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Longitudinal Control of Hypersonic Vehicles Based on Direct Heuristic Dynamic Programming Using ANFIS

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***Abstract*—Since the launch of the scramjet, recent years have witnessed a growing interest in the study of airbreathing hypersonic vehicles. Due to its strong coupling characteristics, high nonlinearity, and uncertain parameters, the control of hypersonic vehicle becomes a great challenge. To deal with those design issues, we propose an adaptive learning control method based on direct heuristic dynamic programming (direct HDP), which is used to track the angle of attack despite the presence of bounded uncertain parameters. Inspired by the adaptive critic designs, direct HDP is one of the adaptive dynamic programming (ADP) methods, which is a model-free reinforcement learning algorithm using the online learning scheme to solve dynamic control problems in realistic complex environment. In this paper, this direct HDP method is improved by embedding the fuzzy neural network (FNN) in the controller design to enhance its self-learning ability and robustness. Simulation results are provided to demonstrate the effectiveness of our proposed method.**

I. Introduction

Airbreathing hypersonic vehicle (AHV) presents a reliable and efficient way to transport at high Mach numbers and carry more load with the airframe-integrated scramjet utilized. Due to the flight conditions of high altitudes and Mach numbers [1], AHV is a potential research objective for its value in the field of military and commerce. For military applications, it has global reach capability and can be used as the platform for satellite launch, recovery, and repair, even for launching anti-satellite weapons. In the field of commercial applications, AHV represents a efficient way to increases payload capability and makes access to space routine [2].

Hypersonic vehicle has a huge difference with the traditional aircraft. Because of its characteristics of high altitudes and high Mach numbers, hypersonic aircraft is sensitive to the changes of atmospheric in actual process of flying, such as the dynamic pressure effect, viscous effects, low-density effect, and so on [3]. Besides, it is difficult to measure and estimate the aerodynamic characteristics of the vehicle. In addition, hypersonic vehicle uses advanced airframe/propulsion integration technology, which makes each part of hypersonic vehicle show strong coupling characteristics [4]. Due to the fact that the dynamics of hypersonic vehicles is highly nonlinear and coupled, the design of control system for AHV is a great challenge on the condition of guaranteeing a stability and satisfactory control performance.

Many linear control methods have been proposed for the control of AHV in resent years, such as linear parameter varying (LPV) method [5], adaptive linear quadratic (ALQ) algorithm [6], and linear quadratic regulation (LQR) method [7]. Among the above approaches, LPV modeling and control are implemented via the design of an uncertain parameter-varying state matrix. The ALQ is described in the altitude and velocity tracking control algorithm for longitudinal model of a generic hypersonic vehicle. Since the characteristics of highly nonlinear and coupled, the capability of the linear approaches to represent the dynamics realistically on the coupling effects is limited.

Nonlinear methods of AHV control include dynamic inversion control based on differential geometry theory and nonlinear dynamic inversion control, such as direct neural control [8] and sliding mode control [9]–[11]. A new approach to designing a robust nonlinear controller for longitudinal flexible body models of canard configured air-breathing hypersonic flight vehicles with significant couplings and interactions was presented in [12]. The design of an adaptive flight control systems was proposed for hypersonic vehicle models, which developed an architecture including a robust adaptive nonlinear inner-loop controller, and a self-optimizing guidance scheme that shapes the reference to be tracked in order to avoid the occurrence of control input saturations in [13]. However, these nonlinear methods usually need precise analytical model to design controllers. Actually, it is difficult for AHV to build analytical models due to its highly nonlinear and time-varying nature.

During the controller design for hypersonic vehicle, varying flight conditions are taken into consideration. The robust output-feedback control was designed in [14] to provide robust velocity tracking with uncertain parameters. The L1 adaptive control architecture was proposed to compensate for parametric uncertainties and unmodeled dynamics for hypersonic vehicle in [15]. Therefore, considering the strong nonlinearity, highly time-varying changes of hypersonic vehicle, and the difficulty in measuring and estimating the aerodynamic characteristics, adaptive methods which do not rely on exact data of flight may be effective.

Adaptive dynamic programming (ADP) is an optimal control scheme using a function approximation structure such as neural network (NN) to approximate the cost function $J(t)$, which avoids the curse of dimensionality and reduces the computation time [16]. The approximate optimal control is obtained by using the offline iteration algorithm or the online update algorithm. In this paper, we use a model-free ADP method called direct heuristic dynamic programming (direct HDP) [17] for controller design of hypersonic vehicle. Direct HDP has unique features [17]. The application of direct HDP is focused on the optimal control of nonlinear and complex system, such as maze navigation [18], real-time tracking problem [19], and unknown discrete-time nonlinear system control [20]. Furthermore, to deal with parametric uncertainties, we use fuzzy neural networks (FNNs) instead of NNs with one-hidden layer in the architecture of direct HDP to express the contextual information of aerodynamic characteristics in nonlinear and dynamic environment. FNN has good fault-tolerance property, which can tolerate the changes of parameters of hypersonic vehicle in practical flight situation [21]. In this way, direct HDP using FNNs may be a promising method to simplify the strong complexities of nonlinear dynamics.

