Ontology-based data semantic management and application in IoT- and cloud-enabled smart homes

メタデータ	言語: eng 出版者: Elsevier 公開日: 2018-03-01 キーワード (Ja): キーワード (En): Smart home, IoT and cloud computing, Data semantic fusion, Ontology data storage, Semantic reasoning 作成者: TAO, Ming, 太田, 香, 董, 冕雄 メールアドレス: 所属:
URL	http://hdl.handle.net/10258/00009567

Ontology-based Data Semantic Management and Application in IoT-based Smart Home

Ming Tao[a], Kaoru Ota[b], Mianxiong Dong[b,*]

[a]*School of Computer, Dongguan University of Technology, Dongguan, China*
[b]*Department of Information and Electronic Engineering, Muroran Institute of Technology, Japan*

Abstract

The emerging technologies of Internet of Things (IoT) and cloud computing have promoted the development of smart home. As the popularity, big volume of heterogeneous data is generated by home entities per day. Representation, management and application of the continuous expanding heterogeneous data in smart home data space have been a critical challenge for further development of smart home industry. To address this issue, a scheme of ontology-based data semantic management and application is proposed in this paper. On the basis of the smart home system model abstracted from the perspective of implementing user requirements, a top-level ontology model facilitating the capture of domain knowledge is structured through the correlative concepts, and a logical data semantic fusion model is designed accordingly. To enhance the ontology data query efficiency in the implementation of the data semantic fusion model, a relational-database based ontology data decomposition storage method is developed by thoroughly investigating the existing storage modes, and the performance is demonstrated by a group of elaborate query and ontology updating operations. Comprehensive applying the stated achievements, ontology-based semantic reasoning with a particularly designed semantic matching rule is studied as well in the work, and a test system of user behavior reasoning is developed to provide accurate and personalized home services. Analytical and experimental results are shown to demonstrate the efficiency.

Keywords: smart home, ontology, data semantic fusion model, ontology data storage, semantic reasoning.

1. Introduction

Smart home running on the platform of family house has achieved significant development in the past decades by taking the advantage of the continuous development of these advanced technologies, such as network communication, automatic control, and so on. By effectively integrating various functional subsystems related to the home life, it attempts to provide more humanized services and make home life more comfortable, safe and energy-efficient in the manner of acquiring and applying knowledge about its occupants and surroundings[1, 2].

Recently, on the basis of the traditional home automation being lack of abundant applications, emerging technology advances in Internet of Things (IoT) have helping to foster the further development and application of smart home. IoT regarded as a global information network for smart objects based on wireless and Internet technologies has been widely employed in the industrial applications[3], and also suited for smart home[4, 5, 6]. In IoT-based smart home, various transmission technologies, e.g., GPRS, 3G/4G for remote access, Bluetooth, ZigBee, WiFi, UWB and 6lowpan for short-distance wireless communications in interior access, can be employed to achieve the interconnection, interworking, interoperation and combined

*Corresponding author: mxdong@mmm.muroran-it.ac.jp
Email addresses: taoming6723@126.com (Ming Tao), k.ota@ieee.org (Kaoru Ota), mxdong@mmm.muroran-it.ac.jp (Mianxiong Dong)

operations of heterogonous home devices and appliances. Especially, these new IoT-based devices and components can support new efficient and fully integrated services that leverage the existing ubiquitous and pervasive communication and computing facilities characterizing the home cyber environment. However, in the typical smart home setting, there is an inevitable problem that multiple or even proprietary devices and service platforms provided by different vendors use heterogeneous communication protocols and standards. Such heterogeneous devices and platforms need to be fully interoperable to support the joint and harmonized execution of household operations. Due to being lack of unified standards, the integration of these home devices and services in specific domains characterized by strong cross-platform interactions results in several administration and operational problems. Fortunately, the advances in cloud computing technology have provided a promising opportunity for addressing this issue. Recently, there are many proposals leveraging cloud computing for implementing smart home systems based on service-oriented architectural model (SOA)[7, 8, 9]. These systems provided a number of software services (e.g., home management or home device control) re-mapped in a typical Software-as-a-Service (SaaS) cloud architecture to reshape home services and applications in the home automation domain. Such services are now required to interact with each other to exchange information and provide a solid basis for implementing collaborative home service in a fully distributed Internet-based environment.

Although the use of both IoT and cloud computing in smart homes is still in its early stage and most of the existing proposals have not fully exploited the potential of these technologies for supporting interoperable architectures and solutions, with the assistance of technology advances in IoT and cloud computing, various intelligent home services have been emerged in endlessly, and the development and application of smart home have been created a new thriving situation. Yet, along with the popularity, a mass of heterogeneous data is generated by home entities per day. Since the device types, structures, information transmission modes and network communication methods are different, the formats, codes and grammars of the generated data have obvious heterogeneity. Representation, management and application of the heterogeneous data in the smart home data space to provide more intelligent and personalized services for home users still have been considered as a challenging research and industrial topic. Recently, ontology theory and technology have been identified as the representative promising means that can be used to address data, knowledge, and application heterogeneity[10, 11, 12, 13, 14, 15], as well as to construct the service-oriented framework in smart home environments[16, 17, 18, 19, 20, 21]. Inspired by the previous research achievements in the proposals, a scheme of ontology-based data semantic management and application is proposed in this paper to address the challenges put forwarded by the continuous expanding smart home data space, which has the following main contributions.

1. From the perspective of implementing user requirements, an abstract model of smart home system is developed, on the basis, a top-level domain ontology model facilitating the capture of domain knowledge is structured through the following correlative ontology concepts, $User$, *ApplicationSystem*, $Service$, *HomeDevice* and *Technology*. Driven by the applications of IoT and cloud computing technologies, the number of ontology in the defined smart home domain ontology model will continue to increase. Considering the issue of accompanied rapid expansion of smart home data space, a data semantic fusion model logically divided into four layers is designed to achieve effective data management and application.

2. In the developed data semantic fusion model, ontology data query is a frequent operation for achieving user requirements, while reasonable ontology data storage mode is the basis of enhancing the effective ontology data query. By thoroughly investigating the existing storage modes, a relational-database based ontology data decomposition storage method is developed, and a group of elaborate query and ontology updating operations are shown to demonstrate the performance.

3. By applying the stated achievements, ontology-based semantic reasoning is studied in the work, where, a semantic matching rule is particularly designed. Analytical and experimental results based on a developed test system of user behavior reasoning are shown to demonstrate the efficiency. In addition, based on the comparisons with representative data-driven and knowledge-driven reasoning methods, the time efficiency and reasoning accuracy are demonstrated as well.

The reminder of this paper is structured as follows. In Section 2, we provide a brief review of the applications of IoT and cloud computing technologies in the smart home scenario, and the ontology-based service-oriented smart home frameworks. In Section 3, a top-level domain ontology model based on an abstract model of smart home system is constructed through correlative concepts, and a logical data semantic fusion model is designed accordingly to achieve effective data management and application in smart home data space. In Section 4, a relational-database based ontology data decomposition storage method is developed by thoroughly investigating the existing storage modes. Comprehensive applying the stated achievements, ontology-based semantic reasoning with a particularly designed semantic matching rule is studied in section 5 and a test system of user behavior reasoning is developed to demonstrate the efficiency. The conclusions and future research are finally summarized in Section 6.

