Design of Fuzzy Logic Controllers by Fuzzy *c*-Means Clustering

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Abstract

In this paper, the use of Fuzzy *c*-means clustering algorithm in the design of membership functions and fuzzy rules of a fuzzy logic controller.are described. In the design procedure, an auto-tuning PID controller was used to operate an example plant which is a model of the air-conditioning system, and the plant operating data were collected. The fuzzy *c*-partition of the data was then analyzed by Fuzzy *c*-means clustering to achieve optimum fuzzy sets and fuzzy rules of the FLC. The FLC was then implemented and simulated in controlling the plant. The results from simulation show that when compared to conventionally designed FLC, the proposed FLC gives better temperature characteristics.

Keywords: - Fuzzy logic controller, Fuzzy *c*-means clustering, Controller design.

1. Introduction

Fuzzy logic controllers first implemented by King et al. [5] on the basis of the fuzzy logic system generalised from the fuzzy set theory originated by Zadeh [12] has appeared to offer a feasible solution to various control problems. Its use in engineering disciplines has been widely spread such that commercial and industrial fuzzy systems have been successfully developed in the last few years. The main attraction undoubtedly lies in the unique characteristics of fuzzy systems. They are capable of handling complex, nonlinear, and sometimes mathematically intangible dynamic systems using simple solutions. However, obtaining an optimal set of membership functions and rules is not an easy task. In most fuzzy control systems, the membership functions and fuzzy rules are derived and tuned by human experts. It requires time, experience, and skills of the operator for the tedious fuzzy design and tuning exercise, and the obtained FLCs may not be optimal. Recently, there has been an extensive amount concentrated on the membership function development and the rule construction in FLC design. For example: Abe et al. [1] proposed a method for fuzzy rule extraction directly from the numerical data, Klawonn et al. [6] discussed on various fuzzy clustering methods for use in the design of FLC, Jang et al. [4] worked on the neural network approach, Meredith et al. [7] carried on the Genetic Algorithm approach.

In this paper, Fuzzy *c*-means clustering algorithm is used in the design of a FLC by optimizing the fuzzy sets and the fuzzy control rules from the operating data of the controlled plant. This paper is organized as follows :-

In Section 2, an example plant, an air-conditioning system model is constructed and described in detail. In Section 3, fuzzy c-means clustering algorithm is explained. The proposed approach – the design of FLC using fuzzy c-means algorithm – is presented in Section 4. In Section 5, the simulation results from the two fuzzy logic controllers, namely, the conventionally-designed and the fuzzy c-means clustering – designed ones are described. Finally, in Section 6, the general conclusion is formulated.

2. Example Plant : Air Conditioning Control System

The control system configuration of the air conditioning system consists of three parts: an air conditioning unit, a fuzzy logic controller and a load simulator, as shown in Fig. 1.

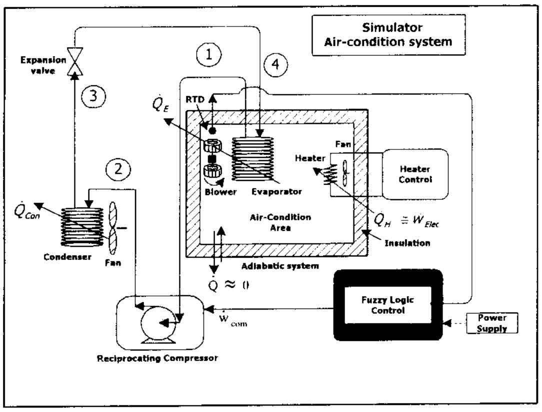

Fig. 1 Model of Air-Conditioning Control System

3. Fuzzy *c*-Means Clustering

The fuzzy *c*-means clustering is a data clustering algorithm [9] in which each data point belongs to a cluster to a degree specified by a membership degree. Bezdek et al. [2] proposed this algorithm as an improvement over earlier hard *c*-means (HCM) clustering be improved with use of fuzzy set method. We classify the various data points as a fuzzy *c*-partition on a universe of data points [9] and assign membership value to it that is determined from the data of each point and the data of a cluster center in each group. Hence, a single point can have partial membership in more than one class and the membership value that the *k*th data point has in the *i*th class with the following notation.

