TELKOMNIKA, Vol.11, No.11, November 2013, pp. 6514~6520
e-ISSN: 2087-278X

Automatic Detection and Processing of Attributes Inconsistency for Fuzzy Ontologies Merging

Yonghong Luo*[1], Zhou Yu[2], Yanhao Zhuang[3], Zhaopeng Zheng[3]
[1]School of Computer and Communication Engineering, Changsha University of Science and Technology
Changsha 410114, Hunan, China
[2]School of Information and Engineering, Henan Institute of Science and Technology
Xinxiang 453003, China
[3]School of Civil Engineering and Transportation, South China University of Technology
Guangzhou 510641, China
*Corresponding author, e-mail: 58720150@qq.com

Abstract

Semantic fusion of multiple data sources and semantic interoperability between heterogeneous systems in distributed environment can be implemented through integrating multiple fuzzy local ontologies. However, ontology merging is one of the valid ways for ontology integration. In order to solve the problem of attributes inconsistency for concept mapping in fuzzy ontology merging system, we present an automatic detection algorithm of inconsistency for the range, number and membership grade of attributes between mapping concepts, and adopt corresponding processing strategy during the fuzzy ontologies merging according to the different types of attributes inconsistency. Experiment results show that with regard to merging accuracy, the fuzzy ontology merging system in which the automatic detection algorithm and processing strategy of attributes inconsistency is embedded is better than those traditional ontology merging systems like GLUE, PROMPT and Chimaera.

Keywords: *fuzzy ontology, ontology merging, automatic detection, attributes inconsistency, membership grade*

1. Introduction

As precise ontology model can't fully represent uncertain knowledge and vague information such as “young people”, ”very expensive” in many application domains, it is necessary to introduce fuzzy ontology for describing fuzzy information. Straccia was the first man to propose the idea of fuzzy ontology [1], which can express fuzzy concepts and fuzzy relations between concepts through integrating fuzzy logic [2]. Nowadays, applied ranges of fuzzy ontology has been gradually extended, but constructing fuzzy ontology with different languages, methods and descriptive ways might result in heterogeneity of multiple ontologies in the same domain. So, semantic fusion of multiple data sources and semantic interoperability between heterogeneous systems in distributed environment such as grid computing [3, 4] and cloud computing [5, 6] usually can be implemented through integrating multiple fuzzy local ontologies. However, ontology merging is one of the valid ways for ontology integration.

Currently there are few works on fuzzy ontology merging. Authors in literature [7, 8] proposed an integration method of fuzzy ontology based on consensus in which integrated algorithm have not be verified by experiments, so the accuracy and effectiveness of fuzzy ontology integration can not be ensure. Literature [9] used concept lattice gluing to merge fuzzy ontologies, and proposed a method of fuzzy ontology merging based on fuzzy concept gluing. Existing various methods of precise ontologies merging mainly include GLUE [10], HCONE [11], PROMPT [12], ASMOV [13] and so on. We all know that these precise methods are semi-automatic, and are not suitable for merging fuzzy ontologies. So, there are still no effective solutions to solve the problem of attributes inconsistency for concept mapping in fuzzy ontologies merging system at present. For the inconsistencies regarding the range, number and membership grade of attributes, fuzzy ontology merging systems need more human intervention to repair inconsistency relations between concepts.

Received April 9, 2013; Revised June 18, 2013; Accepted July 19, 2013

In order to effectively deal with the problem of attributes inconsistency for concept mapping in fuzzy ontologies merging system, and strive to realize full automation of fuzzy ontology merging, we present automatic detection algorithm and corresponding processing strategy for attributes inconsistency according to the aforementioned situation. The elimination of attributes inconsistency for concept mapping during fuzzy ontologies merging includes following three steps: (1) creating initial mapping solution between source fuzzy ontologies based on similarity degree calculating of concept; (2) using detection algorithm of attributes inconsistency to find out all of inconsistent mappings from initial mapping solution; (3) performing corresponding processing strategies according to the types of attributes inconsistency, respectively.

