Z_1)$ using a fuzzy logic system:

$$\mathrm{T}_1(Z_1) = W_1^{\mathrm{T}}\Phi_1(Z_1) + \varepsilon_1(Z_1), \quad |\varepsilon_1(Z_1)| \le \varepsilon_1^*, \quad (22)$$

where $Z_1 = [x, x_d, \dot{x}_d, \xi_1]^{\mathrm{T}}$, and $\varepsilon_1(Z_1)$ is the approximation error bounded by $\varepsilon_1^* > 0$.

Given that $0 < \Phi^{\mathrm{T}}(\cdot)\Phi(\cdot) < 1$, from Lemma 2:

$$\begin{aligned} \frac{\xi_1^3}{k_{b1}^4 - \xi_1^4}\mathrm{T}_1(Z_1) \le &\frac{\theta_1\xi_1^6\Phi_1^{\mathrm{T}}(Z_1)\Phi_1(Z_1)}{2a_1^2(k_{b1}^4 - \xi_1^4)^2\Phi_1^{\mathrm{T}}(X_1)\Phi_1(X_1)} \\ &+ \frac{1}{2}a_1^2\Phi_1^{\mathrm{T}}(X_1)\Phi_1(X_1) \\ &+ \frac{\xi_1^4}{4(k_{b1}^4 - \xi_1^4)^{4/3}} + \frac{1}{4}\varepsilon_1^{*4} \\ \le &\frac{\theta_1\xi_1^6}{2a_1^2(k_{b1}^4 - \xi_1^4)^2\Phi_1^{\mathrm{T}}(X_1)\Phi_1(X_1)} + \frac{1}{2}a_1^2 \\ &+ \frac{\xi_1^4}{4(k_{b1}^4 - \xi_1^4)^{4/3}} + \frac{1}{4}\varepsilon_1^{*4}, \quad (23) \end{aligned}$$

where $\theta_1 = \|W_1\|^2$, $X_1 = [x_1, x_d, \dot{x}_d, \xi_1]^{\mathrm{T}}$, and $a_1 > 0$ is a design parameter.

Substituting Eq. (23) into (21), we finally obtain:

$$\begin{aligned} LV_1 \le &\frac{\xi_1^3}{k_{b1}^4 - \xi_1^4}\Bigg(w_2 + r_2 - \dot{x}_d - \dot{r}_1 + \frac{3}{4}\xi_1(k_{b1}^4 - \xi_1^4)^{1/3} \\ &+ \frac{\theta_1\xi_1^3}{2a_1^2(k_{b1}^4 - \xi_1^4)\Phi_1^{\mathrm{T}}\Phi_1} + \frac{\xi_1\dot{k}_{b1}}{k_{b1}}\Bigg) + \frac{1}{4}\bar{d}_1^4 + \frac{1}{4}l_1^2 \\ &+ \frac{1}{4}\varepsilon_1^{*2} + \frac{1}{2}a_1^2 + r_1\dot{r}_1 - \frac{1}{\gamma_1}\tilde{\theta}_1\dot{\hat{\theta}}_1 + \frac{1}{4}\xi_2^4. \quad (24) \end{aligned}$$

The virtual control law α_1, the error compensation signal $\dot{r}_1$, and the parameter adaptive update rate $\dot{\hat{\theta}}_1$ are designed as:

$$\begin{aligned} \alpha_1 = &-c_1 z_1 - \frac{\hat{\theta}_1\xi_1^3}{2a_1^2(k_{b1}^4 - \xi_1^4)\Phi_1^T\Phi_1} + \dot{x}_d \\ &- \frac{3}{4}\xi_1(k_{b1}^4 - \xi_1^4)^{-1/3} - \frac{\xi_1\dot{k}_{b1}}{k_{b1}}. \quad (25) \end{aligned}$$

$$\dot{r}_1 = (\omega_2 - \alpha_1 + r_2) - c_1 r_1. \quad (26)$$

$$\dot{\hat{\theta}}_1 = \frac{\gamma_1\xi_1^6}{2a_1^2(k_{b1}^4 - \xi_1^4)^2\Phi_1^T\Phi_1} - \sigma_1\hat{\theta}_1. \quad (27)$$

The design parameters satisfy $\kappa_1 > 0$, $c_1 > 0$, and $\sigma_1 > 0$. Through equations (25)–(27), equation (24) can be written as:

$$\begin{aligned} LV_1 \le &-\frac{c_1\xi_1^4}{k_{b1}^4 - \xi_1^4} + r_1(\omega_2 - \alpha_1) + r_1 r_2 - c_1 r_1^2 \\ &+ \frac{\sigma_1}{\gamma_1}\tilde{\theta}_1\hat{\theta}_1 + \frac{1}{4}\xi_2^4 + \rho_1, \quad (28) \end{aligned}$$

where

$$\rho_1 = \frac{1}{4}\bar{d}_1^4 + \frac{1}{4}l_1^2 + \frac{1}{4}\varepsilon_1^{*2} + \frac{1}{2}a_1^2 > 0.$$

It should be noted that the term $\frac{1}{4}\xi_2^4$ will be dealt with in the next step.

Step i $(2 \le i \le n-1)$**:** According to the coordinate transformation in formulas (14) and (1), we have:

$$\begin{aligned} d\xi_i &= dz_i - \dot{r}_i dt \\ &= (x_{i+1} + f_i(x) + d_i(x) - \dot{w}_i - \dot{r}_i)\,dt + h_i^T d\omega. \quad (29) \end{aligned}$$

Select the following Lyapunov function:

$$V_i = V_{i-1} + \frac{1}{4}\log\left(\frac{k_{bi}^4}{k_{bi}^4 - \xi_i^4}\right) + \frac{1}{2}r_i^2 + \frac{1}{2\gamma_i}\tilde{\theta}_i^2, \quad (30)$$

where $k_{bi}(t)$ is the upper bound function of $\xi_i(t)$ defined in the set

$$\Omega_{\xi_i} = \{\xi_i(t) \,|\, |\xi_i(t)| < k_{bi}(t)\}.$$

Here, $\tilde{\theta}_i = \theta_i - \hat{\theta}_i$ is the parameter estimation error, $\hat{\theta}_i$ is the estimate of θ_i, and $\gamma_i > 0$ is the design parameter.