$$\mu_{ik} = \mu_{A_i}(x_k) \in [0,1] \qquad (1)$$

In the determination of the fuzzy *c*-partition [9], a matrix **U** for grouping a collection of *n* data sets into *c* classes, we define an objective function J_m for a fuzzy *c*-partition, where

$$\mathbf{J}_m(\mathbf{U},\mathbf{v}) = \sum_{k=1}^{n}\sum_{i=1}^{c}(\mu_{ik})^{m'}(d_{ik})^2 \qquad (2)$$

where

$$d_{ik} = d(\mathbf{x}_k - \mathbf{v}_i) = [\sum_{j=1}^{m}(x_{kj} - v_{ij})^2]^{1/2} \qquad (3)$$

and μ_{ik} is the membership of the *k*th data point in the *i*th class, d_{ik} is distance measure or Euclidean distance between the *i*th cluster center and the *k*th data point in m-space, m′ is a weighting parameter which has a range m′ $\in [1,\infty)$ and $\mathbf{v}_i$ is *i*th cluster center, which is described by m coordinates and can be arranged in vector form, $\mathbf{v}_i = \{v_{i1}, v_{i2},\ldots,v_{im}\}$. Each of the cluster coordinates for each class can be calculated as

$$v_{ij} = \frac{\sum_{k=1}^{n}\mu_{ik}^{m'}\cdot x_{kj}}{\sum_{k=1}^{n}\mu_{ik}^{m'}} \qquad (4)$$

where j is a variable on the coordinate space, i.e., j = 1, 2, ...,m. The optimum fuzzy c-partition will be the smallest of the partitions described in equation (2); that is,

$$\mathbf{J}_m^*(\mathbf{U}^*,\mathbf{v}^*) = \min_{M_{fc}} \mathbf{J}(\mathbf{u},\mathbf{v}) \qquad (5)$$

The effective algorithm for fuzzy classification is called iterative optimization [9] as follows:-

1. Fix c $(2 \le c < n)$ and select a value for parameter m′. Initialize the partition matrix, $\mathbf{U}^{(0)}$ Each step in this algorithm will be labeled r =0, 1, 2,...
2. Calculate the c centers $\{\mathbf{v}_i^{(r)}\}$ for each step.
3. Update the partition matrix for the *r*th step, $\mathbf{U}^{(r)}$ as follows:

$$\mu_{ik}^{(r+1)} = \left[\sum_{j=1}^{c} \left(\frac{d_{ik}^{(r)}}{d_{jk}^{(r)}} \right)^{2/(m'-1)} \right]^{-1} \quad \text{for } \mathbf{I}_k = \phi \qquad (6)$$

or

$$\mu_{ik}^{(r+1)} = 0 \text{ for all } i \in \tilde{\mathbf{I}}_k \qquad (7)$$

with

$$\mathrm{I}_k = \{ i \mid 2 \le c < n; d_{ik}^{(r)} = 0 \} \qquad (8)$$

and

$$\tilde{\mathbf{I}}_k = \{1, 2, \ldots, c\} - \mathbf{I}_k \qquad (9)$$

and

$$\sum_{i \in \mathbf{I}_k} \mu_{ik}^{(r+1)} = 1 \qquad (10)$$

4. If $\| \mathbf{U}^{(r+1)} - \mathbf{U}^{(r)} \| \le \varepsilon_L$, stop; otherwise set $r = r+1$ and return to step 2.

4. Design of Fuzzy Logic Controller

4.1 Membership Functions Design

In the design process of the FLC, fuzzy rules are defined for two input variables, the error (ER) and the change of error (DE), and single output variable, the control signals (CS) which are used as the input and output variables of the plant. The designs were carried on using the plant of air-conditioning system with the procedures:

4.1.1 With the auto-tuning PID controller operate the plant in steps over its full range of operation and at each step, record the values of the input and output variables of the plant which are shown in Fig. 2,3 and 4. for setpoint at 19 °C.

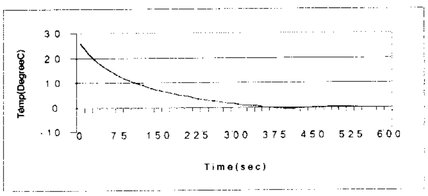

Fig. 2 The Recorded Values of Error

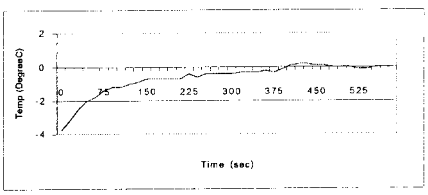

Fig.3 The Recorded Values of Change of Error

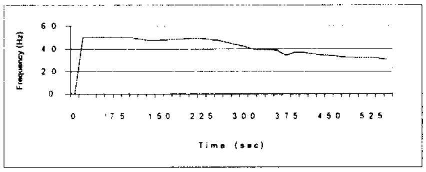

Fig. 4 The Recorded Values of Control Signal

4.1.2 The fuzzy *c*-partitions from 4.1.1 are then analyzed by fuzzy *c*-means clustering algorithms for 7 clusters of data for the input variables and 5 clusters of data for the output variable as shown in Fig. 5 The obtained clusters were then normalized to get the fuzzy sets as shown in Fig. 6, 7 and 8.

