Algorithms for Increasing of the Effectiveness of the Making Decisions by Intelligent Fuzzy Systems

Olga Dolinina¹ and Aleksandr Shvarts²

1. Faculty of Applied Information Technologies, Yury Gagarin State Technical University of Saratov, Saratov 410054, Russia

2. Faculty of Applied Information Technologies, Yury Gagarin State Technical University of Saratov, Saratov 410054, Russia

Abstract: There are considered rule-based intelligent systems using fuzzy inference. Comparative analysis of different approaches and algorithms of making decisions on the base of fuzzy logic is given. Using of the parallel calculations can reduce the time of making decision in case of large-scale systems. Effectiveness of parallel calculations depends on the grouping of the rules and variables. Building of the graph of the dependence of the rules and the graph of dependence of the linguistic variables are suggested. On the base of the developed groups of rules and defuzzification of the linguistic variables we suggest to reduce the time of making decision and therefore to increase the effectiveness of the decision making with using of parallel calculations for each group.

Key words: Intelligent systems, fuzzy inference, increasing of the effectiveness of the making decisions, grouping of the rules and variables, building of the rules' dependence.

1. Introduction

Intelligent systems are one of the most rapidly developing branches of science and technologies. In the majority of cases expert is not able to describe knowledge accurately or express the causation between them. The most popular method to design systems with such uncertainties was introduced by Zadeh [1, 2] and demands special approaches for the knowledge reasoning and making decisions. Modern intelligent systems usually contain thousands of rules. Such large-scale knowledge bases demand special effective methods of knowledge processing. Using of parallel calculations [3] can reduce the time of the making decision but its effectiveness depends on the correct grouping or formation of clusters of rules.

2. Fuzzy Intelligent Systems

Fuzzy rule base is presented in the form of

$$(V, I, G, P, R) \quad (1)$$

with V —set of linguistic variables of the system;

Corresponding author: Olga Dolinina, Ph.D., research fields: knowledge representation, artificial intelligence and validation of intelligent systems. E-mail: olga@sstu.ru.

I —set of input linguistic variables, $I \subset V$;

G —set of output linguistic variables, $G \subset V$;

P —set of intermediate linguistic variables, $P \subset V$, $I \cup G \cup P = V$, $I \cap G = \emptyset$, $I \cap P = \emptyset$, $P \cap G = \emptyset$;

R —set of fuzzy rules.

$$\begin{aligned} \langle r_j, u_j \rangle & \text{ IF } v_{j,1} \text{ is } t_{j,1} \text{ AND } \dots \text{ AND } v_{j,n_j-1} \text{ is } t_{j,n_j-1} \\ & \text{ THEN } v_{j,n_j} \text{ is } t_{j,n_j} \end{aligned} \quad (2)$$

with r_j —unique rule name;

u_j —linguistic certainty degree of the r_j rule;

n_j —number of linguistic variables in the r_j rule;

$v_{j,1}, \dots, v_{j,n_j-1}$ —premises (input variables) for the r_j rule;

$t_{j,1}, \dots, t_{j,n_j-1}$ —values of input linguistic variables (terms) for the r_j rule;

v_{j,n_j} —output linguistic variable (goal) for the r_j rule;

t_{j,n_j} —value of output linguistic variable for the r_j rule.

Fuzzy set is A is presented in the following form

$$A = \{ (x, \mu_A(x)) \mid x \in X \} \quad (3)$$

with X —universal set;

x —element of X set;

$\mu_A(x)$ —membership function.

Membership function $\mu_A(x)$ describes the degree of membership of each $x \in X$ to the fuzzy set A , with $\mu: X \rightarrow [0,1]$. Thereby, $\mu_A(x)$ is 1, if element x is completely included in A and 0, if element x is not included in A . Membership function values on interval $(0, 1)$ describe fuzzy included elements.

Diagram of reasoning engine in fuzzy intelligent system (IS) is presented on Fig. 1, where fuzzification comprises the process of transforming of input variables into grades of membership for linguistic terms of fuzzy sets. The membership function is used to associate a grade to each linguistic term. Defuzzification is the process of producing a quantifiable result in fuzzy logic, given fuzzy sets and corresponding membership degrees.