2. Related Work

Recently, as an emerging technology, IoT is expected to embed computer intelligence into the devices needed for conveniently managing modern home environments, and some preliminary works using IoT technologies to design and implement smart home have been presented. Typically, by integrating IoT and service component technologies, Li et al. [4] develop a smart home system architecture with heterogeneous information fusion. By employing IoT to implement a low cost ubiquitous sensing system, a system framework with data aggregation, reasoning and context awareness for monitoring regular domestic conditions is proposed in [5]. In [6], by using IoT technologies to deploy heterogeneous sensor and actuator nodes for tracing the daily routine of inhabitants, smart home approach is implemented to monitor the activities of inhabitants for wellness detection. However, as more and more home devices from different vendors are equipped with on-board modules that can access the smart home platform, the integration of heterogenous home devices and services characterized by strong cross-platform interactions results in negligible administration and operational problems owing to being lack of unified standards. Fortunately, new solutions emerged to integrate existing home networks, heterogenous sensors, on-board modules in home devices, home gateways and cloud computing for creating smart-home-oriented clouds have provided a promising opportunity for addressing this issue. With OSGi architecture, by using P2P technology to improve communication efficiency and integrating HTTP and XML to implement data interaction, Hu et al.[7] propose a service-oriented architecture for smart-home. Similarly, by using IoT to construct home network, facilitating interactions with smart home devices in the manner of web services in Cloud, and using JSON data format to improve data exchange efficiency, Soliman et al. [8] present an cloud-based approach of developing Smart Home applications. In cloud-based smart home with strong cross-platform operations, privacy protection as an important concern is a significant issue. By defining risk management as cloud service, kirkham et al. [9] propose a architecture of integrating risk and home device management to achieve organized data sharing and private querying.

Note that, promoted by the applications of IoT and cloud computing, various smart home applications and services have been emerged in endlessly. In service-rich smart home scenario, to provide users with accurate and personalized services, ontology theory and technology as promising means are widely used to construct the service-oriented smart home framework currently. Li et al. [16] propose a service-oriented framework with a set of ontology systems to support service and device publishing, discovery and composition, with which, smart home can be rapidly constructed by discovering and combining existing services and workflows. With the analysis of smart home domain ontology, to construct a semantic context for inferring the interaction of policies, Hu et al. [17] propose a semantic web-based policy interaction detection method with rules to model smart home services and policies. By using semantic reasoning with the presented ontology framework, Marco et al. [18] develop a smart home management system to handle energy usage for enhancing the efficiency, Cheong et al. [19] achieve energy savings based on the collected inhabitant's contextual data. By employing and extending existing ontology-based knowledge-driven model, Okeyo et al. [20] propose a hybrid ontological and temporal approach to composite activity modelling and recognition in smart home, Bae [21] also presents a method for recognition of Activities of Daily Living (ADL) in smart homes. In smart home scenarios, ontology-based frameworks and approaches for activity monitoring in elderly care have also attracted many research interests [22, 23, 24]. By using ontology knowledge and ontology-based two-level reasoning to achieve context awareness, Evchina et al. [22] propose a framework of context-aware middleware as a solution for information management in smart home to provide Help-on-Demand services. By extending the smart home domain ontology model with home user's social

Table 1: Ontology concepts and properties.

Ontology Concept	Property				
User	identity	sex	preference	request	...
Application_System	lighting	cooking	heating	cooling	...
Service	entertainment	alarm	communication	nursing	...
Home_Device	light	video/audio	sensors	alarm_device	...
Technology	data transmission	service presentation	device operation	service implementation	...

relationship, Lee et al. [23] propose a integrated context model to provide fully personalized health-care services for specific users. By employing a layered structure to assemble context sensing, contest extraction, context management, context-aware reminders and humanCcomputer interactions, Zhang et al. [24] develop an activity monitoring and reminder delivery framework to reminder users to keep healthy postures during their daily activities.

With the acknowledgement of the achievements in these proposals, to address the issue of rapid expansion experienced by smart home data space, we mainly propose a scheme of data semantic management and application based on the ontology theory and technology in this paper to enhance the data utilization efficiency in achieving user's requests.

3. Ontology-based data Semantic Fusion Model

3.1. Definition of Domain Ontology Model

From the perspective of implementing user requirements, the model of smart home system could be abstracted in Fig. 1, which is composed of user, application system, service, home device and technology. Specifically, supported by technology, user is the sponsor of service requirements, application system as the function system is developed to achieve the user requirements, service as the specific component of application system is responsible for the concrete implementation of refined functions in application system, and home device is the final implementer of the service. The workflow of this model can be described as follows. User requirements firstly are put forwarded to the application system, the requested function services are then invoked in application system, and the corresponding home device implementing the function finally performs the related operations to achieve the user requirements.

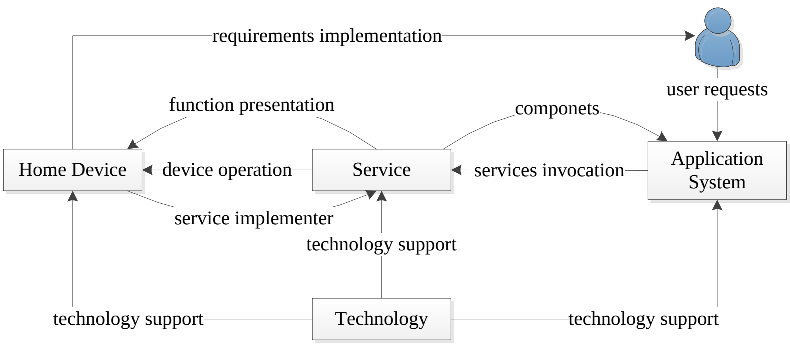


Figure 1: An abstract model of smart home system.

On the basis of developed abstract model of smart home system, by transforming the five elements, $User$, $ApplicationSystem$, $Service$, $HomeDevice$ and $Technology$ into ontology concepts, a top-level ontology model facilitating the capture of domain knowledge is structured through the correlative concepts[25]. The involved ontology concepts and the partial properties characterizing the abstracted concepts are summarized in Table. 1.

In the defined domain ontology model, the relations between correlative concepts to be used as the basis of semantic reasoning, should be defined as well. Developed by Protégé, a simple illustration of relation definitions is shown in Fig. 2. If *smoke_sensor* detects that the abnormal smoke concentration exceeds the pre-defined standard threshold, the *smoke_alarm* service would be invoked, which then would trigger the *smoke_alarm_device* to reminder the user with abnormal situation. Hence, the two mutually-inverse relations, "invoke" and "invokedby", must be defined for *smoke_sensor* and *smoke_alarm*, and another two mutually-inverse relations, "trigger" and "triggeredby" must be defined for *smoke_alarm* and *smoke_alarm_device*. Generally, abnormal smoke concentration may also be accompanied with a fire condition. Similarly, the stated mutually-inverse relations, "invoke" and "invokedby" must be defined for *smoke_sensor* and *fire_alarm*, "trigger" and "triggeredby" must be defined for *fire_alarm* and *fire_alarm_device* as well.

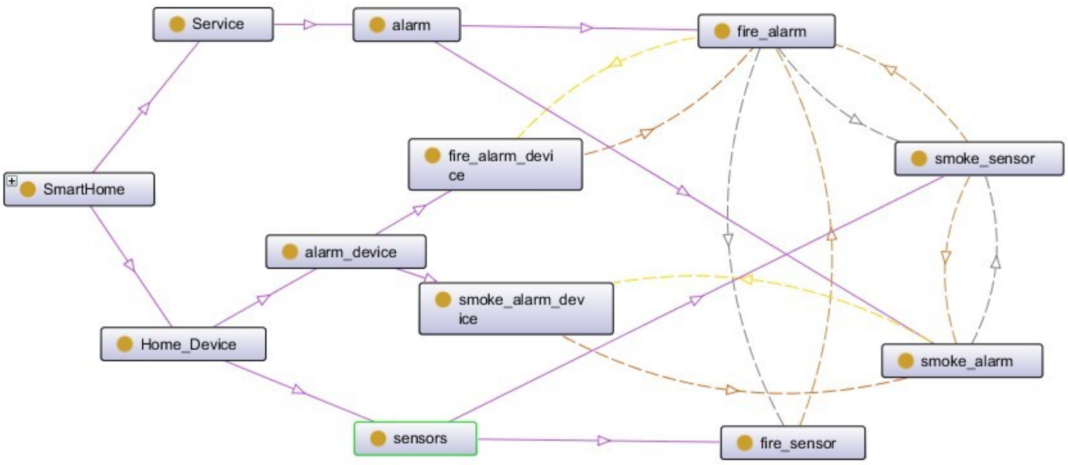


Figure 2: A simple illustration for relation definitions.

