Neurocomputing 174 (2016) 1070–1076

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Neural adaptive control of hypersonic aircraft with actuator fault using randomly assigned nodes

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ARTICLE INFO

Article history:
Received 18 July 2015
Received in revised form
30 September 2015
Accepted 9 October 2015
Communicated by Ning Wang
Available online 19 October 2015

Keywords:
Back-stepping
Single-hidden layer feedforward network
Parameter estimation
Hypersonic flight vehicle

ABSTRACT

This paper investigates the fault-tolerant controller for hypersonic aircraft in case of actuator fault. The robust adaptive controller is designed using command filtered back-stepping scheme. The uncertainty caused by the fault is approximated by randomly assigning nodes of the RBF single-hidden layer feed-forward network (SLFN). The output weight is updated based on the Lyapunov synthesis approach to guarantee the stability of the overall control system. The method is applied on the control-oriented model whose subsystems are written into the linearly parameterized form. Simulation results show that the proposed approach achieves good tracking performance.

1. Introduction

Hypersonic flight control [1–5] is challenging since the longitudinal model of the dynamics is sensitive. In literature, several models have been investigated such as winged-cone model [2], the control oriented model [6] and the nonlinear longitudinal model [7]. The main difficulty of the control law design for the hypersonic aircraft is due to the high complexity of the motion equations and there is little knowledge of the aerodynamic parameters of the vehicle.

With unknown dynamics, there are two ways to design the adaptive controller. One is referred to intelligent control [8–10]. The idea is mainly on using neural networks (NNs) or fuzzy logic system (FLS) to approximate the unknown dynamics. In [11], the neural control of hypersonic flight dynamics is analyzed with singularly perturbed system approach. In [12], the altitude subsystem of the genetic longitudinal dynamics is with cascade structure, and it is written into the strict-feedback form. Furthermore, the dynamics is transformed into the output feedback form and the neural control based on high gain observer is constructed. The design is further improved in [13] with minimal learning parameter technique. In [14–16], the back-stepping control is designed by using Euler expansion of the continuous dynamics while in [17] the design is with prediction function. The other way is to write the unknown dynamics into the linearly parameterized form [18]. Using the parameter estimation, the dynamic surface control is studied in [19].

Despite the uncertainty, different control problems are also widely studied. The flexible effect is analyzed in [20] while in [21], the aerothermoelastic effects are considered. In [19], the case with actuator constraint is studied. In reality, physical components may become faulty, which can cause deterioration in system performance and lead to instability. In [22], the comprehensive review on active and passive design is discussed while in [23,24], the design on flight control is analyzed. In [25], the system fault of near space vehicle is reviewed. In [26,27], the fault tolerant control for hypersonic flight dynamics with multiple actuators is studied. In general, the learning-based active FTC can accommodate more related systems. However, during the controller design with NNs, usually the fault could not be known exactly so that we have no prior information to design the structure. More specifically, we do not know how to select the nodes and parameters. Fortunately, extreme learning machine [28–30] can achieve learning by randomly generating hidden node without the knowledge of the training data [31,32]. The tracking of an unmanned surface vehicle suffering from unknown dynamics and external disturbances with an extreme learning is proposed in [33]. In [34] the constructive and destructive parsimonious extreme learning machines are proposed. The dynamics identification with extreme learning machine can be found in [35].

In this paper, considering the control-oriented model [6] of hypersonic aircraft, the robust adaptive controller is proposed

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http://dx.doi.org/10.1016/j.neucom.2015.10.023
0925-2312/

with parameter estimation and learning FTC in the presence of uncertain dynamics and actuator fault by randomly assigning the nodes.

This paper is organized as follows. SLFN is illustrated in Section 2. The HFV dynamics are demonstrated in Section 3. Section 4 presents the FTC control. The simulation is presented in Section 6. Section 7 presents several comments and final remarks.

