An Improved Semantic Search Model Based on Hybrid Fuzzy Description Logic

Ruixuan Li, Kunmei Wen, Zhengding Lu, Xiaolin Sun, Zhigang Wang
School of Computer Science and Technology,
Huazhong University of Science & Technology,
Wuhan 430074, P.R.China
rxli@hust.edu.cn, kunmei.wen@gmail.com, zdlu@hust.edu.cn
arthursun2005@163.com, wzgang98@163.com

Abstract

We propose an improved semantic search model through integrating inference and information retrieval (IR) based on hybrid fuzzy description logic (DL) and implement it in security domain. A type-2 fuzzy DL is described and employed in the semantic search model. The proposed model is a hybrid one which combines type-1 fuzzy DL and type-2 fuzzy DL. It can not only search the resources according to the trust degree rules based on type-2 fuzzy DL, but also locate the exact resource using IR based on type-1 fuzzy DL. The complete model provides trust degree management to extend the search capabilities. In addition, we build a security ontology based on role-based access control (RBAC) policy. A semantic search system, Onto-SSSE, is implemented based on the basic model. The system can perform queries based on ontology reasoning. The experimental results show that the new system performs better than exiting schemes.

1. Introduction

Semantic Web [1] proposed by Tim Berners-Lee is the next generation of web portals. The aim is to annotate all the resources on the web and establish all kinds of semantic relationships between them understandable for the machine. As the most important application of Semantic Web, semantic search is being got more and more attention. The concept of semantic search is put forward in [2]. Semantic search integrates the technologies of Semantic Web and search engine to improve the search results gained by current search engines and evolves to next generation of search engines built on Semantic Web.

Semantic search finds out the semantic information by means of inferring internal knowledge in Knowledge Base (KB). Description logic (DL) [3, 4] is well known as the base of ontology language such as Web Ontology Language (OWL) [5]. Almost modern DL system are implemented based on tableaux algorithm [6], many optimized technologies [7] are explored. However the performance advantage of reasoning systems can not come up to that of traditional database systems. [8] defines the search object of semantic search. One is searching the Internet. The other is searching the Semantic Web portals. Semantic Web portals are composed of domain ontology and KB. An enhanced model for searching in semantic portals is proposed in [9]. The model combines the formal DL and fuzzy DL [10] to implement the integration of information retrieval and structure query.

Ranking the search results [11, 12] is the key technology of semantic search. Since it is expected that the number of relationships between entities in a KB will be much larger than the number of entities themselves, the likelihood that Semantic Association searches would result in an overwhelming number of results for users is increased, therefore elevating the need for appropriate ranking schemes. In [13], a method is proposed to rank the results according to the important values of web resources based on the technology of modern information retrieval (IR) [14]. The ranking method in [15] focuses on the semantic metadata to find out the complex relationships and predict the user’s requirement to distinguish semantic associations.

With these aspects in mind, we propose a semantic search model that enables the user to find his resources based on trust management. The model is improved and applied to security domain. The proposed model

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combines text IR with semantic inference. Based on the model, a semantic search system, Onto-SSSE, is implemented and evaluated.

The rest of the paper is organized as follows. We present the semantic model in section 2, including basic model, extended model and complete model. The basic model involves the expression of the query, the integration of search and inference to get the semantic information and the ranking method in semantic search. A type-2 fuzzy DL is proposed as the base of the complete semantic search model. After that, in the third section, experiment and evaluation are carried out. Section 4 describes the related work, followed by conclusions and future work in section 5.

2. Semantic Search Model

There are many works on IR models based on DL such as $\mathcal{ALC}$ [16]. Many formal DL conjunctive queries can be rolled up to a single concept expression and reduced to the DL instance retrieval problem. We firstly propose the basic model through integrating formal DL with IR in section 2.1. Then in section 2.2, type-1 $\mathcal{FALC}$ is presented. We improved the basic model through extend the IR model to the one based on type-1 $\mathcal{FALC}$. In section 2.3 type-2 $\mathcal{FALC}$ is proposed and used to replace formal DL to implement trust degree management. Finally we propose the complete model through combining type-1 and type-2 fuzzy $\mathcal{ALC}$ in section 2.4.

