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Learning from NN output feedback control of robot manipulators ☆

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ABSTRACT

In this paper, based on recently developed deterministic learning (DL) theory, we investigate the learning issue in neural network (NN) output feedback control of robot manipulators with unknown system dynamics and disturbance. Our objective is to learn the unknown closed-loop robot system dynamics while tracking to a periodic or periodic-like reference orbit with only joint angle measurements. Firstly, a high-gain observer (HGO) is used to estimate the joint velocities. An adaptive NN output feedback controller is then designed to guarantee the stability of the closed-loop robot system and the tracking performance when tracking a periodic or periodic-like reference orbit. Based on DL theory, when a partial persistence of excitation (PE) condition of the regression subvector is satisfied, part of the neural weights of the employed radial basis function (RBF) NN will converge to their optimal values. The unknown dynamics of robot manipulators can be learned by NN in a local region along the estimated state trajectory and the learned knowledge is stored in constant RBF networks. Secondly, the peaking phenomenon generated by the use of HGO and its adverse effect on learning are analyzed. If the gain of HGO is not chosen too high, the peaking phenomenon will be weakened and the accuracy of the estimated system states can still be guaranteed for learning from robot manipulators control. Thirdly, when repeating same or similar control tasks, the learned knowledge can be recalled and reused to achieve the guaranteed stability and better control performance with little effort. Finally, simulation studies are included to demonstrate the effectiveness of the proposed method.

1. Introduction

Over the last two decades, there has been tremendous progress in the development of controllers for robot manipulators, such as adaptive control [1–3], feedforward and computed torque control [4,5], variable structure control [6,7] and fuzzy control [8,9]. When the robot dynamics are highly uncertain, adaptive and learning control laws have been developed in order to cope with model uncertainties [10–13]. By using neural networks (NNs) to approximate the unknown nonlinearities in robot system dynamics, various adaptive NN control schemes were developed, including NN-based inverse control [14,15], indirect adaptive NN control [16] and direct adaptive NN control [17–20]. In case complete state measurements (especially for velocity of each joint) are not available, adaptive NN output feedback controllers using observers have been studied [21,22]. Though much progress has been achieved, the learning capability of NNs in adaptive NN control, including for adaptive NN output feedback control with observers, is actually very limited. The employed NNs do not have the ability to learn system dynamics in stable closed-loop control of robot manipulators, and need to recalculate (or readapt) the parameters (neural weights) even for repeating exactly the same control tasks.

Recently, a deterministic learning (DL) theory [23,24] was proposed for NN approximation of nonlinear dynamical systems with periodic or recurrent trajectories. It is shown that, by using localized radial basis function (RBF) NNs, almost any periodic or recurrent trajectory can lead to the satisfaction of a partial persistence of excitation (PE) condition. This partial PE condition leads to exponential stability of a class of linear time-varying adaptive systems, and accurate NN approximation of the system dynamics is achieved in a local region along the periodic or recurrent trajectory. In [25], with only output measurements, locally accurate identification of nonlinear system dynamics can still be achieved by using a high-gain observer (HGO). Further, by embedding the learned knowledge of system dynamics into a RBF NN-based nonlinear observer, it is shown that correct state estimation can be achieved according to the internal matching of the underlying system dynamics, rather than by using high gain domination.

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In this paper, we investigate the learning issue in NN output feedback control of robot manipulators with unknown system dynamics and disturbance. Our objective is to track a periodic or periodic-like reference orbit with only joint angle measurements, and learn the unknown closed-loop robot system dynamics. Motivated by [25], firstly, an HGO is used to estimate the joint velocities. An adaptive NN output feedback controller is then designed to guarantee the stability of the closed-loop robot system and the tracking performance when tracking a periodic or periodic-like reference orbit. Based on DL theory, when a partial PE condition of the regression subvector is satisfied, part of the neural weights of the employed RBF NN will converge to their optimal values. The unknown dynamics of robot manipulators can be learned by NN in a local region along the estimated state trajectory and the learned knowledge is stored in constant RBF networks. Secondly, the peaking phenomenon generated by the use of HGO and its adverse effect on learning are analyzed. If the gain of HGO is not chosen too high, the peaking phenomenon will be weakened and the accuracy of the estimated system states can still be guaranteed for learning from robot manipulators control. Thirdly, when repeating same or similar control tasks, the learned knowledge can be recalled and reused to achieve the guaranteed stability and better control performance with little effort.

The rest of the paper is organized as follows. Section 2 briefly describes the problem formulation and preliminaries. Learning from NN output feedback control of robot manipulators, the analysis of peaking phenomenon and its elimination measures is presented in Section 3. Section 4 presents the neural learning control scheme to guarantee the output tracking performance in the same or similar control tasks. Simulation results are included in Section 5. Section 6 contains concluding remarks.

2. Problem formulation and preliminaries

2.1. Problem formulation

The dynamic model for an n-link rigid robot manipulator is assumed to have the following form [5]:

$$M(q)\ddot{q}+V_m(q,\dot{q})\dot{q}+G(q)+F(\dot{q})+d=\tau \tag{1}$$

where $q\in R^n$ is the joint position vector, $\dot{q}\in R^n$ is the joint velocity vector, $\ddot{q}\in R^n$ is the joint acceleration vector; $M(q)\in R^{n\times n}$ is the inertia matrix which is symmetric and positive definite; $V_m(q,\dot{q})\in R^{n\times n}$ is the coriolis and centrifugal loading vector; $G(q)\in R^n$ is the gravitational loading vector; $F(\dot{q})\in R^n$ is the friction vector; $d\in R^n$ is the vector representing external disturbance, and $\tau\in R^n$ is the vector of the applied torque. The dynamic system given by (1) exhibits the following properties which will be utilized in the subsequent control development and stability analysis.

