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Adaptive neural complementary sliding-mode control via functional-linked wavelet neural network

Chun-Fei Hsu

Department of Electrical Engineering, Tamkang University, No. 151, Yingzhuan Road, Tamsui District, New Taipei City 25137, Taiwan, Republic of China

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ABSTRACT

Chaos control can be applied in the vast areas of physics and engineering systems, but the parameters of chaotic system are inevitably perturbed by external inartificial factors and cannot be exactly known. This paper proposes an adaptive neural complementary sliding-mode control (ANCSC) system, which is composed of a neural controller and a robust compensator, for a chaotic system. The neural controller uses a functional-linked wavelet neural network (FWNN) to approximate an ideal complementary sliding-mode controller. Since the output weights of FWNN are equipped with a functional-linked type form, the FWNN offers good learning accuracy. The robust compensator is designed to eliminate the effect of the approximation error introduced by the neural controller upon the system stability in the Lyapunov sense. Without requiring preliminary offline learning, the parameter learning algorithm can online tune the controller parameters of the proposed ANCSC system to ensure system stable. Finally, it shows by the simulation results that favorable control performance can be achieved for a chaotic system by the proposed ANCSC scheme.

1. Introduction

A model-based non-linear control, which requires a system dynamic of control plants in designing a controller, is an important tool to achieve robust behavior. Since the system may be unknown or perturbed, the model-based non-linear control scheme is difficult to be implemented (Slotine and Li, 1991). In general, a tradeoff problem between the mathematical model accuracy and the control performance arises in a model-based non-linear control system. If all uncertainties existed in the control plants are bounded, a sliding-mode control system provides system dynamics with an invariance property to uncertainties (Utkin, 1978; Wang and Su, 2003). But, high gains are adopted and undesirable chattering phenomenon is resulted to guarantee system stable. The chattering phenomenon becomes the most important disadvantage of a sliding-mode controller. To overcome this problem, an adaptive sliding-mode control with system uncertainties estimator is proposed (Huang et al., 2008). An adaptation law is derived to online estimate the upper bounds of system uncertainties; however, it cannot avoid the estimation growing unboundedly.

Many studies on both the neural networks and fuzzy systems integrating adaptive control techniques have represented an alternative design method for the control of unknown or uncertain non-linear systems (Chen et al., 2009; Chen and Tian, 2009; Chiu, 2010; Czarnigowski, 2010; Huang and Lin, 2011; Hsu, 2012; Li et al., 2007; Zhao and Yu, 2009). The success key element is the self-learning ability that the neural networks and fuzzy systems are used to approximate arbitrary linear or non-linear mappings without requiring preliminary offline tuning. Although the neural networks can learn from data and feedback, the meaning associated with each neuron and each weight in the network is not easily interpreted. Alternatively, the fuzzy systems are easily appreciated because they use linguistic terms and the structure of IF–THEN rules. However, the learning capacity of fuzzy systems is less than that of neural networks.

Recently, neuro-fuzzy networks provide the advantages of both neural networks and fuzzy systems, unlike pure neural networks or fuzzy systems alone. Neuro-fuzzy networks bring the low-level learning and computational power of neural networks into fuzzy systems and give the high-level human-like thinking and reasoning of fuzzy systems to neural networks (Chen, 2009; Elmas et al., 2008; Li and Chen, 2008). In addition, a functional-linked neural network (FLNN) is proposed (Patra and Kot, 2002; Toh and Yau, 2005). The basic idea of FLNN is the use of the functional links. These functional links generate non-linear transformations of the original input space before they are fed into the network which constructs the output layer. The FLNN can approximate a non-linear function effectively since it is able to form the output part of neural network by the non-linear combination of input variables. As a result, there has been

E-mail address: fei@ee.tku.edu.tw

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considerable interest in exploring the applications of FLNN to deal with non-linearities and uncertainties of control system (Chen et al., 2008; Lin et al., 2011).

To achieve better learning performance, some researchers have developed the network structure based on wavelet functions to construct a wavelet neural network (WNN) which absorbs the advantages of wavelet decompositions and learning of neural networks (Billings and Wei, 2005; Chen and Hsu, 2010; Hsu, 2011; Ko, 2012). The wavelet functions have the ability to decompose wideband signals into time and frequency domains simultaneously in order to focus on short time intervals for high-frequency components and on long time intervals for low frequency components. This paper presents a functional-linked wavelet neural network (FWNN) which combines the advantages of the FLNN and WNN. Since the output weights of the proposed FWNN are equipped with a functional-linked type form, the FWNN is used for function approximation with faster convergence rate and less computational loading than a multilayer neural network.

