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A Back-Stepping Controller Scheme for Altitude Subsystem of Hypersonic Missile with ANFIS Algorithm

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Abstract

In this paper, we propose a back-stepping controller scheme for the altitude subsystem of hypersonic missile of which model is nonlinear, non-minimum phase, uncertain, and highly coupled. In the scheme, the guidance law is selected as a desired flight path angle that derived from the sliding mode control method. The back-stepping technique is designed and analyzed for the altitude dynamics of hypersonic missiles for maneuvering targets. Additionally, the algorithm of adaptive neuro-fuzzy inference system (ANFIS) is used for estimating the uncertainty of model parameters and Lyapunove theorem is used to examine the stability of closed-loop systems. The simulation indicates that the proposed scheme has shown effectiveness of the control strategy, high accuracy, stability of states, and low-amplitude control inputs in the presence of uncertainties with external disturbance.

Keywords: *Hypersonic Missile, Adaptive Neuro-Fuzzy Inference System (ANFIS), Back-Stepping, Maneuvering Target.*

1. Introduction

The longitudinal model of a hypersonic missile is unstable, nonlinear, non-minimum phase, and highly coupled. The hypersonic missile dynamic is very sensitive to changes in physical and aerodynamic parameters in flight conditions such as high altitude and Mach number for velocity. The Structural feature of hypersonic missile dynamic is based on how the pitch angle and the pitch rate will change greatly in the end phase and it leads to collision error. In order to solve the dynamic changes problem, researchers have started to pay more attention to solving the problem. Back-stepping design [1-4] is a powerful method for designing the controller for hypersonic vehicles. This method makes the design of the feedback control strategy systematic and it consists of recursive determination of the virtual control signal at each step.

This method can guarantee the stability of the system and improves the robustness at the end phase of attack. The dynamic of HM is decoupled to velocity and altitude subsystems that have been transformed into the discrete form [5] and it used back-stepping for control law and neural network for approximating the uncertainties. In [6], considering the parametric model uncertainty and input saturation, the dynamic inverse control is present via back-stepping design in which the dynamic surface control is used. In [7], an integrated guidance and control in three-dimensional space for hypersonic missile which was constrained by impact angle is given. Fuzzy modeling, specially modeling based on T-S fuzzy systems, allow to approximate highly accurate models from a small number of rules, which can work online with the system, properly in the presence of noise, and can be very efficient computationally

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[8-11]. T-S fuzzy modeling is useful for approximating complex nonlinear systems by local linear submodel and fuzzy membership function. In order to approximate the model uncertainties, in [12-16] the unknown parameters are approximated by fuzzy and neural systems. Robust multi-objective H_2 / H_∞ tracking control based on the Takagi–Sugeno fuzzy model for a class of nonlinear uncertain drive systems is presented in [17].

In this paper, the desired flight path angle according to the sliding mode control guidance is given [18] for the altitude subsystem. The design of a MIMO adaptive controller is presented for the altitude subsystem of HM based on back-stepping for maneuvering targets in the presence of uncertainties. In this paper, in order to estimate the uncertainties, ANFIS method is used to approximate HM dynamic uncertainties with higher modeling accuracy. Because ANFIS consists of both artificial neural network (ANN) and fuzzy logic (FL) based on mapping relation between the input and output data by using hybrid learning method to determine the optimal distribution of membership functions in order to estimate the uncertainties, it causes in more accurate model for the better performance of the control laws which resulted in reduce collision error and angle changes in the end phase.

This paper is organized as follows: Section 2 presents the HM model, the discrete model according to Euler expansion is given in Section 3, the proposed controller based on back-stepping, ANFIS parameters estimation, and the stability analyze base on lypanuve are present in Section 4, the results of the simulation are included in Section 5, and in the end, section 6 presents the conclusion.