3.2. Design of data Semantic Fusion Model

Driven by IoT and cloud computing technologies, the number of ontology in the aforementioned smart home domain ontology model will continue to increase, accordingly, the smart home data space will have a rapid expansion as well[26]. Recently, data fusion as a proven technique has received significant attention[27, 28]. However, in smart home data space, due to being lack of unified format specifications, data description method acceptable by home devices and user-oriented operation specifications of different abstraction levels, the application of data fusion still remains a significant challenge. If the semantic concepts of different abstraction levels could be attached on the original smart home data and logical reasoning prototype could be established by employing the domain knowledge based rules, the difficulties of application of data fusion might be effectively solved. To address this issue, based on the aforementioned smart home domain ontology model, an ontology-based data semantic fusion model is designed here to achieve the effective data semantic management and application. Note that, the employed semantic operation mode of smart home data space is shown in Fig. 3, which is based on the standard specification of semantic web and allows the authorized access by home network and Internet.

Logically, as shown in Fig. 4, the architecture of the proposed data semantic fusion model is divided into four layers, *DataSpaceAdaptationLayer*, *OntologyDescriptionLayer*, *SemanticProcessingLayer* and *ApplicationServiceLayer*, which mainly achieve semantic annotation, metadata establishment, ontology mapping and application rule definition. The former three achievements are used to define the static semantic of data object, and the last one is used to define the dynamic semantic.

In the proposed model, heterogeneous data provided by different data sources, such as sensing devices, is taken as the basic data objects and usually stored in several kinds of forms, such as rational database, XML, OWL, textfile, Web services, and so on. By defining the ontology description model for the heterogeneous

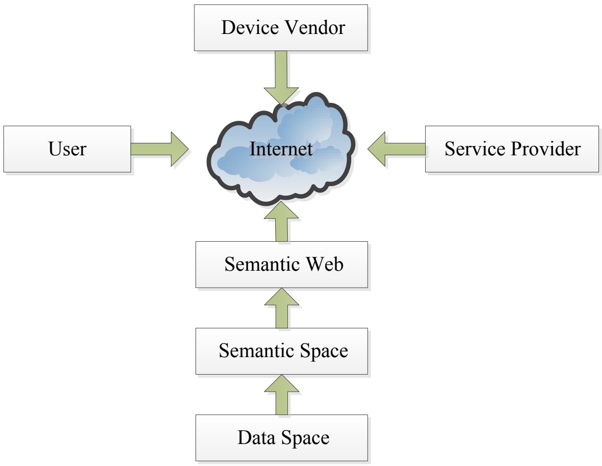


Figure 3: Semantic operation mode of smart home data space.

data from different data sources and establishing the mapping relations between the ontology and data sources using virtual database, the semantics of data object could be expressed and the heterogeneous data fusion could be achieved. As shown in Fig. 5 taking environmental sensor for example, RDF triple is used to describe the data resource for easy to be unparsed and queried, and sensed data is uniquely identified by URI composed by sensing time, location and sensor type.

Rather than defining specific operations, *DataSpaceAdaptationLayer* defines the operation-oriented data semantic description specification by separating the data contents from the presentations. Meanwhile, in terms of the device types and operation modes, a unified operation interface including semantic parameters for different operations is designed by integrating the information, e.g., data scheduling frequency, information distinguish granularity and device scheduling modes, into specific operation procedures. To achieve reasonable data applications in different abstraction extent of smart home data space, *OntologyDescriptionLayer* uses RDFS/OWL to describe the domain knowledge, and the relations between defined concepts to be used as the basis of reasoning should be defined as well. By establishing rules container, ontology representation model and reasoning engine, *SemanticProcessingLayer* is responsible for management and application of the ontology-described information, such as semantic data, operation mode and user requirements, and so on. Additionally, it provides a normal application programmable interface for *ApplicationServiceLayer*. Since different users have different application purposes, there would be a variety of ontology in the presence of multiple users. Therefore, different ontology would use the underlying data objects through the interfaces provided by *OntologyDescriptionLayer*. By providing programmable interfaces for users, *ApplicationServiceLayer* supports multiple modes of standard application services, such as environment sensing services, device operation services, information storage and sharing services, and so on. The implementation process of the data semantic fusion model is shown in Fig. 6.

4. Ontology Data Storage mode

In the implementation process of the designed data semantic fusion model, ontology data query as an important operation will be frequently performed for the data application in achieving the user requirements, so developing a high-efficiency ontology data storage mode still remains an important issue. Additionally, the employed ontology data storage mode would also have a direct impact on the maintenance cost. Currently, in terms of used storage medium, there are three kinds of storage modes, memory storage mode, plain text storage mode and relational database storage mode[29].

In memory storage mode, the constructed ontology data will be read into the memory at a time. Undoubtedly, the speeds of reading and writing ontology data are very fast due to the characteristics of memory reading and writing. However, being subject to the conditions of physical memory, memory storage mode

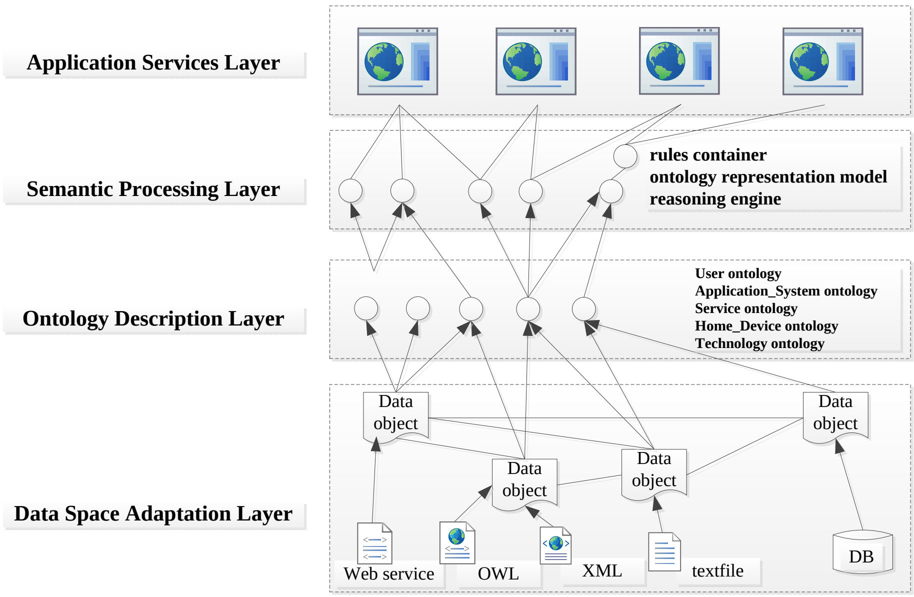


Figure 4: Architecture of data fusion model.