A number of reasoning methods and algorithms have been introduced and discussed since the appearance of fuzzy sets theory. Each of algorithms [4-12] differs from the point of view of sequence and type of operators applied in fuzzyfication, fuzzy inference and defuzzyfication stages. They use also fuzzy rules of different form.

Mamdani [4], Tsukamoto [5], product-sum-gravity [6] and Larsen [7] methods use fuzzy rules, which form is very close to the way of human thinking. Therefore, it would be easier for experts and knowledge engineers to design the rule base.

Using of Tsukamoto inference method requires

only monotonous membership functions, which are unacceptable in many cases.

Sugeno [8], simplified fuzzy inference [9], singleton [10] and SIRMs [11] methods requires crisp number values or coefficients, which calculation is not a trivial task for some areas. However, those methods involve only simple algebraic operators that lead to lower computational cost in comparison with the first group of methods.

SIRMs fuzzy systems contain separate groups of rules (modules) and each of the rules must have the only one premise.

Most of the modern intelligent systems using fuzzy inference have rule bases of high dimension (thousands of rules). This causes the need to use special methods of inference management in order to improve efficiency and minimize calculation time. Existing methods of fuzzy inference allows parallel execution on a number of computational nodes, which can reduce time spent on reasoning process. This paper introduces algorithms for improving efficiency of fuzzy inference in rule-based intelligent systems by grouping of the rules.

In fuzzy rule bases there is a wide range of cases, when it is impossible to process one rule without processing of some other rules before. This problem appears, if the rule's premises contain variables, which are not received from the input of the whole system, but calculated after different rules are processed. Let's take as an example a rule base using 8 linguistic variables (Table 1).

Fig. 1 Diagram of reasoning engine in fuzzy intellectual systems.

Table 1 Linguistic variables in the example rule base.

Linguistic variable	Terms	Linguistic variable	Terms
v_1	$t_{1,1}$	v_5	$t_{5,1}$
	$t_{1,2}$		$t_{5,2}$
	$t_{1,3}$		$t_{5,3}$
v_2	$t_{2,1}$	v_6	$t_{6,1}$
	$t_{2,2}$		$t_{6,2}$
	$t_{2,3}$		$t_{6,3}$
v_3	$t_{3,1}$	v_7	$t_{7,1}$
	$t_{3,2}$		$t_{7,2}$
	$t_{3,3}$		$t_{7,3}$
v_4	$t_{4,1}$	v_8	$t_{8,1}$
	$t_{4,2}$		$t_{8,2}$
	$t_{4,3}$		$t_{8,3}$

Table 2 Example of the rule base.

Rule name	Premises (IF part)	Goal (THEN part)
r_1	$v_1 = t_{1,1}$ AND $v_2 = t_{2,1}$	$v_4 = t_{4,1}$
r_2	$v_1 = t_{1,3}$ AND $v_2 = t_{2,2}$	$v_4 = t_{4,2}$
r_3	$v_2 = t_{2,3}$	$v_4 = t_{4,3}$
r_4	$v_2 = t_{2,1}$	$v_5 = t_{5,3}$
r_5	$v_2 = t_{2,2}$	$v_5 = t_{5,2}$
r_6	$v_2 = t_{2,3}$	$v_5 = t_{5,1}$
r_7	$v_3 = t_{3,1}$	$v_6 = t_{6,1}$
r_8	$v_3 = t_{3,2}$	$v_6 = t_{6,2}$
r_9	$v_3 = t_{3,3}$	$v_6 = t_{6,3}$
r_{10}	$v_3 = t_{3,1}$ AND $v_4 = t_{4,2}$	$v_7 = t_{7,1}$
r_{11}	$v_3 = t_{3,2}$ AND $v_4 = t_{4,3}$	$v_7 = t_{7,2}$
r_{12}	$v_4 = t_{4,3}$ AND $v_5 = t_{5,1}$	$v_7 = t_{7,3}$
r_{13}	$v_5 = t_{5,2}$ AND $v_3 = t_{3,3}$	$v_7 = t_{7,2}$
r_{14}	$v_1 = t_{1,1}$ AND $v_6 = t_{6,3}$	$v_8 = t_{8,1}$
r_{15}	$v_1 = t_{1,2}$	$v_8 = t_{8,2}$
r_{16}	$v_1 = t_{1,3}$ AND $v_6 = t_{6,1}$	$v_8 = t_{8,2}$
r_{17}	$v_1 = t_{1,3}$ AND $v_6 = t_{6,2}$	$v_8 = t_{8,3}$