This paper aims at presenting a direct HDP method using FNNs to address the important but challenging issue in the design of hypersonic vehicle controller. This paper is organized as follows: Section 2 describes the longitudinal model of a generic hypersonic vehicle; Section 3 presents the architecture of direct HDP and the weights updating method of direct HDP using FNNs; the simulation results are shown in Section 4; finally, Section 5 contains the conclusion.

II. Hypersonic Vehicle Model

The longitudinal model of the generic hypersonic vehicle was developed at NASA Langley Research Center [22]. The flight phase of hypersonic vehicle is divided into three stages: climb, cruise, and reentry, using an approach similar to bounce to complete the flight. In the cruise stage, the parameters such as height and speed maintain in a small range, so that the change of the aerodynamic parameters are regular and they can be expressed by a mathematical formula. But in the climb stage and reentry stage, due to the large variation of the height and speed, the atmospheric parameters change greatly.

In the reentry stage, the scramjet is close and the hypersonic vehicle can only control the elevator deflection angle to balance itself. The longitudinal model of hypersonic vehicle can be expressed as follows [23]:

$$\dot{V} = \frac{T\cos\alpha - D}{m} - \frac{\mu}{r^2}\sin\gamma \tag{1}$$

$$\dot{\gamma} = -\frac{L + T\sin\alpha}{mV} - \frac{\mu - V^2 r}{Vr^2}\cos\gamma \tag{2}$$

$$\dot{h} = V\sin\gamma \tag{3}$$

$$\dot{\alpha} = q - \dot{\gamma} \tag{4}$$

$$\dot{q} = \frac{M_{yy}}{I_{yy}} \tag{5}$$

where the system states V, q, h, α, γ are velocity, pitch rate, altitude, angle of attack, and flight path angle, respectively. Here m, I_{yy}, μ represent mass of the flight, moment of inertia, and gravity constant, respectively.

Moreover, in the above equations aerodynamic forces lift L, drag D, thrust T, and the pitching moment M_{yy} are illustrated as:

$$L = 0.5\rho V^2 S C_L \tag{6}$$

$$D = 0.5\rho V^2 S C_D \tag{7}$$

$$T = 0.5\rho V^2 S C_T \tag{8}$$

$$M_{yy} = \frac{1}{2}\rho V^2 S\bar{c}[C_M(\alpha) + C_M(\delta_e) + C_M(q)] \tag{9}$$

$$r = h + R_E \tag{10}$$

where C_D, C_L, C_T denote the drag, lift, and thrust coefficients, respectively. Here δ_e and S are the elevator deflection angle and reference area, ρ and R_E are the air density and radius of the earth, $\bar{c}$ is aerodynamic chord, r is the radial distance from Earth's center. And $C_M(\alpha)$, $C_M(q)$, $C_M(\delta_e)$ are the moment coefficients due to angle of attack, pitch rate, and elevator deflection, respectively. In this paper, we design the controller of hypersonic vehicle in reentry stage. In this stage, the engine is close and the thrust T is set to 0.

Due to the flight conditions of high altitudes and Mach numbers, three aerodynamic parameters C_D, C_L, and C_T cannot be described with accurate mathematical formula. By using the look-up table method [23], we can get the actual flight data, which leads to the strong nonlinear characteristics of the hypersonic vehicle.

When the actual hypersonic vehicle is in flight, the parameters of hypersonic vehicle vary all the time. For instance, with the consumption of gas, the mass of hypersonic vehicle decreases slowly. Considering these situation, the parameter uncertainties are taken into account in the simulation which are described as follows with each bound:

$$m = m_0(1 + \Delta m), \quad |\Delta m| \leq 0.03 \tag{11}$$

$$I_{yy} = I_0(1 + \Delta I), \quad |\Delta I| \leq 0.02 \tag{12}$$

$$S = S_0(1 + \Delta S), \quad |\Delta S| \leq 0.01 \tag{13}$$

$$\rho = \rho_0(1 + \Delta\rho), \quad |\Delta\rho| \leq 0.06 \tag{14}$$

$$\bar{c} = \bar{c}_0(1 + \Delta\bar{c}), \quad |\Delta\bar{c}| \leq 0.01 \tag{15}$$

where m_0, I_0, S_0, ρ_0, and $\bar{c}_0$ are the nominal values.