2. Hypersonic Missile Model

In this paper, the model for the longitudinal dynamic of HM is considered from [19]. This model is comprised of five state variables $X = [v, h, \alpha, \gamma, q\,]$ and two control inputs $u_c = [\,\zeta_e\,, \beta]$, where v is the velocity, h is the altitude, α is the angle of attack, γ is the flight path angle, q is the pitch rate, ζ_e is the elevator deflection, and β is the throttle setting. The relationships between the variables are in equations (1) to (5):

$$\dot{v} = \frac{T\cos\alpha - D}{m} - g\sin\gamma \tag{1}$$

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

$$\dot{\gamma} = \frac{L + T\sin\alpha}{mv} - \frac{g\cos\gamma}{v} \tag{3}$$

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

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

Where:

$\bar{q} = \frac{1}{2}\rho v^2$, $L = \frac{1}{2}\bar{q}SC_L$, $D = \frac{1}{2}\bar{q}SC_D$, $T = \frac{1}{2}\bar{q}SC_T$, $M_{yy} = \bar{q}Sc[C_M(\alpha) + C_M(\zeta_e) + C_M(q)]$, $C_L = 0.6203\alpha$

$C_D = 0.6450\alpha^2 + 0.0043378\alpha + 0.003772$

$C_M(q) = (c/2v)q(-6.796\alpha^2 + 0.3015\alpha + 0.2289)$

$C_M(\alpha) = -0.035\alpha^2 + 0.036617\alpha + 5.3261\times10^{-6}$

$C_M(\zeta_e) = 0.0292(\zeta_e - \alpha)$

$$C_T = \begin{cases} 0.02576\beta & \text{if } \beta < 1 \\ 0.0224 + 0.00336\beta & \text{otherwise} \end{cases}$$

The force and the moment coefficients are listed in table1.

Table 1. Force and the Moment Coefficients

Coefficient	Value	Unit
S	1.7000×10^{-1}	$ft^2.\ ft^2$
Iyy	5.0000×10^{5}	lb. ft
m	3.0000×10^{2}	lb. ft
g	3.2000×10	$ft.\ s^{-2}$
ρ	6.7429×10^{-5}	$Slugs.ft^3$
C	1.7000×10	ft

3. Discrete-Time Model

According to equations (1) - (5), we can decouple the model into two subsystems. The first one is the velocity subsystem and the second one is the altitude subsystem. According to Euler expansion for the sampling period T_s, discrete time model of altitude is written. Where the altitude is related to elevator deflection. The altitude loop has to track maneuvering targets according to desired control inputs.

3.1. The Altitude Subsystem

The altitude command is transformed into the flight path angle tracking. According to the sliding mode control, the demand of flight path angle is generated as:

$$\gamma_d = \sin^{-1}\left(\frac{-k_h\tilde{h}+\dot{h}_r}{v}\right) \quad (6)$$

Where $k_h > 0$ is the design parameter, and the altitude tracking error is defined as: $\tilde{h} = h - h_d$. We define $X_h = [\gamma, \theta, q]$, where $\theta = \gamma + \alpha$, the altitude subsystem (3) - (5) can be rewritten in the following form:

$$\dot{\gamma} = f_\gamma(\gamma) + g_\gamma(\gamma)\,\theta \quad (7)$$

$$\dot{\theta} = f_\theta(\gamma,\theta) + g_\theta(\gamma,\theta)q$$

$$\dot{q} = f_q(\gamma,\theta,q) + g_q(\gamma,\theta,q)u_q$$

$$u_q = \zeta_e$$

$$y_h = \gamma$$

Where:

$$f_\gamma = -\frac{g\cos\gamma}{v} + \frac{T}{mv} - 0.6203\bar{q}S\gamma/mv,$$

$$g_\gamma = 06203\,\bar{q}S/mv, f_\theta = 0, \quad g_\theta = 1,$$

$$g_q = 0.0292\bar{q}Sc/mv$$

$$f_q = \bar{q}Sc[CM(\alpha) + CM(\zeta e) + CM(q)]/I_{yy}$$

In the same way, we can achieve the altitude discrete subsystem from (7) in the following form:

