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DYNAMIC RULE MODIFICATION THROUGH SITUATION ASSESSMENT

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Abstract
In dealing with representing knowledge under uncertainty there is a sustain tendency to increase flexibility in order to avoid problems of inconsistency in the knowledge. Many knowledge systems(information retrieval systems, expert systems) include hybrid representation models. Fuzzy retrieval systems appear as a complement or as an enrichment of this models. In this paper, we describe dynamic rule modification through situation assessment for uncertainty management.

Keywords: Situation assessment model, Fuzzy rule modification

1 Introduction

For most expert system problems, the information concerning design, evaluation, realization, etc, can be classified into two kinds:

- numerical information obtained from symptom measurement
- linguistic information obtained from human-experts.

But in many application areas, we often need to make decision in the situation where we do not have the exact knowledge of the situation. In some cases, we can formulate the problem precisely, but this formulation leads to complicated mathmatical optimization problem of the type that we can not yet solve. Therefore, we need flexible expert systems.

The most flexible approach to date is that of the fuzzy truth-values which is based on fuzzy logic. In fuzzy expert systems, pieces of information (evidences, terms, rules, documents) are usually assumed to carry equal importance and to be indepedent of each other, although it might not be actually the case.

E. Sanches proposed a logic of weighted queries, with possibility of weighting also documents and logical connectors[5].

The possibility for experts and users to express their uncertainty linguistically is a very important step along the flexibility path. Looking at the chronology of the approaches to deal with uncertainty we have noticed a sustained tendency to increase its flexibility in order to avoid problems of inconsistency.

Therefore, we propose fuzzy situation assessment model for dynamic rule modification. In section 2, we explain fuzzy reasoning and degree of belief. In section 3, we explain activation sets. In section 4, we propose situation assessment model. Conclusions are given in section 5.

2 Background

2.1 Generalized Modus Ponens

In fuzzy logic, L.A. Zadeh[1] proposed to enlarge the classical Modus Ponens into a more flexible rule, called the generalized modus ponens, taking into account that, in an observed phenomenon, the premise of classical type "X is A" will rather occur on the form "X is A'", where A' is an attribute of the linguistic variable X, more or less different from A.

$$\begin{array}{c} A' \\ A \rightarrow B \\ \hline B' \end{array}$$

instead of the following ideal scheme :

$$\begin{array}{c} A \\ A \rightarrow B \\ \hline B \end{array}$$

To replace A by A' in the premise of the modus ponens seems to be rough; it would be more realistic to keep in the premise of modus ponens, both A and A' and this is naturally achieved when using conditional formulae.

However, this formulation has some trouble : for instance, not always from $A' = A$, $B' = B$ can be derived. This due to the special link established in the conditional statement between variables X and Y, which is not always totally compatible with the use of the *min* operation for the combination step of the inference process.

2.2 Reasoning with fuzzy truth value

Truth-qualification allows to consider a particular view of fuzzy logic as a fuzzy truth-valued logic, i.e., a logic whose truth values are (linguistic) values of a linguistic variable "truth" whose base variable takes values in the interval.

In this context, the generalized modus ponens inference rule is reformulated as follows[3] :

$$\begin{array}{c} \text{(If X is A then Y is B) is } \eta \\ \text{(X is A) is } \tau \\ \hline \text{(Y is B) } is\ \nu \end{array}$$

2.3 Degrees of belief

The goal of an expert system is to simulate the experts' way of making decisions. For that purpose, an expert system include a knowledge base that contains the knowledge of the experts. Some statements from the knowledge base are believed to be absolutely correct.

However in their decisions, experts also use other statements, about which they are not 100% sure that they are correct, and/or which are not formulated in exact terms.

An intermediate degree of belief means that in addition to "true and false", we must label some statements by some intermediate labels, like "most probably true", "probably false ", etc.

Inside computer, "true" correspond to 1, and "false" to 0. Therefore, it is natural to use numbers from interval[0, 1] to describe the intermediate degrees of belief. So, to describe the experts' degree of belief in a statements A, we must find appropriate number $d(A)$ and $d(B)$ from the interval$[0, 1]$.

Suppose that an expert system contains statements A and B, and we have elicited the degrees of belief $d(A)$ and $d(B)$ from experts. Suppose now that a user wants to know the degree of belief in composite staments A & B.

The two simplest AND and OR opertations were first used for degrees of belief by L. A. Zadeh in :

$f_{\&}(x, y) = \min(x, y)$, $f_{\&}(x, y) = xy$, $f_{\vee}(x, y) = \max(x, y)$, and $f_{\vee}(x, y) = x + y - xy$.

Since then, several other operations have been proposed. One way to choose an operation is to choose many pairs of statements (A_k, B_k), ask experts to estimate $d(A_k)$, $d(B_k)$, and $d(A_k \& B_k)$ for every pair, and choose a function $f_{\&}$ for which $d(A_k \& B_k)$ is the close to $f_{\&}(d(A_k), d(B_k))$.

