규칙기반시스템에서의 퍼지정보처리

Fuzzy Information Processing in Rule-Based Systems

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요 약

애매한 정보를 이용하고 처리하기 위해 퍼지기법을 전문가시스템 분야에 도입하려는 시도가 최근 활발히 진행되어 왔다. 이러한 연구결과로 몇몇 퍼지기법을 사용한 전문가시스템들과 퍼지 전문가시스템 개발도구들이 개발되어 보고되고 있다. 현재 전문가시스템에서 여러가지 방법으로 퍼지기법이 응용되고 있음에도 불구하고 아직 체계적인 응용방법이 제안되지 않은 상황이다. 본 논문에서는 규칙과 사실에 확신도(certainty factor)가 부여되고 속성(attribute)값에 퍼지값(fuzzy value)을 허용하는 규칙기반(rule-based) 전문가시스템에서 발생하는 문제점을 살펴보고 해결방법의 한가지를 제시한다.

일반적인 규칙기반 시스템에서는 정합(matching)연산의 결과가 정합과 비정합으로 명확하게 나타나지만, 규칙과 사실에 퍼지값이 사용될 수 있도록하면, 퍼지값과 보통값(crisp value), 퍼지값과 퍼지값 간의 정합을 해야 하는 문제가 생긴다. 또한 퍼지값을 허용함으로써 퍼지값과 퍼지값, 퍼지값과 보통값간의 비교연산을 해야 하는 문제가 발생한다. 한편, 퍼지값이 규칙과 사실에서 사용되고 확신도를 사용할때 퍼지추론을 어떻게 수행할 것인가도 논란의 대상이다.

본 논문에서는 퍼지값이 도입됨으로써 생기는 퍼지정합과 퍼지비교의 경우를 살펴보고, 이들 연산에 대해 적합도를 계산하는 방법을 제안하고, 이를 추론에 이용하는 방법을 제시한다. 한편, 합성추론방법(compositional rule of inference)에 기반한 퍼지추론 뿐만아니라 일반적인 규칙의 추론도 제공할 수 있는 방법을 제시한다. 또한 범용 전문가시스템 개발도구인 OPS5를 확장하여 제안된 방법들을 수용하도록한 FOPS5(Fuzzy extended OPS5)에 대해서도 기술한다.

1 Introduction

There have been many researches which introduce fuzzy techniques in the expert systems [1][3-5][7-16], and several fuzzy expert system shells have been developed such as: REVEAL, LEONARDO, FRIL, ARIES[1], FLOPS[3], FESS II[4], Z-II[10], ES/KERNEL /W[14], STIM[16].

It has been pointed out that those fuzzy expert system shells suffer from some weak points[8]. Some shells excessively emphasize the role of fuzzy inferencing and thus fail to fully support the functions of conventional expert system shells. Some shells provide insufficient function for fuzzy inferencing though they use fuzzy techniques.

In the application domains, generally most of knowledge is certain and a small portion of knowledge remains uncertain. In this sense, it may be desirable that we have a conventional expert system shell which is extended to process fuzzy information. In this paper, we present a rule-based forward-chaining fuzzy expert system shell, called FOPS5, which is an extension of the conventional expert system shell OPS5[2] to accommodate fuzzy information processing. We take OPS5 as the platform since it is familiar, easy to use and widely used. We aim that FOPS5 is equipped with the same functions as OPS5 and in addition it can process uncertain knowledge.

In the literature, we can find other fuzzy expert system shells[3][4] based on OPS5. FOPS5 has different strategies for fuzzy information processing from them : It uses different methods for fuzzy matching and comparison, and different representation for fuzziness and uncertainty. In addition, it can fully support fuzzy inferencing and provide flexible services for fuzzy information processing.

FOPS5 uses certainty factor(CF) whose value is in [0,9] to represent uncertainty of rules and working memory elements(WMEs, facts). A WME has only one CF(i.e., each attribute of WME does not have its own CF).

