Sensors & Transducers, Vol. 174, Issue 7, July 2014, pp. 292-297

Sensors & Transducers

Near Space Hypersonic Unmanned Aerial Vehicle Dynamic Surface Backstepping Control Design

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Received: 18 April 2014 /Accepted: 30 June 2014 /Published: 31 July 2014

Abstract: Compared with traditional aircraft, the near space hypersonic unmanned aerial vehicle control system design must deal with the extra prominent dynamics characters, which are differ from the traditional aircrafts control system design. A new robust adaptive control design method is proposed for one hypersonic unmanned aerial vehicle (HSUAV) uncertain MIMO nonaffine block control system by using multilayer neural networks, feedback linearization technology, and dynamic surface backstepping. Multilayer neural networks are used to compensate the influence from the uncertain, which designs the robust terms to solve the problem from approach error. Adaptive backstepping is adopted designed to ensure control law, the dynamic surface control strategy to eliminate "the explosion of terms" by introducing a series of first order filters to obtain the differentiation of the virtual control inputs. Finally, nonlinear six-degree-of-freedom (6-DOF) numerical simulation results for a HSUAV model are presented to demonstrate the effectiveness of the proposed method.

Keywords: Hypersonic ummanned aerial vehicle, Neural networks, Dynamic surface, Backstepping.

1. Introduction

Hypersonic ummanned aerial vehicle control technology has attracted a lot of attention in recent years because of highly nonlinear dynamics and high Mach velocity [1-3]. Wang [4] adopted adaptive sliding controller to analyze the longitudinal dynamics of a generic hypersonic air vehicle. Shtessel [5] designed inner and outer sliding mode controller loop to investigate the reentry of hypersonic vehicles, Austin [6] use fuzzy logic control to compensate the unknown nonlinearities, genetic algorithm to optimize the scaling parameters of fuzzy controller. A kind of neural adaptive controller for hypersonic ummanned aerial vehicle is proposed by Xu, Mirmirani and Ioannou [7]. A few recent contributions have also attempted design directly on nonlinear models [8-10]. Most research results were restricted to linearly parameterized and state feedback linearizable.

Different from above work, the paper investigate a MIMO nonaffine nonlinear hypersonic unmanned aerial Vehicle model with general set of uncertainties. Dynamic surface backstepping controller is designed based on Radial-Basis-Function (RBF) neural networks approach. Stability analysis is also shown by the Lyapunov stability theory. Finally, a numerical simulation of a 6-DOF

HSUAV model is preformed to verify the effectiveness of the proposed algorithm and the conclusions are given.

2. Nonlinear HSUAV Model

Winged-cone [1] is one of the main investigate objects with its hypersonic mach number and open aerodynamic parameters, but most research is based on its longitudinal channel model. In this paper we finished Winged-cone's three-axes, highly nonlinear model with general set of uncertainties. The nonlinear dynamic equations are given as follows

$$\dot{x}_1 = f_1(x_1, x_2), \tag{1}$$

$$\dot{x}_2 = f_2(x_2) + b_1(x_2)x_3 + h_1(x_2)u, \tag{2}$$

$$\dot{x}_3 = f_3(x_2, x_3) + b_2 u, \tag{3}$$

We assume that f_1, b_1, h_1, f_2, f_3 and b_2 are unknown and $f_2 = f_{20} + \Delta f_2$, $b_1 = b_{10} + \Delta b_1$, $f_3 = f_{30} + \Delta f_3$, $b_2 = b_{20} + \Delta b_2$, $h_1 = h_{10} + \Delta h_1$, where f_{10}, b_{10}, h_{10}, f_{20}, b_{20} are nominal system parameters, the others are uncertainties. $x_1 = [V\ \ \theta\ \ \psi_c]^T, x_2 = [\alpha\ \ \beta\ \ \mu]^T$, $x_3 = [p\ \ q\ \ r]^T$, $u = [\delta_e\ \ \delta_a\ \ \delta_r]^T$.

The task of the controller is to track the commands signals when aerodynamic model uncertainties exist.

Assumption 1: Ignoring the effect of the fin deflection on the aerodynamic force and viewing it as a part of the uncertainties, namely $h_1(x_1) = 0$.