2. Description of Fuzzy Ontology

Definition 1. A fuzzy ontology can be defined as a 7-tuple form: $\mathrm{FO} = (\mathrm{C, A, V, U, R, Z, I})$ where C is set of concepts, a concept is fuzzy concept if it contains at least one attribute with membership grade or it is set of fuzzy set; A is set of attributes belonging to the concepts in C. An attribute is a fuzzy attribute if its value is a fuzzy set; V is the domain of A. V also can be expressed as a set of attribute values, and $\mathrm{V} = \cup_{a\in A} \mathrm{V_a}$ where V_a is the domain of the attribute a; U is set of membership functions, and the range of each membership function is a concrete fuzzy concept; R is set of fuzzy relations between concepts: $\mathrm{R} = \{\mathrm{R_1, R_2, \ldots, R_n}\}$ where $\mathrm{R_i} \subset \mathrm{C} \times \mathrm{C} \times (0,1]$ for i=1, 2,…, n. A relation is then a set of pairs of concepts with a weight representing the degree to which the relationship should belong; Z is set of axioms, which can be interpreted as integrity constraints or relationships between instances and concepts; I is set of instances. An instance is fuzzy instance if its corresponding concept is fuzzy concept.

Definition 2. A fuzzy concept FC can be defined as a triple form: $\mathrm{FC} = (\mathrm{A^{FC}, V^{FC}, f^{FC}})$ where $\mathrm{A^{FC}} \subset \mathrm{A}$ is set of attributes describing the concept, including fuzzy attributes and precise attributes; $\mathrm{V^{FC}} \subset \mathrm{V}$ is the union of each attribute domain; f^{FC} is set of fuzzy functions which represent the degrees that the attributes of fuzzy concepts describe their concept instances, $\mathrm{f^{FC}}{:}\mathrm{A^{FC}} \to [0,1]$.

Definition 3. A concrete fuzzy concept $\mathrm{cfc} \subseteq \mathrm{C}$ can be defined as a 4-tuple from: $\mathrm{cfc} = (\mathrm{V_{cfc}, V_{cfc}', L_{cfc}, f_{cfc}})$ where cfc is the unique identifier of concrete fuzzy concept; $\mathrm{V_{cfc}} \subseteq \mathrm{V}$ is the domain of concrete fuzzy concept cfc; $\mathrm{V_{cfc}}' \subseteq (0,1]$ presents fuzzy values of the concrete set V_{cfc}; $\mathrm{L_{cfc}} \subseteq \mathrm{V}$ models linguistic qualifiers, which is determined by the strength of the attribute value in V_{cfc}; $\mathrm{f_{cfc}} \in \mathrm{U}$ is a membership function on V_{cfc}, $\mathrm{f_{cfc}}{:}\mathrm{V_{cfc}} \to \mathrm{V_{cfc}}'$, $\forall \mathrm{v} \in \mathrm{V_{cfc}}, \mathrm{f_{cfc}}(\mathrm{v}) \in \mathrm{V_{cfc}}'$.

3. Fuzzy Ontology Mapping

According to the definitions of concrete fuzzy concept (property), the similarity degree between fuzzy concepts or fuzzy properties depends on their fuzzy sets. We assume that $\mathrm{FC_1} = \{\mathrm{A, V, f_A}\}$ and $\mathrm{FC_2} = \{\mathrm{A', V', f_{A'}}\}$ are the concrete fuzzy concepts. V and V’ are the concrete sets, A and A’ are the corresponding fuzzy sets of set V and set V’ respectively.We specify $\mathrm{U} = \mathrm{V} \cup \mathrm{V'}$, the operations between fuzzy subsets can be defined as follows:

$$\forall x \in U,\ f_{A\cap A'}(x) = \min\{f_A(x), f_{A'}(x)\} \quad (1)$$

$$\forall x \in U,\ f_{A\cup A'}(x) = \max\{f_A(x), f_{A'}(x)\} \quad (2)$$

$$\forall x \in U,\ f_{A-A'}(x) = \min\{ f_A(x), 1- f_{A'}(x)\} \tag{3}$$

$$\forall x \in U,\ f_{A'-A}(x) = \min\{1- f_A(x),\ f_{A'}(x)\} \tag{4}$$

A-A' is the fuzzy subset of elements that belong to A and not to A', A'-A is the fuzzy subset of elements that belong to A' and not to A. So, the similarity degree between attribute (concept) a_1 and attribute (concept) a_2 can be calculated with the following expressions:

