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Flight Control System Design by Self-Organizing Fuzzy Logic Controller

Chih-Min Lin* and Jiann-Hwa Maa†
Yuan-Ze Institute of Technology, Chung-Li 32026, Taiwan, Republic of China

Introduction

FUZZY logic control has been proven to be a powerful tool when it is applied to various control problems.[1–4] In general, fuzzy logic control needs to establish fuzzy inference rules, which are preconstructed by an expert. When the rule base, which represents the experience and intuition of human experts, is not available, an efficient control cannot be expected. To tackle this problem, self-organizing fuzzy logic controllers have been proposed.[5,6] This kind of controller has a learning algorithm and is capable of generating and modifying control rules based on an evaluation of the system's performance. The modification of control rules is achieved by assigning a credit to the control action based on the present performance. However, the self-organizing fuzzy control proposed in Refs. 5 and 6 has some problems. Its control rules are sensitive to set-point changes. And the learning algorithm may generate unreliable credit value and lead to incorrect rule modification. Also, the convergent time of the control action is tedious because only the fired rule is modified each time, and finally, the convergence of the control action is not guaranteed.

This Note proposes a new type of design method of self-organizing fuzzy controller and illustrates its application for flight system control. The proposed model reference self-organizing fuzzy controller (MR-SOFC) has two suites of fuzzy logic; one is for control and the other is for learning. The output of the reference model is used as a reference for rule modification instead of a set point, and so incorrect modification caused by change of set point can be avoided. Also, the learning algorithm will modify the control rules according to the fuzzy inference of the reference model output error and its derivative instead of by the fixed value, so that the learning algorithm can proceed more reasonably and the learned rules can converge more quickly and accurately. The MR-SOFC can start to work even from an empty rule base and can achieve satisfactory control performance after several learning runs.

By applying the proposed MR-SOFC to a flight control system, the simulations illustrate that this MR-SOFC can achieve satisfactory performance and robustness when the flight system is subjected to plant variations arising from different flight conditions.

Fuzzy Logic Control

In Fig. 1, the fuzzy controller produces an output by using the fuzzy control rules as well as the system output error and its derivative (e and $\dot{e}$). The rules define the control strategy and correspond to linguistic statements implemented by using fuzzy sets. The rules of a fuzzy controller take the following form:

$$\begin{array}{llll} R_1: \text{If } e \text{ is } A_1, & \text{and } \dot{e} \text{ is } B_1, & \text{then } u \text{ is } r(1) \\ R_2: \text{If } e \text{ is } A_2, & \text{and } \dot{e} \text{ is } B_2, & \text{then } u \text{ is } r(2) \\ \vdots \quad\quad \vdots & \vdots & \vdots \\ R_k: \text{If } e \text{ is } A_k, & \text{and } \dot{e} \text{ is } B_k, & \text{then } u \text{ is } r(k) \end{array} \tag{1}$$

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*Associate Professor, Department of Electrical Engineering.
†Graduate Student, Department of Electrical Engineering.

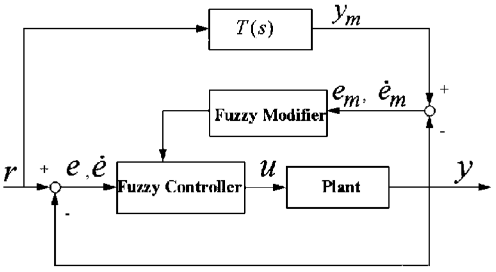

Fig. 1 Block diagram of MR-SOFC.

where $r(i)$, $i = 1, 2, \ldots, k$ are the singleton control actions, which are learned from the fuzzy modifier, and k is the number of the fuzzy rules of the fuzzy controller.

The defuzzification of the controller output is accomplished by the method of center of gravity:

$$u = \frac{\sum_{i=1}^{k} w(i) \times r(i)}{\sum_{i=1}^{k} w(i)} \tag{2}$$

where $w(i)$ is the fired weight of the ith rule. The defuzzified value u in Eq. (2) represents the desired control force.

