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Preliminary communication

Barrier Lyapunov Function-Based Output Feedback Control for a Class of Nonlinear Systems with Constraints

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Abstract: Constraints limit system performance in real-world systems, especially nonlinear control, necessitating rigorous handling to prevent performance degradation and hazards. Aiming at the uncertain nonlinear systems with state constraints, an adaptive neural network output feedback control scheme is proposed based on barrier Lyapunov function (BLF) and backstepping design technique. The nonlinear state observer is designed to estimate the unmeasurable state of the system, and an adaptive neural network is used to approximate the continuous nonlinear unknown function. The BLF is employed to ensure that the system avoids the violation of state constraints. Meanwhile, combined with the dynamic surface control technique, the proposed control scheme can overcome the shortcomings inherent in the backstepping design method in the output feedback control design framework. Based on the Lyapunov theorem, it can be proved that the closed-loop system is stable in the sense that all the variables are guaranteed to be bounded, and the state constraints will not be violated. The performance of the observer and controller is verified by a simulation example of a single link manipulator. Experimental results show that the proposed state observer can estimate the state accurately, and the adaptive output feedback controller based on BLF can make the output track the desired reference trajectory under the condition of unknown system dynamics and unmeasurable system state, which verifies the feasibility and effectiveness of the proposed method.

Keywords: backstepping method; barrier Lyapunov function; dynamic surface control; neural network; nonlinear system; state observer

1 INTRODUCTION

Adaptive control techniques have been widely applied for controlling nonlinear systems [1, 2]. In particular, feedback linearization techniques-based adaptive control has drawn a lot of attention [3]. However, the approaches require prior knowledge about the nonlinearities of the system. Compared with feedback linearization methods, the backstepping technique has the advantage of avoiding the elimination of useful nonlinearities in the design process [4, 5]. The idea of the backstepping design is that the state variables of each subsystem are taken as virtual control inputs of the previous subsystem, and an appropriate Lyapunov function is also selected recursively to analyze stability at the same time. Thus, a new virtual control input is generated at each recursive stage. At the end of the whole design process, the real control law is obtained and the expected design goal is achieved. Therefore, the backstepping technique has been widely used in nonlinear control systems to derive adaptive control schemes.

However, one of the drawbacks of the backstepping technique, the "complexity explosion", occurs due to the fact that the complexity of the controllers increases dramatically as the order of the system increases in the backstepping design process. This "complexity explosion" is caused by the repeated differentiation of the virtual controllers [6]. A dynamic surface control (DSC) technique proposed by Zong et al. [7] eliminated this drawback by introducing first-order filtering of the virtual input at each step of the traditional backstepping technique. Zhou et al. [8] extended the DSC method to adaptive systems with linearly uncertain parameters, thus achieving semi-globally exponential stability for setpoint control. Subsequently, several adaptive neural network (NN) control methods for nonlinear systems have been developed in the literatures [9, 10], incorporating the DSC technique into an approximation-based adaptive control design framework. Wang [9] proposed an adaptive NN-based backstepping control method for a class of nonlinear systems with arbitrary uncertainties in the form of strict feedback. Based on the structural properties of the radial basis function (RBF) NN, Liu et al. [10] generalized the adaptive neural backstepping control to switching nonlinear systems with non-strict feedback structures and proposed an adaptive NN controller.

At the same time, different output feedback controllers have been designed for nonlinear systems with unmeasurable states by using the state observer [11, 12]. However, the schemes were only applicable to nonlinear stochastic systems where the nonlinear dynamical model was known or the unknown parameters appeared linearly with respect to a known nonlinear function. To address the issue of unknown nonlinear dynamic models or non-linearly parameterized system uncertainties, Chen et al. [13] and Li et al. [14] initially proposed an adaptive output feedback control method for a class of uncertain nonlinear stochastic systems using neural networks (NNs) and provided a stability proof for the control system. Building on the findings of [13, 14], Zhang [15] extended these results to a class of large nonlinear stochastic systems with uncertainties. Wang et al. [16] introduced an observer-based adaptive NN output feedback control scheme for a class of stochastic nonlinear systems characterized by a non-strict feedback structure. While adaptive NN backstepping control (ANNBC) methods in the literature [13] and Zhang [15] addressed the problem of unmeasurable states by designing linear reduced-order state observers, these control approaches suffered from the so-called "complexity explosion" problem, which inevitably led to complex and computationally intensive algorithms.

The barrier Lyapunov function (BLF) has been widely used to prevent nonlinear control systems from violating state and output constraints due to physical or performance limitations. Yuan et al. [17] were the first to introduce a barrier function to suppress the transmission of errors at each stage of the backstepping process. Zheng et al. [18] applied the BLF to output constraints to achieve asymptotic tracking of the system without violating these constraints.

To eliminate differentiation in backstepping iterations and ensure full state constraints, studies [19, 20] combined the DSC technique with the BLF. However, these studies did not consider cases where the system state is unmeasurable.

Based on the results of the analysis, this paper proposes an adaptive neural network (NN) output feedback control scheme using a Barrier Lyapunov Function (BLF) for state-constrained nonlinear systems. The innovations of this paper can be summarized as follows:

(1) Considering both state unmeasurability and state constraints of uncertain nonlinear systems, a nonlinear state observer is designed to estimate the unmeasurable states in the system, the BLF is utilized to prevent the system from violating state constraints, and the adaptive NN is utilized to approximate the uncertainty in the system.

(2) Considering the observed and constrained states, the constrained states are transformed into tracking error constraints, and an adaptive NN output backstepping control method based on BLF is proposed by combining BLF and backstepping technology.

(3) The proposed control scheme is shown to guarantee that all signals of the closed-loop system are semi-globally uniformly ultimately bounded (SGUUB) according to the Lyapunov method. Moreover, the observer error and output of the system converge to a small neighbourhood of the origin and do not violate the tracking error constraints.

2 DESCRIPTION OF THE PROBLEM

This paper mainly studies a class of single-input and single-output nonlinear systems with state constraints, and designs an output feedback control scheme to track the desired reference trajectory.

