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Novel auxiliary error compensation design for the adaptive neural control of a constrained flexible air-breathing hypersonic vehicle

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ABSTRACT

This paper investigates the design of auxiliary error compensation for adaptive neural control of the longitudinal dynamics of a flexible air-breathing hypersonic vehicle (FAHV) with magnitude constraints on actuators. The control objective pursued is to steer velocity and altitude to follow their respective reference trajectories in the presence of actuator saturation and system uncertainties. To guarantee the exploited controller's robustness with respect to parametric uncertainties, neural network (NN) is applied to approximate the lumped uncertainty of each subsystem of FAHV model. Different from the traditional parameter updating technique, in this paper, the minimal-learning-parameter (MLP) scheme is introduced to estimate the norm rather than the elements of NN's weight vector while the computational load is reduced. The special contribution is that novel auxiliary systems are developed to compensate both the tracking errors and desired control laws, based on which the explored controller can still provide effective tracking of velocity and altitude commands when the actuators are saturated. Finally, numerical simulations are performed to illustrate the command tracking performance of the proposed strategy.

1. Introduction

Owing to many potential applications in both civilian and military fields, the research on air-breathing hypersonic vehicles (AHVs) has received considerable attention [1,2], as witnessed by the success of NASA's scramjet-powered X-43A and X-51A. However, the flight control design, as the key issue of making AHV feasible and efficient, still presents numerous challenges due to the complexity of the vehicle dynamics, the extreme level of couplings between the propulsion system and the airframe dynamics, as well as the presence of noticeable flexible effects [3,4].

Because of the extreme complexity of the vehicle dynamics, only the longitudinal dynamic model of AHV has been extensively studied [5,6], On the basis of which, various control schemes such as neural control [7,8], predictive control [9], fault-tolerant control [10,11], fuzzy control [12], active robust control [13] and sliding mode control [14] have been reported. In [15], the dynamic model of a flexible AHV (FAHV) is converted into a linearly parameterized formulation, for which the dynamic inversion based back-stepping control is addressed. Though back-stepping design possesses excellent superiority in handling unmatched system uncertainty, it requires the tedious analytic computations of time derivatives of virtual controllers. To deal with such problem, advanced technologies such as sliding mode differentiator [16] and dynamic surface control (DSC) [17–20] are applied. Besides, it is well known that the robustness of back-stepping control needs to be further enhanced via special approaches such as parameter projection [15,21] and nonlinear disturbance observer (NDO) [22,23].

On the other hand, neural approximation has been proved to be a powerful tool for improving the controller's uncertainty attenuation ability [24–27]. On the condition that the unknown function and control gain approached by neural networks (NNs) are strictly positive, two different NNs are introduced to estimate such uncertainties [28]. In [29], the vehicle dynamics are decomposed into two functional systems namely velocity subsystem and altitude subsystem. Moreover, for each subsystem, only one NN is needed [29]. Differently, the NN is employed to estimate the previously developed back-stepping control law instead of the model nonlinearity where a nonsingular direct neural controller is constructed for AHV [3]. It is worth mentioning that the computational ability of computer and hardware is limited. Thereby the minimal-learning-parameter (MLP) method is utilized to regulate the maximum norm of ideal weight vectors rather than their elements while less online parameters are required to be tuned [30].

From a practical perspective, one open problem is that the signal provided by the designed control law cannot be

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Nomenclature

m	vehicle mass
ρ	density of air
$\bar{q}$	dynamic pressure
S	reference area
h	altitude
V	velocity
γ	flight-path angle
θ	pitch angle
α	angle of attack ($\alpha=\theta-\gamma$)
Q	pitch rate
T	thrust
D	drag
L	lift
M	pitching moment
I_{yy}	moment of inertia
$\bar{c}$	aerodynamic chord
z_T	thrust moment arm
Φ	fuel equivalence ratio
δ_e	elevator angular deflection
N_i	ith generalized force
$N_i^{\alpha_j}$	jth order contribution of α to N_i
N_i^0	constant term in N_i
$N_2^{\delta_e}$	contribution of δ_e to N_2
$\beta_i(h,\bar{q})$	ith trust fit parameter
η_i	ith generalized elastic coordinate
ζ_i	damping ratio for elastic mode η_i
ω_i	natural frequency for elastic mode η_i
$C_D^{\alpha^i}$	ith order coefficient of α in D
$C_D^{\delta_e^i}$	ith order coefficient of δ_e in D
C_D^0	constant coefficient in D
$C_L^{\alpha^i}$	ith order coefficient of α in L
$C_L^{\delta_e}$	coefficient of δ_e contribution in L
C_L^0	constant coefficient in L
$C_{M,\alpha}^{\alpha^i}$	ith order coefficient of α in M
$C_{M,\alpha}^0$	constant coefficient in M
$C_T^{\alpha^i}$	ith order coefficient of α in T
C_T^0	constant coefficient in T
h_0	nominal altitude for air density approximation
ρ_0	air density at the altitude h_0
$\tilde{\psi}_i$	constrained beam coupling constant for η_i
c_e	coefficient of δ_e in M
$\frac{1}{h_s}$	air density decay rate

