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Consensus-based distributed cooperative learning control for a group of discrete-time nonlinear multi-agent systems using neural networks☆

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ABSTRACT

This paper focuses on the cooperative learning capability of radial basis function neural networks in adaptive neural controllers for a group of uncertain discrete-time nonlinear systems where system structures are identical but reference signals are different. By constructing an interconnection topology among learning laws of NN weights in order to share their learned knowledge on-line, a novel adaptive NN control scheme, called distributed cooperative learning control scheme, is proposed. It is guaranteed that if the interconnection topology is undirected and connected, all closed-loop signals are uniform ultimate bounded and tracking errors of all systems can converge to a small neighborhood around the origin. Moreover, it is proved that all estimated NN weights converge to a small neighborhood of their common optimal value along the union of all state trajectories, which means that the estimated NN weights reach consensus with a small consensus error. Thus, all learned NN models have the better generalization capability than ones obtained by the deterministic learning method. The learned knowledge is also adopted to control a class of uncertain systems with the same structure but different reference signals. Finally, a simulation example is provided to verify the effectiveness and advantages of the distributed cooperative learning control scheme developed in this paper.

1. Introduction

It is well known that system modeling or identification is one of issues in the control area since uncertainties exist widely. In the past two decades, neural networks (NNs), such as radial basis function (RBF) NNs and multilayer NNs, have been extensively applied to complex uncertain nonlinear control systems. Due to their universal approximation ability, NNs are usually used to model unknown nonlinear functions appearing in systems or controllers in an on-line fashion. This control scheme is called adaptive NN control and Lyapunov stability theory is often employed to analyze closed-loop stability and control performance. Active studies have been carried out in the field of adaptive NN control, e.g., see books Jagannathan (2006), Zhang, Ge, and Hang (2001) and reference therein.

During the development of adaptive NN control, lots of interesting techniques have been proposed to solve main obstacles encountered in control design. As for continuous-time uncertain systems, an adaptive bounding technique is proposed in Polycarpou (1996), where a hyperbolic tangent function is employed to handle unknown upper bounds of NN approximation errors. In Zhang, Ge, and Hang (2000), the singularity problem of virtual/real control is solved by constructing some integral-type Lyapunov function candidates instead of commonly used quadratic ones. In Ge, Hong, and Lee (2004); Tong, Liu, and Li (2010), the Nussbaum gain function method and the adaptive NN or fuzzy control technique are successfully combined to solve the control problem for uncertain systems with an unknown control direction. The obstacle of "explosion of complexity" in adaptive backstepping NN or fuzzy control is overcome well in Tong, Li, Feng, and Li (2011);

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Wang and Huang (2005) by introducing an adaptive dynamic surface technique. For discrete-time systems, the noncausal problem, appearing in discrete-time strict-feedback system, is solved in Ge, Li, and Lee (2003) by transforming the strict-feedback form into a cascade form and constructing some proper Lyapunov function candidates. Vance and Jagannathan (2008) develop an adaptive NN output feedback controller for a class of second-order discrete-time non-strict feedback systems where the non-causal problem encountered during the controller design is confronted by employing a dynamic NN constructed via a feedforward NN with semi-recurrent structure which acts as a one-step predictor. Other representative works on the adaptive NN control for discrete-time systems are found in Chen and Khalil (1995), Jagannathan and Lewis (1996), He and Jagannathan (2007), Yang, Ge, Xiang, Chai, and Lee (2008), Zhang, Lou, and Liu (2009), Zhang, Song, Wei, and Zhang (2011). However, although all these control schemes guarantee that tracking errors converge to a small neighborhood around the origin, few of them investigate the learning capability of NNs during the control process.

The main obstacle in addressing the learning capability of NNs during control process lies in that it is difficult to satisfy the persistently exciting (PE) condition of regressor vectors consisting of RBFs. To solve this difficulty, Chen and Wang (2009), Wang and Hill (2006), Wang and Hill (2007), Wang and Hill (2009), Wang, Hill, and Chen (2003), Wang, Wang, Liu, and Hill (2012) propose the deterministic learning idea, where the learning is based on data produced by unknown but deterministic (instead of stochastic) dynamical system model. By investigation, they find that an appropriately designed adaptive NN controller can learn unknown system dynamics in closed-loop feedback control processes. The deterministic learning is achieved according to the following ingredients: (i) tracking control of the dynamical system states to a periodic reference trajectory; (ii) satisfaction of the partial PE condition along the tracking trajectory by exploiting the localized RBF NNs; (iii) exponential stability of the closed-loop systems; (iv) exponential convergence of the NN weights to small neighborhoods of their optimal values, which guarantees the accurate approximation of the unknown system functions. Consequently, the learned NN weights can be stored and used to control the systems with the same structure and the similar control tasks. Its main advantage is that it can store the learned knowledge as different patterns and select a proper pattern for the next control task. In this sense, it partially achieves the human capability of "learning by doing" and "doing with learned knowledge" Wang and Hill (2006). Therefore, it indeed realizes the intelligences of adaptive NN control. However, people know that, for instance, a person can learn knowledge not only from his own past experiences but also from other persons by cooperation and communication. Based on this fact, an interesting topic is to discuss the deterministic learning control scheme from the cooperative viewpoint.

