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THE FUZZY MAPPING AGGREGATION OPERATOR BASED ON RIMER AND ITS APPLICATION

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Abstract

A fuzzy mapping aggregation operator based on RIMER and its application in Chinese word semantic proofing system for special domain are discussed deeply in this paper. Firstly, the fuzzy mapping aggregation operator based on RIMER are introduced and followed by the corresponding fuzzy inference method. Secondly, the collection of the sensitive words and their substitutions and the soft inference are discussed mainly based on our previous achievements. Then the new flowchart of the semantic analysis and the bases and the modules in the Chinese word proofing system are illustrated subsequently. The experiment shows that it is more feasible and practical method for semantic analysis.

Keywords: Fuzzy Inference; Mapping Aggregation Operator; RIMER; Semantic Analysis.

1. Introduction

Aggregation operators and data fusion methods have received a lot of attention in the recent years. Many new methods with the sound theoretical results have been obtained. Those achievements describe their basic properties and define a roadmap for their use in practical applications. The current theoretical interest to define a good roadmap for aggregation operators is tightly related with an increasing practical interest on using them for building applications [1].

In real world, human beings are constantly making decisions under a linguistic environment. With the help of the aggregation operator, the computer can deal with some works automatically and intelligently. As we known, the aggregation operator plays an important role in the decision-making process. According to the real problems, not only the special evaluation terms but also the key words in the common expressions need to be considered in the linguistics aggregation operators [2].

As we known, fuzzy information is popular in our daily life[3]. In the paper [4], several methods have been summarized for dealing with linguistic information, for instance: (1) The extension principle based method for operations on fuzzy numbers that support the semantics of the linguistic labels; (2) The symbolic method for computations on the indexes of the linguistic terms; (3) A fuzzy linguistic model based method for the linguistic information with a pair of values called 2-tuple, composed by a linguistic term and a number. (4) The direct computing with words method.

Both the methods (1) and (2) process the results in the initial expression domains, which produce the consequent loss of information and hence the lack of precision. The 2-tuple model in the method (3) can deal with the linguistical information without loss of information. And in this paper, we follow the 4th method to aggregate linguistic-valued information based on RIMER below.

The abbreviation of RIMER indicates the rule-base inference methodology using the evidential reasoning approach, which is different from most conventional rule-base inference methods. It is characterized with certain unique features[5]. First, each input can be represented as a distribution on referential values using a belief structure. The main advantage of doing so is that precise data, random numbers, and subjective judgments with uncertainty can be consistently modeled under the unified framework. Second, the ER approach provides a novel procedure for aggregating rules, which can preserve the original features of various types of information [6,7].

The advantages of RIMER is suitable for Chinese word semantic proofing system[8], in which the test words in the proofing text may not the same to the key words of those known special expressions. For example, the test words can be the synonyms, homonym or other substitution of the key words. So the new quantitative method is needed to describe the difference between them. At the same time, the certainty of the known special should be considered in the proofing, because they are collected or extracted from the exist materials related to the special domain[9].

Cooperated with fuzzy theory, the fuzzy mapping aggregation operator based on RIMER is applied to Chinese word semantic proofing system in this paper, and some components of the proofing system is updated with respect to the generalized RIMER based fuzzy aggregation operator.

In what follows, the fuzzy modeling of mapping aggregation operator based on RIMER is introduced in the next section with the corresponding fuzzy inference method. Then the collection of the sensitive words and their substitutions and the soft inference in the system are discussed in Section 2 including the soft inference. In Section 3, the new flowchart of the semantic analysis and the bases and the modules in the system and their relations are presented with experiment. The final section is our conclusions.

2. Fuzzy Modeling of Mapping Aggregation Operator

2.1. *The Mapping Aggregation Operator*

The aggregation operator is used to aggregate the multiple information or knowledge into single result, which seems the mapping from the former to the latter. So the mapping aggregation operator is proposed[10].