III. Direct HDP Based Controller Design

In this section, direct HDP using FNNs is presented. Moreover, the uniformly ultimately boundedness (UUB) result of our proposed approach is provided to select appropriate learning parameters in the action network and critic network of direct HDP under the sufficient condition.

A. Fuzzy Neural Network (FNN)

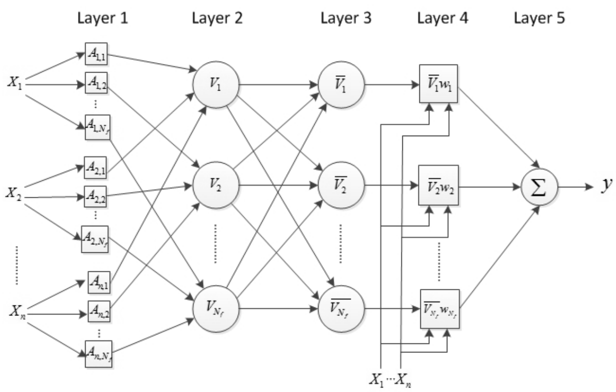


Fig. 1. Architecture of ANFIS

In our proposed approach, FNNs are used in the critic network and action network of the direct HDP. Adaptive-network-based fuzzy inference system (ANFIS) is a neural network implementation of a Takagi-Sugeno (T-S) fuzzy inference system [24]. ANFIS constructs a set of fuzzy if-then rules automatically and optimizes the rules with self-learning of NN. ANFIS applies the hybrid algorithm, which integrates backpropagation (BP) algorithm and least square estimation (LSE) algorithm, so it has rapid learning speed. Assuming that ANFIS shown in Fig.1 has n inputs, i.e., $x_1, \cdots, x_n$, and one output y. The number of fuzzy sets is N_f. Suppose that the rule base contains N_f fuzzy if-then rules of T-S type:

$$\begin{aligned}\text{Rule}j:&\text{ If } x_1 = A_{1j} \text{ and} \cdots \text{and } x_n = A_{nj}, \text{ then}\\ &w_j = z_{1j}x_1 + \cdots + z_{nj}x_n + z_{n+1,j},\\ &z_{1j}, \cdots, z_{n+1,j} \in \mathbb{R}; j = 1, 2, \cdots, N_f.\end{aligned}$$

The output of ANFIS is calculated as follows:

- Layer 1 (Fuzzification Layer)

$$\mu_{A_{ij}}(x_i) = e^{-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}} \qquad (16)$$
$$i = 1, \cdots, n; \quad j = 1, 2, \cdots, N_f$$

  where c_{ij} and σ_{ij} are the excepted value and standard deviation of Gaussian function.

- Layer 2 (Rule Layer)

$$v_j = \mu_{A_{1j}}(x_1) \times \cdots \times \mu_{A_{nj}}(x_n) \qquad (17)$$
$$j = 1, 2, \cdots, N_f$$

- Layer 3 (Normalization Layer)

$$\bar{v}_j = \frac{v_j}{\sum_{j=1}^{N_f} v_j} \qquad (18)$$

- Layer 4 (Defuzzification Layer)

$$\bar{v}_j w_j = \bar{v}_j(z_{1j}x_1 + \cdots + z_{nj}x_n + z_{n+1,j}) \qquad (19)$$
$$j = 1, 2, \cdots, N_f$$

- Layer 5 (Output Layer)

$$y = \sum_{j=1}^{N_f} \bar{v}_j w_j \qquad (20)$$

We can convert the ANFIS to a single-layer NN and the number of nodes in the hidden layer is N_f. Let $p_k(t)$ and $q_k(t)$ be the input and output of the hidden layer in that converted ANFIS. The approximation function can be expressed as follows:

$$p_k(t) = \sum_{i=1}^{n}(\frac{x_i(t) - c_{ik}(t)}{\sigma_{ik}(t)})^2, \quad k = 1, \cdots, N_f \qquad (21)$$

$$q_k(t) = \phi(p_k(t)), \qquad (22)$$

$$y(t) = \frac{\sum_{k=1}^{N_f} w_k(t)q_k(t)}{\sum_{k=1}^{N_f} q_k(t)}, \qquad (23)$$

where after the combination of Layer 1 and Layer 2, the function $\phi(x)$ is defined as

$$\phi(x) = e^{-\frac{1}{2}x} \qquad (24)$$

B. Direct HDP Based Controller

In the past decades, Werbos introduced an approach called ADP. It uses a function approximation structure such as NN to approximate cost function $J(t)$, which avoids the curse of dimensionality and reduces the computation time. The approximate optimal control is obtained by using the offline iteration algorithm or the online update algorithm.

