Study on Visual Knowledge Structure Reasoning

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***Abstract*—Intelligent Topic Map (ITM) embodies the multi-level, multi-granularity and the inherent relevant characteristics of knowledge. With ITM as infrastructure, this paper presents a visual knowledge structure reasoning method integrates the logic-based knowledge reasoning and the structure-based knowledge reasoning. The logic-based knowledge reasoning implements knowledge consistency checking and the implicit associations reasoning between knowledge points, it can help us obtain the optimal description of knowledge. In order to construct the complete knowledge structure, a Knowledge Unit Circle Search strategy for structure-based knowledge reasoning is proposed, by which more detailed semantic association of knowledge is provided and the inherent relevant characteristics of knowledge is obtained. The knowledge reasoning results are visualized by ITM, which provides a visual knowledge map. It is available for users to acquire the knowledge and associations among them. A prototype system has been implemented and applied to the massive knowledge organization, management and service for education.**

***Index Terms*—topic map, intelligent topic map, knowledge reasoning, knowledge visualization**

I. INTRODUCTION

Knowledge reasoning mainly includes two types: the logic-based knowledge reasoning and the structure-based knowledge reasoning. The logic-based knowledge reasoning often used to describe knowledge representation and reasoning based on the logic. It is rigorous, flexible and with a strict formal definition, but the lack of structure constraint. The structure-based knowledge reasoning constructs knowledge based on some data structure, such as vector space, tree, graph, etc. It bodes well for knowledge and the relations between them. Knowledge doesn't exist by itself, since knowledge always has all kinds of relations with other knowledge. According to constructivism theory and cognitive load theory perspective, the inner relevance of knowledge can contribute to achieving consistent with the person's own cognitive pattern, and thereby the cognitive efficiency can be increased [1], but knowledge reasoning can not guarantee as effective as logical representation. So, a knowledge representation model should be built to integrate these two types of knowledge reasoning in order to obtain the satisfactory knowledge reasoning results [2]. Moreover, the reasoning results should be displayed by visual knowledge structure. Its goal is to transfer and create new knowledge through using visualizations.

Topic Map(TM) is an ISO standard (ISO/IEC 13250) that describes knowledge structures and associates them with information resources [3] [4]. Topic map constructs a structured semantic network above the knowledge resources. It describes the concepts and the semantic relations between them, and can locate the resources which are associated with the concepts and realize the concrete objects to be joined with abstract concepts. It provides a visual knowledge map, which is available for users to acquire knowledge and associations among them. However, the conventional topic map can not provide users with efficient knowledge navigation, and we unable to acquire the implicit knowledge for it lack of reasoning abilities. So, we extend the conventional topic map in structure and enhance the reasoning functions, which is defined Intelligent Topic Map (ITM) [5]. EXTM (Extended XTM) extended the syntax and semantics of XTM (XML for Topic Maps) [6] so that it can describe ITM elements (such as clusters, topics, knowledge elements), and provides a model and grammar for representing the structure of ITM and defining reasoning rules. EXTM makes XML extend to the semantic field. It defines an abstract, graphics-based knowledge association model and allows the logic-based knowledge reasoning to discover new knowledge.

We propose a novel method of visual knowledge structure reasoning with the intelligent topic map as infrastructure, which can efficiently implement both the structure-based knowledge reasoning and the logic-based knowledge reasoning. The reasoning results are visualized by ITM. It provides a visual knowledge map, which is available for users to acquire the knowledge and associations among them. Visualization navigation capabilities of exploiting the created knowledge structures are based on hyperbolic geometry concepts and provide users with intuitive access mechanisms to the required knowledge.