By Definition 1 and formula (14), we can see that the differential operator of formula (30) is:

$$\begin{aligned} LV_i = LV_{i-1} &+ \frac{\xi_i^3}{k_{bi}^4 - \xi_i^4}\Big(\xi_{i+1} + w_{i+1} - \alpha_i + \alpha_i + r_{i+1} \\ &+ f_i + d_i - \dot{w}_i - \dot{r}_i + \frac{\xi_i \dot{k}_{bi}}{k_{bi}}\Big) \\ &+ \frac{\xi_i^2(3k_{bi}^4 + \xi_i^4)}{2(k_{bi}^4 - \xi_i^4)^2}\|h_i\|^2 + r_i\dot{r}_i - \frac{1}{\gamma_i}\tilde{\theta}_i\dot{\hat{\theta}}_i. \end{aligned} \tag{31}$$

According to Lemma 2 and Assumption 3, the following inequality holds:

$$\frac{\xi_i^3 \xi_{i+1}}{k_{bi}^4 - \xi_i^4} \le \frac{3}{4}\xi_i^4(k_{bi}^4 - \xi_i^4)^{-4/3} + \frac{1}{4}\xi_{i+1}^4, \tag{32}$$

$$\frac{\xi_i^3 d_i}{k_{bi}^4 - \xi_i^4} \le \frac{3}{4}\xi_i^4(k_{bi}^4 - \xi_i^4)^{-4/3} + \frac{1}{4}\bar{d}_i^4, \tag{33}$$

$$\frac{\xi_i^2(3k_{bi}^4 + \xi_i^4)}{2(k_{bi}^4 - \xi_i^4)^2}\|h_i\|^2 \le \frac{\xi_i^4(3k_{bi}^4 + \xi_i^4)^2\|h_i\|^4}{4l_i^2(k_{bi}^4 - \xi_i^4)^4} + \frac{1}{4}l_i^2. \tag{34}$$

Substituting formula (32)-formula (34) into formula (31), we can get:

$$\begin{aligned} LV_i \le LV_{i-1} &+ \frac{\xi_i^3}{k_{bi}^4 - \xi_i^4}\Bigg(w_{i+1} - \alpha_i + \alpha_i + r_{i+1} \\ &+ f_i - \dot{w}_i - \dot{r}_i + \frac{3}{2}\xi_i(k_{bi}^4 - \xi_i^4)^{-1/3} \\ &+ \frac{\xi_i(3k_{bi}^4 + \xi_i^4)^2}{4l_i(k_{bi}^4 - \xi_i^4)^3}\|h_i\|^4 + \frac{\xi_i \dot{k}_{bi}}{k_{bi}}\Bigg) \\ &+ \frac{1}{4}\bar{d}_i^4 + \frac{1}{4}l_i^2 + r_i\dot{r}_i - \frac{1}{\gamma_i}\tilde{\theta}_i\dot{\hat{\theta}}_i + \frac{1}{4}\xi_{i+1}^4. \end{aligned} \tag{35}$$

As there is an unknown nonlinear term in $F_i(\cdot)$, which cannot be directly eliminated, an unknown smooth function is constructed as:

$$\begin{aligned} \mathrm{T}_i(Z_i) = f_i - \dot{w}_i &+ \frac{3}{2}\xi_i\left(k_{bi}^4 - \xi_i^4\right)^{-1/3} \\ &+ \frac{\xi_i(3k_{bi}^4 + \xi_i^4)^2}{4l_i}\left(k_{bi}^4 - \xi_i^4\right)^{-3}\|h_i\|^4, \end{aligned}$$

where fuzzy logic system is used to approximate $\mathrm{T}_i(Z_i)$, and $Z_i = [x, w_i, \dot{w}_i, \xi_i]^T$. According to Lemma 3:

$$\mathrm{T}_i(Z_i) = W_i^T\Phi_i(Z_i) + \varepsilon_i(Z_i), \quad |\varepsilon_i(Z_i)| \le \varepsilon_i^*, \tag{36}$$

where $\varepsilon_i(Z_i)$ is the approximation error and $\varepsilon_i^* > 0$ is its upper bound. Since $0 < \Phi^T(\cdot)\Phi(\cdot) < 1$, Lemma 2 gives:

$$\begin{aligned} \frac{\xi_i^3}{k_{bi}^4 - \xi_i^4}\mathrm{T}_i(Z_i) &\le \frac{\theta_i\xi_i^6\Phi_i^T(Z_i)\Phi_i(Z_i)}{2a_i^2(k_{bi}^4 - \xi_i^4)^2\Phi_i^T(X_i)\Phi_i(X_i)} \\ &\quad + \frac{1}{2}a_i^2\Phi_i^T(X_i)\Phi_i(X_i) \\ &\quad + \frac{\xi_i^4}{4(k_{bi}^4 - \xi_i^4)^{4/3}} + \frac{1}{4}\varepsilon_i^{*4} \\ &\le \frac{\theta_i\xi_i^6}{2a_i^2(k_{bi}^4 - \xi_i^4)^2\Phi_i^T(X_i)\Phi_i(X_i)} + \frac{1}{2}a_i^2 \\ &\quad + \frac{\xi_i^4}{4(k_{bi}^4 - \xi_i^4)^{4/3}} + \frac{1}{4}\varepsilon_i^{*4}, \end{aligned} \tag{37}$$

where $\theta_i = \|W_i\|^2$ and $X_i = [x_i, w_i, \dot{w}_i, \xi_i]^T$. The design parameter $a_i > 0$.

Substituting inequality (37) into (35), we obtain:

$$\begin{aligned} LV_i \le LV_{i-1} &+ \frac{\xi_i^3}{k_{bi}^4 - \xi_i^4}\Bigg(w_{i+1} - \alpha_i + \alpha_i + r_{i+1} - \dot{r}_i \\ &+ \frac{3}{4}\xi_i(k_{bi}^4 - \xi_i^4)^{1/3} + \frac{\theta_i\xi_i^3}{2a_i^2(k_{bi}^4 - \xi_i^4)\Phi_i^T\Phi_i} + \frac{\xi_i\dot{k}_{bi}}{k_{bi}}\Bigg) \\ &+ \frac{1}{4}\bar{d}_i^4 + \frac{1}{4}l_i^2 + \frac{1}{4}\varepsilon_i^{*2} + \frac{1}{2}a_i^2 \\ &+ r_i\dot{r}_i - \frac{1}{\gamma_i}\tilde{\theta}_i\dot{\hat{\theta}}_i + \frac{1}{4}\xi_{i+1}^4. \end{aligned} \tag{38}$$

The virtual control law α_i, the error compensation signal $\dot{r}_i$, and the parameter adaptive update rate $\dot{\hat{\theta}}_i$ are designed as:

$$\begin{aligned} \alpha_i = &-c_i z_i - \frac{\hat{\theta}_i\xi_i^3}{2a_i^2(k_{bi}^4 - \xi_i^4)\Phi_i^T\Phi_i} - \frac{1}{4}\xi_i(k_{bi}^4 - \xi_i^4) \\ &- \frac{3}{4}\xi_i(k_{bi}^4 - \xi_i^4)^{-1/3} - \frac{\xi_i\dot{k}_{bi}}{k_{bi}}. \end{aligned} \tag{39}$$

$$\dot{r}_i = (\omega_{i+1} - \alpha_i + r_{i+1}) - c_i r_i. \tag{40}$$

$$\dot{\hat{\theta}}_i = \frac{\gamma_i\xi_i^6}{2a_i^2(k_{bi}^4 - \xi_i^4)^2\Phi_i^T\Phi_i} - \sigma_i\hat{\theta}_i. \tag{41}$$

The design parameters satisfy $\kappa_i > 0$, $c_i > 0$, and $\sigma_i > 0$. Through equations (39)–(41), equation (38) can be rewritten as:

$$\begin{aligned} LV_i \le &-\sum_{j=1}^{i}\frac{c_j\xi_j^4}{k_{bj}^4 - \xi_{bj}^4} + \sum_{j=1}^{i} r_j(\omega_{j+1} - \alpha_j) + \sum_{j=1}^{i} r_j r_{j+1} \\ &- \sum_{j=1}^{i} c_j r_j^2 + \sum_{j=1}^{i}\frac{\sigma_j}{\gamma_j}\tilde{\theta}_j\hat{\theta}_j + \frac{1}{4}\xi_{i+1}^4 + \sum_{j=1}^{i}\rho_j, \end{aligned} \tag{42}$$

where

$$\rho_j = \frac{1}{4}\bar{d}_j^4 + \frac{1}{4}l_j^2 + \frac{1}{4}\varepsilon_j^{*2} + \frac{1}{2}a_j^2 > 0.$$

It should be noted that the term $\frac{1}{4}\xi_{i+1}^4$ will be dealt with in the next step.

