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Trajectory tracking in aircraft landing operations management using the adaptive neural fuzzy inference system

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ABSTRACT

The adaptive neural fuzzy inference system is used to simulate trajectory tracking in aircraft landing operations management. The advantage of the approach is that by using the linguistic representation ability of fuzzy sets and the learning ability of neural networks, the approximate linguistic representations can be improved or updated as more data become available. This approach is illustrated by the use of both zero and first order Takagi–Sugeno inference systems [T. Takagi, M. Sugeno, Fuzzy identification of systems and its application to modeling and control, IEEE Transactions on Systems, Man, and Cybernetics 15 (1) (1985) 116–132] with auto-landing flight path data.

1. Introduction

A major challenge in modern aircraft design is the controllability of the flight vehicle. When an airplane is in the air, not all atmospheric factors acting on it can be controlled by human efforts. The trajectory tracking of a landing plane is a useful approach but is an unpredictable and sophisticated process. It is difficult to devise an approach that allows modern control theory to deal with this nonlinear control problem in a systematic way.

Various investigators have studied this control problem. For example, Al-Hiddabi and McClamroch [2] used nonlinear control theory in developing a controller for conventional aircraft take-off and landing based on trajectory tracking control. Liu and Harmon [3] presented a real-time control and simulation investigation for aircraft landing requiring stability and robustness with respect to variations in speed, weight, center-of-gravity and time delays. Zou and Devasia [4] demonstrated the use of a previous-based stable-inversion technique in online output-tracking. Shan et al. [5] proposed a synchronized trajectory-tracking control strategy using a feed forward term and a PD feedback control term for multiple experimental three-degrees-of-freedom helicopters.

Fuzzy logic and/or neural network systems have also been applied to solve aircraft control problems. Pistauer and Bernhardi-Griasson [6] proposed a method for the design and implementation of a helicopter flight mechanic model with a specific fuzzy system structure. Wood and Schneider [7] used fuzzy expert system tools to control anti-submarine helicopters. Gharieb and Nagib [8] presented a general hierarchical fuzzy control design for a multi-variable helicopter system. Jorgensen and Schley [9] described a simplified neural network baseline model for aircraft control. Juang and Chio [10] presented an aircraft landing control based on fuzzy networks. McMichael et al. [11] examined the combined application of fuzzy methods and genetic algorithms in flow control. Melin and Castillo [12] described a hybrid method for adaptive intelligent control of aircraft systems. The hybrid approach was obtained by the combined use of neural network, fuzzy logic and fractal theory.

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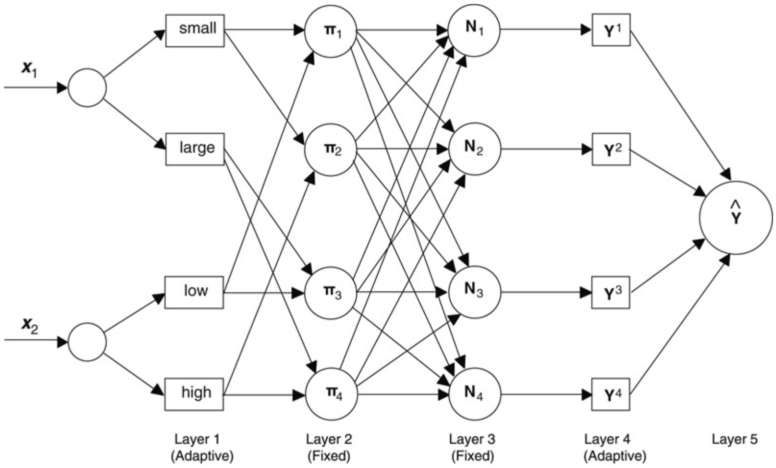

Fig. 1. Architecture of fuzzy adaptive network.

In this paper, the adaptive neural fuzzy inference system (ANFIS) is proposed for trajectory tracking in the nonlinear control of aircraft landing. Specifically, only longitudinal stability and control analysis are considered; and the open-loop pitch angle or the pitch angle of the elevator (PAE) is considered as the output of the system.

The fuzzy neural inference system will be summarized in Section 2 and the application of this ANFIS system to trajectory tracking with some numerical results will be presented in Section 3. The numerical auto-landing flight path data used are obtained from Shen et al. [13,14]. Finally, Section 4 presents some discussion.

2. Fuzzy inference system

To illustrate the fuzzy adaptive network, let us consider the following simple four fuzzy IF-THEN rules:

R^1: If (x_1 is small *AND* x_2 is low), then ($Y = Y^1 = p_0^1 + p_1^1 x_1 + p_2^1 x_2$)
R^2: If (x_1 is small *AND* x_2 is high), then ($Y = Y^2 = p_0^2 + p_1^2 x_1 + p_2^2 x_2$)
R^3: If (x_1 is large *AND* x_2 is low), then ($Y = Y^3 = p_0^3 + p_1^3 x_1 + p_2^3 x_2$)
R^4: If (x_1 is large *AND* x_2 is high), then ($Y = Y^4 = p_0^4 + p_1^4 x_1 + p_2^4 x_2$)

where x_1 and x_2 are input linguistic variables, and "small" and "large" are fuzzy sets. The above rules are known as the first order Takagi–Sugeno inference system [1]. For a zero order Takagi–Sugeno inference system, the x's after "then" are set equal to zero.

The fuzzy adaptive network, or the adaptive neural fuzzy inference system (ANFIS) [15–17] for these fuzzy rules is illustrated in Fig. 1, which is essentially a neural network except for the fact that some of the nodes are adaptive nodes where fuzzy membership functions are stored. To distinguish these adaptive nodes, rectangles are used to represent them. For example, the nodes in layers 1 and 4 are adaptive nodes, while the nodes in layers 2 and 3 are fixed nodes.

In this paper, the above Takagi–Sugeno fuzzy system, similar to that represented in Fig. 1, is used to simulate trajectory tracking of aircraft landing operations. Let node n in layer m be denoted by $o_{m,n}$; the node functions on each layer are summarized as follows [15]:

Layer 1: The input of this node is denoted by x_1 and o_{i,h_i} is the hth fuzzy set, which is a linguistic term. The output of node n is defined by

$$o_{1,n} = \mu_{o_{i,h_i}}(x_i), \quad \text{for } h_i = 1, 2, \ldots, p_i, \text{ and } i = 1, 2, \ldots, q \tag{1}$$

where $\mu_{o_{i,h_i}}$ is a membership function of o_{i,h_i}, and p_i is the number of fuzzy sets associated with x_i. The membership function used is the Gaussian function with the parameter set $\{v_{i,h_i}, \sigma_{i,h_i}\}$ and is given as:

$$\mu_{o_{i,h_i}}(x_i) = \mathrm{e}^{[-(\frac{x_i - v_{i,h_i}}{\sigma_{i,h_i}})]}. \tag{2}$$

Layer 2: The nodes in this layer are fixed. The output of these nodes is given by

$$o_{2,r} = w^r = \prod_{i=1}^{q} \mu_{o_{i,h_j}}(x_j), \quad \text{for all } h_i \tag{3}$$

where h_i is the hth fuzzy set associated with x_i, and $h_i = 1, 2, \ldots, n_i$.

Layer 3: Each fixed node in this layer normalizes the output in layer 2, given by

$$o_{3,r} = \bar{w}^r = \frac{w^r}{\sum_{r=1}^{m} w^r}. \tag{4}$$