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Guaranteeing prescribed performance for air-breathing hypersonic vehicles via an adaptive non-affine tracking controller



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ABSTRACT

Keywords: Air-breathing hypersonic vehicles (AHVs) Prescribed performance Neural network (NN) Non-affine models Minimal-learning parameter (MLP) This paper investigates a prescribed performance control strategy for air-breathing hypersonic vehicles (AHVs) based on neural approximation. Different from the existing studies, the explored controllers are derived from non-affine models instead of affine ones. For the velocity dynamics, an adaptive neural controller containing only one neural network (NN) is addressed via prescribed performance control. Specially, the altitude dynamics is transformed into a pure feedback non-affine model instead of a strict feedback one. Then a novel adaptive neural controller is exploited without using back-stepping. Also, only one NN is utilized to approximate the lumped unknown nonlinearity of the altitude subsystem. By the merit of the minimal-learning parameter (MLP) scheme, only two learning parameters are required for neural approximation. The highlights are that the proposed control methodology possesses concise control structure and a low computational cost and moreover it can guarantee the tracking errors with prescribed performance. Finally, simulation results for an AHV model are provided to demonstrate the efficacy of the proposed control approach.

1. Introduction

It is well-known that the flight control design for air-breathing hypersonic vehicles (AHVs) is challenging since the vehicle dynamics is complex, uncertain and highly coupled [1–3]. Moreover, the slender geometry and the flexibility of the vehicle structure result in notable flexible effects. The vibrational modes, in turn, may significantly affect the aerodynamic forces [4–6]. Besides, owing to the fact that AHVs usually flight at hypersonic speed, the transient performance of the control system must be good [7].

Various attempts have been made in the literature on control design for the affine models of AHVs. To handle the problem of system uncertainty, robust L_{∞} -gain control [8] and self-scheduled H_{∞} control [9] are addressed for an AHV. For an AHV subject to mismatched uncertainties, a predictive flight control method [10] is proposed and a nonlinear disturbance observer (NDO) is designed for robustness enhancement. In Ref. [11], novel finite time integral sliding mode controller is developed for the longitudinal model of an AHV. To reduce high frequency chattering, a NDO is introduced to provide disturbance estimation for feedforward compensation [11]. Moreover, a high order sliding mode control approach with continuous control inputs is presented for a flexible AHV to provide robust tracking of velocity and altitude commands [12]. For the attitude control of AHVs, an active disturbance rejection control (ADRC) strategy [13] and an ADRC based trajectory linearization control (TLC) methodology [14] are proposed.

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On the basis of the immersion and invariance theory, a new output feedback control scheme is studied for an AHV [15]. From a practical perspective, fault tolerant control methods [16–18] and constrained control schemes [19–24] are also presented for AHVs.

With strict assumptions, the altitude dynamics of AHVs can be rewritten as strict feedback affine formulation, which makes back-stepping achievable [25-29]. Despite its superiority in dealing with unmatched uncertainties, there are still some universal shortcomings connected with back-stepping control. A serious one is the problem of "explosion of terms" caused by the repeated differentiations of virtual control laws. In Ref. [30], a neural back-stepping controller is derived and the problem of "explosion of terms" is eliminated by using a singularly perturbed system. Furthermore, by introducing a first-order filter at each step of back-stepping design, there is no need of analytic differentiations of virtual controllers [23,24]. In Ref. [31], a new tracking differentiator is constructed to cope with the problem of "explosion of terms". Another shortcoming of back-stepping is that its robustness with respect to uncertainties is needed to be further enhanced via additional technologies such as the parameter projection scheme [3,4,19], NDO technique [27,31,32], Kriging system [26] and neural approximation [23,24,29,30,33,34]. Note the fact that the computational ability of computer or hardware is limited. Thus, a lot of efforts have been made to reduce the computational load of neural approximation. In Ref. [35], a novel back-stepping design with less online parameters is achieved on the basis of an extreme learning machine. By



