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Development and Evolution of RT Ontology for Automatic Service Generation System in Kukanchi

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***Abstract*—This paper presents a novel approach for RT Ontology development, including ontology learning and evolution mechanism. In service robotics systems, understanding the relationship between everyday objects and user intention is the key feature to provide suitable services according to context. RT Ontology has shown to be an efficient technique to represent this relationship. In the proposed method, text corpus grabbed from search engines and lightweight natural language processing techniques were used for term extraction and enabling RT Ontology automatic creation. On the other hand, ontology evolution mechanism is introduced. With these learning and evolution capabilities, the presented RT Ontology model may adapt dynamically to the changes of environment and human activities. This will help to improve the robustness of current RT service generation systems, while reduce much of required labor work for ontology development. Experiments were conducted to show the effectiveness of proposed method.**

I. Introduction

RECENTLY, many efforts have been invested in the research of service robotics, which is hopefully the solution for potential problems of the aging population in the future. Robots are expected to coexist with human and provide everyday services in human daily living environment.

In Kukanchi-"Interactive Human-Space Design and Intelligent", the body of robot system is changing from conventional single multi-purpose robot to the whole structured environment embedded in human's daily living and incorporated with distributed intelligence. Many researchers have been conducting research in this field to solve a variety of problems such as the design of intelligent space, the methods for data aggregation and sensor fusion, and especially the development of robotic service generation systems.

Robots and human now can live together in structured environment equipped with distributed sensors networks, pyroelectric sensors [1] or RFIDs [2]. Human can interact with robot system not only by voice, but also by natural pointing gesture [3].

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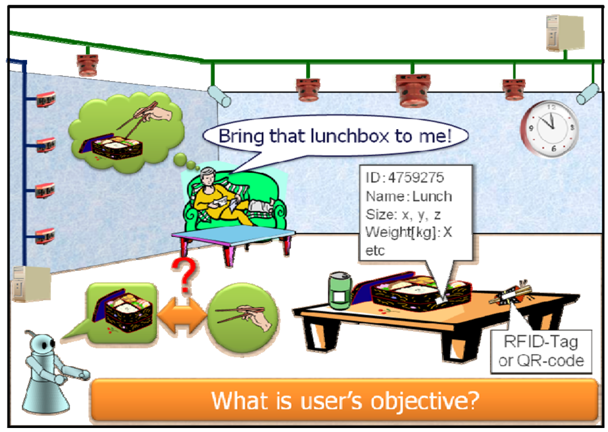

Fig. 1. The role of user's objective to RT service generation

Researches are also conducted to realize the Robot Technology (RT) services in real life. In [4] cooking support system performed cooking procedure recognition and provides suggestion via interactive display screen. In [5] librarian robot was designed to arrange books on bookshelves.

In our research, we focus on the "objects delivery" task of assistive robots, in which user can asks robot to automatically grab some objects and deliver to user's position. This is a basic and helpful RT service for the disabled and elderly users in their daily living.

We work on the improvement of "objects delivery" task by incorporating human's intention into the execution of the task. Fig. 1 shows an example of the improved "objects delivery" scenario. When the user asks for the lunchbox, robot understands that user's intention is having lunch and then it may automatically provides additional tools such as chopsticks or spoons to user.

In this example, the relationship between lunchbox, chopsticks and the eating action is very common sense to human. However, robot is still not capable of understanding this common knowledge. Therefore, in order for the robot to provide more intuitive "objects delivery" service, the common relationship between human intention and everyday objects needs to be extracted and modeled in a machine-readable format.

In previous researches, RT Ontology was proposed as a solution for the above problem. RT Ontology is an ontology created by Web Ontology Language (OWL) to represent the common knowledge of everyday human activities and related objects. The main objective of RT Ontology is to transfer this common knowledge to service robotic systems, therefore enables more intuitive human-robot interface and robot services.

Based on RT Ontology, Ukai et al has implemented a Physical Agent System which is cable of generating tsuide-tasks according to the interaction between human and objects [6]. Fukusato combined natural human-robot interface with RT ontology to generate domestic user services [7]. These researches have shown the effectiveness or RT Ontology in robotics service generation systems. However, there is not sufficient discussion on the development of RT Ontology.

