A Self-Organizing and Trainable Fuzzy-Neural Controller

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I. Introduction

In recent years there has been a significant increase in the number of applications of fuzzy logic control. These applications include welding, automobile speed control, aircraft flight control, robot control, elevator control, and train control [1]. The design technique common to these applications follows the conventional fuzzy set formulation which relies on the human expert's knowledge [4]. A set of linguistic variables is derived by the expert, and a membership function of each variable is subjectively characterized. Then, a finite set of fuzzy rules (or IF/THEN knowledge base) is developed, which uses the defined linguistic variables. In both steps, the expert's knowledge is essential. However, this classical approach presents several drawbacks in the following cases. 1) If the expert's knowledge is not available, the system cannot be designed. 2) Frequently the expert's knowledge is incomplete or incorrect. 3) If a fuzzy system receives an unexpected response which was not prescribed by the linguistic variables, the system responds with a "don't know state" instead of some approximation. 4) The fuzzy rules constructed by the expert do not usually cover all possible combinations of input variables due to the large dimensionality of the variable space. To overcome these problems, we propose a self-organizing and trainable fuzzy-logic controller where the expert's knowledge is estimated through artificial neural-network (ANN) approaches.

In this paper, the implementation of a self-organizing and trainable fuzzy-neural controller is introduced. The system is based on the clustering technique of self-organizing feature-map and the ANN training of the connectionest network architecture. During the self-organizing phase, the membership functions of the input variables are roughly approximated. Subsequently, a supervised learning algorithm fine tunes the parameters of the membership functions and constructs the fuzzy rules. This characteristic of the proposed system derives a general-purpose modeling of the fuzzy logic controller in the absence of expert's knowledge or in the case of systems with a large number of control variables.

II. The Proposed Fuzzy Controller

The fuzzy controller model

Before describing the controller, we establish the basic fuzzy model to be used. We begin the discussion with the definition of the linguistic variables and values [1]. A value A_i of a linguistic variable A is defined as a normalized convex fuzzy set on the real line R such that:

$$\max_{x_i \in X} \mu_{A_i}(x_i) = 1 \tag{1}$$

where X is region of support of A, $\mu_{A_i}(x_i)$ denotes the membership function of x_i in A_i, and x_0 is referred to as the mean value of A_i if $\mu_{A_i}(x_0) = 1$.

After the linguistic variables are determined, the control policy is represented by a finite collection of fuzzy rules of the form:

Rule i: if (A is A_i) and (B is B_i) $\cdots$, then (Z is Z_i)

where $A, B, \cdots$ are linguistic input variables and Z is the linguistic consequence (output) variable. Generalizing these rules, the consequence Z may be expressed as a function of the input variables [4]:

$$\begin{aligned} Z_i &= f_i(A, B, \cdots) \\ &= w_0 + w_1^A A_1 + w_2^A A_2 + \cdots + w_1^B B_1 + w_2^B B_2 + \cdots \end{aligned} \tag{2}$$

where w_k^Y denotes the weight of kth fuzzy value of the linguistic variable Y through the ith rule. The final crisp control values are obtained through a defuzzification process expressed as

$$z^* = \frac{\sum_{i=1}^{n} \alpha_i f_i(A, B, \cdots)}{\sum_{i=1}^{n} \alpha_i} \tag{3}$$

where α_i is the strength of the rule i given by

$$\alpha_i = \mu_{A_i}(s_A) \wedge \mu_{B_i}(s_B) \wedge \cdots$$

where $\wedge$ denotes the fuzzy conjunction operator (e.g., min operator) and s_A is the sensor reading of the fuzzy variable A. In the design of a fuzzy controller, the unknown entities determined by the expert are the membership functions defined in (1) and the fuzzy rules in (2). It is usually not too difficult to specify these entities if a system is controlled only by a small number of control state variables. However, as the number of variables increases, this task becomes extremely difficult. In this paper, we propose to estimate both the membership function and the fuzzy rules from a finite set of training examples using neural network training techniques, as described below.

Fuzzy neuron

As it is proven in [2], any continuous function can be uniformly approximated by a continuous ANN (connectionest model) with one hidden layer, given that the activation function of each node is continuous and nondecreasing. Thus, it is feasible to represent a membership function using an ANN structure. Moreover, different types of fuzzy membership functions used in fuzzy control systems mostly fall into one of the following four types: (1) monotonic, (2) triangular, (3) trapezoidal, and (4) bell shaped [1]. Considering these basic shapes, an efficient representation of the general membership function can be derived through an ANN structure. We propose a three node ANN structure which has two sigmoid-type hidden nodes and one summing output node to approximate the basic four shapes of membership functions. In a mathematical form, the proposed membership function is represented as,

$$\mu_A(x) = v_1 f_1(x) + v_2 f_2(x), \tag{4}$$

where the function $f_i(x)$ is a sigmoid node defined by

$$f_i(x) = \frac{1}{1 + e^{-a_i(x+c_i)}}. \tag{5}$$

In this model, a_i controls the slope of the sigmoid and c_i controls the position on x-axis of the sigmoid transition-area. Note that if either v_1 or v_2 is zero, the three node structure approximates monotonic membership functions; if $v_1 = 1$ and $v_2 = -1$, it approximates triangular, bell, or trapezoidal shapes through the proper selection of c_1, c_2, a_1, and a_2.

The self-organizing and trainable fuzzy controller

Since it is assumed that the expert's knowledge needed to construct the membership functions is not available, each membership function is estimated from the training data. For this task, we propose to utilize Kohonen's self-organizing feature map clustering technique [6] (due to limited space this technique is not described). This procedure approximates the distribution of the membership functions and finds their mean values.

After the completion of the self-organizing process, the system changes its mode into a supervised learning phase, where a fine tuning of the membership functions and the derivation of the fuzzy rules are achieved. For the supervised learning, we propose to employ a simple gradient search method on a quadratic objective function. In essence, this method minimizes the quadratic objective function given by

$$E = \sum_i (z_i - z_i^*)^2 \tag{6}$$

where z_i is the desired output and z_i^* is the defuzzified output given in (3). This supervised training allows the system to discover the fuzzy rules in addition to the fine adjustment of the membership functions. Notice that due to the self-organizing procedure, most stochastic features are already captured in the network structure; thus, the speed of the convergence is faster than the backpropagation approach [3]. The training algorithm is described in the paper.

Our initial simulation study indicates that the network's approximation closely matches the human expert's knowledge. In the main paper, we present simulation results on the control of Sugeno's fuzzy car [5], demonstrating the application of the proposed controller.

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