2.1. Basic Model

The model is inspired by the idea that integrates search and inference. So it can not only search the resources and the relationships between them based on formal DL reasoning, but also locate the exact resource using traditional IR.

Whether a document d is relevant to a query Q is modeled as a triple [D, Q, R(d_i, Q)] where D is the set of documents d_i, Q is a query, R(d_i, Q) is the similarity between d_i and Q, here $d_i \in D$. In DL-based IR models, documents and queries are modeled as DL individuals and concepts respectively. The search problem is then reduced to the DL instance retrieval problem which can be answered by a DL reasoning engine.
We assume that the readers are familiar with the basics of DL. The syntax and semantics of $\mathcal{ALC}$ constructors have been represented in Table 1.

2.1.1. Query Form. A query is defined as the form Qi = Qi1 ∩ Qi2 ∩ Qi3 the semantic search model. Here Qi1 means concept, Qi2 is any formal query about the relationships between resources and Qi3 is a keyword query. Qi1 and Qi2 are implemented based formal DL reasoning in the basic model while Qi3 is carried out through traditional text IR technology. So there are four typical queries as follows:

Q_{i1}: Concept Query, form as Q_{i1} = "C" where C means a concept.

Q_{i2}: Relationship Query, form as Q_{i2} = "C_1"& "C_2" where C_1 and C_2 are concepts.

Q_{i3}: Keyword Query, form as Q_{i3} = "D" where D means a keyword which appears in the text. In fact, Q_{i3} belongs to traditional query.

Qi1∩Qi3: Conjunctive Query, form as Qi1∩Qi3 = ("C") ∩ "D" where C means a concept and D means a keyword. To implement Qi1∩Qi3, we need combine formal DL reasoning and traditional IR.

Table 1. The syntax and semantics of $\mathcal{ALC}$ constructors

Constructor	Syntax	Semantics
Top (Universe)	$\top$	Δ^I
Bottom (Nothing)	$\bot$	ϕ
Atomic Concept	A	$A^I \subseteq \Delta^I$
Atomic Role	R	$R^I \subseteq \Delta^I \times \Delta^I$
Conjunction	$C \cap D$	$C^I \cap D^I$
Disjunction	$C \cup D$	$C^I \cup D^I$
Negation	$\neg C$	$\Delta^I \setminus C^I$
Value restriction	$\forall R.C$	$\{ a \in \Delta^I \mid \forall b \in \Delta^I, (a,b) \in R^I \to b \in C^I \}$
Full existential quantification	$\exists R.C$	$\{ a \in \Delta^I \mid \exists b \in \Delta^I, (a,b) \in R^I \wedge b \in C^I \}$

2.1.2. Reasoning based on DL. We implement three kinds of reasoning based on DL in the semantic search model. The architecture of the Knowledge Base based on Description Logic is showed in Figure 1.

The first is *Concept Reasoning*. Given $Q_i = Q_{i1}$ where Q_{i1} means concept, we can get all the sub concepts.

The second is *Relationship Reasoning*. Given $Q_i = Q_{i2}$ where Q_{i2} includes two concepts, we can get the relationship between them or null if there is not any relationship.

The third is *Conjunctive Query Reasoning*. In fact it integrates inference with search by providing both formal query and keyword query. Given $Q_i = Q_{i1} \cap Q_{i3}$ where Q_{i1} means concept and Q_{i3} is a keyword query,

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the semantic search model firstly performance Q_{i1} to retrieve all the instances the concept has. Then the model carries out Q_{i3} to locate the exact resource.

So the basic model can not only locate the exact place of the resource using the traditional IR but also improve the precision through reducing the scope of retrieval and the recall through reasoning to discovery implicit information.