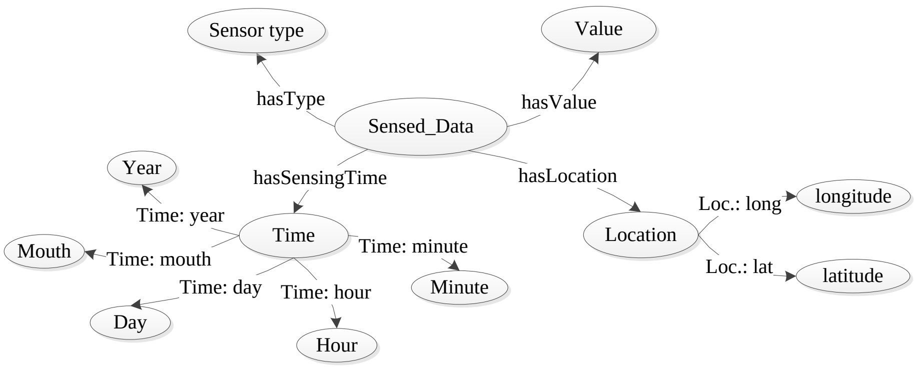


Figure 5: Description of heterogeneous data generated by experimental sensors.

is only suitable for small-scale ontology data that could be read into the memory at a time, but not for large- or media-scale ontology data which would exceed the memory capacity. In plain text storage mode, the ontology data is stored in the form of logically and semantically complete files. The common file formats mainly including OWL, RDF, XML, etc., are managed and modified by ontology editing tools, e.g., Protégé. If an ontology file needs to be edited, the ontology editing tool would open and read the ontology file into the memory, and the modified part would be wrote into the file by memory later on. Since there are frequent I/O operations in such mode, it is only suitable for small-scale ontology as well. With the growing scale of ontology data, the inherent defects of such mode will have serious impact on the storage efficiency. In relational database storage mode, although the information stored in relational database is a two-dimensional table, a ontology model with relatively complex mesh structure presenting the internal logical relations of ontology classes, e.g., properties and constraints, could be transformed into several relational tables in relational database by using some mapping schemes[30]. Recently, both Protégé and Jena have the support for importing the ontology data into relational database[31], and the content in each generated table is determined by the used mapping scheme.

Comparatively, since relational database has efficient storage and query capabilities and good ability of

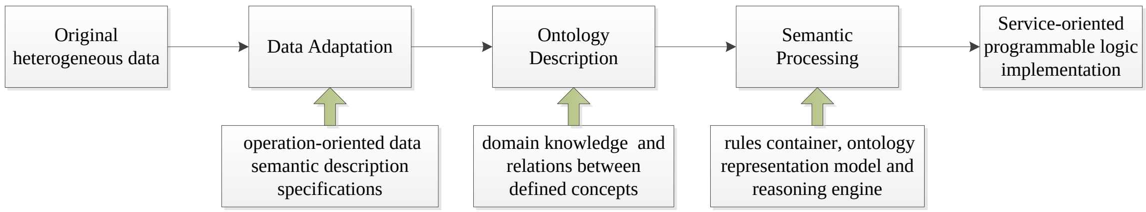


Figure 6: Implementation process of data semantic fusion model.

Table 2: Comparisons of the three relational-database based ontology data storage methods.

Storage Method		Structural Stability	Structural Readability	Query Efficiency	Application Scale
Horizontal		Unstable	Higher	Lower	Small
Vertical		Stable	Lower	Higher	Medium or small
Decomposition	Class-based	Unstable	Higher	Lower	Medium or small
	Property-based	Unstable	Higher	Lower	Medium or small
Hybrid		Unstable	Uncertain	Lower	Medium or small

transaction management, making full use of the relational database storage mode for ontology data has been the focus of many researchers for years. With different storage structures and contents, relational-database based ontology data storage has different storage methods as well. Mainly, there are three kinds of storage methods, horizontal storage, vertical storage and decomposition storage. The comparisons of the three relational-database based ontology data storage methods are summarized in Table. 2.

Both horizontal and vertical storage methods use a single table to store ontology information. In horizontal storage method, the classes and instances in the ontology model will be taken as records in relational model, and the instance names, types, properties, relations and constraints will be taken as the columns of table in relational database. In vertical storage method, all the semantic information in ontology model will be transformed into the form of RDF triples, and an ontology model will be transformed into a complete data table. In decomposition storage method, it will decompose the ontology data in terms of the class or property and transform the decomposed structures into relational models. Hence, multiple tables will be used to store an ontology information. Since the stated three relational-database based storage methods have respective shortcomings and specific applies, the hybrid storage method is developed in terms of the characteristics and scales of ontology model. However, there is no a widely used and approved hybrid storage method so far.

In terms of the stated thoroughly analysis of ontology data storage modes, we can clearly see that the existing modes are not applicable to the constantly expanding smart home data space driven by the applications of IoT and cloud computing. To address this issue, a new relational-database based ontology data decomposition storage method is designed here, in which, the transformation from ontology model to relational model must follow these principles, e.g., 3NF and BCNF required by relational database, good scalability of ontology model, complete semantic information, stable and clear rational structure with high query efficiency. Since the ontology model is developed by Protégé and stored in the form of OWL files in this work, the structures of OWL files must be transformed to store the ontology model in relational database. For different kinds of storage objects, the method of transforming ontology model into relational model is described as follows.

1. Ontology classes

In the defined ontology model, class as one of the important components is the frequent operation object in the query process, and instances, properties and constrains in the ontology model all have direct or indirect relations with classes, so a complete table named *OntologyClass* is necessary to be created for ontology classes. The structure of *OntologyClass* developed by Oracle SQL Developer is shown as follows.

CREAT TABLE “SmartHome”.“OntologyClass”

{“classID” NUMBER(*,0) NOT NULL ENABLE,

“classURI” VARCHAR(60 BYTE),
“className” VARCHAR(20 BYTE),
“classType” VARCHAR(20 BYTE)}

2. Ontology properties

(1) Property as another important component could be categorized into object-type property and data-type property. Due to being frequently used in query process, a complete table named *Property* is necessary to be created for common properties. The structure of *Property* is shown as follows, in which, the content in *Domain* field is the $classID$ in *OntologyClass*, and the *Range* field will be given different values in terms of different property type.

CREAT TABLE “SmartHome”.“Property”
{“propertyID” NUMBER(*,0) NOT NULL ENABLE,
“propertyURI” VARCHAR(60 BYTE),
”propertyName” VARCHAR(20 BYTE),
“propertyType” VARCHAR(20 BYTE),
“propertyDomain” VARCHAR(20 BYTE)
“propertyRange” VARCHAR(20 BYTE)}

(2) Mainly, there are five kinds of property characters, e.g., $Symmetric$, $Functional$, $Transitive$ and $Inversefunctional$ are unary relations, and $inverseOf$ is a binary relation. Due to less usage in the query process, a table named $Property - Character$ is created for the former four property characters, whose structure is shown as follows, and the last one will be stored in the table $Property - Relation$ created in the following.

CREAT TABLE “SmartHome”.“Property-Character”
{“propertyID” NUMBER(*,0) NOT NULL ENABLE,
“characterValue” VARCHAR(20 BYTE)}

(3) The types of ontology property constraints mainly include $allValuesFrom$, $someValuesFrom$, *Cardinality*, *maxCardinality*, *minCardinality* and $hasValue$. Similarly, due to less usage in the query process, a table named $Propery - Constraint$ with the following structure is created for the property constraints.

CREAT TABLE “SmartHome”.“Property-Constraint”
{“propertyID” NUMBER(*,0) NOT NULL ENABLE,
“propertyType” VARCHAR(20 BYTE),
“constraintValue” VARCHAR(20 BYTE)}

3. Ontology instances

In the defined ontology model, instance as the specific data description has great data volume. A table named $Instance$ is created for the instances, whose structure is shown as follows. Since each instance has multiple properties and corresponding values, only the content combination of $instanceName$, $propertyID$ and $propertyValue$ can uniquely identify a specific instance, and the fields of $instanceName$, $propertyID$ and $propertyValue$ are adapted as the composite primary key.