Property 1. *The derivative of the inertia matrix and the disturbance is bounded, that is, there exist k_m and d_m such that $\|\dot{M}\|\le k_m$, $\|d\|\le d_m$, where k_m and d_m are positive constants, and $\|\cdot\|$ denotes the Euclidean norm.*

Property 2. *The reference trajectory and its first and second time-derivatives, namely $q_d\in R^n$, $\dot{q}_d\in R^n$ and $\ddot{q}_d\in R^n$ are periodic and bounded.*

Our objective is to design an adaptive NN output feedback controller by using only joint position measurements for system (1) such that (1) all the signals in the closed-loop systems are bounded and the estimated joint velocity obtained through an HGO can arbitrarily approximate the true state; (2) the joint position q asymptotically tracks the desired joint position q_d; (3) the RBF NN can learn the unknown dynamics of system (1) in the stable control process; and (4) the learned knowledge can be reused for tracking same or similar trajectories.

2.2. Localized RBF networks

The RBF networks can be described by $f_{nn}(Z)=\sum_{i=1}^{N} w_i s_i(Z)=W^T S(Z)$, where $Z\in\Omega_Z\subset R^p$ is the input vector, $W=[w_1,\ldots,w_N]^T\in R^N$ is the weight vector, N is the NN node number, and $S(Z)=[s_1(\|Z-\mu_1\|),\ldots,s_N(\|Z-\mu_N\|)]^T$ is the regressor vector, with $s_i(\|Z-\mu_i\|)=\exp[-(Z-\mu_i)^T(Z-\mu_i)/\eta_i^2]$, with $i=1,\ldots,N$ being a Gaussian RBF, μ_i being the center of the receptive field and η_i being the width of the receptive field. It has been proven in [26] that an RBF network, with sufficiently large node number N and appropriately placed node centers and variances, can approximate any continuous function $f(Z):\Omega_Z\to R$ over a compact set $\Omega_Z\subset R^q$ to arbitrary accuracy according to $f(Z)=W^{*T}S(Z)+\epsilon$, $\forall Z\in\Omega_Z$, where W^* are the ideal constant weights, ϵ is the approximation error. It is normally assumed that there exists the ideal weight vector W^* such that $|\epsilon|<\epsilon^*$ (with $\epsilon^*>0$) for all $Z\in\Omega_Z$. Moreover, for any bounded trajectory $Z(t)$ within the compact set Ω_Z, $f(Z)$ can be approximated by using a limited number of neurons located in a local region along the trajectory: $f(Z)=W_\zeta^{*T}S_\zeta(Z)+\epsilon_\zeta$, where the subscript $(\cdot)_\zeta$ stands for the regions close to the trajectory $Z(t)$, $S_\zeta(Z)=[s_{j1}(Z),\ldots,s_{j\zeta}(Z)]^T\in R^{N_\zeta}$, with $N_\zeta<N$, $|s_{j_i}|>\iota(j_i=j_1,\ldots,j_\zeta)$, $\iota>0$ is a small positive constant, $W_\zeta^*=[\omega_{j_1}^*,\ldots,\omega_{j_\zeta}^*]$, and ϵ_ζ is the approximation error, with $\epsilon_\zeta=O(\epsilon)=O(\epsilon^*)$.

Based on the previous results on the PE property of RBF networks, Wang and Hill [23] have proved that for a localized RBF network $W^T S(Z)$ whose centers placed on a regular lattice, almost any recurrent trajectory $Z(t)$, can lead to the satisfaction of the PE condition of regressor subvector $S_\zeta(Z)$.

2.3. DL theory

In DL theory, identification of system dynamics of general nonlinear systems is achieved according to the following elements: (i) employment of localized RBF networks; (ii) satisfaction of a partial PE condition; (iii) exponential stability of the adaptive system along the periodic or recurrent orbit; and (iv) locally accurate NN approximation of the unknown system dynamics [23].

Choose

$$\overline{W}=mean_{t\in[t_a,t_b]}\widehat{W}(t) \tag{2}$$

with $[t_a,t_b]$, $t_b>t_a>T$ representing a time segment after the transient process. Locally accurate approximation of system dynamics along the tracking orbit φ_ζ can be obtained as follows [23]:

$$f(Z)=W_\zeta^{*T}S_\zeta(Z)+\epsilon_\zeta=\widehat{W}^T S(Z)+\epsilon_1=\overline{W}^T S(Z)+\epsilon_2 \tag{3}$$

where both ϵ_1 and ϵ_2 are close to ϵ^*.

In [24], a lemma about the exponential stability of a class of linear time-varying systems associated with adaptive neural control of nonlinear systems with unknown affine terms is presented as follows:

$$\begin{bmatrix}\dot{e}_1\\ \dot{e}_2\\ \dot{\theta}\end{bmatrix}=\begin{bmatrix} & A(t) & \begin{matrix}0\\ S^T(t)\end{matrix}\\ 0 & -\Gamma S(t)G(t) & 0\end{bmatrix}\begin{bmatrix}e_1\\ e_2\\ \theta\end{bmatrix} \tag{4}$$

with $e_1\in R^{n-q}$, $e_2\in R^q$, $\theta\in R^p$, $A(\cdot):[0,\infty)\to R^{n\times n}$, $S(\cdot):[0,\infty)\to R^{p\times q}$, $G(\cdot):[0,\infty)\to R^{q\times q}$ and $\Gamma=\Gamma^T>0$. For ease of description, define $B(t)=[0\ S(t)]\in R^{p\times n}$, $P(t)=block\text{-}diag\{I,G(t)\}\in R^{n\times n}$, where *block-diag* here refers to block diagonal form and let $C(t)=\Gamma B(t)P(t)$.