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Research Article

Robust decentralized hybrid adaptive output feedback fuzzy control for a class of large-scale MIMO nonlinear systems and its application to AHS

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ABSTRACT

This paper presents a novel observer-based decentralized hybrid adaptive fuzzy control scheme for a class of large-scale continuous-time multiple-input multiple-output (MIMO) uncertain nonlinear systems whose state variables are unmeasurable. The scheme integrates fuzzy logic systems, state observers, and strictly positive real conditions to deal with three issues in the control of a large-scale MIMO uncertain nonlinear system: algorithm design, controller singularity, and transient response. Then, the design of the hybrid adaptive fuzzy controller is extended to address a general large-scale uncertain nonlinear system. It is shown that the resultant closed-loop large-scale system keeps asymptotically stable and the tracking error converges to zero. The better characteristics of our scheme are demonstrated by simulations.

1. Introduction

In recent years, the design of intelligent control systems [1], along with the synthesis of classical controllers [2], has attracted considerable attention in the control community. It is well-known that there are direct and indirect approaches for adaptive fuzzy or neural control. Indirect adaptive fuzzy control (IAFC) models unknown plants using fuzzy linguistics (that is, "If-Then" rules), while direct adaptive fuzzy control (DAFC) is designed directly to incorporate fuzzy

"If-Then" control knowledge. Many indirect [3–6] or direct [6–11] adaptive control algorithms for uncertain nonlinear systems have been proposed based on state or output feedback, although neither IAFC nor DAFC can simultaneously incorporate the two sorts of foregoing fuzzy information. To make best use of the advantages of both the kinds of adaptive controllers, several combined adaptive control algorithms were proposed in [6,12–14]. The proposed hybrid indirect and direct adaptive controllers can be integrated by a weighting factor α. However, the schemes have some limitations. First, the approach proposed in [6] can be used only for a class of systems with positive input gains. Second, the combined adaptive fuzzy control (CAFC) in [12] is suitable only for robot manipulators with some special properties, whereas the controller in [13] builds upon an unsupported algorithm because the derivative of the constructed Lyapunov function candidate is incorrect in nature. Third, the algorithms proposed in [6,12,13] are restricted to the nonlinear systems with measurable states. However, all the state variables are often unavailable in a complex uncertain nonlinear system. To resolve this problem, output feedback or observer-based adaptive control techniques were developed and become indispensable control strategies in complicated systems. A kind of hybrid adaptive fuzzy-neural output feedback controller, whose supervisory control and update laws are subject to the full observation error vector, was investigated in [14]. However, the methodology of computing the observation error was not given in the report. Hence the design of observer-based CAFC for nonlinear systems still remains a challenging problem.

Many adaptive control schemes through state feedback were also investigated for multi-input multi-output (MIMO) nonlinear systems [15–25]. In adaptive fuzzy or neural control schemes, an

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adaptive controller generally contains a fuzzy logic or neural network controller for rough tuning and a robust compensator for fine tuning. It should be stressed that, unlike the design of a controller for a single-input single-output (SISO) nonlinear system, the design of an indirect adaptive control for an MIMO nonlinear system may encounter a singularity problem. Suppose that the MIMO nonlinear system under consideration is in the form $\mathbf{y}^{(r)} = \mathbf{F}(\mathbf{x}) + \mathbf{G}(\mathbf{x})\mathbf{u}$ where $\mathbf{F}(\mathbf{x}) \in R^p, \mathbf{G}(\mathbf{x}) \in R^{p\times p}$ are unknown nonlinearities, $\mathbf{x} \in R^n, \mathbf{u} \in R^p, \mathbf{y} \in R^p$ are the state vector, output variable, and input variable, respectively. A tracking control law, $\mathbf{u} = \hat{\mathbf{G}}^{-1}(\mathbf{x}, \mathbf{\Theta}_g)[\mathbf{v} - \mathbf{F}(\mathbf{x}, \mathbf{\Theta}_f)]$ is ill-defined as long as the parameterized approximation $\hat{\mathbf{G}}(\mathbf{x}, \mathbf{\Theta}_g)$ of the actual input $\mathbf{G}(\mathbf{x})$ is singular, where $\mathbf{\Theta}_f, \mathbf{\Theta}_g$ are proper tunable parameter matrices and $\mathbf{v}$ is the control to be designed. To solve this problem, a parameter projection algorithm was appended to restrain the estimated parameter $\mathbf{\Theta}_g$ from fleeing a feasible region where $\hat{\mathbf{G}}(\mathbf{x}, \mathbf{\theta}_g)$ always keeps regular [15]. But the scheme causes new problems such as difficulty in specifying a practicable region and an overburdened load on computation. In [19], the authors did not consider the problem of the controller singularity and assumed the term was regular implicitly. Furthermore, the projection algorithm presented in [16] tried to solve the controller singularity problem but the bounded norm of $\hat{\mathbf{G}}(\mathbf{x}, \mathbf{\theta}_g)$ is not enough to ensure the existence of both $\hat{\mathbf{G}}^{-1}(\mathbf{x}, \mathbf{\theta}_g)$and $[\hat{\mathbf{G}}(\mathbf{x}, \mathbf{\theta}_g)\hat{\mathbf{G}}(\mathbf{x}, \mathbf{\theta}_g)]^{-1}$. While these control architectures are restricted to the nonlinear systems with measurable state variables, adaptive control algorithms using output feedback were developed for MIMO nonlinear systems in [26–28]. However, the approach in [27] supposed that $\hat{\mathbf{G}}(\mathbf{x}, \mathbf{\theta}_g)$ was always invertible, did not take into account the controller singularity problem. Moreover, the algorithms in [27,28] supposed that a Riccati-like matrix equation is always solvable. However, this assumption is very conservative. A classical adaptive output feedback control scheme was put forward in [26] using a high-gain observer, but it presupposes that the input gain matrix has nonzero leading principle minors. It is clear that there is no a mature method coping with the problem of controller singularity in MIMO nonlinear systems, and it is extremely necessary to develop an advanced control scheme for uncertain MIMO nonlinear systems to resolve the problem.