Suppose x_i (i=1, 2, …, n) be the input and Y be the output, then the aggregation operator is defined as follows:

$$Y = F(x_1, x_2, ..., x_n) \tag{1}$$

in which x_i is interval value, linguistic value or symbolic value, denote the combination of all values of x_i as X, Y maybe have the same value to x_i. F is a mapping from X to Y. Obviously, Y can extend to represent a vector of (y_1, y_2, …, y_m). So the equation (1) is a multi-input and multi-output expression. In this mapping, each element of X corresponds a only value of Y, which need to be defined before aggregation. Owing to the values of x_i and y_j are finite, the mapping can be generated and stored in database automatically under the condition of aggregation requirements.

In the following research, the condition of m=1 in Y is considered. Then the aggregation operator above is counterpoint to a simple evaluation system with two layers, one upper item and several lower items. Then an evaluation system has the hierarchical frame with multiple layers and many evaluation items, which can be regarded as a combination of multiple mapping aggregation operators[2].

2.2. *The Rule-base Inference Methodology using the Evidential Reasoning*

Formally, a rule-based model is represented as

$R = \langle U, A, D, F \rangle$ (2)

where $U = \{U_i;\ i=1, \ldots, T\}$ is the set of antecedent attributes, with each of them taking values (or propositions) from an array of finite sets $A = \{A_1, A_2, \ldots, A_T\}$. $A_i = \{A_{ij}; j = 1, \ldots, J_i = |A_i|\}$ is a referential set of values (or propositions) for an attribute U_i ($i = 1, \ldots, T$), and the values or propositions in A_i (e.g., A_{ij}) are referred to as referential values, which can be taken in different types of value. The array $\{U_1, U_2, \ldots, U_T\}$ defines a list of finite conditions, representing the elementary states of a problem domain, which may be linked by '$\wedge$' or '$\vee$' connectives. Note that '$\wedge$' is a logical connective to represent the 'AND' relationship and '$\vee$' a logical connective to represent the 'OR' relationship. $D = \{D_n;\ n = 1, \ldots, N\}$$ is the set of all consequents, which can either be conclusions or actions. F is a logical function, reflecting the relationship between conditions and their associated conclusions.

In the paper [5], a so-called packet rule using a belief structure is proposed with belief degrees, attribute weights, and rule weights, where all possible consequents are associated with belief degrees. A collection of packet rules constitute a rule base with a belief structure (called a belief rule base) as

R_k : If ($A_1^k \wedge A_2^k \wedge \ldots \wedge A_{T_k}^k$) then $\{(D_1, \overline{\beta}_{1k}), (D_2, \overline{\beta}_{2k}), \ldots, (D_N, \overline{\beta}_{Nk})\}$ (3)

($\sum_{i=1}^{N} \overline{\beta}_{ik} \le 1$, a rule weight θ_k and attribute weights $\delta_{k1}, \delta_{k2}, \ldots, \delta_{kT_k}$, $k \in \{1, \ldots, L\}$

where A_i^k ($i = 1, \ldots, T_k$) is the referential value of the ith antecedent attribute in the kth rule, T_k the number of antecedent attributes used in the kth rule, and $\overline{\beta}_{ik}$ ($i \in \{1, \ldots, N\}$) is the belief degree to which D_i is believed to be the consequent in the kth packet rule, the input satisfies the packet antecedents $A_k = \{A_1^k, A_2^k, \ldots, A_{T_k}^k\}$. If $\sum_{i=1}^{N} \overline{\beta}_{ik} = 1$, the kth packet rule is said to be complete; otherwise, it is incomplete. The condition $\sum_{i=1}^{N} \overline{\beta}_{ik} = 0$ denotes total ignorance about the output, given the input in the kth packet rule. θ_k is the relative weight of the kth rule, and $\delta_{k1}, \delta_{k2}, \ldots, \delta_{kT_k}$ are the relative weights of the T_k antecedent attributes used in the kth rule. L is the number of all packet rules in the rule base.