Step n**:** According to the coordinate transformation in formulas (1) and (14), we obtain:

$$\begin{aligned} d\xi_n &= dz_n - \dot{r}_n dt \\ &= (u(\nu) + f_n(x) + d_n(x) - \dot{w}_n - \dot{r}_n)\, dt + h_n^{\mathrm{T}}\mathbf{d}\omega. \end{aligned} \tag{43}$$

Select the following *Lyapunov* function:

$$V_n = V_{n-1} + \frac{1}{4}\log\left(\frac{k_{bn}^4}{k_{bn}^4 - \xi_n^4}\right) + \frac{1}{2}r_n^2 + \frac{1}{2\gamma_n}\tilde{\theta}_n^2, \quad (44)$$

where $k_{bn}(t)$ is the upper bound function of $\xi_n(t)$ defined in the set $\Omega_{\xi_n} = \{\xi_n(t) \mid |\xi_n(t)| < k_{bn}(t)\}$. $\tilde{\theta}_n = \theta_n - \hat{\theta}_n$ is the parameter estimation error, $\hat{\theta}_n$ is the estimate of θ_n, and $\gamma_n > 0$ is a design parameter.

By Definition 1 and formula (14), the differential operator of formula (44) is:

$$\begin{aligned} LV_n = LV_{n-1} &+ \frac{\xi_n^3}{k_{bn}^4 - \xi_n^4}\Big(m\nu + d(\nu) + f_n + d_n \\ &- \dot{w}_n - \dot{r}_n + \frac{\xi_n \dot{k}_{bn}}{k_{bn}}\Big) \\ &+ \frac{\xi_n^2(3k_{bn}^4 + \xi_n^4)}{2(k_{bn}^4 - \xi_n^4)^2}\|h_n\|^2 + r_n\dot{r}_n - \frac{1}{\gamma_n}\tilde{\theta}_n\dot{\hat{\theta}}_n. \quad (45) \end{aligned}$$

According to Lemma 2 and Assumption 3, the following inequalities hold:

$$\frac{\xi_n^3 d(\nu)}{k_{bn}^4 - \xi_n^4} \le \frac{3}{4}\xi_n^4(k_{bn}^4 - \xi_n^4)^{-4/3} + \frac{1}{4}\overline{d}^4, \quad (46)$$

$$\frac{\xi_n^3 d_n}{k_{bn}^4 - \xi_n^4} \le \frac{3}{4}\xi_n^4(k_{bn}^4 - \xi_n^4)^{-4/3} + \frac{1}{4}\overline{d}_n^4, \quad (47)$$

$$\frac{\xi_n^2(3k_{bn}^4 + \xi_n^4)}{2(k_{bn}^4 - \xi_n^4)^2}\|h_n\|^2 \le \frac{\xi_n^4(3k_{bn}^4 + \xi_n^4)^2\|h_n\|^4}{4l_n^2(k_{bn}^4 - \xi_n^4)^4} + \frac{1}{4}l_n^2. \quad (48)$$

Substituting formulas (46)–(48) into formula (45), we obtain:

$$\begin{aligned} LV_n \le LV_{n-1} &+ \frac{\xi_n^3}{k_{bn}^4 - \xi_n^4}\Bigg(m\nu + f_n - \dot{w}_n - \dot{r}_n \\ &+ \frac{3}{2}\xi_n(k_{bn}^4 - \xi_n^4)^{-1/3} \\ &+ \frac{\xi_n(3k_{bn}^4 + \xi_n^4)^2}{4l_n}(k_{bn}^4 - \xi_n^4)^{-3}\|h_n\|^4 + \frac{\xi_n\dot{k}_{bn}}{k_{bn}}\Bigg) \\ &+ \frac{1}{4}\overline{d}_n^4 + \frac{1}{4}l_n^2 + r_n\dot{r}_n - \frac{1}{\gamma_n}\tilde{\theta}_n\dot{\hat{\theta}}_n + \frac{1}{4}\overline{d}^4. \quad (49) \end{aligned}$$

As there is an unknown nonlinear term in $F_n(\cdot)$ which cannot be directly eliminated, an unknown smooth function is constructed as:

$$\begin{aligned} \mathrm{T}_n(Z_n) = f_n - \dot{w}_n &+ \frac{3}{2}\xi_n(k_{bn}^4 - \xi_n^4)^{1/3} \\ &+ \frac{\xi_n(3k_{bn}^4 + \xi_n^4)^2}{4l_n}(k_{bn}^4 - \xi_n^4)^{-3}\|h_n\|^4. \end{aligned}$$

Using a fuzzy logic system to approximate $\mathrm{T}_n(Z_n)$ with $Z_n = [x, w_n, \dot{w}_n, \xi_n]^T$, and according to Lemma 3:

$$\mathrm{T}_n(Z_n) = W_n^T\Phi_n(Z_n) + \varepsilon_n(Z_n), \quad |\varepsilon_n(Z_n)| \le \varepsilon_n^*, \quad (50)$$

where $\varepsilon_n(Z_n)$ is the approximation error and $\varepsilon_n^* > 0$ its upper bound.

Since $0 < \Phi^T(\cdot)\Phi(\cdot) < 1$, Lemma 2 implies:

$$\begin{aligned} \frac{\xi_n^3}{k_{bn}^4 - \xi_n^4}\mathrm{T}_n(Z_n) &\le \frac{\theta_n\xi_n^6\Phi_n^T(Z_n)\Phi_n(Z_n)}{2a_n^2(k_{bn}^4 - \xi_n^4)^2\Phi_n^T(X_n)\Phi_n(X_n)} \\ &\quad + \frac{1}{2}a_n^2\Phi_n^T(X_n)\Phi_n(X_n) \\ &\quad + \frac{\xi_n^4}{4(k_{bn}^4 - \xi_n^4)^{4/3}} + \frac{1}{4}\varepsilon_n^4 \\ &\le \frac{\theta_n\xi_n^6}{2a_n^2(k_{bn}^4 - \xi_n^4)^2\Phi_n^T(X_n)\Phi_n(X_n)} \\ &\quad + \frac{1}{2}a_n^2 + \frac{\xi_n^4}{4(k_{bn}^4 - \xi_n^4)^{4/3}} + \frac{1}{4}\varepsilon_n^{*4}, \end{aligned} \quad (51)$$

where $\theta_n = \|W_n\|^2$, $X_n = [x_n, w_n, \dot{w}_n, \xi_n]^T$, and $a_n > 0$.