Manuscript received April 3, 2010; accepted February 10, 2011.
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doi:10.4304/jsw.6.5.783-790

II. Related Works

The knowledge representation model which is able to integrate logic reasoning and structure reasoning includes XML, RDF, ontology, etc. XML provides a flexible, general, rich structured information representation and convenient for the cooperative processing of heterogeneous knowledge [7]. RDF is an effective means of semantic information description [8]. Ontology establishes a classified hierarchy by defining the concepts and the relevance between them, and thus to build the semantic space of concepts [9]. However, they are not in an intuitive and graphical way to display knowledge, and there is no relationship between the resources and the related concepts contained. The structure of topic map composed of Topics, Associations and Occurrences (TAO) [10], which describes the concepts and the semantic relationships between them and can locate the resource which are associated with the concept. TM establishes a structured semantic web above the resources level and implements the semantic organization and joining between the physical resource entities and the abstract concepts. Topic maps are dubbed "the GPS of the information universe". TM can be applied to cross-system since the XTM (XML for Topic Maps) syntax is based on XML and is an exchangeable data standard. The greatest advantage of TM is the discovery and visualization of knowledge architecture [11] [12]. Graphic display based on topic map is more perceivable, it can provide visual knowledge navigation mechanism. Topic map inherits the characteristics of knowledge organization methods such as index, glossary, thesaurus, taxonomy, concept map, ontology, etc. Consequently, topic map adapts to knowledge logical organization and becomes the state-of-art semantic technologies, such as the application of topic maps technology in context of e-learning environment, especially based on analyses of topic relative semantic structure, and used topic maps to represent learning resources and associated semantics such as metadata [13][14][15]. H. Lu, et al proposed a novel concept of intelligent topic map for knowledge organization and knowledge services, which embodies the multi-level, multi-granularity and inherent relevant characteristics of knowledge and realizes knowledge reasoning [16].

III. ITM Description

A. Overview of ITM Structure

The structure of topic map is shown in Fig. 1. It composed of Topics, Associations and Occurrences (TAO). In order to overcome the drawbacks of topic map, we add a clustering level and a knowledge element level in ITM, which depicts the hierarchical relation of "cluster - topic - knowledge element - occurrence". The structure of ITM is shown in Fig. 2.

Cluster: Each cluster contains several closely related topics so that the topics in the same cluster are similar in some sense. Clusters provide the effective navigation and browsing mechanism for users.

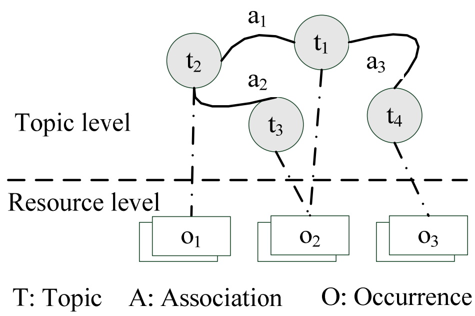

Figure 1. The structure of conventional topic map.

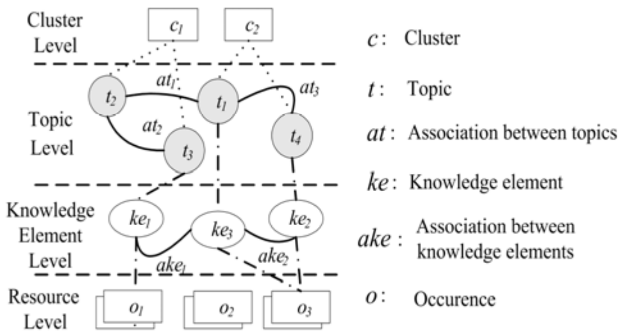

Figure 2. The structure of intelligent topic map.

Definition 1: When given an ITM, a cluster (c) is defined as following two tuples:

$c = (Nc, Tc)$

Nc —the name of cluster

Tc —the set of all topics in the c

Topic: It can be any "thing" (such as a person, an entity, a concept, really anything) — regardless of whether it exists or has any other specific characteristics.

