Expert Systems with Applications 39 (2012) 564–573

Contents lists available at ScienceDirect

Expert Systems with Applications

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

Indirect adaptive self-organizing RBF neural controller design with a dynamical training approach

Chun-Fei Hsu [a,*], Chien-Jung Chiu [b], Jang-Zern Tsai [b]

[a] Department of Electrical Engineering, Tamkang University, No. 151, Yingzhuan Rd., Danshui Dist., New Taipei City 25137, Taiwan, ROC
[b] Department of Electrical Engineering, National Central University, Jung-Li 320, Taiwan, ROC

A R T I C L E I N F O

Keywords:
RBF network
Adaptive control
Neural control
Self-organizing
Dynamical learning rate

A B S T R A C T

This study proposes an indirect adaptive self-organizing RBF neural control (IASRNC) system which is composed of a feedback controller, a neural identifier and a smooth compensator. The neural identifier which contains a self-organizing RBF (SORBF) network with structure and parameter learning is designed to online estimate a system dynamics using the gradient descent method. The SORBF network can add new hidden neurons and prune insignificant hidden neurons online. The smooth compensator is designed to dispel the effect of minimum approximation error introduced by the neural identifier in the Lyapunov stability theorem. In general, how to determine the learning rate of parameter adaptation laws usually requires some trial-and-error tuning procedures. This paper proposes a dynamical learning rate approach based on a discrete-type Lyapunov function to speed up the convergence of tracking error. Finally, the proposed IASRNC system is applied to control two chaotic systems. Simulation results verify that the proposed IASRNC scheme can achieve a favorable tracking performance.

1. Introduction

If an exact model of control plants is known, there exists an ideal controller to achieve a favorable control performance by canceling all the system dynamics (Slotine & Li, 1991). Unfortunately, the mathematical model of control plants is difficult to develop accurately. A tradeoff between stability and accuracy is necessary for the performance of ideal controller. To attack this problem, many researchers using intelligent control approaches to construct advanced controllers based on neural network (NN) approximation ability (Chauhan, Ravi, & Karthik, 2009; Chen, Lin, & Chen, 2008; Elmas, Ustun, & Sayan, 2008; Hanbay, Turkoglu, & Demir, 2008; Hsu, 2011; Hsu, Lin, & Lee, 2006; Kumarawadu & Lee, 2006; Peng, 2010; Zhao, 2008). The basic issue of NN-based adaptive neural controllers provides online learning algorithms that do not require preliminary off-line tuning. The adaptive laws are derived based on the gradient descent method or Lyapunov synthesis method to guarantee the system stability of the control system.

Though the NN-based adaptive neural controllers have been widely adopted to control the unknown nonlinear system, how to determine the learning rates of parameter adaptation laws requires some trial-and-error tuning procedures. For a small learning rate, convergence of tracking error can be easily guaranteed, but with slow convergence speed. If the learning rate is too large, the parameter adaptation laws may lead to instability of the control systems. To solve this problem, a dynamical learning rate is determined (Lin & Peng, 2004; Lin, Huang, & Chou, 2007; Wai & Chuang, 2010; Yeh & Tsai, 2010). A discrete-type Lyapunov function is utilized to determine the learning rates of parameter adaptation laws (Lin & Peng, 2004; Yeh & Tsai, 2010). However, an exact calculation of Jacobian term cannot be determined due to the unknown control dynamics. An evolutionary computation is used to determine the learning rates of parameter adaptation laws (Lin et al., 2007; Wai & Chuang, 2010); however, the computation loading is heavy and lacks real-time adaptation ability.

Another drawback of the NN-based adaptive neural controllers is how to determine the network structure of the used NN. It is difficult to consider the balance between a number of hidden neurons and a desired performance. If the number of hidden neurons is chosen too large, it will be great than necessary so that the computation loading is not suitable for practical applications. If the number of hidden neurons is chosen too small, the learning performance may be not good enough to achieve a desired control performance due to the inevitable approximation error. To solve this problem, a self-organizing structure approach is proposed for the structure adaptation of NN (Bortman & Aladjem, 2009; Chen, 2009; Hsu, 2008; Hsu & Cheng, 2008; Huang, Saratchandran, & Sundararajan, 2005; Leung & Tsoi, 2005; Yeh & Chang, 2006). A new hidden neuron is generated when a input signal is too far from the current hidden neurons and an existing hidden neuron is canceled when the hidden neuron is insignificant.

* Corresponding author.
E-mail addresses: fei@ee.tku.edu.tw, fei@chu.edu.tw (C.-F. Hsu), intel@ms63.hinet.net (C.-J. Chiu), jztsai@ee.ncu.edu.tw (J.-Z. Tsai).

