Towards the Detection of Potential Contradictions in Fuzzy Ontology Using a High Level Net Approach Integrated with Uncertainty Inference

Ke Wang  
School of Economics and Management,  
Tongji University,  
Shanghai, China  
Mr. wangkk@gmail.com

James N.K. Liu  
Department of Computing,  
The Hong Kong Polytechnic University,  
Kowloon, Hong Kong  
csnklju@comp.polyu.edu.hk

Wei-min Ma  
School of Economics and Management,  
Tongji University,  
Shanghai, China  
mawm@tongji.edu.cn

Abstract—The interest of this paper is focused on the detection of some potential contradictions in fuzzy ontology. A high level net approach integrated with uncertainty inference is proposed for this purpose. It makes use of a State Controlled Coloured Petri Net (SCCPN), which has been proposed for ontology representation and verification in our previous work. In this paper, the SCCPN model designed to handle the case of typical ontology with crisp logic is extended and modified to model the fuzzy ontology. Uncertainty inference is integrated in the net to deal with the imprecise or vague information. This work presents a formal definition of the extended SCCPN for modeling fuzzy ontologies and the knowledge inference with uncertainty as well as formulating the formal verification of some potential contradictions in fuzzy ontology.

Keywords—fuzzy ontology; ontology verification; Petri net; contradiction; uncertainty inference

I. INTRODUCTION

Since typical ontology based on crisp logic may be insufficient to handle imprecise or vague information that is commonly encountered in our real-life knowledge, fuzzy ontology has been proposed by integrating fuzzy logic into ontology (e.g. [1,2,3]). It has been shown that fuzzy logic allows for bridging the gap between human-understandable soft logic and machine-readable hard logic [4,5]. The integration of fuzzy logic makes an ontology more powerful to deal with the imprecise or vague information [6].

With considerable progress made, the problem of how to evaluate (or verify and validate) a fuzzy ontology emerges [7,8]. It is becoming even more important and critical for effective application in increasingly complex and sophisticated real-world domains.

In our previous work [9], a formal technique for ontology representation and inference was proposed, based on which an automatic technique for ontology verification can be developed so as to be able to detect and identify potential anomalies in an ontology. It makes use of a State Controlled Coloured Petri Net (SCCPN) [10], which is a high level net that combines the Coloured Petri Nets [11,12] and State Controlled Petri Nets [13] used for representing knowledge (rule) base.

In this paper, the SCCPN model designed to handle the case of typical ontology with crisp logic is being extended and modified to model the fuzzy ontology. A high level net approach integrated with uncertain inference is introduced for detecting potential anomalies in fuzzy ontology.

The remainder of this paper is organized as follows: we first give some preliminary definitions on fuzzy ontology in Section II. Then we illustrate how to model a fuzzy ontology by extended SCCPN and also present the formal definition of the extended SCCPN in Section III. After that, the knowledge inference with uncertainty in extended SCCPN is discussed in Section IV. Finally, Section V formulates the formal verification of some potential contradictions in fuzzy ontology.

II. PRELIMINARY DEFINITIONS ON FUZZY ONTOLOGY

Fuzzy ontology is an integration of fuzzy logic in typical ontology with crisp logic. It is underpinned by fuzzy sets and fuzzy relations, which provide a sound and rigorous method to represent knowledge with uncertainty [14,15].

In this work, we adopt a formal definition of fuzzy ontology as follows.

Definition 1 (Fuzzy ontology). A fuzzy ontology is a tuple $FO = (IN, AT, CL, FR)$, where

- $IN$ is a finite set of individuals (or instances, i.e., the basic objects in a domain);
- $AT$ is a finite set of attributes describing the individuals;
- $CL$ is a finite set of classes (or concepts);
- $FR$ is a finite set of fuzzy relations on $IN \times CL$, $AT \times CL$, or $CL \times CL$, i.e., $FR \equiv \{(x,y),\mu_{[	ext{rule}]}(x,y)\}$ where $(x,y) \in IN \times CL \lor AT \times CL \lor CL \times CL$ and $\mu_{[	ext{rule}]}(x,y) \in [0,1]$.

In the following discussion, we mainly focus on the taxonomic relations in a fuzzy ontology, for the purpose of detecting some potential anomalies which may be induced by this kind of relations.