CREAT TABLE “SmartHome”.“Instance”
{“instanceID” NUMBER(*,0) NOT NULL ENABLE,
“propertyID” NUMBER(*,0) NOT NULL ENABLE,
“propertyValue” VARCHAR(20 BYTE) NOT NULL ENABLE,
“instanceURI” VARCHAR(20 BYTE),
“instanceName” VARCHAR(20 BYTE),
“classID” NUMBER(*,0)}

4. Ontology relations

(1) In the defined ontology model, the relations of classes as the most important relations are frequently used in the query process, whose types mainly include $subClassOf$, $superClassOf$, $equivalentClass$ and $disjointClass$. To enhance the query efficiency, a separate table named $Class - Relation$ with the following structure is necessary to be created to store class relations.

CREAT TABLE “SmartHome”.“Class-Relation”
{“oneClassID” NUMBER(*,0) NOT NULL ENABLE,

“anotherClassID” NUMBER(*,0) NOT NULL ENABLE,
“relationType” VARCHAR(20 BYTE)}

(2) Although the number of properties in the defined ontology model is relatively small, the relations of properties are frequently used in the query process. Hence, a table named $Property - Relation$ with the following structure is created to store property relations, in which, the types of property relations mainly include $subPropertyOf$, $superPropertyOf$, $equivalentProperty$ and $inverseOf$.

CREAT TABLE “SmartHome”.“Property-Relation”
{“onePropertyID” NUMBER(*,0) NOT NULL ENABLE,
“anotherPropertyID” NUMBER(*,0) NOT NULL ENABLE,
“relationType” VARCHAR(20 BYTE)}

(3) A table named $Instance - Relation$ with the following structure is also needed to be created for storing instance relations, in which, the types of instance relations mainly include $SameAs$, $differentFrom$ and $AllDifferent$.

CREAT TABLE “SmartHome”.“Instance-Relation”
{“oneInstanceID” NUMBER(*,0) NOT NULL ENABLE,
“anotherInstanceID” NUMBER(*,0) NOT NULL ENABLE,
“relationType” VARCHAR(20 BYTE)}

By the stated transforming operations, the ontology data storage structure in relational database model can be represented in Fig. 6, in which, setting primary key for achieving ontology entity integrity constraint and setting the constraint relations between primary key and foreign key for achieving referential integrity constraint are the necessary operations when creating tables. From Fig. 6, we can clearly see that the proposed method of transforming ontology model into relational model can transform multi-dimensional relations into binary relations with clear logical structure, and completely reserve the semantic information in the defined ontology model with tables as little as possible.

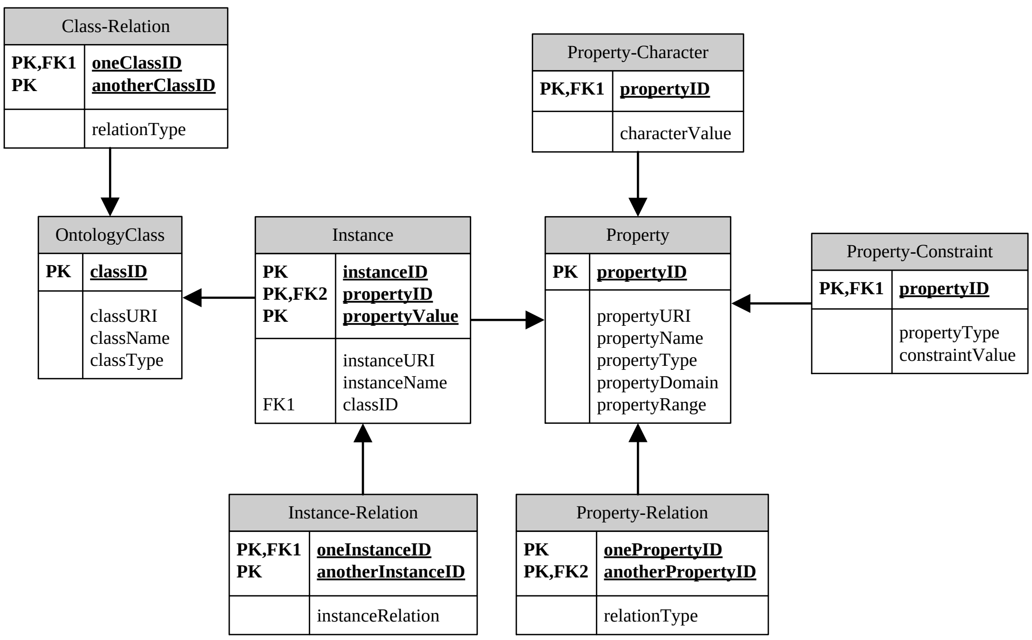


Figure 7: Ontology storage structure in relational database model.

To evaluate the efficiency of the designed relational-database based ontology data decomposition storage method, a testbed is conducted on Oracle 13g platform, the performance parameters of the executing host are Win 7, Inter(R) Core(TM) i5-3450 CPU @ 3.10GHz, 3.10GHz, X64, 4GB (RAM). As stated in Table. 2, comparatively, vertical storage method has higher query efficiency than the other relational-database based

Table 3: Description of three ontology test files.

	Number of classes	Number of properties	Number of class instances	Number of property instances
testfile-1	25	10	200	900
testfile-2	50	20	500	2600
testfile-3	75	30	800	6000

Table 4: Test results of four kinds of representative query operations.

<table>
<tr><th rowspan="2"></th><th rowspan="2">Storage Method</th><th colspan="4">Query Responding Time (ms)</th></tr>
<tr><th>Instance Query</th><th>Subclass Query</th><th>Equivalence Class Query</th><th>Property Domain Query</th></tr>
<tr><td rowspan="2">testfile-1</td><td>Vertical Storage</td><td>102</td><td>113</td><td>121</td><td>103</td></tr>
<tr><td>Decomposition Storage</td><td>95</td><td>93</td><td>110</td><td>95</td></tr>
<tr><td rowspan="2">testfile-2</td><td>Vertical Storage</td><td>383</td><td>438</td><td>312</td><td>235</td></tr>
<tr><td>Decomposition Storage</td><td>111</td><td>98</td><td>116</td><td>105</td></tr>
<tr><td rowspan="2">testfile-3</td><td>Vertical Storage</td><td>1213</td><td>1521</td><td>406</td><td>1026</td></tr>
<tr><td>Decomposition Storage</td><td>215</td><td>105</td><td>123</td><td>113</td></tr>
</table>

storage methods. To simplify the experiments and without less of generality, vertical storage method is only selected for comparison studies. Since there is no unified smart home ontology test set, and the scale of smart home ontology model defined in this paper is too small to convincingly demonstrate the efficiency of the designed relational-database based decomposition storage method, LUBM as a recommended test set of university ontology model is employed here[32].

It is well known that the quality of storage method is mainly indicated by the query performance, so the following stated test scheme including four kinds of representative query operations will be conducted on three ontology test files with increasing sizes shown in Table. 3. The three ontology test files generated by UBA in LUMB are stored in Oracle database by using vertical storage method and the designed relational-database based ontology decomposition storage method for comparisons.

(1) Query all instances of a class. For example, the presentation of querying all instances of the student class is shown as $\langle ?X\ rdf:type\ STUDENT\rangle$.

(2) Query all subclasses of a class. For example, the presentation of querying all subclass of the department class is shown as $\langle ?X\ rdf:subClassOf\ DEPARTMENT\rangle$.

(3) Query the equivalence classes of a class. For example, the presentation of querying the equivalence classes of the course class is shown as $\langle ?X\ rdf:equivalent\ COURSE\rangle$.

(4) Query the domain of a property. For example, the presentation of querying the domain of a department is shown as $\langle DEPARTMENT\ rdf:domain\ ?X\rangle$.

