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Fact Gathering Using Ant Colony Optimization

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Abstract: Fact Gathering means generating rule base from available numerical data or data base. The intelligence of a fuzzy system lies in its rule base. Generating rule base is one of the most important and difficult tasks when designing fuzzy systems. Various rule base generation methods are used such as Neural networks, genetic algorithms, biogeography based optimization approach, ant colony optimization and particle swarm optimization which can be found in the literature. Designing fuzzy systems is an optimization problem. So in this paper, we introduce an Ant Colony optimization (ACO) approach to generate an optimized fuzzy rule base from available numerical data i.e. Fact Gathering. The ACO technique is inspired by real ant colony observations. It is a multi-agent approach to solving difficult combinatorial optimization problems. In the ACO meta-heuristic, artificial ant colonies cooperate in finding good solutions for difficult discrete optimization problems. Here, Ant paths help to determine the consequent parameters of generated rules.

Keywords: Fact Gathering,rule base, designing fuzzy systems, Ant colony optimization.

1. INTRODUCTION

The design of fuzzy systems can be regarded as an optimization problem. To ease design efforts and improve system performance, researchers have proposed designs using EC[1] and SI[2] techniques. ACO is SI technique inspired by real ant colony observations. It is a multi-agent approach to solving difficult combinatorial optimization problems such as the traveling salesman problem (TSP) (Dorigo& Gambardella, 1997; Dorigo et al., 1996)[3, 4] . In the ACO meta-heuristic, artificial ant colonies cooperate in finding good solutions for difficult discrete optimization problems. Fuzzy system design consists of structure and parameter designs, where structure learning determines the number of fuzzy rules and fuzzy sets in each input variable and parameter learning determines the free parameter in the antecedent and consequent parts. Most studies for fuzzy system optimization are used either pre-defined and fixed structures or defined the number of membership functions for each input variable in advance and searched the significant rules from a huge rule-base. In contrast to those studies, this paper presents a fuzzy system whose structure is designed through a Fuzzy C-means clustering method and rule base is optimized through ACO.

2. A FUZZY RULE BASE SYSTEM

A fuzzy rule based system consists of four major modules: fuzzification, inference engine, knowledge base and defuzzification module [5]. The fuzzification module transforms the crisp input(s) into fuzzy values. These values are then processed in fuzzy domain by inference engine based on the knowledge base supplied by the domain expert(s). The knowledge base is composed of the Rule Base (RB), characterizes the control goals and control policy of the domain expert by a set of linguistic control rules, and of the Data Base (DB), containing the term sets and the membership functions defining their semantics. Finally, the processed output is transformed from fuzzy domain to crisp domain by defuzzification module. The structure of a linguistic Fuzzy rule-based system is shown in Figure 1.

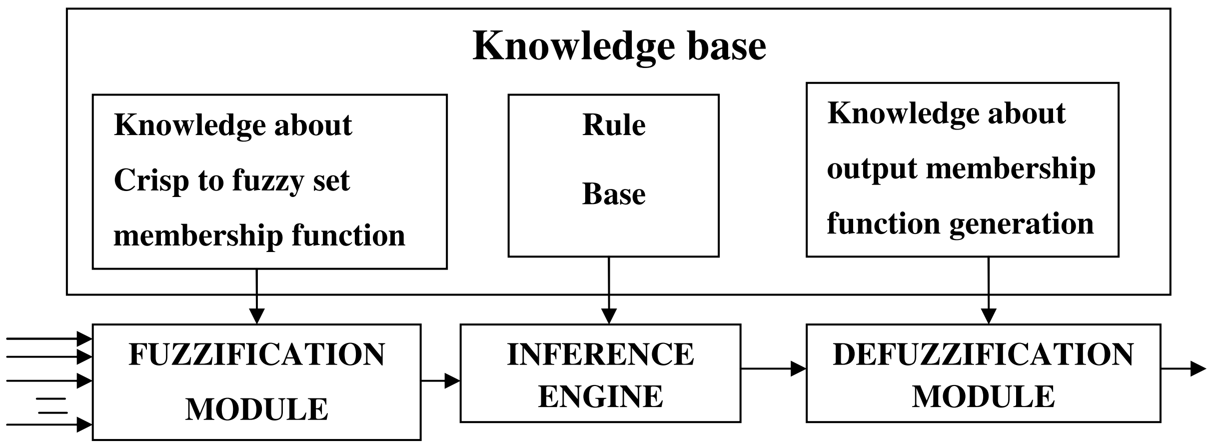

Figure.1. structure of fuzzy rule base system

The structure of a rule base can be stated as follows [6]:

Ri : if Xi is Ai1 … Xn is Ain then Y is Bj

Where Ain and Bj are fuzzy sets defined on the input and output domains respectively. *X*1…Xn and Y are input and output linguistic variables, respectively, and Ai1 … Ain and Bj linguistic labels, each one of them having associated a fuzzy set defining its meaning.The if part of rule base is called antecedent and then part is called consequent. Usually the antecedent of a given rule has more than one part and consequent has only one part.

3. SIMPLE- ANT COLONY OPTIMIZATION (S-ACO) ALOGORITHM

It has four steps based on the behavior of real ants colonies[7].