Definition 2: When given an ITM, a topic (t) is defined as following six tuples:

$t = (Nt, At, Dt, E, g, f)$

Nt —the name of topic

$At = \{at_1, at_2, ..., at_n\}$ — a set of associations with topic Nt

$Dt = \{dt_1, dt_2, ..., dt_m\}$ — a set of topic association types ($m \le n$)

$E = \{e_1, e_2, ..., e_n\}$ —a set of elements relevant to Nt, the element is cluster, topic or knowledge element

Function $g : At \to E$ —given a association relevant to element

Function $f : At \to Dt$ —given a association relevant to type

Definition 3: When given an ITM, a knowledge element (ke) is defined as following six tuples:

$ke = (Nke, Ake, Dke, E, g, f)$

Nke —the name of knowledge element

$Ake = \{ake_1, ake_2, ..., ake_n\}$ —a set of associations with knowledge element Nke

$Dke = \{dke_1, dke_2, ..., dke_m\}$ — a set of knowledge element association types ($m \le n$)

$E = \{e_1, e_2, ..., e_n\}$ —a set of elements relevant to Nke

Function $g : At \to E$ —given a association relevant to element

Function $f : At \to Dt$ —given a association relevant to type

Occurrence: representing information resources relevant to a particular topic. An occurrence can be a document, a picture or video depicting the topic, a simple mention of the topic in the context of something else.

Association: A topic association asserts a relationship between two or more topics.

Definition 4: When given an ITM, an association (a) is defined as following three tuples:

$a = (e_1, e_2, d)$

e_1 , e_2 —the elements of ITM

d—the association type

ITM provides strong paradigm and concept for the semantic structuring of linked networks. It can establish the relations among unstructured information resources, thereby allowing to link heterogeneous, unmodified resources of information semantically by creating a semantic web and implement concrete objects to be joined with abstract concepts. It lays a foundation for high-quality structure-based knowledge reasoning.

B. EXTM

XTM was proposed by Newcomb and Biezunsk. It provides a model and grammar for representing the structure of information resources used to define the topics and their associations. Moreover, we enhance the reasoning functions in ITM. We establish corresponding logical reasoning rules and grammar, and then realize knowledge representation and knowledge reasoning.

<Extm rule definition>::=
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'</'Extm: Rule-in'>'
'<'Extm: Rule-out'>'
{<Conclusion definition>} 1-n
'</'Extm: Rule-out'>'
'</'Extm: Rule'>'

<Precondition defination>::=<atom proposition>|<atom proposition with logical operators>

<Conclusion defination>::=<atom proposition>|<atom proposition with logical operators>

<atom proposition with logical operators>::=<atom proposition> <logical operation> <atom proposition>

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<logical operators>::={AND |OR |NOT}

<atom proposition>::='<'Extm: Logic-item'>' <appoint predication> <the member number of predication> <atom proposition setup> '</'Extm: Logic-item'>'

<appoint predication>::='<'owltm: predication rdf:resource="&owltm:<predication>"'/>'

<predication>::={partOf | subClassOf | instanceOf | propertyOf | reasonOf | preconditionOf| caseOf | referenceOf, and so on}

<the member number of predication>::='<'Extm: Atom-member'>' <the member number> '</'Extm: Atom-member'>'

<atom proposition setup>::='<'Extm: AtomSet'>'{<item setup>}1-n '</'Extm: AtomSet'>'

<item setup>::='<'Extm:ItemSet rdf:resource="#<resource name >"'/>'

IV. VISUAL KNOWLEDGE STRUCTURE REASONING

The visual knowledge structure reasoning method using ITM includes three parts: the logic-based knowledge reasoning, the structure-based knowledge reasoning and visualization of reasoning results. The top-down method is adopted to define the abstract workflow as following:

Step 1: Defining the top-level composite processes. As shown in Fig. 3, three composite processes which named "LogicKnowledgeReasoning", "StructureKnowledgeReasoning" and "VisualizationDisplay" are defined, respectively. "Join" denotes the former processes must be finished before the last one is started. The input of process "VisualizationDisplay" is the reasoning results while the outputs of it is the visual knowledge structure.

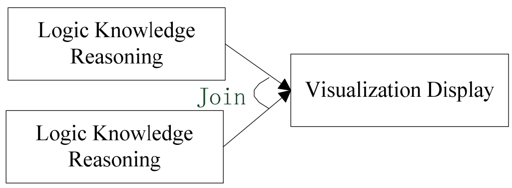

Figure 3. The top-level definition of composite processes.

Step 2: Refining the definition of process "LogicKnowledgeReasoning" as shown in Fig. 4, it includes two processes: the knowledge consistency checking and the implicit associations reasoning.

