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Neural-network-based output-feedback adaptive dynamic surface control for a class of stochastic nonlinear time-delay systems with unknown control directions

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ABSTRACT

This paper focuses on the problem of output-feedback adaptive stabilization for a class of stochastic nonlinear time-delay systems with unknown control directions. First, based on a linear state transformation, the unknown control coefficients are lumped together and the original system is transformed to a new system for which control design becomes feasible. Then, after the introduction of an observer, an adaptive neural network (NN) output-feedback control scheme is presented for such systems by using dynamic surface control (DSC) technique and Lyapunov–Krasovskii method. The designed controller ensures that all the signals in the closed-loop system are 4-Moment (or 2-Moment) semi-globally uniformly ultimately bounded. Finally, a numerical example is given to demonstrate the feasibility and effectiveness of the proposed control design.

1. Introduction

In recent years, the topic of stability analysis and control design for stochastic nonlinear systems has been an intensive area of research [1–8]. Some nonlinear control design methods such as Lyapunov function approach, backstepping technique, and approximation-based control method were extended to the case of stochastic nonlinear systems. Especially, by using neural network or fuzzy system, many adaptive control schemes have been developed for some classes of stochastic nonlinear systems with unstructured uncertainties. When only system output can be measured, the problem of output-feedback stabilization has been investigated for some classes of stochastic nonlinear systems by using the systematic backstepping techniques [9–15]. However, an obvious drawback in the traditional backstepping design is the problem of 'explosion of complexity', which is caused by the repeated differentiations of some nonlinear functions such as virtual controllers. To avoid the problem of 'explosion of complexity', the DSC method has been proposed by introducing a first-order filtering of the virtual control law at each step of the conventional backstepping design procedure for some classes of deterministic nonlinear systems in [16]. Moreover, the DSC method was extended to the approximation-based control [17], decentralized control [18], output-feedback stabilization [19], and control of time-delay systems [18–20]. Since the DSC has been extended to the adaptive neural output-feedback stabilization for a class of stochastic nonlinear systems in [21], it has been used to solve the output-feedback stabilization problem for stochastic nonlinear strict-feedback systems [22], stochastic nonminimum phase nonlinear systems [23], stochastic MIMO (Multiinput and Multioutput) nonlinear systems [24], and stochastic nonlinear large-scale systems [25,26]. Unfortunately, these aforementioned DSC designs for stochastic nonlinear systems did not consider the time-delay and the unknown control direction.

On the other hand, the unknown control direction may be encountered in a variety of practical systems, such that the control design for such systems will be quite difficult. In comparison with lots of research results in deterministic nonlinear systems [27–33], there are only a few results on control for stochastic nonlinear systems. In [3], the problem of adaptive fuzzy control has been presented for a class of stochastic strict-feedback nonlinear systems with unknown control direction. In [34], an adaptive neural controller design was addressed for a general class of stochastic nonlinear pure-feedback systems with unknown control direction by combining the decoupled backstepping technique and the Nussbaum Gain Function (NGF) approach. In addition,

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a Razumikhin–Nussbaum lemma was proposed to solve the adaptive NN control problem for a class of stochastic nonaffine time-delay systems with unknown control direction in [35], and was extended to a general class of stochastic pure-feedback time-delay systems [36]. However, these results are obtained in state-feedback control. To the author's best knowledge, the output-feedback control problem of stochastic nonlinear time-delay systems with unknown control directions still remains an open problem.

Inspired by the aforementioned discussion, we will investigate the problem of adaptive output-feedback stabilization for a class of stochastic systems with time-varying delays and unknown control directions. First, we introduce a linear state transformation, such that the original system is transformed to a new system for which control design becomes feasible. An observer is designed to give the estimates of states. Moreover, by combining the DSC technique, Radial Basis Function (RBF) NN approximation, NGF approach and Lyapunov-Krasovskii method, an adaptive neural output-feedback controller is constructed for such systems under some suitable assumptions on system nonlinear functions. The main contributions lie in the following:

(1) The problem of adaptive neural output-feedback stabilization is first investigated for a class of stochastic nonlinear systems with time-varying delays and unknown control directions. The technique difficulties from the unknown control directions and time-varying delays are solved by employing the NGF method and the Lyapunov–Krasovskii method.
(2) By using the DSC technique, the proposed design can avoid the problem of 'explosion of complexity' inherent in the traditional backstepping design. Therefore, the proposed controller can become much simpler than the conventional backstepping controller.

The rest of this paper is organized as follows. Section 2 gives some preliminaries and the formulation of the problem. The main design procedure and stability analysis of adaptive neural output-feedback controller is developed in Section 3. In Section 4, a simulation example is given to illustrate the effectiveness of the proposed controller. Finally, this paper will be concluded in Section 5 with a brief discussion of the results.

2. Preliminary knowledge and system formulation

2.1. Notations

For the purpose of simplicity, the time variable t is omitted from the corresponding functions and the argument of some function is omitted whenever no confusion can arise from the context. For example, f_i represents $f_i(\cdot)$.