3. Controller Design

3.1. RBF Neural Network

In the controller design RBF NN is used to approximate the unknown function $\phi(\cdot)$. In a compact set, RBF NN can be expressed as

$$\hat{\phi}(\cdot) = \hat{W}S^T(\cdot), \tag{4}$$

where $\hat{W} \in R^p$ is the tuning weight matrix and $\phi(\cdot)$ is the vector composed of Gauss functions. Given a smooth function $\phi(\cdot)$, where Ω is the compact subset of R^m, and $\delta > 0$, there exist a Gauss function vector $S: R^m \mapsto R^p$ and an optimal weight matrix W^* such that $|\phi(x) - W^* S^T(x)| \le \delta,\ \forall x \in \Omega$. Define

$$h(x) - W^* S^T(x) \overset{\Delta}{=} \Delta h(x), \tag{5}$$

as NN reconstruction error. The optimal weight matrix W^* is only used in the analysis.

Assumption 2: Given a smooth function $\phi(\cdot)$ and NN estimator (6), there exists a optimal weight matrix W^* such that $|\Delta\phi(x)| \le \varepsilon_h$, where $\varepsilon_h > 0$ is a constant, $\forall x \in \Omega_x \subset R^m$, and m is the dimension of the input space.

Assumption 3: There exists constant $g_{iu} > g_{i0} > 0$ to make

$$\begin{aligned} 0 < g_{i0} < \left| g_i(\bar{x}_i, x_{i+1}) := \partial f_i(\bar{x}_i, x_{i+1}) / \partial x_{i+1} \right| \\ \le g_{iu} < \infty, \forall \bar{x}_n \in \Omega, i = 1, \ldots, n-1 \end{aligned}.$$

3.2. Dynamic Surface Backstepping Controller Design

Step 1, Define error surface $z_1 = x_1 - x_{1d}$, $x_{1d} = [V_d\ \ \theta_d\ \ \psi_{cd}]^T$ is the system anticipant track, z_1 derivative is

$$\dot{z}_1 = f_1(x_1, x_2) - \dot{x}_{1d}, \tag{6}$$

Defining $v_1 = -\dot{x}_{1d} + k_1 z_1, k_1 > 0$. By using Assumption 2 and $\partial v_1 / \partial x_2 = 0$, we can get the following inequality

$$\partial\left[f_1(x_1, x_2) + v_1 \right] / \partial x_2 > g_{10} > 0$$

From literature [11] we can get that there has an ideal virtual control function $x_2 = x_{2d}^*(x_1, v_1)$, so

$$f_1(x_1, x_{2d}^*) + v_1 = 0, \tag{7}$$

Suppose

$$f_1(x_1, x_2) = f_1(x_1, x_{2d}^*) + g_{1\lambda_1}(x_2 - x_{2d}^*), \tag{8}$$

$$\begin{aligned} x_{2\lambda_1} = \lambda_1 x_2 + (1 - \lambda_1)x_{2d}^*, g_{1\lambda_1} := g_1(x_1, x_{2\lambda_1}), \\ 0 < \lambda_1 < 1 \end{aligned}$$

According to function (6), (7), so that

$$\dot{z}_1 = -k_1 z_1 + g_{1\lambda_1}(x_2 - x_{2d}^*), \tag{9}$$

Suppose

$$x_{2d}^{*} = x_{2d0} + W_1^{*T} S_1\left(V_1^{*T} X_1\right) + \varepsilon_1, \qquad (10)$$

where x_{2d0} is the certain part of x_{2d}^{*}, Multilayer NN $W_1^{*T} S_1\left(V_1^{*T} X_1\right) + \varepsilon_1$ can be used to approach the uncertain part of x_{2d}^{*},where X_1 is the input of above NN, $|\varepsilon_1| \le \varepsilon_{1u}$ s the NN approaching error, and $\varepsilon_{1u} > 0$.

Considering x_{2d}^{*} is hard to be acquired in the factual controller design. Introduce a new state variable x_{2d}, which can be obtained by the following first-order filter

$$\begin{gathered} \delta_2 \dot{x}_{2d} + x_{2d} = \overline{x}_{2d}, x_{2d}(0) = \overline{x}_{2d}(0) \\ \overline{x}_{2d} = -l_1 z_1 + \dot{x}_{1d}, \end{gathered} \qquad (11)$$

Then we choose desired virtual control value as follow

$$x_{2d} = -l_1 z_1 + x_{2d0} + \hat{W}_1^T S_1\left(\hat{V}_1^T X_1\right) + r_1, \qquad (12)$$

where $c_1 > 0$ is the designed parameter, r_1 is the inducted robust item and will be embodied as follow.

