Computers and Electrical Engineering 000 (2016) 1–14

Contents lists available at ScienceDirect

Computers and Electrical Engineering

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

Robust control of electrically driven robots using adaptive uncertainty estimation

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ARTICLE INFO

Article history:
Received 8 October 2015
Revised 5 August 2016
Accepted 7 August 2016
Available online xxx

Keywords:
Adaptive uncertainty estimation
Robust control
Taylor series
Electrically driven robot manipulators
SCARA robot

ABSTRACT

This paper presents a novel robust control for electrically driven robot manipulators by designing an adaptive uncertainty estimator based on the first order Taylor series. The estimator is simple and model-free in a decentralized structure. The uncertainty is then efficiently compensated in the control system. The controller does not require the bounding functions as an advantage over the conventional robust controller. Therefore, it is simpler, less computational, and more efficient. It is verified by stability analysis and its effectiveness is shown through comparisons with a terminal sliding mode control approach and a Legendre polynomials uncertainty bound estimator simulated on a SCARA robot driven by permanent magnet dc motors.

1. Introduction

Many research efforts have paid attention to the model-based control [1–4]. However, a precise model is not available in practice. In addition, complex models may not be used in the control laws for avoiding the computational burden and practical difficulties. Therefore, a simpler model known as nominal model is preferred to design a controller. As a result, the control system faces uncertainty raised from differences between the nominal model and actual system. Generally, the uncertainty may include the parametric uncertainty, unmodeled dynamics, and external disturbances. The control performance is thus dependent on how well the uncertainty can be estimated and compensated.

Various control methods have been developed to overcome uncertainty. According to whether they estimate uncertainty to compensate it or not, they may be classified into either indirect or direct compensation of uncertainty, respectively. Among the direct methods, one may address adaptive control, robust control, direct time-delay control, fuzzy control and neural network control. Adaptive control efficiently compensates the parametric uncertainty. Alternatively, robust control can compensate a wide uncertainty, including parametric uncertainty, unmodeled dynamics and external disturbances. However, it requires known bounds of uncertainty. The direct time-delay control can easily compensate the uncertainty without estimation [5]. The robustness of PD controllers for manipulators was proven via singular perturbations [6]. One may suggest a model-free control such as fuzzy interval control [7] or neural network control [8]. A fuzzy system can be used as a universal approximator for any nonlinear function. This feature has been efficiently used to design fuzzy control such as adaptive fuzzy control [9] and adaptive neuro-fuzzy control [10]. However, stability analysis becomes complex due to the complexity of the fuzzy system [11].

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http://dx.doi.org/10.1016/j.compeleceng.2016.08.005

The indirect compensation of uncertainty method estimates the uncertainty to compensate it in the robust control system. An adaptive sliding mode control for robot manipulators has used an uncertainty estimator to compensate uncertainty [12]. The uncertainty estimation has found various applications in perturbation estimation [13], uncertainty bound parameter estimation [14], disturbance estimation [15], and time-delay control [16]. The uncertainty estimation was effectively used in two control strategies, namely active disturbance rejection control [17] and model-free control [18] for electrically driven robot manipulators.

Function approximation methods such as neural networks [19] and fuzzy logic [20] were used to design a model-free uncertainty estimator. Alternatively, the trigonometric functions [21], orthogonal functions, Fourier series and Taylor series can be used to design an uncertainty estimator, as well. However, the higher order terms should be ignored due to computational efficiency and ease of implementation. Instead, the approximation error is caused and the estimator performance may be degraded. If the higher order terms cannot be neglected, fuzzy systems and neural networks are more effective than a series in function approximation. This paper uses the first order Taylor series, which has the simplest structure compared with the mentioned methods to design a model-free uncertainty estimator.

Most of robust control approaches need the uncertainty bound as a crucial parameter to complete their control laws. In these approaches the uncertainty bound should be known in advance or estimated. Overestimation of this parameter will result in saturation of input and higher frequency of chattering in the switching control laws, while underestimation will increase the tracking error.

To the best of our knowledge, this is the first time of using the first-order Taylor series expansion to propose an adaptive estimator of uncertainty for the robust control of electrically driven robot manipulators. The novel robust controller is model-free, thus is robust against uncertainties associated with robot dynamics. It is superior to the model-based estimators in terms of simplicity of design, ease of implementation and less time-consuming. It does not need to define the bounding functions as used for the robust estimators and to be linearized in parameters as used for the adaptive estimators. The proposed control approach is compared with a terminal sliding mode control (TSMC) approach [19], which estimates nonlinear system dynamics by Radial-Basis-Function Neural Networks (RBFNNs) and also is compared with a control method using Legendre parameters uncertainty estimator [14].