The test results are shown in Table. 4. In vertical storage method, ontology model is represented by RDF triple, and only a single table is used to store ontology data in the database. When the ontology scale is small, the data volume in the table is not big, so the query responding time of vertical storage method is slightly more than that of the proposed decomposition storage method. However, with the increase of the ontology scale, the data volume in the table will be rapidly expanded. Since the whole table will be traversed for any query operations, the expanded data volume will result in obvious increased query responding time, so the query efficiency is significantly decreased. In the designed decomposition storage method, by creating separate tables for class, property, instance and relation in the ontology model, different kinds of ontology data are stored in different tables, so different query requests will be performed in corresponding tables. With such clear logical storage structure, we can clearly see that the query efficiency outperforms that of vertical storage method from the test results, even in the condition with large-scale ontology data.

Additionally, ontology updating efficiency is another important indicator for evaluating the efficiency of ontology storage method. In the above three ontology test files, with the increase of ontology scale, the comparison of ontology updating time of vertical storage method and the proposed decomposition storage method is shown in Fig. 8. From the stable ontology storage structure of the proposed decomposition storage method shown in Fig.5, *OntologyClass* as a upper-level table is created to store all ontology classes. Once updating the ontology data, ontology classes could be updated quickly by managing *OntologyClass*. In most cases, with the increase of ontology scale, only the *Instance* and *Propery* tables need to be updated, and only several records must be added in the corresponding tables without changing the basic structures and relations of the created tables. Comparatively, with the increase of ontology scale, re-constructing the storage structure to reflect the updating information in vertical storage method will require significant time cost.

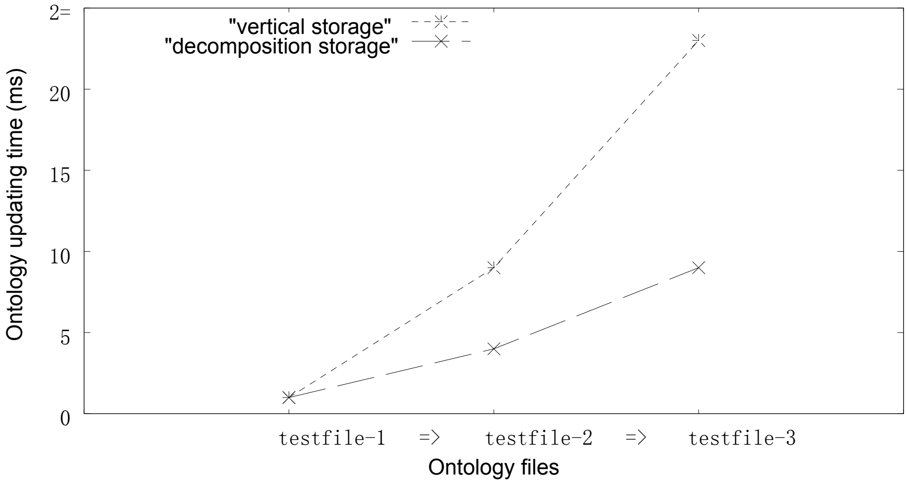


Figure 8: Comparison of ontology updating efficiency.

5. Ontology-based Semantic Reasoning

Reasoning is an important inherent function of ontology, and reasoning rules can be attached as a part of the defined ontology model to infer the information implied into them. Recently, SWRL and SQWRL are used as the main tools of choice for defining the reasoning rules necessary to implement the mutual understanding and interactions among the heterogeneous home devices and services involved [33]. For the home growing energy concerns, SWRL and SQWRL based semantic reasoning rules are defined to enhance the efficiency of energy usage [18, 19]. For elderly care or providing accurate and personalized services for users, they are also defined for user activity modelling, recognition and monitoring [20, 21, 22, 23, 24]. Here, with the stated achievements, ontology-based semantic reasoning is studied to provide accurate and personalized services requested by users as well, in which, various semantic reasoning rules must be defined and imported into the rules container in the developed architecture of data fusion model. In particular, a semantic matching rule is defined as follows, in which, due to the great quantity in calculating the semantic matching degree [34, 35], a synthesization based improved method for calculating the semantic matching degree is developed. Firstly, a set of candidate concepts is generated by calculating semantic similarity for concept pairs extracted from the ontology instances, and then, respectively, obtaining the structure-based concept similarity by weighted synthesizing similarities of parent nodes, child nodes and brother nodes, and obtaining the property-based concept similarity by weighted synthesizing similarities of data-type properties and object-type properties. By weighted synthesizing structure-based and property-based concept similarities, the semantic matching degree is finally obtained accordingly. With the defined semantic matching rule for user behavior reasoning, if user requests and home environment are determined, by calculating semantic matching degree between the current home environment semantic and the historical semantic, a services set with the optimal semantic correlation would be obtained. Accordingly, the home devices binding the corresponding services will be triggered to adaptively adjust the running parameters to provide accurate and personalized services for users as requested.

Input: the defined ontology model, the currently known information of semantic instances, historical information of semantic instances

Output: a services set with the optimal semantic correlation

Procedure:

(1) Input the currently known ontology instances $O_i(I(i_1), I(i_2), ..., I(i_n))$, and obtain historical ontology instances $O_j(I(i_1), I(i_2), ..., I(i_n))$.

(2) Calculate the semantic matching degree denoted as $sim(O_i, O_j)$ for O_i and O_j.

Extract concept pairs for O_i and O_j, and calculate semantic similarity for concept pairs;

Generate the set of candidate concepts;

Calculate structure-based concept similarity in the set of candidate concepts;

Calculate similarity of parent nodes;

Calculate similarity of child nodes;

Calculate similarity of brother nodes;

Obtain the final structure-based concept similarity by weighted synthesizing the similarities;

Calculate property-based concept similarity in the set of candidate concepts;

Calculate similarity of data-type properties;

Calculate similarity of object-type properties;

Obtain the final property-based concept similarity by weighted synthesizing the similarities;

Weighted synthesize structure-based and property-based concept similarities to obtain the final $sim(O_i, O_j)$;

(3) With a given threshold γ, if $sim(O_i, O_j) > \gamma$, import the services used by historical ontology instances into a service container named $serviceMap$. Assuming the set of matching services is represented as $\{S_1, S_2, ..., S_m\}$, where, the Key of a service is the ID and the $Value$ is the times of satisfying the semantic similarity conditions.

(4) In $serviceMap$, extract the top N services with the maximal $Value$, and the home devices binding the corresponding services will be triggered to satisfy users requests.

To demonstrate the efficiency of the designed semantic matching rule, a test system of user behavior reasoning is developed to provide personalized home services. In the experimental scene, thirty sensors, such as temperature sensor, humidity sensor, pressure sensor, infrared sensor, optical sensor, and so on, are deployed in different locations to track user's behaviors. The backend system is developed in Eclipse platform, and Protégé 4.3 is used to implement the ontology model. Taking heating behavior for example, the reasoning rule is show in Fig. 9. Given a environmental condition, if the heating request is determined, the *heating_device* would be opened and adaptively adjust the running parameters accordingly.

$$
\begin{aligned}
&Location(?x) \wedge ((temperature\_sensor(?t) \wedge atLocation(?loc., ?x) \wedge swrlb: greaterThan(?t, temperature.threshold)) \\
&\vee (humidity\_sensor(?h) \wedge atLoaction(?loc., ?x) \wedge swrlb: greaterThan(?h, humidity.threshold)) \\
&\vee (pressure\_sensor(?p) \wedge atLoaction(?loc., ?x) \wedge swrlb: greaterThan(?p, presure.threshold)) \\
&\vee (...)) \\
&\wedge (heating\_device(?hd) \wedge hasFunction(?hd, heating) \wedge atLocation(?hd, ?x)) \\
&\rightarrow Open\_heating\_device(?hd) \wedge Adjust\_heating\_device(?hd)
\end{aligned}
$$

Figure 9: An example of reasoning rule for heating behavior.