Remark 1[5]: Antecedent attributes or the number of attributes is not required to be the same from one rule to another, even though they share a common consequent set $D = \{D_n;\ n = 1, \ldots, N\}$.

In our previous work[8], a nonlinear multiple input single output relationship is expressed by Mamdani-type fuzzy model.

$R(r)$: If (x_1 is A_1^r) and (x_2 is A_2^r) and …(x_n is A_n^r) then Y is B_r with certainty factor α_r (4)

Assume the propositions of A_i^k (i=1, …, T_k) in rule (3) is "x_i is A_i^r", so the following result can be achieved.

Remark 2: Rule (4) is the special case of rule (3), with $\{\overline{\beta}_{1k}, \overline{\beta}_{2k}, \ldots, \overline{\beta}_{Nk}\}$ and $\{\delta_{k1}, \delta_{k2}, \ldots, \delta_{kT_k}\}$being given special values. In fact, if $\overline{\beta}_{ik} = B_r$, $\overline{\beta}_{jk} = 0$ ($j \neq i$, j = 1, …, N) are applied, and $\delta_{ki} = 1$(i = 1, …, T_k) are used in rule (3), then rule (4) can be established with $k = r$, $\theta_k = \alpha_r$ and $T_k = n$.

So the incomplete packet rule (3) has the chance to support the Chinese word semantic proofing with $\delta_{ki} \neq 1$(i = 1, …, T_k). A belief rule base given in the form shown in rule (3) represents functional mappings between antecedents and consequents with uncertainty. It provides a more informative and realistic scheme for uncertain knowledge representation. Note that the degrees of belief $\overline{\beta}_{ik}$ could be assigned directly by experts, or more generally, they may be trained and updated using dedicated learning algorithms or up-to-date information regarding the inputs and outputs of a rule-based system is available. Once such a belief rule base is established, the knowledge contained in the belief rule base can be used to perform inference for given inputs. The inference procedure is investigated in the following subsections.

2.3. *The Construction of Fuzzy Mapping Aggregation Rule Base*

For each rule the antecedent defines a fuzzy region of the input space, $U_1 \times U_2 \times \ldots \times U_n$, such that if the input lies in this region the consequent holds. Taken as a collection, the antecedents of all rules form a fuzzy partition in the input space, and the consequents of all rules form a fuzzy partition of the output space. The process of finding the output of a fuzzy model for a given value of input is called the “inference” process. The choice of the term inference as opposed to solving is a result of the logical structure in which the fuzzy inference system is rooted.

In order to construct the new rule base for Chinese word proofing, the following learning process needs to be proceeded.

1) Based on our previous rule base, the database structure is modified under the guideline of rule (3) with $\delta_{ki} \neq 1 (i = 1, \ldots, T_k)$ and N=1;

2) Collect the relative materials, obtained each (δ_{ki}, α_i^k)(i=1, …, J_i) of each attributes in antecedent and $\bar{\beta}_k$ of the kth rule by judging the weight by experts;

3) Use the simple weighted multiplicative aggregation function to calculate α^k:

$$\alpha_k = \prod_{i=1}^{T_k} (\alpha_i^k)^{\bar{\delta}_{ki}} \tag{5}$$

where

$$\bar{\delta}_{ki} = \frac{\delta_{ki}}{\max_{\{i=1,\ldots,T_k\}}\{\delta_{ki}\}} \tag{6}$$

4) Owing to the importance of T_k in the Chinese word proofing, so we calculate θ_k:

$$\theta_k = T_k + \alpha_k \tag{7}$$

5) In the inference process, the only β_k can be obtained based on the given $\bar{\beta}_k$:

$$\beta_k = \bar{\beta}_k \frac{\sum_{i=1}^{T_k} \tau(i,k) \sum_{j=1}^{J_i} \alpha_{ij}}{\sum_{i=1}^{T_k} \tau(i,k)} \tag{8}$$

where $\tau(i,k) = 1$ when U_i is used in define R_k (i=1, …, T_k), otherwise $\tau(i,k) = 0$. α_{ij} is the degree to which the input A_i^* belongs to the referential value A_{ij} with $\alpha_{ij} \geq 0$ and $\sum_{j=1}^{J_i} \alpha_{ij} \leq 1$ (i = 1, 2, …, T) and $\alpha_i^k \in \{\alpha_{ij}$; j=1,…, $J_i\}$. Here T is the total number of different antecedent attributes involved in all the rules in a rule base. See the detail in the paper [5].

