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Adaptive fuzzy control of aircraft wing-rock motion

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ABSTRACT

In the paper, two adaptive fuzzy control schemes including indirect and direct frameworks are developed for suppressing the wing-rock motion that is a highly nonlinear aerodynamic phenomenon in which limit cycle roll oscillations are experienced by aircraft at high angles of attack. In the two control topologies, a dynamic fuzzy system called Extended Sequential Adaptive Fuzzy Inference System (ESAFIS) is constructed to represent the dynamics of the wing-rock system. ESAFIS is an online learning fuzzy system in which the rules are added or deleted based on the input data. In the indirect control scheme, the ESAFIS is used to estimate the nonlinear dynamic function and then a stable indirect fuzzy controller is designed based on the estimator. In the direct control scheme, the ESAFIS controller is directly designed to imitate an ideal stable control law without determining the model of the dynamic function. Different from the original ESAFIS, the adaptive tuning algorithms for the consequent parameters are established in the sense of Lyapunov theorem to ensure the stability of the overall control system. A sliding mode controller is also designed to compensate for the modelling errors of ESAFIS by augmenting the indirect/direct fuzzy controller. Finally, comparisons with a neuron control scheme using the RBF network and a fuzzy control scheme with Takagi–Sugeno (TS) system are presented to depict the effectiveness of the proposed control strategies. Simulation results show that the proposed fuzzy controllers achieve better tracking performance with dynamically allocating the rules online.

1. Introduction

Wing rock is a highly nonlinear aerodynamic phenomenon in which limit cycle roll oscillations are experienced by aircraft at high angles of attack [1]. The wing-rock motion is a concern because it may cause a loss of stability in the lateral/directional mode due to the large amplitudes and high frequencies of the rolling oscillations, thus degrading the maneuverability, tracking accuracy and operational safety of the high-performance fighters. To understand the underlying mechanism of the wing-rock motion, some research has been conducted on the motion of slender delta wings and several theoretical models that describe the nonlinear rolling motion are developed using simple differential equations [2,3]. During the past decades, many control techniques have been developed [4–7]. Based on the differential models, the control strategies used to suppress the wing-rock motion include nonlinear optimal feedback control [5], the adaptive control based on the feedback linearization [6] and the robust H_∞ control [7]. Although these methods are successful in controlling the wing-rock motion, a key assumption in these methods is that the system nonlinearities are known a priori, which is generally not applicable in the real world. The reason is that the aerodynamic parameters governing wing rock are inadequately understood and thus an accurate mathematical model for the wing-rock motion can not be obtained. These present significant difficulties to the controller design using conventional control techniques.

A fuzzy inference system provides an effective means of capturing the approximate, inexact nonlinear mappings using a series of if–then fuzzy rules and thus has been widely applied in the control of nonlinear systems [8–11]. Since in the wing-rock motion situation the model information is inexact and the operating conditions are uncertain, the rule based fuzzy controllers have been developed to suppress its oscillations in [12] and [1] where three term sets and seven term sets have been employed for the fuzzification of the control variables, respectively. Numerical results have been presented to demonstrate the robustness of the fuzzy controllers. However, these methods create the fuzzy inference rules for fuzzy controllers according to the designer experience and have no on-line learning ability. If the fuzzy rules are not appropriate and deviate from the requirement of the system itself, this may result in poor performance. Besides, although the rules are correct, it is hard to determine the appropriate parameters for the fuzzy rules. Inappropriate parameters also may result in poor performance. Neural networks possess an inherent structure

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suitable for learning and reconstructing complex nonlinear mappings and thus some control techniques based on neural networks have been proposed for the control of wing-rock motion [13–15]. With the learning capabilities of neural networks, the effects of nonlinearities and system uncertainties are compensated, thereby improving the stability, convergence and robustness of the control system.

Combining the advantages of the neural network (learning) and the fuzzy inference system (approximation reasoning) one can develop fuzzy-neural system which exhibits both the above characteristics. Some adaptive fuzzy control schemes based on fuzzy neural systems have been developed for suppressing the wing-rock motion. In [16], a supervisory fuzzy controller is designed using a recurrent fuzzy neural network which is inherently a recurrent multilayered neural network for realizing fuzzy inference with dynamic fuzzy rules. In the method, the parameters of fuzzy systems are adjusted based on the gradient descent method and the Lyapunov stability theorem to increase the learning capability. The existing methods, regardless of the neural-network based controllers or fuzzy based controllers demonstrate good performance in the control of wing-rock motion, but the network structure or system structure, that is the number of hidden neurons or the number of fuzzy rules need to be predefined by trail-and-error before learning. This may cause redundant or inefficient computation, thereby decreasing the flexibility and numerical processing capability of the controller.

