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Young Im CHO*

FUZZY INFERENCE METHOD FOR INTELLIGENT ARTIFICIAL SYSTEM

A fuzzy control system which is a typical system utilizing fuzzy model is mainly using the **Max-Min CRI** (Compositional Rule of Inference) method by Zadeh and Mamdani for fuzzy inference. But the Max-Min CRI method suffers from drawbacks including: error-prone weighting strategy, inefficient compositional rule of inference, and subjective formulation of membership functions. Because of these problems in the Max-Min CRI method, the inference often results in significant error regions specifying the difference between the desired outputs and the inferred outputs. To overcome such problems, we propose here a new fuzzy inference system for artificial intelligence control.

1. INTRODUCTION

The most important thing to implement modern high technologies is how to define a fuzzy control model. In order to do that, it has been adopted that mathematical models are regarded as control system models. However, there are some problems. That is to say, mathematical system models cannot represent real control models and its linguistic meanings perfectly of the controller. To resolve these problems, fuzzy theory was proposed by Zadeh [1] for modelling an approximate reasoning called Compositional Rule of Inference (CRI) [1]. Mamdani [2] improved the CRI method using 'max' and 'min,' called Max-Min CRI method.

However, there is a critical problem in the CRI method, which equivalently combines rules for an inference. It produces a big error for a premise which is very similar or identical to one of premises in rules. It is because the importance of rules is not taken into the consideration for inference. In this paper, we propose a novel fuzzy inference method to reduce the error by providing weights to composition of rules according to the similarity of premises.

In the experimental section, we show that the proposed similarity measure can reduce a lot of error regions compared with the conventional Max-Min CRI method using the example of D.C. series motor controller. Also, we compared the performance of similarity of our method with that proposed by Takefuji [3] and Turksen [4]. Their methods are briefly explained in the following section.

There has been studied in similarity measures. Gau et al. [5] and Hong [6] proposed a similarity measure between two vague sets. They introduced a set of modified similarity measures which are reasonable in a more general sense rather than a special case. Sessa [7] proposed a similarity-based SLD resolution for approximate reasoning, and then approximate inferences are possible since similarity relation allows us to manage alternative instances of entities that can be considered "equal" with a given degree. Niittymaki et al. [8] applied the SLD technique to design the traffic signal controller. Lin [9] introduced a new asymmetry-similarity-measure-based neural fuzzy inference system (ASM-NFIS) based on the similarity measure of asymmetric Gaussian membership functions, and the parameter learning is based on a supervised gradient descent method.

However, most papers have discussed the above similarity measure in too general points of view. A similarity measure needs not to have generality but to have specialty according to domain area and inference methods. The above mentioned similarity measures cannot apply to the Max-Min CRI method, because they cannot be guaranteed except estimating of language similarities. Also, as the measuring equation is too complicated, much simpler measure should be proposed in real time system such as D.C. series motor controller [10, 11].

2. PROPOSED ALGORITHM

The conventional CRI is the fuzzy inference method with multiple rules using 'max' and 'min' operators and is represented by possibility distribution values [2,3]. Let 'X is A' and 'Y is B' be a fuzzy statement of premise and its conclusion, respectively. For a rule, the possibility distribution values of a specific premise fuzzy set A and its corresponding conclusion fuzzy set B can be denoted as $\Pi_X = \mu_A$ and $\Pi_Y = \mu_B$ as seen in eq. (1). Here, μ_A and μ_B is a membership function of fuzzy set A and B, respectively.

$$IF\ X\ is\ A\ THEN\ Y\ is\ B \rightarrow IF\ \Pi_x = \mu_A\ THEN\ \Pi_Y = \mu_B \tag{1}$$

Eq. (1) can be expressed in a membership function as following:

$$\begin{aligned}\mu_{B'}(v) &= \underset{u\in U, v\in V}{Max} \underset{i=1,n}{Min}(\mu_{A'}(u), \mu_{A_i}(u) \rightarrow \mu_{B_i}(v)) \\ &= \underset{u\in U, v\in V}{Max} \underset{i=1,n}{Min}(MaxMin(\mu_{A'}(u), \mu_{A_i}(u)), \mu_{B_i}(v))\end{aligned} \tag{2}$$

* Professor, Dept. Of Computer Science, University of Suwon, KOREA

where $u \in U$ and $v \in V$ (U and V are universe of discourses). Also, A_i and B_i are the premise and its conclusion of rule i, here i = 1, 2, ..., n. This produces a big error for a premise which is very similar or identical to one of premises in rules due to no consideration of importance of rules. The more similar is the test premise to the premise, the more error we can have. Let's have fuzzy rule base with three rules as seen in Table 1.