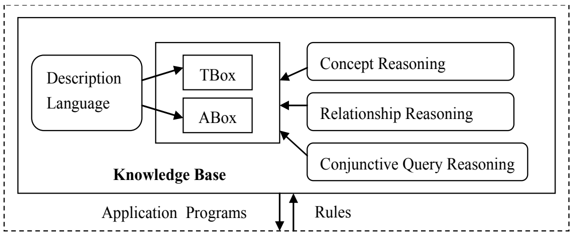

Figure 1. Architecture of the Knowledge Base based on Description Logic

2.1.3. Result Ranking. Ranking the search results is very important for the implementation of semantic search. It is possible that the number of relationships between entities in a KB will be much larger than the number of entities themselves. We provide a ranking scheme based on the ranking value. The Ranking value for the query Qi is defined as the form $R_i = R_{i1} + R_{i2} + R_{i3}$ for the query $Q_i = Q_{i1} \cap Q_{i2} \cap Q_{i3}$. Here R_{i1} is the ranking value for Q_{i1}, at the same time R_{i2} is the value for Q_{i2} and R_{i3} is that for Q_{i3}. The reasoning result is used to compute the values of R_{i1} and R_{i2}.

For Q_{i1} all the instances of the concept are returned. If d is the instance of the query Q_{i1} then the corresponding R_{i1}=1, otherwise the value equals to 0. It is typical Boolean Model.

For R_{i2}, it is possible to return many relationships between two concepts. So the value R_{i2} is determined by the important value of the relationship. For every relationship in domain ontology we define an important value I_i which is between o and 1. So it is reasonable to get the conclusion $R_{i2} = I_i$.

R_{i3} is corresponding to Q_{i3}. Searching is used to locate the resource through keyword query. Therefore we use traditional tf-idf method to compute the value of R_{i3}. There are only four form queries including Q_{i1}, Q_{i2}, Q_{i3} and $Q_{i1} \cap Q_{i3}$. For the query $Q_{i1} \cap Q_{i3}$, the value $R_i = \min\{ R_{i1}, R_{i3}\}$. We can get the conclusion that the value of R must be in the range between 0 and 1.

2.2. Extended Model

2.2.1. Type-1 $\mathcal{FALC}$. Classic DL such as $\mathcal{ALC}$ cannot deal with the imprecise description just like: a concept can be defined with an axiom only to a certain degree. To solve this problem in DLs, Straccia presented $\mathcal{FALC}$ [10] which is an extension of $\mathcal{ALC}$ with fuzzy features, to support fuzzy concept representation. Because Straccia used a point number to describe the fuzzy concepts and individuals in $\mathcal{FALC}$, we call the $\mathcal{FALC}$ type-1 $\mathcal{FALC}$. In order to make the paper self-contained, we summarize the Fuzzy-ALC briefly.

As same as classic $\mathcal{ALC}$, we define A, C and R as the set of atomic concepts, complex concepts, and roles. It is easy to prove that $C \cap D$, $C \cup D$, $\neg C$, $\forall R.C$ and $\exists R.C$ are also fuzzy concept. The fuzzy interpretation in $\mathcal{FALC}$ is a pair $I = (\Delta^I, \cdot^I)$, and $\cdot^I$ is an interpretation function mapping fuzzy concept and role into a membership degree function $C^I = \Delta^I \rightarrow [0,1]$ and $R^I = \Delta^I \times \Delta^I \rightarrow [0,1]$. The interpretation $\cdot^I$ of $\mathcal{FALC}$ must satisfy the equations that we present as follows: for all $d \in \Delta^I$

$$\top^I(d) = 1$$

$$\bot^I(d) = 0$$

$$(C \cap D)^I(d) = \min\{C^I(d), D^I(d)\}$$

$$(C \cup D)^I(d) = \max\{C^I(d), D^I(d)\}$$

$$\neg C^I(d) = 1 - C^I(d)$$

$$(\forall R.C)^I(d) = \inf_{d' \in \Delta^I} \max\{1 - R^I(d, d'), C^I(d)\}$$

$$(\exists R.C)^I(d) = \sup_{d' \in \Delta^I} \min\{R^I(d, d'), C^I(d)\}$$

The most important part of $\mathcal{FALC}$ is to use the membership degree function to describe the individuals that belong to fuzzy concept. However, using the point number to denote the value of membership degree has many restrictions. In fact, it is very difficult, even impossible to deal with the real world problems with the "point value" fuzzy sets, which are called type-1 fuzzy sets.