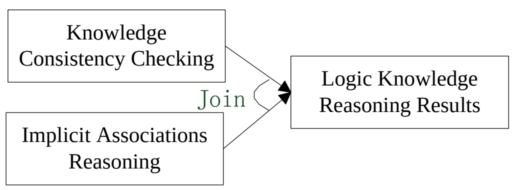

Figure 4. The definition of "LogicKnowledgeReasoning"

A. The Knowledge Consistency Checking

In the process of ITM constructing, conflicts can be caused by many reasons, like the differences of people's understanding, the marking of knowledge resources, and the constructing of knowledge organization. These conflicts cause information redundancies, contradictions and mistakes. The knowledge consistency checking can eliminate them and can help us obtain the optimal description of ITM. It includes the reflexivity checking, loop transitivity checking, knowledge redundancy checking and knowledge contradiction checking.

Reflexivity checking: If an element (topic or knowledge element) of ITM is associated with itself, there exists reflexivity conflict. It is defined as follows:

$$\exists e \in ITM, e\, A\, e \tag{1}$$

When the reflexivity conflict is detected, the association between the same elements would be deleted.

Loop transitivity checking: If there is an association loop between the two directly related elements of ITM, there exists a loop transitivity conflict. It is defined as follows:

$$\exists e_1 \in ITM, \exists e_2 \in ITM, e_1\, A\, e_2 \wedge e_2\, A\, e_1 \tag{2}$$

When the transitivity conflict is detected, one of the associations between the elements would be deleted.

Knowledge redundancy checking: There exists redundancy if have the same elements (topics or knowledge elements) in an ITM.

$$\exists e_1 \in ITM, \exists e_2 \in ITM, e_1 = e_2 \tag{3}$$

Though knowledge redundancy is not a mistake on semantics, it would be resolved when it is detected for ensuring certainty and uniqueness.

Knowledge redundancy checking includes two steps: the same elements searching and merging.

First, we adopt a similarity measure algorithm for topics (or knowledge elements) which called Comprehensive Information-based Similarity Measure Algorithm (CISMA) [17]. This algorithm describes how similar the related topics (or knowledge elements) are. The process used in the similarity algorithm consists of syntactic matching, semantic matching, and pragmatic matching. For an element pair (e_1, e_2), we calculate the similarity as follows:

$$SIM\left(e_1, e_2\right) = w_1 SIM_{Syntax}\left(e_1, e_2\right) + w_2 SIM_{Semantics}\left(e_1, e_2\right) \\ w_3 SIM_{Pragmatics}\left(e_1, e_2\right) \tag{4}$$

$SIM_{Syntax}(e_1, e_2)$: denotes syntactic matching. It is used to compute the syntactic similarity by analyzing the character composition of elements.

$SIM_{Semantics}(e_1, e_2)$: denotes semantic matching. It analyses the static semantic similarity with aspect to synonyms.

$SIM_{Pragmatics}(e_1, e_2)$: denotes pragmatic matching. It computes dynamic semantic similarity, which resolves the problem of polysemy.

w is weight.

Second, merging the same elements adopt the following rules.

Rule 1: Attribute Merging (AM). When given a merging element, AM is defined as following five tuples:

$AM = \left(Ne, Na, D, V_I, \theta\right)$

Ne —the name of element

Na —the name of attribute

D —the values range of Na

$V_I = \left\{I_1, I_2, ..., I_n\right\}$ —a set of Na values in range of D

θ —merging operator

If given a question about attribute merging $AM = \left(Ne, Na, D, V_I, \theta\right)$, its solution K_a is defined as follows:

$$K_a = (Ne, Na, D, \theta(I_1, I_2, ..., I_n)) \tag{5}$$

Rule 2: Element Merging (EM). If element $e1$ has high similarity with $e2$ in ITM, the two elements would be merged into one element ($e1$ or $e2$). Element merging is defined as following four tuples:

$EM = \left(NE, E_A, E_{AI}, E_\theta\right)$

$NE = \{ne_1, ne_2, ..., ne_k\}$ —a set of the element name

$E_A = \left\{A_1, A_2, ..., A_n\right\}$ —a set of all EM attributes

$E_{AI} = \left\{E_{I1}, E_{I2}, ..., E_{In}\right\}$ —a set of all attribute values