Define error state value as $z_2 = x_2 - x_{2d}$, then the dynamic function of error state value z_1, then

$$\begin{aligned} \dot{z}_1 &= -k_1 z_1 + g_{1\lambda_1}\left(z_2 + x_{2d} - x_{2d}^{*}\right) = -k_1 z_1 + g_{1\lambda_1}\left(z_2 - c_1 z_1\right) \\ &+ g_{1\lambda_1}\left[\tilde{W}_1^T\left(\hat{S}_1 - \hat{S}_1' \hat{V}_1^T X_1\right) + \hat{W}_1^T \hat{S}_1' \tilde{V}_1^T X_1 + d_{u1} - \varepsilon_1 + r_1\right], \end{aligned} \qquad (13)$$

Suppose

$$V_1 = \frac{1}{2g_{1\lambda_1}} z_1^2 + \frac{1}{2}\tilde{W}_1^T \Gamma_{W1}^{-1} \tilde{W}_1 + \frac{1}{2} tr\left\{\tilde{V}_1^T \Gamma_{V1}^{-1} \tilde{V}_1\right\}, \qquad (14)$$

where $\Gamma_{W1} = \Gamma_{W1}^T > 0, \Gamma_{V1} = \Gamma_{V1}^T > 0$ are the parameters to be designed. Taking the time derivative of V_1, we have

$$r_1 = -z_1\left(\left\|X_1 \hat{W}_1^{T} \hat{S}_1'\right\|_F^2 + \left\|\hat{S}_1' \hat{V}_1^{T} X_1\right\|^2 + 1/2\right) / \eta_1, \qquad (15)$$

$$\begin{aligned} \dot{\hat{W}}_1 &= \Gamma_{W1}\left[-\left(\hat{S}_1 - \hat{S}_1' \hat{V}_1^T X_1\right) z_1 - \sigma_{W1} \hat{W}_1\right] \eta_1 > 0, \\ \dot{\hat{V}}_1 &= \Gamma_{V1}\left[-X_1 \hat{W}_1^T \hat{S}_1' z_1 - \sigma_{V1} \hat{V}_1\right] \end{aligned} \qquad (16)$$

Step 2, By the error surfaces $z_2 = x_2 - x_{2d}$. So we have

$$\dot{z}_2 = f_{10}(x_2) + b_{10}(x_2) x_3 - \dot{x}_{2d} + \left(\Delta f_2(x_2) + \Delta b_1(x_2) x_3\right) \qquad (17)$$

$$= f_{20}\left(x_2\right) + b_{10}\left(x_2\right) x_3 - \dot{x}_{2d} - \Delta,$$

with $\Delta = -(\Delta f_1(x_2) + \Delta b_1(x_2) x_3)$ is the uncertain term. By employing the neural approximator to approximate Δ.

Step 3, Define the error surfaces $z_3 = x_3 - x_{3d}$. In this step, we consider the third equation of (8) to design the actual control input for the hypersonic aircraft. Let x_{3d} pass through a first-order filter, a new state variable x_{3d} can be obtained

$$\begin{gathered} \delta_3 \dot{x}_{3d} + x_{3d} = \overline{x}_{3d}, x_{3d}(0) = \overline{x}_{3d}(0) \\ \overline{x}_{3d} = -l_2 z_2 + \dot{x}_{2d}, \end{gathered} \qquad (18)$$

After differentiating the error surface z_3, we get

$$\dot{z}_3 = c_3\left(f_3 + b_2 u - \dot{x}_{3d}\right), \qquad (19)$$

We propose an ideal control input

$$u^{*} = -b_3^{-1}\left(k_3 z_3 + f_3\left(x_2, x_3\right) - \dot{x}_{3d}\right) + b_{20}^T\left(x_2\right) z_2 + k z_3, \qquad (20)$$