According to the output of critic network used in ADP, ADP can be categorized as [25] [26]: heuristic dynamic programming (HDP), dual heuristic programming (DHP), and globalized dual heuristic programming (GDHP). The action dependent version of HDP and DHP are formed when the critics inputs are augmented with the controllers output.

The direct HDP was developed in [17] which is most relevant to action dependent HDP (ADHDP). Compare to other ADP structure, the advantage of direct HDP is that the previous J value is stored and calculated with current J value in order to obtain the temporal difference used in training. As a result, it is a model-free approach. Therefore, the direct HDP can be applied to realistic and complex control problems, such as cart-pole system [27] and power system stability control [28]. The improvement of direct HDP is focus on the combination with other NN [27], [29], [30]. Thus, in this paper direct HDP using FNNs may be a promising method in improving the classical direct HDP to control the hypersonic vehicle.

As shown in Fig.2, direct HDP is structured to estimate the cost function J in the Bellman equation of dynamic programming.

$$J(t) = \sum_{k=0}^{\infty} \alpha^k U(t+k) \qquad (25)$$

where α $(0 < \alpha < 1)$ is a discount factor, U is the utility function, $r(t)$ is the reinforcement signal. And the inputs are the n measured states, i.e., $x(t) = (x_1(t), \cdots, x_n(t))^{\mathrm{T}}$, and the outputs are the m actions, i.e., $u(t) = (u_1(t), \cdots, u_m(t))^{\mathrm{T}}$.

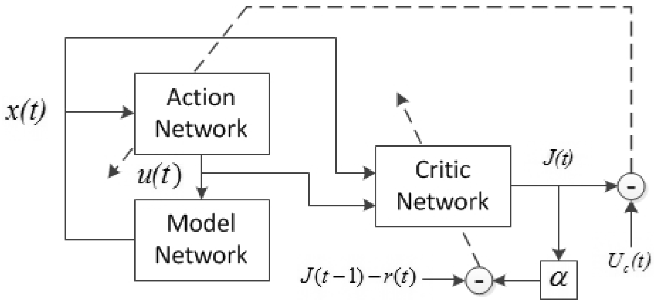


Fig. 2. Architecture of direct HDP

Without any ambiguity and for the ease of discussion, from now the subscript "a" and "c" stand for the action network and critic network, respectively. According to (22), $\phi_c(t) = (q_{c_1}, \cdots, q_{c_k})^{\mathrm{T}}$ and $\phi_a(t) = (q_{a_1}, \cdots, q_{a_k})^{\mathrm{T}}$ are the hidden layer vectors of the critic network and action network, respectively. N_{fc} and N_{fa} are the numbers of fuzzy rules in the critic network and action network.

The critic network of direct HDP is used to calculate J as an approximate of the optimal value function J^*. The critic network tries to minimize the following error E_c measured over time:

$$E_c(t) = 0.5 \times e_c^2(t) \tag{26}$$
$$e_c(t) = \alpha J(t) - r(t) + J(t-1) \tag{27}$$

The critic network weights $\hat{w}_c$ is updated as

$$\begin{aligned} \hat{w}_c(t+1) &= \hat{w}_c(t) - l_c \frac{\partial E_c(t)}{\partial \hat{J}(t)} \frac{\partial \hat{J}(t)}{\partial \hat{w}_c(t)} \\ &= \hat{w}_c(t) - \alpha l_c \phi_c(t)[\alpha \hat{w}_c(t)^{\mathrm{T}} \phi_c(t) \\ &\quad + r(t) - \hat{w}_c^{\mathrm{T}}(t-1)\phi_c(t-1)]^{\mathrm{T}} \end{aligned} \tag{28}$$

where l_c is the learning rate of critic network.

The action network of direct HDP is to backpropagate the error between the desired objective U_c and the approximator J. In our proposed approach, U_c is set to zero. The action network tries to minimize the square error E_a below

$$E_a(t) = 0.5 \times e_a^2(t) \tag{29}$$
$$e_a(t) = J(t) - U_c(t) \tag{30}$$

The action network weight $\hat{w}_a$ is updated as

$$\begin{aligned} \hat{w}_a(t+1) &= \hat{w}_a(t) - l_a \frac{\partial E_a(t)}{\partial \hat{J}(t)} \frac{\partial \hat{J}(t)}{\partial \hat{u}(t)} \frac{\partial \hat{u}(t)}{\partial \hat{w}_a(t)} \\ &= \hat{w}_a(t) - l_a \phi_a(t)[\hat{w}_c(t)^{\mathrm{T}} C(t)] \\ &\quad \times [\hat{w}_c(t)^{\mathrm{T}} \phi_c(t)]^{\mathrm{T}} \end{aligned} \tag{31}$$

where l_a is the learning rate of action network. And $C(t)$ is a matrix of $N_{fc} \times m$ dimension, and its elements can be expressed as

$$\begin{aligned} C_{kj}(t) &= \frac{-\phi_{c_k}(t)(u_j(t) - c_{c_{j+n,k}}(t))}{\sigma^2_{c_{j+n,k}}(t)} \\ k &= 1, \cdots, N_{fc}; \quad j = 1, \cdots, m. \end{aligned} \tag{32}$$

