A Reasoning Approach of Human Activity Based on Ontology Model in Home Intelligent Space

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Abstract - To solve the problem of lack of representation and reasoning of knowledge in human activity understanding in home environment, the activity reasoning method based on ontology model in intelligent space is presented. Firstly, a knowledge model of human activity domain based on the ontology technology is established. Then, the data-concept conversion mechanism centered on the human-object interaction relationship is applied to realize the conceptual representation of activity knowledge in intelligent space. On this basis, in order to make the best of activity domain knowledge, we use the semantic network rule language to build a knowledge rule base of human activity domain. The complex human activities in the current state are inferred by matching the real-time ontology in home intelligent space and the knowledge in rule base. Finally, the experimental results show that the method can effectively realize the reasoning of human activity.

Index Terms - Intelligent space; Ontology technology; Human activity; Semantic reasoning

I. INTRODUCTION

Human activity recognition and understanding can be divided into data-driven methods and knowledge-based methods. Traditionally, techniques for human activity recognition have focused on the branch of pattern recognition and machine learning, which have been widely studied in the last decade. In particular, deep learning that has greatly improved the recognition rate of human activity is applied. However, the solution is to start from the perspective of pattern recognition, they have not inherited semantics and management mechanisms[1]. In the environment of humanrobot integration, the home service robot should be able to effectively identify and understand human activity in combination with actual home scene information. It should express the activity knowledge of simple action recognized and combine the prior knowledge of the activity field to realize the activity reasoning.

Ontology can be regarded as a tool for information modeling at the semantic level and the knowledge level. It can be used to describe the connections between resources and reveal the resources themselves and the more complex and rich semantic relationships between resources. Furthermore, It can enable semantic integration of information and knowledge sharing, as well as improve the ability of knowledge expression, search and reasoning[2,3]. The use of ontology to study human activity reasoning in home intelligent space has special research significance. The approach is proposed to use

the ontology model and define semantic rules to share information in different semantic spaces and to infer context information based on semantic rules[4]. A methodology is presented to extract the meaning of human activities by combing the information of the hand motion and object properties and reason about the intended human behaviors by obtaining the semantic rules[5]. The approach based on ontology can model and reason the attributes of the Activities of Daily Living(ADL) domain to accurately recognize the user's ADL[6,7]. However, they use description logic method with limited reasoning ability to recognize activity. This paper introduce a semantic-based approach for segmenting sensor data series using ontology to recognize an elderly persons complex activities[8]. A fuzzy ontology is proposed for human activity recognition, which solves the problems of the modeling and reasoning of vague, incomplete and uncertain knowledge[9]. But fuzzy ontology introduces fuzzy description logic to make modeling and reasoning become complicated. A probabilistic ontology recognition framework is presented for multilevel human activities. The authors divide human activity into atomic gesture, manipulative gesture, simple activity and complex activity, as well as verify the feasibility of the framework by means of probabilistic reasoning[10]. In [11], the authors design an activity recognition system that integrates probabilistic inference through Markov Logic Network with the represented domain ontology. But this paper needs further research of knowledge engineering to enhance performance. A multi-domain knowledge sharing and reuse method is presented to improve the quality of service in the home environment. The paper studies the activity understanding approach based on multisensor and activity template, which can realize the recognition of user intention and the reasoning of service. However, the focus is on the reasoning and verification of robot service tasks[12].

In view of human activity reasoning research, most of the current research directions are the improvement of general ontology. Relatively speaking, there is not much research on human activity modeling and reasoning based on ontology in home intelligence space. Therefore, this paper studies the reasoning methods of human activity in intelligent space from the perspective of knowledge-driven approaches. In home environment, human's complex activities are inseparable from related objects. So, this paper takes the family intelligence space as the research background, makes full use of the field knowledge and constructs the human-object interaction

complex activity ontology model in home intelligent space system. We also establish the activity rules to semantically reason. Finally, the reasoning task of human activity in intelligent space is completed.