In fuzzy ontology, the fuzzy subsumption relation is naturally extended from the crisp subsumption relation, a basic relation with binary logic in typical ontology, by...
allowing the truth value to range between 0 and 1. It is an anti-symmetric (partial order) relation between classes, and represents the strength of the subclass/superclass relationships. Formally, fuzzy subsumption is defined as follows.

**Definition 2 (Fuzzy subsumption)** [14]. With respect to an arbitrary \( \alpha \)-cut (\( 0 < \alpha \leq 1 \)) level, a class (concept) \( cl_i \in CL \) is the subclass (sub-concept) of another superclass (super-concept) \( cl_j \in CL \) if and only if \( \forall in_i \in \{ z \in IN | \mu_{ic}(z,cl_i) \geq \alpha \} \) , \( \mu_{ic}(in_i,cl_j) \geq \alpha \), where \( \mu_{ic}(in_i,cl_j) \) denotes the membership value of the individual (object) \( in_i \) belonging to the class (concept) \( cl_j \).

It is obvious to see that fuzzy subsumption relation generalizes the classical crisp subsumption relation, since crisp subsumption is only a special case of fuzzy subsumption, if the threshold value \( \alpha \) only takes value that \( \alpha = 1 \).

Similarly, the fuzzy exclusion relation can be defined by Definition 3.

**Definition 3 (Fuzzy exclusion)**. With respect to an arbitrary \( \beta \)-cut (\( 0 < \beta \leq 1 \)) level, two classes (concepts) \( cl_i \in CL \) and \( cl_j \in CL \) are exclusive of each other if and only if (i) \( \forall in_i \in \{ z \in IN | \mu_{ic}(z,cl_i) \geq \beta \} \) , \( \mu_{ic}(in_i,cl_j) \leq 1 - \beta \); and (ii) \( \forall in_i \in \{ z \in IN | \mu_{ic}(z,cl_i) \geq \beta \} \) , \( \mu_{ic}(in_i,cl_j) \leq 1 - \beta \); where \( \mu_{ic}(in_i,cl_j) \) denotes the membership value of the individual (object) \( in_i \) belonging to the class (concept) \( cl_j \).

Fuzzy exclusion is a symmetric relation between two classes. When the threshold value \( \beta \) only takes value that \( \beta = 1 \), the fuzzy exclusion relation becomes the crisp exclusion relation. Here \( \beta \) represents the strength of the fuzzy exclusion relation. It also can be explained as \( \beta = 1 - \chi \) where \( \chi \) represents the similarity measure of two classes.

Figure 1 shows an example of fuzzy ontology. The fuzzy subsumption relation and fuzzy exclusion relation are both depicted in the figure. The values labeled on the links represent the strength of the relationship.

**III. Modeling Fuzzy Ontology by Extended SCCPN**

In our previous work [9], State Controlled Coloured Petri Nets were introduced for the purpose of ontology representation and inference. The SCCPN was initially proposed for the formal description and verification of hybrid rule/frame based expert systems [10]. It is a combination of Coloured Petri Nets proposed by Jensen [16] and State Controlled Petri Nets proposed by Liu and Dillon [17,18].

In this paper, the SCCPN model designed to handle the case of typical ontology with crisp logic is being extended and modified to model the fuzzy ontology. In such a net, each output arc that connects the transition and the output place will carry a parameter, representing the strength of the fuzzy relation.

Figure 2 shows the mapping of the fuzzy ontology (illustrated in Fig. 1) in the extended SCCPN. The structure of this net consists of a set of places modeling the classes in the fuzzy ontology, and a set of transitions linked to the places by a set of directed arcs modeling the fuzzy relations between classes.

The fuzzy subsumption relation is represented by a transition linking places from subclass to its superclass. For the case that a class is the subclass of more than one class, these subsumption relations are combined and modeled by one transition whose input place is the subclass and output places are its superclasses (e.g. the transition among opera singer, singer and actor). The notation “( \( Y, \alpha \))” on the output arc denotes that the execution of the transition will deduce a true state of its output place and the truth-value is
influenced by the parameter $\alpha$ which indicates the strength of this fuzzy relation.

Since the fuzzy exclusion relation is a symmetric relation between two classes, it is modeled by two transitions in opposite directions (see the transitions between adolescent and elder). Similarly, the strength of the fuzzy exclusion relation $\beta$ is labeled on the output arcs. The notation “($(N, \beta)$)” on the output arc denotes that the execution of the transition will deduce a denial of its output place and the truth-value of this denial is influenced by the parameter $\beta$.