$E_\theta = \left\{\theta, \theta_1, \theta_2, ..., \theta_n\right\}$ —a set of merging operators for each attribute used

If given a question about elements merging $EM = \left(NE, E_A, E_{AI}, E_\theta\right)$, its solution K_{ea} is defined as follows:

$$K_{ea} = (\theta(ne_1, ne_2, ..., ne_k), EA, \theta_1(E_{I1}) \cup \theta_2(E_{I2}), ..., \theta_n(E_{In})) \tag{6}$$

Rule 3: Association Merging (AssM). When two elements are merged, the association merging would be considered. It is defined as following three tuples:

$AssM = \left(NE, E_R, \theta\right)$

$NE = \{ne_1, ne_2, ..., ne_k\}$ —a set of the element name

$E_R = \left\{\left(R_{S1}, R_{O1}\right), \left(R_{S2}, R_{O2}\right), ..., \left(R_{Sn}, R_{On}\right)\right\}$ —a set of elements related to NE

R_{Sn} —association type

R_{On} —association object

θ —merging operator

Through knowledge consistency checking, we can obtain an ideal ITM description. It lays a foundation for the structure-based knowledge reasoning.

B. The Implicit Associations Reasoning

The implicit associations reasoning can discover new associations between elements and can help us obtain new knowledge. In this paper, we mainly discuss the association of *subClassOf*, *instanceOf*, *memberOf*, *precorderOf*, and *postorderOf*.

subClassOf: When given element t_a and t_b, *subClassOf* (t_a, t_b) indicates topic t_a is a subclass of t_b, t_a is called sub-topic and t_b is called the relevant parent-topic. Knowledge reasoning rules based on *subClassOf* is as follows:

$$subClassOf\left(t_a, t_b\right) \wedge subClassOf\left(t_b, t_c\right) \\ \rightarrow subClassOf\left(t_a, t_c\right) \tag{7}$$

$$subClassOf\left(t_a, t_b\right) \wedge hasAttribute\left(t_b, A\right) \rightarrow hasAttribute\left(t_a, A\right) \quad (8)$$

$$subClassOf\left(t_a, t_b\right) \wedge instanceOf\left(i, t_a\right) \rightarrow instanceOf\left(i, t_b\right) \quad (9)$$

$instanceOf$. For the element e and its instance set I_e , the association between $i\left(i \in I_e\right)$ $instanceOf\left(i, e\right)$ denotes i is an instance of e . Knowledge reasoning rule based on $instanceOf$ is as follows:

$$instanceOf\left(i, e\right) \wedge hasProperty\left(e, P\right) \rightarrow hasProperty\left(i, P\right) \quad (10)$$

$memberOf$: $memberOf\left(M, W\right)$ denotes M is a member of W . $memberOf$ and $instanceOf$ are two kinds of completely different associations, it emphasizes on the association between elements.

preorderOf and postorderOf : The $preorderOf$ represents that one elements B is comes out before another element A , denoted as $preorderOf\left(B, A\right)$. The $postorderOf$ represents that A is comes out after B , denoted as $postorderOf\left(A, B\right)$. Knowledge reasoning rules based on the $preorderOf$ and $postorderOf$ associations are as follows:

$$preorderOf\left(B, A\right) \wedge preorderOf\left(A, C\right) \rightarrow preorderOf\left(B, C\right) \quad (11)$$

$$postorderOf\left(A, B\right) \wedge postorderOf\left(B, C\right) \rightarrow postorderOf\left(A, C\right) \quad (12)$$

Inverse relation between $preorderOf$ and $postorderOf$:

$$preorderOf\left(B, A\right) \rightarrow postorderOf\left(A, B\right) \quad (13)$$

$$postorderOf\left(A, B\right) \rightarrow preorderOf\left(B, A\right) \quad (14)$$

In addition to the above association types, there are *causalOf*, *referenceOf*, *exampleOf*, and so on.

Step 3: Refining the definition of process "StructureKnowledgeReasoning" as shown in Fig. 5, it includes two processes: Get user interest node and Structure reasoning method.