Chaotic system is a non-linear deterministic system that displays complex, noisy-like and unpredictable behavior. It can be observed in many non-linear circuits and mechanical systems (Chen and Dong, 1993). For control engineers, control of a chaotic system has become a significant research topic in physics, mathematics and engineering communities. This paper proposes an adaptive neural complementary sliding-mode control (ANCSC) system which is composed of a neural controller and a robust compensator for a chaotic system. The neural controller uses a FWNN to approximate an ideal complementary sliding-mode controller and the robust compensator is designed to eliminate the effect of the approximation error introduced by the neural controller. The parameter learning algorithm online tune the control parameters based on the gradient descent method and the Lyapunov stability sense. To show the effectiveness of the proposed ANCSC system, a comparison among the complementary sliding-mode control (Wang and Su, 2003), the functional-linked RBF network control (Lin et al., 2011) and the proposed ANCSC is performed. In the simulation study, it is shown that the proposed ANCSC system can achieve better control performance than other methods.

This paper is organized as follows: Section 2 describes the dynamics of a chaotic system and the control problem for chaotic systems is formulated. In Section 3, an ANCSC system is designed with a FWNN. Then, numerical simulations that confirm the validity and feasibility of the proposed method are shown in Section 4. Finally, conclusions are presented in Section 5.

2. Problem statement

Chaotic phenomena have been observed in numerous fields of science such as physics, chemistry, biology and ecology (Chen and Dong, 1993; Lin et al., 2010; Pan et al., 2011; Wu and Bai, 2009). It can be observed in many non-linear circuits and mechanical systems. Consider a second-order chaotic system such as Chen and Dong (1993)

$$\ddot{x} = -p\dot{x} - p_1 x - p_2 x^3 + q\cos(\omega t) + u = f(\mathbf{x}) + u \tag{1}$$

where x is the displacement, $f(\mathbf{x}) = -p\dot{x} - p_1 x - p_2 x^3 + q\cos(\omega t)$ is the system dynamics, t is the time variable, ω is the frequency, u is the control effort, p controls the size of the damping, p_1 controls the size of the restoring force, p_2 controls the amount of non-linearity in the restoring force, q controls the amplitude of the periodic driving force, and ω controls the frequency of the periodic driving force. In this paper, we chose that $p = 0.4$, $p_1 = -1.1$, $p_2 = 1.0$, and $\omega = 1.8$. Depending on the choices of these constants, the solutions of system (1) may display complex phenomena, including various periodic orbits behaviors and some chaotic behaviors as Chen and Dong (1993). To observe the complex phenomena, the time responses of the uncontrolled chaotic system with initial point (0,0) for q=2.1 and q=7.0 are shown in Fig. 1(a) and (b), respectively. For the time responses with q=2.1, an uncontrolled chaotic trajectory can be found, but a period motion chaotic trajectory happens with q=7.0. It is shown that the uncontrolled chaotic system has different trajectories for different system parameters.

The dynamics of a chaotic system are highly time varying and non-linear. The control objective of this paper is to find a control law so that the system state x can track a state command x_c closely. To achieve this control objective, define a tracking error and a sliding surface as Wang and Su (2003)

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

$$s = \dot{e} + 2ke + k^2 \int_0^t e(\tau)d\tau \tag{3}$$

where k is a positive constant. Next, a complementary sliding surface is designed as Wang and Su (2003)

$$s_c = \dot{e} - k^2 \int_0^t e(\tau)d\tau. \tag{4}$$

A significant result concerning the relationship between s and s_c can be obtained as

$$\dot{s}_c = \dot{s} - k(s + s_c). \tag{5}$$

Differentiating (3) with respect to time and using (1), we can obtain

$$\dot{s} = \ddot{e} + 2k\dot{e} + k^2 e = \ddot{x}_c - f(\mathbf{x}) - u + 2k\dot{e} + k^2 e. \tag{6}$$

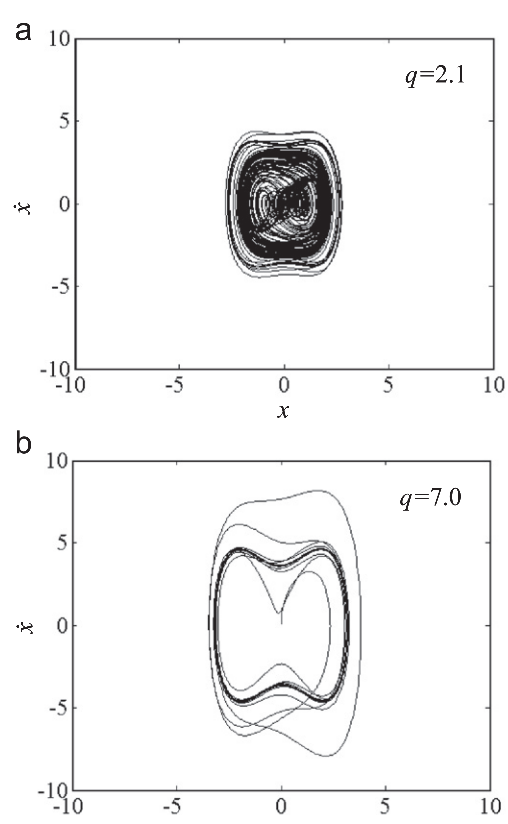

Fig. 1. Behavior of uncontrolled chaotic system.