This paper is organized as follows. Section 2 explains modeling of the robotic system, including the robot manipulator and motors. Section 3 develops the proposed control approach. Section 4 describes the Taylor series expansion of uncertainty estimator. Section 5 presents the stability analysis for the control system. Section 6 illustrates the simulation results. Finally, Section 7 concludes the paper.

2. Modeling

The robot manipulator consists of n links interconnected at n joints into an open kinematic chain. The mechanical system is assumed to be perfectly rigid. Each link is driven by a permanent magnet dc motor through the gears. The dynamics of electrically driven robot can be described as [23]

$$\boldsymbol{D}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}\left(\boldsymbol{q}, \dot{\boldsymbol{q}}\right)\dot{\boldsymbol{q}} + \boldsymbol{g}(\boldsymbol{q}) = \boldsymbol{\tau_r} - \boldsymbol{\tau_f}\left(\dot{\boldsymbol{q}}\right) \tag{1}$$

$$\boldsymbol{J}\boldsymbol{r}^{-1}\ddot{\boldsymbol{q}} + \boldsymbol{B}\boldsymbol{r}^{-1}\dot{\boldsymbol{q}} + \boldsymbol{r}\boldsymbol{\tau_r} = \boldsymbol{K_m}\boldsymbol{I_a} \tag{2}$$

$$\boldsymbol{R}\boldsymbol{I_a} + \boldsymbol{L}\dot{\boldsymbol{I}}_{\boldsymbol{a}} + \boldsymbol{K_b}\boldsymbol{r}^{-1}\dot{\boldsymbol{q}} + \boldsymbol{\varphi} = \boldsymbol{v} \tag{3}$$

where $\boldsymbol{q} \in R^n$ is the vector of joint positions, $\boldsymbol{D}(\boldsymbol{q})$ the $n \times n$ matrix of manipulator inertia, $\boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}}) \in R^n$ the vector of centrifugal and Coriolis torques, $\boldsymbol{g}(\boldsymbol{q}) \in R^n$ the vector of gravitational torques, $\boldsymbol{\tau_f}(\dot{\boldsymbol{q}}) \in R^n$ the vector of friction torques, $\boldsymbol{\tau_r} \in R^n$ the joint torque vector of robot. $\boldsymbol{J}$, $\boldsymbol{B}$ and $\boldsymbol{r}$ are the $n \times n$ diagonal matrices for motor coefficients, namely the actuator inertia, damping, and reduction gear, respectively. $\boldsymbol{K_m}$ is a diagonal matrix of the torque constants, $\boldsymbol{I_a} \in R^n$ is the vector of motor currents, $\boldsymbol{v} \in R^n$ is the vector of motor voltages and $\boldsymbol{\varphi} \in R^n$ is a vector of external disturbances. $\boldsymbol{R}$, $\boldsymbol{L}$ and $\boldsymbol{K_b}$ represent the $n \times n$ diagonal matrices for the coefficients of armature resistance, inductance, and back-emf constant, respectively. Note that vectors and matrices are represented in bold form for clarity. By using Eqs. (1)–(3), the state-space model can be represented as

$$\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}) + \boldsymbol{b}(\boldsymbol{v} - \boldsymbol{\varphi}) \tag{4}$$

where $\boldsymbol{v}$ is considered as the inputs, $\boldsymbol{x}$ is the state vector and $\boldsymbol{f}(\boldsymbol{x})$ is of the form

$$\boldsymbol{f}(\boldsymbol{x}) = \begin{bmatrix} \boldsymbol{x}_2 \\ \left(\boldsymbol{J}\boldsymbol{r}^{-1} + \boldsymbol{r}\boldsymbol{D}(\boldsymbol{x}_1)\right)^{-1}\left(-\left(\boldsymbol{B}\boldsymbol{r}^{-1} + \boldsymbol{r}\boldsymbol{C}(\boldsymbol{x}_1, \boldsymbol{x}_2)\right)\boldsymbol{x}_2 - \boldsymbol{r}\boldsymbol{g}(\boldsymbol{x}_1) + \boldsymbol{K_m}\boldsymbol{x}_3 - \boldsymbol{r}\boldsymbol{\tau_f}(\boldsymbol{x}_2)\right) \\ -\boldsymbol{L}^{-1}\left(\boldsymbol{K_b}\boldsymbol{r}^{-1}\boldsymbol{x}_2 + \boldsymbol{R}\boldsymbol{x}_2\right) \end{bmatrix} \tag{5}$$

$$\boldsymbol{b} = \begin{bmatrix} 0 \\ 0 \\ \boldsymbol{L}^{-1} \end{bmatrix}, \quad \boldsymbol{x} = \begin{bmatrix} \boldsymbol{q} \\ \dot{\boldsymbol{q}} \\ \boldsymbol{I_a} \end{bmatrix}$$