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A Modularized Multi-strategy Fuzzy Ontology Mapping Method

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Abstract: To overcome the problem that the traditional ontologies are difficult to handle uncertain knowledge, by virtue of the features of fuzzy ontology and the advantages of ontology modularization cooperated with multi-strategy ontology mapping, a Semantic Web oriented fuzzy ontology model and its corresponding modularized multi-strategy fuzzy ontology mapping method are proposed, respectively. By using the approach of iterative correction, the mapping results are merged and repaired so that the mapping results are more reliable and the efficiency and accuracy of fuzzy ontology mapping can be improved.

Key words: Fuzzy ontology, ontology modularization, fuzzy ontology mapping, fuzzy ontology merging, fuzzy ontology integration

INTRODUCTION

The ontology definition that an ontology is an explicit specification of a conceptualization (Studer *et al.*, 1998) means that the ontology should have the four features of conceptualization, explicitness, formal and sharing. The majority of current ontologies are developed and used in this traditional manner. Assigned to acting as a sort of semantic expression knowledge about concepts and their relationship, ontology is explicit required necessarily in the ontology structure but is uncertain actually existing in the real world. For this reason, the traditional ontology can't be well used in handing uncertain knowledge. Therefore, it is unsuitable and unscientific to employ the absolute explicit concepts, attributes and relationships in ontology structure for representing the movable, changeable, developmental wide world. Consequently, it is necessary and reasonable to extend the traditional precise ontology to fuzzy ontology.

Furthermore, the effective solution for the issues of ontology heterogeneity and ontology reusability is ontology integration and ontology mapping is one of the most effective methods. But simplex mapping method has low efficiency and accuracy in processing large ontology. In order to get a better effect, ontology should firstly be modularized and then be mapped using the multi-strategy.

FUZZY ONTOLOGY

Fuzzy ontology composed of fuzzy concepts, attributes and instances is an extension of traditional precise ontology. It is more suitable for describing domain knowledge and better able to solve the problem of uncertain reasoning (Abulaish and Dey, 2006).

Fuzzy ontology has been developed for several years and is utilized in some fields. For example, one literature proposed a fuzzy ontology model used in the news and meteorological extraction (Lee *et al.*, 2005), one literature came up with the expression and construction for the fuzzy linguistic variable ontology (Zhai *et al.*, 2009), one literature put forward an abstract search engine based on fuzzy ontology (Widyantoro and Yen, 2001), one literature presented a fuzzy ontology model aiming at the semantic information query (Yang *et al.*, 2010) and one literature raised the traffic domain knowledge modeling based on spatiotemporal fuzzy ontology (Li and Wang, 2009). But there is still no unified fuzzy ontology model or formalization given by the academia. In this study, a Semantic Web oriented fuzzy ontology model is proposed in summary as definition 1.

Definition 1: Semantic Web fuzzy ontology is a 6-tuple like $O_F = (C_F, P_F, R_F, I, F, A_F)$, here in:

- C_F is the set of fuzzy concepts and also can be called class. Each element in it is the concept which needs formal description. These concepts have particular fuzziness in themselves. For instance, young man (which can be called young man, 18-28 or 16-32 years old), apple (fruit or electronic product), etc.
- P_F is the set of fuzzy attributes. Each attribute $p_F \in P_F$ is a triple as $p_F = (v_F, q_F, f)$. Here, v_F is the value of the attribute; q_F is the qualifier of the attribute value; f is the restraint of the value. For example, weather is a concept and has attribute of air temperature which can be fuzzy valued as high, medium or low and has fuzzy qualifier like a little, extremely, quite or general. The common types of restraint f are type restraint f_t, cardinal number restraint f_c and range restraint f_r.

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Besides, there is a key distinction that one attribute is not confirmed belonging to the concept which needs a fuzzy attribute membership degree u_{attr} to quantify