Such that

$$\begin{aligned} \dot{z}_3 &= f_3\left(x_2, x_3\right) + b_2 u - \dot{x}_{3d} + b_2 u^{*} - b_2 u^{*} \\ &= -l_2 z_3 + b_2\left(k z_3 + b_{10}^T\left(x_2\right) z_2\right) + b_2\left(u - u^{*}\right), \end{aligned} \qquad (21)$$

where $k_2, k > 0$ are the design parameters. Here u^{*} is not available. Assume

$$\begin{aligned} u^{*} &= -b_{20}^{-1}\left(l_2 z_3 + f_{30} - \dot{x}_{3d}\right) \\ &+ b_{10}^T z_2 + k z_3 + W_3^{*T} S_3\left(\hat{V}_3^{*T} X_3\right) + \varepsilon_3 \end{aligned}, \qquad (22)$$

and choose the control input

$$\begin{aligned} u &= -b_{20}^{-1}\left(l_2 z_3 + f_{30} - \dot{x}_{3d}\right) + b_{20}^T z_2 \\ &+ k z_3 + \hat{W}_3^T S_3\left(\hat{V}_3^T X_3\right) + v_3 \end{aligned}, \qquad (23)$$

Choose the following adaptive laws and the robust term

$$\begin{aligned} \dot{\hat{W}}_3 &= \Gamma_{W3}\left[\left(\hat{S}_3 - \hat{S}_3' \hat{V}_3^T Z_3\right) z_3^T - \sigma_{W3} \hat{W}_3\right] \\ \dot{\hat{V}}_3 &= \Gamma_{V3}\left[Z_3\left(\hat{S}_3' \hat{W}_3 z_3\right)^T - \sigma_{V3} \hat{V}_3\right] \\ v_3 &= z_3\left(\left\|\hat{W}_3^T \hat{S}_3'\right\|_F^2 \left\|X_3\right\|^2 + \left\|\hat{S}_3' \hat{V}_3^T X_3\right\|_F^2 + 2\right) / \eta_3, \end{aligned} \qquad (24)$$

Suppose

$$V_3 = \frac{1}{2} z_2^T z_2 - \frac{1}{2} z_3^T b_2^{-1} z_3 + \sum_{i=1}^{2} \left(\frac{1}{2} tr\left\{ \tilde{W}_i^T \Gamma_{Wi}^{-1} \tilde{W}_i \right\} + \frac{1}{2} tr\left\{ \tilde{V}_i^T \Gamma_{Vi}^{-1} \tilde{V}_i \right\} \right), \quad (25)$$

Selecting $k > b_d$, then

$$\dot{V}_3 \le -l_1 \left\| z_2 \right\|^2 + l_2 z_3^T b_2^{-1} z_3 + \sum_{i=1}^{2} \left(-\frac{\sigma_{Wi}}{2} \left\| \tilde{W}_i \right\|^2 - \frac{\sigma_{Vi}}{2} \left\| \tilde{V}_i \right\|^2 + c_i \right) \le 0, \quad (26)$$

4. Numerical Simulation Results

In order to validate the effectiveness and validity of the proposed method, nonlinear 6-DOF simulation results for a HSUAV model are presented. The controller design parameters are chosen as follows, $l_1 = 11, l_2 = 13$, $\sigma_{W_i} = \sigma_{V_i} = 0.01$, $\eta_2 = \eta_3 = 1$. Simulation results are shown in the following figures from Fig. 1 to Fig. 7.

From the simulation results, it can be shown that the control system has good stability, performance and robustness, even if the large model uncertainties exist.

5. Conclusions

This paper presented a nonlinear adaptive controller for a HSUAV with a general set of uncertainties. The nonlinear adaptive controller is designed using dynamic surface backstepping control techniques and fully tuned RBF neural networks. Lyapunov stability theory is used to prove the stability of the system and derive the tuning rules for updating all parameters of the RBF neural networks. Finally, a nonlinear 6-DOF numerical simulation of a HSUAV model is performed to demonstrate the good performance of the proposed method.

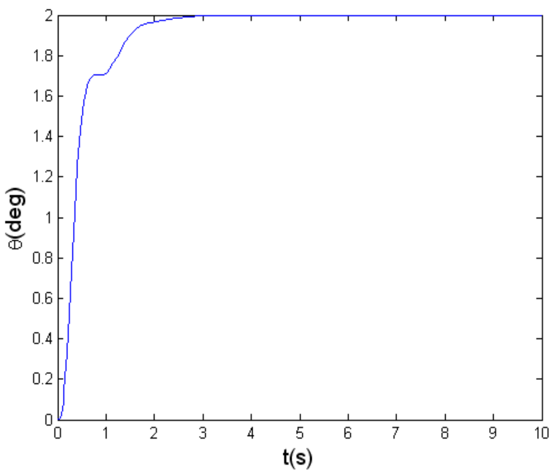

Fig. 1. Tracking curve of θ.