C. Uniformly Ultimately Boundedness (UUB) of Direct HDP using ANFIS

In [31], a UUB result for the direct HDP learning controller is provided under mild and intuitive conditions. In this paper, we use ANFIS in the critic network and action network within the framework of direct HDP and we can prove that the estimation errors of the weights in ANFIS remain UUB. The UUB result of our proposed approach requires the following conditions:

1) Let w_c^* and w_a^* be the optimal weights for the critic and action network, respectively, and assume they are bounded by two positive constants, i.e.,
$$\|w_c^*\| \le w_{cm} \qquad \|w_a^*\| \le w_{am} \tag{33}$$
where $w_{cm}, w_{am} \in \mathbb{R}^+$ are two known positive constants.
2) The errors between the optimal weights w_c^*, w_a^* and their estimates $\hat{w}_c(t), \hat{w}_a(t)$ are UUB, respectively, provided that the following conditions are satisfied:
$$\frac{1}{\sqrt{2}} < \alpha < 1, \quad l_c < \frac{1}{\alpha^2 N_{fc}}, \quad l_a < \frac{1}{N_{fa}} \tag{34}$$
where N_{fa} and N_{fc} are the numbers of fuzzy rules in the action network and critic network, respectively.

The above results give a simple sufficient condition which can be used to guide the selection of learning rates in direct HDP using ANFIS to maintain stability of the weight updates.

IV. Experiment

A. Parameter Setting

Here we use the error between the flight speed, pitch angular velocity, height, attack angle, and heading angel as the inputs of action network in direct HDP. The rudder angle is used as the control signal. According to [32], we set the initial value described in Table I. In the simulation,

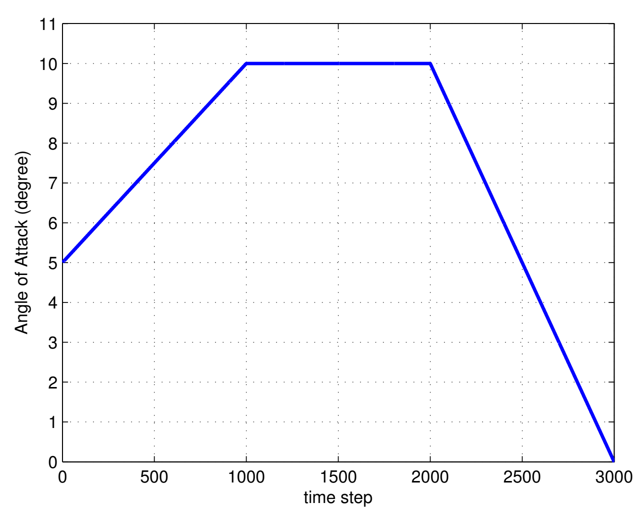


Fig. 3. Angle of attack command

the control parameter is bounded within $[-30, 30]$deg. The simulation lasts 120s and each time step is $0.02s$.

TABLE I. INITIAL VALUE OF AHV MODEL

Parameter	Initial value
V	6000 m/s
γ	0 deg
h	60000 m
α	2 deg
q	0 deg/s

TABLE II. NOMINAL VALUE OF AHV MODEL

Parameter	Nominal Value
m_0	4353 kg
I_0	34979.599 kg$\cdot$m^2
S_0	3.45 m^2
ρ_0	1.225 kg/m^3
$\bar{c}_0$	12.7 m
R_e	6.3713×10^6 m
μ	3.98855×10^{14} N$\cdot$m^2/kg

In the simulation, the number of the fuzzy rules in the critic network and action network are set to 4. The discount factor is set to $\alpha = 0.95$. The internal cycle of the critic network and action network are set to 50 and 100, respectively. The internal training error threshold for the critic network and action network are set to 0.05 and 0.005, respectively. According to the UUB result mentioned above, the learning rates of two networks are 0.1 and they satisfy the conditions (34).

B. Experimental Results without Parameter Uncertainties

According to [33], the attack angle command is shown in Fig.3 .