Note that control tokens are introduced to control the firing or execution of transitions. A transition becomes active when at least one of its input places has a control token and is enabled if a transition is active and the transition condition is met (i.e., all its input places have the correct state tokens). Self-loop arcs associated with each input place of a transition are introduced to maintain the state of a class while inferring, i.e., the execution of a transition will not affect the state of its input places. For simplicity, the self-loop arcs are not depicted in Fig. 2.

The formal definition of the extended SCCPN is given as follows.

**Definition 4 (Extended SCCPN).** The extended SCCPN that models a fuzzy ontology is a 10-tuple $Net' = (\Sigma, P, T, A, N, C, G, E, I, \Pi)$, where

$\Pi$ is a finite set of parameters within the interval $[0, 1]$, representing the strength of the fuzzy relation;

$\Sigma$ is a finite set of non-empty types, called colour set;

$P$ is a finite set of places;

$T$ is a finite set of transitions;

$A$ is a finite set of arcs;

$P \cap T = P \cap A = T \cap A = \emptyset$;

$N : A \rightarrow P \times T \cup T \times P$ is a node function that maps each arc into a pair where the first element is the source node and the second is the destination node. The two nodes must be of different kinds (i.e. one of the nodes must be a place while the other must be a transition).

$C : P \rightarrow \Sigma$ is a colour function that maps each place into a colour set;

$G : T \rightarrow \text{boolean value}$ is a guard function that is defined from $T$ into expressions such that: $\forall t \in T : Type(G(t)) = \text{BooleanValue} \wedge Type(Var(G(t))) \subseteq \Sigma$;

$E : A \rightarrow \text{expression}$ is an arc expression function that is defined from $A$ into expressions such that: $\forall a \in A : Type(E(a)) = C(p(a))_{\text{ms}} \wedge Type(Var(E(a))) \subseteq \Sigma$,

where $p(a)$ is the place of $N(a)$ and $MS$ stands for multi-set or bags;

$I : P \rightarrow \text{expression}$ is an initialization function that is defined from $P$ into closed expressions such that:

$\forall p \in P : Type(I(p)) = C(p)_{\text{ms}}$.

**Definition 5 (Node function).** The node functions

$N : A \rightarrow P \times T \cup T \times P$ can be further classified into the following 4 different types:

$B : T \rightarrow P$ is an input control function, a mapping from transitions to the bags of places;

$O : T \rightarrow P$ is an output control function, a mapping from transitions to the bags of places;

$B : T \rightarrow P$ is an input state function, a mapping from transitions to the bags of places;

$O : T \rightarrow P$ is an output state function, a mapping from transitions to the bags of places.

And for each transition $t_i \in T$ in the extended SCCPN,

$B_i(t_i) \cap O_i(t_i) \neq \emptyset, B_i(t_i) \cap O_i(t_i) = \emptyset$, such that:

$p_j \in B_i(t_i) \Rightarrow p_j \in O_i(t_i), p_j \in B_i(t_i) \Rightarrow p_j \notin O_i(t_i)$.

**IV. KNOWLEDGE INFERENCE WITH UNCERTAINTY IN EXTENDED SCCPN**

In this section, we first illustrate the inference in the extended SCCPN by examples, and then provide some formal definitions that are to be used in the detection of potential anomalies.

To denote the assertion (true state) or denial (false state) of the places, two types of coloured state token, respectively indicated by “$y$” and “$n$”, are used to represent the dual states of the place with uncertainty measures. The presence of a state token $y(\mu)$ makes the state of the place become true, and $\mu(\mu > 0)$ denotes the degree of the assertion or can be seen as an uncertainty quantity measuring the possibility of the state to be true. A state token $n(\sigma)$ represents the denial of the place, and similarly $\sigma(\sigma > 0)$ denotes the degree of the denial.

As mentioned above, a transition becomes active when at least one of its input places has a control token. When a transition is active and each input place has a state token $y(\mu)$, the transition is enabled and is ready for firing. The effect of firing a transition is to remove all tokens from an input place and deposit appropriate tokens in output places in accordance with the input and output functions for that transition. The self-loop arc associated with the input place will maintain its former state by returning the state token to the place after the firing.

Specially, Fig. 3 and Fig. 4 illustrate the inference of a fuzzy subsumption relation and a fuzzy exclusion relation, respectively.