- R_F is a set of fuzzy relationships among concepts. Any relationship $r_F \in R_F$ is a five-tuple, $R_F = (c_1, c_2, t, s_F, U)$. c_1 and c_2 are concepts in C_1; t is the relationship type like intersection, inclusion, non-intersect, complementarity, equation, order etc.; s_F is the intensity of relationship which can be a value between 0 to 1, or can be fuzzy concept or fuzzy number; U is the domain of s_F
- I is a set of fuzzy instances and also the abstract concept instantiation which can be called object. The more instances there are, the more detailed it is and the easier the relationship degree between fuzzy concepts which has the example and a particular domain can be judged. But for the fuzzy ontology, whether there are some instances belong to a concept or not is sometimes uncertain or vague. Then a fuzzy instance membership degree u_{inst} is used for these instances to quantify
- F is a set of membership functions. Membership functions which varied by different concepts are used for calculating the membership degree generally. There are instance membership degree S_{inst} and attribute membership degree S_{attr} in F too
- A_F is a set of fuzzy rules. $a_F \in A_F$ is the fuzzy rule. a_F expresses the expert's experience or the rule commonly admitted by people. Normally, fuzzy rules are not identically true

ONTOLOGY MODULARIZATION

Ontology modularization is the mechanism of obtaining ontology modules from existing ontologies and it can be regarded as the function mapping from ontology to ontology modules. Ontology modularization is the mission critical of the Semantic Web ontology reuse and development. If ontology is modular processed with the principle of high cohesion but low coupling, the issues of large ontology maintenance and ontology partial reuse, which are the primal issues of ontology using in current Semantic Web, can be effectively solved.

It should be noted that the small ontology which has less concepts and the ontology which has strong relevance among concepts are not need modularization for which can lower the efficiency. The modular operations mainly aim at the large ontology and the little relevance ontology. Therefore, before modularization the ontology size and association between the ontology internal concepts should firstly be calculated to see if it is needed to be modularized.

Modularization condition: In the thesis, this issue is analyzed mainly from the following two aspects: one is the number of concepts in fuzzy ontology and the other is the relevancy degree of the concepts in ontology. If there are too many ontology concepts waiting to be operated, or the relevancy degree between concepts is loose, it is quite necessary to modularize them, respectively. Otherwise, mapping is used directly. Definition 2 and 3 give a detailed description of the precondition of modularization.

Definition 2: C_N is set as the number of the concepts in fuzzy ontology, m is the number of concepts which are suitable for direct mapping. Then the specific value between C_N and m is called ontology mapping scale M_{scale} as Eq. 1 shows:

$$M_{scale} = \frac{C_N}{m} \tag{1}$$

where, m is usually valued as 250 (Chen, 2009). When the number of concepts of ontology is more than 250, its mapping efficiency would be significantly reduced. Hence, the ontology whose number of concepts is above 250 should be firstly modularized and then mapped to improve mapping efficiency. Certainly, the value m can be adjusted with specific mapping requirement. If $M_{scale}>1$, the ontology should be modularized; otherwise, the relevancy degree of the concepts in ontology which defined in definition 3 should be calculated according to Eq. 2.

Definition 3: Consume u is the concept membership degree in ontology, $C_{u>0.5}$ represents the concepts whose relevant degree is more than 0.5, then the relevancy degree $C_{relation}$ of the concepts is calculated as Eq. 2 shows:

$$C_{relation} = \frac{\sum_{i=1}^{n} C_{u>0.5}}{n} \tag{2}$$

The modularization is not necessary when the ontology scale is comparatively smaller and the relevance degree of concepts is greater than the given threshold. In that case, mapping can be processed directly.

Modularization method and evaluation: For a large ontology which needs to be clustered, there are two aspects to be considered. One is that if the structures are similar, the other is to compare the grammar similarity.

Definition 4: Assume that c_i and c_j are two classes and c_{ij} is their public parent class. dephOf (c_k) returns the depth of c_k in class hierarchy relationship. Then, the aff (c_i, c_j) called the structure affinity degree is calculated as Eq. 3 (Tu *et al*., 2005):

$$\mathrm{aff}_s(c_i, c_j) = \frac{2 \cdot \mathrm{depthOf}(c_{ij})}{\mathrm{depthOf}(c_i) + \mathrm{depthOf}(c_j)} \quad (3)$$

In this study, only the structure affinity degree between classes satisfied $|\mathrm{depthOf}(c_i) \; \mathrm{depthOf}(c_j)| \geq 1$ is calculated to get appropriate result, considering of the time consumption.

