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Trajectory tracking of nonlinear system using multiple series-parallel dynamic neural networks

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ABSTRACT

This paper presents a novel approach of adaptive control for unknown nonlinear continuous-time dynamic system using series-parallel dynamic neural networks (SPDNN) and multiple models. Dynamic neural networks are introduced into the multiple models adaptive control (MMAC), which can improve the adaptation ability of controllers for the plant with wide-range uncertain parameters. The adaptive law of SPDNN weight with unmodeled dynamics is derived from Lyapunov stability theory. In order to assure the effectivity of the controller, the projection algorithm is used to avoid the weight through zero. Multiple combinations of identification models based on SPDNN are used to cover the uncertainty of the plant. Based on the identification error, an effective switching scheme is applied to choose the best model and controller at every instant. The simulation results demonstrate that the proposed adaptive control using multiple dynamic neural networks models can achieve remarkable control performance for nonlinear continuous-time system.

1. Introduction

Adaptive control of nonlinear system using neural network has become an interesting topic since a decade [1–5]. Many researches have shown that artificial neural networks are an effective method to model and control complex nonlinear systems, especially for those systems whose mathematical modeling is extremely difficult.

Over the years, with the research on adaptive neural network control having been done more and more, it is getting more refined and sophisticated. As to these uncertain complex systems, an adaptive neural output feedback tracking control for a class of uncertain nonlinear multi-input–multi-output (MIMO) systems in the discrete-time form has been studies in [6,7] presents an adaptive output-feedback neural network control scheme stochastic nonlinear time-varying delay systems with unknown control directions. Via the dynamic surface control (DSC) technique and neural networks' approximation capability, [8] proposed a novel adaptive NN control scheme for a class of pure-feedback stochastic nonlinear systems. The adaptive neural network control technique can also be combined with many other intelligent control algorithms, and produce a better control performance. Using a single neural network to approximate the lumped unknown part of the system, combined with robust control, [9] studies an adaptive neural network control approach for uncertain strict-feedback nonlinear systems with unknown dead-zone and disturbances. By employing radial-basis-function neural network to account for system uncertainties and combining 'dynamic surface control' and 'minimal learning parameter' techniques, [10] presents a robust adaptive tracking control approach for strict-feedback single-input-single-output nonlinear systems.

According to the connection of the neural networks, they can be classified as static (feedforword) or dynamic (feedback) nets. The main drawback of a static net is that its update does not exploit the information on the local neural networks structure. By contrast, dynamic neural networks can successfully overcome this limitation thanks to the feedback mechanism. Structurally speaking, there exist two kinds of structures in dynamic neural network model: 'Parallel dynamic neural network(PDNN)' [11] and 'Series-parallel dynamic neural network (SPDNN)' [12,13]. More details on the description of these structures may be found in [14].

In the past few years, traditional adaptive control were mainly are usually based on a fixed or slowly adaptive model, implicitly assuming that the operating environment was either time invariant or slowly time variant. However, situations like changes in operating conditions, failure or degradation of component, or unexpected changes in system dynamics may all violate this, particularly the assumption of small parametric uncertainty. For unexpected changes in system, traditional adaptive control show poor performance. Adaptive control with multiple models lead to a more intelligent behavior and improve adaptation ability of controllers for the plant with wide-range uncertain parameters. So, multiple models adaptive control has been a very hot research filed, and is by no means new. The earliest MMACs appeared around the 1960s and the 1970s. Several authors [15–17]

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studied multiple Kalman filter-based models to improve the accuracy of the state estimate in estimation and control problem. In 1990s, multiple models adaptive control with tuning and switching was introduced by K.S. Narendra. During this period, both fixed models [18,19] and fixed and adaptive models [20,21] were proposed for improving the transient response. An comprehensive about MMAC can be found in [23].

With the development of neural networks, more attention has been paid in control theory of MMAC using neural networks [5,24–27] as well as in its applications [28–30]. Xiao and Wen [25] introduced MMAC to iterative learning control. Multiple fuzzy neural network models are used to approximate the possible description of error model. Fu and Chai [26] proposed a multi-variable adaptive control approach for a class of unknown nonlinear multi-variable discrete-time dynamical systems. The proposed adaptive control scheme is composed of a linear adaptive controller, a neural-network-based nonlinear adaptive controller and a switching mechanism. Guo and Jiang [28] presented a new control strategy which combines between multiple models and adaptive reconfiguration for actuator fault. In [5], Zhai et al. presented multiple models switching control using SPDNN to improve the transient performance for a class of nonlinear discrete-time systems. However, the proposed scheme consists of generalized minimum variance (GMV) controllers which are based on the known nominal linear multiple models rather than nonlinear multiple models. On the other hand, they constructed the SPDNN identification model without the unmodeled dynamic. In [24], the support vector machine (SVM) with fuzzy modeling are introduced to MMAC. The authors [24,27] just considered the number of models on the impact of the control quality. They did not involve the multiple kinds of combination of fixed models and adaptive models.