2.1 Nonlinear System

Consider the single-input and single-output nonlinear systems with state constraints as follows:

$$\begin{cases} \dot{x}_i = f_i\left(\underline{x}_i\right) + \alpha_i x_{i+1} + d_i, 1 \le i \le n-1 \\ \dot{x}_n = f_n\left(\underline{x}_n\right) + \alpha_n u + d_n \\ y = x_1 \end{cases} \tag{1}$$

where $\underline{x}_i = \left[x_1, ..., x_i\right]^T$ is the state variable, which is assumed to be observable, and $\left[\, x_i \right] < k_{ai}$, where $\left[\, x_i \right] < k_{ai}$ is the boundary of the system state x_i, a_i, $i = 1, ..., n$, is the known positive definite controller gain; d_i denotes the disturbance of the system; u and y are the input and output variables, respectively. $f\left(\underline{x}_i\right)$ is continuous nonlinear unknown function, with the subscription n representing the system order. For convenience, the nonlinear function $f_i\left(\underline{x}_i\right)$ is represented by f_i.

The control objective is to design a suitable feedback control law for the constrained nonlinear system Eq. (1), so that the output y can track the desired reference trajectory y_d in the presence of unknown system dynamics f_i, unmeasurable system states $x_j (j = 2, \dots, n)$ and constrained system states.

Without loss of generality, we can generalize the following assumptions.

Assumption 1: The reference trajectory y_d has continuous n-order time derivatives and are all bounded.

Assumption 2: The disturbance is bounded, i.e. $\left|d_i\right| \le d_i^*$, where d_i^* is a known constant.

Assumption 3: There exist known constants $m_i > 0$, $i = 1, 2, \dots, n$, such that $\left|f_i\left(\varsigma_1\right) - f_i\left(\varsigma_2\right)\right| \le m_i \left\|\varsigma_1 - \varsigma_2\right\|$.

In actual systems, physical constraints usually lead to bounded derivatives of reference trajectories, while continuity and bounded ensure the stability of the system's behavior. On the other hand, the disturbance of a real system usually has a maximum value, and the known limits of the disturbance help ensure that the system can operate stably under all possible disturbances. Moreover, the nonlinear function satisfies the Lipschitz condition, ensuring that there is a "controllable" relationship between the input and output of the system, where m_i is the Lipschitz constant, and helps in the design of the controller. Based on the above considerations, assumptions 1 - 3 are given.

2.2 Neural Network

The Multilayer NNs have excellent performance in function approximation [21], and are commonly used for the identification of nonlinear continuous functions. A typical three-layer multi-input and single-output NN can be described as:

$$y = \sum_{j=1}^{h} \omega_j \varphi_j \left(\sum_{i=1}^{n} v_{ji} x_i + \theta_j\right) = \omega^T \phi(\cdot) \tag{2}$$

where n and h are the number of neurons in the input and hidden layers, respectively; x and y are the input and output vectors of the NN, respectively; ω_j, $j = 1, \dots, h$ is the adjustable weight parameter of the network; Assuming that the weights v_{ij} and threshold θ_j are fixed, where $j = 1, \dots, h$ and $i = 1, \dots, n$; $\omega = \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_h \end{bmatrix}$, $\phi(\cdot) = \begin{bmatrix} \varphi_1\left(\sum_{i=1}^{n} v_{1i} x_i + \theta_1\right) \\ \vdots \\ \varphi_h\left(\sum_{i=1}^{n} v_{hi} x_i + \theta_h\right) \end{bmatrix}$

Select a nonlinear activation function $\varphi(x)$ as:

$$\varphi(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3}$$

2.3 Barrier Lyapunov Function

To prevent the output from violating the constraint, we use a BLF , defined as follows: $V(x)$ is a scalar function, defined with respect to the system $\dot{x} = f(x)$ on an open region D containing the origin, that is continuous, positive definite, has continuous first-order partial derivatives at every point of D, has the property $V(x) \to \propto$ as x approaches the boundary of D, and satisfies $V(x(t)) \le b \forall t \ge 0$ along the solution of $\dot{x} = f(x)$ for

$x(0) \in D$ and some positive constant b. A BLF may be symmetric or asymmetric, as illustrated in Fig. 1.

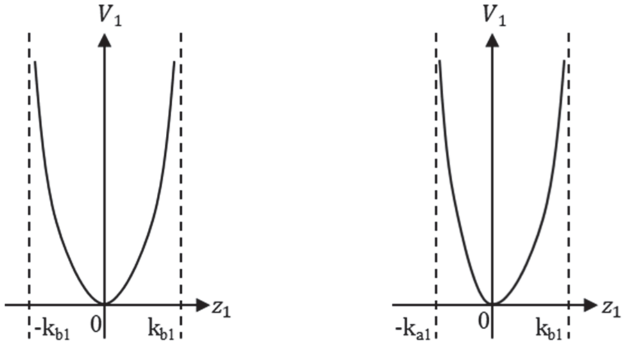

Figure 1 Schematic illustration of a Symmetric (left) and an Asymmetric (right) Barrier Lyapunov Function

According to the above definition and description, the value of BLF tends to infinity as the function variable approaches the constraint boundary. This means that when the BLF remains bounded by the design controller, the function variable will always remain within the constraint boundary.

3 METHOD
3.1 Nonlinear Velocity Observer Design

Firstly, to facilitate the design of the observer, Eq. (1) is rewritten as:

$$\begin{cases} \dot{\underline{x}}_n = A\underline{x}_n + f_o\left(\underline{x}_n\right) + Bu + d \\ \qquad y = C^T \underline{x}_n \end{cases} \tag{4}$$

where

$$A = \begin{bmatrix} 0 & \alpha_1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \alpha_n \\ 0 & 0 & 0 & 0 \end{bmatrix},\ f_o\left(\underline{x}_n\right) = \begin{bmatrix} f_{o1}\left(\underline{x}_1\right) \\ f_{o2}\left(\underline{x}_2\right) \\ \vdots \\ f_{on}\left(\underline{x}_n\right) \end{bmatrix} = \begin{bmatrix} f_1\left(\underline{x}_1\right) \\ f_2\left(\underline{x}_2\right) \\ \vdots \\ f_n\left(\underline{x}_n\right) \end{bmatrix},$$

$$B = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \alpha_n \end{bmatrix},\ d = \begin{bmatrix} d_1 \\ \vdots \\ d_n \end{bmatrix}, C = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

Define $\hat{\underline{x}}_i = \left[x_1, \hat{x}_2, \hat{x}_i\right]$ as the estimated state variable, and $\tilde{\underline{x}}_i = \left[x_1 - \hat{x}_1, x_i - \hat{x}_i\right]^T$ is the state observation error.