C^i denotes the family of all the functions with continuous i-th partial derivatives; $\|A\| = \sqrt{A^T A}$ denotes the Euclidean norm for vector A or the induced Euclidean norm for the matrix A; $\|A\|_\infty = \max_{i,j}|a_{ij}|$ denotes the infinity norm of matrix $A \in R^{m\times n}$; $\mathrm{Tr}(A)$ denotes the trace of A; $\lambda_{\max}A$ denotes the largest eigenvalue of matrix A; $E[Y]$ denotes the expectation of stochastic variable Y.

2.2. Preliminaries

Consider the following system:

$$dx = f(t,x)\,dt + h^T(t,x)\,d\omega \tag{1}$$

where $x \in R^n$ is the state, ω is r-dimensional standard Brownian motion, and f, h are vector-value or matrix-value function with appropriate dimensions. We define the operator $\mathcal{L}$ known as infinitesimal generator for C^2 function $V(t,x)$ as follows:

$$\mathcal{L}V(t,x) = \frac{\partial V}{\partial t} + \frac{\partial V}{\partial x} f + \frac{1}{2}\,\mathrm{Tr}\left\{h \frac{\partial^2 V}{\partial x^2} h^T\right\}. \tag{2}$$

Definition 1 (*Du et al. [32]*). Any even differentiable function $N(\zeta): R \to R$ is called a Nussbaum-type function if it has the following properties [37]:

$$\lim_{s\to\infty} \sup \int_0^s N(\zeta)\,d\zeta = +\infty,$$
$$\lim_{s\to\infty} \inf \int_0^s N(\zeta)\,d\zeta = -\infty. \tag{3}$$

Definition 2 (*Du et al. [32]*). Any even differentiable function $N(\zeta): R \to R$ is of NGF (or called Ryan-type NGF) if the following Ryan-type conditions hold [38]:

$$\lim_{s\to\infty} \sup \frac{1}{s}\int_0^s N(\zeta)\,d\zeta = +\infty,$$
$$\lim_{s\to\infty} \inf \frac{1}{s}\int_0^s N(\zeta)\,d\zeta = -\infty. \tag{4}$$

Many even functions such as $\zeta^2 \cos(\zeta)$, $\exp(\zeta^2)\cos((\pi/2)\zeta)$ can serve as a Ryan-type NGF. Moreover, some properties of Nussbaum functions are given in [31]. In this paper, $\zeta^2 \cos(\zeta)$ is chosen as a Ryan-type NGF. To facilitate control system design, the following lemmas is developed.

Lemma 1. *Let $\zeta(t)$ be a smooth function defined on $[0, t_f)$ and $N(\cdot)$ be a Nussbaum-type function; consider the stochastic nonlinear system (1), if there exists a positive definite, radially unbounded function $V(t,x) \in C^2([0,t_f), R^n)$, and constants $C_i > 0$ $(i = 1, 2)$, satisfying the following inequality:*

$$\mathcal{L}V(t,x) \le -C_1 V(t,x) + N(\zeta)\dot{\zeta} + C_2, \tag{5}$$

then $EV(t,x)$ is bounded on $[0, t_f)$.

Proof. See the Appendix.

Remark 1. $N(\zeta)$ is not necessarily to be an even function. If $N(\zeta)$ is chosen as an odd function, e.g. $N(\zeta) = \exp(\zeta^2)\sin((\pi/2)\zeta)$, the lemma can be easily proven by the similar procedure in the Appendix.

Lemma 2 (*Young's inequality, Deng and Kristic [2]*). *For $\forall (x,y) \in R^2$, the following inequality holds:*

$$xy \le \frac{\varepsilon^p}{p}|x|^p + \frac{1}{q\varepsilon^q}|y|^q$$

where $\varepsilon > 0$, $p > 1$, $q > 1$ and $(p-1)(q-1) = 1$.

In this paper, a continuous function $f(\cdot): R^n \to R$ will be approximated by the Gaussian RBF NNs. Namely, $\hat{f} = \hat{W}^T S(Z)$, where $Z \in \Omega_{NN} \subset R^n$ is the input vector, $\hat{W} = [w_1, \dots, w_l]^T \in R^l$ is the weight vector and the kernel vector is $S(Z) = [s_1(Z), s_2(Z), \dots s_l(Z)]^T$ with active function $s_i(Z)$ being chosen as the commonly used Gaussian functions

$$s_i(Z) = \exp\left[\frac{-\|Z-\mu_i\|^2}{\nu^2}\right], \quad i = 1, 2, \dots, l$$

where $\mu_i = [\mu_{i1}, \dots, \mu_{in}]^T$ is the center of the receptive field and ν is the width of the Gaussian function. By choosing enough nodes, NN can approximate any continuous function over a compact region $\Omega_{NN} \subset R^n$ with arbitrary accuracy, namely

$$f(Z) = W^{*^T} S(Z) + \delta(Z), \quad \forall Z \in \Omega_{NN}. \tag{6}$$