Nomenclature:

L^k = Length of ant K's path , ρ= evaporation constant, ρ∊ (0,1]

$\Delta\tau^k$ = increment in pheromone quantity = 1/ L^k

N_i^k = neighborhood of ant k when at node i. , α = a constant = 2

Step 1. Ant's Path-Searching Behavior : This step is used for finding the next node. For this, At each node, a constant amount of pheromone is assigned to all the arcs. When located at the node i an ant k use the pheromone trails τ_{ij} to compute the probability of choosing j as next node:

$$P_{ij}^{k} = \begin{cases} \tau_{ij}^{\alpha} / \sum_{l \epsilon Ni}{}^{k} \tau_{ij}^{\alpha}, \text{ if } j \epsilon N_i^{k}; \\ 0, \text{ if } j\ j \epsilon N_i^{k} \end{cases} \quad (1)$$

Step 2. Path Retracing and Pheromone Update: When ant K reaches the destination node, then ant retraces step by step the same path back to source node. During its return travel to the source the ant K deposits an amount $\Delta\tau^{k}$ of pheromone on arcs it has visited. In particular, if ant k is in the backward mode and it traverses the arc (i, j), it changes the pheromone value τ_{ij} as follows:

$$\tau_{ij} \tau_{ij} + \Delta\tau^{k} \quad \leftarrow \quad (2)$$

Step 3. Pheromone Trail Evaporation: Pheromone trails evaporates with exponential speed. Pheromone trails are evaporated by applying the following equation to all the arcs:

$$\tau_{ij} (1-\rho)\ \tau_{ij} \quad \leftarrow \quad (3)$$

Step 4:.Termination Condition: The program stops if at least one termination condition applies:

1. A maximum number of algorithm iteration has been reached.
2. If end of edge is the terminal node.

PROBLEM FORMULATION

The aim of this paper is to develop an optimized Rule-base for a fuzzy system. In order to determine the optimal Rule-base consider a Sugeno type fuzzy system [8] shown in figure 2.It consists of four major modules, *i.e.*, fuzzifier, rule composition module (fuzzy 'MIN' operators), implication module (fuzzy 'MUL' operators in this case), and defuzzification module. The overall computed output can be written as:

$$\text{Computed output} = \sum_{i} (\text{Wi} * \text{Ci}) / \sum \text{Wi} \quad (4)$$

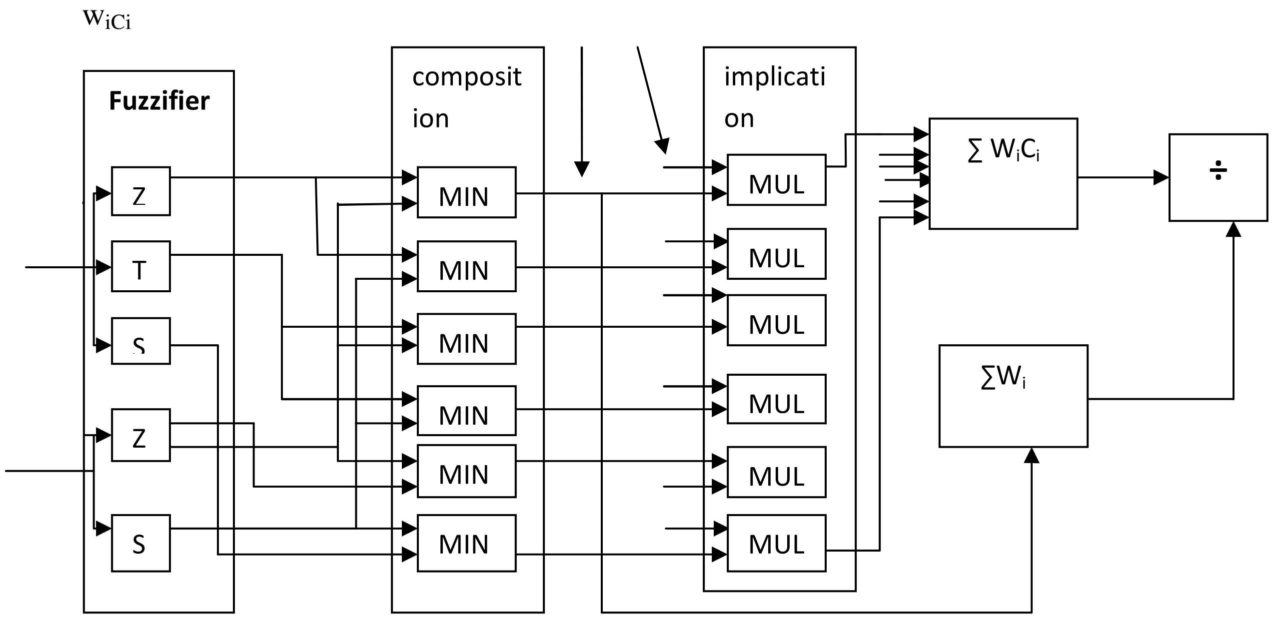

Figure .2. Sugeno type fuzzy system

The number of fuzzy rules can be defined as :

$$R = \sum_{i=1}^{n} \text{mi}$$

But these R rules are due to combination of membership functions of various inputs and these are incomplete as we could have knowledge only about antecedent part and consequents are yet unknown. Because for any set of inputs W_i are easily computed by fuzzifier and rule composing modules, the right hand side of output expression (4) can be evaluated if we could choose the proper values for C_i's.

We compare this computed output with actual output as given in data set and find error. Let the error be defined as follows:

Error E = Actual output(as given in the data set) – computed output (as given in equation 4).

The appropriate values of $C_i$can be findsuch that the difference between the computed output and the actual output is minimum. Now the main problem of rule base generation is minimization of error.

We apply S-ACO (simple-ant colony optimization) algorithm to evaluate rule base.

CONCLUSION: In this paper we discussed about fact gathering in a fuzzy system using ant colony optimization. For this, we consider sugeno type fuzzy system. The proposed workwill be used to solve optimization problems of fuzzy IF-THEN rules. As IF-THEN expression of rules is close to natural language. So therules are simple and easy for users to understand.

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