In Fig. 3(a), a state token $y(0.8)$ and a control token (denoted by a black dot) are both present in the place of opera singer; thus the transition is enabled.

For the inference of fuzzy subsumption relation, a MIN operator is used in the output function to deduce the degree of the assertion of the output place. Provided that the state
Inference with the fuzzy subsumption relation

The token in an input place is \( y(\mu_i) \) and the relation between the associated output place and this input place is labeled by \( "(Y, \alpha)" \) (i.e. the strength of this fuzzy subsumption relation is \( \alpha \)), then the firing of the transition will deduce a true state of the output place and the truth-value (i.e. the degree of the assertion of the output place) is \( \mu_2 = \text{MIN}(\mu_i, \alpha) \). The new state token created in the output place is denoted by \( y(\mu_i) \).

The inference of fuzzy subsumption can be simply described as:

\[
y(\mu_i) \xrightarrow{(Y, \alpha)} y(\mu_2) \quad \text{and} \quad \mu_2 = \text{MIN}(\mu_i, \alpha).
n\]

Fig. 3(b) shows the result of firing the transition which is enabled in Fig. 3(a), and now no transition is enabled. The inference result implies that an individual belonging to the class opera singer with membership value of 0.8 may be also a singer and an actor, with the possibility of 0.8 and 0.7, respectively.

Figure 4 illustrates the inference of a fuzzy exclusion relation. In Fig. 4(a), a state token \( y(0.8) \) and a control token are both present in the place of adolescent, thus the transition \( t_1 \) is enabled.

For the inference of fuzzy exclusion relation, a MIN operator is also used in the output function to deduce the degree of the denial of the output place. Provided that the state token in an input place is \( y(\mu) \) and the relation between the associated output place and this input place is labeled by \( "(N, \beta)" \) (i.e. the strength of this fuzzy exclusion relation is \( \beta \)), then the firing of the transition will deduce a denial of the output place and the truth-value of the denial (i.e. the degree of the denial of the output place) is \( \sigma = \text{MIN}(\mu, \beta) \). The new state token created in the output place is denoted by \( n(\sigma) \).

The inference of fuzzy exclusion can be simply described as:

\[
y(\mu) \xrightarrow{(N, \beta)} n(\sigma) \quad \text{and} \quad \sigma = \text{MIN}(\mu, \beta).
n\]

Fig. 4(b) shows the result of firing the transition \( t_1 \) in Fig. 4(a), and now no transition is enabled. The inference result implies that an individual belonging to the class adolescent with membership value of 0.8 can not be an elder, with the possibility of 0.8.

The states of the extended SCCPN can be formally represented by markings. The formal analysis of knowledge inference in extended SCCPN is based on the reachable markings generated by transition firings in the net. In the extended SCCPN, a marking \( M \) is composed of \( M_s \) and \( M_c \), which represents the marking for the state tokens, and \( M_c \), which represents the marking for the control tokens. Formally, they are defined as follows.

**Definition 6 (Marking).** A marking \( M \) of the extended SCCPN is a function that

\[
\text{sc}(s, M) = \text{sp}(s, M)p, \quad \text{where} \quad s(M) \text{ depicts the distribution of state tokens in the places.}
\]

\[
c(M) \text{ represents the distribution of control tokens in the places.}
\]

Note that the multi-set (or bag) is employed here to allow multiple appearances of the same state tokens.

![Figure 3. Inference with the fuzzy subsumption relation](image)

![Figure 4. Inference with the fuzzy exclusion relation](image)
If a marking $M'$ is obtained from $M$ by the execution of transition $t$, it is said that $M'$ is directly reachable from $M$, denoted as $M[t] > M'$.

**Definition 7 (Reachable).** A marking $M^n$ is said to be reachable from a marking $M^0$ if and only if (iff) there exists a finite sequence of firings that transform $M^0$ into $M^n$, i.e. a sequence having $M^n$ as an initial marking and $M^0$ as an end marking such that $M^0[t_1] > M^1[t_2] > M^2[\cdots] M^{n-1}[t_n] > M^n$, where $n$ is a natural number denoting the length of the sequence. Denoting $\phi = (t_1, t_2, \cdots, t_n)$, it is said that $M^n$ is reachable from $M^0$ by $\phi$, and being denoted as $M^n = \delta(M^0, \phi)$.

