Neurocomputing 125 (2014) 72–80

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Robust adaptive neural network control for a class of uncertain nonlinear systems with actuator amplitude and rate saturations

Ruyi Yuan*, Xiangmin Tan, Guoliang Fan, Jianqiang Yi

Institute of Automation, Chinese Academy of Sciences, Beijing, PR China

A R T I C L E I N F O

Available online 1 March 2013

Keywords:
Actuator saturation
RBF neural network
Adaptive control
Robust control

A B S T R A C T

An adaptive controller which is designed with a priori consideration of actuator saturation effects and guarantees H^{∞} tracking performance for a class of multiple-input–multiple-output (MIMO) uncertain nonlinear systems with extern disturbances and actuator saturations is presented in this paper. Adaptive radial basis function (RBF) neural networks are used in this controller to approximate the unknown nonlinearities. An auxiliary system is constructed to compensate the effects of actuator saturations. Furthermore, in order to deal with approximation errors for unknown nonlinearities and extern disturbances, a supervisory control is designed, which guarantees that the closed loop system achieves a prescribed disturbance attenuation level so that H^{∞} tracking performance is achieved. Steady and transient tracking performance are analyzed and the tracking error is adjustable by explicit choice of design parameters. Computer simulations are presented to illustrate the efficiency of the proposed controller.

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1. Introduction

All physical actuators in control systems have amplitude and rate limitations. For example, the elevator of an aircraft can only provide a limited force or torques in a limited rate. Actuator amplitude limitation or rate limitation constitutes a fundamental limitation on many linear or nonlinear control design techniques and has attracted the attention of numerous researchers. The controllers that ignore actuator limitations may cause the closed loop system performance to degenerate or even make the closed system unstable, and decrease the lifetime of the actuators, or damage the actuators. Higher performance may be expected if a controller is designed with a priori considering of the actuator saturation effects.

The design of stabilizing controllers with a priori consideration of the actuator saturation effects for nonlinear systems with unknown nonlinearities and external disturbances is a challenging problem. Zhou [1] proposed an adaptive backstepping scheme to design an adaptive controller for a class of uncertain nonlinear single-input–single-output (SISO) systems in the presence of input saturations. To deal with saturations, an auxiliary system with the same order as that of the plant was constructed to compensate the effect of saturation. Farrell et al. [2–5] presented an adaptive backstepping approach and an online approximation based adaptive backstepping approach for unknown nonlinear systems with known magnitude, rate, bandwidth constraints on intermediate states or actuators without disturbance. Those approaches also used auxiliary systems for generating a modified tracking error to guarantee stability during saturation. Command filtered adaptive backstepping approaches [6–9] were also proposed to deal with the constraints on the control surfaces and the control states. For single input uncertain nonlinear systems in the presence of input saturation and unknown external disturbance, robust adaptive backstepping control algorithms were also developed by introducing a well defined smooth function and using a Nussbaum function which was used to compensate for the nonlinear term arising from the input saturation [10].

Dynamic inversion [11,12] approach is a widely used nonlinear control technique. However, the effects of actuator saturations have not been addressed with nominal dynamic inversion algorithm, so certain modifications are required. Tandale [13] proposed an adaptive dynamic inversion controller for a class of nonlinear systems with control saturation constraints. Enomoto [14] investigated the dynamic inversion control for nonlinear systems with control saturation constraints by Lyapunov synthesis. For a class of uncertain nonlinear dynamical systems in Brunovsky form, Lavretsky [15] proposed a dynamic inversion based adaptive control framework to provide stable adaptation in the presence of input constraints. The proposed design methodology can protect the control law from actuator position saturation. For a class of nonlinear systems which, in the presence of saturation, were controlled by nonlinear dynamic inversion

* Correspondence to: Room 719, 95 Zhongguancun East Road, 100190 Beijing, PR China. Tel.: +86 10 62550985 16.

E-mail addresses: ruyi.yuan@ia.ac.cn (R. Yuan), xiangmin.tan@ia.ac.cn (X. Tan), guoliang.fan@ia.ac.cn (G. Fan), jianqiang.yi@ia.ac.cn (J. Yi).

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http://dx.doi.org/10.1016/j.neucom.2012.09.036

controllers, an anti-windup compensation scheme was also proposed [16–18]. Neural network technique [19,20] was also used to handle actuator saturations problem. Calise [21] introduced a neural network based method termed as Pseudo-Control Hedging (PCH) for addressing a wide class of plant input characteristics such as actuator position limits, actuator rate limits, time delay, and input quantization. Chen et al. [22] also introduced a radial basis function neural network based controller for uncertain MIMO nonlinear systems with input saturations. The control design for nonlinear systems with actuator saturations was also be investigated by optimal control [23], nearly optimal control [24], nonlinear model predictive control [25] and fault tolerant scheme [26], etc. However, there are still few results for the control of uncertain nonlinear systems by taking actuator saturations into account in the controller design and analysis.