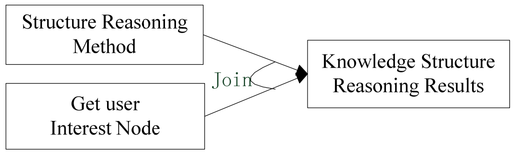

Figure 5. The definition of "StructureKnowledgeReasoning"

Structure reasoning method: Since knowledge is highly correlated with each other, in order to acquire the complete knowledge structure, we must implement the semantic implication extension, the semantic relevant extension and the semantic class belonging confirmation. According to the characteristics of ITM, we propose an extended algorithm based on knowledge unit circle, named Knowledge Unit Circle Search (KUCS) strategy.

Before discussing what can be reasoned based on knowledge structure in ITM, we would like to define three concepts: knowledge path and knowledge radius.

Definition 1: Knowledge path. In ITM, if there is a sequence $e_p, e_1, e_2, ..., e_m, e_q$, and there are association between $\left(e_p, e_1\right), \left(e_1, e_2\right), ..., \left(e_m, e_q\right)$ respectively in ITM, then we said that there exists a knowledge path between concept e_p and e_q .

Definition 2: Knowledge radius. A knowledge path is a sequence of consecutive elements in ITM, and the knowledge radius is the minimum number of elements traversed in a knowledge path, i.e., the length of the path.

KUCS is described as follows:

```
r = 1; // r is knowledge radius
for ∀t ∈ T do   //T is the set of topic
  if associationOf(t_point, t)=true then
    set_T ⇐ t; HashSet ⇐ t;
  else
    set_T ⇐ t;
end
while r ≤ R do
    for ∀t_h ∈ HashSet do
      for ∀t ∈ T do
          if associationOf(t_h, t)=true then
              set_T ⇐ t; HashSet1 ⇐ t;
      end
    end
    r=r+1; HashSet = HashSet1;
end
for ∀t ∈ set_T do
    if associationOf(t, ke)=true then
       set_KE ⇐ ke;
    if associationOf(t, c)=true then
       set_C = set_C ∪ {c};
end
ETM_building();
```

Through the structure-based knowledge reasoning, we can obtain all the knowledge elements, topics, cluster, and resource occurrence which are associated with the knowledge point within a certain knowledge radius.

Step 4: Refining the definition of process "VisualizationDisplay" is shown as follows:

Based on the ITM logical representation of knowledge, the visual knowledge map constructing tool is designed, it is free software coded by Java applet, to assist users in sharing, and navigating the domain knowledge. The ITM document is visually displayed as a double-layer network, the schematic diagram is shown in Fig. 6.

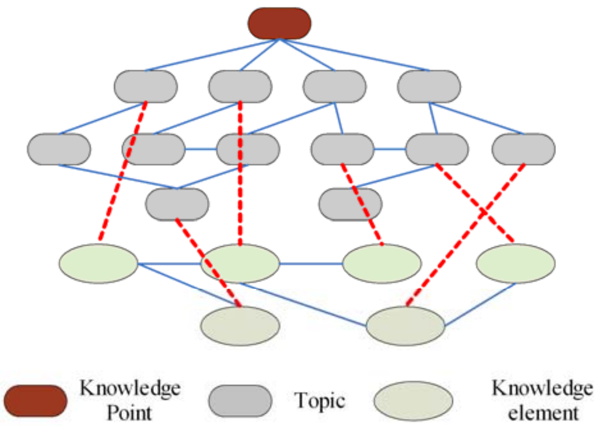

Figure 6. The schematic diagram of visual Knowledge map constructing.

Clusters, topics and topic associations are represented in the upper layer in which fillet rectangular node is regarded as a topic. The dark node is regarded as the knowledge point. Each edge is regarded as an association of topics. When user clicking the edge, it will display the association type. Knowledge elements and their associations are in the lower layer in which ellipse node is regarded as a knowledge element. Each edge is regarded as an association of knowledge elements. When user clicking the edge, it will display the association type. When clicking the nodes in the knowledge element layer, it will display the occurrences which are associated with the knowledge element.