The inference in Fig. 4 is represented by markings as shown in Fig. 5. For simplicity, the markings are presented in the form of a matrix in which the first column denotes the marking of state tokens (i.e. $M_i$) and the second column denotes the marking of control tokens (i.e. $M_C$). In Fig. 5, $M^a$ is directly reachable from $M^a$ by $t_1$, denoted as $M^a[t_1] > M^b$.

V. DETECTING POTENTIAL CONTRADICTIONS

Ontology has been widely used in many areas, such as knowledge management, natural language processing, information retrieval, and especially the semantic web which is increasingly popular. However, ontologies can hardly be absolutely free from errors and anomalies, no matter they are built by ontologists or automatic extraction techniques. For instance, some possible errors have been presented in [19] and [20]. With the increasingly complex and sophisticated real-world domains, it is becoming even more important and critical for its effective application that ontology be formally verified.

For the case of fuzzy ontology, the introduction of fuzzy relationships and uncertain inference will reduce the possible errors and anomalies, since the state domain space has been expanded to accept a certain degree of uncertainty and plausible states, which would have been rejected in a closed and binary world of discourse [17]. As follows, one type of anomaly that contradiction is presented in this paper and its formal verification is also given.

The anomaly of contradiction in the fuzzy ontology is analogous to that in the typical ontology based on crisp logic. Both of them refer to the situation that conflicting conclusions are deducible from the ontology, which being modeled in the net is that both assertion (true state) and denial (false state) tokens are co-existing in the corresponding place. The difference lies in that a certain degree of uncertainty and plausible states are accepted in the fuzzy ontology.

To determine the consistency of the state of a place with different types of state tokens, a mutual exclusivity bound, $(\varepsilon^+, \varepsilon^-)$ (both $\varepsilon^+$ and $\varepsilon^-$ fall in $[0,1]$), is attached to each place. If the truth-vale of the assertion and denial of a place both reach or exceed this bound, we say contradiction occurs. In other words, the presence of the two state tokens that $y(\mu \geq \varepsilon^+)$ and $n(\sigma \geq \varepsilon^-)$ in a same place indicates a conflicting state.

An example of contradiction is shown in Figure 6. It shows the relationships of three classes (young signer, adolescent and elder). Note that an additional fuzzy subsumption relation (from the class young signer to elder) is added into the fuzzy ontology, which does not exist in Fig. 1. It is to be illustrated that this additional fuzzy subsumption relation introduces contradiction, with respect to a certain exclusivity bound (say $(\varepsilon^+, \varepsilon^-) = (0.5,0.5)$).

The fuzzy ontology in Fig. 6 is modeled by the extended SCCPN as shown in Fig. 7(a) and it has been initialized by assigning a state token $y(0.8)$ and a control token in the place of young singer. The presence of these two tokens enables the transition $t_1$.

By executing $t_1$ in Fig. 7(a), a new state of the net can be obtained as shown in Fig. 7(b). Two new state tokens $y(0.8)$ and $y(0.6)$ are respectively created in the output places of adolescent and elder. In addition, each output place is also assigned a control token. Meanwhile, the control token in the input place is destroyed, and the state token is returned to the input place via the self-loop arc.

After the firing of $t_1$, both transitions $t_1$ and $t_2$ are enabled consequently, as shown in Fig. 7(b). If execute the transition $t_1$ in Fig. 7(b), similarly, a new result of inference can be obtained as shown in Fig. 7(c).

In Fig. 7(c), both the assertion (true state) and denial
(false state) of the same place occurs. With respect to the exclusivity bound \((0.5,0.5)\), the presence of the two tokens \(y(0.6)\) and \(n(0.8)\) in the place of elder indicates a contradictory state.

The inference of firing the sequence \(t_3\) and \(t_1\) is represented by markings as shown in Fig. 8. \(M^0\), \(M^1\) and \(M^2\) respectively denote the states of the net shown in Fig. 7(a), 7(b) and 7(c). By checking these markings, it is also easy to see that contradictory state appears in the marking \(M^2\), with respect to the exclusivity bound \((0.5,0.5)\).

As shown by the above example, the detection of potential contradictions can be done based on the formal description of the inference, and consequently, formal technique for the detection can be proposed. It is done exhaustively by minimally initiating the sequence of transitions and closely examining the reachable markings.

By examining the alternative paths and markings generated from the initial marking, the anomaly of contradiction in fuzzy ontology can be detected. The verification is formalized as follows.

