



Learning from adaptive neural network control of an underactuated rigid spacecraft



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ABSTRACT

In this paper, based on recently developed deterministic learning (DL) theory, we investigate the problem of stabilization for an underactuated rigid spacecraft with unknown system dynamics. Our objective is to learn the unknown underactuated system dynamics while tracking to a desired orbit and design the control law to achieve stabilization. First, the system dynamic and kinematic equations are given, the kinematic equation is described by the (w, z) parametrization. Second, an adaptive neural network (NN) controller with the employed radial basis function (RBF) is designed to guarantee the stability of the underactuated rigid spacecraft system and the tracking performance. The unknown dynamics of underactuated rigid spacecraft system can be approximated by NN in a local region and the learned knowledge is stored in constant RBF networks. The accessorial variables γ_1 and γ_2 are imported in the designing course of the control laws via backstepping method. Third, when repeating same or similar control tasks, the learned knowledge can be recalled and reused to achieve guaranteed stability with little effort. Finally, simulation studies are included to demonstrate the effectiveness of the proposed method.

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1. Introduction

Recently, there has been increasing interest in designing controllers for the orientation and tracking problems of the underactuated rigid spacecraft [1–15]. Underactuated control is a scenario where a system is with fewer independent control inputs than degrees of freedom. Rigid spacecraft models with two controls cannot be locally asymptotically stabilized by means of smooth pure state feedbacks [16]. Available stabilization methods include time-varying feedbacks [16–19] and discontinuous feedbacks [20–22]. Readers can refer to [4] for a complete literature survey (up to the time of its publication) of attitude control of rigid spacecraft using reduced inputs.

In [16], explicit smooth periodic time-varying feedback has been proposed. It combined center manifold theory with time-averaging and Lyapunov techniques. To yield exponential stabilization, an almost continuous and periodic control law was proposed in [17] by switching between two different control laws and by using homogeneous method and Lyapunov technique. Time-varying control laws were used in [18] to circumvent the topological obstruction to smooth stabilizability due to Brockett's condition [23]. Nevertheless, most of the existing time-varying control results suffer from the drawback that the designed control laws are very complex and the conver-

gence of system states is slow. In the discontinuous feedbacks, several research results have been achieved. For example, stabilizing feedback control laws were proposed in [24] for the kinematic system of an underactuated axisymmetric spacecraft subject to input constraints. The flat outputs of the system were computed and used to generate reference trajectories for the tracking problem. In [8], under zero-momentum restriction, a singular quaternion feedback controller was first derived based on the generalized dynamic inverse method to stabilize the attitude kinematics. By introducing a novel saturated function, this controller was developed into a switching control logic to account for the singularities as well as yielding bounded inputs. Then a full-state feedback with bounded wheel speeds was synthesized to globally reorientate the spacecraft to any desired orientation.

Precise attitude control in the presence of uncertain nature of spacecraft dynamical systems has attracted considerable research interest in the existing literature [25–31]. Although the existing literature addresses important issues related to attitude control of spacecraft, such as adapting the control system to modeling uncertainties, only limited results explicitly deal with underactuated systems [32]. How to approximate the unknown system dynamics of the underactuated spacecraft during the stable closed-loop control process still remains a problem.

Recently, a deterministic learning (DL) theory [33,34] was proposed for neural network (NN) approximation of nonlinear dynamical systems. 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

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partial PE condition leads to exponential stability of a class of linear time-varying adaptive systems. Accurate NN approximation of the system dynamics is achieved in a local region along the periodic or recurrent trajectory. This provides us with a new solution to the problem of approximating the unknown system dynamics of the underactuated spacecraft during the stable closed-loop control process.

In this paper, based on DL theory, we investigate the problem of stabilization for an underactuated rigid spacecraft with unknown system dynamics. Our objective is to learn the unknown under-actuated system dynamics while tracking to a desired orbit and design the control law to achieve stabilization. First, the system dynamic and kinematic equations are given, the kinematic equation is described by the (w, z) parametrization. Second, an adaptive NN controller with the employed RBF is designed to guarantee the stability of the underactuated rigid spacecraft system and the tracking performance. The unknown dynamics of the underactuated rigid spacecraft system can be approximated by NN in a local region and the learned knowledge is stored in constant RBF networks. The accessory variables γ_1 and γ_2 were imported in the designing course of the control laws via backstepping method. Third, when repeating same or similar control tasks, the learned knowledge can be recalled and reused to achieve guaranteed stability with little effort.

The rest of the paper is organized as follows. Section 2 briefly describes the problem formulation and preliminaries. Section 3 gives the equations of motion. Learning from NN control of under-actuated spacecraft is presented in Section 4. Section 5 presents the neural learning control scheme to guarantee control performance in same or similar control tasks. Simulation results are included in Section 6. Section 7 contains concluding remarks.

