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Full length article

A data-driven adaptive controller for a class of unknown nonlinear discrete-time systems with estimated PPD

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ABSTRACT

An adaptive control scheme based on data-driven controller (DDC) is proposed in this article. Unlike several DDC techniques, the proposed controller is constructed by an adaptive fuzzy rule emulated network (FREN) which is able to include human knowledge based on controlled plant's input–output signals within the format of IF-THEN rules. Regarding to this advantage, an on-line estimation of pseudo partial derivative (PPD) and resetting algorithms, which are commonly used by DDC, can be omitted here. Furthermore, a novel adaptive algorithm is introduced to minimize for both tracking error and control effort with stability analysis for the closed-loop system. The experimental system with brushed DC-motor current control is constructed to validate the performance of the proposed control scheme. Comparative results with conventional DDC and radial basis function (RBF) controllers demonstrate that the proposed controller can provide the less tracking error and minimize the control effort.

1. Introduction

Recently, several control algorithms based on data-driven controller (DDC) or model-free adaptive control (MFAC) have been introduced to compensate the requirement of mathematical model developed under the controlled plant for traditional model based control (MBC) schemes [1]. Only the set of input–output data is required to construct those controllers and its stability can be proved under reasonable assumptions [2–4]. Generally, the on-line estimation of pseudo partial derivative (PPD) of the controlled plant is necessary for design DDC schemes [5]. Those estimation techniques can be used under the assumption that PPD varies slowly over the time. The resetting algorithm for PPD is required when the change of control effort is very small. Moreover, many open problems for DCC method are unraveling such as how to verify the generalized Lipschitz condition, how to select the length of PPD vector and how to guarantee the convergence and stability of tracking problems [1].

The stability analysis is barely objective but the optimum controller is usually preferred [6] for several practical control systems. By solving the nonlinear Hamilton–Jacobi–Bellman (HJB), adaptive dynamic programming (ADP) schemes had been developed to minimize an infinite cost function for both the error signal and the control effort [7]. Artificial neural networks (ANN) have been utilized to estimate the nearly optimum solution with value and policy iterations as critic and action networks [8,9]. The inner iteration and the off-line learning phase are required within the sampling interval [10]. The implementation of this control scheme with physical systems is under developing because of the complexity of computation, the requirement of off-line learning phase and the limitation for a class of nonaffine discrete-time systems [11].

In this work, a novel control scheme, which is applied to DC-motor current control application, is proposed without any requirement of mathematical model of the controlled plant. This plant is considered as a class of nonaffine discrete-time systems which can be simplified by the equivalent compact dynamic linearization (CFDL) under reasonable assumptions. The on-line estimation of PPD and resetting algorithm can be neglected by using an adaptive network called fuzzy rule emulated network (FREN) as a direct controller. Furthermore, the completed estimation of plant Jabobian parameter [12] can be omitted because the proposed learning algorithm requires only the approximated minimum and maximum values of PPD. Those minimum and maximum values can be estimated by our technique which will be discussed in

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section 4. The relation between armature voltage and current of DC motors can be written in the format of IF-THEN rule as this example "IF *we need to increase armature current* THEN *we must supply more armature voltage*" [13,14]. Those IF-THEN rules can be included to FREN-controller by network's architecture and parameters setting [15,16].

The experimental results with a commercial grade DC-motor validate the control scheme's performance. Moreover, the advantage of the proposed controller is demonstrated by comparative results with the radial basis function (RBF) controller [17] and the conventional DDC scheme [5].

2. DC motor driving and a class of nonlinear discrete-time systems

In Fig. 1, an electronic circuit is designed to drive a brushed DC motor with armature current measurement. In this work, the motor driving system is considered as the nonlinear plant for a class of discrete-time systems which can be described by

$$y(k+1) = f\left(y(k), \cdots, y(k-n_y), u(k), \cdots, u(k-n_u)\right), \tag{1}$$

where $y(k) \in \mathbb{R}$ denotes as the output voltage [V] represented the armature current by U_1 B and R_{3-6} and $u(k) \in \mathbb{R}$ stands for the control voltage [V] at the time index k. The nonlinear function $f(\cdot)$ and system orders n_y and n_u are definitely unknown. This electronic circuit is constructed by a 2-channel operational amplifier U_1 (TL072). Those resistors are given as R_0 10kΩ, R_{1-2} 1kΩ, R_3 10Ω, R_4 1kΩ and R_{5-6} 10kΩ. Two match-pair transistors Q_{1-2} are selected as 2N4921 and 2N4920, respectively. A commercial DC motor model FF-050SK is selected as our demonstration device "M". The current sense circuit has current–voltage gain as

$$y(k+1) = 0.11 I_M, \tag{2}$$

when I_M denotes the motor current [mA]. According to conventional MFAC algorithms, those following assumptions are stated.