In fact, cooperative strategy has been studied in the consensus problem of multi-agent systems, e.g., see survey articles Cao, Yu, Ren, and Chen (2013), Ren, Beard, and Atkins (2007), Olfati-Saber, Fax, and Murray (2007) and books Ren and Cao (2011); Tian (2012). The basic idea under consensus algorithms is that all agents asymptotically achieve the same dynamic by using only local information exchange. In this way, the final states of all agents reach an agreement. This is a cooperative strategy in which sharing information is necessary. Today, as consensus theory evolves, studies have been devoted to its applications such as wireless sensor network Kar and Moura (2010), formation control Fax and Murray (2004), flocking Olfati-Saber (2006), and neural network Chen et al. (2014), Cheng, Hou, Tan, Lin, and Zhang (2010), Hou, Cheng, and Tan (2009). From our viewpoint, the applications of consensus idea should not be only limited to the aforementioned aspects. It is interesting to find more application aspects for consensus idea. For example, it would be possible to apply the consensus idea to addressing the deterministic learning theory for uncertain multi-agent systems.

Based on the above observations, in this paper we attempt to propose a novel learning scheme, called distributed cooperative learning (DCL) scheme, for a group of unknown but identical discrete-time systems, where the NN controllers can learn the same uncertain system functions during the control process in a distributed cooperative fashion. There indeed exist some applications that motivate us to study such a DCL scheme. For example, the formation problem of vehicles such as ships Do (2011), helicopters Ben et al. (2008) satellites Canup and Ward (2002) and robots Hou et al. (2010), has been widely studied, where each vehicle just can obtain real-time information from partial vehicles instead of all vehicles due to the limitation of communication range. For this problem, on one hand, although the conventional centralized learning (CL) scheme might have better performances than DCL scheme, it cannot be used due to the lack of global communication ability. On the other hand, all existing works employ the decentralized learning (DL) schemes where each system does not utilize real-time learned NN weights from other systems to update its own NN weights, thus each system just learns its local dynamic based on its local NN input signals. To overcome drawbacks of CL/DL schemes, in this paper, we propose the DCL scheme which allows systems to real-time share their learned NN weights locally instead of globally. The first issue in this learning scheme is how to establish a suitable communication topology among the different systems for sharing information. Then, we further guarantee the learning ability of RBF NNs during the control process. Finally, we will investigate the advantages and disadvantages of this DCL scheme by comparing with the previous CL scheme and the DL scheme.

The main contributions of this paper are summarized as follows. We establish an interconnection topology among the NN weight update laws to make all designed controllers to share their estimated weights on-line. This idea is borrowed from the consensus algorithm of multi-agent systems in the existing literature, but it is different from the existing consensus works where the multi-agents only share their states such as velocities and positions. By appropriately combining algebraic graph theory and Lyapunov stability theory, we prove that all estimated NN weights exponentially converge to a small neighborhood of their optimal values over a domain consisting of the union of all recurrent state trajectories if the communication topology is undirected and connected. The main advantage of the DCL scheme is that the learned RBF NNs have the better generalization capability than ones obtained by the deterministic learning scheme. Moreover, it has the better fault-tolerant ability since the learning scheme is distributed.

The rest of this paper is organized as follows. In Section 2, we present preliminaries on algebraic graph theory, PE and RBF NNs. The design procedure of the DCL control scheme and the main results are shown in Section 3. Section 4 discusses the exploitation of past experience in the NN learning control. Simulation results are given in Section 5 to illustrate and verify the main results presented in this paper. Finally, conclusions are made in Section 6.

Notations. R, $R_{\geq 0}$ and Z_+ denote, respectively, the set of real numbers, the set of nonnegative real numbers and the set of positive integers; $R^{m\times n}$ denotes the set of $m \times n$ real matrices; R^n denotes the set of $n \times 1$ real column vectors; $\mathbf{1}_N$ is a column vector with N elements being 1; $e_i \in R^N$ represents a column vector whose ith element is one; I_m denotes the $m \times m$ identity matrix; $\mathrm{diag}(G_i)$ denotes a block diagonal matrix with diagonal block G_i; $\otimes$ denotes the Kronecker product. Denote the open ball $B_r = \{x \in R^n : \|x\| < r\}$ with r being an arbitrary positive constant; $|\cdot|$ is the absolute value of a real number, and $\|\cdot\|$ is the 2-norm of a vector or a matrix; $\lambda_{\max}(\cdot)$ and $\lambda_{\min}(\cdot)$ are the maximum eigenvalue and the minimum eigenvalue of a real matrix, respectively.