To represent fuzzy concepts, fuzzy values can be used as attribute values of rules and WMEs. In FOPS5, fuzzy values are restricted to fuzzy sets defined in the number domains(e.g. real numbers, integers). Here, fuzzy values indicate linguistic terms defined by possibility distribution[17].

Knowledge base is composed of rules and WMEs. Rules can be grouped into conventional production rules(p rules in OPS5) and fuzzy production rulebases. Fuzzy production rulebase consists of a collection of fuzzy rules whose all antecedent(left hand side, LHS) and consequent(right hand side, RHS) attributes have only fuzzy values.

The paper is organized as follows. Section 2 presents fuzzy knowledge processing of FOPS5 such as fuzzy matching, fuzzy comparison, uncertainty propagation, and memory update. Section 3 describes the design and implementation of FOPS5. Finally, section 4 draws a conclusion.

2 Fuzzy Information Processing

2.1 Fuzzy Matching and Fuzzy Comparison

By introducing fuzzy values and certainty factors in the knowledge representation, we have some problems to be solved : fuzzy matching, fuzzy comparison, uncertainty propagation.

Since the attributes can have fuzzy values, the possible combinations of rules and WMEs can be shown in Table 1, according to the properties of attribute values in LHS and RHS of rule and WMEs to be matched.

Among the eight possible combinations, the conventional expert system shells support only the case 8(*crisp rule* : *crisp WME*). For other cases but the case 6, some special treatments are needed to process the matching between fuzzy values and between fuzzy value and crisp value.

The cases 5 and 7 are the special cases(*rule with crisp LHS* : *fuzzy WME*) to which there has been as yet no expert system shell to tackle. In spite of that, these cases are prone to happen in the real world. Suppose a rule that `IF height is 170cm THEN clothes size is L type` and a fact that `Kim is` *tall*. In this situation, it makes sense to infer that `it is highly possible that Kim's clothes size is L type`.

Table 1. Combination types of rule and WMEs

case	LHS of rule	RHS of rule	matched WME
1	fuzzy	fuzzy	fuzzy
2	fuzzy	fuzzy	crisp
3	fuzzy	crisp	fuzzy
4	fuzzy	crisp	crisp
5	crisp	fuzzy	fuzzy
6	crisp	fuzzy	crisp
7	crisp	crisp	fuzzy
8	crisp	crisp	crisp

FOPS5 is developed to handle the above all cases. The combinations of the cases 1 and 2 can be processed by the fuzzy inference method such as the compositional rule of inference(CRI) method[17], etc.. In the practical knowledge representation, fuzzy values, crisp values and relational comparisons may be mixed up in the LHS of rules. Consider the following rule and WMEs excerpted from a cow-bull mating knowledge base used in the milk producing farms.

IF (X.sex is cow) and (Y.sex is bull)
  and (X.height is *short*) and (Y.height is *tall*)
  and (X.age is 5) and (X.stength < Y.strength)
THEN (X.mate is Y) and (Y.fitness is *good*)

(X: sex is cow, age is *young*, height is 160cm, strength is *weak*)
(Y: sex is bull, age is 7, height is *middle*, strength is *normal*)

Figure 1: An example of fuzzy knowledge base

In the above, the linguistic terms *short, tall, good, young, weak, middle* and *normal* are fuzzy values. The LHS of the rule consists of a crisp part(`X.mate is Y`) and a fuzzy part(`Y.fitness is` *good*). When the two WMEs are given to the rule, the inference engine has to perform three fuzzy matching(*short*: *160* [case 2,4], *tall*: *middle* [case 1,3], *5*: *young* [case 5,7]) and a fuzzy comparison(*weak* < *normal*). Here, we can anyway apply the CRI type fuzzy inference to the rule since it has fuzzy values in both its LHS(*short, tall*) and RHS(*good*). In this situation, it is doubtful whether it is meaningful to modify the value of Y.fitness by fuzzy inferencing.