Then, according to the observability theory of systems, it can be concluded that system Eq. (4) is observable, so the nonlinear velocity observer can be designed as follows:

$$\dot{\hat{\underline{x}}}_i = A\hat{\underline{x}}_n + f_o\left(\hat{\underline{x}}_i\right) + Bu + k_o\hat{\underline{x}}_1 \tag{5}$$

where $f_o\left(\hat{\underline{x}}_i\right) = \begin{bmatrix} f_{o1}\left(x_1\right) \\ f_{o2}\left(x_2\right) \\ \vdots \\ f_{on}\left(x_n\right) \end{bmatrix}, k_o = \begin{bmatrix} k_{01} \\ \vdots \\ k_{on} \end{bmatrix}$ is the observer gain, and $\hat{f}_{oi}\left(\hat{\underline{x}}_i\right)$ denotes the continuous nonlinear unknown function based on the observed state.

Combining Eq. (4) and Eq. (5), the observation error is given as:

$$\dot{\tilde{\underline{x}}}_n = A_o\tilde{\underline{x}}_n + \tilde{f}_o + d \tag{6}$$

where $A_o = A - k_0C^T, \tilde{f}_o = \begin{bmatrix} \tilde{f}_{o1} \\ \vdots \\ \tilde{f}_{on} \end{bmatrix}, \tilde{f}_{oi} = f_{oi}\left(\underline{x}_i\right) - \hat{f}_{oi}\left(\hat{\underline{x}}_i\right)$.

In order to ensure the stability of the observer, the choice of k_o should be such that the matrix A_o is a Hurwitz matrix, and there exists a positive-definite matrix P_o satisfying that:

$$A_o^T P_o + P_o A_o = -Q_o \tag{7}$$

where Q_o is a positive definite matrix.

Considering the system model Eq. (1), assume that Assumptions 1 - 3 are satisfied, the nonlinear velocity observer is defined as Eq. (5), and the choice of k_o makes matrix A_o satisfy Eq. (7), then the observer errors $\tilde{\underline{x}}_n$ are SGUUB.

Consider the following Lyapunov function:

$$V_o = \frac{1}{2}\left(\tilde{\underline{x}}_n^T P_0 \tilde{\underline{x}}_n\right)^2 \tag{8}$$

Differentiating the above Lyapunov function, one can obtain:

$$\begin{aligned} \dot{V}_o &= \tilde{\underline{x}}_n^T P_o \tilde{\underline{x}}_n \left[\tilde{\underline{x}}_n^T\left(A_o^T P_o + P_o A_o\right)\tilde{\underline{x}}_n + 2\tilde{\underline{x}}_n^T P_o\left(\tilde{f}_o + d\right)\right] \le \\ &\le -\lambda\left\|\tilde{\underline{x}}_n\right\|^4 + 2\tilde{\underline{x}}_n^T P_o \tilde{\underline{x}}_n \tilde{\underline{x}}_n^T P_o \tilde{f}_o + 2\tilde{\underline{x}}_n^T P_o \tilde{\underline{x}}_n \tilde{\underline{x}}_n^T P_o d \end{aligned} \tag{9}$$

where $\lambda_{\min}\left(P_o\right)\lambda_{\min}\left(Q_o\right)$. $\lambda_{\min}\left(P_o\right)$ and $\lambda_{\min}\left(P_o\right)$ are the minimum eigenvalues of the matrices P_o and Q_o, respectively.

Considering Assumptions 2 - 3 and Young's inequality, we can obtain:

$$2\tilde{\underline{x}}_n^T P_o \tilde{\underline{x}}_n \tilde{\underline{x}}_n^T P_o \tilde{f}_o \le \frac{3}{2}a_o^{\frac{4}{3}}\left\|P_o\right\|^{\frac{8}{3}}\left\|\tilde{\underline{x}}_n\right\|^4 + \frac{1}{2a_o^4}\left(\sum_{i=1}^n m_i^2\right)^2\left\|\tilde{\underline{x}}_n\right\|^4 \tag{10}$$

$$2\tilde{\underline{x}}_n^T P_o \tilde{\underline{x}}_n \tilde{\underline{x}}_n^T P_o d \le \frac{3}{2}a_o^{\frac{4}{3}}\left\|P_o\right\|^{\frac{8}{3}}\left\|\tilde{\underline{x}}_n\right\|^4 + \frac{1}{2a_o^4}\left\|d^*\right\|^4 \tag{11}$$

where $a_o > 0$ and its value should satisfy $p_0 = \lambda - 3a_o^{\frac{4}{3}} \left\| P_o \right\|^{\frac{8}{3}} - \frac{1}{2a_o^4}\left(\sum_{i=1}^{n} m_i^2\right)^2 > 0$.

Substituting in Eq. (10), Eq. (11) into Eq. (9), we get:

$$\dot{V}_o \le -p_0 \left\| \underline{\tilde{x}}_n \right\|^4 + \frac{1}{2a_o^4}\left\| d^* \right\|^4 \tag{12}$$

According to Eq. (12), we can obtain:

$$\dot{V}_o \le -\rho_0 V_o + \in_o \tag{13}$$

where $\rho_0 = \frac{p_0}{\left\| P_o \right\|^2}$, $\in_o = \frac{1}{2a_o^4}\left\| d^* \right\|^4$. According to the Lyapunov stability theorems, the closed-loop system is stable.