Definition 5: Assume that d_i and d_j are made as the description of classes c_i and c_j respectively. Then the grammar similarity degree between c_i and c_j is calculated as Eq. 4:

$$\mathrm{sim}(c_i, c_j) = \mathrm{comm}(d_i, d_j) - \mathrm{diff}(d_i, d_j) + \mathrm{winkler}(d_i, d_j) \quad (4)$$

Herein, comm(d_i, d_j) represents the common part of d_i and d_j, diff(d_i, d_j) represents the different part between them (Hu *et al*., 2006) and winkler(d_i, d_j) is the improvement of the formula (Winkler, 1999).

The two aspects are summarized to gain the synthetical relevance degree as definition 6.

Definition 6: link(c_i, c_j) is set as the synthetical relevance degree between classes c_i and c_j, shown as Eq. 5:

$$\mathrm{link}(c_i, c_j) = \beta * \mathrm{aff}_s(c_i, c_j) + (1-\beta) * \mathrm{sim}(c_i, c_j) \quad (5)$$

Herein, $\beta \in [0, 1]$ and the choice of β is decided upon the class hierarchy structure and the language feature.

Besides, a threshold e should be set here according to the ontology itself. But the value should not be too big because it may cause the sparsity among classes. If e is too big, many data islands are produced, that is an ontology is divided into many modules and one module is consisted of only a few classes. That makes the efficiency lower and inconvenient for the next operation. So, the degrees of cohesion and coupling are introduced to evaluate the quality of modularization.

Definition 7: Assume that B_i and B_j are set two modules, and function numbOf(B_k) is the number of classes in B_k after analysis. The quality (B_i, B_j) is shown as Eq. 6:

$$\mathrm{quality}(B_i, B_j) = \frac{\sum_{c_i \in B_i, c_j \in B_j} \mathrm{link}(c_i, c_j)}{\mathrm{numbOf}(B_i) \cdot \mathrm{numbOf}(B_j)} \quad (6)$$

If B_i and B_j are the same module, the formula is the calculation of cohesion degree and the bigger the value is, the higher quality the modularization has. Otherwise, the formula is the calculation of coupling degree and the smaller the value is, the higher quality the modularization has.

FUZZY ONTOLOGY MAPPING

Fuzzy ontology mapping algorithm: Fuzzy ontology mapping algorithm is as below.

Input: B_i and B_j.
Output: Mapping table.

The algorithm procedure is shown as Table 1, where, (k_i, v_j) is entity pair in B_i and B_j, (k'_i, v'_j) is entity pair bottom-up to (k_i, v_j) in B_i and B_j.

Mapping strategy

Structure similarity strategy:

Rule 1: If the two entities have the same URI, then they are equal and their similarity degree is 1

Rule 2: If the two entities are apposition, then they are equal and their similarity degree is 1

Rule 3: If their parent nodes of the two entities have mapping relationship, then they might have too

Rule 4: If their child nodes of the two entities have mapping relationship, then they might have too

Rule 5: If their brother nodes of the two entities have mapping relationship, then they might have too

Semantic similarity strategy: In this thesis, edit distance (Levenshtein, 1966) method is adopted to calculate the semantic similarity degree between concepts as Eq. 7 shows:

$$\mathrm{sim}'_{\mathrm{ling}}(c_1, c_2) = \max\left(0, \frac{\min(|c_1|, |c_2|) - \mathrm{ed}(c_1, c_2)}{\min(|c_1|, |c_2|)}\right) \quad (7)$$

Table 1: Mapping algorithm procedure

Algorithm: Fuzzy ontology mapping
1: Initialize: i= 1, i< = max{num(B), num(B_j)};
2: If URI(k_i) = URI(v_j) , then go to 4, else continue;
3: Call WordNet, if k_i = v_j, then continue, else i++ and goto 1;
4: Put (k_i, v_j) into temporary mapping table;
5: If i = max{num(B_i), num(B_j)}, then continue, else i++ goto 1;
6: Get neighbour node (k'_i, v'_j), move (k_i, v_j) to mapping repair table;
7: Calculate $\mathrm{sim}'_{\mathrm{ling}}$($k'_i$, v'_j), use WordNet to repair and get $\mathrm{sim}_{\mathrm{ling}}$($k'_i$, v'_j);
8: Calculate $\mathrm{sim}_{\mathrm{inst}}$($k'_i$, v'_j) and $\mathrm{sim}_{\mathrm{attr}}$($k'_i$, v'_j);
9: Mapping fuse to obtain sim(k'_i, v'_j);
10: If sim(k'_i, v'_j)> threshold, then 4, else continue;
11: If temporary mapping table is null, then continue, else go to 6;
12: Add all the non-mapping nodes to the mapping repair table;
13: Iteration repair nodes from top to bottom in mapping repair table;
14: Move mapping repair table to final mapping table;
15: End;

where, $|c_1|$ is the length of string c_1, $\min(|c_1|, |c_2|)$ is the shorter one of c_1 and c_2 and $ed(c_1, c_2)$ is the least frequency of operation, including insertion, replacement and deletion etc., which converts c_1 to c_2.