In the situation that fuzzy values, crisp values and relational comparison predicates are mixed, thus, FOPS5 reflects only the matching degree of the LHS to the certainty of the inferred results(i.e., results produced by the RHS of fired rule) without applying fuzzy inferencing to such rules.

Meanwhile, for the purpose of fuzzy inferencing, FOPS5 has a mechanism to handle a collection of fuzzy rules whose LHS and RHS attributes have only fuzzy values in a module. It makes it possible to define a set of fuzzy rules as a module and to apply fuzzy inference to the module. On fuzzy inferencing, all fuzzy rules of the module are executed in parallel.

2.2 Measures for Fuzzy Matching

To evaluate the matching degree of fuzzy LHS and fuzzy/crisp WMEs as in the cases 1 to 4, we propose the following measures. The measures have a value within the interval [0,1]. The value 0 indicates the mismatch, whereas 1 indicates the full match. The more closely WME matches LHS, the greater the value of measure is. Here, A is a fuzzy value of LHS, and B and c are a fuzzy value and a crisp value of WMEs, respectively. A^α is the α-cut[17] of A and $|A^\alpha|$ is the interval length of A^α.

– Matching degree $M(A,B)$ of fuzzy LHS value A and fuzzy WME value B :

$$M(A,B) = \int_0^1 \frac{|A^\alpha \cap B^\alpha|}{|B^\alpha|} d\alpha$$

The measure $M(A,B)$ embodies the entailment principle [17]. That is, when $A \equiv B$ or $A \supset B$, $M(A,B)$ is equal to 1.

– Matching degree $M(A,c)$ of fuzzy LHS value A and crisp WME value c :

$$M(A,c) = \mu_A(c)$$

For the cases 5 and 7, we use the measure $M(c,A)$ to estimate the matching degree of crisp LHS c and fuzzy WME A. In the following formula, X denotes the universe of discourse for the fuzzy value A, *Supp*(A) denotes the support of the fuzzy value A, and $\mu_A(c)$ is the membership degree of c against A.

$$M(c,A) = \left(1 - \frac{|Supp(A)|}{|X|}\right)\left(1 - \frac{\int_{-\infty}^{\infty} \mu_A(x)dx}{|Supp(A)|}\right)\mu_A(c)$$

The measure $M(c,A)$ gives more larger value as the $|Supp(A)|$ is shorter, the shape of A is thinner and $\mu_A(c)$ is larger.

2.3 Measures for Fuzzy Comparison

To allow the fuzzy comparisons in the LHS of rules, we propose the following measures for the comparison between fuzzy values and between fuzzy value and crisp value. The measures take as their range the interval [0,1], and gives larger value as the satisfaction degree of comparison grows. In the formula, $I^{\alpha}_{B>A}$ denotes the part of B^{α} which is greater than $\max\{A^{\alpha}\}$ and $I^{\alpha}_{A>c}$ denotes the part of A^{α} greater than c.

– Fuzzy comparisons between fuzzy value A and fuzzy value B :

$$M(A > B) = \int_0^1 \frac{|I^{\alpha}_{A>B}| + 0.5|A^{\alpha} \cap B^{\alpha}|}{|A^{\alpha}| + |I^{\alpha}_{B>A}|} d\alpha$$

$$M(A \geq B) = \int_0^1 \frac{|I^{\alpha}_{A>B}| + |A^{\alpha} \cap B^{\alpha}|}{|A^{\alpha}| + |I^{\alpha}_{B>A}|} d\alpha$$

$$M(A < B) = \int_0^1 \frac{|I^{\alpha}_{A<B}| + 0.5|A^{\alpha} \cap B^{\alpha}|}{|B^{\alpha}| + |I^{\alpha}_{B<A}|} d\alpha$$

$$M(A \leq B) = \int_0^1 \frac{|I^{\alpha}_{A<B}| + |A^{\alpha} \cap B^{\alpha}|}{|B^{\alpha}| + |I^{\alpha}_{B<A}|} d\alpha$$