In [27], the authors proposed an adaptive controller for MIMO nonlinear systems with control input limitations by using an auxiliary system and extended tracking errors which were used in neural network parameter update laws to compensate the effects of control input limitations. In this paper, for the control of a class of MIMO uncertain nonlinear systems in the presence of disturbances and actuator saturations, dynamic inversion [11] based controller which can generate constrained control signal is designed. Adaptive RBF neural networks are used to approximate unknown nonlinearities. An auxiliary system is constructed to compensate the effects of actuator amplitude and rate saturations. This auxiliary system and compensation scheme are different from [27], so that the extended tracking error in [27] is no longer needed. A supervisory control is designed to attenuate the effects of approximation errors and external disturbance so as to guarantee a H^∞ tracking performance. The performance of the closed loop system is obtained through Lyapunov analysis. The bounds of tracking errors can be adjusted by tuning the design parameters. The proposed controller can generate control signals satisfying actuator amplitude and rate limitations, and guarantee a H^∞ tracking performance of the closed loop system.

The rest of this paper is organized as follows. In Section 2, the problem statement is presented. In Section 3, the adaptive control scheme is discussed, and the closed loop system performance is analyzed. A numerical example is shown in Section 4. Section 5 concludes the paper. Throughout this paper, $|\cdot|$ indicates the absolute value, $\|\cdot\|$ indicates the Euclidean vector norm, and $\|\cdot\|_2$ indicates the L_2 norm.

2. Problem formulation

Consider the class of MIMO systems described by the following differential equations:

$$\begin{aligned} &\dot{x}_{i1} = x_{i2} \\ &\vdots \\ &\dot{x}_{i,r_i-1} = x_{ir_i} \\ &\dot{x}_{ir_i} = f_i(\mathbf{x}) + \sum_{j=1}^{m} g_{ij}(\mathbf{x})u_j + d_i \\ &y_i = x_{i1}, \quad i = 1, \ldots, m \end{aligned} \tag{1}$$

which also can be rewritten in the following compact form:

$$\mathbf{y}^{(n)} = \mathbf{F}(\mathbf{x}) + \mathbf{G}(\mathbf{x})\mathbf{u} + \mathbf{d} \tag{2}$$

where $\mathbf{y} = [y_1, \ldots, y_m]^T \in \mathbf{R}^m$ is the output vector; $\mathbf{y}^{(n)} \stackrel{\text{def}}{=} [y_1^{(r_1)}, \ldots, y_m^{(r_m)}]^T \in \mathbf{R}^m$, $\sum_{i=1}^m r_i = n$; $y_i^{(r_i)} = d^{r_i} y_i / dt^{r_i}$; $\mathbf{x} = [x_{11}, \ldots, x_{1r_1}, \ldots, x_{m1}, \ldots, x_{mr_m}]^T \in \mathbf{R}^n$ is the state vector available for measurement; $\mathbf{u} = [u_1, \ldots, u_m] \in \mathbf{R}^m$ is the control vector with

$$|u_i| \le u_{i\max}, \quad \dot{u}_i \le v_{i\max} \tag{3}$$

where $u_{i\max}$ and $v_{i\max}$ denote the actuator amplitude and rate limits respectively. $\mathbf{F}(\mathbf{x}) = [f_1(\mathbf{x}), \ldots, f_m(\mathbf{x})] \in \mathbf{R}^m$, $\mathbf{G}(\mathbf{x}) = [g_{ij}(\mathbf{x})]_{m\times m} \in \mathbf{R}^{m\times m}$ ($[\cdot]_{m\times m}$ represents a $m\times m$ matrix) are continuous unknown functions of the state $\mathbf{x}$. d_i denotes the external disturbances which is unknown but bounded and satisfies $\int_0^T d_i^2 dt < \infty$. $\mathbf{d} = [d_1, \ldots, d_m] \in \mathbf{R}^m$.

The control objective is to force y_i to follow a given bounded reference signal y_{id} in the presence of actuator saturations and extern disturbances. For (2) to be controllable, we assume that $\sigma(\mathbf{G}(\mathbf{x})) \neq 0$ for $\mathbf{x}$ in certain controllability region $\mathbf{U}_c \in \mathbf{R}^n$, where $\sigma(\mathbf{G}(\mathbf{x}))$ denotes the minimum singular value of the matrix $\mathbf{G}(\mathbf{x})$.

