Automatica 89 (2018) 398–406

Contents lists available at ScienceDirect

Automatica

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

Brief paper

Composite learning robot control with guaranteed parameter convergence☆

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ARTICLE INFO

Article history:
Received 10 February 2016
Received in revised form 11 May 2017
Accepted 25 September 2017

Keywords:
Adaptive control
Closed-loop identification
Robot manipulator
Composite learning
Exponential stability
Parameter convergence

ABSTRACT

Parameter convergence is desirable in adaptive control as it enhances the overall stability and robustness properties of the closed-loop system. However, a stringent condition termed persistent excitation (PE) must be satisfied to guarantee parameter convergence in the conventional adaptive control. This paper provides the first result of parameter convergence without the PE condition for adaptive control of a general class of robotic systems. More specifically, we develop a composite learning robot control (CLRC) strategy to achieve fast and accurate parameter estimation under a condition termed interval excitation (IE) which is much weaker than the PE condition. In the composite learning, a time-interval integral of a filtered regressor is utilized to construct a prediction error such that the time derivative of plant states is not necessary, and both the prediction error and a filtered tracking error are employed to update the parameter estimate. The closed-loop system is proven to be globally exponentially stable under the IE condition. Robustness against external disturbances of the CLRC is analyzed in the Lyapunov sense. An illustrative example shows the effectiveness and superiority of the proposed approach.

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1. Introduction

Adaptive control is desirable in robotic systems because of the uncertain and time-varying properties of robot parameters (Slotine & Li, 1991). Generally, adaptive control has two different schemes, namely an indirect scheme where plant parameters are estimated online for the calculation of controller parameters, and a direct scheme where the plant model is parameterized in terms of controller parameters that are estimated directly without plant parameter estimation (Ioannou & Sun, 1996). Composite adaptive control is an integrated direct and indirect adaptive control strategy which feeds back both tracking errors and prediction errors to update parameter estimates (Pan, Sun, & Yu, 2016). The advantages of the composite adaptation include the following: (1) the composite error feedback is useful for speeding up convergence of both tracking errors and parameter estimation errors; (2) due to the smoothness of control responses, smaller tracking errors and faster parameter estimation can be achieved via higher adaptation gains without exciting high-frequency unmodeled dynamics (Slotine & Li, 1991). After originally proposed by Slotine and Li (1989), composite adaptive robot control (CARC) has attracted great attention and many results can be found in the literature (Barambones & Etxebarria, 2001, 2002; Ciliz, 2005, 2006; Kim & Ahn, 2013; Pan, Sun, Pan, & Yu, 2016; Patre, MacKunis, Johnson, & Dixon, 2010; Yu & Lloyd, 1997; Yuan, 1996; Yuan & Stepanenko, 1993; Zergeroglu, Dixon, Haste, & Dawson, 1999). However, like the classical adaptive control, CARC does not guarantee parameter convergence, i.e., accurate parameter estimation, unless a condition termed *persistent excitation* (PE) is fulfilled (Slotine & Li, 1991). It is well known that the PE condition is very stringent and often infeasible in practice (Farrell, 1997). Even when PE exists, the rate of parameter convergence in adaptive control highly depends on the PE strength generally resulting in a slow convergence speed (Hsu & Costa, 1987).

The ability to learn is one of the fundamental features of autonomous intelligent behavior which is reflected by parameter convergence in adaptive control systems (Antsaklis, 1995). The benefits brought by parameter convergence include accurate online identification, superior trajectory tracking, and robust adaptation without parameter drift (Lin & Kanellakopoulos, 1998). A desired compensation adaptive robot control (DCARC) approach, which includes a linear feedback term, a square damping term, and

☆ This work was supported in part by the National Natural Science Foundation of China under Grant No. 61703295, and in part by the Defense Innovative Research Programme, MINDEF of Singapore under Grant No. MINDEF-NUSDIRP/2012/02. The material in this paper was not presented at any conference. This paper was recommended for publication in revised form by Associate Editor Thomas Bo Schön under the direction of Editor Torsten Söderström.

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https://doi.org/10.1016/j.automatica.2017.11.032
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an adaptive feedforward compensator, was proposed in Sadegh and Horowitz (1990), where the parameter estimate is updated by a least-squares algorithm with forgetting, and exponential stability of the closed-loop system is guaranteed by a semi-PE condition. A sufficient condition to satisfy semi-PE in DCARC is that the regressor is periodic (Sadegh & Horowitz, 1990). Although the semi-PE condition is relaxed compared with the original PE condition, it is still stringent for practical applications.