$$Sim(a_1,a_2) = \sup_{x\in U}\ f_{A\cap A'}(x) \rightarrow Sim(a_1,a_2) = \sup\{\min\{ f_A(x),\ f_{A'}(x)\}\} \tag{5}$$

$$Sim(a_1,a_2) = \sup_{x\in U}\ f_{A\cup A'}(x) \rightarrow Sim(a_1,a_2) = \sup\{\max\{ f_A(x),\ f_{A'}(x)\}\} \tag{6}$$

$$Sim(a_1,a_2) = \sup_{x\in U}\ f_{A-A'}(x) \rightarrow Sim(a_1,a_2) = \sup\{\min\{ f_A(x), 1- f_{A'}(x)\}\} \tag{7}$$

$$Sim(a_1,a_2) = \sup_{x\in U}\ f_{A'-A}(x) \rightarrow Sim(a_1,a_2) = \sup\{\min\{1- f_A(x),\ f_{A'}(x)\}\} \tag{8}$$

Therefore, the similarity degree of attributes between fuzzy concepts of FC_1 and FC_2 can be calculated as follows:

$$AS(FC_1, FC_2) = \frac{\sum_{i=1}^{n} Sim(a_i^{FC_1}, a_i^{FC_2})}{\max(|FC_1|,|FC_2|) - \frac{||FC_1| - |FC_2||}{2}} \tag{9}$$

Where a^{FC_1} and a^{FC_2} are attributes belonging to FC_1 and FC_2, respectively; $|FC_1|$ and $|FC_2|$ denote the number of attributes for FC_1 and FC_2, respectively; n is the maximum value of $|FC_1|$ and $|FC_2|$.

The calculation of similarity degree between fuzzy concepts usually needs to take into multiple important factors of concepts like name, semantic and so on account. Here we determine the final similarity degree between fuzzy concepts through aggregating name similarity, semantic similarity and attribute similarity.

The name similarity between concepts [14] is calculated as follows:

$$NS(FC_1, FC_2) = \frac{\max(l(FC_1), l(FC_2)) - EditDist(FC_1, FC_2)}{\max(l(FC_1), l(FC_2))} \tag{10}$$

The semantic similarity between concepts [13] is calculated as follows:

$$SS(FC_1, FC_2) = \frac{2 \times IC(sub(FC_1, FC_2))}{IC(FC_1) + IC(FC_2)} \tag{11}$$

Where IC [15] is the function that returns information content of a concept [16], the information content of FC can be calculated as follows:

$$IC(FC) = 1 - \frac{\log(hypo(FC)+1)}{\log(TN)} \tag{12}$$

Finally, the integrated similarity degree between fuzzy concepts can be calculated as follows:

$$S(FC_1, FC_2) = \frac{w_a \times AS(FC_1, FC_2) + w_n \times NS(FC_1, FC_2) + w_s \times SS(FC_1, FC_2)}{3} \tag{13}$$

Where w_a, w_n and w_s denote the weight of attribute similarity, name similarity and semantic similarity respectively, and $w_a + w_n + w_s = 1$.

With the formula of similarity degree between fuzzy concepts, the initial mapping algorithm between fuzzy ontologies is as follows:

Input: Source ontologies FO_1 and FO_2, w_a, w_n, w_s
Output: mapping list of concepts between FO_1 and FO_2
Begin
```
Step 1: n=|FO1|; m=|FO2|; k=0; //|FOi| denote the number of concepts in FOi
Step 2: for i=1 to n do
Step 3:     for j=1 to m do
Step 4:         s= S(C1i,C2j); // Cxy indicate that the current sequence number of
            concept is y in FOx
Step 5:         if s>λ then
Step 6:             mapping_list[k++]=( C1i,C2j);
Step 7:         end if
Step 8:     end for
Step 9: end for
```
End.

4. Detection Algorithm of Attributes Inconsistency

Definition 4 (Range Inconsistency of Attributes). Given that the range of object attribute a of concept C in ontology O_1 is R, the range of object attribute a' of concept C' in ontology O_2 is R', and $R \neq R'$. Then, we call mapping (C, C') as range inconsistency of attribute because of its violation of property subsumption criteria.