This paper aims to introduce a novel method of RT Ontology learning from text data. Physical objects in human daily living are mapped to textual symbols using tagging technologies such as RFID. Then the relationship between these symbols is extracted from a text corpus collected by using Internet search engines. RT Ontology will be automatically created based on these relationships. Experiments are also conducted to show the effectiveness of proposed methods in our physical agent system.

The rest of this paper is organized as follows. Section II reviews some related research. Section III describes our system structure, followed by the detailed description of RT Ontology learning and evolution in Section IV. Section V shows experiment result and section VI makes necessary conclusion.

II. Related Research

In the research of ontology technology in service robotics, Ukai [6] proposed the RT Ontology to model the relationship between events, objects and human objectives, to generate additional tasks according to user's situation. The structure of RT Ontology was presented but the ontology learning method was not defined.

Philipose et al. [2] presented PROACT system with the abilities of extracting ADLs (Activity of Daily Living) model of from RFID sensor data, as well as mining these models from text data and Google Conditional Probabilities. However, the mining algorithm is based on structured input data downloaded from special websites such as wikihow.com, ehow.com so supporting a wide range of activities is still an open problem.

Murakami [4] applied text mining techniques to build the model of cooking procedures based on recipes description. This algorithm depends on hand-crafted text data taken from cookbooks so it may not to adapt to human activities.

Yamaguchi [8] proposed the use of multi-layer ontology with user request, robot service, robot function, robot structure, object, insertion task and recovery task ontologies to implement Semantic Robot Services framework. DODDLE-OWS was also suggested as a possible tool to learn this ontology. However, DODDLE does not provide automated ontology creation capability.

For human life pattern monitoring, Mori et al. [1] implemented probabilistic data summarization algorithm from pyroelectric sensor data to extract human's pattern of daily activities over a long period.

Niitsuma [9] presented the method to extract human activities model from the interaction with spatial memories in intelligent space.

III. System Structure

A. RT Ontology

Ontology is the formal representation of the knowledge conventionally used in Semantic Web applications. With the capability of representing the semantic relationship between symbolized concepts, ontology has been used in various other applications such as bioinformatics or health care systems.

In our work, ontology and OWL language are utilized as the mechanism to represent the relationship between environment objects and human activities.

As the initial research on automatic creation of RT Ontology, we adopt a two-layer RT Ontology model. Fig. 2 represents our RT Ontology model with some example data.

The first layer shows relationships between objects and human's intention. Here we define human intention as the possible actions that a user can do with an object. For example, regarding the postcard object, a user may want to read it or write something on it.

The second layer represents the relationship between human activities and the necessary tools. For instance, cutter or scissors are required for the cutting activity.

B. Physical agent system

Fig. 3 presents the configuration of our automatic RT service generation system. The system is built on a structured environment with distributed sensor network and RFID tagged objects.

Local data server (LDS) is the real time database which stores information from the sensor network, including human position, objects position and object status. Each tagged object will be map to a textual representation in LDS by its ID and name. RT-Post and RT-Box are robot technology enabled household devices. Pioneer 3 is the mobile robot which can navigate around the room with the