Self-Organizing Learning Algorithm

The fuzzy modifier is the essential part of the process of learning. In Fig. 1, the MR-SOFC modifies the control rules with the reference model output error e_m and its derivative $\dot{e}_m$. The rule modifier is a fuzzy system, and the fuzzy modification rules are as follows:

$$\begin{array}{llll} R_m1: \text{If } e_m \text{ is } C_1, & \text{and } \dot{e}_m \text{ is } D_1, & \text{then } \delta u \text{ is } p(1) \\ R_m2: \text{If } e_m \text{ is } C_2, & \text{and } \dot{e}_m \text{ is } D_2, & \text{then } \delta u \text{ is } p(2) \\ \vdots \quad\quad \vdots & \vdots & \vdots \\ R_mn: \text{If } e_m \text{ is } C_n, & \text{and } \dot{e}_m \text{ is } D_n, & \text{then } \delta u \text{ is } p(n) \end{array} \tag{3}$$

where the inference outputs $p(j)$, $j = 1, 2, \ldots, n$ are singletons. The defuzzification output δu is also accomplished by the method of center of gravity.

For the modification of the control rules in Eq. (1), the modification credit value $\Delta r(i)$ of each rule must be appropriate. In Refs. 5 and 6, only the fired rule is modified each time. Here we propose the rules modification criterion by fuzzy inference values, i.e., the modification credit value $\Delta r(i)$ of each rule is based on its fired weight $w(i)$ in Eq. (2). Thus, the learning algorithm can proceed more reasonably, and the learned rules can converge more quickly and accurately. The self-organizing modification algorithm is proposed as follows:

$$\Delta r(i) = \delta u \times \frac{w(i)}{\sum_{i=1}^{k} w(i)} \tag{4}$$

$$r(i) = r(i) + \Delta r(i) \tag{5}$$

Equation (4) means that the credit value of each control rule is proportional to its fired weight of fuzzy inference. The modified control action $r(i)$ in Eq. (5) is then used for the next step fuzzy control in Eq. (1).

The fuzzy sets A_j and B_j in Eq. (1) are given with 11 triangular membership functions, and C_i and D_i in Eq. (3) are given with 7 triangular membership functions.

Flight Control System Design Example

In the following, the short period longitudinal mode of the F-4E flight control system is considered as the design example.[7] Using Ref. 8, the transfer function forms of $q(s)/\delta_e(s)$ (pitch rate/deviation of elevator deflection) for four typical flight conditions, where s is the Laplace operator, are given as follows.

Flight condition 1:

$$P_1(s) = \left.\frac{q(s)}{\delta_e(s)}\right|_{\mathrm{FC1}} = \frac{-13.239(s + 0.884)}{(s + 3.068)(s - 1.228)} \tag{6}$$

Flight condition 2:

$$P_2(s) = \left.\frac{q(s)}{\delta_e(s)}\right|_{\mathrm{FC2}} = \frac{-36.269(s+1.554)}{(s+4.904)(s-1.784)} \tag{7}$$

Flight condition 3:

$$P_3(s) = \left.\frac{q(s)}{\delta_e(s)}\right|_{\mathrm{FC3}} = \frac{-11.308(s+0.637)}{(s+1.878)(s-0.560)} \tag{8}$$

Flight condition 4:

$$P_4(s) = \left.\frac{q(s)}{\delta_e(s)}\right|_{\mathrm{FC4}} = \frac{-12.320(s+0.821)}{(s+1.923)(s-0.640)} \tag{9}$$

Here we take the average value of poles, zeros, and steady-state gains of these flight conditions as the nominal plant

$$P_0(s) = \frac{-19.576(s+0.974)}{(s+2.943)(s-1.053)} \tag{10}$$

For model reference self-organizing fuzzy logic control, we need to establish an adequate reference model for the learning supervisor. Using Ref. 8, the reference model is chosen as

$$T_m(s) = \frac{6.036(s+7)}{s^2+11.7s+42.25} \tag{11}$$

which yields 0.69-s peak time and 0.76% maximum overshoot. The unit-step response of this reference model is shown in Fig. 2, which justifies the desired time response.

