Engineering Applications of Artificial Intelligence 53 (2016) 74–85

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

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

Modeling of unstructured uncertainties and robust controlling of nonlinear dynamic systems based on type-2 fuzzy basis function networks

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ARTICLE INFO

Article history:
Received 4 November 2015
Received in revised form
21 March 2016
Accepted 29 March 2016
Available online 16 April 2016

Keywords:
Fuzzy control
Robust control
TS fuzzy model
FBFN model
Unstructured uncertainties

ABSTRACT

This paper proposes new methods for modeling unstructured uncertainties and robust controlling of unknown nonlinear dynamic systems by using a novel robust Takagi Sugeno fuzzy controller (RTSFC). First, a new training algorithm for an interval type-2 fuzzy basis function network (FBFN) is proposed. Next, a novel technique is presented to convert the interval type-2 FBFN to an interval type-2 Takagi Sugeno (TS) fuzzy model. Based on the interval type-2 TS and type-2 FBFN models, a robust controller is presented with an adjustable convergence rate. Since the type-2 fuzzy model with its new training technique can effectively capture the unstructured uncertainties and accurately estimate the upper and lower bounds of unknown nonlinear dynamic systems, the stability condition of the proposed control system is much less conservative than other robust control methods that are based on norm bounded uncertainties. Simulation results on an electrohydraulic actuator show that the RTSFC can reduce steady state error under different conditions while maintaining better responses than the other robust sliding mode controllers.

1. Introduction

For unknown dynamic systems, many robust adaptive control techniques have been proposed based on the parameters of a universal approximator (Lee and Tomizuka, 2000; Lee, 2011). Goyal et al. (2015) introduced a robust sliding mode control based on Chebyshev neural networks. Chadli and Guerra (2012) proposed a robust static output feedback for a discrete Takagi–Sugeno (TS) fuzzy system. The stability conditions in their studies are represented in terms of a set of linear matrix inequalities (LMI) conditions. An observer-based output feedback nonlinear robust control of nonlinear systems with parametric uncertainties were introduced by Yao et al. (2014a) to provide a sufficient condition for robust stabilization of the systems when all state variables are not available for measurement. By using a Lyapunov–Krasovskii function (LKF), Hu et al. (2012) introduced a stability condition to stabilize discrete stochastic systems with mixed time delays, randomly occurring uncertainties, and randomly occurring nonlinearities. However, since these methods represented uncertainties as functions of system parameters, they are not applicable for cases where the causes of uncertainties are not known (unstructured uncertainties).

In general, most of the papers in the literature only investigate the stability of fuzzy control systems with structured uncertainties (Lee et al., 2001; Lin et al., 2013; Sato, 2009; Sloth et al., 2009). Unstructured uncertainties, however, represent a much more general class of nonlinear systems and can incorporate model inaccuracies and measurement noise. One method to represent unstructured uncertainties is to model a nonlinear system by a linear system with norm bounded uncertain matrices. Wang et al. (2014) proposed a set of LMIs that need to be solved at each time step to obtain a control solution that satisfies some performance criteria. However, since finding the LMI solution requires special computing tools, real time computation is a challenge in this case especially when the sampling time is relatively small. Furthermore, the solution of the LMIs might not be found because representing a highly nonlinear system by a set of linear systems will lead to large values of uncertainty norms due to linearization error. Another approach that deals with nonlinear systems with unstructured uncertainties is a combination of backstepping and small gain theorem (Li et al., 2014; Liu et al., 2014; Tong et al., 2009). Hsu et al. (2015) proposed the intelligent nonsingular terminal sliding-mode controller and used the Lyapunov theory to prove the stability of the control system. By using the Lyapunov method, Salgado et al. (2014) introduced the proportional derivative fuzzy control supplied with second order sliding mode differentiation. Baghbani et al. (2016) proposed a robust adaptive fuzzy controller

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http://dx.doi.org/10.1016/j.engappai.2016.03.010
0952-1976/

by minimizing the H_2 energy and tracking cost function. However, the above methods can only be applied to a certain class of nonlinear dynamic systems where the input is represented by a linear term in the system's mathematical model. Gao et al. (2012) presents an approach to control general nonlinear systems based on Takagi–Sugeno (T–S) fuzzy dynamic models. The method uses LMI approach to design the TS fuzzy controller to stabilize systems with norm bounded unstructured uncertainties. However, obtaining the bounded norms of uncertain nonlinear systems was not addressed in the paper and the LMI conditions for norm bounded uncertainties are generally conservative.

To capture the uncertainties in systems, type-2 fuzzy systems (Karnik et al., 1999) have been introduced, in which the type-2 fuzzy set is utilized. However, due to the complexity of the rule uncertainties and computational requirements to calculate the output, modeling nonlinear systems by using type-2 fuzzy systems is a very computationally intensive process. This leads to the concept of an interval type-2 fuzzy-logic system, in which the secondary membership functions of either the antecedents or the consequents are simplified to an interval set. Similar to type-1 fuzzy systems, the combination of type-2 fuzzy systems and neural networks brings different intelligent modeling and optimization techniques to obtain rule bases and membership functions without the need of an expert knowledge. Méndez and de los Angeles Hernandez (2009) presented a technique to obtain an interval type-2 fuzzy neural network by the orthogonal least square and back propagation methods. Rubio-Solis and Panoutsos (2015) proposed a modeling framework for an interval type-2 radial basis function neural network via a granular computing and adaptive back propagation approaches. However, the uncertainties represented in type-2 fuzzy neural systems are normally not in the form that can be easily used to design a robust controller. Furthermore, there is a lack of a theoretical stability analysis for type-2 fuzzy neural network based control systems.