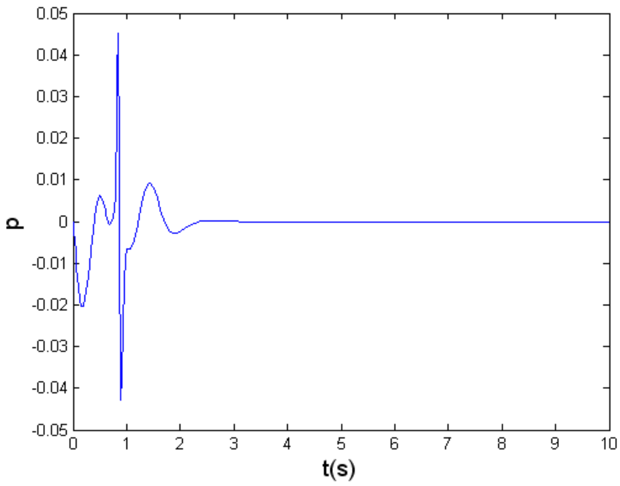

Fig. 2. Tracking curve of p.

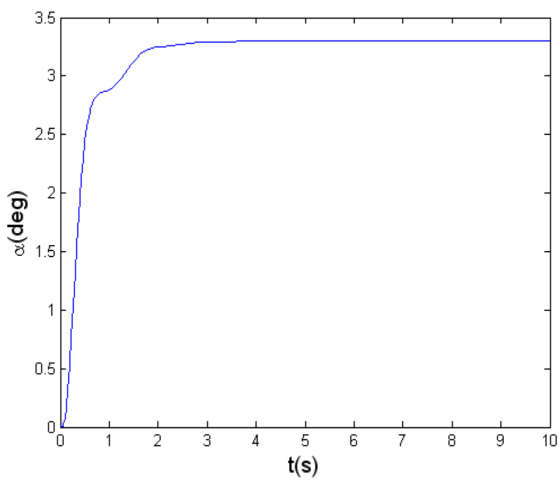

Fig. 3. Tracking curve of α.

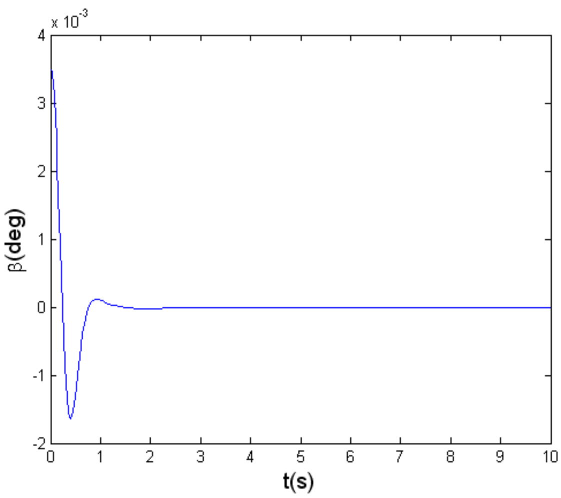

Fig. 4. Tracking curve of β.

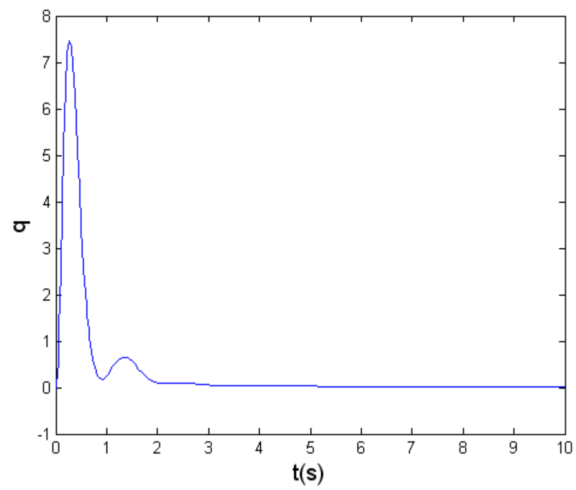

Fig. 5. Tracking curve of q.