When a concept is constituted of multi-words, similarity matrix of the words is adopted to calculate the concept semantic similarity degree. When mapping the $concept_1$ and $concept_2$, the word sets of $\{w_1,\ldots,w_i\}$ and $\{w_1, \ldots, w_j\}$ are firstly obtained after segmentation. The word w_i in $concept_1$ is mapped with the most similar word w_j in $concept_2$. Then the similarity degree named sim(wi, con_2) between w_i and $concept_2$. So, the semantic similarity degree between $concept_1$ and $concept_2$ is gained from Eq. 8:

$$\mathrm{sim}(\mathrm{con}_1, \mathrm{con}_2) = \frac{\sum_{i=1,\ldots,n} \mathrm{sim}(w_i, \mathrm{con}_2)}{n} \tag{8}$$

Among it, n is the number of words in $concept_1$.

The method is simple and easy to be realized. But it has two problems: One is that some words have close structure but remote semanteme, like healthy and wealthy; the other is that some words have remote structure but close semanteme, like rich and wealthy.

For the issues above, the WordNet is adopted to revise.

Rule 6: If $sim_{ling}(c_1, c_2) = 1$, then (c_1, c_2) is added to the temporary mapping table

Rule 7: If $sim_{ling}(c_1, c_2) \geq 0.5$, c_1 and c_2 are appositions or hyponymy in WordNet, then (c_1, c_2) is added to the temporary mapping table

If the results neither meet rule 6 nor rule 7, the similarity degrees of instance and attribute are calculated.

Instance similarity strategy: For precise ontology, the Jaccard similarity coefficient formula and machine learning method are generally adopted to calculate the joint probability distribution. Then the instance similarity is obtained by comparing the shared instances. In this thesis, a calculation method of fuzzy ontology instance similarity is proposed based on original method. The following example is to explain.

Example: Assume that C_1 and C_2 are two concepts waiting to be mapped. $S_1 = \{a_1, a_2, a_3, a_4, a_5, a_6, a_8\}$ is the fuzzy instance set of C_1. $S_2 = \{a_2, a_3, a_5, a_6, a_7, a_8\}$ is the fuzzy instance set of C_2. $F_1 = \{u_{11}, u_{12}, u_{13}, u_{14}, u_{15}, u_{16}, u_{18}\}$ is the membership degree set of instances in S_1 for C_1. $F_2 = \{u_{22}, u_{23}, u_{25}, u_{26}, u_{27}, u_{28}\}$ is the membership degree set of instances in S_2 for C_2. S_1 and S_2 have common fuzzy instance like a_2, a_3, a_5, a_6, a_8. Then the membership degrees are combined into couples: $a_2 = (u_{12}, u_{22})$, $a_3 = (u_{13}, u_{23})$, $a_5 = (u_{15}, u_{25})$, $a_6 = (u_{16}, u_{26})$, $a_8=(u_{18}, u_{28})$. The instance should be deleted if its membership degree is less than 0.5, because there is more than fifty percent possibility that the instance isn't belong to the concept. Assume $u_{12} = 0.2<0.5$, a_2 isn't belong to the common instances of C_1 and C_2. So a_3, a_5, a_6, a_8 are considered in the calculation. a_3 is made as an example to calculate the membership degree belonging to $C_1 \cap C_2$ as Eq. 9 shows:

$$\mu_{a_3 \in c_1 \cap c_2} = \frac{\mu_{13}}{\mu_{13}+\mu_{23}} \cdot \mu_{13} + \frac{\mu_{23}}{\mu_{13}+\mu_{23}} \cdot \mu_{23} = \frac{\mu_{13}^2+\mu_{23}^2}{\mu_{13}+\mu_{23}} \tag{9}$$

If the result above is more than a threshold λ, a_3 is regarded as the common instance of C_1 and C_2. Otherwise, a_3 is not and should be deleted.