Definition 5 (Number Inconsistency of Attribute). Given that the attribute set of concept C is $A = \{a_1, a_2, \ldots, a_m\}$, the attribute set of concept C' is $A' = \{a'_1, a'_2, \ldots, a'_n\}$, and $m \neq n$. Then, we call mapping (C, C') as number inconsistency of attribute.

Definition 6 (Membership Inconsistency of Attribute).Given that the attribute set of concept C is A, the attribute set of concept C' is A'. Then, we call mapping (C, C') as membership inconsistency of attribute between C and C' if $u_a(C) \neq u_a(C')$ for $\forall a\ (a \in A \cap A')$.

The detection algorithm of attributes inconsistency is as follows:

Input: mapping_list
Output: different type sets of attributes inconsistency
Begin
```
Step 1:  n=mapping_list.length;
Step 2:  for (i=0; i<n-1;i++) do
Step 3:      Mapping mp1=mapping_list(i);
Step 4:      for (j=i+1;j<n;j++) do
Step 5:          Mapping mp2=mapping_list(j);
Step 6:          for each attribute in mp1.Concept1
Step 7:              If (attribute.rangeConcept disjoint mp2.Concept2) then
Step 8:                  adding mp1 to range_inconsistency[];
Step 9:              end if
Step 10:         end for
Step 11:     end for
Step 12: end for
Step 13: for (i=0;i<n;i++) do
Step 14:     Mapping mp=mapping_list(i);
Step 15:     A=get_attribues(mp.Concept1);
Step 16:     B= get_attribues(mp.Concept2);
Step 17:     if (|A|!=|B|) then
Step 18:         adding mp to number_inconsistency[];
Step 19:     end if
Step 20: end for
```

Step 21: for (i=0;i<n;i++) do
Step 22: Mapping mp=mapping_list(i);
Step 23: for $\forall$a in (mp.Concept$_1$.A ∩ mp.Concept$_2$.B) do
Step 24: if u$_a$(mp.Concept$_1$)!=u$_a$(mp.Concept$_2$) then
Step 25: adding mp into membership_inconsistency[];
Step 26: end if
Step 27: end for
Step 28: end for
End.

5. Processing of attribute inconsistency

The initial mapping list obtained from fuzzy ontologies mapping mainly contains three types of attributes inconsistency: range inconsistency, number inconsistency and membership degree inconsistency.

(1) Processing for range inconsistency of attribute

Problem description: for mapping (FC$_1$, FC$_2$), FC$_1$ is a concept in ontology O$_1$ that includes a object attribute p$_1$ with range of R$_1$; FC$_2$ is a concept in ontology O$_2$ that also includes a object attribute p$_2$ with range of R$_2$; $p_1 = p_2$, $R_1 \neq R_2$.

Merging processing strategy: we reset the range for object attribute p generated by p$_1$ and p$_2$ after FC$_1$ and FC$_2$ were merged into FC, and let $R(p) = R_1(p_1) \cup R_2(p_2)$.

(2) Processing for number inconsistency of attribute

Problem description: for mapping (FC$_1$, FC$_2$), FC$_1$ is an concept in ontology O$_1$ with attributes set $A_1 = \{a_{11}, a_{12}, \ldots, a_{1m}\}$, FC$_2$ is an concept in ontology O$_2$ with attributes set $A_2 = \{a_{21}, a_{22}, \ldots, a_{2n}\}$, but $m \neq n$.

Merging processing strategy: Merging the concepts of FC$_1$ and FC$_2$ into a concept FC, then the attributes set A of concept FC needs to be set to the union of A$_1$ and A$_2$, i.e. $A = A_1 \cup A_2$ and $|A| = m + n - |A_1 \cap A_2|$.

(3) Processing for membership grade of attribute

Problem description: for mapping (FC$_1$, FC$_2$), FC$_1$ is an concept in ontology O$_1$ with attributes set A$_1$, FC$_2$ is an concept in ontology O$_2$ with attributes set A$_2$. For $\forall a$ （$a \in A_1 \cap A_2$）, there will always be $u_a(FC_1) \neq u_a(FC_2)$.