Substituting formula (51) into (49), we obtain:

$$\begin{aligned} LV_n \le LV_{n-1} &+ \frac{\xi_n^3}{k_{bn}^4 - \xi_n^4}\Bigg(m\nu - \dot{r}_n + \frac{3}{4}\xi_n(k_{bn}^4 - \xi_n^4)^{-1/3} \\ &+ \frac{\theta_n\xi_n^3}{2a_n^2(k_{bn}^4 - \xi_n^4)\Phi_n^T\Phi_n} + \frac{\xi_n\dot{k}_{bn}}{k_{bn}}\Bigg) \\ &+ \frac{1}{4}\overline{d}_n^4 + \frac{1}{4}l_n^2 + \frac{1}{4}\varepsilon_n^{*2} + \frac{1}{2}a_n^2 \\ &+ r_n\dot{r}_n - \frac{1}{\gamma_n}\tilde{\theta}_n\dot{\hat{\theta}}_n + \frac{1}{4}\overline{d}^4. \quad (52) \end{aligned}$$

The virtual control law α_n, the error compensation signal $\dot{r}_n$, and the parameter adaptive update law $\dot{\hat{\theta}}_n$ are designed as:

$$\begin{aligned} \nu = \frac{1}{m}\Bigg(&- c_n z_n - \frac{\hat{\theta}_n\xi_n^3}{2a_n^2(k_{bn}^4 - \xi_n^4)\Phi_n^T\Phi_n} \\ &- \frac{1}{4}\xi_n(k_{bn}^4 - \xi_n^4) - \frac{3}{4}\xi_n(k_{bn}^4 - \xi_n^4)^{-1/3} - \frac{\xi_n\dot{k}_{bn}}{k_{bn}}\Bigg), \end{aligned} \quad (53)$$

$$\dot{r}_n = -c_n r_n, \quad (54)$$

$$\dot{\hat{\theta}}_n = \frac{\gamma_n\xi_m^6}{2a_n^2(k_{bn}^4 - \xi_n^4)^2\Phi_n^T\Phi_n} - \sigma_n\hat{\theta}_n. \quad (55)$$

The design parameters satisfy $\kappa_n > 0$, $c_n > 0$, and $\sigma_n > 0$. Substituting (53)–(55) into (52) yields:

$$\begin{aligned} LV_n \le &-\sum_{j=1}^{n}\frac{c_j\xi_j^4}{k_{bj}^4 - \xi_{bj}^4} + \sum_{j=1}^{n-1}r_j(\omega_{j+1} - \alpha_j) \\ &+ \sum_{j=1}^{n-1}r_j r_{j+1} - \sum_{j=1}^{n}c_j r_j^2 + \sum_{j=1}^{n}\frac{\sigma_j}{\gamma_j}\tilde{\theta}_j\hat{\theta}_j \\ &+ \sum_{j=1}^{n}\rho_j + \frac{1}{4}d^4, \quad (56) \end{aligned}$$

where $\rho_j = \frac{1}{4}\overline{d}_j^4 + \frac{1}{4}l_j^2 + \frac{1}{4}\varepsilon_j^{*2} + \frac{1}{2}a_j^2 > 0$.

IV. STABILITY ANALYSIS

Theorem 1: Consider a class of stochastic nonlinear systems with dead-time input and non-strict feedback (1). On the premise that the above assumptions hold and the initial state of the system meets $x_i(0) \in \Omega_{x_i} = \{x_i \,||x_i(0)| \le k_{ci}(t)\}, i = 1, 2, \cdots, n$, the control rates

(25), (39) and (53), parameter update rates (27), (41) and (55), and error compensation signals (26), (40) and (54) are selected. Then, all closed-loop signals can be guaranteed to be semiglobally uniform and ultimately bounded with the probability of a quarter of a moment of an appropriate compact set, and all states of the system x_i satisfy the predefined time-varying constraint $|x_i| \le k_{ci}(t)$. The tracking error of the system can converge to a small expected neighborhood. The initial value of the residual error signal a satisfies:

$$\Psi_{\xi_i} = \left\{ \xi_i \,\middle|\, |\xi_i(0)| \le k_{bi} \sqrt[4]{1 - e^{-\left(4V_i(0) + \frac{4\beta_0}{\alpha_0}\right)}} \right\}. \quad (57)$$

Proof: Select the following $Lyapunov$ function:

$$V_n = V_{n-1} + \frac{1}{4}\log\left(\frac{k_{bn}^4}{k_{bn}^4 - \xi_n^4}\right) + \frac{1}{2}r_n^2 + \frac{1}{2\gamma_n}\tilde{\theta}_n^2. \quad (58)$$

According to the analysis in the previous section, the differential operator of equation (58) is:

$$\begin{aligned} LV_n \le & -\sum_{j=1}^{n} \frac{c_j \xi_j^4}{k_{bj}^4 - \xi_{bj}^4} + \sum_{j=1}^{n-1} r_j(\omega_{j+1} - \alpha_j) + \sum_{j=1}^{n-1} r_j r_{j+1} \\ & - \sum_{j=1}^{n} c_j r_j^2 + \sum_{j=1}^{n} \frac{\sigma_j}{\gamma_j}\tilde{\theta}_j\hat{\theta}_j + \sum_{j=1}^{n}\rho_j + \frac{1}{4}d^4. \end{aligned} \quad (59)$$

In order to unify the form of the error compensation signal, according to Lemma 2:

$$\sum_{j=1}^{n-1} r_j r_{j+1} \le \sum_{j=1}^{n-1}\frac{r_j^2}{2} + \sum_{j=1}^{n-1}\frac{r_{j+1}^2}{2} \le \sum_{j=1}^{n} r_j^2. \quad (60)$$

According to the boundedness theorem in the literature [20], we have:

$$|w_{j+1} - \alpha_j| \le \Xi_j. \quad (61)$$

Further, according to Lemma 2:

$$\begin{aligned} \sum_{j=1}^{n-1} r_j(w_{j+1} - \alpha_j) &\le \sum_{j=1}^{n-1}\frac{r_j^2}{2} + \sum_{j=1}^{n-1}\frac{\Xi_j^2}{2} \\ &\le \sum_{j=1}^{n}\frac{r_j^2}{2} + \sum_{j=1}^{n}\frac{\Xi_j^2}{2}. \end{aligned} \quad (62)$$

Substituting formulas (60)–(62) into (59), we obtain:

$$\begin{aligned} LV_n \le & -\sum_{j=1}^{n}\frac{c_j\xi_j^4}{k_{bj}^4 - \xi_{bj}^4} - \sum_{j=1}^{n}\left(c_j - \frac{3}{2}\right)r_j^2 + \sum_{j=1}^{n}\frac{\sigma_j}{\gamma_j}\tilde{\theta}_j\hat{\theta}_j \\ & + \sum_{j=1}^{n}\rho_j + \frac{1}{4}d^4 + \sum_{j=1}^{n}\frac{\Xi_j^2}{2}. \end{aligned} \quad (63)$$