**Proposition 1 (Verification of contradiction).** For a given initial marking \(M^0\), that minimally enables a nontrivial transition sequence \(\phi\), iff the fuzzy ontology has contradiction with respect to a mutual exclusivity bound \((\varepsilon^+,\varepsilon^-)\), then \(\exists \phi , \exists p (p \in P\), indicates a particular place), such that these sequences have the following properties:

1. \(\phi \neq \phi\);
2. \(M^0 = \delta(M^0,\phi)\), \(M^* = \delta(M^0,\phi)\);
3. \(M^0_w = \emptyset\);
4. \(\exists y(\mu_p) \in M^w, \exists n(\sigma_p) \in M^w\);
5. \(\mu_p \geq \varepsilon^{+}, \sigma_p \geq \varepsilon^{-}\).

In the above proposition, Property (1) denotes that \(\phi\) and \(\phi\) are two different sequences. Property (2) denotes that the marking \(M^*\) is reachable from the initial marking \(M^0\) by the sequence \(\phi\), and \(M^*\) is reachable from \(M^0\) by the sequence \(\phi\). Property (3) denotes that no state token is deposited in the place \(p\) in the initial marking \(M^0\). Property (4) denotes that there exists a state token \(y(\mu_p)\) in the place \(p\) in the marking \(M^w\), and a state token \(n(\sigma_p)\) in the place \(p\) in the marking \(M^w\). Property (5) denotes that the truth-value of the assertion and denial of the place \(p\) both reach or exceed the predefined exclusivity bound.

In other words, together with properties (3), (4) and (5), it indicates that two state tokens \(y(\mu_p \geq \varepsilon^{+})\) and \(n(\sigma_p \geq \varepsilon^{-})\) which denote conflicting states are created in the place \(p\) in the marking \(M^w\), and a state token \(n(\sigma_p)\) in the place \(p\) in the marking \(M^w\). Properties (1) and (2) imply that these two markings \(M^w\) and \(M^*\) are inferred from the initial marking via different paths.

**Figure 7.** The inference that deduces contradiction

**Figure 8.** The inference in Fig. 7 represented by markings
VI. CONCLUSION

A high level net approach integrated with uncertainty inference is proposed for detecting some potential contradictions in fuzzy ontology in this paper. This technique makes use of a State Controlled Coloured Petri Net. The SCCPN for ontology representation and verification in the case of typical ontology with crisp logic is extended and modified for the case of fuzzy ontology which involves imprecise or vague information. The state domain space has been expanded to accept a certain degree of uncertainty and plausible states, which would have been rejected in a closed and binary world of discourse.

The anomaly of contradiction in the fuzzy ontology is analogous to that in the crisp ontology. The difference lies in that a certain degree of uncertainty and plausible states are accepted in the fuzzy ontology. To determine the consistency of the state of a place with different types of state tokens, a mutual exclusivity bound is attached to each place. As a result, the anomaly of contradiction can be detected by examining the alternative paths and markings generated from an initial marking. If the truth-value of the assertion and denial of a place both reach or exceed the predefined bound, we say contradiction occurs. The formal verification of some potential contradictions in the fuzzy ontology can thus be formulated.

Note that the interest of this paper is focused on the detection of some potential contradictions in fuzzy ontology which may be induced by taxonomic relations, and thus only fuzzy subsumption and fuzzy exclusion relations are considered in this work. This consideration much simplifies the structure of the net used to model a fuzzy ontology, as shown by the examples presented in this paper. However, the proposed extended SCCPN is also appropriate for modeling a more sophisticated fuzzy ontology, which may contain some other kinds of relations and information. By distinguishing places and transitions into different types, the extended SCCPN will provide a much richer modeling capability for the fuzzy ontology representation and verification, as shown in our previous work [9] on the SCCPN which is used to model typical ontologies with crisp logic.

As mentioned above, only contradiction is discussed in this paper, but it is to be anticipated that other types of anomalies in fuzzy ontology can also be detected and identified by this approach. Our future work will thus focus on the further extension of the proposed approach as well as the detection of some other potential anomalies, such as redundancy and circularity.

ACKNOWLEDGMENT

The authors are grateful for the partial support of GRF grant 5237/08E, CRG grant G-U756 and eLDSS grant EL083F0030 of The Hong Kong Polytechnic University.

REFERENCES