2.2.2. Extended Model Using Type-1 $\mathcal{FALC}$. The extended model is improved based on the basic model mentioned above. In extended model we use type-1 $\mathcal{FALC}$ to replace IR model. The model is one combining classic $\mathcal{ALC}$ with type-1 $\mathcal{FALC}$ where $\mathcal{ALC}$ modeling formal query and type-1 $\mathcal{FALC}$ for traditional IR.

Using type-1 $\mathcal{FALC}$ to replace IR model, change is happened in the extended model for the keyword query Qi3. In IR model we get ranking value R_{i3} for the query Q_{i3}. So we can consider that documents that are IR-relevant with a relevant value R_{i3} as the individuals of the concept with a fuzzy degree, and the fuzzy degree is equal to the R_{i3}. Here traditional IR query

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Qi3 is modeled as a fuzzy concept in type-1 $\mathcal{FALC}$. It is the same as the basic model that the value $R_i = \min\{R_{i1}, R_{i3}\}$.

2.3. Type-2 Fuzzy $\mathcal{ALC}$

To handle the problem in real world better, Zadeh first presented type-2 fuzzy sets ten years after he presented type-1 fuzzy sets in 1965. We argue about the features of the type-2 fuzzy sets at first in this section. Then we will focus on type-2 fuzzy $\mathcal{ALC}$ and its method to represent and reason knowledge.

2.3.1. Type-2 Fuzzy Sets. Different from the type-1 fuzzy sets, type-2 fuzzy sets use an interval to show the membership. They have grades of membership that are themselves fuzzy. Each grade of the membership is a number in interval [0,1]. We denote the membership in type-2 fuzzy sets with $\overline{\mu_A}$ instead of μ_A in type-1, which is defined as follows:

$$\overline{\mu_A}(x) = [\mu_A^L(x), \mu_A^U(x)] \quad \textbf{(1)}$$

In (1) we present: $\mu_A^L(x), \mu_A^U(x) : U \to [0,1]$, and $\forall x \in U, \mu_A^L(x) \le \mu_A^U(x)$. We call $\mu_A^L(x)$ and $\mu_A^U(x)$ the primary membership and secondary membership, and x is an instance in the fuzzy sets U.

It is obvious that type-2 fuzzy sets can be reduced to type-1 fuzzy sets when the primary membership equals the secondary one. So a type-1 fuzzy set is embedded in a type-2 fuzzy set. In addition, a type-2 fuzzy set is three-dimensional, and its new third dimension can provide new design degrees of freedom for handling uncertainties. The difference between type-1and 2 fuzzy sets can be displayed in Figure 2.

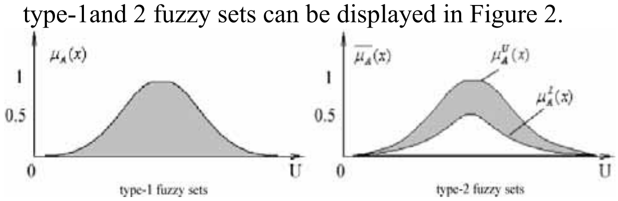

Figure 2. Difference between type-1 and type-2 fuzzy sets.

2.3.2. The syntax and semantics of type-2 fuzzy $\mathcal{ALC}$. Different from $\mathcal{FALC}$ the type-2 fuzzy $\mathcal{ALC}$, Δ^I is not a set of numbers in scope [0,1] but a set of pairs, which have the form like (a, b). And it must satisfy $0 \le a \le b \le 1$.

Based on type-2 fuzzy sets, we propose a new type fuzzy DL named type-2 fuzzy $\mathcal{ALC}$. The syntax and semantics of type-2 fuzzy ALC constructors are shown in Table 2.