According to Lemma 2 and the identity $\tilde{\theta}_j = \theta_j - \hat{\theta}_j$, we have:

$$\tilde{\theta}_j\hat{\theta}_j = \tilde{\theta}_j(\theta_j - \tilde{\theta}_j) \le \frac{\theta_j^2}{2} - \frac{\tilde{\theta}_j^2}{2}. \quad (64)$$

Substituting (64) into (63), and according to Lemma 4:

$$\begin{aligned} LV_n \le & -\sum_{j=1}^{n}\frac{c_j\xi_j^4}{k_{bj}^4 - \xi_{bj}^4} - \sum_{j=1}^{n}\left(c_j - \frac{3}{2}\right)r_j^2 + \sum_{j=1}^{n}\frac{\sigma_j\tilde{\theta}_j^2}{2\gamma_j} \\ & + \sum_{j=1}^{n}\rho_j + \frac{1}{4}d^4 + \sum_{j=1}^{n}\frac{\Xi_j^2}{2} + \sum_{j=1}^{n}\frac{\sigma_j\theta_j^2}{2\gamma_j} \\ & \le \alpha_0 V_n + \beta_0. \end{aligned} \quad (65)$$

where

$$\begin{aligned} \alpha_0 &= \min\left\{4c_j, 2(c_j - \frac{3}{2}), \sigma_j,\ j = 1, 2, \ldots, n\right\}, \\ \beta_0 &= \sum_{j=1}^{n}\rho_j + \frac{1}{4}d^4 + \sum_{j=1}^{n}\frac{\Xi_j^2}{2} + \sum_{j=1}^{n}\frac{\sigma_j\theta_j^2}{2\gamma_j}. \end{aligned} \quad (66)$$

Since the parameter selection must satisfy $\alpha_0 > 0$ and $\beta_0 > 0$, it is required that $c_j > 0$, $c_j > \frac{3}{2}$, $\sigma_j > 0$, and $\rho_j > 0$. According to Lemma 1:

$$0 \le E[V(t)] \le E[V(0)]e^{-\alpha_0 t} + \frac{\alpha_0}{\beta_0}, \quad \forall t > t_0. \quad (67)$$

From equations (58) and (67), it follows that:

$$\frac{1}{4}\log\left(\frac{k_{bi}^4}{k_{bi}^4 - \xi_i^4}\right) \le E[V(0)]e^{-\alpha_0 t} + \frac{\alpha_0}{\beta_0}. \quad (68)$$

Further, we obtain:

$$|\xi_i(0)| \le k_{bi}\sqrt[4]{1 - e^{-\left(4V_i(0) + \frac{4\beta_0}{\alpha_0}\right)}}. \quad (69)$$

■

Remark. According to the above theorem, the residual error signal ξ_i, the compensation signal r_i, and the parameter estimation error $\tilde{\theta}_i$ are bounded. Given that $\xi_i = z_i + r_i$, the error signal z_i is also bounded. Since the unknown parameter θ_i is constant, its estimation $\hat{\theta}_i$ is bounded, thus the virtual control rate α_{i-1} is bounded. Consequently, the filtered signal w_i is bounded, and finally the state variable $x_i = z_i + w_i$ of the system is also bounded.

In order to understand the design flow of the control algorithm, the following is the control flow chart in Fig 1.

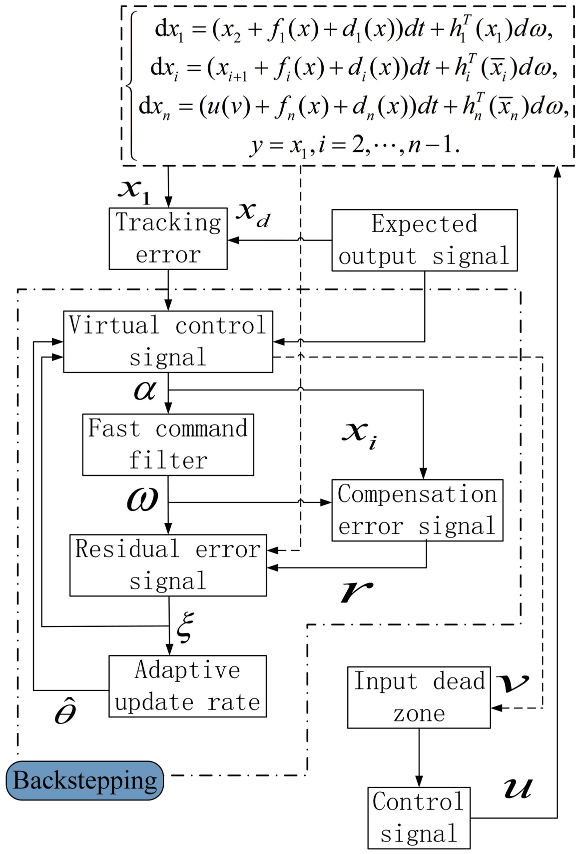

Fig. 1. Control flow chart of the control method in this script

V. Simulation Example

A. Comparative analysis with existing methods

In order to verify the effectiveness of the proposed control scheme, consider the following non-strict feedback stochastic nonlinear system with dead-zone input:

$$\begin{cases} dx_1 = (x_1 + 0.2(x_2 + x_3) + \cos(x_2))\,dt \\ \qquad + 0.3(0.2 + \sin(x_1))dw, \\ dx_2 = (x_2 + 0.1\cos((x_1 + x_3)x_2) + \sin(x_1 x_3))\,dt \\ \qquad + 0.3x_1 x_2 dw, \\ dx_3 = (u + x_2 x_3 + \sin(x_2)\cos(x_1))\,dt \\ \qquad + 0.1(1 + \cos(x_3))dw, \\ \quad y = x_1. \end{cases}$$

Here, x_1, x_2 are the state variables, and u, y represent the control input and system output. The tracking signal is $x_d = 0.4\sin(t)$. The system function components are summarized in Table I.

TABLE I
Stochastic Nonlinear System Functions

Component f_i	Component d_i	Component h_i
$0.2(x_2 + x_3)$	$\cos(x_2)$	$0.3(0.2 + \sin(x_1))$
$0.1\cos((x_1 + x_3)x_2)$	$\sin(x_1 x_3)$	$0.3x_1 x_2$
$x_2 x_3$	$\sin(x_2)\cos(x_1)$	$0.1(1 + \cos(x_3))$

To achieve the control objectives, the time-varying state constraints are set as follows: $k_{c1} = 4 + 0.3\sin(0.22t)$, $k_{c2} = 4 + \sin(t)$, and $k_{c3} = 6.5 + 2\sin(2t)$. Dead-zone input parameters are $c_r = 0.4$, $c_l = -1.9$, $m_r = 1$, and $m_l = 1.2$. The system parameters and initial conditions are shown in Table II.