V. Empirical Evaluation

A. The Experimental Data

We built the corpus of Computer Network, which includes 34007 topics, 3307 knowledge elements, 4317 associations between topics, 2214 associations between knowledge elements, 1872 associations between topic and knowledge element and 7031 domain-specific terms.

B. The Logic Knowledge Reasoning Experiment

We implement the knowledge consistency checking and the implicit relations reasoning experiment respectively. The knowledge consistency checking includes the reflexivity checking and loop transitivity checking, knowledge redundancy checking and contradiction checking. The implicit relations reasoning can discover the new associations between elements. The results are shown in Table 1.

TABLE I.
Logic Knowledge Reasoning Results

Checking item	**Statistics**
Reflexivity checking	72
Transitivity checking	216
Redundancy checking	161
Contradiction checking	19
New associations	
New associations between topics	516
New associations between knowledge elements	312

The main conflict type is transitivity conflict, which makes up 52% of total conflicts, knowledge redundancy conflict type makes up 34% of total conflicts, and knowledge reflexivity conflict and knowledge transitivity conflict make up 14% of total conflicts. Conflicts can be caused by many reasons. The ITM corpus construction is a process that needs many people's collaboration and many times of revision, and the local ITM to be reused, they first need to be merged or aligned to one another to produce a single integrated and reconciled global ITM that deals with a larger domain of interest. In the process of building, conflicts can be caused by many reasons, so the consistency checking is a key component of knowledge reasoning strategy. The implicit relations reasoning can reason out new associations between topics (or knowledge elements), provide knowledge structure more detailed semantic association and provide inherent relevant characteristics of knowledge to constructing the complete knowledge structure, but we find that some reasoning relations between topics (or knowledge elements) are not tight enough.

C. The Knowledge Structure Reasoning Experiment

We select a topic "TCP/IP protocol" as knowledge point and different knowledge radius to carry out the structure-based knowledge reasoning experiment. It returns all the knowledge elements and topics which are associated with the knowledge point within a certain knowledge radius. The structure-based knowledge reasoning results is shown in Fig. 7. With the knowledge radius increasing, the number of topics, knowledge elements and relations continuously increase. When knowledge radius is equal to 2, the structure-based knowledge reasoning results include ten topics (such as "IP protocol", "TCP/IP protocol", "TCP protocol", etc.) and twelve associations between the topics, six knowledge elements ("TCP protocol definition", "IP protocol definition", "TCP/IP protocol definition", etc.) and five associations between the knowledge elements, and six relations between the topic and knowledge element. The knowledge structure is depicted in Fig. 8.

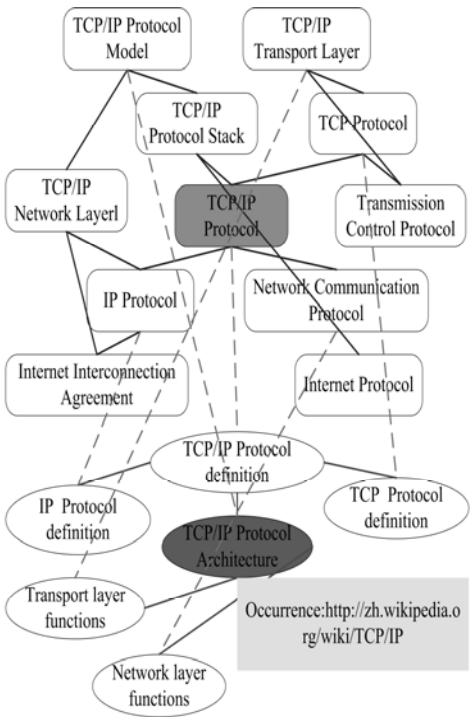

Figure 7. The structure-based knowledge reasoning results.

VI. CONCLUSIONS

The proposed visual knowledge structure reasoning model provides us a means to organize, discovery and display knowledge. Visual knowledge structure reasoning based on ITM not only achieves the better structure-based knowledge reasoning results and provides users with intuitive access mechanisms for the required knowledge. Knowledge has been provided by a stereo knowledge map and hence overcomes the shortcoming of linear display. The ongoing work is knowledge organization, knowledge search and knowledge reasoning can be carried out by computing cloud with huge computing ability and storage capacity distributed and parallel. We hope that the real visual knowledge structure reasoning system will be widely deployed in the future.