the matrix of rules dependencies. Following algorithm is used:

The rule base contains 17 rules (Table 2).

Variables v_4 , v_5 and v_6 are intermediate, as they are used both in rules' premises and goals. Values of these variables need to be calculated as a result of rules r_1 , r_2 , r_3 , r_4 , r_5 , r_6 , r_7 , r_8 and r_9 processing.

Rules r_{10} , r_{11} , r_{12} , r_{13} , r_{14} , r_{16} and r_{17} contain intermediate variables in their premises parts, so they cannot be processed before these variables values are calculated.

New algorithms which allow to define the order of the processing of the rules in the knowledge base by preliminary grouping of the rules, have been introduced to solve this problem.

3. Exploring Dependencies in the Rule Base

Rules Dependencies. The first stage is to generate

Step 1. Initialize zero-filled matrix DR with dimension of $|R| \times |R|$ ($|R|$ —cardinal number of R

set).

Step 2. For each $r_j \in R$ execute Step 3.

Step 3. For each $r_q \in R$, $r_q \neq r_j$ execute Step 4.

Step 4. If $v_{j,n_j} \in G_q$, then $DR_{j,q} = 1$ and $DR_{q,j} = -1$.

DR is an adjacency matrix of the directed graph of rules dependencies. This graph can be used to define each rule predecessor rules.

Each rule $r_j \in R$ is mapped to a value $\rho(r_j)$, which represents sequence number of a group of processed rules. This sequence number means that rule r_{j_1} cannot be processed before r_{j_2} , if $\rho(r_{j_2}) < \rho(r_{j_1})$.

3.1 Calculating the Sequence Number of a Group of Processed Rules

Step 1. Initialize zero-filled set RO , $|RO| = |R|$.

Step 2. $j = 1$.

Step 3. If $j \leq |R|$, then go to Step 4, else go to Step 10.

Step 4. $i = 1$.

Step 5. If $i \leq |R|$, then go to Step 6, Step 8.

Step 6. If $DR_{j,i} = -1$, then go to Step 9.

Step 7. $i = i + 1$.

Step 8. $ro_j = 1$.

Step 9. $j = j + 1$. Go to Step 3.

Step 10. $j = 1$, $c = 0$.

Step 11. If $j \leq |R|$, then go to Step 12, else go to Step 20.

Step 12. $i = 1$, $m = 1$.

Step 13. If $i \leq |R|$, then go to Step 14, else go to Step 17.

Step 14. If $DR_{j,i} = -1$, then go to Step 15, else go to Step 16.

Step 15. If $ro_i > m$, to $m = ro_i$.

Step 16. $i = i + 1$. Go to Step 13.

Step 17. If $ro_j < m + 1$, to $c = 1$.

Step 18. $ro_j = m + 1$.

Step 19. $j = j + 1$. Go to Step 11.

Step 20. If $c = 0$, then go to Step 21, else go to Step 10.

Step 21. For each r_j : $\rho(r_j) = ro_j$.

Using calculated values of $\rho(r_j)$ following sets are formed

$$RG_m : r_j \in RG_m \Leftrightarrow \rho(r_j) = m \quad (4)$$

$$m = \overline{1, \dots, L_R}$$

where, L_R —total number of groups of processed rules.

3.1 Linguistic Variables Dependencies

Fuzzy inference involves not only calculation of membership functions for each rule r_j , but also defuzzification of rules' goals. Sequence of goal variables defuzzification is not simply obtained from rules dependencies graph, because, each variable can be used in the right part of many rules with different value of $\rho(r_j)$.