TABLE II
Design Parameters and Initial States

Parameter Group 1	**Parameter Group 2**	**Initial Conditions**
$k_1 = k_2 = k_3 = 5.7$	$a_1 = a_2 = a_3 = 2$	$\theta(0) = [0.25, 1.1, 0.5]^T$
$\sigma_1 = \sigma_2 = \sigma_3 = 0.1$	$\gamma_1 = \gamma_2 = \gamma_3 = 1$	$x(0) = [0.01, 0.01, 0.01]^T$
$k_{b1}(t) = 3.4 + 0.2\sin(t)$	$h_1 = h_2 = h_3 = 20$	$r(0) = [0.1, 0.1, 0.1]^T$
$k_{b2} = 3.9 + 0.9\sin(t)$	$k_{b3} = 6.5 + \sin(2t)$	$w(0) = [0, 0, 0]^T$

Under the same initial conditions and constraints, the control scheme proposed in this paper is compared with the following two control schemes: Hu and Liu [21] prevents "differential explosion" by introducing a first-order filter, and adopts coordinate transformation and backstepping control strategy to deal with the performance function. Although the design steps and calculation amount of the controller are simplified, the order of the adopted filter is low, and there is no filter error compensation function. Compared with the second-order fast command filter (13) proposed in this chapter, the control accuracy of the system may be slightly insufficient. Wei and Li [22] proposes a backstepping control strategy based on second-order fast command filtering and traditional nonlinear transformation. Nonlinear transformation is used to deal with time-varying state constraints, and new variables are introduced for system transformation, and complex transformation conditions must be met between old and new variables. Compared with the control strategy proposed in this paper, it is more complicated and even leads to deterioration of the stability of the system.

Fig 2 shows the tracking of the system output signal to a given reference signal under three control schemes. It can be seen that the control method proposed in this paper has good tracking performance and excellent system tracking accuracy. In reference [21], its accuracy is not as good as the method proposed in this paper, because the speed of the first-order filter it uses is slow, and compared with the command filter, it has no filtering error compensation function. In reference [22], although the second-order fast filter is used, the traditional performance function processing method is extremely complicated, which leads to poor stability of the system output. At the same time, the output trajectories of the system under the three control schemes are all within the time-varying state constraints.

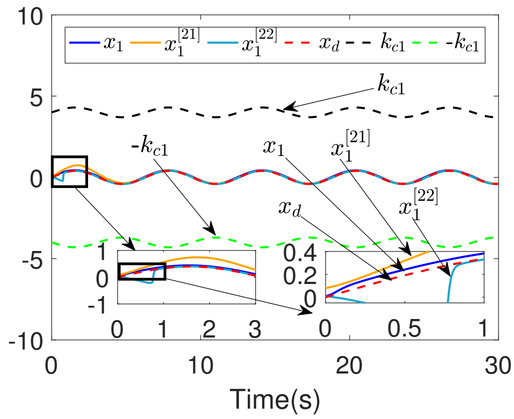

Fig. 2. Output signal x_1 and tracking signal x_d under the constraint of time-varying state

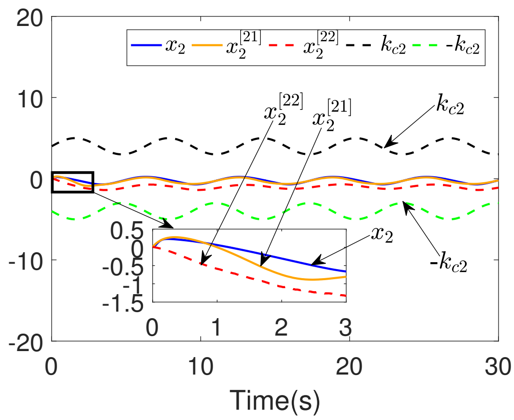

Fig. 3. State of the system x_2 under the constraint of time-varying state

Figs 3-4 show the change curves of system states x_2 and x_3 under three control schemes. It can be seen that the control method proposed in this paper and in reference [21] is more stable than the control method proposed in reference [22]. At the same time, the trajectories of the states of the system x_2 and x_3 under the three control schemes are all within the state constraints. Fig 5 is the curve of the adaptive parameter update rate, which reflects the online estimation process of unknown parameters in the system. It can be seen that their values are all greater than 0, which is in accordance with the

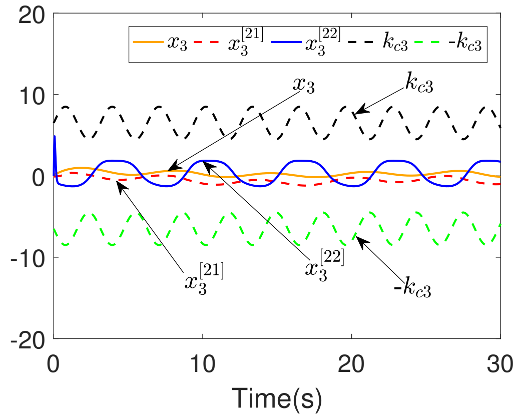

Fig. 4. State of the system x_3 under the constraint of time-varying state

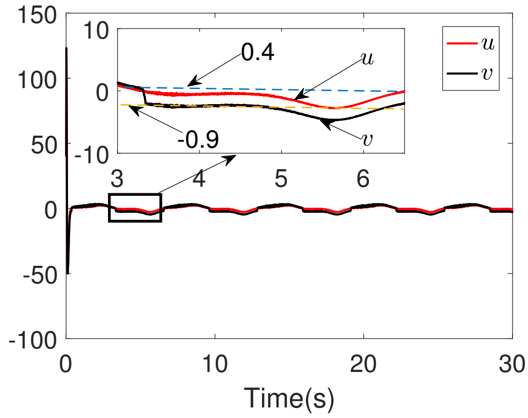

Fig. 7. Actual control signal u and virtual control signal v

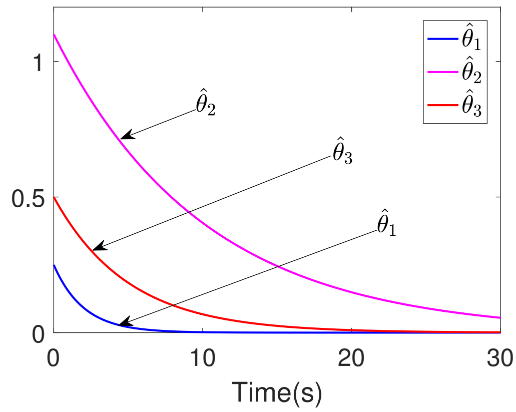

Fig. 5. Adjustment of parameters $\hat{\theta}_1$, $\hat{\theta}_2$ and $\hat{\theta}_2$

parameter form given in this paper. Fig 6 is the variation curve of the error compensation signals r_1, r_2, r_3, which reflects the online compensation process of filtering error $w_{i+1} - \alpha_i$ in the system.