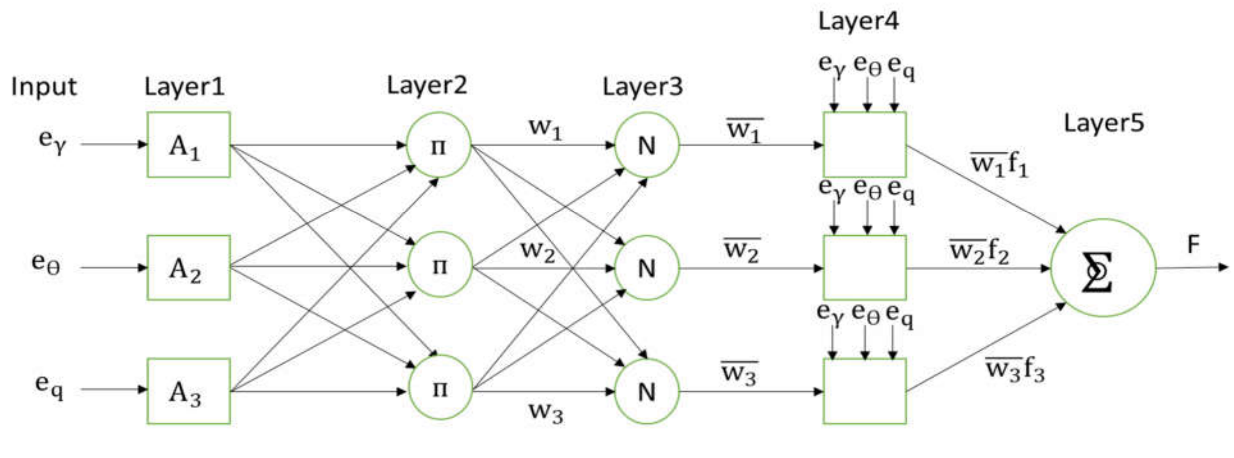

Fig. 1. Structure of ANFIS method.

$$\gamma(k+1) = \gamma(k) + T_s[f_\gamma(k) + g_\gamma(k)\theta(k)]$$

$$\theta(k+1) = \theta(k) + T_s[f_\theta(k) + g_\theta(k)q(k)] \quad (8)$$

$$q(k+1) = q(k) + T_s[f_q(k) + g_q(k)u_q(k)]$$

4. Discrete-Time Controller

In this paper, we aimed to design a back-stepping controller for the altitude loop. The proposed controller is designed for maneuvering targets. Three steps back-stepping controller designed. In the presence of uncertainties, the proposed controller can guarantee the stability of closed-loop systems and forces the tracking error of all states to zero. The control design problem is to select u_c= [ζe], so that the altitude track the desired commanded value γ_d. The novelty in this paper is the algorithm of ANFIS which is used for approximating the uncertainties of the dynamic and it is a very powerful method in order to approximate a higher accuracy model based on input-output data. Neuro-adaptive learning techniques are used to calculate the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data which are variable during the learning process. The fuzzy inference system is modeling the input/output data according to TS-Fuzzy algorithm. T-S fuzzy weights are achieved based on the membership function, and Gaussian membership function is used for Takagi-Sugeno fuzzy estimator.

4.1. Controller Design for Altitude Loop

Define $e_\gamma(k) = \gamma(k) - \gamma_d(k)$, and $\gamma_d(k)$ is given in (6). Then,

$$e_\gamma(k+1) = \gamma(k) + T_s[f_\gamma(k) + g_\gamma(k)\theta(k)] - \gamma_d(k+1) \quad (9)$$

Then, the desired control input achieved as:

$$\theta_d(k) = g_\gamma(k)^{-1}\left[\frac{1}{Ts}\left[(z_1 e_\gamma(k) - \gamma(k) + \gamma_d(k+1)\right] - f_\gamma(k)\right] \quad (10)$$

$\gamma_d(k+1)$ and $f_\gamma(k)$ are unknown functions. The uncertainties defined as:

$$f_1 = -\gamma(k) + \gamma_d(k+1) - T_S f_\gamma(k) \quad (11)$$

Define $e_\theta(k) = \theta(k) - \theta_d(k)$, and $\theta_d(k)$ is given in (10). Then,

$$e_\theta(k+1) = \theta(k) + T_s[f_\theta(k) + g_\theta(k)q(k)] - \theta_d(k+1) \quad (12)$$