During the attach angle tracking for a hypersonic vehicle without parameter uncertainties, simulations are conducted for 120s in two methods: ADP and direct HDP using ANFIS in which each time step is 0.02s. All parameters are used in their nominal values. Simulation results of attach angle are shown in Fig.4. From Fig.4, we can see that ADP with single-layer NN and direct HDP using ANFIS can track the attack angle signal. From Fig.5, it shows that ADP with single-layer NN has a large fluctuation at the beginning of simulation and with the online learning of direct HDP, our proposed method performs well.

Fig.6 shows the change of the velocity, path angle, altitude, and pitch rate, respectively. From Fig.6, we can know that the hypersonic vehicle is slowly landing.

C. Experimental Results with Parameter Uncertainties

During the attach angle tracking for a hypersonic vehicle with parameter uncertainties, simulations are conducted for 120s in two methods: ADP and direct HDP using ANFIS in which each time step is 0.02s. Simulation results are shown in Fig.7. The bound of uncertain parameters is provided in (11)-(15) and the uncertainties are all set to be uniformly distributed random numbers within the bound.

When the uncertainties are added to the mass of the flight, the moment of inertia, reference area, and throttle

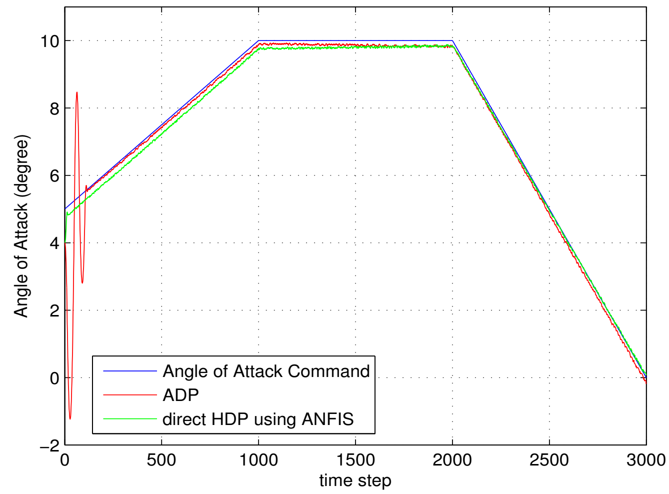


Fig. 4. Experimental result of attach angle without parameter uncertainties

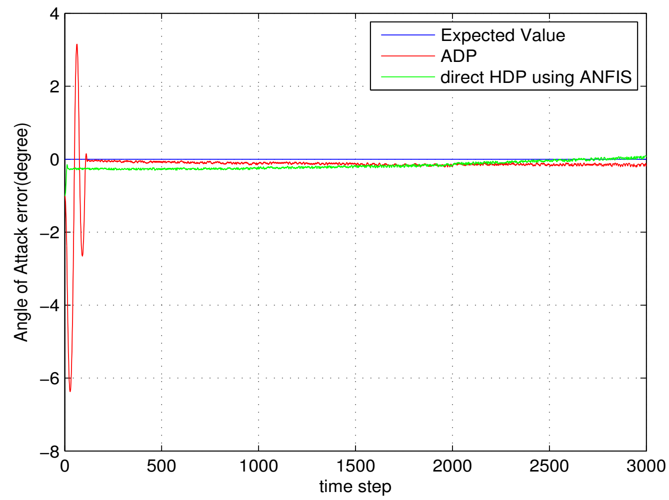


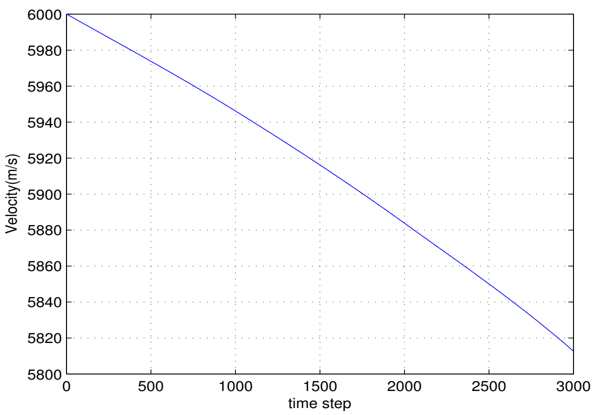
Fig. 5. Tracking error without parameter uncertainties

setting, direct HDP using ANFIS performs better than ADP with single-layer NN. From Fig.8, we can see that our proposed approach can well track the angle of attack command with the increase of the time step. However, ADP with single-layer NN can no longer track the command signal anymore. It means that when the number of online learning step increases, ANFIS can reduce the tracking error and direct HDP using ANFIS exhibits strong robustness despite the presence of bounded uncertain parameters.