With the developed system, three family members with different preferences participate into three kinds of behavior reasoning tests, where, unsweetened or low-glycemic index food, e.g., tea, coffee and juice, are the preferences of member-1, in contrast, member-2 prefers sweet food, e.g., honey, milk, cocoa, and member-3 like any flavor drinks. These daily preferences have been defined in the user ontology model. The test results are shown in Table. 5, from which, we can clearly see that the average reasoning accuracy is well acceptable owing to the improvements in the defined semantic matching rule for user behavior reasoning. Additionally, since the preferences classifications of member-1 and member-2 are more fine-grained than that of member-3 in the defined user ontology model, the services set obtained by the designed semantic matching rule will

Table 5: Test results of user behavior reasoning

Family Member	User Behaviors			
	making tea	cooking coffee	drinking milk	Average Accuracy
member-1	100%	100%	92.5%	97.5%
member-2	94.8%	92.6	100%	95.8%
member-3	94.6%	93.8%	95.1%	94.5%

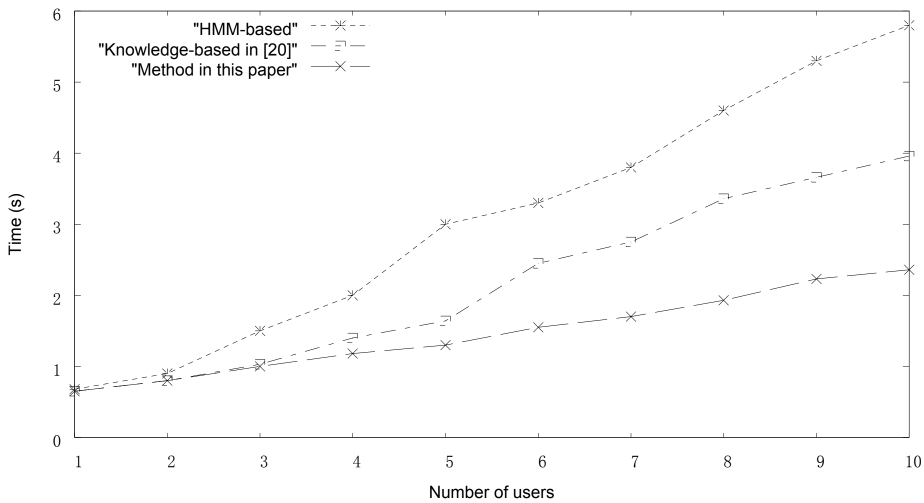
have better semantic correlation, and the average accuracy of behavior reasoning of the former two members is higher than that of the last one, that is, if the classification of user preferences is more fine-grained, the accuracy of user behavior reasoning would be higher. In conclusion, the integrality of user behavior ontology model has a direct influence on the reasoning accuracy of user behaviors as well.

Additionally, to verify the time efficiency and accuracy of user behavior reasoning, Hidden Markov Model (HMM) based user behavior reasoning as a representative data-driven method and the proposal in [20] as a representative knowledge-driven method are used for comparison studies. By selecting the *cooking* behavior of ten users for testing, the comparative results are shown in Fig. 10, from which, we can clearly see that, with the increase of the number of participating users, the time efficiency of HMM-based method with a lot of data acquisition cost is far below that of the two knowledge-driven semantic reasoning methods, and the reasoning accuracy of HMM-based method is decreased owing to the interference of acquired data of multiple users. For knowledge-driven user behavior semantic reasoning, ontology data queries are the main operations. Through establishing both ontological activity model for the relations between activities and the involved entities and temporal activity model for the relations between constituent activities of a composite activity, and developing temporal entailment rules to support the interpretation and inference of composite activities, the method described in [20] has available reasoning accuracy, but the comparatively complex operations in the defined models have seriously influence on the time efficiency. With the stated improvements in the defined semantic matching rule for user behavior reasoning, the method in this paper also has available reasoning accuracy. In addition, by using the developed relational-database based decomposition storage method with clear logical storage structure and complete semantic information, the method in this paper outperforms the other two methods on the query efficiency and further improve the time efficiency of user behavior semantic reasoning as well.

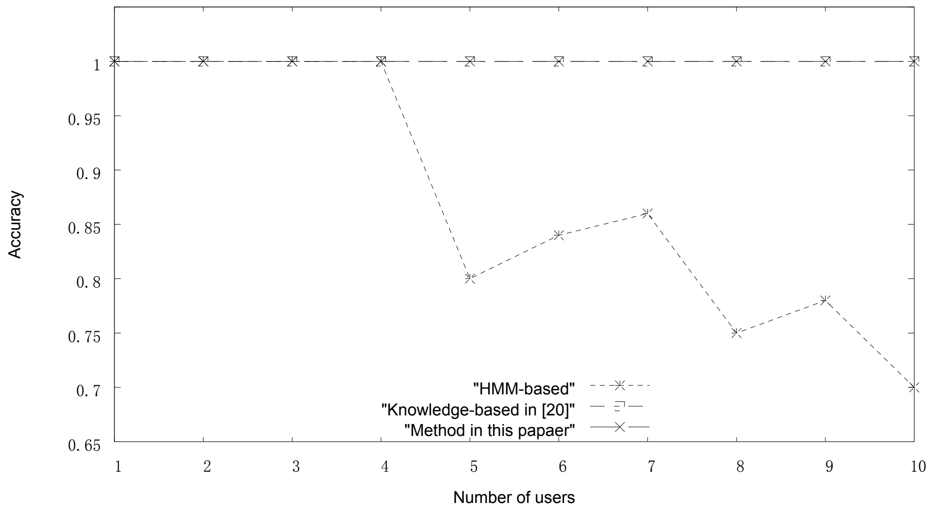
6. Conclusion

With the development of smart home services promoted by the emerging technologies of IoT and cloud computing, the volume of heterogeneous data in smart home data space has been performing continuous expansion. For achieving effective representation, management and application of the heterogeneous data, a scheme of ontology-based data semantic management and application is proposed in this paper. By abstracting a smart home system model from the perspective of implementing user requirements, a top-level domain ontology model is firstly constructed through the correlative concepts, on the basis, a logical data semantic fusion model is designed to achieve effective data management and application. In the data semantic fusion model, by thoroughly investigating the existing ontology data storage modes, a relational-database based decomposition storage method is developed to enhance ontology data query efficiency, and a group of elaborate query and ontology updating operations have been conducted to demonstrate the performance. By comprehensively applying the stated achievements, ontology-based semantic reasoning with a particularly designed semantic matching rule is studied in the work. The reasoning accuracy and time efficiency are finally demonstrated by a test system of user behavior reasoning.

Although ontology has been identified as one of the most promising means that can be used to construct the service-oriented framework in smart home environments, with the further application of IoT and cloud computing, the continuous expanding smart home data space resulted from emerging home devices and services has put forwarded some new critical challenges. Continuously enriching the domain ontology model, optimizing the data fusion model and improving the storage efficiency of ontology data to provide more accurate and personalized services for users as the future work will be further explored.



(a) Time efficiency of user behavior reasoning



(b) Accuracy of user behavior reasoning

Figure 10: Comparisons for user behavior reasoning.

Acknowledgements

This study is supported in part by National Natural Science Fund, China (Grant No. 61300198), Guangdong University Scientific Innovation Project (No. 2013KJCX0177 & No. 2014KTSCX188), outstanding young teacher training program of education department of Guangdong province (YQ2015158).

References

[1] R. A. Muhammad, B. I. R. Mamun, A. M. A. Mohd, A Review of Smart HomesPast, Present, and Future, IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews 42 (6) (2012) 1190–1203.

