Engineering Applications of Artificial Intelligence 52 (2016) 135–144

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

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

PI adaptive LS-SVR control scheme with disturbance rejection for a class of uncertain nonlinear systems

Omid Naghash-Almasi [a], Mohammad Hassan Khooban [b,*]

[a] Department of Electrical Engineering and Computer Sciences, University of California, Berkeley, CA 94720, USA
[b] Institute of Electrical Engineering, Shahid Bahonar College, Technical and Vocational University, Shiraz, Iran

ARTICLE INFO

Article history:
Received 6 June 2015
Received in revised form
26 November 2015
Accepted 27 November 2015
Available online 22 March 2016

Keywords:
Disturbance Rejection
Indirect adaptive control
Least square support vector regression
Lyapunov synthesis
Nonlinear systems
Uncertainty

ABSTRACT

Developing controller for uncertain nonlinear systems in the presence of disturbances is an important and still challenging problem. Adaptive control method asserts to adapt system parameters against uncertainties, if only uncertainties change sufficiently slowly. Alternatively, if uncertainties stay in known bounds, robust control approaches claim to ensure system stability. In this paper, a Proportional–Integral (PI) indirect adaptive Least Squares Support Vectors Regression (LS-SVR) control scheme for a class of uncertain nonlinear system in the presence of large and fast disturbances is proposed. The LS-SVR is used to approximate the nonlinear uncertainty which must be bounded, whereas in comparison to robust control methodologies no requirement needs for bounds to be known. The asymptotic stability of the control scheme is proved by using Lyapunov synthesis. The simulation study is performed on a second-order inverted pendulum system in the presence of fast against slow and large against small disturbances to demonstrate the effectiveness of the proposed control scheme.

1. Introduction

In the theory of control, significant developments have been made in nonlinear feedback methods for at least the past three decades (Boutalis et al., 2014; Slotine and Li, 1991; Marino and Tomei, 2013). Generally, to implement the nonlinear feedback control method the precise mathematical model of the system is required (Åström and Björn, 2013; Khalil and Grizzle, 1996). The mathematical model is needed to accurately describe the dynamic and physical behavior of a plant. This issue is still quite challenging for nonlinear systems. Due to existing nonlinearity or parametric uncertainty of a plant, uncertainty is inevitable in a system model. Besides, ambient sources may cause external disturbances which can have impact on behavior of a system. In addition, simple system modeling leads to simpler controller design which can considerably reduce the implementation cost. Uncertainties may arise from the lack of information about system modeling, inexact friction modeling, component faults, and etc. And disturbances are derived from the unknown effect of existing physical phenomena in the environment (Khooban and Niknam, 2015; Diao and kevin, 2002; Wai, 2007; Mohammad Hassan, 2014).

Many researchers have been studied adaptive controllers under the terms of system parameters change gradually to overcome the uncertainties of a system model (Åström and Björn, 2013; Khalil and Grizzle, 1996). On the other side, robust adaptive controllers have been designed because of the existing disturbances in the environment and the lack of robustness property in adaptive controller to cope with the disturbances (Yao and Masayoshi, 1997; Wang et al., 2014; Esmaieli et al., 2014). In order to apply adaptive feedback control method to nonlinear system, identification technique should be employed to approximate those uncertainties and disturbances as well. Clearly, offline system identification techniques cannot be used, because uncertainties and disturbances may change over time. To this end, online universal function approximation methods such as fuzzy systems or neural networks have dealt with the unknown uncertainties and disturbances of systems in many control problems. Nowadays, it is a transparent fact that universal approximator can approximate any given real continuous function on a compact set to an arbitrary accuracy (Diao and Kevin, 2002; Wang, 1999; Wang et al., 2002; Ghaemi et al., 2014; Montúfar, 2014).

Fuzzy systems are one of the well-known universal approximation methods, which can incorporate linguistic information in expert human operators. This feature is used in the control schemes design of a stable adaptive fuzzy controller based on Lyapunov synthesis for a class of unknown nonlinear system. The control schemes use fuzzy systems to approximate the unknown functions and uncertainties to obtain certainty equivalence control

* Corresponding author.
E-mail addresses: mhkhoban@gmail.com, khooban@sutech.ac.ir (M.H. Khooban).

http://dx.doi.org/10.1016/j.engappai.2015.11.009

law. Adaptive fuzzy control schemes based on how they use fuzzy systems are classified into two categories, i.e. direct and indirect. Direct adaptive fuzzy controllers use fuzzy systems as controllers. In other words, they incorporate fuzzy IF-THEN rules directly into themselves. On the other side, adaptive fuzzy controllers which use fuzzy systems as models of the plants are indirect adaptive fuzzy controllers, i.e. they use fuzzy IF-THEN rules to describe the plant (Wang et al., 2002; Wang, 1996; Wei et al., 2014). Wang (1996) proposed a general control approach based on Lyapunov theory to design a stable adaptive controller with a supervisory controller. Many researchers have addressed a lack of robustness in the adaptive fuzzy control scheme of Wang and attempted to improve it (Shahnazi and Akbarzadeh-T, 2008; Nie and Wan Tan, 2011; Zhang and Zhang, 2006). In Yang and Ren (2003) an adaptive fuzzy robust tracking control method introduced, which used Takagi–Sugeno type fuzzy systems to approximate unknown uncertain functions and uncertain gain function. For meticulous details about analysis and design of model-based fuzzy control systems, see Feng (2006).

