Design of Reduced Rule Multi Input Single Output Fuzzy Controller

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Abstract

It is a well known fact that the performance of a process controlled by a fuzzy logic controller (FLC) can be improved by increasing the number of rules present in the rule base. The rules can be increased either by increasing the number of inputs or by increasing the linguistic variables. In either case with increase in number of rules the computational time and computational memory required increases thereby slowing down the process. In this paper the number of linguistic variables of conventional FLC are increased from 3 to 7 thereby increasing the number of rules and then a novel method utilizing the concept of equilibrium with clustering is proposed where in the number of rules are reduced. By using the proposed method the number rules are reduced but at the same time the performance of the process is not compromised with reduced rules. The proposed method is applied to different processes and the simulation results are presented and analyzed to show the effectiveness of the proposed method.

Keywords: Fuzzy logic controller, reduction of rules, equilibrium value, clustering, computational memory and computational time.

Introduction

Fuzzy logic controllers (FLCs) are increasingly applied to many systems with nonlinearity and uncertainty and it is based on experience of a human operator. While controlling a plant a skilled human operator manipulates the output of the controller based on error and change in error with an aim to reduce the error with a shortest
possible time. Conventional fuzzy classifiers consist of interpretable if-then rules with fuzzy antecedents and class labels in the consequent part. The antecedents or the more popularly known if-parts of the rules partition the input space into a number of fuzzy regions by fuzzy sets, while the consequents or then-parts describe the output of the classifier in these regions. Fuzzy logic improves rule-based classifiers by allowing the use of overlapping class definitions and improves the interpretability of the results by providing more insight into the decision making process.

Fuzzy logic, however, is not a guarantee for interpretability, as was also recognized in [1, 2]. Hence, real effort is required to keep the resulting rule-base transparent. The automatic determination of compact fuzzy classifiers rules from data has been approached by several different techniques: neuro-fuzzy methods [3], genetic-algorithm (GA) based rule selection [4], and fuzzy clustering in combination with GA-optimization [5]. Generally, the bottleneck of the data-driven identification of fuzzy systems is the structure identification that requires nonlinear optimization. Thus for high-dimensional problems, the initialization of fuzzy model becomes very significant. Common initializations methods such as grid-type partitioning [4] and rule generation on extreme initialization, result in complex and non-interpretable initial models and the rule-base simplification and reduction steps become computationally demanding. To avoid these problems, fuzzy clustering algorithms [6] were put forward.

Tari et. al [7] presented clustering method in which the structure is captured through rough constructs such as rough prototypes themselves. In [8] Valls et. al presented a method in which background knowledge was used for developing the cluster models. Pedrycz et. al. proposed a method of fuzzy clustering using view points [9]. It is presented that the view points are available to the clustering problem and are helpful in communicating the real meaning of the problem in which the results of the clustering are directly utilized. Chiu [10] presented an effective method for extracting fuzzy rules using a cluster estimation method known as subtractive clustering that is helpful in extracting rules from high dimensional characteristic area. The FCM clustering method utilizes priori knowledge of the number of clusters. When a FCM requires desired number of clusters and initial approximate positions of each cluster center, the output fuzzy rules mainly depend on the choice of the original values. In [11] a robust fuzzy local information c-means algorithm was proposed which can detect the clusters of an image overcoming the disadvantage of the Fuzzy c-means and their variants. In this paper a novel method utilizing the concept of equilibrium value with clustering is proposed to reduce the number of rules while keeping the performance of the control system at the same level.

**Fuzzy Logic Controller**

The basic structure of Mamdani type fuzzy logic controller is shown in Fig. 1. As shown in Fig. 1, FLC comprises of four basic parts namely fuzzifier, knowledge (rule) base, inference and defuzzifier.

The scale mapping and fuzzification of the input variables is done by fuzzifier. Hence, all the input variables are scaled and are fuzzified. The process of
fuzzification essentially means that the measured crisp input signals that have numerical values are transformed into fuzzy quantities understandable by the fuzzy controller, also sometimes referred as linguistic variables. This process of fuzzification is usually executed by using membership functions.

The knowledge base block consists of data base and the linguistic control rule base. The linguistic control rules and fuzzy data manipulation are made by the information given by the data base. The rule base specifies the control actions by using a set of linguistic control rules provided by an expert. The FLC after viewing the input signals uses the control rules to determine the suitable control action. A set of “if-then” rules are present in the rule base.

The third part inference is the heart of the FLC which has the potential of simulating human decision making based on fuzzy notion and of inferring fuzzy control actions by utilizing the fuzzy implications. After the fuzzifier transforms the input variables into respective linguistic variables, the inference block evaluates the set of “if-then” rules present in the rule base of the fuzzy controller. After evaluating the rules a result is obtained in linguistic form.

The result hence obtained above is a linguistic value which is not understandable by the process to be controlled. To transform this linguistic value into a real output defuzzification is performed. The scale mapping and defuzzification is performed by defuzzifier. The output of the defuzzifier is non-fuzzy, real control action from the inferred fuzzy control action by utilizing membership function. The block diagram of a conventional two input single output FLC is shown in Fig. 2.
The numbers of rules that are possible in the rule base of a (FLC) are given by

\[ R = N^i \]  

(1)

where 
- \( R \) = No. of rules in the rule base of fuzzy controller
- \( N \) = No. of linguistic variables that can be considered for each input
- \( i \) = No. of inputs.

Considering the above equation the rules that are possible for two input and 3 or 5 or 7 linguistic variables (L.V.) are given in table 1, table 2 and table 4 respectively.

**Table 1:** Fuzzy rules for 2 input 3 L.V.

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<th>e / ( \Delta e )</th>
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<th>ZE</th>
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**Table 2:** Fuzzy rules for 2 input 5 L.V.