This paper is structured as follows: Section II covers the construction process of the activity domain knowledge model. Section III explains conceptual representation of the data information. Section IV contains the activity semantic rules based on SWRL and the overall framework. Section V discusses related work in activity reasoning. Summary and future work are presented in Section VI.

II. ACTIVITY DOMAIN KNOWLEDGE MODEL IN HOME INTELLIGENT SPACE

The home environment in intelligent space by distributing various sensors in a distributed manner can work stably, accurately, and efficiently while reducing the service robot device[13]. In order to solve the problem of interaction and fusion between information in intelligent space and the heterogeneity of hardware devices, it is necessary to uniformly represent the collected service object information. OWL (web ontology language) is an ontology language using description logic as its semantic and reasoning support. It has strong description and reasoning ability.

OWL has three sub-languages, namely OWL Lite, OWL DL and OWL Full. OWL Lite is the simplest in syntax structure of three languages. It is mainly suitable for constructing ontology with simple class hierarchy, so its expression ability is limited. OWL DL is much richer than OWL Lite. It is based on description logic. It can be used for automatic reasoning so that the computer can know the level of classification in the ontology and whether the various concepts in the ontology are consistent. OWL Full is the most expressive of the three sub-languages and is suitable for situations where require very strong expressive power. Because of its powerful expressive ability, it doesn't have efficient reasoning ability.

Therefore, this paper uses the OWL DL language to construct an ontology-based human activity model in intelligent space. The human activity model is constructed with the intelligent space system as its sensing layer. The distributed installation sensors in the intelligent space are used to obtain real-time user information and environmental information[14]. According to the data information, the domain level is divided and the concepts are abstracted. The hierarchical class structure declares it to realize the representation of human complex activity information.

The ontology-based human activity model presented in this paper organizes and fuses information related to the service object in a specific home scene. The complex human activity consists of simple actions and environmental information. So, the ontology model is divided into two domains, the user domain and the environment domain. At the same time, the information in intelligent space is hierarchically expressed in the domain of its ontology. As shown in fig. 1.



Fig. 1 Model hierarchy in intelligent space

The User Domain mainly saves basic information and activity information related to the user in home intelligent space. The Environment Domain stores classification information and location information related to objects in the home intelligent space. Attribute restrictions are added under the premise of class division. Object properties are defined by the user establishes relationships between classes. It includes the domain and value domain. Data properties are descriptions of the inherent properties of users, objects, etc, such as the user's basic information, the classification information and the physical information of the object. The knowledge model based on ontology is completed in intelligent space in fig. 2.

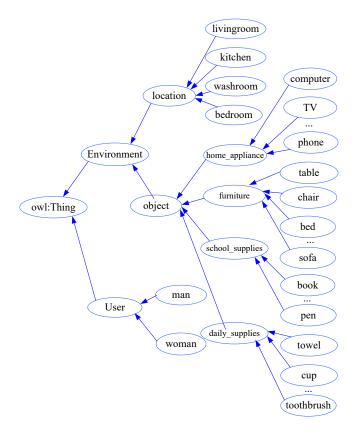


Fig. 2 The knowledge model in intelligent space

The Environment class includes the subclass object and subclass location. The object class declares the object that

exists objectively in the home environment. The location class declares the name of the room in home environment. The User class includes the subclass man and subclass woman, which represents user information.

III. CONCEPTUAL REPRESENTATION OF DATA INFORMATION

The ontology technology is used to realize information fusion and knowledge representation in intelligent space. However, there are unprocessed raw data information in reality, lack of adaptability to human activity representation and thus reducing the reasoning ability of human activity. Therefore, this paper adopts the idea of fuzzy set. It establishes data fuzzy mechanism and maps simple data description information into accurate concept representation. Human-object interaction is information about the interaction between a person and his or her environment. Human-object interaction research usually makes the following assumptions: When performing a specific activity, it involves a series of target objects. Such as, reading a book, drinking a cup, drinking a mop and cleaning the ground with a mop. Usually, objects have their respective uses and usage methods, while their respective role information in the human-object interaction is weakened. So, in general, we can represent human-object interaction by defining the user's action state and the target object that is touched. In describing the humanobject interaction which is human centered, constructing activity recognition and reasoning with human-object interaction as the core helps to recognize the interaction activity between the person and the object.