Nomenclature:		$C_D^{\delta_e^i}$	<i>i</i> th order coefficient of δ_e in <i>D</i>
_	and the second second	$C_D^{lpha^i}$	<i>i</i> th order coefficient of α in <i>D</i>
<i>c</i>	aerodynamic chord	$C_I^{\alpha^i}$	<i>i</i> th order coefficient of α in L
ρ_0	air density at the altitude h_0	C^{a^i}	ith order coefficient of α in M
$1/h_s$	air density decay rate	$C_{M,\alpha}$	In order coefficient of a m m
h	altitude	C_T^{α}	<i>i</i> th order coefficient of α in <i>T</i>
α	angle of attack ($\alpha = \theta$ - γ)	$\beta_i(h, \overline{q})$	ith trust fit parameter
C_{e}	coefficient of δ_e in M	$N_i^{\alpha_j}$	<i>j</i> th order contribution of α to N_i
$C_L^{\delta_\ell}$	coefficient of $\delta_{\rm e}$ contribution in <i>L</i>	L	lift
c_D^0	constant coefficient in D	I_{yy}	moment of inertia
c_l^0	constant coefficient in L	ω_i	natural frequency for elastic moden _i
$c^0_{M,\alpha}$	constant coefficient in M	\mathbf{R}^n	n-dimensional Euclidean space
c_T^0	constant coefficient in T	h_0	nominal altitude for air density approximation
N_i^0	constant term inN _i	Θ	pitch angle
$\widetilde{\psi_i}$	constrained beam coupling constant for n_i	Q	pitch rate
$N_2^{\delta_{e}}$	contribution of $\delta_{\rm e}$ to N_2	М	pitching moment
ζ_i	damping ratio for elastic moden _i	S	reference area
$\overline{\rho}$	density of air	•	the absolute value of a scalar
D	drag	•	the 2-norm of a vector
\overline{q}	dynamic pressure	Т	thrust
$\overline{\delta}_{\mathrm{e}}$	elevator angular deflection	Z_T	thrust moment arm
γ	flight-path angle	т	vehicle mass
Φ	fuel equivalence ratio	V	velocity
η_i	ith generalized elastic coordinate	R	the set of all real numbers
N _i	<i>i</i> th generalized force		
	v		

employing the minimal-learning parameter (MLP) approach [21,22] to adjust the norm rather than the elements of the ideal weight vector, the learning parameters become less. In Refs. [36,37], the altitude dynamics is converted into pure feedback formulation, based on which, a novel adaptive neural controller is devised without back-stepping. Thus, the complex recursive design process is avoided.

Despite the above progress in the flight control of AHVs, further studies are still required. It is noted that all the previous controllers are designed based on affine modes and little concerns the prescribed performance of the control system. However, the AHV model has no affine appearance of the control inputs [38,39]. In this paper, we exploit a novel adaptive neural controller with prescribed performance for an AHV using a non-affine model. Firstly, the vehicle dynamics is decomposed into the velocity subsystem and the altitude subsystem with non-affine formulation to be controlled separately. Then, an adaptive neural prescribed performance controller is devised for the velocity subsystem based on the MLP method. Thirdly, the altitude dynamics is transformed into a pure feedback non-affine form such that a novel adaptive neural control approach is achieved without back-stepping. Finally, the semi-globally uniformly ultimately boundedness of all the closed-loop system signals is proved and the effectiveness of the design is validated by simulation results. The main contributions of this paper are summarized as follows:

- In comparison with the existing control schemes derived from affine models, the proposed controller exhibits better practicability since it is explored by utilizing a non-affine model. Moreover, the developed controller can guarantee the velocity and altitude tracking errors with satisfactory prescribed performance.
- 2. Compared with the adaptive neural back-stepping control [22–24], a lower complexity and computational burden design is achieved in this study. There is no need of the complicated recursive design process of back-stepping. Furthermore, the computational cost is quite low since less neural networks (NNs) and learning parameters are needed.

The rest of this paper is outlined as follows. Section 2 presents the AHV model and preliminaries. The control design process is shown in

Section 3. The simulation results are presented in Section 4 and the conclusions are proposed in Section 5.

2. AHV model and preliminaries

2.1. Model description

In this paper, we consider the longitudinal dynamic model of an AHV taken from Refs. [38,39]. The equations of motion consist of five rigid-body states *V*, *h*, γ , θ , *Q* and two flexible states η_1 and η_2 .

$$\dot{V} = \frac{T\cos(\theta - \gamma) - D}{m} - g\sin\gamma$$
(1)

$$\dot{h} = V \sin \gamma$$
 (2)

$$\dot{\gamma} = \frac{L+T\sin(\theta-\gamma)}{mV} - \frac{g}{V}\cos\gamma$$
(3)

$$\dot{\theta} = Q$$
 (4)

$$\dot{Q} = \frac{M + \widetilde{\psi}_1 \vec{\eta}_1 + \widetilde{\psi}_2 \vec{\eta}_2}{I_{yy}}$$
(5)

$$k_1 \ddot{\eta}_1 = -2\zeta_1 \omega_1 \dot{\eta}_1 - \omega_1^2 \eta_1 + N_1 - \widetilde{\psi}_1 \frac{M}{I_{yy}} - \frac{\psi_1 \psi_2 \ddot{\eta}_2}{I_{yy}}$$
(6)

$$k_{2}\ddot{\eta}_{2} = -2\zeta_{2}\omega_{2}\dot{\eta}_{2} - \omega_{2}^{2}\eta_{2} + N_{2} - \widetilde{\psi}_{2}\frac{M}{I_{yy}} - \frac{\widetilde{\psi}_{2}\widetilde{\psi}_{1}\ddot{\eta}_{1}}{I_{yy}}$$
(7)

The approximations of T, D, L, M, N_1 and N_2 are defined as [39]:

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