ACKNOWLEDGMENT

This work is supported in part by Northeast Asia Chinese International Promotion Information Platform (Hanban). This work was also supported in part by the National High-Tech Research and Development Plan of China under Grant No. 2008AA01Z131.

REFERENCES

[1] J. van Merriënboer and P. Ayres, "Research on cognitive load theory and its design implications for e-learning," Educational Technology Research and Development, vol. 53, no. 3, pp. 5-13, 2005.
[2] Q. Wang, L. Rong, and K. Yu, "Visual knowledge reasoning on typed categorical structure," Proc. 5th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD-08), pp. 684-688, 2008.
[3] "ISO/IEC 13250 Topic Maps Second Edition," Information Technology Document Description and Processing Languages, 19 May 2002.
[4] "ISO/IEC JTC 1/SC 34, ISO/IEC 13250-2: Information Technology-Topic Maps-Part 2: Data Model," http://www.isotopicmaps.org/sam/sam-model/data-model.pdf, 2008.
[5] H. Lu and B. Feng, "The intelligent topic map-based multi-resource knowledge services system," Journal of Information and Computational Science, Binary Information Press, United States, vol. 7, no. 3, pp. 657-665, June 2010.
[6] S. Pepper and G. Moore, "XML Topic Maps (XTM) 1.0," http://www.topicmaps.org/xtm/1.0/index.html, 2002.
[7] C. Baru, A. Gupta, B. Ludäscher, R. Marciano, Y. Papakonstantinou, P. Velikhov, and V. Chu, "XML-based information mediation with MIX," ACM SIGMOD Record, vol. 28, pp. 597-599, 1999.
[8] P. A. Silva, C. M. F. A. Ribeiro, and U. Schiel, "Formalizing ontology reconciliation techniques as a basis for meaningful mediation in service related tasks," Proc. ACM first Ph.D. workshop in CIKM'07, pp. 147-154, 2007.
[9] J. L. Seng and I. L. Kong, "A schema and ontology-aided intelligent information integration," Expert Systems with Applications, vol. 36, pp. 10538-10550, 2009.
[10] S. Pepper, "The TAO of topic maps-finding the way in the age of infoglut," http://www.gca.org/papers/xmleurope2000/papers/s11-01.html
[11] H. Lu, B. Feng, and X. Chen, "Extended topic map: knowledge collaborative building for distributed knowledge resource," Proceedings of the 12th IEEE/IFIP Network Operations and Management Symposium (NOMS 2010), IEEE Communication Society, pp. 128-135, Osaka, Japan, April 2010.
[12] A. Korthaus, M. Aleksy, and S. Henke, "A distributed knowledge management infrastructure based on a Topic Map grid," International Journal of High Performance Computing and Networking, vol. 6, pp. 66-80, 2009.
[13] K. Olsevicova, "Application of topic maps in e-learning environment," ACM SIGCSE Bulletin, vol. 37, pp. 363, 2005.
[14] J. Qiu, Y. Yao, Y. Wang and X. Wang, "Research of e-government knowledge navigation system based on XTM," Proceedings of the 2006 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology, pp. 586-589, 2006.
[15] M. Ouziri, "Semantic integration of web-based learning resources: a topic maps based approach," Proceedings of the 6th International Conference on Advanced Learning Technologies, pp. 875-879, 2006.
[16] H. Lu and B. Feng, "Intelligent topic map: a new approach to multi-resource knowledge service," Proceedings of the 2009 IEEE International Conference on Intelligent Computing and Intelligent Systems (ICIS 2009), IEEE Computer Society, pp. 373-377, November 2009.
[17] H. Lu, B. Feng, and X. Li, "Novel Similarity Algorithm of Extended Topic Maps for Multi-Resource Knowledge Fusion," Journal of Xi'an Jiaotong University, vol. 44, no. 2, pp. 23-27, February 2010.

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