0957-4174/$ - see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2011.07.047

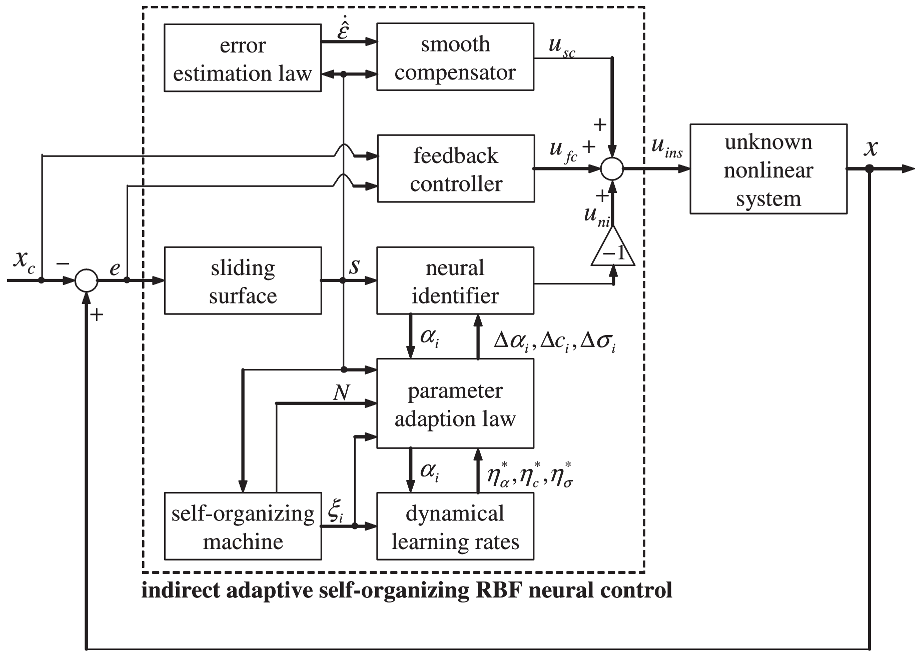

Fig. 1. Block diagram of the IASRNC system for an unknown nonlinear system.

This paper is to design an indirect adaptive self-organizing RBF neural control (IASRNC) system which is composed of a feedback controller, a neural identifier and a smooth compensator. The neural identifier containing a self-organizing RBF (SORBF) network is designed to online estimate the system dynamics and the smooth compensator is designed to dispel the effect of minimum approximation error introduced by the neural identifier. An online parameter training methodology, using the gradient descent method and Lyapunov stability theorem, is proposed to increase the learning capability of the SORBF identifier. Further, to speed up the convergence of tracking error and controller parameters, analytical method based on a discrete-type Lyapunov function is proposed to determine the dynamical learning rates of parameter adaptation laws. Finally, the proposed IASRNC system is applied to control two chaotic systems. Simulation results show that the proposed IASRNC system can achieve a favorable control performance.

2. Sliding-mode control system design

A mathematical model of control plants can be expressed in the nth-order form as

$$x^{(n)} = f(\mathbf{x}) + u, \tag{1}$$

where $\mathbf{x} = [x, \dot{x}, \ldots, x^{(n-1)}]^T$ is a state vector of plants which is assumed to be available for measurement, $f(\mathbf{x})$ is a nonlinear system dynamics which can be unknown, and u is a control input. The control objective is to find a control law so that a state trajectory x can track a command x_c closely. Define a tracking error as

$$e = x - x_c. \tag{2}$$

Assume that the system dynamics is known, (1) can represent a nominal model of a nonlinear dynamic system as

$$x^{(n)} = f_n(\mathbf{x}) + u, \tag{3}$$

where $f_n(\mathbf{x})$ is a mapping that represents the nominal behavior of $f(\mathbf{x})$. If uncertainties occur, i.e., parameters of system deviate from the nominal value, the system can be modified as

$$x^{(n)} = f_n(\mathbf{x}) + u + \Delta f(\mathbf{x}), \tag{4}$$

where $\Delta f(\mathbf{x})$ denotes system uncertainties with a assumption $|\Delta f(\mathbf{x})| \leqslant F$ in which F is a given positive constant. It is well known that the major advantage of a sliding-mode control system is its insensitivity to parameter variations and external disturbance once the system trajectory reaches and stays on a sliding surface (Slotine & Li, 1991). A sliding surface is defined as

$$s = e^{(n-1)} + k_1 e^{(n-2)} + \cdots + k_n \int_0^t e(\tau)d\tau, \tag{5}$$

where k_i, $i = 1, 2, \ldots, n$ are positive constants. A sliding-mode control law is given as

$$u_{sm} = u_{eq} + u_{ht}. \tag{6}$$

The equivalent controller u_{eq} is represented as

$$u_{eq} = -f_n(\mathbf{x}) + x_c^{(n)} - k_1 e^{(n-1)} \cdots - k_{n-1}\dot{e} - k_n e \tag{7}$$

and the hitting controller u_{ht} is designed to guarantee system stability as

$$u_{ht} = -Fsgn(s), \tag{8}$$

where $sgn(\cdot)$ is a sign function. Substituting (6)–(8) into (4) yields

$$e^{(n)} + k_1 e^{(n-1)} + \cdots + k_{n-1}\dot{e} + k_n e = \Delta f(\mathbf{x}) - Fsgn(s) = \dot{s}. \tag{9}$$

An important concept of sliding-mode control is to make the system satisfy the reaching condition and guarantee sliding condition. Consider a candidate Lyapunov function in the following form as

$$V_1 = \frac{1}{2}s^2. \tag{10}$$

Differentiating (10) with respect to time and using (9) obtain

$$\dot{V}_1 = s\dot{s} = \Delta f(\mathbf{x})s - F|s| \leqslant |\Delta f(\mathbf{x})||s| - F|s| = -(F - |\Delta f(\mathbf{x})|)|s| \\ \leqslant 0. \tag{11}$$

In summary, the sliding-mode control law in (6) can guarantee the system stability in the sense of Lyapunov theorem (Slotine & Li, 1991). Because the system dynamics may be unknown or perturbed, the sliding-mode control law cannot be implemented. Moreover, a large control gain F often causes an outcome of a large