This paper proposes a novel composite learning robot control (CLRC) strategy to achieve fast and accurate parameter estimation without the PE condition. The difference between the composite adaptation and the composite learning lies in the exploitation of online data. In the composite adaptation, only instantaneous data are exploited to update parameter estimates, whereas in the composite learning, online historical data (OHD) together with instantaneous data are exploited to update parameter estimates. The design procedure of the proposed approach is given as follows: First, the classical CARC law in Slotine and Li (1989) is presented to facilitate control synthesis; second, a novel prediction error is constructed to utilize OHD; third, the prediction error is applied together with a filtered tracking error to update the parameter estimate; finally, global exponential stability of the closed-loop system is established under a condition termed *interval excitation* (IE) which is much weaker than the PE condition. *The significance of this study is that it provides the first result of parameter convergence without the PE condition for adaptive robot control.* The price of implementing the proposed CLRC is that extra computational time is required to calculate the prediction error and extra memory is required to store OHD.

In the remainder of this article, Section 2 formulates the control problem, Section 3 presents the CLRC design, Section 4 provides illustrative results, and Section 5 draws conclusions. Throughout this article, $\mathbb{R}$, $\mathbb{R}^+$, $\mathbb{R}^n$ and $\mathbb{R}^{m\times n}$ denote the spaces of real numbers, positive real numbers, real n-vectors and real $m \times n$-matrices, respectively, L_2 and L_∞ denote the spaces of square-integrable and bounded signals, respectively, $\lambda_{\min}(A)$ and $\lambda_{\max}(A)$ denote the minimal and maximal eigenvalues of A, respectively, $\min\{\cdot\}$ and $\max\{\cdot\}$ denote the minimum and maximum operators, respectively, $\|\mathbf{x}\|$ denotes the Euclidean norm of $\mathbf{x}$, $\mathrm{diag}(\cdot)$ is a diagonal matrix, and $\Omega_c := \{\mathbf{x} | \|\mathbf{x}\| \le c\}$ is the ball of radius c, where $\mathbf{x} \in \mathbb{R}^n$, $A \in \mathbb{R}^{n\times n}$, $c \in \mathbb{R}^+$, and n and m are positive integers. For the sake of brevity, in the subsequent sections, the arguments of a function may be omitted while the context is sufficiently explicit.

2. Problem formulation

Consider a class of n-link robotic systems described by an Euler–Lagrange formulation (Kelly, Santibanez, & Loria, 2005; Khalil, 2015; Spong, Hutchinson, & Vidyasagar, 2006):

$$M(\boldsymbol{q})\ddot{\boldsymbol{q}} + C(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + D\dot{\boldsymbol{q}} + G(\boldsymbol{q}) = \boldsymbol{\tau} \tag{1}$$

in which $\boldsymbol{q}(t) = [q_1(t),\ q_2(t), \ldots, q_n(t)]^T \in \mathbb{R}^n$ is a joint angular position, $M(\boldsymbol{q}) \in \mathbb{R}^{n\times n}$ is an inertia matrix, $C(\boldsymbol{q}, \dot{\boldsymbol{q}}) \in \mathbb{R}^{n\times n}$ is a centripetal-Coriolis matrix, $D\dot{\boldsymbol{q}} \in \mathbb{R}^n$ is a viscous friction torque, $G(\boldsymbol{q}) \in \mathbb{R}^n$ is a gravitational torque, $\boldsymbol{\tau}(t) \in \mathbb{R}^n$ is a control torque, and n is the number of links. To facilitate presentation, let

$$H(\boldsymbol{q}, \dot{\boldsymbol{q}}, \boldsymbol{v}, \dot{\boldsymbol{v}}) := G(\boldsymbol{q}) + D\dot{\boldsymbol{q}} + C(\boldsymbol{q}, \dot{\boldsymbol{q}})\boldsymbol{v} + M(\boldsymbol{q})\dot{\boldsymbol{v}} \tag{2}$$

with $\boldsymbol{v} \in \mathbb{R}^n$ being an auxiliary variable. In this study, it is assumed that $\boldsymbol{q}$ and $\dot{\boldsymbol{q}}$ are measurable, and the following properties of the system (1) with revolute joints are available (Spong et al., 2006).

Property 1. *$M(\boldsymbol{q})$ is symmetric positive-definite, and satisfies $m_0 I \le M(\boldsymbol{q}) \le \bar{m} I$, where $m_0, \bar{m} \in \mathbb{R}^+$ are some constants.*

Property 2. *$\dot{M}(\boldsymbol{q}) - 2C(\boldsymbol{q}, \dot{\boldsymbol{q}})$ is skew-symmetric such that $\boldsymbol{\xi}^T(\dot{M}(\boldsymbol{q}) - 2C(\boldsymbol{q}, \dot{\boldsymbol{q}}))\boldsymbol{\xi} = 0$, $\forall \boldsymbol{q}, \dot{\boldsymbol{q}}, \boldsymbol{\xi} \in \mathbb{R}^n$.*