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**Proposed Methods**

It can be seen from the tables that as the linguistic variables are increasing the number of rules present in the rule base are also increasing. Although the performance of the process control increases with increase in number of rules but at the same time with increase in number of rules the computational time and computational memory required increases considerably thereby slowing down the process control.

**Equilibrium Value Method**

Hence, to reduce the number of rules present in the rule base of FLC a novel method known as equilibrium value method is proposed in which an equilibrium value is computed by assigning a value to each linguistic variable in the domain \([-1, 1]\). If the assigned value of the linguistic variable is less than the obtained equilibrium value either for error or change in error then that rule is neglected or not fired. In this way the number of rules present in the rule base can be reduced considerably [12]. With the above proposed method the number of rules that are present in table 1 are reduced from 9 to 4, rules in table 2 are reduced from 25 to 4 and rules in table 3 are reduced from 49 to 16. The number of rules in table 1 and 2 are reduced considerably, but the rules present in the table 3 can further be reduced by utilizing subtractive clustering [10].

**Subtractive Clustering**

Considering a sample set of n data points \(A = \{a_1, a_2, \ldots, a_n\}\) in M dimensional space where each data sample, \(a_i\) is defined by \(m\) features in the universe \(A\) i.e. \(a_i = \{a_{i1}, a_{i2}, \ldots, a_{im}\}\). Now we are required to generalize the data points in each dimension so that they are bounded by a unit hypercube or hyper-spherical cluster. Each data point is considered as a possible cluster center and the measure of potential of data point \(a_i\) is defined by (2)

\[
P_i = \sum_{j=1}^{n} e^{-\alpha \left\| a_i - a_j \right\|^2}
\]  

(2)
where $\alpha = 4/c_a^2$, $c_a$ is a positive constant, $a_i$ and $a_j$ are data points, $P_i$ is the potential of data points and $\| \|$ is a Euclidean norm or distance. Let $a_1^*$ be the location of the first cluster center and $P_i^*$ be its potential value. The potential value of each data point is revised by the (3)

$$P_i \leftarrow P_i - P_1^* e^{-\beta \|a_i - a_1^*\|^2}$$

(3)

where $\beta = (2/c_b)^2$

(4)

and $c_b$ is another positive constant. The constant $c_b$ is effectively the radius defining the neighborhood that will have measurable reductions in potential. In the present work the value of $c_b = \sqrt{2}$, $c_a$ is chosen so that good distance is maintained between two clusters. The output of the proposed fuzzy controller will be

$$u(k) = \Delta u(k) + u(k-1)$$

(5)

The equations of error, change in error and change in change in error are given as

$$e(k) = r - y$$
$$\Delta e(k) = e(k) - e(k-1)$$

(6)

By utilizing the proposed subtractive clustering the number of rules for 2 input 7 linguistic variables are further reduced from 16 rules to 8 rules i.e. altogether the rules are reduced from 49 to 8 for 2 input 7 linguistic variables thereby considerably reducing the computational memory and computational time required.

**Simulation results and Discussions**

The main aim of this method is to see whether the proposed reduced rule method is able to achieve the same level of performance even after reducing the number of rules. The conventional FLC is represented by CFLC, equilibrium value method FLC is represented by EVMFLC and equilibrium value with clustering FLC is represented by EVMCFLC. The proposed method of reducing the rules by using equilibrium value with clustering is applied to second order and third order systems to validate the effectiveness of the proposed method and these are represented by the transfer functions as

$$G_1(s) = \frac{1}{(s + 1)(s + 2)}$$

(7)

$$G_2(s) = \frac{1.5}{s^3 + 6s^2 + 11s + 6}$$

(8)
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Fig. 3 Response of system 1 with conventional FLC

Fig. 4 Response of system 1 with EVMFLC

Fig. 5 Response of system 1 with EVMFLC and EVMCFLC – a comparison
Fig. 6 Response of system 2 with conventional FLC

Fig. 7 Response of system 2 with EVMFLC

Fig. 8 Response of system 2 with EVMFLC and EVMCFLC – a comparison
The response of system 1 for CFLC, EVMFLC and EVMCFLC are shown in Fig. 3 to Fig. 5 and for system 2 the responses are shown in Fig. 6 to Fig. 8 for the above three controllers. As can be seen from these figures the response of the system is improved in terms of peak overshoot and settling time with increase in number of rules of CFLC though there is a little increase in rise time. With increased rules the computational time increases which slows down the process. In order to reduce the number of rules the equilibrium value method with clustering applied and the response of the system 1 and system 2 are shown in Fig. 4 and Fig. 7 respectively for EVMFLC and for EVMCFLC the response is shown in Fig. 5 and Fig. 8 for system 1 and 2 respectively. It is observed from the simulation results that we are able to achieve almost the similar performance even with the reduced rule thereby reducing the computational memory and computational time requirement and hence it can be said that the proposed scheme is superior as it is able to achieve the similar performance but with reduced rules.

Conclusions

It is well known fact that with increased rules the performance of fuzzy controller increases but with increases requirement of computational memory and computational time. In this paper two approaches are presented to reduce the number of rules present in the rule base of fuzzy controller. The first method utilizes the equilibrium value method in which first an equilibrium value is calculated and then if the error or change in error is less than this equilibrium value then it is neglected. In this way the rules are reduced from 49 to 16 for a 2 input fuzzy controller with 7 linguistic variables. In the second method subtractive clustering is applied to the resultant 16 rules and this is able to reduce the rules to 8. This means that altogether the rules are reduced from 49 to 8 thereby reducing the stress on computational memory to a considerable extent. To validate the proposed methods simulations are performed and analyzed by applying these methods to second order and third order systems. The proposed methods are found to be in good agreement with the published work.

References