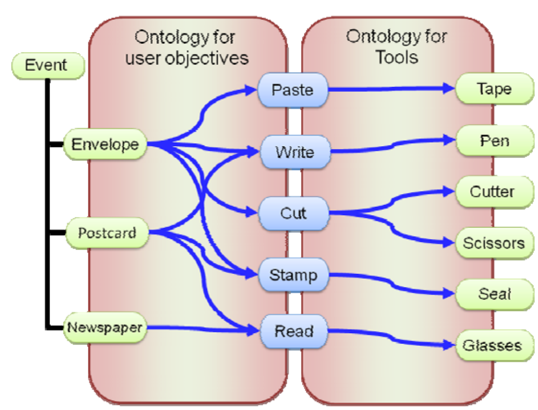

Fig. 2. RT Ontology model

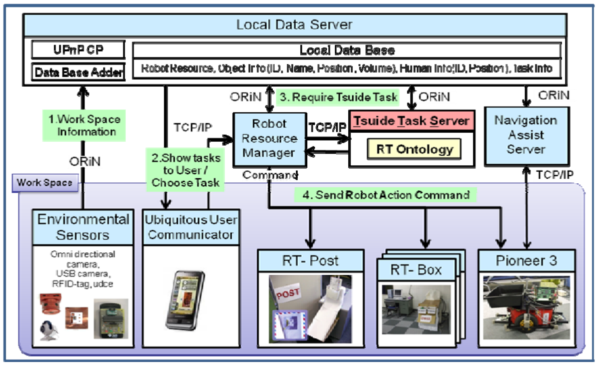

Fig. 3. Experiment system configuration.

support of the Navigation Assist Server. The interface between human and robotic system is implemented via a Ubiquitous User Communicator (UUC).

When user sends a command to the system-called main task, the Tsuide Task Server makes necessary reasoning about user's intention based on RT Ontology and generates additional tasks-called Tsuide Tasks. Tsuide Tasks are the tasks to provide the additional objects to user; these objects are called tsuide-object. Then Robot Resource Manager controls the robot and RT-devices to provide the complete service to user.

Our ontology learning and evolution method is used to develop and maintain the RT Ontology for use in the service reasoning module in this system. Its role is very important to provide the necessary services to user, regarding user's intention.

C. RT Ontology learning process

This paper proposes a novel method to develop RT Ontology by using lightweight natural language processing (NLP) techniques, together with ontology evolution mechanism. Fig. 3 shows our system structure.

For the learning process, the first step is corpus generation. Corpus generation module will get the list of available objects from an environment description file, and then sends queries to some available search engines to collect textual data related to these objects.

Learning algorithm is implemented in Ontology learning component, including some lightweight NLP techniques. Textual data in the generated corpus will be tagged by a tag-of-speech tagger, and then the output will be used to mine the relationship between objects (nouns) and actions (verbs). Finally, RT Ontology will be created base on the extracted relationship.

IV. RT Ontology Learning and Evolution

A. Environment description

In our daily living space, the total number of potential objects surrounding us may be very high. However, the set of objects that really exist in a specific environment such as living room or dining room is limited. This set of objects is the source of the potential human activities in corresponding environment.

Let $T = \{t_1, t_2, ..., t_n\}$ be the set of n tagged objects in one environment, each object t_i has a set of related common human activities $A_i = \{a_{i1}, a_{i2}, ..., a_{ik_i}\}$, $i = \overline{1, n}$. As the number of objects n and the number of activities k_i for each object t_i are limited, the total number of activities in $\{A_i\}$ is also limited.

Based on this consumption, we define the objects set T of a specific environment by a description file. Then the learning and evolution algorithm is limited within the set T to avoid unnecessary redundant data. With this approach, different environments will be described by their own description files and hence have their own RT Ontologies.

Environment description file is represented by XML structure, in which each object is denoted by two attributes: Object ID and Object name. These properties are the same as the symbolic representation of the object in LDS. Fig. 4 shows a sample environment description file.

TABLE I
Occurrence Frequency of Objects in Open ANC

knife	pen	paper	envelope	scissors
162	31179	9215	358	36

TABLE II
Co-occurrence Frequency of Objects in Open ANC

	pen	paper	envelope	scissors
knife	113	15	10	12
pen		1416	123	10
paper			112	110
envelope				10

B. Corpus preparation

Preparing sufficient corpus is very important for ontology learning. In our research, we built the necessary corpus by querying data from search engines.

Currently much of available ontologies are domain specific, such as biology or biomedical. They usually depend on special set of terms and have carefully classified corpus for learning. Unlike these ontologies, the RT Ontology describes relationship between real life objects and human activities like *"envelop"-"open"-"scissors"* or *"lunchbox"-"eat"-"chopsticks"*. The text data that contains information on these objects and relationships are sparsely distributed over text documents, regardless of document

```
<environment>
<object><id>001</id><name>pen</name></object>
<object><id>003</id><name>knife</name></object>
<object><id>004</id><name>paper</name></object>
<object><id>008</id><name>tea</name></object>
<object><id>010</id><name>tape</name></object>
<object><id>011</id><name>glue</name></object>
<object><id>014</id><name>book</name></object>
</environment>
```

Fig. 4. Sample environment description file.