Table 2. The syntax and semantics of type-2 fuzzy $\mathcal{ALC}$ constructors

Constructor	Syntax	Semantics
Top (Universe)	$\top$	Δ^I
Bottom (Nothing)	$\perp$	ϕ
Atomic Concept	$A_{[a,b]}$	$A^I_{[a,b]} \subseteq \Delta^I$
Atomic Role	$R_{[a,b]}$	$R^I_{[a,b]} \subseteq \Delta^I \times \Delta^I$
Conjunction	$C_{[a,b]} \cap D_{[c,d]}$	$(C \cap D)^I_{[\min(a,c),\min(b,d)]}$
Disjunction	$C_{[a,b]} \cup D_{[c,d]}$	$(C \cup D)^I_{[\max(a,c),\max(b,d)]}$
Negation	$\neg C_{[a,b]}$	$C^I_{[1-b,1-a]}$
Value restriction	$\forall R_{[a,b]}.C_{[c,d]}$	$\forall y.\max(R_{[1-b,1-a]}(x,y), C_{[c,d]}(y))$
Full existential quantification	$\exists R_{[a,b]}.C_{[c,d]}$	$\exists y.\min(R_{[a,b]}(x,y), C_{[c,d]}(y))$

2.4. Complete Model

The complete model is a hybrid model which combines type-1 $\mathcal{FALC}$ and type-2 fuzzy $\mathcal{ALC}$. The complete model use type-2 fuzzy $\mathcal{ALC}$ to replace the formal DL in the extended model. In real world, there are the imprecise terminological axiom (TBox) and fuzzy individual membership (ABox). It is necessary to maintain trust degree for both of TBox and ABox. We apply type-2 fuzzy $\mathcal{ALC}$ to deal with the description in ontology for trust degree management (OntoTD) with OWL. So the complete model combines two kinds of fuzzy DLs. We set trust degree for the concepts and individuals. Trust management is fundamental for information security in networks. We design a simple ontology named OntoTD for trust management shown in Figure 3.

Subject cannot always trust another one arbitrarily in real world, although it does in classic DLs. We use the type-2 fuzzy ALC to describe the imprecise information like the degree of trust in OntoTD. Figure 4 denotes the fuzzy change in TD_Rlue in extended OntoTD. As we mentioned, adding two properties can describe the fuzzy atomic concept in ALC. From that we can describe the imprecise knowledge in OntoTD.

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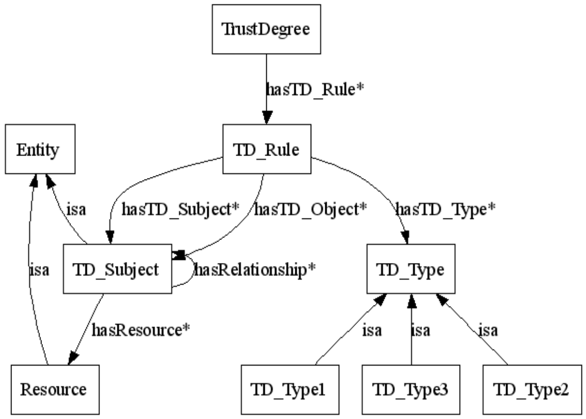

Figure 3. Architecture of OntoTD

TD_Rule		
hasTD_Type	Instance*	TD_Type
hasTD_Subject	Instance*	TD_Subject
hasTD_Object	Instance*	TD_Subject
hasUpperBound	Float*	
hasLowerBound	Float*	

Figure 4. Fuzzy class in extended OntoTD

3. Implementation and Evaluation

3.1. Architecture of Semantic Search Model

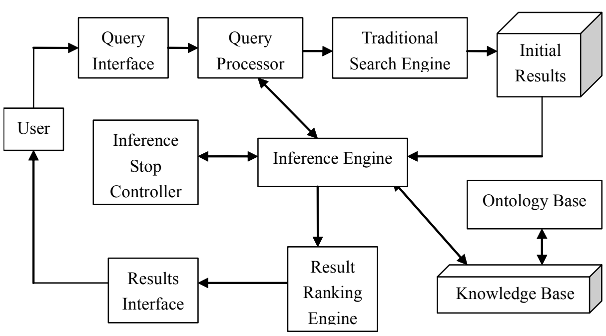

Figure 5. Architecture of the proposed semantic search conceptual model

We propose the architecture of the semantic search conceptual model. The architecture of the model is shown in Figure 5.