2. Preliminaries

2.1. 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 $Z \in \Omega_Z \subset \mathbb{R}^p$ is the input vector, $W = [w_1, \dots, w_N]^T \in \mathbb{R}^N$ is the weight vector, N is the NN node number, and $S(Z) = [s_1(\|Z - \mu_1\|), \dots, s_N(\|Z - \mu_N\|)]^T$ is the regressor vector, with $s_i(\|Z - \mu_i\|) = \exp\left[-\frac{(Z - \mu_i)^T(Z - \mu_i)}{\eta_i^2}\right]$, $i = 1, \dots, N$ 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 [35] that an RBF network, with sufficiently large node number N and appropriately placed node centers and variances, can approximate any continuous function $f(Z) : \Omega_Z \rightarrow \mathbb{R}$ over a compact set $\Omega_Z \subset \mathbb{R}^q$ 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 subscript $(\cdot)_\zeta$ stands for the regions close to the trajectory $Z(t)$, $S_\zeta(Z) = [s_{j_1}(Z), \dots, s_{j_{N_\zeta}}(Z)]^T \in \mathbb{R}^{N_\zeta}$, with $N_\zeta < N$, $|s_{j_i}| > \iota$ ($j_i = j_1, \dots, j_{N_\zeta}$), $\iota > 0$ is a small positive constant, $W_\zeta^* = [w_{j_1}^*, \dots, w_{j_{N_\zeta}}^*]$, and ϵ_ζ is the approximation error, with $\epsilon_\zeta = O(\epsilon) = O(\epsilon^*)$.

Based on the previous results on PE property of RBF networks, Wang and Hill [33] has 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 $S_\zeta(Z)$.

2.2. 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; (iv) locally accurate NN approximation of the unknown system dynamics [33]. Choose

$$\bar{W} = \text{mean}_{t \in [t_a, t_b]} \hat{W}(t) \quad (1)$$

with $[t_a, t_b]$, $t_b > t_a > T$ representing a time segment after the transient process, $\hat{W}$ being the estimate of W^* . Locally accurate approximation of system dynamics along the tracking orbit φ_ζ can be obtained as follows [33]:

$$f(Z) = W_\zeta^{*T} S_\zeta(Z) + \epsilon_\zeta = \hat{W}^T S(Z) + \epsilon_1 = \bar{W}^T S(Z) + \epsilon_2 \quad (2)$$

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

In [34], 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:

$$\begin{bmatrix} \dot{e}_1 \\ \dot{e}_2 \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} A(t) & 0 \\ 0 & S^T(t) \\ 0 - \Gamma S(t)G(t) & 0 \end{bmatrix} \begin{bmatrix} e_1 \\ e_2 \\ \theta \end{bmatrix} \quad (3)$$

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

Assumption 1. There exists a $\phi_M > 0$ such that, for all $t \geq 0$, the following bound is satisfied

$$\max \left\{ \|B(t)\|, \left\| \frac{dB(t)}{dt} \right\| \right\} \leq \phi_M \quad (4)$$

Assumption 2. There exist symmetric matrices $P(t)$ and $Q(t)$ such that $A^T(t)P(t) + P(t)A(t) + \dot{P}(t) = -Q(t)$. Furthermore, $\exists p_m, p_M, q_m$ and $q_M > 0$ such that, $p_m I \leq P(t) \leq p_M I$ and $q_m I \leq Q(t) \leq q_M I$.

With Assumptions 1 and 2, Liu et al. [34] stated that system (3) is uniformly globally exponentially stable in the compact set Ω if $S(t)$ satisfies the PE condition. The proof is omitted here for clarity and conciseness.

3. Equation of motion

3.1. Dynamics model

The equations describing the rotational motion of a rigid body are Euler's equations of motion [36]. Assume that the actuators are reaction wheels and one reaction wheel failure on the Z -axis. Neglect the disturbance torque, and the corresponding dynamic equation for the underactuated spacecraft is [36]

$$\begin{cases} \dot{\omega}_1 = \frac{I_2 - I_3}{I_1} \omega_2 \omega_3 + \frac{T_1}{I_1} \\ \dot{\omega}_2 = \frac{I_3 - I_1}{I_2} \omega_1 \omega_3 + \frac{T_2}{I_2} \\ \dot{\omega}_3 = \frac{I_1 - I_2}{I_3} \omega_1 \omega_2 + \frac{T_3}{I_3}, \end{cases} \quad (5)$$

where $\omega_1, \omega_2, \omega_3$ denote the components of the body angular velocity vector with respect to the body principal axes, T_1, T_2, T_3 are the external torques, and the positive scalars I_1, I_2, I_3 are the principal moments of inertia of the body with respect to its center

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