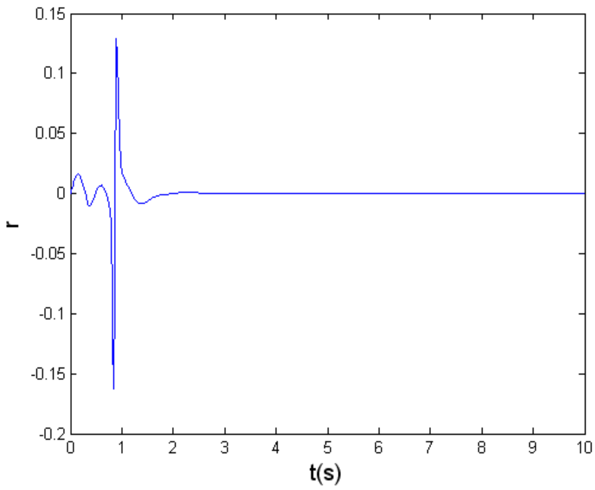

Fig. 6. Tracking curve of r .

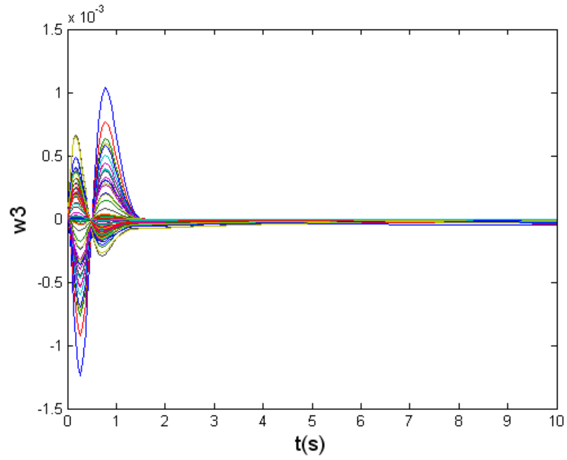

Fig. 7. W_3 tuning weight.

Appendix

The winged-cone dynamics model

$$\dot{V} = \frac{1}{m}[P\cos\alpha\cos\beta + qS(C_{D,\alpha} + C_{D,\delta_e}\delta_e + C_{D,\delta_a}\delta_a + C_{D,\delta_r}\delta_r)] - g\sin\theta$$

$$\dot{\theta} = \frac{1}{mV}[P(\sin\alpha\cos\mu + \cos\alpha\sin\beta\sin\mu) + (qS(C_{L,\alpha} + C_{L,\delta_e}\delta_e + C_{L,\delta_a}\delta_a))\cos\mu - (qS(C_{Y,\beta}\beta + C_{Y,\delta_e}\delta_e + C_{Y,\delta_a}\delta_a + C_{Y,\delta_r}\delta_r))\sin\mu] - \frac{g}{V}\cos\theta$$

$$\dot{\psi}_c = -\frac{1}{mV\cos\theta}[P(\sin\alpha\sin\mu - \cos\alpha\sin\beta\cos\mu) + (qS(C_{L,\alpha} + C_{L,\delta_e}\delta_e + C_{L,\delta_a}\delta_a))\sin\mu + (qS(C_{Y,\beta}\beta + C_{Y,\delta_e}\delta_e + C_{Y,\delta_a}\delta_a + C_{Y,\delta_r}\delta_r))\cos\mu]$$

$$\dot{\alpha} = -\frac{1}{mV\cos\beta}[qs(C_{L,\alpha} + C_{L,\delta_e}\delta_e + C_{L,\delta_a}\delta_a) + P\sin\alpha] - p\cos\alpha\tan\beta + q\sin\alpha\tan\beta + r$$

$$\dot{\beta} = \frac{1}{mV}[qs(C_{Y,\beta}\beta + C_{Y,\delta_e}\delta_e + C_{Y,\delta_a}\delta_a + C_{Y,\delta_r}\delta_r) - P\cos\alpha\sin\beta] + p\sin\alpha + q\cos\alpha$$

$$\dot{\mu} = p - \mathrm{tg}\,\vartheta(q\cos\mu - r\sin\mu)$$

$$\dot{p} = \frac{qSb}{J_x}(C_{l,\beta}\beta + C_{l,\delta_e}\delta_e + C_{l,\delta_a}\delta_a + C_{l,\delta_r}\delta_r + C_{l,p}\frac{b}{2V}p + C_{l,q}\frac{b}{2V}q) + \frac{1}{J_x}(J_y - J_z)qr$$