In this paper, we present a novel approach of adaptive control of nonlinear continuous-time system using dynamic neural networks and multiple models. Multiple combinations of identification models (fixed model or adaptive model) based on SPDNN are used to cover the uncertainty of the plant. Based on the identification error, an effective switching scheme is applied to choose the best model and controller at every instant. We consider not only the number of models but also the combinations of models. Furthermore, considering the unmodeled dynamic, we determine the learning law and the control strategy of SPDNN models with unmodeled dynamic. Meanwhile, comprehensive simulation experiments will show that the proposed approach achieve remarkable control performance.

The rest of the paper is organized as follows: first, the controlled nonlinear system and the identification model based on SPDNN are defined in Section 2. Then, nonlinear systems trajectory tracking using single SPDNN identification model can be considered in Section 3. Some assumptions and theorems about neural networks and adaptive laws are given. Following this, adaptive control using multiple SPDNN identification models, the switching scheme and the proof of global stability with arbitrarily switching are proposed in Section 4. The simulation experiments are shown in Section 5 and finally some conclusions are drawn in Section 6.

2. Identification based on spdnn

The nonlinear system to be identified is given as

$$\dot{x}_t = f(x_t, u_t, t) \tag{1}$$

where

$$x_t = [x_{1,t}, x_{2,t}, \ldots x_{n,t}]^T \in \Re^n$$
$$u_t = [u_{1,t}, u_{2,t}, \ldots u_{m,t}]^T \in \Re^m$$

In order to identify the nonlinear system, we construct dynamic neural networks. Structurally speaking, there are two kinds of structure of dynamic neural networks: 'Parallel model' and 'Series-parallel model'.

The 'Parallel model' can be described as

$$\dot{\hat{x}}_t = A\hat{x}_t + W_{1,t}\sigma(V_{2,t}\hat{x}_t) + W_{2,t}\phi(V_{2,t}\hat{x}_t)\gamma(u_t)$$

The 'Series-parallel model'

$$\dot{\hat{x}}_t = A\hat{x}_t + W_{1,t}\sigma(V_{2,t}x_t) + W_{2,t}\phi(V_{2,t}x_t)\gamma(u_t)$$

where $\hat{x}_t$ is the identified state, x_t is the current state provided by the plant.

Compared with the parallel model, in the series-parallel model the output of the plant (rather that the identification model) is feedback into the identification model as shown in Fig. 1(b) *There are two main advantages of the series-parallel model over the parallel one* [14].

(i) If the plant is BIBO stable, all the signals used in the identification procedure (i.e., inputs to the neural networks) are bounded.
(ii) Since no feedback loop exists in the model, the adaptive learning law can be used to adjust the parameters reducing computational substantially.

Because parallel identification model does not include the system status, identification model and the controlled plant connect in parallel, control input must be obtained online. Thus, comparing with SPDNN, PDNN shows poor stability. However, SPDNN with the system status in identification model can be used to identify controlled plant on-line or off-line. The SPDNN model show better stability. This has practical implication if the identification model is to be used off line.

In this paper, we construct SPDNN identification model as follow:

$$\dot{\hat{x}}_t = A\hat{x}_t + W_{1,t}\sigma(x_t) + W_{2,t}\phi(x_t)\gamma(u_t) \tag{2}$$

where

$$\hat{x}_t = [\hat{x}_{1,t}, \hat{x}_{2,t}, \cdots \hat{x}_{n,t}]^T \in \Re^n$$

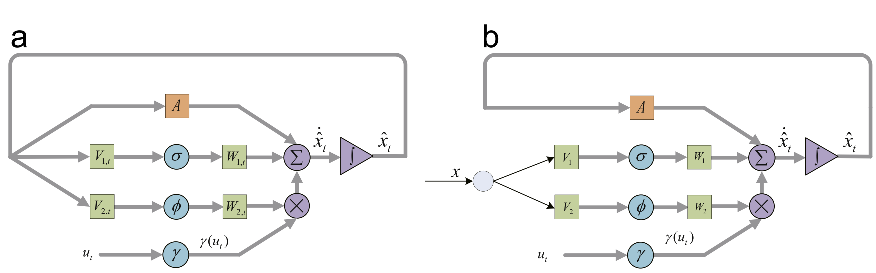

Fig. 1. The structure of dynamic neural networks: (a) Parallel model. (b) Series-parallel model.