An approach to tackle this problem is the use of adaptive learning algorithms for constructing a fuzzy control system systematically and automatically. In the paper, novel adaptive fuzzy control schemes in the indirect and direct frameworks are designed based on the Extended Sequential Adaptive Fuzzy Inference System (ESAFIS) [17] for the control of wing-rock motion. ESAFIS is developed based on the SAFIS algorithm [18] for improving the learning accuracy and computational speed. Similar to SAFIS, the ESAFIS algorithm consists of two aspects: determination of the fuzzy rules and adjustment of consequent parameters in fuzzy rules. ESAFIS uses the concept of modified *influence* of a fuzzy rule to add and remove rules during learning. ESAFIS starts with no fuzzy rules and based on the data builds up a compact rule base. The modified *influence* of a fuzzy rule is defined as its contribution to the system output in a statistical sense, which avoids the uniform distribution of the input data required in SAFIS. The ESAFIS algorithm offers a fast online learning algorithm due to the dynamical recruitment or deletion of fuzzy control rules without predefinition. Its outstanding computational efficiency in terms of learning speed, adaptability and generalization has been verified in our latest work [17].

In the proposed adaptive fuzzy control schemes, the fuzzy controllers are built employing ESAFIS to approximate the nonlinear dynamics of wing-rock motion. However, different from the original ESAFIS algorithm where a Recursive Least-Square Error (RLSE) is used to adjust the consequent parameters, they are updated based on the stable adaptive laws derived from a Lyapunov function that is an effective way to guarantee the stability of the closed-loop system and has been widely applied to solve many practical control problems [19–21]. And also a sliding controller is incorporated into the fuzzy controller and activated to work with the fuzzy controller for offsetting the modelling errors of the ESAFIS.

This paper is organized as follows. Section 2 introduces the dynamic model of the wing-rock motion under consideration. Section 3 gives a brief review of the ESAFIS algorithm. In Section 4, the design procedure of the adaptive fuzzy controllers is introduced. Section 5 shows the simulation results by controlling the wing-rock system. Section 6 presents the conclusions from this study.

Table 1
Coefficients of rolling moment with angle of attack α.

α	a_1	a_2	a_3	a_4	a_5
15.0	−0.01026	−0.02117	−0.14181	0.99735	−0.83478
21.5	−0.04207	−0.01456	0.04714	−0.18583	0.24234
22.5	−0.04681	0.01966	0.05671	−0.22691	0.59065
25.0	−0.05686	0.03254	0.07334	−0.35970	1.46810

2. Problem formulation

The nonlinear wing-rock motion for an 80° slender delta wing developed by Nayfeh et al. [3] is considered in the study, whose dynamics is described by the following differential equation:

$$\ddot{\phi} = \left(\frac{\rho U_\infty^2 Sb}{2I_{xx}}\right) C_l - D\dot{\phi} + u \tag{1}$$

where ϕ is the roll angle, ρ is the density of air, U_∞ is the freestream velocity, S is the wing reference area, b is the chord, I_{xx} is the mass moment of inertia, D is the damping coefficient and fixed as 0.0001, u is the control input, and C_l is the roll moment coefficient that is given by,

$$C_l = a_1\phi + a_2\dot{\phi} + a_3\phi^3 + a_4\phi^2\dot{\phi} + a_5\phi\dot{\phi}^2 \tag{2}$$

The aerodynamic parameters a_1–a_5 are nonlinear functions of the angle of attack α and presented in Table 1.

Substituting Eq. (2) into Eq. (1), the wing-rock dynamics then is rewritten as,

$$\ddot{\phi} + \omega^2\phi = \mu_1\dot{\phi} + b_1\dot{\phi}^3 + \mu_2\phi^2\dot{\phi} + b_2\phi\dot{\phi}^2 + u \tag{3}$$

The coefficients in the above equation are given by the following relations:

$$\omega^2 = -Ca_1, \quad \mu_1 = Ca_2 - D, \quad \mu_2 = Ca_4, \quad b_1 = Ca_3, \quad b_2 = Ca_5 \tag{4}$$

where $C(= \rho U_\infty^2 Sb/2I_{xx})$ is a fixed constant and equal to 0.354.

The values of the coefficients in Eq. (3) could be obtained for any angle of attack according to any interpolation method. [3] has pointed out that the observed onset angle where μ_1 is zero corresponding to the onset of wing rock is "19–20°". This can be verified by observing the properties of the open-loop system with $u = 0$. The simulations are done under two specific angles of attack, viz, $\alpha = 15°$ that is smaller than the observed onset angle and $\alpha = 25°$ that is larger than the observed onset angle. Fig. 1(a) and (b) present the time process of the calculated roll angle and the roll rate given by Eq. (3) for $\alpha = 15°$. From the two figures, one can observe that the roll oscillations are stable and the wing-rock motion does not occur. But the oscillation time is very long, which increases the maneuverability burden. The time process of the roll angle and its roll rate for $\alpha = 25°$ are given in Fig. 2(a) and (b). In this case, the wing-rock motion occurs and appears limit cycle roll oscillations. Thus the control objective here is to suppress the wing rock whatever the angle of attack is, i.e., maintain the roll angle and the roll rate at the zero conditions in a fast speed.

By choosing state variables $x_1 = \phi$ and $x_2 = \dot{\phi}$, the state equations of the wing-rock dynamics will be

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= f(x_1, x_2) + u \end{aligned} \tag{5}$$

where $f(x_1, x_2) = -\omega^2\phi + \mu_1\dot{\phi} + b_1\dot{\phi}^3 + \mu_2\phi^2\dot{\phi} + b_2\phi\dot{\phi}^2$ is assumed to be bounded real continuous nonlinear function.