By solving in Eq. (13), it can be obtained that $0 \le V_o(t) \le \left[V_o(t) - \frac{\in_o}{\rho_o} \right] e^{-\rho_o t} + \frac{\in_o}{\rho_o}$, which implies that the observation errors $\underline{\tilde{x}}_n$ are SGUUB.

The setting of observer gain k_o will affect the convergence of observation errors. Specifically, too large a gain will result in a faster rate of convergence. But this can lead to a stronger noise effect. However, too small gain value will cause slow convergence speed and easily lead to overshoot of the system. Therefore, the gain k_o should be carefully adjusted to achieve the appropriate performance of the observer.

3.2 BLF-Based Adaptive Neural Network Output Feedback Control

In this section, the constrained states are transformed into tracking error constraints, and an ANNBC scheme is designed for controlling the constrained nonlinear system Eq. (1) based on the BLF. Utilizing the approximation capability of the NN, the unknown continuous nonlinear function f_i in the constrained nonlinear system Eq. (1) can be approximated as:

$$\hat{f}_i = \hat{\omega}_i^T \phi_i(\cdot) \tag{14}$$

where $\hat{f}_i$ is the estimated value of f_i using a NN, and $\hat{\omega}_i^T$ is the estimated weight of the NN. Assuming that ω_i^* is the ideal weight, and ε_i is the estimation error, then the nonlinear function f_i can be expressed as:

$$f_i = \omega_i^{*T} \phi_i(\cdot) + \varepsilon_i \tag{15}$$

Suppose that there exists a specified constraint region $\Omega_\omega = \left\{ \omega \in R^h : \|\omega\| \le M_\omega \right\}$, the ideal weight $\omega^*$is within the tight set Ω_ω, then $\hat{f}_i$ can be as close as possible to f_i. The ideal weight can be defined as:

$$\omega^* = arg \min_{\omega \in \Omega_\omega} \left\{ sup \left| \hat{f}_i - f_i \right| \right\} \tag{16}$$

Then the estimation error of the nonlinear function f_i is:

$$\tilde{f}_i = f_i - \hat{f}_i = \tilde{\omega}_i^T \phi_i(\cdot) + \varepsilon_i \tag{17}$$

where $\tilde{\omega}_i = \omega_i^* - \hat{\omega}_i$ is the estimation error of the weight parameter.

Assumption4: The estimation errors are bounded, i.e. $|\varepsilon_i| \le \varepsilon_i^*$, $i = 1, ..., n$, where ε_i^* is a known constant.

For the constrained nonlinear system Eq. (1), considering the unmeasurable and constrained state of the system, the design steps of the backstepping based adaptive output feedback control scheme are as follows:

Step 1 ($i = 1$): The purpose of this step is to make the error $e_1 = y - y_d$ as small as possible. Giving $i = 1$ in the nonlinear system Eq. (1), the first subsystem is represented as:

$$\dot{x}_1 = f_1 + \alpha_1 x_2 + d_1 \tag{18}$$

Define the first dynamic surface error as:

$$e_1 = y - y_d = x_1 - y_d \tag{19}$$

Its derivative is as follows:

$$\dot{e}_1 = f_1 + \alpha_1 x_2 - \dot{y}_d + d_1 \tag{20}$$

From assumption 1, we can obtain that y_d is bounded. Considering $|x_1| < k_{a1}$, it can be obtained that $|e_1| < k_{c1}$, where $k_{c1} > 0$. The first BLF is chosen as:

$$V_1 = \frac{1}{2}\ln\frac{k_{c1}^2}{k_{c1}^2 - e_1^2} + \frac{1}{2}\tilde{\omega}_1^T \eta_1^{-1} \tilde{\omega}_1 \tag{21}$$

where, $\eta_1 > 0$ is the adaptive positive definite gain matrix.

In this paper, the logarithmic function is selected as the BLF, as shown in the first term on the right of Eq. (21), where is the tracking error, and is the given tracking error constraint boundary. When the tracking error approaches the constraint boundary, it will make the value of BLF tend to infinity. Therefore, as long as the BLF is bounded in the closed-loop system, it can ensure that the tracking error is always within the constraint range.

Differentiating the above BLF and substituting into Eq. (19) yields:

$$\dot{V}_1 = \frac{e_1 \dot{e}_1}{k_{c1}^2 - e_1^2} + \tilde{\omega}_1^T \eta_1^{-1} \dot{\tilde{\omega}}_1 = \frac{e_1\left(f_{1b} + \alpha_1 x_2 - \dot{y}_d + d_1\right)}{k_{c1}^2 - e_1^2} + \tilde{\omega}_1^T \eta_1^{-1} \dot{\tilde{\omega}}_1 \tag{22}$$

Consider x_2 as a virtual control input and select virtual controller x_{2d} as follows:

$$x_{2d} = \alpha_1^{-1}\left(-k_1 e_1 + \dot{y}_d - \hat{\omega}_1^T \phi_1(\cdot)\right) - \hat{r}_2 \tag{23}$$

Defining $\hat{e}_2 = \hat{x}_2 - z_2, \hat{r}_2 = \hat{x}_2 - x_{2d}$, and considering Eq. (18) to Eq. (23), one obtains:

$$\dot{V}_1 = \frac{k_1 e_1^2}{k_{c1}^2 - e_1^2} + \frac{e_1 \tilde{\omega}_1^T \phi_1(\cdot)}{k_{c1}^2 - e_1^2} + \frac{e_1 \varepsilon_1}{k_{c1}^2 - e_1^2} + \frac{e_1 d_1}{k_{c1}^2 - e_1^2} + \\ + \frac{\alpha_1 e_1 \tilde{x}_2}{k_{c1}^2 - e_1^2} \tilde{\omega}_1^T \eta_1^{-1} \dot{\tilde{\omega}}_1 \tag{24}$$

The adaptive updating law of the weight is chosen as:

$$\dot{\hat{\omega}}_1 = -\eta_1 \left(\hat{\omega}_1 - \frac{\phi_1(\cdot) e_1}{k_{c1}^2 - e_1^2} \right) \tag{25}$$