In the inference process, the rule with the highest θ_k will be activated and its β_k is used to prompt the degree of non-truth.

3. The Preparation for Fuzzy Mapping Aggregation Operator

In our previous research, the collection of sensitive words is mentioned and the rigid inference, the soft inference with the conception matching, the role matching and the quotation matching are investigated from the fuzzy mapping aggregation rules' point of view.

Based on those achievements, the improving research focuses on the soft inference. The mapping aggregation operator based on RIMER is adopted to better the Chinese word proofing effect in semantic analysis. In order to simplify the contributions here, the comparisons with the previous achievements are mentioned as follows.

3.1. *The Collection of Sensitive Words and their Substitutions*

As to the special domain, some words are sensitive in the sentence expression, which can be collected by investigation of the corresponding experts or some regulations. So the first step is the collection of sensitive words. Furthermore, the synonym of the sensitive words is considered with the similarity between them. All those information are saved in Table 1, which lists the main fields in database table.

Table 1. The sensitive words and their substitution

No	Sensitive Words	Substitution	Similarity	Create Time	Modify Time	…
1	X1	S1	0.8	2013-01-04	…	
2	X1	S2	0.7	…		
3	X2	S3	0.9			
…						

In Table 1, the field ‘No’ is the primary key for unique indexing. The ‘substitution’ field will be assigned with the synonym or the homonyms of the corresponding sensitive word. The same sensitive word may have several ‘substitution’ with independent similarity, which is identified by different record (line). The value of the ‘similarity’ field in different records is determined by the material analysis and experts' evaluation in the corresponding domain.

3.2. *The Soft Inference*

The soft inference is an important part of the Chinese word proofing system, which is realized based on a background knowledge named scenarized knowledge [11,12], which includes the thesaurus, classified relation. In our research work, the following aggregation rule with one output D_k is considered to describe the fuzzy mapping relations among the components in expression. D_k means 'not-true' in proofing as before.

R_k: If ($A_1^k \wedge A_2^k \wedge \ldots \wedge A_{T_k}^k$) then D_k with a belief degree β_k, a rule weight θ_k and attribute weights δ_{k1}, δ_{k2}, …, δ_{kT_k} (9)

So A^k_i (i=1,…,T_k) which means the referential value of the ith antecedent attribute in the kth rule is corresponding to the expression of 'X_i is A^i_r' in the previous rule. Here, the former rule sequence number k is equal to the latter footnote number r. The value of A^k_i is the result of the membership function $A^i_k(x_i)$, which is illustrated in Figure 1.

In Figure 1, U_{si} be the synonymous or similar word set of x_i including itself, which can have the positive matching, U_{ai} be the antonyms set of x_i which can have the negative matching, then $U_i = U_{si} \cup U_{ai}$. Otherwise, $A^i_r(x_i)$=0.

The real line A-B do not means the membership function A^i_r is linear but the elements in U_i have the membership degree in [-1,1]. The fuzzy mapping aggregation rules saved in different databases are come from the practical requirements and need to be used in inference procedure. In the database, the synonym and the antonyms of the conception or the role below are saved in the tables like Table1, in which the 'Similarity' field is in [-1,1] correspondingly.