The desired control input is given as:

$$q_d(k) = g_\theta(k)^{-1}\left[\frac{1}{Ts}\left[(z_2 e_\theta(k) - \theta(k) + \theta_d(k+1)\right] - f_\theta(k)\right] \quad (13)$$

$\theta_d(k+1)$ And $f_\theta(k)$ are unknown functions. Thus, the uncertainty is defined as:

$$f_2 = -\theta(k) + \theta_d(k+1) - T_S f_\theta(k) \quad (14)$$

Define $e_q(k) = q(k) - q_d(k)$, and $q_d(k)$ is given in (13). Then,

$$e_q(k+1) = q(k) + T_s[f_q(k) + g_q(k)u(k)] - q_d(k+1) \quad (15)$$

The desired control input given as:

$$u(k) = g_q(k)^{-1}\left[\frac{1}{Ts}\left[(z_3 e_q(k) - q(k) + q_d(k+1)\right] - f_q(k)\right] \quad (16)$$

$q_d(k+1)$ And $f_q(k)$ are unknown functions. Thus, the uncertainty is defined as:

$$f_3 = -q(k) + q_d(k+1) - T_S f_q(k) \quad (17)$$

4.2. ANFIS Method

In this section, the algorithm of an adaptive neuro-fuzzy inference system (ANFIS) is designed and analyzed for the system to approximate the unknown functions. A brief definitions about the principles of ANFIS are given which are based on [20]. This algorithm is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. (ANFIS) consists both artificial neural network (ANN) and fuzzy logic (FL) which gives the mapping relation between the input and output data by using hybrid learning method to determine the optimal distribution of membership functions. The ANFIS has the advantage of good applicability as it can be interpreted as local linearization modeling and conventional linear techniques for state estimation and control are directly applicable in comparison with other algorithms. A network obtained this way could use excellent training algorithms that neural networks have at their disposal to obtain the parameters that would not have been possible in fuzzy logic architecture. Neuro-adaptive learning techniques are responsible for computing the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data which are variable during the learning process. The fuzzy inference system is modeling the input/output data according to TS-Fuzzy algorithm. The structure of the mentioned method compromises into 5 layers that each on has several nodes according to node function. In the first layer, the input values as error of states are given in order to determine the membership functions which is commonly called fuzzification layer. The second layer is responsible for generating the firing strengths of the rules. Due to its task, the second layer is denoted as "rule layer". Next in the third layer, computed firing strengths by diving each value for the total firing strength are normalized. In the fourth layer, normalized values are given as input and the mentioned parameters are adjusted. The values returned by this layer are the defuzzification ones and those values are passed to the last layer to return the final output. The structure of ANFIS method has shown in figure (1).

- **Layer 1**: Each node in this layer is a square node with a node functions as follow:

$$O_{1,1}=\mu\, A_1(e_\gamma(k)), A_1(e_\gamma(k+1)) = \exp\left\{-\left(\frac{e_\gamma(k+1)-a_{q1}}{b_{q1}}\right)^2\right\}$$

$$O_{1,2}= \mu\, A_2(e_\theta(k)), A_2(e_\theta(k+1))= \exp\left\{-\left(\frac{e_\theta(k+1)-a_{q2}}{b_{q2}}\right)^2\right\}$$

$$O_{1,3}= \mu\, A_3(e_q(k)), A_3(e_q(k+1))= \exp\left\{-\left(\frac{e_q(k+1)-a_{q3}}{b_{q3}}\right)^2\right\}$$

Where$e_\gamma(k)$, $e_\theta(k)$ and $e_q(k)$ are the input nodes and A_1, A_2 and A_3 are the membership function which are usually adopted to a bell shape with maximum and minimum equal to 1 and 0 respectively. a_{qi} and b_{qi} i=1, 2, 3 are center and standard deviation of Gaussian function.

Layer 2: In this layer, every node is multiple the incoming signals.

$$W_{1,2,3}= \mu\, A_1(e_\gamma(k))\times\mu\, A_2(e_\theta(k))\times\mu\, A_3(e_q(k)) \quad (18)$$

The output $W_{1,2,3}$ represents the firing strength of a rule.