To construct the human-object relationship from the perspective of human research, we mainly choose the body, the head and the hand. The body refers to the center of gravity of the person. In the human-object interaction, many activities are done by the head and hands, such as making a phone call, operating a computer and opening a refrigerator. Based on these three parts, the interaction relationship between objects in the human and home environment is represented from the spatial distance relationship.

Using fuzzy set ideas, data information is mapped to conceptual representations through custom hierarchical partitioning. This mapping method improves the unity of ontology knowledge expression and provides support for semantic reasoning of human activity.

IV. DEFINITION OF ACTIVITY RULES

The use of ontology to construct a human activity model in home intelligent space is conducive to clear and reasonable expression of domain knowledge. At the same time, it is helpful to provide a description of the relationship between the concept and the attribute relationship for the construction of human activity rules. We use the Semantic Web Rule Language (SWRL) to establish the required rules[15]. Combining the constructed ontology knowledge base, it can not only provide powerful logical representation and reasoning ability, but also solve the problem of lack of reasoning ability.

The basic form of the SWRL rule is used to represent the derivation of premise and conclusion [16]. Both the premise

and the conclusion can include single or multiple basic propositions. The basic propositions are logical AND. The rule is body → head, Where body represents the basic form of the premise of reasoning and head represents the result of the reasoning. The premise of the SWRL rule comes from the classes, attributes, and instances of the Environment and User fields in the ontology model. The conclusions of the SWRL rules come from domain knowledge. The rule indicates content provided based on home environment information and user simple action information. It fully considers the relationship between human-object interaction in activity. The human activity inference rule base is constructed. Some rules are as follows.

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Rule1:
User(?x)^towel(?y)^haslocation(y,z) \rightarrow haslocation(x,z)
Table(?x)^furniture(?y)^subclassof(y,z)\rightarrowsubclassof(x,z)
Rule3:
User(?x)^has_act(?x,"walk") \rightarrow
hasbehaviour(?x,"walk in the livingroom")
man(?x)^has act(?x,"sit") \rightarrow hasbehaviour(?x,"sit on the sofa")
Rule5:
woman(?x)^bed(?y)has act(?x,"lie")^has dis hand(?y,"touch")
has dis head(?y,"touch")→hasbehaviour(?x,"lie on the bed")
Rule6:
man(?x)^cup(?y)^hasact(?x,"sit") ^has dis hand
(?y,"touch") ^has dis head(?y,"touch")
→hasbehaviour(?x,"sit and drink water")
Rule7:
woman(?x)^phone(?y)^hasact(?x,"walk") ^has dis hand
(?y,"touch") ^has dis head(?y,"touch")
→hasbehaviour(?x,"walk and call the phone")
Rule8:
man(?x)^book(?y)^hasact(?x,"sit") ^has dis hand
(?y,"touch") ^has dis head(?y,"close")
→hasbehaviour(?x,"sit and read the book")
woman(?x)^computer(?y)^hasact(?x,"sit") ^has dis hand
(?y,"touch")
^has dis head(?y,"close")^has dis body(?y,"close")
→hasbehaviour(?x,"sit and use the computer")
Rule10:
man(?x)^apple(?y)^hasact(?x,"walk") ^has dis hand
(?y,"touch") ^has dis head(?y,"touch")
 →hasbehaviour(?x,"walk and eat the apple")
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The intelligent space ontology provides the factual conditions of activity reasoning. The activity rule base provides the basis of inference rules. The formation of the Jess inference engine comes from two conditions. The first is to map the ontology knowledge base to the fact base in Jess through the ontology parser. The second is to parse the written SWRL rules into the rule base in Jess through the rule parser. The Jess inference engine can complete the ontology query and rule matching so that it can realize the reasoning task of