implemented because of actuator constraint [30–32]. Noting that the closed-loop system may encounter performance limitations or even lose stability theoretically if the actuator is saturated, the additional system proposed in [33] is introduced to compensate the desired control law [30,31]. Though the auxiliary error compensation strategy of that study is little complicated, the boundedness of velocity and altitude tracking errors can still be achieved when the physical limitations on actuators are in effect [30,31]. In [21,28], a simple auxiliary system established in [34] is adopted to modify the initial tracking error and the desired controller. However, when the control inputs constraints are in effect, the boundedness of velocity and altitude tracking errors cannot be achieved theoretically in that studies.

Motivated by the above discussions, in this paper, a novel auxiliary error compensation strategy is proposed for the adaptive neural control of a constrained FAHV to provide robust tracking of velocity and altitude reference trajectories. By viewing the flexible effects as system uncertainties, the longitudinal dynamics of FAHV are decomposed into two functional subsystems namely the respective velocity subsystem and altitude subsystem. To ensure the controller's robustness, NN is applied to estimate the lumped uncertainty of each subsystem. The MLP scheme is utilized to adjust the norm of NN's weight vector. In this way, less adaptive parameters are required for neural approximation. Especially, novel auxiliary systems are exploited to cope with the problem of control inputs constraints. Finally, simulation results are presented to demonstrate the efficacy of the proposed control methodology. The special advantages of the approach proposed herein include:

1. With the novel design of auxiliary system, the effect of actuator saturation is eliminated, and the boundedness of velocity and altitude tracking errors can still be guaranteed even when the physical limitations on actuators are in effect.
2. The computational cost is quite low since less NNs and adaptive parameters are needed to be regulated online in this paper.

The remainder of this paper is organized as follows. Section 2 presents the FAHV model. Adaptive neural controllers are addressed in Section 3. Numerical simulation studies are made in Section 4 and the conclusions are proposed in Section 5.

Notation: The notations used in this paper are fairly standard. Throughout this paper, $\mathbf{R}^n$ represents n-dimensional Euclidean space; $\mathbf{R}$ denotes the set of all real numbers; $\|\bullet\|$ means the norm of a vector; $|\bullet|$ stands for the absolute value of a scalar.

2. FAHV model

2.1. Model description

The FAHV model adopted in this study is developed by Bolender and Doman [5]. Fig. 1 shows the longitudinal sketch and force map for a FAHV. It is assumed that the FAHV presented has unity depth into the paper and that air behaves as if it is a perfect gas (i.e., the ratio of specific heats is a constant) [15]. The aerodynamic forces acting on the vehicle are synthesized as a lift component, denoted by L, and a drag component, represented by D. L and D are respectively vertical to and converse the velocity direction. Moreover, the thrust T acting on the vehicle is along the body axis. For more details, the reader could refer to [5,6]. The equations of motion of the longitudinal dynamics are expressed as [6]

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

$$\dot{h}=V\ \sin\ \gamma \tag{2}$$

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

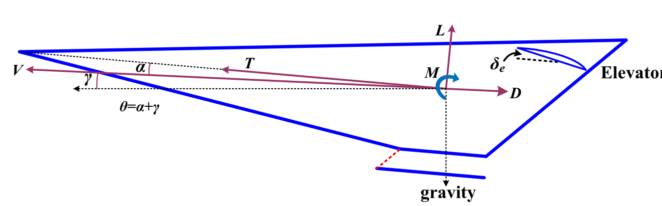

Fig.1. Geometry and force map of a FAHV model.