Fig 7 shows the change curves of the virtual control signal and the actual control signal. It can be seen that when the virtual control signal is greater than 0.4, the actual control signal after inputting the dead-time function is: When the virtual control signal is within the range of, the actual control signal after inputting the dead zone function is: When the

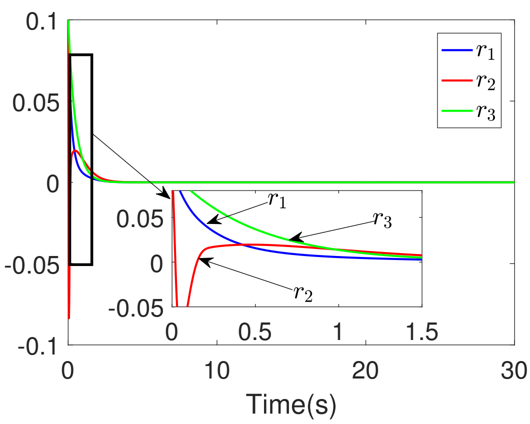

Fig. 6. Error compensation signals r_1, r_2 and r_3

virtual control signal is less than -1.9, the actual control signal is less than after entering the dead-zone function. The control input signal of the system has a slight jitter at first, which is because the uncertain stochastic nonlinear system is selected in this paper, and random disturbance and uncertain disturbance will occur.

B. Engineering case study with stochastic constraints

To evaluate the effectiveness of the proposed control strategy, a simulation is conducted on a single-link manipulator driven by a brushed DC motor (BRDCM). The trajectory tracking problem is formulated based on the dynamic model described in [23–25]:

$$\begin{cases} M\ddot{q} + B\dot{q} + N\sin(q) = I + D_1, \\ \quad L\dot{I} + RI + K_b\dot{q} = u. \end{cases} \tag{70}$$

where q, $\dot{q}$, and $\ddot{q}$ represent the angular position, velocity, and acceleration of the manipulator link, respectively. I denotes the armature current of the motor, and u is the actual control input. Defining $x_1 = q$, $x_2 = \dot{q}$, and $x_3 = I$, the model can be rewritten in state-space form as:

$$\begin{cases} \dot{x}_1 = x_2, \\ \dot{x}_2 = \dfrac{1}{M}(-Bx_2 + x_3 - N\sin(x_1) + D_1), \\ \dot{x}_3 = \dfrac{1}{L}(u - Rx_3 - K_b x_2). \end{cases} \tag{71}$$

The system output is defined as $y = x_1$. The physical parameters are selected as $M = 1$, $B = 1$, $N = 2$, $L = 1$, $R = 1$, and $K_b = 2$.

To assess control performance in the presence of stochastic disturbances, the corresponding stochastic nonlinear system is given by:

$$\begin{cases} dx_1 = (x_2 + 0.2\sin(x_1x_2x_3))\,dt + 0.15\cos(x_1)d\omega, \\ dx_2 = (x_3 - 2\sin(x_1) - x_2 + 0.2\cos(x_2x_3))\,dt \\ \qquad + \sin(0.4x_1x_2)d\omega, \\ dx_3 = (-2x_2 - x_3 + x_3\cos(x_1x_2) + u(v))\,dt \\ \qquad + 0.1\sin(x_3)d\omega, \\ \; y = x_1. \end{cases} \tag{72}$$

Here, x_1, x_2, and x_3 are the system states, v is the virtual control input, u is the actual control input, and y is the system output. The reference trajectory is defined as $x_d = \sin(0.2t) + 0.2\sin(t)$. The stochastic disturbance terms are: $d_1 = 0$, $d_2 = 0.2\cos(x_2 x_3)$, and $d_3 = x_3\cos(x_1 x_2)$.

The fuzzy membership function is expressed as:

$$u_{F_i^l}(X_i) = \exp\left[-\frac{1}{2}(X_i + 4 - l)^2\right], \quad i = 1, 2, 3, \quad l = 1, 2, \ldots, 7. \tag{73}$$

The corresponding fuzzy basis function is given by:

$$\varphi_l(X_i) = \frac{\prod_{i=1}^{n} u_{F_i^l}(X_i)}{\sum_{l=1}^{N}\left(\prod_{i=1}^{n} u_{F_i^l}(X_i)\right)}, \quad i = 1, 2, 3, \quad l = 1, 2, \ldots, 7. \tag{74}$$

To satisfy time-varying state constraints, the upper bounds are set as:

$$k_{c_1} = 2 + 0.1\sin(t), \quad k_{c_2} = 2.5 + \sin(t), \quad k_{c_3} = 2 + 2\sin(2t)$$

The parameters for the dead-zone nonlinearity are specified as:

$$c_r = 1, \quad c_l = -3, \quad m_r = 1.5, \quad m_l = 2$$

The remaining simulation parameters and initial conditions are listed in Table III.

TABLE III
DESIGN PARAMETERS AND INITIAL STATE

Design Parameters 1	Design Parameters 2	Initial State
$k_1 = k_2 = k_3 = 5$	$a_1 = a_2 = a_3 = 7$	$[\theta_1(0), \theta_2(0), \theta_3(0)]^T = [0.25, 1.1, 0.5]^T$
$h_1 = h_2 = h_3 = 25$	$\gamma_1 = \gamma_2 = \gamma_3 = 1$	$[x_1(0), x_2(0), x_3(0)]^T = [0.0, 0.1, 0.1]^T$
$\sigma_1 = 1$, $\sigma_2 = 1.2$, $\sigma_3 = 1.4$	$k_{b1} = 1.6 - 0.1\sin(t)$	$[\omega_1(0), \omega_2(0), \omega_3(0)]^T = [0, 0, 0]^T$
$k_{b2} = 1.5 + 0.5\sin(t)$	$k_{b3} = 2 + \sin(2t)$	$[r_1(0), r_2(0), r_3(0)]^T = [0.1, 1.0, 0.1]^T$

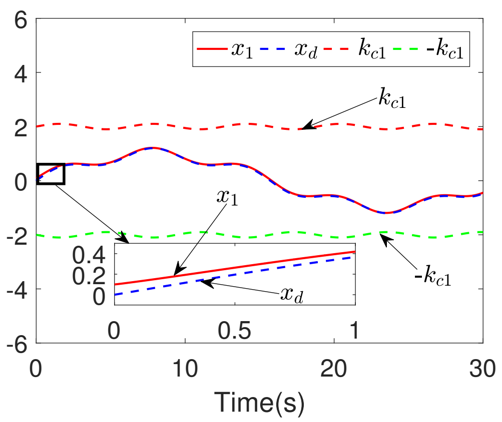

Fig. 8. Tracking performance of the output x_1 and reference x_d under time-varying constraints

The simulation results are illustrated in Figures 8–13. Figure 8 presents the trajectory tracking behavior of the system output x_1 with respect to the reference signal x_d under time-varying state constraints. The output remains confined within the prescribed limits and exhibits accurate tracking. When the initial state is close to the reference, the

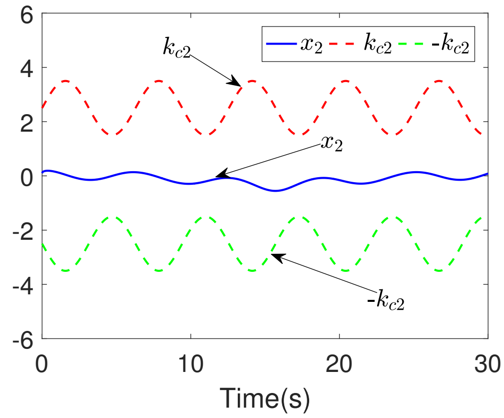

Fig. 9. System state x_2 response under time-varying constraint conditions

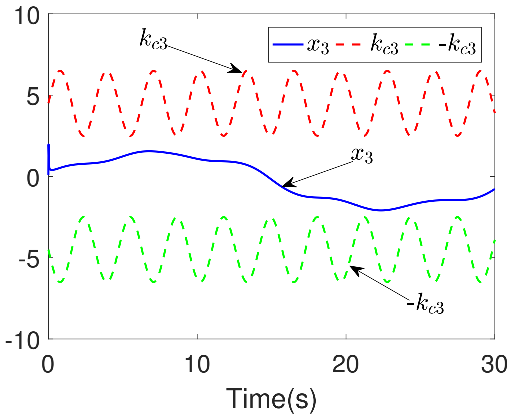

Fig. 10. System state x_3 response under time-varying constraint conditions

convergence speed improves and the system demonstrates stronger resistance to external disturbances.