3.2. RBAC Security Ontology and Description of Instances

To implement semantic search in security domain, we build RBAC security ontology shown in Figure 6. Nine basic classes are created. They are *Policy, PolicyRule, Priviledge, Entity, Resource, Agent, Subject, Role* and *Action*. The arrow between two classes indicates the relationships between them.

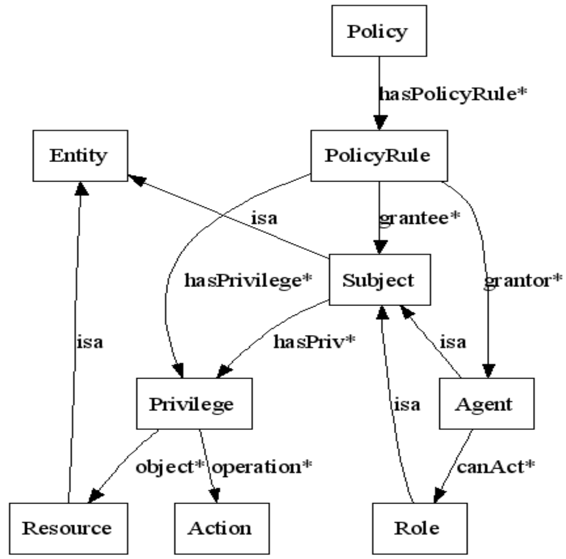

Figure 6. RBAC security ontology

We use OWL DL as our ontology language. As one of W3C's standards, OWL DL is widely used in application. To illustrate semantic search more clearly, we give role instances hierarchy graph as demonstrated in Figure 7.

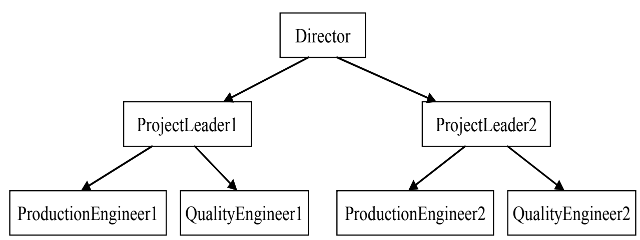

Figure 7. Role instances hierarchy graph

3.3. Results and Evaluation

We implement Ontology Security Semantic Search Engine (Onto-SSSE) in Java based on the basic semantic search model. We used the Lucene search engine as the traditional search engine based on keyword query and Jena as the reasoning tool based on RBAC security ontology. We have carried out experiments on Onto-SSSE. The Table 3 gives the search results for some typical queries.

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Table 3. Semantic search results

Query ID	Query Form	Query Item	Reasoning Type	Query Result
Q_1	Q_{i1}	"Director"	Concept Reasoning	Sub-roles:ProjectLeader1,ProductionEngineer1, QualityEngineer1,ProjectLeader2, ProductionEngineer2,QualityEngineer2; Privileges:(browse,webpage11), (browse,webpage12), ……
Q_2	Q_{i2}	"ProjectLeader1"& "ProductionEngineer1"	Relationship Reasoning	seniorRoleOf
Q_3	$Q_{i1} \cap Q_{i3}$	"Director & computer"	Conjunctive Query Reasoning	webpage list: webpage11, webpage21…. Where include the text "computer" in these web pages

Table 4. Comparison between the basic semantic search with traditional method

Query Form	Reasoning Type	Traditional Method	Semantic Search
Q_{i1}	Concept Reasoning	Not support	Support
Q_{i2}	Relationship Reasoning	Not support	Support
Q_{i3}	No Reasoning	Support	Support
$Q_{i1} \cap Q_{i3}$	Conjunctive Query Reasoning	Not support	Support

Q_1 is a simple query just for the concept Q_1 = "Director", we get all the sub-roles of Director and all the privilege these roles have. Q_2 is a query for the relationship. The result is seniorRoleOf between ProjectLeader1 and ProductionEngineer1. Q_3 is the simple keyword query, because the default user or role has no required privilege, so Null is returned. Q_4 is a Conjunctive Query as the form "Director & computer", the result returned is the webpage list where the pages include the text "computer".

As pointed out in [22], currently there is no commonly agreed evaluation methodology and benchmark for semantic search. We constitute our research group's evaluation dataset. The results are analyzed positively in 90%. We mainly compare our system with traditional method based on keyword query shown in Table 4.