human activity. The intelligent spatial reasoning framework based on ontology model is shown in fig. 3. Relationship description (has dis hand) has dis head, Has dis body) Ontology Result of Jess Relevant visual data parser Reasoner reasoning Ontolov in Knowledge representation Intelligence space Rule:User(?x)^cup(?y)^hasact(?x," sit") ^has_dis_hand(?y," touch")
^has_dis_head(?y," touch") ->> hasbehavior(?x," sit_and_drink_water"

Fig. 3 Architecture of activity reasoning

V. EXPERIMENTAL RESULTS AND ANALYSIS

This paper uses Protégé software and inference engine JESS based on JAVA development language to implement activity reasoning. First, according to the image from the visual sensor in intelligent space, we choose the trained RPN(Region Proposal Network) network model [17] to extract the candidate box to complete data pre–processing part. The fuzzy set idea is used to realize the conceptual representation of the data and the concept is added to the ontology model, which completes dynamic updating of the ontology. Combining ontology domain knowledge and rule domain knowledge, we complete the activity reasoning task. It mainly summarizes the five categories of human activities in home intelligent space. Among them, the human activities are fetching objects, using objects, playing objects and reading/watching objects, others.

A. Implementation of ontology model

The constructed ontology model in intelligent space is shown in fig.4. The ontology part mainly involves classes, attributes and individual. In order to verify whether the constructed ontology is correct, the Tableaux algorithm is used. The algorithm is to check concepts consistency in the description logic. As shown the result of the verification in fig.5. The result is that the ontology constructed in this paper is reasonable, and the response time of each part is

Check concept consistency=8(ms), Compute inferred hierarchy=54(ms), Compute equivalent classes=2(ms). The total response time is 64 milliseconds.



Fig. 4 The ontology model in intelligent space

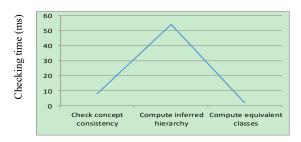


Fig. 5 The check time of each part

B. Reasoning about human activity

In this paper, the inference response time is used as a performance evaluation index to verify the timeliness of the reasoning method. The test environment is Inter(R) Core(TM) i7 x86CPU, 4 GB RAM and Windows 7.

The results are shown in fig.6 and fig.7. Fig.6 shows the relationship between the inference response time and the number of rules when the number of individuals is 100. Fig. 7 shows the relationship between the inference response time and the number of individuals when the number of rules is 50.

From fig.6 and fig.7, the response time will increase when the number of instances and rules increase. Overall, the average response time of activity reasoning is within an acceptable range, so it satisfies the reasoning of common activities summarized in home intelligent space.

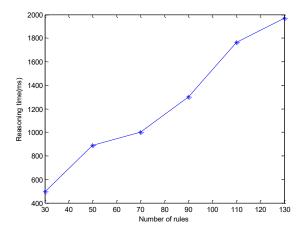


Fig. 6 The response time about rules

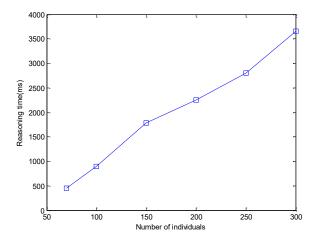


Fig. 7 The response time about individuals

VI. CONCLUSION

This paper mainly studies the activity reasoning in home intelligent space. The ontology technology is used to hierarchically express information in the intelligent space. On this basis, the corresponding knowledge rules are established and the Jess inference engine is used to match the input information with ontology in the intelligent space. Therefore, the task of human activity reasoning is completed. Experimental results show that the method has certain advantages.

However, the ontology model in home intelligent space is relatively simple, which involves a limited number of activities and further research work is needed. At the same time, how to use ontology technology to construct a complex activity model in home intelligent space from the temporal is also the direction of future research.

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