Substituting Eq. (25) into Eq. (24) and considering $\dot{\tilde{\omega}}_1 = -\dot{\hat{\omega}}_1$, one can obtain:

$$\dot{V}_1 = -\frac{k_1 e_1^2}{k_{c1}^2 - e_1^2} + \frac{e_1 \varepsilon_1}{k_{c1}^2 - e_1^2} + \frac{e_1 d_1}{k_{c1}^2 - e_1^2} + \frac{\alpha_1 e_1 \tilde{x}_2}{k_{c1}^2 - e_1^2} \tilde{\omega}_1^T \hat{\omega}_1 \tag{26}$$

Let x_{2d} pass through a first-order filter **Pogreška! Izvor reference nije pronađen.** to obtain z_2:

$$\tau_2 \dot{z}_2 + z_2 = x_{2d}, z_2(0) = x_{2d}(0) \tag{27}$$

where τ_2 is the time constant.

Step 2: $(2 \le i \le n-1)$: The i th subsystem is represented as follows:

$$\dot{x}_i = f_i + \alpha_i x_{i+1} + d_i \tag{28}$$

Define the ith dynamic surface error as:

$$\hat{e}_i = \hat{x}_i - z_i \tag{29}$$

Choose $x_{(i+1)d}$ as the virtual controller, then the derivative of the tracking error can be expressed as:

$$\hat{e}_i = f_i + \alpha_i \hat{r}_{i+1} + \alpha_i x_{(i+1)d} - \dot{z}_i + k_{oi}\tilde{x}_1 + \alpha_i \tilde{x}_{i+1} - \alpha_i \tilde{x}_i - \tilde{f}_{oi} \tag{30}$$

where $\hat{r}_{i+1} = \hat{x}_{i+1} - x_{(i+1)d}$.

From Section Nonlinear velocity observer design, $\hat{x}_i = x_i - \tilde{x}_i$ is bounded when $\tilde{x}_i$ is bounded, and it follows from Eq. (27) that z_i is bounded. Then, $|\hat{e}_i| < k_{ci}$ can be derived from Eq. (29), where $k_{ci} > 0$.

Select the ith BLF as:

$$V_i = V_{i-1} + \frac{1}{2}\ln\frac{k_{ci}^2}{k_{c1}^2 - \hat{e}_1^2} + \frac{1}{2}\tilde{\omega}_i^T \eta_i^{-1} \tilde{\omega}_i \tag{31}$$

Differentiating the BLF above and substituting into Eq. (30) yields:

$$\dot{V}_i = \dot{V}_{i-1} + \frac{\hat{e}_i\left(f_i + \alpha_i \hat{r}_{i+1} + \alpha_i x_{(i+1)d} - \hat{e}_i \dot{z}_i\right)}{k_{c1}^2 - \hat{e}_1^2} + \\ + \frac{\hat{e}_i\left(k_{oi}\tilde{x}_1 + \alpha_i \tilde{x}_{(i+1)} - \alpha_i \tilde{x}_i - \tilde{f}_i\right)}{k_{c1}^2 - \hat{e}_1^2} + \tilde{\omega}_i^T \eta_i^{-1} \dot{\tilde{\omega}}_i \tag{32}$$

Select the virtual control input as:

$$x_{(i+1)d} = \alpha_i^{-1}\left(-k_i \hat{e}_i + \dot{z}_i - \hat{\omega}_i^T \phi_i(\cdot)\right) - \hat{r}_{i+1} \tag{33}$$

The adaptive updating law of the weight is chosen as:

$$\dot{\hat{\omega}}_1 = -\eta_1 \left(\hat{\omega}_1 - \frac{\phi_1(\cdot) \hat{e}_1}{k_{c1}^2 - \hat{e}_1^2} \right) \tag{34}$$

Substituting the relevant equations into Eq. (32), one can obtain:

$$\dot{V}_i = \dot{V}_1 - \sum\nolimits_{j=2}^{i} \frac{k_j \hat{e}_j^2}{k_{cj}^2 - \hat{e}_j^2} + \\ + \sum\nolimits_{j=2}^{i} \frac{\hat{e}_j}{k_{cj}^2 - \hat{e}_j^2}\left(k_{oj}\tilde{x}_1 + \alpha_i \tilde{x}_{(j+1)} - \alpha_j \tilde{x}_j + \varepsilon_j - \tilde{f}_{oj}\right) \tag{35}$$

Let $x_{(i+1)d}$ pass through a first-order filter **Pogreška! Izvor reference nije pronađen.** to obtain z_{i+1}.

$$\tau_{i+1}\dot{z}_{i+1} + z_{i+1} = x_{(i+1)d}, z_{i+1}(0) = x_{(i+1)d}(0) \tag{36}$$

where τ_{i+1} is the time constant.

Step n: The nth subsystem is represented as follows:

$$\dot{x}_n = f_n + \alpha_n u + d_n \tag{37}$$

Define the nth dynamic surface error as:

$$\hat{e}_n = \hat{x}_n - z_n \tag{38}$$

Taking the derivative of Eq. (38) yields:

$$\hat{e}_n = f_n + \alpha_n u - \dot{z}_n + k_{on}\tilde{x}_1 - \tilde{f}_{on} \tag{39}$$

Similarly, we can obtain $|\hat{e}_n| < k_{cn}$, where $k_{cn} > 0$. Choosing the nth BLF as:

$$V_n = V_{n-1} + \frac{1}{2}\ln\frac{k_{cn}^2}{k_{cn}^2 - \hat{e}_n^2} + \frac{1}{2}\tilde{\omega}_n^T \eta_n^{-1} \tilde{\omega}_n \tag{40}$$

Differentiating the BLF above and substituting into Eq. (39) yields:

$$\dot{V}_n=\dot{V}_{n-1}+\frac{e_n}{k_{cn}^2-\hat{e}_n^2}\left(f_n+\alpha_n u-\dot{z}_n+k_{on}\tilde{x}_1-\tilde{f}_{on}\right)+\tilde{\omega}_n^T\eta_n^{-1}\dot{\tilde{\omega}}_n \quad (41)$$