By applying the proposed self-organizing fuzzy logic control to the nominal plant, the step responses of the training process are given in Fig. 3, which shows that even if the plant is unstable, the training process can stabilize the system and achieve the convergence of the system performance to the reference model. By applying the learned fuzzy control rules to the F-4E flight system control, the control performance is demonstrated in Fig. 2, which shows that the MR-SOFC design method can achieve satisfactory performance and robustness when the flight system is subjected to plant variations arising from different flight conditions.

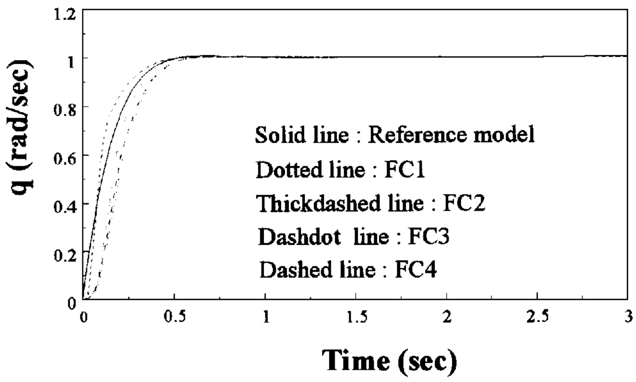

Fig. 2 Step responses of F-4E flight system for different flight conditions; command input q_c = 1 rad/s.

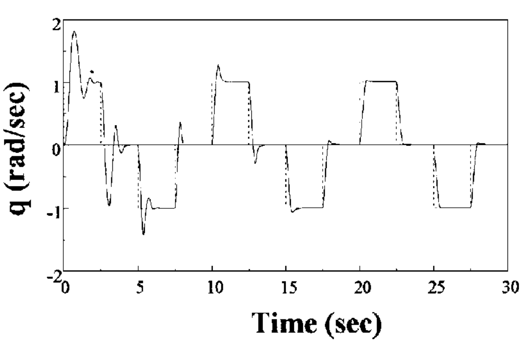

Fig. 3 Step responses of the training process.

Conclusion

The design method of MR-SOFC is proposed. By using this design method, a fuzzy rule base is learned to control the F-4E flight system. The simulations indicate that the proposed self-organizing fuzzy logic flight control can achieve satisfactory performance and robustness with respect to plant variations arising from different flight conditions.

Acknowledgments

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Minimum Drag Control Allocation

Wayne C. Durham,* John G. Bolling,† and Kenneth A. Bordignon†
Virginia Polytechnic Institute and State University, Blacksburg, Virginia 24061

Introduction

IN Ref. 1, we described a method of control allocation based on the instantaneous rate limits of the control effectors. The chief drawback to this method was the fact that the current positions were dependent on the path (in moment space) followed and would generally result in nonzero deflections in response to zero moment demands. The problem was alleviated by continuously applying unused rate capabilities to drive the solution toward one with the desired characteristics via the null space of the control effectiveness matrix.

We have long advocated the idea of including forces as well as moments in the effects of the controls[2] that would, among other benefits, permit the determination of minimum control generated drag during cruise or maneuvering. Thus, to include just drag, we have not the three-dimensional attainable moment subset (ΔAMS), but the four-dimensional attainable objective subset (ΔAOS), whose coordinates are the three moments plus drag. The moments required of the control effectors are determined by the control law and may be considered to be specified. Because we are in the ΔAOS we

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*Associate Professor, Aerospace and Ocean Engineering Department, 215 Randolph Hall. Senior Member AIAA.

†Graduate Assistant, Aerospace and Ocean Engineering Department, 215 Randolph Hall.