3 Design of fuzzy expert system model

Suppose we have the following problem : the situation facing human experts is so complicated that no mathematical model exist for it, or, the mathematical model is strongly nonlinear that a design method does not exist.

To design such an expert system, we first need to see what information is available. We consider dynamic rule modication through situation assessment model.

Since here already is a human expert who is successfully controlling the system, there are two kinds of information available to us :

- the experience of the human expert
- sampled situation data that are recorded from successful control by the human expert.

The experience of the human expert is usually expressed as some linguistic "IF-THEN" rules that state in what situation(s) which action(s) should be taken.

3.1 Activation sets

Roberts[2] suggested elsewhere that such knowledge can take a form of activation sets which define the applicability of production rules, to the input of the inferential structure. The input to the inferential is a subset of the transient, domain-dependant knowledge of an expert system.

The possibility of changing the production rules is classified as :

(1) dynamic activation of rules,
(2) dynamic de-activation of rules, and
(3) dynamic modification of rules.

The meta knowledge, i.e., the activation sets can be represented as relational tables.

Consider, for example, an inferential structure which consists of the following rules :

rule 1 : if A and B then conclusion 1
rule 2 : if A and C then conclusion 2
rule 3 : if B and D then conclusion 3

The concept of activation sets is general enough to allow great flexibility in the choice of desired control resolution level. For the above set of rules the finest resolution level will treat the set A, B, C, D as the basic control "input", in which case the table will take the following form :

Table 1

rule	A	B	C	D
rule1	1	1	0	0
rule2	1	0	1	0
rule3	0	1	0	1

Table 2

rule	A and B	A and C	B and D
rule1	1	0	0
rule2	0	1	0
rule3	0	0	1

In the above tables the cell values are crisp, 0, 1,

and may be used to represent only two facts :

(1)the activation set participates in a rule
(2)the rule does not exist

4 Situation assessment model

When it is applied to rule-based expert systems there are two basic issues to be concerned with :

(1) The use of linguistic variables in representation of experts' knowledge or rules.
(2) The deduction of conclusions from observation of symptoms and rules in a knowledge base.

In this paper, we propose dynamic rule modification in order to improve non-exact knowledge of situation.

Dynamic rule modification is a matter of changing a cell value about situation.

The inferential structure may then be "flagged" as modified, and would need to"look up" the value. Conceptually, there are some steps in the proposed situation model.

Step 1. Assignment of degree of belief

Above, we described an idealized situation, in which we can describe degrees of belief by exact real value.

We can therefore assign a degree to each rule that represents our belief of its usefulness. We can ask an expert to estimate his degree of belief on a scale from 0 to 10. If he selects 8, then we take $d(A) = 8/10$

For example,

It is a trivial extension to allow meta knowledge to be graded in their sense. The cells of the Table 1 and 2 will simply be allowed to hold values from the fuzzy interval $[0, 1]$, instead of the crisp 0, 1 set. These fuzzy values are then manipulated by the controller of an expert system.

Table 3

rule	A and B	A and C	B and D
rule1	d_1	0	0
rule2	0	d_2	0
rule3	0	0	d_3

For every d_i is fuzzy interval value of belief $(i = 1, \cdots, n)$

Step 2. Aquisition of changed situation knowledge

In practice, the situation is more complicated because experts can not describe their degree of belief precisely. Therefore, observated situation cell value is different from initial cell value.

The the situation cell value of a rule is defined as product of the degrees of its components. This is important in practical applications, because real numerical data have different reliabilities, e.g, some real data can be very bad.

Where, situation cell value(d_s) is sum of components

$$d_s = \sum C_i$$
$$i = 1, \cdots, n$$

For good data we assign higher interval value, and for bad data we assign lower interval value.

Step 3. Situation assessment

Situation assessment uses resemblance threshold(j) to determine whether a rule should be fired or be modified.

First,we calculate $\tau(d_s, d_i)$. In fact, $\tau(d_s, d_i)$ is, in some sense, the best solution to the inequality

- If $\tau(d_s, d_i) \leq j$ then rule firing
- If $\tau(d_s, d_i) \geq j$ then rule modification.

the function j acts as a resemblance threshold, i.e. if the resemblance of two possibility distribution is less than j then the conclusion of rule is the only suitable output.

Step 4. Rule modification

If the resemblance measured through τ is bigger than j then the inferred possibility distribution has a resemblance with the rule modification which is also bigger.

The inferential structure may then be 'flagged' as modified. These modifications can be stored as control experience of an expert system, and strategies as well as analyses can be developed based on it.

If $\tau(d_s, d_i)$ is great upper maximum limitation then which rules are considered "de-activated". A de-activated rule may not be allowed to participate in the reasoning process.

5 Conclusion

In this paper, we have shown dynamic rule modification of an expert system through situation assessment. The major advantage of the proposed approach is its abitily to handle ignorance of situation knowledge. In order to dynamically change inferential structure an expert system, its control structure must be explicitly implemented and equipped with meta knowledge about the inferential structure. If an expert system is goal-directed, then its goal can be defined in terms of activation tables. The control of an expert system can learn them dynamically for some arbitrary period of time.

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