Layer 3: Every node in this layer is a fixed node, marked by a circle and labeled N, with the node function to normalize the firing strength by calculating the ratio of the i[th] node firing strength to the sum of all rules' firing strength.

$$O_{3,i} = \overline{W_i} = \frac{W_i}{W_1+W_2+W_3}, \text{ for } i=1,2,3 \quad (19)$$

Layer 4: Every node in this layer is an adaptive node, marked by a square, with node function.

$$O_{4,i}= \overline{W_i}\, f_i, \text{ for } i=1,2,3 \quad (20)$$

Where f_i for i=1,2,3 are the fuzzy if-then rules as follow:

Rule 1: If $e_\gamma(k+1)$ is $A_{1k}(e_\gamma(k+1))$ then $f_1 = \sum_{k=1}^{n}\theta_1(k)\, e_\gamma(k+1)$ (21)

Rule 2: If $e_\theta(k+1)$ is $A_{2k}(e_\theta(k+1))$ then $f_2 = \sum_{k=1}^{n}\theta_2(k)\, e_\theta(k+1)$ (22)

Rule 3: If $e_q(k+1)$ is $A_{3k}(e_q(k+1))$ then $f_3 = \sum_{k=1}^{n}\theta_3(k)\, e_q(k+1)$ (23)

Layer 5: Every node in this layer is a fixed node, with the node function to compute the overall output by Equation (24).

$$O_{5,i}= \sum_{i=1}^{3}\overline{W_i}\, f_i \quad (24)$$

4.3. Stability

The control Lyapunov function candidate for flight path angle is selected as:

$$L_\gamma(k) = \frac{1}{2}\left(e_\gamma^2(k) + \tilde{w}_1^T(k)\Gamma^{-1}\tilde{w}_1(k)\right) \quad (25)$$

The first difference from (25) is obtained as:

$$\Delta L_\gamma(K) = L_\gamma(k+1) - L_\gamma(k) = \frac{1}{2}\Big(e_\gamma^2(k+1) - e_\gamma^2(k)) + \frac{1}{2}(\tilde{w}_1^T(k+1)\Gamma^{-1}\tilde{w}_1(k+1) - \tilde{w}_1^T(k)\Gamma^{-1}\tilde{w}_1(k)\Big) \quad (26)$$

From (9) and (10), it can be concluded:

$$e_\gamma(k+1) = z_1 e_\gamma(k) - f_1(k) - \varepsilon_1 \quad (27)$$

Then,

$$e_\gamma^2(k) = \frac{1}{z_1}\left[e_\gamma(k)e_\gamma(k+1) + f_1(k)e_\gamma(k) + \varepsilon_1 e_\gamma(k)\right] \quad (28)$$

With placement (28) into (26):

$$\Delta L_\gamma(K) = \frac{1}{2}\left[-\frac{f_1(k)e_\gamma(k)}{z_1} - \frac{\varepsilon_1 e_\gamma(k)}{z_1}\right] + \frac{1}{2}(\tilde{w}_1^T(k+1)\Gamma^{-1}\tilde{w}_1(k+1) - \tilde{w}_1^T(k)\Gamma^{-1}\tilde{w}_1(k) \quad (29)$$

$\Gamma < 0$ So, $\Delta L_\gamma(K) < 0$.

Define the Lyapunov function candidate for pitch angle is selected as:

$$L_\theta(k) = \frac{1}{2}(e_\theta^2(k) + \tilde{w}_2^T(k)\Gamma^{-1}\tilde{w}_2(k)) \quad (30)$$

Then,

$$\Delta L_\theta(K) = \frac{1}{2}\left[-\frac{f_2(k)e_\theta(k)}{z_2} - \frac{\varepsilon_2 e_\theta(k)}{z_2}\right] + \frac{1}{2}(\tilde{w}_2^T(k+1)\Gamma^{-1}\tilde{w}_2(k+1) - \tilde{w}_2^T(k)\Gamma^{-1}\tilde{w}_2(k) \quad (31)$$

$\Gamma < 0$ So, $\Delta L_\theta(K) < 0$.