$$\dot{q} = \frac{qS}{J_x}[(b\cdot C_{n,\beta} + X_{cg}\cdot C_{Y,\beta})\cdot\beta + (b\cdot C_{n,\delta_e} + X_{cg}\cdot C_{Y,\delta_e})\cdot\delta_e + (b\cdot C_{n,\delta_a} + X_{cg}\cdot C_{Y,\delta_a})\cdot\delta_a + (b\cdot C_{n,\delta_r} + X_{cg}\cdot C_{Y,\delta_r})\cdot\delta_r] + \frac{qSb^2}{2J_yV}\cdot C_{n,p}\cdot p + \frac{qSb^2}{2J_yV}\cdot C_{n,q}\cdot q + \frac{1}{J_y}(J_z - J_x)pr$$

$$\dot{r} = \frac{qS}{J_z}[(c\cdot C_{m,\alpha} + X_{cg}C_{D,\alpha}\sin\alpha + X_{cg}C_{L,\alpha}\cos\alpha) + (c\cdot C_{m,\delta_e} + X_{cg}C_{D,\delta_e}\sin\alpha + X_{cg}C_{L,\delta_e}\cos\alpha)\cdot\delta_e + (c\cdot C_{m,\delta_a} + X_{cg}C_{D,\alpha}\sin\alpha + X_{cg}C_{L,\alpha}\cos\alpha)\cdot\delta_a + (c\cdot C_{m,\delta_r} + X_{cg}C_{D,\alpha}\sin\alpha + X_{cg}C_{L,\alpha}\cos\alpha)\cdot\delta_r] + \frac{qSc^2}{2J_zV}\cdot C_{m,r}\cdot r + \frac{1}{J_z}(J_x - J_y)pq$$

$$f_1(x_1) = \begin{bmatrix} -\frac{1}{mV\cos\beta}[qS(C_{L,\alpha} + C_{L,\delta_e}\delta_e + C_{L,\delta_a}\delta_a) + P\sin\alpha \\ \frac{1}{mV}[qS(C_{Y,\beta}\beta + C_{Y,\delta_e}\delta_e + C_{Y,\delta_a}\delta_a + C_{Y,\delta_r}\delta_r) - P\cos\alpha\sin\beta] \\ 0 \end{bmatrix}$$

$$b_1(x_1) = \begin{bmatrix} -\cos\alpha tg\beta & \sin\alpha tg\beta & 1 \\ \sin\alpha & \cos\alpha & 0 \\ 1 & -tg\vartheta\cos\gamma & tg\vartheta\sin\gamma \end{bmatrix}$$

$$h_1(x_1) = \begin{bmatrix} -\frac{qSC_{L,\delta_e}}{mV\cos\beta} & 0 & -\frac{qSC_{L,\delta_a}}{mV\cos\beta} \\ \frac{qSC_{Y,\delta_e}}{mV} & \frac{qSC_{Y,\delta_r}}{mV} & \frac{qSC_{Y,\delta_a}}{mV} \\ 0 & 0 & 0 \end{bmatrix}$$

$$f_2(x_1,x_2) = \begin{bmatrix} \frac{J_y - J_z}{J_x}\cdot\omega_y\omega_z + \frac{qbS}{J_x}\cdot C_{l,\beta}\beta \\ +\frac{qb^2S}{2J_xV}(C_{l,\omega_x}\omega_x + C_{l,\omega_y}\omega_y) \\ \frac{J_x - J_z}{J_y}\cdot\omega_x\omega_z + \frac{qS}{J_y}\cdot(bC_{n,\beta} + x_{cg}C_{Y,\beta})\beta \\ +\frac{qb^2S}{2J_yV}(C_{n,\omega_x}\omega_x + C_{n,\omega_y}\omega_y) \\ \frac{J_x - J_y}{J_z}\cdot\omega_x\omega_y + \frac{qS}{J_z}\cdot(c\cdot C_{m,a} + x_{cg}C_{D,a}\sin\alpha \\ +x_{cg}C_{L,a}\cos\alpha) + \frac{qc^2S}{2J_zV}C_{m,q}\omega_z \end{bmatrix}$$

Acknowledgements

The paper is supported by National Nature Science Foundation of China 61174031, Aviation Science Foundation of China 20130184001.

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