Table 1. The membership functions of fuzzy rules

Rule Base				
Rule 1	IF	X is A_1	THEN	Y is B_1
Rule 2	IF	X is A_2	THEN	Y is B_2
Rule 3	IF	X is A_3	THEN	Y is B_3

where A_i and B_i are fuzzy sets, i = 1, 2, 3. Also, the rules can be represented in membership functions as seen in Fig. 1. If A' is given as seen in Fig. 2 (a), then B is obtained as following figure. Defuzzification procedure activates with eq. (3).

$$\mu_B = \underset{y \in Y}{Max}\, \mu_{B_i}(y), \quad for \quad 1 \le i \le 3 \tag{3}$$

And then, the defuzzification value can be computed using the centre of area (COA) [2, 3] as following.

$$Defuzzification\ value = \frac{\int \mu_B(y) \cdot y dy}{\int \mu_B(y) dy} \tag{4}$$

From Fig.1 and Fig. 2, even though the test premise is identical to the premise of Rule 1, its estimated conclusion is far deviated from desired conclusion because of the combining rules of inference. In order to reduce the inference error from eq. (4) due to the error region in the conclusion as marked in Fig. 2(b), we provide weights to the rules according to the similarity of test premise to the premises of rules. In this Letter, the error region can be defined as the area characterized by the difference between the fuzzy conclusions.

For $\forall\ u \in U$, the similarity, denoted as $S(A, A')$, between two fuzzy sets A and A' is determined by the following equation.

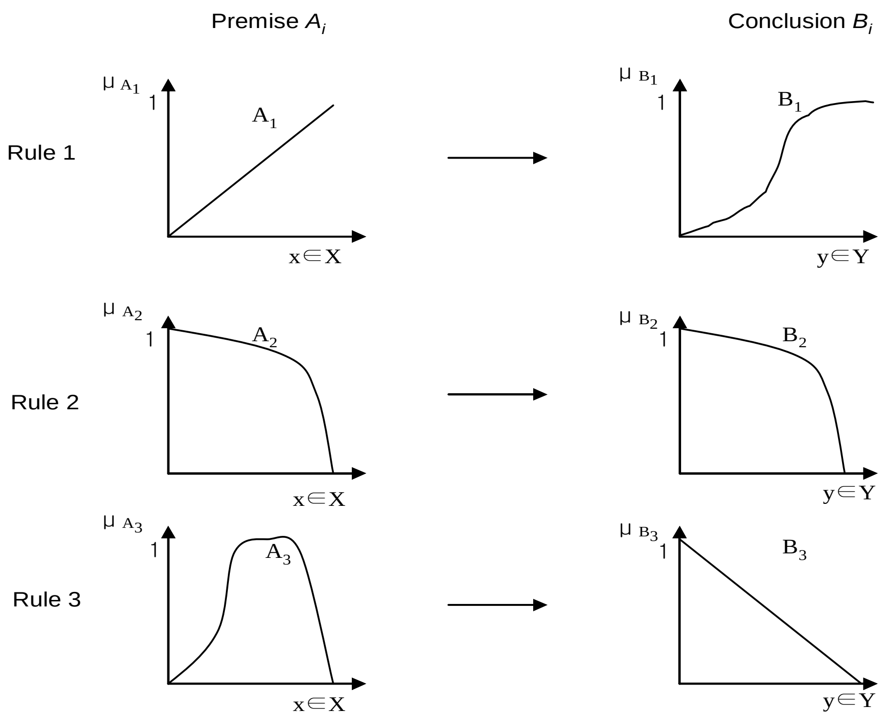
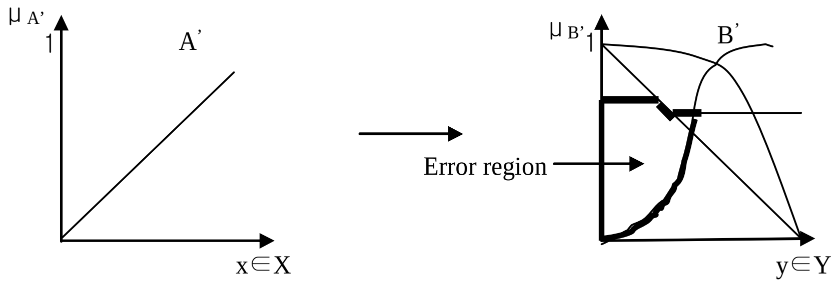


Fig. 1. The membership functions of fuzzy rules



(a) Given premise (b) Corresponding conclusion

Fig. 2. Inferred B' for given A'

$$S(A,A') = \frac{\int(\mu_A(u) \wedge \mu_A{}'(u))du}{\int(\mu_A(u) \vee \mu_A{}'(u))du}, \quad \text{for } \forall u \in U \tag{5}$$

where '∧' and '∨' means '*min*' and '*max*' operation, respectively. Eq. (5) can be demonstrated in a graphical manner using a triangle-shaped fuzzy membership functions as Fig. 3. The shadowed part is the intersection of two fuzzy sets and the skewed line part is the union of them. Max-Min CRI is used for computing conclusion as seen in eq. (6).