Property 3. *$H(\boldsymbol{q}, \dot{\boldsymbol{q}}, \boldsymbol{v}, \dot{\boldsymbol{v}})$ can be linearly parameterized as follows:*

$$H(\boldsymbol{q}, \dot{\boldsymbol{q}}, \boldsymbol{v}, \dot{\boldsymbol{v}}) = \Phi^T(\boldsymbol{q}, \dot{\boldsymbol{q}}, \boldsymbol{v}, \dot{\boldsymbol{v}})W \tag{3}$$

where $\Phi : \mathbb{R}^{4n} \mapsto \mathbb{R}^{N\times n}$ is a smooth regressor, $W \in \Omega_{c_w} \subset \mathbb{R}^N$ is an unknown constant parameter, $c_w \in \mathbb{R}^+$ is a known constant, and N is the dimension number of W.

Property 2 implies that the internal forces do no work, which is applicable for any kind of arm-type robots. The following definitions are also introduced to facilitate control analysis and synthesis (Pan, Zhang, & Yu, 2016).

Definition 1. A bounded signal $\Phi(t) \in \mathbb{R}^{N\times n}$ is of IE over $[T_e - \tau_d, T_e]$ if $\exists T_e, \tau_d, \sigma \in \mathbb{R}^+$ such that $\int_{T_e-\tau_d}^{T_e} \Phi(\tau)\Phi^T(\tau)d\tau \ge \sigma I$.

Definition 2. A bounded signal $\Phi(t) \in \mathbb{R}^{N\times n}$ is of PE if $\exists \sigma, \tau_d \in \mathbb{R}^+$ such that $\int_{t-\tau_d}^{t} \Phi(\tau)\Phi^T(\tau)d\tau \ge \sigma I, \forall t \ge 0$.

Let $\boldsymbol{q}_d(t) = [q_{d1}(t),\ q_{d2}(t), \ldots, q_{dn}(t)]^T \in \mathbb{R}^n$ denote a desired output satisfying $\boldsymbol{q}_d, \dot{\boldsymbol{q}}_d, \ddot{\boldsymbol{q}}_d \in L_\infty$ and $\hat{W}(t) \in \mathbb{R}^N$ be an estimate of W. Define a position tracking error $\mathbf{e}(t) := \boldsymbol{q}_d(t) - \boldsymbol{q}(t)$, a filtered tracking error $\mathbf{e}_f(t) := \dot{\mathbf{e}}(t) + \Lambda\mathbf{e}(t)$ and a parameter estimation error $\tilde{W}(t) := W - \hat{W}(t)$, where $\Lambda \in \mathbb{R}^{n\times n}$ is a positive-definite diagonal matrix. Our objective is to develop a proper control strategy for the robotic system (1) such that exponential convergence of both $\mathbf{e}$ and $\tilde{W}$ is guaranteed under certain conditions.

Remark 1. The robotic system (1) can be rewritten as follows:

$$\ddot{\boldsymbol{q}} = M^{-1}(\boldsymbol{q})\big(-C(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} - D\dot{\boldsymbol{q}} - G(\boldsymbol{q})\big) + M^{-1}(\boldsymbol{q})\boldsymbol{\tau}(t)$$

where $M^{-1}(\boldsymbol{q})$ is a control gain function. Our previous composite learning approaches of Pan, Sun, Liu, and Yu (2017), Pan and Yu (2016) and Pan, Zhang et al. (2016) are only valid for the case with M^{-1} being a known constant, and it is not straightforward to extend these approaches to the case with an unknown functional $M^{-1}(\boldsymbol{q})$. Additionally, in the approaches of Pan et al. (2017) and Pan and Yu (2016), the joint acceleration $\ddot{\boldsymbol{q}}$ must be estimated for the calculation of prediction errors, which inevitably increases computational cost and decreases parameter estimation accuracy.

3. Composite learning control design

3.1. Closed-loop robot dynamics

Differentiating $\mathbf{e}_f$ with respect to time t and multiplying both sides of the resultant equality by $M(\boldsymbol{q})$, we obtain

$$M(\boldsymbol{q})\dot{\mathbf{e}}_f = M(\boldsymbol{q})(\ddot{\boldsymbol{q}}_d + \Lambda\dot{\mathbf{e}}) - M(\boldsymbol{q})\ddot{\boldsymbol{q}}.$$

Noting the expression of $M(\boldsymbol{q})\ddot{\boldsymbol{q}}$ from (1), we get

$$M(\boldsymbol{q})\dot{\mathbf{e}}_f = M(\boldsymbol{q})\dot{\boldsymbol{v}} + C(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + D\dot{\boldsymbol{q}} + G(\boldsymbol{q}) - \boldsymbol{\tau}$$

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