Merging processing strategy: First merging the concepts of FC$_1$ and FC$_2$ into a concept FC, i.e. $(FC_1, FC_2) \rightarrow C$. If there will always be $u_a(FC_1) \neq u_a(FC_2)$ for $\forall a \in A_1 \cap A_2$, we can calculate the membership grade of concept FC on attribute a as follows:

$$U_a(FC) = \min\{u_a(FC_1), u_a(FC_2)\} \tag{14}$$

6. Experimental Results and Analysis

In order to check if the detection algorithm of attributes inconsistency and corresponding processing strategy proposed in this paper are effective, we developed a fuzzy ontology merging system based on the detection algorithm and processing strategy (FOMS), in which we carried out the experiment of fuzzy ontology merging for five fuzzy ontologies obtained from modified OAEI Conference ontology. The experimental data is shown in Table 1.

Table 1. Description of Experimental Data

Ontology name	Number of concepts	Number of attributes	Number of relations
lasted	140	21	38
Edas	104	25	30
openConf	62	26	24
Confious	57	9	52
Linklings	37	20	31

We first implemented the pairwise merging for five ontologies in Table 1 with FOMS, GLUE, PROMPT and Chimaera. Then, we compared the execution time of FOMS with those of GLUE, PROMPT and Chimaera, the comparison results are shown in Table 2.

Table 2. The Time Consumption of Comparison for All Merging Systems

Merging objects	FOMS	GLUE	PROMPT	Chimaera
(lasted,Edas)	753	749	755	756
(lasted, openConf)	528	535	524	522
(lasted, Confious)	504	511	496	498
(lasted, Linklings)	369	366	374	377
(Edas,openConf)	492	500	492	490
(Edas, Confious)	381	382	391	378
(Edas, Linklings)	258	246	263	259
(openConf,Confious)	221	223	234	222
(openConf, Linklings)	233	236	242	245
(Confious, Linklings)	200	211	206	213

Table 2 indicates that the time consumption of FOMS is almost equal to those of GLUE, PROMPT and Chimaera, even the average time consumption of FOMS is slightly lower than those of GLUE, PROMPT and Chimaera. For the accuracy of merging, FOMS proposed in this paper is obviously higher than GLUE, PROMPT and Chimaera (shown in Figure 1). In Figure 1, E/o represents the ontology merging between Edan and openConf, the representations for E/C, E/L etc are similar to E/o.

Therefore, the method proposed in this paper is more suitable for the merging of fuzzy ontologies than methods for the merging of precise ontologies like GLUE, PROMPT. During the validation of initial mappings in FOMS, the system only needs to execute pruning based on the results of depth analysis, thus reduces the number of suspected erroneous mappings. So, it saves time and cost of overall system.