Assumption 1: The partial derivatives of $f(\cdot)$ are continuous with respect to the control effort $u(k)$.

Assumption 2: The nonlinear system described in (1) is generalized Lipschitz. That means the positive constant l must be defined when $|\Delta y(k+1)| \le l|\Delta u(k)|$, when $\Delta y(k+1) = y(k+1) - y(k)$ and $\Delta u(k) = u(k) - u(k-1)$.

According to those upper assumptions, the following lemma can be obtained.

Lemma 2.1 *The nonlinear system (1), which is satisfied by assumption 1 and 2 with $|\Delta u(k)| \neq 0$ for time index k, can be transformed into the equivalent compact form dynamic linearization (CFDL) as*

$$\Delta y(k+1) = \Phi(k)\Delta u(k), \tag{3}$$

when $\Phi(k)$ is pseudo partial derivative (PPD), $\Delta y(k+1) = y(k+1) - y(k)$ and $\Delta u(k) = u(k) - u(k-1)$.

The proof of this lemma is given in the appendix A.

In this work, only minimum and maximum boundaries of $\Phi(k)$ are required to design the controller with the following constrain

$$\Phi_m < |\Phi(k)| < \Phi_M, \tag{4}$$

$\forall k = 1,2,\cdots$, when Φ_m and Φ_M stand for minimum and maximum values of $|\Phi(k)|$, respectively. The example and discussion will be given in the section 4 to estimate those values by input–output data set of the controlled plant.

3. Closed-loop system and controller design

The closed-loop control scheme is illustrated by block diagram in Fig. 2. The control effort u forces the output y to follow the desired trajectory r or y_d. This control effort is generated by an adaptive network FREN which can be written as

$$u(k) = \beta^T(k)\phi(e(k)), \tag{5}$$

when $e(k)$ stands for the error signal defined by

$$e(k) = r(k) - y(k). \tag{6}$$

The vector $\beta(k)$ denotes as a set of adjustable parameters and $\phi(k)$ is a vector of membership functions. The setting for both $\beta(k)$ and $\phi(k)$ will be demonstrated later in section 4. To tune adjustable parameters β, the cost function is defined by

$$J(k+1) = \frac{1}{2}\gamma_1 e^2(k+1) + \frac{1}{2}\gamma_2 u^2(k), \tag{7}$$

when γ_1 and γ_2 are positive constants which will be discussed next. Unlike several weight tuning algorithms for neural networks, both tracking error and control effort are able to be minimized. By using a gradient search, the tuning law for β can be obtained as

$$\beta(k+1) = \beta(k) - \eta \frac{\partial J(k+1)}{\partial \beta(k)}, \tag{8}$$

where η denotes as the learning rate. The partial derivative term $\partial J(k+1)/\partial\beta(k)$ can be determined by

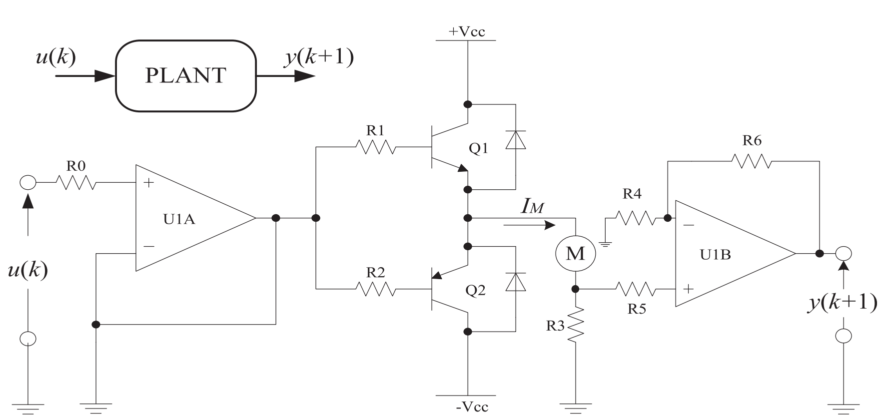

Fig. 1. DC-Motor driving circuit and block diagram.