Despite the positive features of fuzzy systems, large number of fuzzy rules emerged when fuzzy systems are used for approximating high-order systems, i.e. real applications, and also in multiple input multiple output (MIMO) systems (Wai, 2007; Wang et al., 2014; Wei et al., 2014; Rong and Zhao, 2010). Hence, the control scheme based on fuzzy approximation approach will be complex and have a high computational cost.

Neural networks are alternative approaches to deal with the uncertainties, due to their universal approximation capability (Khooban and Niknam, 2015; Wei et al., 2014; Zargarzadeh et al., 2014). In adaptive neural control, both direct and indirect forms, neural networks are used to identify the unknown parts of a complex system model. They are implemented simply and usually achieve good precision in their approximations; however, some difficulties arise in usage of these methods as follows:

A suitable structure, i.e. the number of layers and neurons, training speed rate, adequate input and output data, should be chosen for neural networks especially in large-scale control problems to avoid training process trap into local minima and overfitting problem (Xu and Chen, 2004; Chunli et al., 2010; Hong et al., 2008).

Suykens proposed Least Square Support Vector Regression (LS-SVR) for function estimation problems (Suykens et al., 2001; Gestel et al., 2002). LS-SVR has a strong mathematical foundation and has made a major breakthrough in neural networks. It has strong generalization ability and can find the global minimum, thus it avoids trapping local minima. Moreover, a great advantage is its data driven structure since no requirement is needed for determining the number of hidden layers and neurons-like (Hong and Xu, 2008; Suykens et al., 2001; Gestel et al., 2002; Chuang, 2007). Therefore, it becomes an excellent tool for regression estimation problems thanks to all those features.

Many researchers have been used LS-SVR to perform approximating unknown nonlinear functions in adaptive controls (Chunli et al., 2010) and (Zhicheng et al., 2012; Mahmoud, 2011; Wang et al., 2012; Xie et al., 2010; Ko and Lee, 2013). An indirect adaptive control approach based on LS-SVM proposed for a class of nonlinear dynamic systems with unknown nonlinearities (Wang et al., 2012). In (Xie et al., 2010), LS-SVR used for approximation of nonlinear functions in indirect adaptive control and the updating rule of LS-SVM parameters derived from Lyapunov stability theory.

In this paper, a two-level indirect-adaptive LS-SVR control scheme for a class of uncertain system is proposed by considering external disturbances that are bounded but the magnitude of those bounds is not needed to be known. The proposed control strategy contains a PI-type switching structure appropriately deals with the unknown bounded large-and-fast disturbances while providing a smooth control signal. The asymptotic stability of control strategy is proved by using Lyapunov synthesis. A second-order nonlinear inverted pendulum is employed to demonstrate the effectiveness of the control scheme in approximation part and its robustness in confronting large-and-fast disturbances.

The rest of the paper is organized as follows. In Section 2.1, the problem formulation and assumptions are defined. Then, in Section 2.2, the LS-SVR formulation and the universal approximation capability of LS-SVR are briefly reviewed. In Section 3, an adaptive LS-SVR control scheme is proposed and stability and error convergence of the closed-loop control system are discussed in detail. A simulation example using an inverted pendulum system under various disturbances is performed to support the proposed control scheme in Section 4. Finally, Conclusions are drawn in Section 5.

2. Problem statement

2.1. Problem statement and assumptions

Consider a class of Single-Input Single-Output (SISO) n-th order nonlinear system in the following form (Shahnazi and Akbarzadeh-T, 2008):

$$x^{(n)} = f\left(x, \dot{x}, \ldots, x^{(n-1)}\right) + g\left(x, \dot{x}, \ldots, x^{(n-1)}\right)u(t) + d(x,t)$$
$$y = x \tag{1}$$

where f and g are unknown bounded nonlinear functions in which no prior knowledge is needed for bounds to be known and $d(x,t)$ is an unknown external disturbance. Furthermore, $u \in R$ and $y \in R$ are the control signal and the output of the system, respectively. $X^T = \left[x, \dot{x}, \ldots, x^{(n-1)}\right] = [x_1, x_2, \ldots, x_n] \epsilon R^n$ is the state vector of the system assumed to be available for measurement. The following assumption is considered for the nonlinear system mentioned in (1) by the authors.

Assumption 1. (Shahnazi and Akbarzadeh-T, 2008): An unknown constant D is the bound of the external disturbance $d(x,t)$, i.e.,

$$\left|d(x,t)\right| \le D \tag{2}$$

Assumption 2. (Shahnazi and Akbarzadeh-T, 2008): In order to have a controllable system, it is required that $g(x,t) \ne 0$ in (1). $g(x,t)$ is assumed to be positive, i.e., $g(x,t) > 0$. By contrast, $g(x,t)$ can be negative and the control signal is derived in a similar way. The *control objective* is to design a controller to provide the control signal u based on LS-SVR and an adaptation law for adjusting controller parameters so that the X state vector of the system in (1) follows a given desired trajectory state $X_d^T = \left[x_d, \dot{x}_d, \ldots, x_d^{(n-1)}\right]$ in the presence of external disturbance $d(x,t)$. Therefore, by using the designed controller the tracking error in (3) should converge to zero.

$$E = x - x_d = \left[e, \dot{e}, \ldots, e^{(n-1)}\right]^T \tag{3}$$

Assumption 3. (Shahnazi and Akbarzadeh-T, 2008): The desired trajectory vector X_d is continuous, measurable, and bounded with a known positive constant Ψ.

$$\left\|x_d\right\| < \Psi \tag{4}$$

2.2. Least square support vector regression

The SVR formulation was modified by (Gestel et al., 2002) at two points: First, instead of inequality constraints takes equality constraints and changes the quadratic programming to a linear programming. Second, a squared loss function is taken from the