3. Design of adaptive controllers

To begin, define $\tau_1, \ldots, \tau_m$ as follows:

$$\tau_i = y_{id}^{(r_i)} + \sum_{j=1}^{r_i} \lambda_{ij} e_i^{(j-1)}, \quad i = 1, \ldots, m$$

where y_{id}, $i = 1, \ldots, m$ are the reference signals, $e_i = y_{id} - y_i$ $(i = 1, \ldots, m)$ are the tracking errors, $\lambda_{i1}, \ldots, \lambda_{ir_i}$ are parameters which make sure that the roots of the equation $s^{r_i} + \lambda_{ir_i} s^{r_i - 1} + \cdots + \lambda_{i2} s + \lambda_{i1} = 0$ are all in the open left-half complex plane.

If $\mathbf{F}(\mathbf{x})$ and $\mathbf{G}(\mathbf{x})$ are known and the constrains on control inputs are ignored, then based on dynamic inversion algorithm, the control law:

$$\mathbf{u}_{c'} = \mathbf{G}^{-1}(\mathbf{x})(-\mathbf{F}(\mathbf{x}) + \boldsymbol{\tau}) \tag{4}$$

can be applied to (2) to achieve the following asymptotically stable tracking:

$$\begin{bmatrix} e_1^{(r_1)} + \sum_{j=1}^{r_1} \lambda_{1j} e_1^{(j-1)} \\ \vdots \\ e_m^{(r_m)} + \sum_{j=1}^{r_m} \lambda_{mj} e_m^{(j-1)} \end{bmatrix} = \mathbf{0} \tag{5}$$

in the case of no external disturbances.

Because $\mathbf{F}(\mathbf{x})$ and $\mathbf{G}(\mathbf{x})$ are unknown vector and matrix respectively, the above control law (4) cannot be implemented in practice. Besides, there is no guarantee that $\mathbf{u}_{c'}$ satisfies the actuator constraints (3). It is well known that neural networks [19,20] can be used as universal approximators to approximate any continuous functions at any arbitrary accuracy as long as the network is big enough. In this work, in order to treat this tracking control design problem, radial basis function (RBF) neural networks are used to approximate the unknown functions, that is, $f_i(\mathbf{x})$, $i = 1, \ldots, m$, and $g_{ij}(\mathbf{x})$, $i,j = 1, \ldots, m$ are approximated as follows:

$$f_i(\mathbf{x}) \approx \hat{f}_i(\mathbf{x}|\boldsymbol{\Theta}_{f_i}) = \boldsymbol{\Theta}_{f_i}^T \boldsymbol{\Phi}_{f_i}(\mathbf{x}), \quad i = 1, \ldots, m \tag{6}$$

$$g_{ij}(\mathbf{x}) \approx \hat{g}_{ij}(\mathbf{x}|\boldsymbol{\Theta}_{g_{ij}}) = \boldsymbol{\Theta}_{g_{ij}}^T \boldsymbol{\Phi}_{g_{ij}}(\mathbf{x}), \quad i, j = 1, \ldots, m \tag{7}$$

where $\boldsymbol{\Theta}_{f_i} \in \mathbf{R}^{M_{f_i}}$, $\boldsymbol{\Theta}_{g_{ij}} \in \mathbf{R}^{M_{g_{ij}}}$ are weight vectors, and $\boldsymbol{\Phi}_{f_i}(\mathbf{x}) \in \mathbf{R}^{M_{f_i}}(\mathbf{x})$, $\boldsymbol{\Phi}_{g_{ij}}(\mathbf{x}) \in \mathbf{R}^{M_{g_{ij}}}(\mathbf{x})$ are radial basis vectors, M_{f_i}, $M_{g_{ij}}$ are the corresponding dimensions of the basis vectors. Denote

$$\hat{\mathbf{F}}(\mathbf{x}|\boldsymbol{\Theta}_{\mathbf{F}}) = \begin{bmatrix} \hat{f}_1(\mathbf{x}) \\ \vdots \\ \hat{f}_m(\mathbf{x}) \end{bmatrix}, \quad \hat{\mathbf{G}}(\mathbf{x}|\boldsymbol{\Theta}_{\mathbf{G}}) = \begin{bmatrix} \hat{g}_{11}(\mathbf{x}) & \cdots & \hat{g}_{1m}(\mathbf{x}) \\ \vdots & \ddots & \vdots \\ \hat{g}_{m1}(\mathbf{x}) & \cdots & \hat{g}_{mm}(\mathbf{x}) \end{bmatrix} \tag{8}$$

Then $\hat{\mathbf{F}}(\mathbf{x}|\boldsymbol{\Theta}_{\mathbf{F}})$ is an estimation of $\mathbf{F}(\mathbf{x})$, and $\hat{\mathbf{G}}(\mathbf{x}|\boldsymbol{\Theta}_{\mathbf{G}})$ is an estimation of $\mathbf{G}(\mathbf{x})$.

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