Define the Lyapunov function candidate for pitch rate is selected as:

$$L_q(k) = \frac{1}{2}\left(e_q^2(k) + \tilde{w}_3^T(k)\Gamma^{-1}\tilde{w}_3(k)\right) \quad (32)$$

Then,

$$\Delta L_q(K) = \frac{1}{2}\left[-\frac{f_3(k)e_q(k)}{z_3} - \frac{\varepsilon_3 e_q(k)}{z_3}\right] + \frac{1}{2}(\tilde{w}_3^T(k+1)\Gamma^{-1}\tilde{w}_3(k+1) - \tilde{w}_3^T(k)\Gamma^{-1}\tilde{w}_3(k) \quad (33)$$

$\Gamma < 0$ So, $\Delta L_q(K) < 0$.

5. Simulation

In this section, the simulation results are compared with the results of [21]. In [21], the back-stepping method is used for the controller and T-S fuzzy law is used for approximating the uncertainty. In this study, an upward maneuvering target is considered. In the simulation shapes, time units are considered in second. The hypersonic missile starts from the state as v = 15000 ft/s, h = 118110 ft, α = 0 deg, ϴ = 0 deg, and γ = 0 deg. The target states is v = 2780 ft/s and h = 118210 ft. The reference commands are generated by the filter [5]:

$$\frac{h_T}{h_M} = \frac{0.16^2}{((K+2)+0.7\ 6(K+1)+0.16)^2} \quad \text{M=missle, T= target}$$

$$\frac{v_T}{v_M} = \frac{0.16^2}{((K+2)+0.7\ 6(K+1)+0.16)^2}$$

Some of the control parameters in the proposed method are selected as: $z_1 = 0.95$, $z_2 = 0.9$ from relevant references such as [21] and other control parameters are achieved based on the tried and error method for better accuracy and effectiveness of the proposed method. The dynamic gains for the controller are selected as: $z_3 = 0.95$, $\varepsilon = 0.1$ and $T_S = 0.01$.

The initial value for weight was designed at $w_i = 0.001$, i = 1, 2, 3, and Γ is negative. Parameters of the membership functions are selected as: $a_{q1} = 0.5$, $a_{q2} = 0.4$, $a_{q3} = 0.7$ and $b_{q1} = 5$, $b_{q2} = 3$, $b_{q3} = 4$. The attack angle, flight path angle, altitude, elevator deflection and estimation weights for altitude loop are shown in figures (2) - (6). The altitude tracking has shown that the target has upward maneuvering which HM tracks the trajectory calculated by guidance law. From the angle of attack and the flight path angle figures, it can be concluded that the altitude control law track desired value of flight path angle and the attack angle are concluded by guidance law. Another positive outcome from these figures for the proposed method in comparison the reference paper refers to reduce angle changes and collision error in the end phase which is resulted from higher accuracy approximating the dynamic uncertainties by ANFIS estimator.

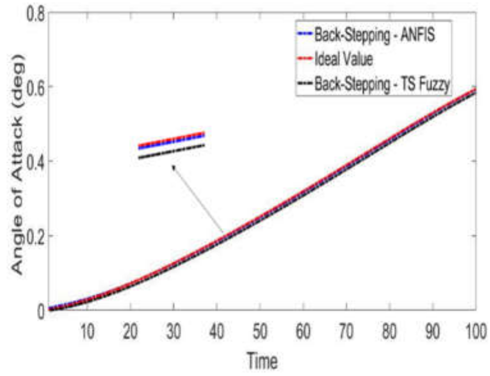

Fig. 2. Angle of attack.

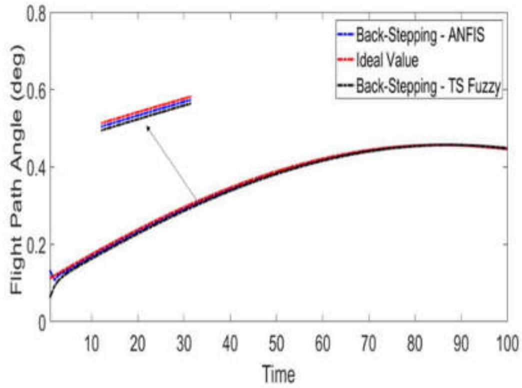

Fig. 3. Flight path angle.