$$\begin{aligned} \mu_{B'}(v) &= \underset{u\in U, v\in V}{Max} \underset{i=1,n}{Min}(\mu_{A'}(u), (\mu_{A_i}(u) \to \mu_{B_i}(v)) \times S(A', A_i)) \\ &= \underset{u\in U, v\in V}{Max} \underset{i=1,n}{Min}(MaxMin(\mu_{A'}(u), \mu_{A_i}(u)) \times S(A', A_i), \mu_{B_i}(v)) \end{aligned} \tag{6}$$

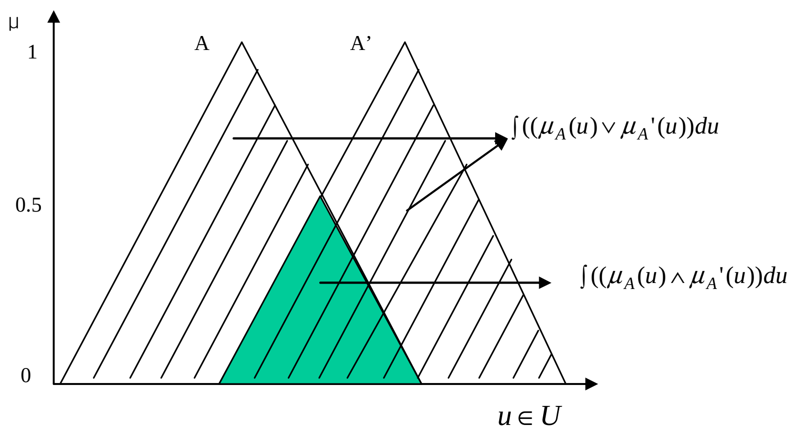


Fig. 3. The similarity measure

If there are two fuzzy sets with triangle type membership functions, the similarity degree between two fuzzy sets is straight-forward.

We compared the performances of our weighted similarity method, the conventional method, and two other similarity methods proposed by Turksen and Takefuji. Turksen's similarity is computed using the below equation.

$$SM = \frac{1}{1+DM} \; where, DM = 1 - \underset{u\in U}{Max}\, \mu_{A\cap B}(x) = 1 - \beta \tag{7}$$

where *A* and *B* are fuzzy sets. The Takefuji's similarity is computed as seen eq. (8).

$$\begin{aligned} \sigma &= 1 - \frac{d}{a+a'} \; where, d = \sum_{i=1}^{m} Max(A_1(x_i), A_1^{'}(x_i), A'(x_i)) \\ a &= \sum_{i=1}^{m} Max(A_1(x_i)) \\ a' &= \sum_{i=1}^{m} Max(A_1{}'(x_i)) \end{aligned} \tag{8}$$

where *A* and *A′* are fuzzy sets.

Table 2. The performance comparison

Input premise	Desired output	CRI	Turksen	Takefuji	Our method
Nu(Null)	1900	1763	1780	1800	1882
Z(Zero)	1600	1500	1510	1600	1600
S(Small)	1200	1200	1200	1200	1200
M(Medium)	800	1000	900	900	800
L(Large)	600	800	800	700	600
VL(Very large)	600	600	600	600	600

Table 2 shows the performance comparison of the various fuzzy inference methods such as CRI, Turksen, Takefuji, and our method. When the input premise is Nu (Null), the output of the conventional CRI is 1763. The inference error is 137 (=1900−1763). For Turksen’s method and Takefulju, the error is 120 (=1900−1780) and 100 (=1900-1800). For our method, the error is 17 (=1900-1882). From the result, our method provides the smallest error.

For the *Z* (*Zero*) input premise, Takefuji’s method and our method provide the smallest error. For the *S* (*Small*) input premise, the outputs of all methods are identical to the desired output. For the *M* (*Medium*) and *L* (*Large*) input premises, our method provides the smallest error. For *VL* (*Very Large*) input premise, the outputs of all methods are identical to the desired output. Therefore, our method is the most improved fuzzy inference method in D.C. series motor compared with other fuzzy inference methods.

3. CONCLUSION

A novel weighted CRI was proposed, and it was shown that our method outperforms the conventional CRI using the above practical example. Also, it was shown in the experimental section that our method can be applicable to real time control systems, especially for the case that similar or identical premises to the given premises in rules frequently happens.

However, our method can not be appropriate for the cases compromises of input premises are needed. To take into the consideration, we need to do further work for developing a method which automatically selects the premises with high similarity and ignores the premises with small similarity. Then, compromising those input promises using our method will give better fuzzy inference performance for fuzzy control system.

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