$$M(A = B) = \int_0^1 \frac{|A^{\alpha} \cap B^{\alpha}|}{|A^{\alpha} \cup B^{\alpha}|} d\alpha$$

$$M(A <> B) = 1 - M(A = B)$$

– Fuzzy comparisons between fuzzy value A and crisp value c :

$$M(A > c) = M(A \geq c) = \int_0^1 \frac{|I^{\alpha}_{A>c}|}{|A^{\alpha}|} d\alpha$$

$$M(A < c) = M(A \leq c) = \int_0^1 \frac{|I^{\alpha}_{A<c}|}{|A^{\alpha}|} d\alpha$$

$$M(A = c) = \left(1 - \frac{|Supp(A)|}{|X|}\right)\left(1 - \frac{\int_{-\infty}^{\infty} \mu_A(x)dx}{|Supp(A)|}\right)\mu_A(c)$$

$$M(A <> c) = 1 - M(A = c)$$

2.4 Uncertainty Propagation

Each rule and WME have a certainty factor to represent uncertainty. To determine the certainty factor of the inferred result, the certainty factors of rule and WMEs and the matching degree of LHS are combined.

We take as the matching degree β of LHS the minimum value among the matching degrees of fuzzy matchings and fuzzy comparisons and the certainty factors λ of matched WMEs. We regard the certainty factor γ of the inferred result as the multiplication of the matching degree β and the certainty factor τ of rule.

Each rule has a threshold value Γ. So only the rules whose matching degree β is greater than or equal to the threshold Γ, can be fired.

2.5 Memory Update

There are three commands `make`, `modify`, `delete` in the RHS of rule that can change working memory(WM). When these commands are met in the course of inferencing, they are managed in the following way.

make When the certainty factor γ of inferred result is greater than or equal to the threshold Γ of its corresponding rule, we create a new WME with the certainty factor γ.

modify When a non-assigned attribute is modified, the attribute is assigned with the inferred result and the certainty factor of its corresponding WME is updated with the minimum value of the original certainty factor and the inferred certainty factor γ.

When we intend to modify an already assigned attribute, we can modify it only if the certainty factor γ of inferred result is greater than or equal to that of its corresponding WME.

delete When the certainty factor of WME is greater than or equal to that of inferred result, we remove the WME from WM.

3 FOPS5 (Fuzzy extended OPS5)

3.1 Syntax

The syntax of FOPS5 is taken after that of OPS5 and extended to represent fuzzy values and certainty factors. Thus the application programs written in OPS5 can be recognized in FOPS5.

```
(p select_mate [0.9]
    {<num>(cow ^strength <A> ^height short ^N-candidate <val>)}
    (bull ^strength > <A> ^height tall)
  -->
    (modify <num> ^status marked ^N-candidate (compute <val> + 1))
    (make candidate ^name <N> ^fitness good)
)

(make cow [1.0] ^name Gerritt ^age 4 ^height 160 ^N-candidate 0
      ^status unmarked ^strength strong)
```

Figure 2: Examples of FOPS5 syntex

In the above example, the terms *short, tall, good, strong* and *good* indicate fuzzy values, and [0.9] and [1.0] indicate certainty factors.

By introducing fuzzy values, FOPS5 has to provide some functions for membership function definition of fuzzy values(linguistic terms), linguistic term registration to attributes, definition of fuzzy proposition rulebase, usage of fuzzy proposition rulebase, and so on.

3.2 Definition of membership function

Fuzzy values are defined by parameterized membership functions(triangular(`tri`) / trapezoidal(`trap`) fuzzy numbers) or paired(`paired`) representation as follows:

(`tri` 1 2.5 3) : triangular fuzzy number
(`trap` 1 2 3 4) : trapezoidal fuzzy number
(`paired` (1 0.2) (2 0.4) (3 0.8) (4 0.6)) : paired representation

Figure 3: Examples of membership function definition

3.3 Linguistic term registration to attribute

To register linguistic terms to attributes, the top-level command **`fzterm`** is provided as follows:

(**`fzterm`** *class-name ^attribute-name*
  (*fzterm1 membership-function-defn*)
  (*fzterm2 membership-function-defn*))

In the above, *class-name* and *attribute-name* indicate the class of WME and attribute to which linguistic terms are registered, *fzterm1* and *fzterm2* denote the name of linguistic terms and *membership-function-defn* the membership function definition given in the above example.