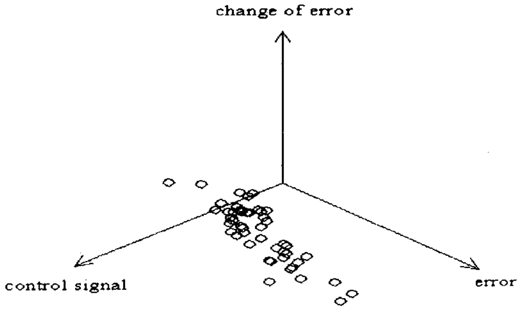

Fig. 5. The Converged Fuzzy Partition for Temperature Control in the Control System

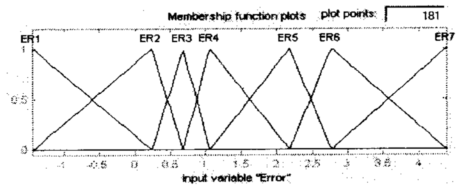

Fig. 6 Fuzzy Sets of Error

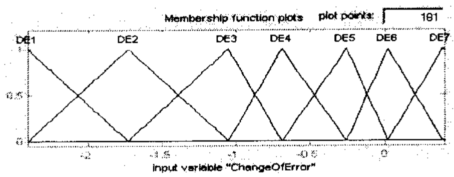

Fig. 7 Fuzzy Sets of Change of Error

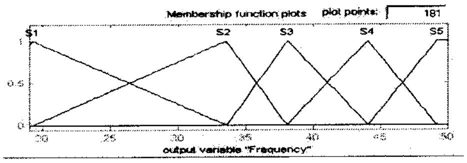

Fig. 8 Fuzzy Sets of Control Signal

4.2 Derivation of Fuzzy Rules

We project the fuzzy clusters of the input variables, error and change of error to the output variables of the plant and fuzzy rules can then be obtained from the projections.

5. Simulation Results

The fuzzy *c*-means clustering designed FLC was tested on the setpoint of 25°C for the air-conditioner model of 1.8 m. wide, 2 m. long and 1.5 m. high and the results were compared to the results by conventional designed FLC on the same setpoint, the systems were able to give the output response and energy saving as follows:-

5.1 Operating characteristics temperature (°C) vs time (sec.) of the air-conditioning system controlled by the conventional designed FLC is shown in Fig. 9.

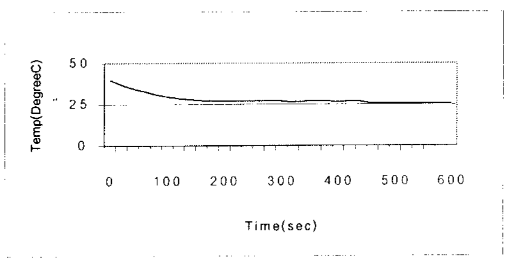

Fig. 9. Temperature Characteristics of The Conventional Designed FLC

5.2 Operating characteristics temperature (°C) vs time (sec.) of the air-conditioning system controlled by the fuzzy *c*-means clustering designed FLC is shown in Fig.10

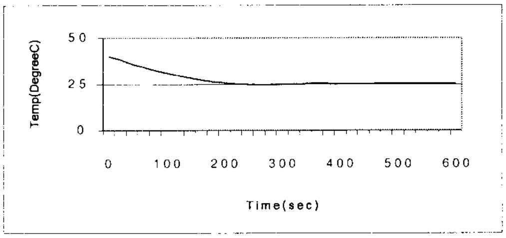

Fig. 10. Temperature Characteristics of The Fuzzy *c*-Means Clustering Designed FLC

6. Conclusion

In this paper, an application of fuzzy *c*-means algorithms in the design of the fuzzy sets for the fuzzy logic controller of the temperature control in an air conditioning system has been investigated. The results from simulation show that the fuzzy *c*-means clustering designed FLC gives the temperature characteristics that are better than the conventional designed FLC.

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