[2] S. a.-s. Ameena, H. A. Mohammed, M. A. S. Magdy, Smart Home Activities: A Literature Review, Electric Power Components and Systems 42 (3) (2014) 294–305.

[3] J. Gubbi, R. Buyya, S. Marusic, M. Palaniswami, Internet of Things (IoT): A vision, architectural elements, and future directions, Future Generation Computer Systems 29 (7) (2013) 1645C–1660.

[4] B. Li, J. Yu, Research and application on the smart home based on component technologies and Internet of Things, Procedia Engineering 15 (2011) 2087–2092.

[5] S. D. T. Kelly, N. K. Suryadevara, S. C. Mukhopadhyay, Towards the Implementation of IoT for Environmental Condition Monitoring in Homes, IEEE Sensors Journal 13 (10) (2013) 3846–3853.

[6] H. Ghayvat, S. Mukhopadhyay, X. Gui, N. Suryadevara, WSN- and IOT-Based Smart Homes and Their Extension to Smart Buildings, Sensors 15 (5) (2015) 10350–10379.

[7] S. Hu, C. Tang, F. Liu, X. Wang, A distributed and efficient system architecture for smart home, International Journal of Sensor Networks 20 (2) (2016) 119–130.

[8] M. Soliman, T. Abiodun, T. Hamouda, J. Zhou, C.-H. Lung, Smart home: Integrating Internet of Things with web services and cloud computing, in: IEEE International Conference on Cloud Computing Technology and Science (CloudCom), Vol. 2, IEEE, 2013, pp. 317–320.

[9] T. Kirkham, D. Armstrong, K. Djemame, M. Jiang, Risk driven Smart Home resource management using cloud services, Future Generation Computer Systems 38 (2014) 13–22.

[10] K.-L. Skillen, L. Chen, C. D. Nugent, M. P. Donnelly, W. Burns, I. Solheim, Ontological user modelling and semantic rule-based reasoning for personalisation of Help-On-Demand services in pervasive environments, Future Generation Computer Systems 34 (2014) 97–109.

[11] R.-C. Chen, Y.-H. Huang, C.-T. Bau, S.-M. Chen, A recommendation system based on domain ontology and SWRL for anti-diabetic drugs selection, Expert Systems with Applications 39 (4) (2012) 3995–4006.

[12] C. Qu, F. Liu, M. Tao, Ontologies for the Transactions on IoT, International Journal of Distributed Sensor Networks (2015) 1–12.

[13] C. Qu, F. Liu, M. Tao, D. Deng, An OWL-S based specification model of dynamic entity services for Internet of Things, Journal of Ambient Intelligence and Humanized Computing 7 (1) (2016) 73–82.

[14] W. Wang, S. De, R. Toenjes, E. Reetz, K. Moessner, A comprehensive ontology for knowledge representation in the Internet of Things, in: IEEE International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom), IEEE, 2012, pp. 1793–1798.

[15] N. D. Rodríguez, M. P. Cuéllar, J. Lilius, M. D. Calvo-Flores, A survey on ontologies for human behavior recognition, ACM Computing Surveys 46 (4) (2014) 43–76.

[16] W. Li, Y. H. Lee, W. T. Tsai, J. Xu, Y. S. Son, J. H. Park, K. D. Moon, Service-oriented smart home applications: composition, code generation, deployment, and execution, Service Oriented Computing and Applications 6 (1) (2012) 65–79.

[17] H. Hu, D. Yang, L. Fu, H. Xiang, C. Fu, J. Sang, C. Ye, R. Li, Semantic Web-based policy interaction detection method with rules in smart home for detecting interactions among user policies, IET communications 5 (17) (2011) 2451–2460.

[18] G. Marco, M. Nucci, P. Francesco, Towards an ontology framework for intelligent smart home management and energy saving, in: IEEE International Symposium on Industrial Electronics, IEEE, 2011, pp. 1753–1758.

[19] Y.-G. Cheong, Y.-J. Kim, S. Y. Yoo, H. Lee, S. C. Chae, H.-J. Choi, An ontology-based reasoning approach towards energy-aware smart homes, in: IEEE Consumer Communications and Networking Conference (CCNC), IEEE, 2011, pp. 850–854.

[20] G. Okeyo, L. Chen, H. Wang, Combining ontological and temporal formalisms for composite activity modelling and recognition in smart homes, Future Generation Computer Systems 39 (2014) 29–43.

[21] I.-H. Bae, An ontology-based approach to ADL recognition in smart homes, Future Generation Computer Systems 33 (2014) 32–41.

[22] Y. Evchina, A. Dvoryanchikova, J. L. M. Lastra, Ontological framework of context-aware and reasoning middleware for smart homes with health and social services, in: IEEE International Conference on Systems, Man, and Cybernetics (SMC), IEEE, 2012, pp. 985–990.

[23] H. Lee, J. Kwon, Ontology Model-based Situation and Socially-Aware Health Care Service in a Smart Home Environment, International Journal of Smart Home 7 (5) (2013) 239–250.

[24] S. Zhang, P. McCullagh, C. Nugent, H. Zheng, N. Black, An ontological framework for activity monitoring and reminder reasoning in an assisted environment, Journal of Ambient Intelligence and Humanized Computing 4 (2) (2013) 157–168.

[25] J. Ye, G. Stevenson, S. Dobson, A top-level ontology for smart environments, Pervasive and Mobile Computing 7 (3) (2011) 359–378.

[26] S. K. Sowe, T. Kimata, M. Dong, K. Zettsu, Managing heterogeneous sensor data on a big data platform: IoT services for data-intensive science, in: IEEE 38th International Computer Software and Applications Conference Workshops (COMPSACW), IEEE, 2014, pp. 295–300.
[27] B. Khaleghi, A. Khamis, F. O. Karray, S. N. Razavi, Multisensor data fusion: A review of the state-of-the-art, Information Fusion 14 (1) (2013) 28–44.
[28] L. Sorber, M. V. Barel, L. D. Lathauwer, Structured Data Fusion, IEEE Journal of Selected Topics in Signal Processing 9 (4) (2014) 586–600.
[29] J. Lu, L. Ma, L. Zhang, B. Jean-Sébastien, C. Wang, Y. Pan, Y. Yu, SOR: a practical system for ontology storage, reasoning and search, in: 33rd international conference on Very large data bases (VLDB), Vol. 1, IEEE, 2007, pp. 1402–1405.
[30] S. Muhammad, B. Amna, ERMOS: An Efficient Relational Mapping for Ontology Storage, in: IEEE International Conference on Advanced Management Science (ICAMS), Vol. 1, IEEE, 2010, pp. 399–403.
[31] D. Moldovan, M. Antal, D. Valea, C. Pop, T. Cioara, I. Anghel, I. Salomie, Tools for mapping ontologies to relational databases: A comparative evaluation, in: IEEE International Conference on Intelligent Computer Communication and Processing (ICCP), IEEE, 2015, pp. 77–83.
[32] Y. Guo, Z. Pan, J. Heflin, LUBM: A benchmark for OWL knowledge base systems, Web Semantics: Science, Services and Agents on the World Wide Web 3 (2) (2005) 158–182.
[33] C. Bettini, O. Brdiczka, K. Henricksen, J. Indulska, D. Nicklas, A. Ranganathan, D. Riboni, A survey of context modelling and reasoning techniques, Pervasive and Mobile Computing 6 (2) (2010) 161–180.
[34] P. Shvaiko, J. Euzenat, Ontology Matching: State of the Art and Future Challenges, IEEE Transactions on Knowledge and Data Engineering 25 (1) (2013) 158–176.
[35] D. Sánchez, M. Batet, D. Isern, A. Valls, Ontology-based semantic similarity: A new feature-based approach, Expert Systems with Applications 39 (9) (2012) 7718–7728.