In some large-scale systems, the exchange of information between subsystems is physically impossible, the computing capacity is low, some information is hard to obtain, and uncertainties exist in the systems. As a result, decentralized control approaches are widely used to handle these problems. Recently, various decentralized control algorithms have been presented for intercon-nected SISO linear [29] and nonlinear [30–32] systems in which the state variables are assumed to be measurable. In addition, decentralized control techniques and linear matrix inequalities (LMI) were applied together to address output regulation or tracking control problems for several special classes of SISO interrelated nonlinear systems [33,34]. In [34], the controlled plants are simply limited to linear subsystems coupled by nonlinear interconnections satisfying some constraints. Observer-based decentralized intelligent control designs were also developed for SISO large-scale nonlinear systems [35–40]. However, it is worth pointing out that there are many substantive problems that remain unsolved. Above all, cooperation or communication is required between subsystems, so the propounded indirect or direct control algorithms [35–37] are unable to be numbered among real decentralized control techniques naturally. Second, a fuzzy-observer-based decentralized H_∞ controller proposed in [39], which uses Takagi–Sugeno (T–S) fuzzy models and LMI, is subject to a conservative assumption on an integral inequality, and does not fall into a fuzzy adaptive control category. Third, the input gains of the large-scale systems [34–38] were considered as positive constants rather than unknown nonlinear functions. This restriction substantially narrows the applications of the proposed decentralized controllers. Fourth, the decentralized adaptive neural network controller design in [40] is restricted to large-scale systems with input saturation. Hence decentralized adaptive output feedback intelligent control system synthesis is an open problem for large-scale MIMO nonlinear systems that contain nonlinear subsystems coupled with nonlinearities.

To resolve these problems, we develop a novel decentralized CAFC scheme via output feedback for a class of large-scale MIMO uncertain nonlinear systems. Their SISO version has been investigated in [30,32]. The main contributions of this study are (1) we combine a state observer, a sliding mode method and strictly-positive real (SPR) conditions in the design of the decentralized controller to make it possible to apply the method to a class of MIMO large-scale nonlinear systems in which state variables are not measurable, the input gains and subsystems as well as the interconnections are unknown and nonlinear. This removes the conservative constant assumptions on the input gains in [2,3,5,11,25,33–36,38]; (2) we preclude the singularity problem by presenting a design framework for a modified decentralized CAFC scheme to ensure the definiteness of the controller; (3) we use a weighting factor to flexibly integrate the control efforts of the IAFC and DAFC based upon the knowledge of the plant and controller. This greatly improves the control performance of the CAFC system; (4) we also take into account the transient performance of the CAFC subsystem and do not require a priori knowledge of the upper bounds on lumped uncertainties. All the signals of the closed-loop interconnected systems stay uniformly ultimately bounded (UUB) and the outputs asymptotically track the desired trajectories, i.e., the tracking errors converge to zero rather than the UUB property in [3,18,19,25,35,36]. The validity of the developed algorithms is illustrated using a complicated nonlinear system. Simulation results show that the tracking errors and control efforts of the CAFC systems are smaller than those of the IAFC and DAFC systems.

The rest of this paper is organized as follows. In Section 2, the problem under investigation is formulated and an observer-based fuzzy system is explained. Section 3 introduces the decentralized CAFC algorithm via output feedback and establishes its properties using Lyapunov's direct approach. The CAFC design is modified and the transient performance is analyzed in Section 4. An application of the decentralized CAFC algorithm in controlling a large-scale MIMO nonlinear system is conducted in Section 5. Concluding remarks are made in Section 6.

2. Problem formulation and preliminaries

2.1. Controlled plants

Consider a class of large-scale MIMO partially uncertain nonlinear systems that are composed of N interconnected subsystems. The ith subsystem is described by

$$\dot{\mathbf{X}}_i = \overline{\mathbf{F}}_i(t, \mathbf{X}) + \overline{\mathbf{G}}_i(\mathbf{X}_i)\mathbf{u}_i,$$
$$\mathbf{y}_{i0} = \mathbf{h}_i(t, \mathbf{X}) \tag{1}$$

where $\overline{\mathbf{F}}_i \in R^p, \overline{\mathbf{G}}_i \in R^{p\times p}, \mathbf{h}_i \in R^p$ are uncertain nonlinear smooth vector fields; $\mathbf{X}_i \in R^{n_i}$ is the state vector, with $\mathbf{X} = (\mathbf{X}_1^T, \dots, \mathbf{X}_N^T)^T$; $\mathbf{r}_i = (r_{i1}, \dots, r_{ip})^T, n_i, \mathbf{u}_i \in \mathbf{R}^p, \mathbf{y}_{i0}$ are the relative degree vector, state space dimension, control input, and system output, respectively; and $\sum_{i=1}^N n_i$ denotes the overall dimension of the state space of the large-scale system. Input-output accurate linearization [32] allows us to write the subsystem (1) as

$$\mathbf{y}_i^{(\mathbf{r}_i)} = \mathbf{F}_i(\mathbf{X}_i) + \mathbf{G}_i(\mathbf{X}_i)\mathbf{u}_i + \mathbf{c}_i(\mathbf{X}, t),$$
$$\dot{\boldsymbol{\psi}}_i = \mathbf{W}_i(\mathbf{X}), i = 1, \dots, N, \tag{2}$$