Hydraulic positioning systems are important in different industries such as transportation, agriculture and aerospace. The effects of nonlinear frictions are considered as the most important obstacle for improving the precision of hydraulic actuators. Nonlinear friction exists in all hydraulic systems (Wang et al., 2008). The friction uncertainty includes stribeck effect, hysteresis, spring-like characteristics, stiction and varying break-away force (Lin et al., 2013). It has also been known that nonlinear friction is very difficult to model, and hence it is considered as the sources of uncertainties for which many controllers have been implemented to demonstrate their robustness in recent years (Lin et al., 2013; Mandal et al., 2015; Wang et al., 2008; Yao et al., 2014b).

This paper proposes a new method to train an interval type-2 fuzzy basis function network (FBFN) (cf. Section 2). The training algorithm not only further improves the performances of the fuzzy neural network system but also provides a framework to design a robust TS fuzzy controller. FBFNs have been used as models for many nonlinear systems in the literature (Jin and Shin, 2015; Lin, 2007; Ngo and Shin, 2015) since an FBFN was proven to be a universal approximator (Wang and Mendel, 1992). The antecedent of the interval type-2 FBFN in this study is obtained by using the adaptive least square with genetic algorithm (Lee and Shin, 2003) while the interval values of the consequent are obtained by the active set method. A new technique is also proposed to convert an interval type-2 FBFN to an interval type-2 TS fuzzy model (cf. Section 3). Based on the interval type-2 TS model and the interval type-2 FBFN, a robust controller that is not only robust but also produces good transient performances when implemented on nonlinear systems with unstructured uncertainties is presented (cf. Section 4).

2. Training interval type-2 FBFN models by using genetic algorithm and active set method

This section provides a new training method to obtain the type-2 FBFN that can capture unstructured uncertainties within an unknown nonlinear system. Consider a class of nonlinear dynamical system with m inputs and n state variables (m and n are positive integers), which can be represented by the following state space equation:

$$\mathbf{x}(k+1) = \mathbf{f}(\mathbf{x}(k), \mathbf{u}(k)), \quad \mathbf{x}(0) = \mathbf{x}_0 \tag{1}$$

where $\mathbf{x}(k) = [x_1(k), \ldots, x_n(k)]^T$ is the vector of measurable state variables, $\mathbf{u}(k) = [u_1(k), \ldots, u_m(k)]^T$ is the input vector, k is the time instance, $\mathbf{f}$ is the vector of functions that are locally Lipschitz nonlinear and real continuous in a compact set. The locally Lipschitz property of $\mathbf{f}$ ensures that the solution of the state space equations is existent and unique (Khalil, 2002).

It has been proven by Wang and Mendel (1992) that a linear combination of fuzzy basis functions are capable of uniformly approximating any real continuous function on a compact set to arbitrary accuracy. In this paper, to approximate future states of a nonlinear system, an interval type-2 FBFN model can be constructed from the input and measurable state variable data through a set of J fuzzy rules, in which rule R^j to calculate the future value of the state variable x_p has the following form:

Rule R^j: IF $x_1(k)$ is X_1^j AND … $x_n(k)$ is X_n^j AND $u_1(k)$ is U_1^j AND … $u_m(k)$ is U_m^j

$$\text{THEN } \tilde{y}(k+1) = \tilde{x}_p(k+1) = \tilde{Y}^j, \quad j = 1, \ldots, J \tag{2}$$

where $u_1(k) \ldots u_m(k)$ are the inputs at time instance k. $x_1(k) \ldots x_n(k)$ are the measured state variables. $\tilde{y}(k+1)$ is the interval output of the FBFN. $X_1^j \ldots X_n^j$ and $U_1^j \ldots U_m^j$ are type-1 fuzzy sets of rule R^j characterized by Gaussian membership functions $\mu_{X_p^j}(x_i)$ and $\mu_{U_q^j}(u_j)$ ($p = 1, \ldots, n;\ \ q = 1, \ldots, m$) with the centers c_{Xp}^j, c_{Uq}^j and standard deviations σ_{Xp}^j, σ_{Uq}^j:

$$X_p^j = \left(x_p, \mu_{X_p^j}(x_p)\right), \quad \mu_{X_p^j}(x_p) = \exp\left[-\frac{1}{2}\left(\frac{x_p - c_{Xp}^j}{\sigma_{Xp}^j}\right)^2\right] \tag{3}$$

$$U_q^j = \left(u_q, \mu_{U_q^j}(u_q)\right), \quad \mu_{U_q^j}(u_q) = \exp\left[-\frac{1}{2}\left(\frac{u_q - c_{Uq}^j}{\sigma_{Uq}^j}\right)^2\right] \tag{4}$$

$\tilde{Y}^j$ is a type-2 interval fuzzy set. $\tilde{Y}^j$ is determined by w_l^j and w_r^j, which are the two end points of its centroid interval set: $\tilde{Y}^j = (x, \mu_{\tilde{Y}^j}(x))$, $\mu_{\tilde{Y}^j}(x) = 1$ when $x \in [w_l^j \ \ w_r^j]$.

By assuming that the singleton fuzzier, product inference and centroid defuzzifier are used in the inferencing process, for a crisp input vector

$$\mathbf{z} = (z_1, \ldots, z_{m+n}) = (x_1, \ldots, x_n, u_1, \ldots, u_m)^T \tag{5}$$

the output of the type-2 FBFN described in (2) is an interval number and can be calculated by (Lee and Shin, 2003; Liang and Mendel, 2000):