Figures 9 and 10 depict the dynamic responses of the state variables x_2 and x_3, respectively. Both state trajectories consistently evolve within their respective time-dependent boundaries, without exceeding constraint limits. This validates the robustness of the proposed control strategy in enforcing state constraints. Minor fluctuations are observable in the curves, which can be attributed to the stochastic nature of the system. These oscillations arise from

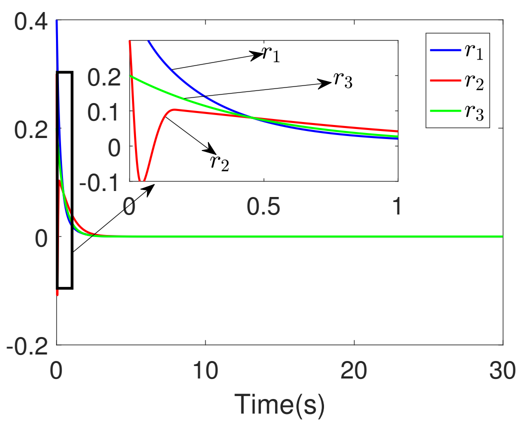

Fig. 11. Error compensation signals: r_1, r_2, and r_3

internal nonlinear interactions and uncertainty factors, but their amplitudes remain minimal and are confined within acceptable bounds, ensuring that overall system performance is not compromised.

Figure 11 shows the evolution of the error compensation signals r_1, r_2, and r_3, which are designed to mitigate filtering errors introduced by the command filter. While command filtering effectively smooths control signals and suppresses high-frequency noise, it can introduce lag-induced deviations. These compensation terms dynamically correct such deviations, thereby enhancing the precision of the filtered commands and contributing to reliable control performance.

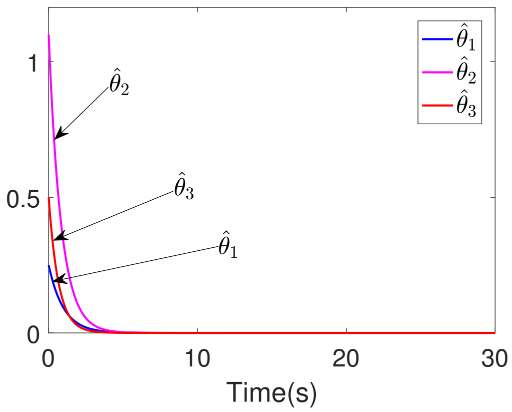

Fig. 12. Adaptive parameter estimates: $\hat{\theta}_1$, $\hat{\theta}_2$, and $\hat{\theta}_3$

Figure 12 illustrates the online adaptation of the parameter estimates $\hat{\theta}_1$, $\hat{\theta}_2$, and $\hat{\theta}_3$. All estimates remain strictly positive throughout the simulation, in accordance with the theoretical design of the adaptive law. Their convergence behavior further confirms the system's ability to perform real-time estimation of uncertain dynamics, which is essential for maintaining adaptive control capability.

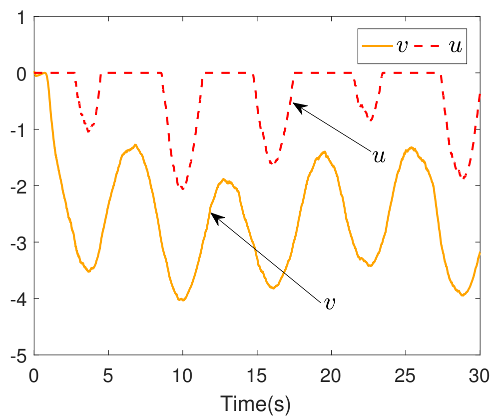

Fig. 13. Actual control input u and virtual control signal v

Figure 13 compares the actual control input u with the virtual control signal v. When $v < -3$, the control input u enters a saturation region, which is caused by the dead-zone nonlinearity inherent in the actuator model. Within this region, u no longer responds linearly to v, resulting in saturation behavior. Outside the dead-zone, u follows the predefined piecewise function accurately, indicating proper signal tracking. At the early stage of control, slight jitter is observed in u due to external stochastic disturbances. However, this effect diminishes quickly as the adaptive mechanism takes effect, leading to stable system operation and fulfillment of all control objectives.

C. Discussion

The numerical studies demonstrate that the proposed adaptive CFC scheme, which integrates a BLF and a second-order fast command filter, enables each state to respect its prescribed time-varying bounds while ensuring SGUUB tracking in probability. Compared with first-order filtered backstepping and conventional DSC benchmarks, our controller achieves tighter steady-state accuracy and faster transient convergence, chiefly because the auxiliary error compensation term effectively cancels the phase lag introduced by the filter. Moreover, by decomposing the dead-zone nonlinearity into a linear gain and a bounded disturbance, the design avoids restrictive inverse mappings and retains robustness against asymmetric, slowly varying saturation. The fuzzy logic approximator converges rapidly owing to the compact domain imposed by the BLF, and its weight adaptation remains bounded, which precludes parameter drift. Finally, the single-link manipulator example under stochastic perturbations confirms that the scheme preserves performance even when process noise magnitudes approach the dead-zone thresholds, highlighting practical applicability to electromechanical drives where sensor jitter and input dead zones coexist.

VI. Conclusion

In this paper, an adaptive fuzzy command filtering control strategy has been developed for non-strict feedback stochastic nonlinear systems subject to time-varying all-state constraints and actuator dead-zone inputs. To handle these dynamic constraints efficiently, a novel coordinate transformation coupled with a barrier Lyapunov function is introduced, avoiding the restrictive matching conditions imposed by traditional transformations. The nonlinear dead-zone input problem is simplified by decomposing it into a linear part and a bounded disturbance, facilitating controller design. Additionally, a fuzzy logic system is utilized to approximate unknown nonlinear terms within the system dynamics. A second-order fast command filter effectively mitigates the "differential explosion" phenomenon, with auxiliary signals compensating for any filtering errors. Stability analysis demonstrates that the proposed control scheme ensures all signals remain bounded in probability and conform to control specifications. Simulation results validate the superior performance and practicality of the presented control approach.

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