Supposing the membership degrees of a_3, a_5, a_6, a_8 are more than λ, the instance similarity degree between C_1 and C_2 is calculated as below, that is the number of common instances comparing to the number of all instances of the concept:

$$\mathrm{sim}_{inst}(c_1, c_2) = \frac{a_3+a_5+a_6+a_8}{a_1+a_2+a_3+a_4+a_5+a_6+a_7+a_8} = \frac{4}{8} = 0.5$$

Attribute similarity strategy: The attribute similarity strategy is almost the same with the instance similarity strategy. The instance is just replaced by attribute. Due to space limitations, it will not be introduced again.

Mapping fusion: $sim_{ling}(c_1, c_2)$, $sim_{inst}(c_1, c_2)$ and $sim_{attr}(c_1, c_2)$ can be obtained according to the above methods. But in order to ensure the accuracy of the mapping results, mapping fusion as Eq. 10 shows among the three is needed:

$$\mathrm{sim}(c_1, c_2) = \alpha \cdot \mathrm{sim}_{ling}(c_1, c_2) + (1-\alpha) \cdot (w_1 \cdot \mathrm{sim}_{inst}(c_1, c_2) + w_2 \cdot \mathrm{sim}_{attr}(c_1, c_2)) \tag{10}$$

where α is a weight whose value is dependent on the reality. If the semantic similarity degrees of the ontology are generally high and the structure similarity and attribute similarity degrees are lower or the ontology instances and attributes are not defined completely, α is larger. Otherwise, the α is smaller. Moreover, w_1 and w_2 whose computing methods are shown as Eq. 11 and 12, which represent the weights of instance and attribute similarity degree, respectively.

$$w_1 = \frac{I_{proportion}}{I_{proportion} + A_{proportion}} \tag{11}$$

$$w_2 = \frac{A_{proportion}}{I_{proportion} + A_{proportion}} \tag{12}$$

where, $I_{proportion}$ and $A_{proportion}$ represent the proportions of instances and attributes, respectively and their specific definitions are shown as Definition 8 and 9.

Definition 8: $|In_i|$ is set as the number of the source ontology instances. $|In_j|$ is set as the number of the target ontology instances. Generally, $|In_i|$ is less than $|In|_j$ Then, $I_{proportion}$ is called instance proportion and calculated as Eq. 13:

$$I_{proportion} = \left(1 - \frac{1}{|In_i| + |In_j| + a}\right) \times \frac{|In_i|}{|In_j|} \tag{13}$$

where, a is a number which is greater than or equal to 1. Its effect is that when $|In_i|+|In_i| = 0$, the denominator would not be meaningless or $I_{proportion}$ would not be a negative number.

Definition 9: $|An_i|$ is set as the number of the source ontology attributes. $|An_j|$ is set as the number of the target ontology attributes. Generally, $|An_i|$ is less than $|An_j|$. Then, $A_{proportion}$ is called attribute proportion and calculated as Eq. 14 shows:

$$A_{proportion} = \left(1 - \frac{1}{|An_i| + |An_j| + b}\right) \times \frac{|An_i|}{|An_j|} \tag{14}$$

Similarly, b is a number which is greater than or equal to 1. Its effect is the same as a.

Mapping correction: In order to get higher accuracy of the results, mapping correction is required after the initial mapping. In this thesis, iterative correction method is adopted to repair the mapping results taking into account of the efficiency, automation and feasibility.

Rule-based reasoning and information of ontology hierarchy structure are used to repair the results in accordance with the order from top to bottom of the ontology hierarchy structure. For each iteration, the impacts of the newly discovered concept pairs to the existing concept pairs have to be considered. Then the newly discovered concept pairs are added and the wrong ones are deleted and the unreasonable ones are adjusted until no new revision.

When a new mapping pair is found, the probability of finding other similar pairs will be relatively high in the surrounding (parent node, child node and brother node) according to rule 3, 4 and 5. So, in the first iteration, the mapped concept pairs are mainly used to compare with its neighbors and up and down nodes to find new mappings. In subsequent iterations, the adjustments of the last round are firstly considered and then the nodes close to the nodes which have been adjusted are compared. Practices show that, no matter how large the involved ontology is, almost no new mappings are produced after 8 times iterations.

FUZZY ONTOLOGY MERGING

The fuzzy ontologies are merged according to the mapping and mapping results in the previous section.