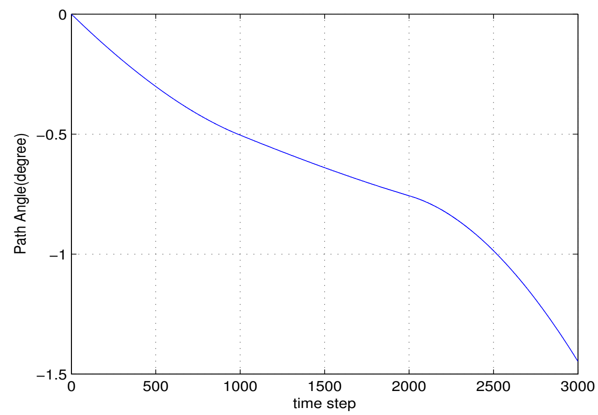
Fig.9 shows the change of the velocity, path angle, altitude, and pitch rate, respectively. From the change of altitude, we can see that the hypersonic vehicle is slowly landing.

V. CONCLUSION

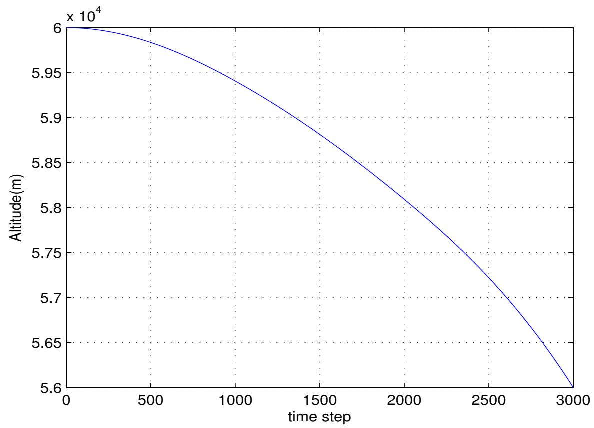
In this paper, a direct HDP method using ANFIS is designed for the control of hypersonic vehicle. Direct HDP takes advantage of the potential scalability of adaptive