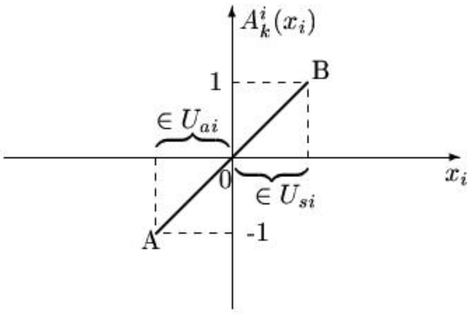

Figure 1 The new membership function for the soft inference

On the basis of the new membership function above, the scenarized knowledge representation is proposed and the matching needs to discuss in the following two types [8].

3.2.1. *Conception Matching*

This method is used to match the knowledge which isn't scenarized, such as name description, main-class description, substitute description and relative description. Based on the semantic relations, including synonymous relation, similar relation, contrary relation, generic relation and irrespective relation, the matching rules for the name descriptions are list as following.

- Positive Matching: synonymous, similar or generic relation,
- Negative Matching: contrary relation,
- Not Matching: irrespective relation.

As to the others descriptions, the classification knowledge are used to match ignorance of the characteristic of the knowledge objects.

3.2.2. *Role Matching*

This method is used to match the scenarized knowledge, in which the roles are the basic components in knowledge representation. Based on the existing syntax scenarized templates, whether the two scenarized knowledge match each other can be gained from the following rules.

1) Positive Matching: the two scenarized knowledges use the same template and the amount of the negative matching roles is oven;

2) Negative Matching: the two scenarized knowledges use the same template and the amount of the negative matching roles is odd;

3) Not Matching: the two scenarized knowledges use the different templates or the same template but more than one roles mismatching.

From the fuzzy mapping aggregation rules above, the soft inference is more powerful to describe the relative knowledge in the special domain. For example, the positive matching and the negative matching of the scenarized knowledges can be easily obtained from the product of the α_i^k with its symbol. It is valuable for our proofing system with several advantages, such as higher inference efficiency, better knowledge coverage, more operation practicability for the editor.

Remark 3: The similarity is correspond to α_{ij} or α_i^k. So the absolute value of the field 'similarity' needs to use in equation (5)-(8).

3.2.2. *Learning and Update Methods of Rules*

Indispensably, the learning function is designed in our intelligent word semantic proofing system for the users' requirements. If the user finds out a new rule in the same domain, he can input it into the rule base with the appointed format and operation. When the fuzzy mapping aggregation rules are needed to be updated, the three types of update operation are considered usually.

The addition operation is used to enrich the knowledge bases which save the fuzzy mapping aggregation rules. The necessary work needs to be finished is to judge the paradox among the rules, which can be solved by different priority values.

Certainly, the modification operation needs to judge the paradox, too. And the certainty factor or belief degree β_k maybe updated with modification after new statistics and the experts' evaluation.

And the deletion operation is simple for rules. But for the sensitive words, each rule related to them will be checked carefully.

4. Experiments

Based on our previous work[8] and fuzzy mapping aggregation operator, the corresponding experiment is carried out for validation like before.

4.1. *The New Flowchart of the Semantic Analysis*

Based on the standard sentence analysis procedure, the new flowchart of our system (see Figure 2) is proposed for a special domain because most steps of the standard sentence analysis procedure has low efficiency, especially for Chinese.

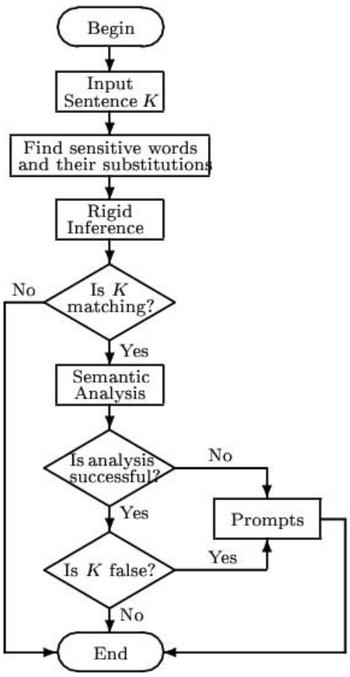

Figure 2 The new flowchart of the semantic analysis

In this flowchart, the sensitive words and their substitutions are found firstly and the rigid inference is adopted for judging the correlation with the special domain and finding the relative sentences in an article. Then the standard sentence analysis is carried out for the sentences resulted from the semantic analysis including following soft inference step.