So, it is important to discover dependencies between linguistic variables. Following algorithm is used to generate the matrix of dependencies:

Step 1. Initialize zero-filled matrix D with dimension of $|V| \times |V|$.

Step 2. For each $v_k \in V$ execute Step 3.

Step 3. For each $v_h \in V$, $v_h \neq v_k$ execute Step 4.

Step 4. For each $r_j \in R$ execute Step 5.

Step 5. If $v_k \in G_j$ and $v_h = v_{j,n_j}$, then $DV_{k,h} = 1$ and $DV_{h,k} = -1$.

DV is an adjacency matrix of directed graph of linguistic variables dependencies. This graph can be used to find each variable predecessors.

Each rule $r_j \in R$ is mapped to a value $\rho(r_j)$, which represents sequence number of a group of processed rules. This sequence number means that rule r_{j_1} cannot be processed before r_{j_2} , if $\rho(r_{j_2}) < \rho(r_{j_1})$.

Each linguistic variable $v_k \in V$ is mapped to a

value $\rho(v_k)$, which represents sequence number of a group of defuzzified variables. This sequence number means that variable v_{k_1} cannot be defuzzified before v_{k_2} , if $\rho(v_{k_2}) < \rho(v_{k_1})$.

3.2 Calculating the Sequence Number of a Group of Defuzzified Variables

Step 1. Initialize zero-filled set VO , $|VO| = |V|$.

Step 2. $k = 1$.

Step 3. If $k \leq |V|$, then go to Step 4, else then go to Step 10.

Step 4. $h = 1$.

Step 5. If $h \leq |V|$, then go to Step 6, else then go to Step 8.

Step 6. If $DV_{k,h} = -1$, then go to Step 9.

Step 7. $h = h + 1$.

Step 8. $vo_k = 1$.

Step 9. $k = k + 1$. Go to Step 3.

Step 10. $k = 1$, $c = 0$.

Step 11. If $k \leq |V|$, then go to Step 12, else then go to Step 20.

Step 12. $h = 1$, $m = 1$.

Step 13. If $h \leq |V|$, then go to Step 14, else then go to Step 17.

Step 14. If $DV_{k,h} = -1$, then go to Step 15, else then go to Step 16.

Step 15. If $vo_h > m$, to $m = vo_h$.

Step 16. $h = h + 1$. Go to Step 13.

Step 17. If $vo_k < m + 1$, to $c = 1$.

Step 18. $vo_k = m + 1$.

Step 19. $k = k + 1$. Go to Step 11.

Step 20. If $c = 0$, then go to Step 21, else then go to Step 10.

Step 21. For each v_k : $\rho(v_k) = vo_k$.

Using calculated values of $\rho(v_k)$ following sets are formed

$$VG_m : v_k \in VG_m \Leftrightarrow \rho(v_k) = m \quad (5)$$

$$m = \overline{1 \dots L_V}$$

where, L_V —total number of groups of defuzzified variables.

Any variable $v_k : \rho(v_k) = 1$ is input variable ($v_k \in I$) and there is no need to defuzzify it.

Effectiveness of the suggested algorithms have been proved by a set of the experimental tests generated with randomly chosen parameter values of the rules. Three types of the membership functions (Z-type, triangle, S-type) have been analyzed. The number of the rules differed from 1,000 to 50,000 in the experiment. The result got from the experiment showed that the processing time of the rules with using of the developed algorithms is at least 30% less than in comparison with the Mamdani method.

4. Conclusions

The suggested algorithms of formation of the groups of fuzzy rules for processing and defuzzification of the knowledge base can be used to reduce the full time of the making solution in fuzzy intelligent systems by applying of parallel calculations for each group of rules. Effective parallel processing is impossible without grouping the rules in advance, because transitive dependencies allow often only sequential processing. The result got from the experiment showed that the processing time of the rules with using of the developed algorithms is at least 30% less than in comparison with the Mamdani method.

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