2. SLFN

For N arbitrary distinct samples $(\mathbf{x}_i, \mathbf{t}_i)$, where $\mathbf{x}_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \in R^n$ and $\mathbf{t}_i = [t_{i1}, t_{i2}, \ldots, t_{im}]^T \in R^m$, standard SLFN with $\tilde{N}$ hidden neurons can be expressed as follows:

$$\sum_{i=1}^{\tilde{N}} \beta_i G(\mathbf{x}_j; \mathbf{w}_i, b_i) = \mathbf{o}_j, \quad j = 1, \ldots, N \tag{1}$$

where $\mathbf{w}_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^T$ and b_i are the learning parameters of hidden nodes, $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$ is the weight vector connecting the ith hidden neuron and the output neurons and $G(\mathbf{x}_j; \mathbf{w}_i, b_i)$ is the output of the ith hidden node with respect to input $\mathbf{x}_j$.

Let $\mathbf{x} = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N]$, $\mathbf{w} = [\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_{\tilde{N}}]$ and $\mathbf{b} = [b_1, b_2, \ldots, b_{\tilde{N}}]$. The standard SLFN with $\tilde{N}$ hidden neurons each with function $g(x)$ can approximate these N samples with zero error means that $\sum_{j=1}^{N} \| \mathbf{o}_j - \mathbf{t}_j \| = 0$, i.e., there exist β_i, $\mathbf{w}_i$ and b_i such that

$$\mathbf{H}(\mathbf{x}; \mathbf{w}, \mathbf{b})\beta = \mathbf{T} \tag{2}$$

in which

$$\mathbf{H}(\mathbf{x}_1, \ldots, \mathbf{x}_N, \mathbf{w}_1, \ldots, \mathbf{w}_{\tilde{N}}, b_1, \ldots, b_{\tilde{N}}) = \begin{bmatrix} G(\mathbf{x}_1; \mathbf{w}_1, b_1) & \cdots & G(\mathbf{x}_1; \mathbf{w}_{\tilde{N}}, b_{\tilde{N}}) \\ \vdots & \cdots & \vdots \\ G(\mathbf{x}_N; \mathbf{w}_1, b_1) & \cdots & G(\mathbf{x}_N; \mathbf{w}_{\tilde{N}}, b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}},$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N} \times m} \quad \text{and} \quad \mathbf{T} = \begin{bmatrix} \mathbf{t}_1^T \\ \vdots \\ \mathbf{t}_N^T \end{bmatrix}_{N \times m}$$

In the case of $\tilde{N} \ll N$ and $\mathbf{H}$ being a nonsquare matrix, one may be interested to find $\hat{\mathbf{w}}_i, \hat{b}_i, \hat{\beta}_i$ $(i = 1, \ldots, \tilde{N})$ such that

$$\| \mathbf{H}(\hat{\mathbf{w}}_1, \ldots, \hat{\mathbf{w}}_{\tilde{N}}, b_1, \ldots, b_{\tilde{N}})\hat{\beta} - \mathbf{T} \| = \min_{\mathbf{w}_i, b_{i,\beta}} \| \mathbf{H}(\mathbf{w}_1, \ldots, \mathbf{w}_{\tilde{N}}, b_1, \ldots, b_{\tilde{N}})\beta - \mathbf{T} \| \tag{3}$$

For RBF hidden nodes with Gaussian function $g(\cdot)$, $G(\mathbf{x}_j; \mathbf{w}_i, b_i)$ is given by

$$G(\mathbf{x}_j; \mathbf{w}_i, b_i) = g(b_i \| \mathbf{x}_j - \mathbf{w}_i \|) \tag{4}$$

where $\mathbf{w}_i$ and b_i are the center and impact factor of the ith RBF node. The RBF network is a special case of SLFN with RBF nodes in its hidden layer. Each RBF node has its own centroid and impact factor and its output is given by a radially symmetric function of the distance between the input and the center.