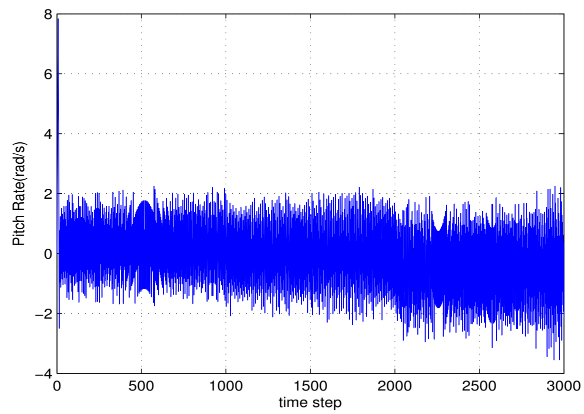
(a) Velocity



(b) Path Angle



(c) Altitude



(d) Pitch Rate

Fig. 6. Experimental Results without parameter uncertainties

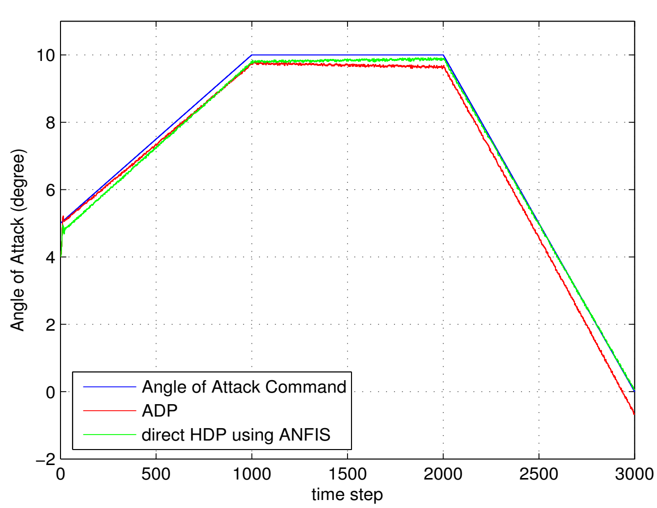


Fig. 7. Experimental Result of attach angle with parameter uncertainties

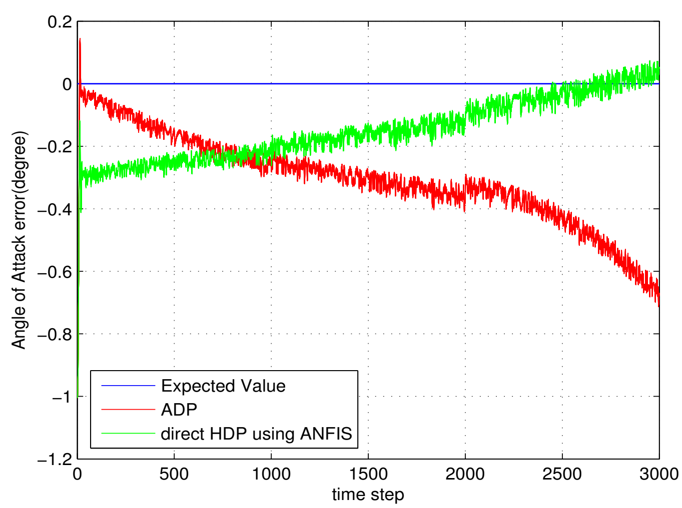
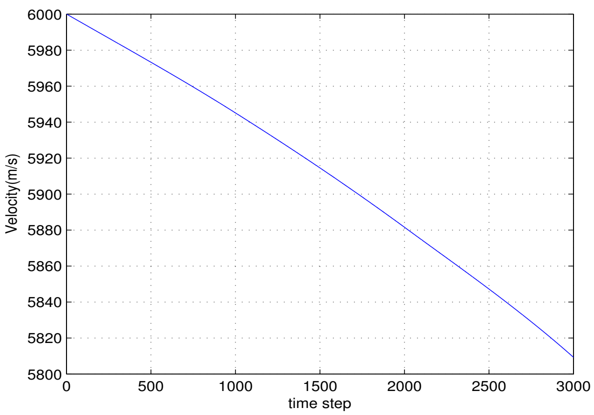
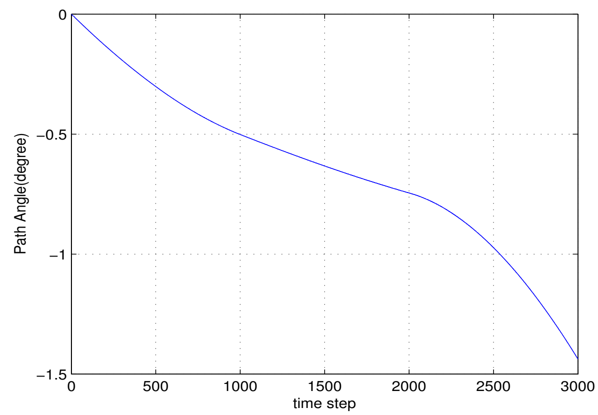


Fig. 8. Tracking error with parameter uncertainties

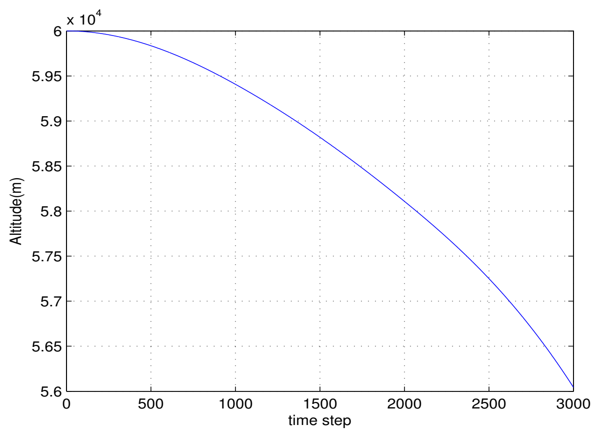
critic designs and Q-learning to achieve optimal control. Considering the highly time-varying changes of hypersonic vehicle and the difficulty in measuring and estimating the aerodynamic characteristics, we embed ANFIS in the critic network and action network of direct HDP to achieve better fault-tolerance performance. To make sure that the estimation errors of the weights in our approach remain UUB, we give a simple sufficient condition for the selection of the



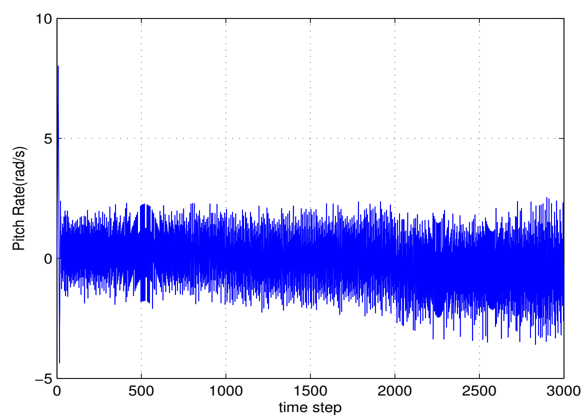
(a) Velocity



(b) Path Angle



(c) Altitude



(d) Pitch Rate

Fig. 9. Experimental results with parameter uncertainties

learning rates in direct HDP related to the number of fuzzy rules in ANFIS. Simulation results prove the practicality and efficiency of our proposed method.

ACKNOWLEDGMENT

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