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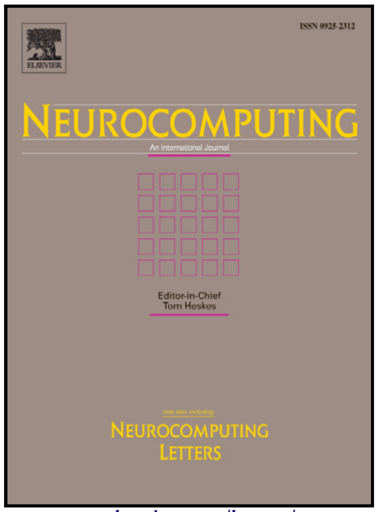

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Neural-Network-Based Decentralized Control of Continuous-Time Nonlinear Interconnected Systems with Unknown Dynamics☆

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Abstract

In this paper, we establish a neural-network-based decentralized control law to stabilize a class of continuous-time nonlinear interconnected large-scale systems using an online model-free integral policy iteration (PI) algorithm. The model-free PI approach can solve the decentralized control problem for the interconnected system which has unknown dynamics. The stabilizing decentralized control law is derived based on the optimal control policies of the isolated subsystems. The online model-free integral PI algorithm is developed to solve the optimal control problems for the isolated subsystems with unknown system dynamics. We use the actor-critic technique based on the neural network and the least squares implementation method to obtain the optimal control policies. Two simulation examples are given to verify the applicability of the decentralized control law.

Keywords: Adaptive dynamic programming, decentralized control, optimal control, policy iteration, neural networks.

1. Introduction

Decentralized control method using local information of each subsystem is an efficient and effective way in the control of interconnected systems. This overcomes the limitations of the traditional control method that requires sufficient information between subsystems. Unlike a centralized controller, a decentralized controller can be designed independently for local subsystems and make full use of the local available signals for feedback. Therefore, the decentralized controllers have simpler architecture, and are more practical than the traditional centralized controllers. Various decentralized controllers have been established for large-scale interconnected systems in the presence of uncertainties and information structure constraints [1, 2, 3, 4, 5, 6, 7]. Generally speaking, a decentralized control law is comprised of some noninteracting local controllers corresponding to the isolated subsystems, not the overall system. In many situations, the design of the isolated subsystems is very important. In [8], the decentralized controller was derived for the large-scale system using the optimal control policies of the isolated subsystems. Therefore, the optimal control method can be applied to facilitate the design process of the decentralized control law.

The optimal control problem of nonlinear systems has been widely studied in the past few decades. The optimal control policy can be obtained by solving Hamilton-Jacobi-Bellman (HJB) equation which is a partial differential equation. Because of the curse of dimensionality [9], this is a difficult task even in the case of completely known dynamics. Among the methods of solving the HJB equation, adaptive dynamic programming (ADP) has received increasing attention owing to its learning and optimal capacities [10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]. Reinforcement learning (RL) is another computational method and it can interactively find an optimal policy [21, 22, 23, 24]. Al-Tamimi et al. [25] proposed a greedy iterative ADP to solve the optimal control problem for nonlinear discrete-time systems. Park et al. [26] used multilayer neural networks (NNs) to design a finite-horizon optimal tracking neuro-controller for discrete-time nonlinear systems with quadratic cost function. Abu-Khalaf and Lewis [27] established an offline optimal control law for nonlinear systems with saturating actuators. Vamvoudakis and Lewis [28] derived a synchronous policy iteration (PI) algorithm to learn online continuous-time optimal control with known dynamics. Vrabie and Lewis [29] derived an integral RL method to obtain direct adaptive optimal control for nonlinear input-affine continuous-time systems with partially unknown dynamics. Jiang and Jiang [30] presented a novel PI approach for continuous-time linear systems with complete unknown dynamics. Liu et al. [31] extended the PI algorithm to nonlinear optimal control problem with

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