3. Hypersonic aircraft model

3.1. Flight dynamics

Consider the control-oriented model of the longitudinal dynamics of a generic hypersonic aircraft from [6] with five equations

$$\dot{V} = \frac{T \cos\alpha - D}{m} - g \sin\gamma \tag{5}$$

$$\dot{h} = V \sin\gamma \tag{6}$$

$$\dot{\gamma} = \frac{L + T \sin\alpha}{mV} - \frac{g \cos\gamma}{V} \tag{7}$$

$$\dot{\alpha} = q - \dot{\gamma} \tag{8}$$

$$\dot{q} = \frac{M_{yy}}{I_{yy}} \tag{9}$$

This model is composed of five state variables $X_h = [V, h, \alpha, \gamma, q]^T$ and two control inputs $U_h = [\delta_e, \Phi]^T$.

Given the reference signal h_r, the altitude tracking error is defined as $\tilde{h} = h - h_r$. The following flight path angle command is selected:

$$\gamma_d = \arcsin\left(\frac{-k_h\tilde{h} - k_i \int \tilde{h}\, dt + \dot{h}_r}{V} \right) \tag{10}$$

where $k_h > 0$, $k_i > 0$ are positive constants.

Define $x_1 = \gamma, x_2 = \theta_p, x_3 = q$, $\theta_p = \alpha + \gamma$, $u_f = \delta_e$. The following subsystem is obtained:

$$\begin{aligned} \dot{x}_1 &= g_1 x_2 + f_1 - f_0 \\ \dot{x}_2 &= x_3 \\ \dot{x}_3 &= g_3 u_f + f_3 \end{aligned} \tag{11}$$

where

$$f_0 = -\frac{g}{V}\cos x_1, \quad f_1 = \frac{L_0 - L_\alpha \gamma + T \sin\alpha}{mV} = \omega_{f1}^T \theta_{f1}$$
$$g_1 = \frac{L_\alpha}{mV} = \omega_{g1}^T \theta_{g1}, \quad f_3 = \frac{M_T + M_0(\alpha)}{I_{yy}} = \omega_{f3}^T \theta_{f3},$$
$$g_3 = \frac{M_{\delta_e}}{I_{yy}} = \omega_{g3}^T \theta_{g3}$$

The actuator fault is considered as

$$u_f(t) = \begin{cases} u(t), & t < 5 \\ u(t) + f, & t \geq 5 \end{cases} \tag{12}$$

where f=0.1, $u(t)$ is the signal to be designed.

For more detail of the definition, refer to [19] for more detail.

3.2. Control goal

By functional decomposition, the dynamics can be decoupled into two functional subsystems named attitude subsystem and velocity subsystem. Given the tracking reference V_r and h_r, the velocity and altitude controllers are designed respectively in case of uncertain parameters and unknown system fault.

4. Controller design for attitude subsystem

The controller design is mainly on command filter technique [36]. In the final step, the system fault is approximated by randomly assigning the nodes.

Step 1: Define $\tilde{x}_1 = x_1 - x_{1d}$. Take θ_p as virtual control and design x_{2c} as

$$\hat{g}_1 x_{2c} = -k_1 \tilde{x}_1 - \hat{f}_1 + f_0 + \dot{x}_{1d} - \hat{g}_1 \xi_2 \tag{13}$$

where $k_1 > 0$ is the design parameter, $\hat{f}_1 = \omega_{f1}^T \hat{\theta}_{f1}$, $\hat{g}_1 = \omega_{g1}^T \hat{\theta}_{g1}$, ξ_2 will be defined in Step 2.

Introduce a new state variable x_{2d}, which can be obtained by the following first-order filter:

$$\varepsilon_2 \dot{x}_{2d} + x_{2d} = x_{2c}, \quad x_{2d}(0) = x_{2c}(0) \tag{14}$$

Introduce signal ξ_1

$$\dot{\xi}_1 = -k_1 \xi_1 + \hat{g}_1 (x_{2d} - x_{2c}), \quad \xi_1(0) = 0 \tag{15}$$