Select the control law as follows:

$$u=\alpha_n^{-1}\left(-k_n\hat{e}_n+\dot{z}_n-\hat{\omega}_n^T\phi_n(\cdot)\right) \quad (42)$$

The adaptive updating law of the weight is chosen as:

$$\dot{\hat{\omega}}_n=-\eta_n\left(\hat{\omega}_n-\frac{\phi_n(\cdot)\hat{e}_n}{k_{cn}^2-\hat{e}_n^2}\right) \quad (43)$$

Substituting the relevant equations into Eq. (41), one can obtain:

$$\dot{V}_n=\dot{V}_1-\sum\nolimits_{j=2}^{n}\frac{k_j\hat{e}_j^2}{k_{cj}^2-\hat{e}_j^2}+\sum\nolimits_{j=2}^{n}\frac{\hat{e}_j}{k_{cj}^2-\hat{e}_j^2}\left(\varepsilon_j-\tilde{f}_{oj}+k_{oj}\tilde{x}_1\right)- -\sum\nolimits_{j=2}^{n}\tilde{\omega}_j^T\hat{\omega}_j \quad (44)$$

Theorem: For the nonlinear uncertain system Eq. (1), suppose that the system states are all unmeasurable and bounded, and Assumptions 1 - 4 are satisfied.If the output feedback control laws Eq. (23), Eq. (33), and Eq. (42) are chosen, the adaptive laws are designed as Eq. (25), Eq. (34), and Eq. (43), then the overall closed-loop system is stable. Moreover, 1) all the signals in the closed-loop system remain bounded; 2) the tracking error converges to a small neighborhood of the origin without violating constraints.

Proof: Choosing the BLF as follows:

$$V_c=V_n=V_1-\frac{1}{2}\sum\nolimits_{j=2}^{n}\ln\frac{k_{cj}^2}{k_{cj}^2-\hat{e}_j^2}+\frac{1}{2}\sum\nolimits_{j=2}^{n}\tilde{\omega}_j^T\eta_j^{-1}\tilde{\omega}_j= =\frac{1}{2}\ln\frac{k_{c1}^2}{k_{c1}^2-e_1^2}+\frac{1}{2}\sum\nolimits_{j=2}^{n}\ln\frac{k_{cj}^2}{k_{cj}^2-\hat{e}_j^2}+\frac{1}{2}\sum\nolimits_{i=2}^{n}\tilde{\omega}_i^T\eta_i^{-1}\tilde{\omega}_i \quad (45)$$

According to Eq. (44), it can be obtained:

$$\dot{V}_c\le-\frac{k_1e_n^2}{k_{c1}^2-e_1^2}+\frac{e_1\left(\alpha_1\tilde{x}_2+\varepsilon_1+d_1\right)}{k_{c1}^2-e_1^2}- -\sum_{j=2}^{n}\frac{k_je_j^2}{k_{cj}^2-e_j^2}\sum\nolimits_{j=2}^{n}\frac{\hat{e}_j}{k_{cj}^2-e_j^2}\left(\varepsilon_j-\tilde{f}_{oj}f_n+k_{oj}\tilde{x}_1\right)-\sum\nolimits_{i=1}^{n}\tilde{\omega}_i^T\hat{\omega}_i \quad (46)$$

Define the positive constant $k_i=k_{0i}+k_{\varepsilon i}$, where $k_{0i}>0$, $k_{\varepsilon i}>0$, $i=1, 2, \dots, n$. Consider the following Young's in equality:

$$-k_{\varepsilon 1}e_1^2+e_1\left(\alpha_1\tilde{x}_2+\varepsilon_1+d_1\right)\le\frac{\alpha_1^2\tilde{x}_2^2+\varepsilon_1^2+d_1^2}{4k_{\varepsilon i}} \quad (47)$$

$$-k_{\varepsilon j}e_j^2+e_j\left(\varepsilon_j+\tilde{f}_{oj}+k_{oj}\tilde{x}_1\right)\le\frac{\varepsilon_j^2-m_{oj}^2\tilde{x}_j^2+k_{oj}^2\tilde{x}_1^2}{4k_{\varepsilon j}}, \quad j=2, 3, \dots, n \quad (48)$$

$$\sum\nolimits_{i=1}^{n}\tilde{\omega}_i^T\hat{\omega}_i\le\frac{1}{2}\left(\sum\nolimits_{i=1}^{n}\omega_i^{*T}\omega_i^*-\sum\nolimits_{i=1}^{n}\tilde{\omega}_i^T\tilde{\omega}_i\right) \quad (49)$$

Substituting Eq. (47) to Eq. (49) into Eq. (46) yields:

$$\dot{V}_c\le-\frac{k_{\varepsilon 1}e_1^2}{k_{c1}^2-e_1^2}-\sum_{j=2}^{n}\frac{k_{oj}\hat{e}_j^2}{k_{cj}^2-\hat{e}_j^2}-\sum\nolimits_{i=1}^{n}\tilde{\omega}_i^T\tilde{\omega}_i+\omega_c \quad (50)$$

where:

$$\omega_c=\frac{\alpha_1^2\tilde{x}_2^2+\varepsilon_1^2+d_1^2}{4k_{\varepsilon i}\left(k_{c1}^2-e_1^2\right)}+\sum_{j=2}^{n}\frac{\varepsilon_j^2-m_{oj}^2\tilde{x}_j^2+k_{oj}^2\tilde{x}_1^2}{4k_{\varepsilon j}\left(k_{cj}^2-\hat{e}_j^2\right)}+ +\frac{1}{2}\sum_{i=1}^{n}\omega_i^{*T}\omega_i^*\le\sum_{i=1}^{n}\frac{\Delta_i}{4k_{\varepsilon i}}+\frac{1}{2}\sum_{i=1}^{n}M_{\omega_i}\le\in_c \ \Delta_i= =\sum_{i=1}^{n}\varepsilon_i^2+\sum_{j=2}^{n}\left(m_{oj}^2\tilde{x}_j^2+k_{oj}^2\tilde{x}_1^2\right)+\alpha_1^2\tilde{x}_2^2+d_1^2$$