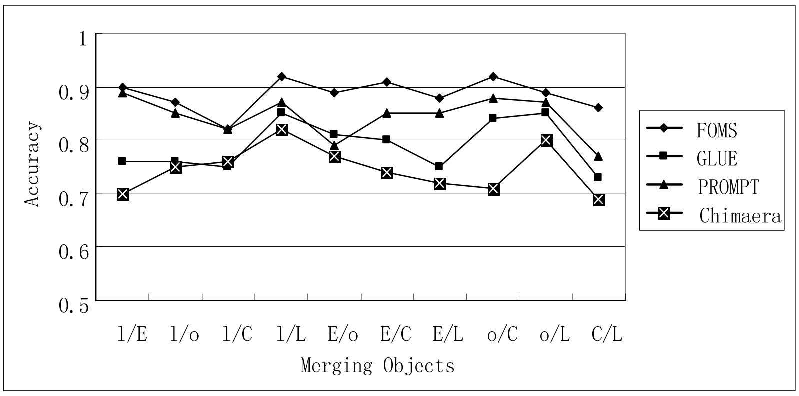

Figure 1. The Comparison of Merging Accuracy for All Merging Systems

7. Conclusion

Due to the differences on tool and language for different R&D teams to construct fuzzy ontologies, especially on the understanding and description of concept structure, so that it can lead to the heterogeneity of various fuzzy ontologies in the same domain. Therefore, we have presented an automatic detection algorithm for the attributes inconsistency of concepts mapping in this paper, and implemented a fuzzy ontology merging system (FOMS). FOMS only need to analyze the results of initial mapping solution, then can find out all of the attribute inconsistency mappings and correct them with processing strategy of attribute inconsistency. Experimental results demonstrate that FOMS has obtained the desired effect on merging accuracy, time consumption and automatic detection ability of consistency. In the future, we will highlight the following works: (1) Modifying the detection algorithm of attribute inconsistency to improve the merging accuracy for FOMS, and applying it to the domain of intelligent transport system. (2) For fuzzy ontologies described with different languages, studying on the automatic detection of semantic inconsistency during the merging of fuzzy ontologies.

Acknowledgements

This work was supported by National Natural Science Foundation of China (Grant no. 51277015) and Hunan Province Science and Technology Planning Project of China (Grant no. 2011GK3114).

References

[1] Fernando Bobillo, Umberto Straccia. Fuzzy ontology representation using OWL 2. *International Journal of Approximate Reasoning*. 2011; 52(7): 1073-1094.
[2] Gary Meehan, PMike Joy. Animated fuzzy logic. *Journal of Functional Programming*. 1998; 8(5): 503–525.
[3] P Brezany, A Woehrer, AM Tjoa. The Grid: vision, technology development and applications e & i Elektrotechnik und Informationstechnik. 2006; 123(6): 251-258.
[4] Ian Foster, Carl Kesselman, Steven Tuecke. The anatomy of the Grid: Enabling scalable virtual organizations. *International Journal of High Performance Computing Applications*. 2001; 15(3): 200~222.
[5] VV Arutyunov. Cloud computing: Its history of development, modern state, and future considerations. *Scientific and Technical Information Processing*. 2012; 39(3):173-178.
[6] Gordon Blair, Fabio Kon, Walfredo Cirne, etc. Perspectives on cloud computing: interviews with five leading scientists from the cloud community. *Journal of Internet Services and Applications*. 2011; 2(1): 3-9.
[7] Trong Hai Duong, Ngoc Thanh Nguyen. *Fuzzy Ontology Integration Using Consensus to Solve Conflicts on Concept Level*. Proceedings of New Challenges for Intelligent Information and Database Systems. Daegu. 2011; 33-42.
[8] Hai Bang Truong, Ngoc Thanh Nguyen. *A Multi-attribute and Multi-valued Model for Fuzzy Ontology Integration on Instance Level.* Proceedings of the 4th Asian conference on Intelligent Information and Database Systems. Kaohsiung. 2012; 187-197.
[9] Li Zhaohai, Li Guanyu. Concept lattice gluing based fuzzy ontology merging method. *Application Research of Computers.* 2012; 29(7): 2517–2519 (In Chinese).
[10] Fan Li. *An Improved Method about the Similarity Calculation of Ontology.* Proceeding of 2010 International Conference on Multimedia Technology. Ningbo. 2010; 1-4.
[11] Kotis K, Vouros GA, Stergiou K. Towards automatic merging of domain ontologies: The HCONE-merge approach. *Web semantics.* 2006; 4(1): 60-79.
[12] Euzenat J, Valtchev P. *Similarity-based ontology alignment in OWL-Lite*. Proceedings of the 16th European Conference on Artificial Intelligence. Valencia. 2004; 333-337.
[13] Jean-Marya YR, Shironoshitaa EP, Kabuka MR. Ontology matching with semantic verification. *Web semantics.* 2009; 7(1): 235–251.
[14] Ming Mao, Yefei Peng. Michael Spring.An adaptive ontology mapping approach with neural network based constraint satisfaction. *Web Semantics*. 2010; 8(1):14-25.
[15] P Resnik. *Using information content to evaluate semantic similarity in a taxonomy*. Proceedings of International Joint Conference on Artificial Intelligence. Montréal. 1995; 448-453.
[16] N Seco, T Veale, J Hayes. *An intrinsic information content metric for semantic similarity in WordNet.* Proceedings of the 16th European Conference on Artificial Intelligence. Valencia. 2004; 1089–1090.