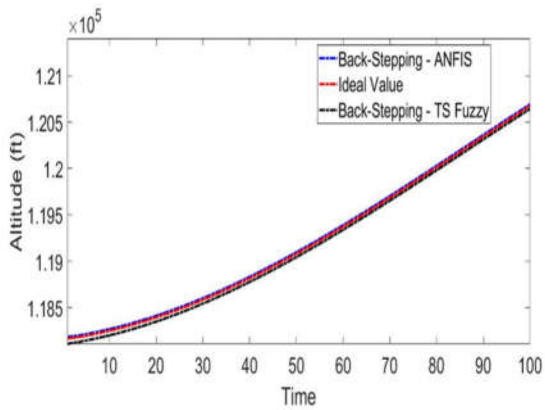

Fig. 4. Altitude

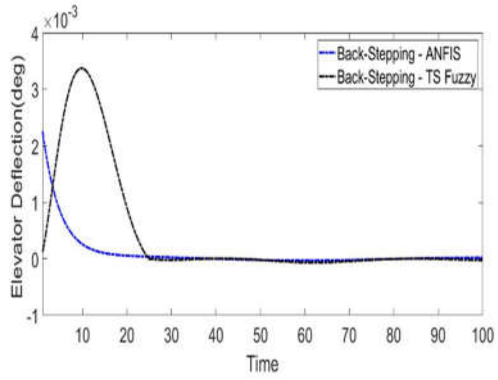

Fig. 5. Elevator Deflection

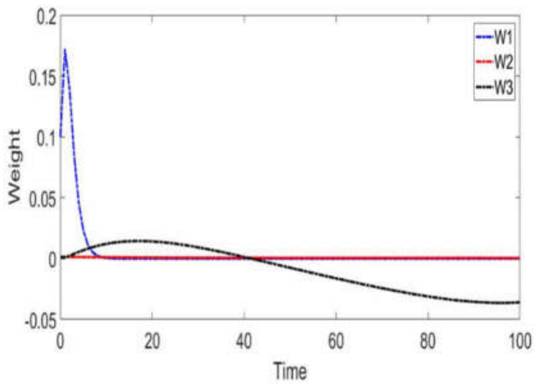

Fig. 6. Weights

From figure (4) it can be concluded that the proposed controller can guarantee the stability of the closed-loop systems and forces the tracking of altitude to attack a target. Due to figure (5) it is noticeable that except better performance of the closed-loop system which contains fewer collision error and fluctuates response, the amount of control cost for the proposed method is lesser in comparison with [21]. Simulations showed the high accuracy and effectiveness of proposed guidance and control law with applying ANFIS estimation for approximate the uncertainty of HM dynamic.

Finally, numerical index is given in table 2 which shows sum of squared errors and sum of squared control signals for the proposed method in comparison with [21]. The numerical data confirms that proposed method has better performance and fewer control costs.

Table. 2. Numerical Index

Name of Index	Proposed Method	Reference paper [21]
$\sum_{k=1}^{n}(\mathbf{u2}(\mathbf{k}))^2$	0.0007	0.0019
$\sum_{k=1}^{n}(\mathbf{e}_\gamma(\mathbf{k}) + \mathbf{e}_\theta(\mathbf{k}) + \mathbf{e}_q(\mathbf{k}))^2$	0.0265	0.0349

6. Conclusion

In this paper, the altitude dynamic of the hypersonic missile was transformed into discrete form based on Euler expansion formula. Taking the target maneuvered into consideration, the guidance law was generated for the altitude subsystem as flight path angle. The proposed method considered Back-Stepping Controller with adaptive neuro-fuzzy inference system (ANFIS) algorithm to approximate the uncertainties in discrete form. By comparing the proposed method for approximating the uncertainties with T-S fuzzy in the reference paper it can be concluded that, (ANFIS) estimator obtains better accurate models which resulted in better precision for performance of the control laws and reduce of collision error and the better performance to keep angles on desired values in the end phase. The simulation results have shown the high accuracy, stability of the states, lower oscillation, and effectiveness of control laws in the presence of uncertainty.

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