According to the observer analysis in Section Nonlinear velocity observer design, it can be concluded that the observation error $\tilde{x}_i$ is bounded. Therefore, we can obtain that $\in_c$ is a defined positive constant based on Assumptions 2 - 4. Define the error signal as:

$$\zeta=\left[\hat{e}_1, \hat{e}_2, \dots, \hat{e}_n, \tilde{\omega}_1, \dots, \tilde{\omega}_n\right]^T \quad (51)$$

Then Eq. (50) is bounded, i.e.:

$$\dot{V}_c\le-\frac{1}{2}\lambda_{\min}\left(Q_c\right)\|\zeta\|^2+\in_c \quad (52)$$

where $Q_c=\begin{bmatrix}diag\left(2k_{01}, \dots, 2k_{0n}\right) & 0\\ 0 & I_{n\times n}\end{bmatrix}$.

Considering the Lyapunov function Eq. (45), one obtains:

$$\frac{1}{2}\lambda_{\min}\left(P_c\right)\|\zeta\|^2\le V_c\le\frac{1}{2}\zeta^TP_c\zeta\le\frac{1}{2}\lambda_{\max}\left(P_c\right)\|\zeta\|^2 \quad (53)$$

where $P_c=\begin{bmatrix}I_{n\times n} & 0\\ 0 & diag\left(\eta_1^{-1}, \dots, \eta_n^{-1}\right)\end{bmatrix}$.

According to Eq. (52) and Eq. (53), it can be obtained:

$$\dot{V}_c\le-\frac{\lambda_{\min}\left(Q_c\right)}{\lambda_{\max}\left(P_c\right)}V_c+\in_c\le-\rho_cV_c+\in_c \quad (54)$$

where $\rho_c \le -\dfrac{\lambda_{\min}(Q_c)}{\lambda_{\max}(P_c)}$. According to the Lyapunov stability theorems, the closed-loop system is stable. Solving in Eq. (54) yields:

$$0 \le V_c(t) \le \left[V_c(t_0) - \frac{\epsilon_c}{\rho_c} \right] e^{-\rho_c t} + \frac{\epsilon_c}{\rho_c} \tag{55}$$

This means that the tracking error $[e_1, \hat{e}_2, ..., \hat{e}_n]$ and the adaptive weight error $\tilde{\omega}_i$ are both bounded.

Based on the above analysis, we can get $e_j = x_j - z_j = \hat{e}_j + \tilde{x}_j, j = 2, 3, ..., n$. Because the observation error $\tilde{x}_j$ is bounded, which is proved in Section Nonlinear velocity observer design, and because $\hat{e}_j$ is bounded, it can be concluded that e_j is bounded. Since $e_1 = x_1 - y_d$ and y_d are both bounded, we get that x_1 is bounded. From $e_i = x_i - x_{id}, i = 2, ..., n$ and the definition of virtual controller x_{id} in Eq. (23) and Eq. (33), we have that x_i remains bounded and the tracking error $|\hat{e}_i| < k_{ci}$ satisfies the constraints. Based on Eq. (42), we conclude that the control input u is also bounded. According to the system assumption that the function $f_i(x)$ is continuous, these functions are bounded in any determined compact set, so the optimal weight ω_i^* is bounded. Meanwhile, since $\tilde{\omega}_i$ is bounded, it follows that the estimated weight $\hat{\omega}_i$ is bounded. Therefore, all signals in the closed-loop system remain bounded.

4 SIMULATION EXPERIMENT

In this section, a simulation example is given to demonstrate the effectiveness of the proposed control method. Considering a single-link robotic manipulator with motor dynamics, the dynamics model can be represented as in literatures [22, 23]:

$$\begin{cases} M\ddot{q} + C\dot{q} + F\sin q = \beta + d \\ D\dot{\beta} + H\beta = u - L\dot{q} \end{cases} \tag{56}$$

where q, $\dot{q}$ and $\ddot{q}$ represent the position, velocity and acceleration of joint, respectively. β and $\dot{\beta}$ represent the motor shaft angle and velocity, respectively. d the torque disturbance, and u is the control input of the motor torque. Assuming that $x_1 = q, x_2 = \dot{q}$ and $x_3 = \beta$, the above equation can be expressed in the following form:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \left(-\dfrac{F}{M}\sin x_1 - \dfrac{C}{M}x_2 \right) + \dfrac{1}{M}x_3 + \dfrac{1}{M}d \\ \dot{x}_3 = \left(-\dfrac{L}{D}x_2 - \dfrac{H}{D}x_3 \right) + \dfrac{1}{M}u \end{cases} \tag{57}$$

In this simulation, the parameter values of the system are set as follows: M = 0.0642, F = 2.2816, F = 2.2816, C = 0.0181, H = 5, L = 0.9, D = 0.025. The external disturbance is set as $d = 0.5\left(x_1^2 + x_2^2\right)\sin(1.5t)$. The reference trajectory is y_d = sin$t$, and the system output is y = x_1. The initial condition of the system is $x_1 = x_2 = x_3 = 0$. The design parameters of the observer and controller are chosen as k_o = [180; 120; 60]; k_1 = 180; k_2 = 120; k_3 = 60; $\tau_2 = \tau_3$ = 0.005, $\eta_2 = \eta_3$ =1.5, k_{c1} = 1.5, k_{c2} = 1, k_{c3} = 10. The observation values, errors of the observer, and the position tracking performance of the system under the proposed control scheme, are shown in Fig. 2 to Fig. 5, respectively.