Fuzzy ontology merging and conflict processing rules

Merging rules: Assume that O_S is the source fuzzy ontology and O_T is the target one. The rules below should be observed while merging.

Rule 1: According to the results of the modularization, the module which has more concepts and clearer hierarchy is set as O_T and the other one is set as O_S

Rule 2: Classes C_S in O_S are merged into classes C_T in O_T based on C_T

Rule 3: If there is no class that matches the C_S in O_T, it needs to create class C_T which matches the C_S, and add the attributes and instances of C_S to C_T

Rule 4: The similar concepts in mapping table are merged as identical concept. If the concepts in O_T are abbreviations but in O_S are intact, the concepts in O_S are regarded as the standard, otherwise, the concepts in O_T are the standard

Rule 5: The similar attributes are merged as identical attribute. If the attributes in C_T are abbreviations but in C_S are intact, the attributes in C_S are regarded as the standard, otherwise, the attributes in C_T are the standard. The common attributes are added into the common attribute set $\{C_A\}$. The attributes which are in C_S but not in C_T are added into C_T. Meanwhile, The non-public ones are added into non-public attribute set $\{UC_A\}$

Rule 6: The instances are processed as the attributes in rule 5. Then the sets $\{C_1\}$ and $\{C_2\}$ can be gotten

Rule 7: If there are concepts which are in O_S but not in O_T, the concepts are constructed in O_S and the father-son relationship of them in O_T must be remained. If the father-son concept nodes both have mappings in O_T, they are merged according to the rules above, otherwise, they are constructed in O_T according to this rule

Table 2: Fuzzy ontology merging algorithm

Algorithm: Fuzzy ontology merging algorithm
1: O_T and O_S are determined according to merging rule 1;
2: Initialize: i = 1, i <= max{num(C_S), num(C_T};
3: If there are mappings between classes in O_S and classes in O_T, then continue, else goto 11;
4: Classes are merged according to merging rule 4;
5: If there are conflicts between classes, then continue, else go to 7;
6: The conflicts are handled according to conflict processing rule 1;
7: The attributes are merged according to merging Rule 5;
8: The instances are merged according to merging rule 6, then go to 14;
9: Classes are added in O_T according to merging rule 7;
10: If there are conflicts between classes, then continue, else go to 12;
11: The conflicts are handled according to conflict processing rule 2;
12: Attributes are added in O_T according to merging rule 8;
13: Instances are added in O_T according to merging rule 9;
14: If i = max {num(C_S), num(C_T)}, then go to 16, else continue;
15: I++, returu to 2;
16: End

Rule 8: When adding new concept attributes, all of them are added into {C_A} and {UC_A} is null

Rule 9: When adding new concept instances, all of them are added into {C_I} and {UC_I} is null

Conflict processing rules:

Rule 1: (The conflict of the hierarchy relationship while concepts being merged) When the two concepts waiting to be merged have the hierarchical structure conflict, the hierarchy of concepts in O_T, usually, is regarded as standard and the hierarchy of concepts in O_S should be adjusted to it. But if the concepts in O_S are the apposition relationship in WordNet, the apposition relationship are the standard and the hierarchy of concepts in O_T should be adjusted to it

Rule 2: (The conflict of the hierarchy relationship when concepts been added) In this situation, the ontology whose concept relationships are more complete is the standard. That means if there is a new concept in O_S which should be added into O_T, the relationship between the concepts in O_T should be adjusted to the relationship in O_S

Fuzzy ontology merging algorithm: Fuzzy ontology merging algorithm is given in Table 2, its input and output are mapping table and target fuzzy ontology, respectively.

CONCLUSION

In this study, the Semantic Web fuzzy ontology model is proposed based on a comprehensive analysis of the existing fuzzy ontology models and the modularized multi-strategy fuzzy ontology mapping integration methods aiming at this model is also proposed. The large ontology is divided into several modules according to the principle of high cohesion but low coupling. These modules not only are convenient to the future reuse of the ontology but also make the ontology mapping become easier to operate. This multi-strategy mapping method is fully integrated with the characteristics of fuzzy ontology, and the mapping operation can be effectively done by using the membership degree in the instance and attribute mapping. And the mapping results are iterative corrected and weighted to fuse. Lastly, the heterogeneous fuzzy ontologies in the same field are merged to achieve tight ontology integration.

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