4.2. *The Bases and Modules in the System*

As an integrated system, the syntax analysis is considered as a basic work. The bases and models and the relation among them in the system are shown in Figure 3.

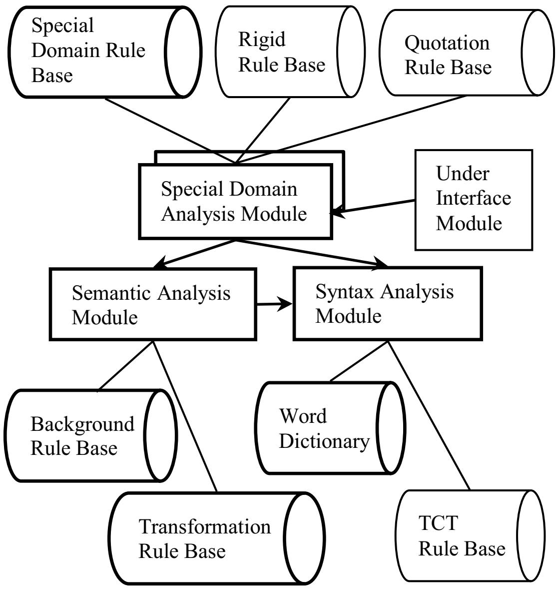

Figure 3 The bases and modules in the system

In Figure 3, the thin line indicates the relation between the model and the bases and the thick line with arrow indicate the reference relation among the models. Those components with thick frame are updated corresponding to the fuzzy mapping aggregation operator based on RIMER.

The “Word Dictionary” and the “TCT Rule Base”[10] are the necessary bases for the syntax analysis module and the former appends the ‘similarity’ information. The “Special Domain Rule Base” saves the soft inference rules based on RIMER. The synonymous strings, the similar strings and the others are also saved in the “Background Rule Base” with the ‘similarity’ information, their relative transformation rules in the “Transformation Rule Base”.

The “Special Domain Analysis Module” manages the rule bases and the modules, learn new rules and save them in the corresponding bases with respect to the new flowchart above. The “Syntax Analysis Module” finishes the basic works in syntax analysis, such as syncopating the sentences and words, labeling the words' type and analyzing the syntax. The "Semantic Analysis Module" can transfer the syntax frame into scenarized knowledge frame and finish the soft inference. All the modules are updated because of the change of the relative base.

The "User Interface Module" includes a Microsoft Word's embedding module and a special software for user convenience. Those two programs operate the same rule base for the same proofing results. Obviously, the common functions for the word processing are included in the separate software, such as file functions, clipboard functions and word format functions, which are unnecessary to take into account in Microsoft Word. The comparison between this method and the existing method is considered. Owing to the uniform inference procedure with fuzzy theory, the computational complexity is decreased with better efficiency. The belief degree θ_k makes the user check his paper with the different certainty like before. Some syntax proofing like the homophone or the homograph resulted from the different Chinese input method can be checked in new system.

From the description above, the frame of this system is universal and the special domain can be easy changed when a different domain rule base is used. The collection rules in special domain is our first test data and the experiment results show that this is a more feasible and effective method for semantic analysis, especially for Chinese.

5. Conclusions

In this paper, a fuzzy mapping aggregation operator based on RIMER and its application in Chinese word semantic proofing system for special domain are discussed deeply. Based on the fuzzy mapping aggregation operator and its inference method, the collection of the sensitive words and their substitutions and the soft inference are updated in detail. Then the new flowchart of semantic analysis and the bases and the modules in the system are introduced subsequently. The experimental results show that the intelligent system is more effective and the computer can work well with the computational intelligence [13]. Our future research will focus on the more applications of natural language processing[14].

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