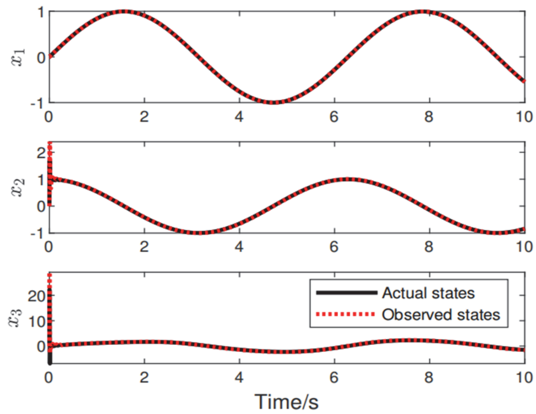

Figure 2 Actual and observed states

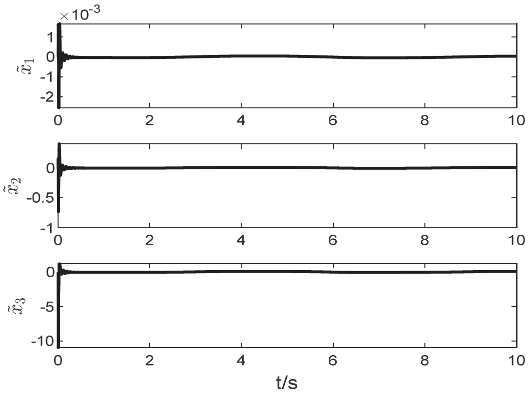

Figure 3 Estimated errors of the observer

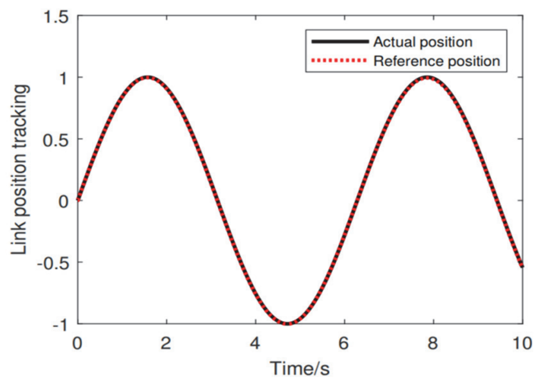

Figure 4 Actual position y and reference position y_d

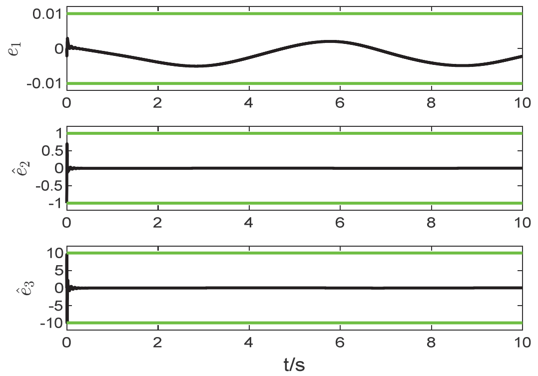

Figure 5 Tracking errors

It can be seen from Fig. 2 and Fig. 3 that the designed state observer can accurately estimate the link speed and motor speed of the single-link robotic manipulator. As shown in Fig. 4, the system output position can accurately track the reference input position y_d; Fig. 5 shows the tracking error curve of the system, where the green line represents the constraint boundary of the error, and it can be seen that the tracking error does not violate the constraint, that is, the tracking error satisfies the constraint $|\hat{e}_i| < k_{ci}$. Tab. 1 presents the root mean square error (*RMSE*) for system state observation and tracking. The *RMSE* data indicates that the observer and controller can ensure that the error converges within a small neighborhood.

Table 1 RMSE for state observation and tracking

	RMSE observed	*RMSE* tracked
Connecting rod position	3.10×10^{-3}	1.01×10^{-4}
Connecting rod speed	2.28×10^{-2}	2.34×10^{-2}
Motor angle	3.38×10^{-1}	2.79×10^{-1}

Fig. 6 shows the changes in the estimated weights of the NN used by the controller. Fig. 6, it can be concluded that the estimated weights of the NN eventually converge to the ideal values. The results in Fig. 2 to Fig. 6 indicate that the proposed control scheme can achieve the predetermined control goal, that is, it can enable the output to track the expected reference trajectory in the presence of unknown system dynamics and unmeasurable system states.

To verify the feasibility of the proposed scheme in the actual system, we conducted 100 identical experiments, and obtained that the average running time is 2.756 s, which is less than the total simulation time 10s of the system from the experimental results, but the average resource consumption is 102 M. Therefore, the realization of the proposed control strategy in the real-time system still needed to be optimized.

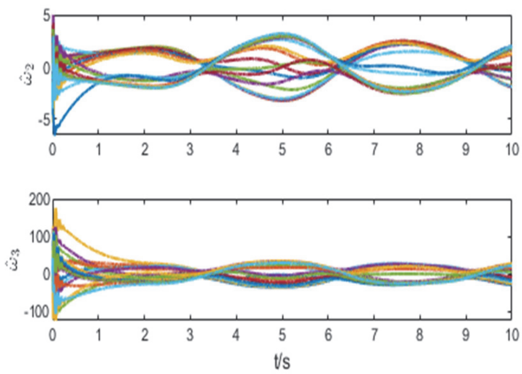

Figure 6 Estimation of the neural network's weights

This paper considers state/output constraints in system control design in advance, and then constructs a suitable controller to theoretically ensure that the state/output constraints will not be violated. At the same time, it proves that the control properties of the closed-loop system are valid.

5 CONCLUSION

In this paper, an adaptive NN output feedback control scheme based on BLF is proposed for a class of state-constrained uncertain affine nonlinear systems. Firstly, a nonlinear state observer is designed to estimate the unmeasurable states of the system. Then, the design of the BLF-based output feedback control scheme is realized by introducing the DSC technique based on BLF into the NN-based adaptive control design framework. The proposed control system can overcome the "complexity explosion" problem inherent in the backstepping design method. In addition, stability analysis gives that all closed-loop signals are bounded, and the system state error converges to a small neighborhood of the expected trajectory without violating the constraints. Finally, the results of numerical simulation experiments validate the effectiveness and performance of the proposed scheme. In the future work, we will consider the application of the control strategy to more complex or variable real-world systems, or extending it to multi-agent systems.

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