3.4 Definition of fuzzy production rulebase

To define fuzzy production rulebases, FOPS5 provides the command **`fzrule`**. The following example shows an example of fuzzy production rulebase.

```
(fzrule heath-estimate-RB
  (inference Max-Min-CRI)   ; inference method
  (defuz COG)               ; defuzzification method
  (4 : weight height : health)   ; # of rules : input var's : output var's
  (fzterm                   ; definition of fuzzy terms
        (weight (light (trap 0 0 50 70))
                (heavy (trap 50 70 100 100)))
        (height (short (trap 0 0 155 175))
                (tall (trap 155 175 200 200)))
        (health (bad (trap 0 0 4 6))
                (good (trap 4 6 10 10))))
  (rules        ; rule bases
        (^weight heavy ^height short --> ^health bad)
        (^weight heavy ^height tall  --> ^health good)
        (^weight light ^height tall  --> ^health good)
        (^weight light ^height short --> ^health bad)))
```

Figure 4: Example of fuzzy production rulebase definition

3.5 Usage of fuzzy production rulebase

To invoke fuzzy inferencing for fuzzy production rulebase, the command **fzinfer** is provided which can be used at the top-level and the RHS of rule.

```
(fzinfer heath-estimate-RB
        (^weight [very heavy])
        (^height [tri 165 170 175]))
```

3.6 Fuzzy Inferencing

There are two commands p, **fzrule** to define rules in FOPS5. The command **p** plays the role of defining the same kind of rules as p of OPS5. For these rules, fuzzy values are allowed as attribute values and a certainty factor is given. The command **fzrule** takes charge of defining fuzzy production rulebases.

FOPS5 does not apply fuzzy inferencing to rules defined by **p** command. Instead of that, the matching degree between LHS of rule and WMEs is evaluated and it is reflected to the certainty factor of the inferred results. FOPS5 uses the proposed measures for fuzzy matching and comparison to evaluate matching degree. FOPS5 applies fuzzy inferencing to rules defined by **fzrule** command.

In Table 1, we can handle the cases 1 and 2 by using fzrule command and the cases 3 to 8 by using p command.

3.7 Inference Engine

The inference engine of FOPS5 cycles over the three steps of *match, select* and *execute.* In the match step, the instantiation of each rule is found. The instantiation is an ordered pair whose first item is the name of a rule and whose second item is a list of WMEs that match the LHS of rule with a consistent set of bindings. In the selection step, when there are more than one rule instantiations one instantiation is selected for firing. In the execution step, the actions of the RHS of the selected rule are performed.

To make the matching operations efficient the RETE match algorithm[6] is used in the match step. As the selection strategy, FOPS5 provides the modified MEA and LEX algorithm[2] which consider matching degree as well as recency.

FOPS5 is implemented with Common Lisp language on SPARC workstation.

4 Conclusion

In this paper, we investigate the problems to be solved when we allow fuzzy values and certainty factors to rules and facts. We propose some methods to manage fuzzy matchings and fuzzy comparisons which are incurred by permitting fuzzy values in the attribute values. In addition, an inference strategy for these knowledge bases is proposed.

In the proposed platform, the fuzzy information processing is flexibely supported: The CRI-type fuzzy inference as well as the conventional (match-execute type) inference are fully supported. When some fuzzy facts are given, it is possible to infer some meaningful information from crisp rules.

On the basis of the proposed methods, we present an fuzzy expert system shell called FOPS5 which extends OPS5 to accommodate fuzzy information processing. FOPS5 has the role as the conventional expert system shell OPS5. In addition, it can support fuzzy inferencing and provides flexible services for fuzzy information processing.

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