The dataset is made up of the RBAC security ontology (including 12classess, 16 properties and 20 individuals) and the set of campus web pages (the size of the index is more than 200M). General traditional search engines can only perform the keyword query without inference. From the table 4 we can find that Semantic search engine Onto-SSSE can perform not only traditional query but also complex query through concept and relationship reasoning. We can use Onto-SSSE as a traditional search engine through imputing the keyword query item. Besides this it can help us find the concept, the relationship between them. So the new semantic search system Onto-SSSE performs better than traditional one especially about the reasoning function.

4. Related Work

Tap Knowledge Base (KB) [17] is implemented by Stanford University, IBM and other research institutions. Tap KB brings Semantic Web technology into Google to improve the search efficiency through providing additional results. The two kinds of different results are shown on the same page. However, the search object is still the traditional resource, not the one on Semantic Web. The method only responds the keyword query, not supporting the form query, so it could not integrate information retrieval and formal semantic query tightly. [18] provides an ontology-based information retrieval model to support result ranking. The method transforms the keyword query to structure query, not combining them.

Swoogle, a prototype system of IR is provided in [19]. The search results are physical documents on Semantic Web (such as RDF and OWL files).

However, Swoogle has not used the semantic structure information in documents. When the large documents are queried, the useful information is very little and user need analyze the whole file to locate the semantic information.

The premise of search technologies today is primarily centered around enabling search for entities or on the Semantic Web. Most relationships were emphasized as the heart of the Semantic Web. Correspondingly, efforts must be made to accomplish the purpose of searching complex relationships between Semantic Web resources. Such search capabilities may become the foundation for a relationship search engine [15].

As the logic base for ontology language, Description Logics (DLs) define the relevant concepts of the domain (terminologies) and use these concepts to specify properties of objects and individuals occurring in the domain [3] to represent the knowledge of an application domain. With the rapid development of ontology, recently DLs have gained more and more popularity due to their application in many areas especially in Semantic Web.

However, the classical DLs can only define the certain concepts and properties, and that the answer of inference only returns "True" or "False", which cannot solve the fuzzy problem of ontology system in real world. For example, some applications in Semantic Web, such as semantic document retrieval often need to search and manage imprecise information. Therefore, the fuzzy DLs are designed to expand the classic DLs to make it more applicable to ontology system.

Most fuzzy logic systems (FLSs) are based on type-1 fuzzy sets that are proposed by Zadeh in 1965 [20]. Fuzzy set theory has been applied to many fields including approximate reasoning, data mining, decision analysis and other hybrid systems. Lately, fuzzy sets were applied to DLs and ontology systems. Meghini [21] proposed a preliminary fuzzy DL as a tool for modeling multimedia document retrieval, but reasoning algorithm was not presented. Straccia presented Fuzzy AL-language with letter “C” for “complement” (FALC) [10] formalized in 2001, which was a type-1 fuzzy extension of ALC. In [22], Straccia extended the SHOIN(D) to a fuzzy version. However, for the reason that the membership grade for each input in type-1 fuzzy set, there may be limitations in the ability of type-1 FLSs including type-1 fuzzy DL, to model and minimize the effect of uncertainties. Thus, because of the limit of Type-1 fuzzy sets, FALC and fuzzy SHOIN(D) can hardly express complex fuzzy information clearly.

5. Conclusions and Future Work

In this paper we propose a conception model for semantic search and apply it to security domain. A type-2 fuzzy DL is proposed. We combine text IR with semantic reference in the model. The model extends the search capabilities of existing methods through combining the type-1 fuzzy DL and type-2 fuzzy DL. It can also answer some complex queries such as the relationships between resources. A semantic search system is implemented based on the model. The experimental results show that the new system performs better than the exiting schemes.

We plan to get improvement in the following aspects. The first is to perform search in a larger dataset. The second is to improve the reasoning efficiency. The reasoning efficiency can not satisfy the users. The third aspect is to formalize and implement the extended model and the complete model since we only implement the basic model at present. We are confident that the scalable Onto-SSSE system will be well integrated with fuzzy DL.

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