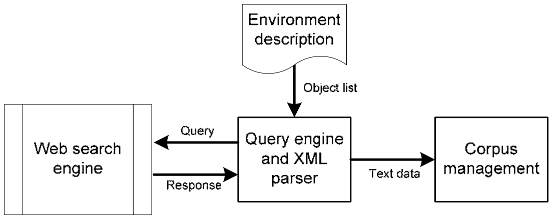

Fig. 5. Corpus generation based on search engines.

types or topics.

We investigated the Open American National Corpus (Open ANC) which includes more than 14 million words from ten different domains and in both speaking and writing context. Table I shows the occurrence frequency of five common real life objects in Open ANC. Table II shows co-occurrence of these objects in the same context. These figures show that the off-the-shelf corpus OpenANC may not be suitable for RT Ontology learning.

In order to build the corpus for RT Ontology learning and avoid getting too much irrelevant text data, our approach makes use of currently available search engines. Fig. 5 shows the process of corpus generation. From the object list *T* in environment description file, the query engine builds query sentence for each pair of objects *(t_i, t_j)*. Then the query is sent to Yahoo and Bing Web search engines by using Yahoo BOSS and Microsoft Bing APIs respectively. The XML response strings from search engines will be parsed to get only the plain text abstract element for each search result and build up the corpus.

For experiment, we worked with 16 common real life objects and generated 120 pairs of corresponding terms. For each pair of object, we collected 1000 search results from each search engine. The resulting final corpus from the two above search engines contains 35 MB of text data with about 6 million words. The average number of occurrence for each term is 30,000 and co-occurrence of every term-pair is 2000. Comparing with Open ANC, our corpus is more compact but contains less redundant data.

C. RT Ontology learning from text data

After having the above corpus, the RT Ontology learning problem becomes the problem of mining relationship between nouns (represent for objects) and related verbs (represent for tasks). Our proposed learning algorithm is divided into three steps:

1) Step 1: Term extraction by lightweight NLP techniques.

Given two arbitrary objects in the set *T*, represented by the two nouns t_i and t_j, we consider four sentence structures that describe the relationship between t_i and t_j, as below

- *<"… t_i do something with t_j …">*
- *<"… tj do something with ti …">*
- *<"… do something with ti and tj…">*
- *<"… ti and tj do something …">*

As the verb phrase "do something" in these sentences may represent the potential task related to t_i and t_j, we extract these verb phrases using part-of-speech tagging technique.

For each sentence in the corpus related to the noun t_i, the words surrounding t_i is tagged by the LingPipe part-of-speech tagger. To reduce noise and calculation cost, for each noun t_i, only N_w words that stand before and after t_i in the sentence are considered for tagging. N_w ranges from 3 to 6 for tuning the algorithm. After tagging, the verb terms with "vb", "vbg", "vbd" or "vbn" tags are converted to simple form. Then a collection of verb terms that co-occurred with the noun t_i is built with corresponding co-occurrence frequency. From these verb terms, a set of possible tasks for each object t_i is generated $A_i = \{a_{i1}, a_{i2}, ..., a_{ik_i}\}$, $i = \overline{1,n}$ with corresponding frequency $F_i = \{f_{i1}, f_{i2}, ..., f_{ik_i}\}, i = \overline{1,n}$.

2) Step 2: Task candidate selection.

In this step, the map between objects and tasks is created. Given two objects t_i and t_j with corresponding task sets A_i and A_j, a link between t_i and t_j is created for each common task $a \in A_i \cap A_j$. The link is labeled by task name *a*. By applying this step for all possible pair t_i and t_j, we create a graph in which the nodes represent objects in *T* and the edges between two arbitrary nodes *i* and *j* represent the list of candidate tasks that correspond to t_i and t_j. Fig. 6 shows an example task map with five objects. For each path in the map, weighting value is set by the corresponding term co-occurrence frequency number.

3) Step3: RT Ontology creation.

RT Ontology is created based on the object-task graph from step 2. For each node in the graph, by following the edges started from the node, information on the corresponding object and task is annotated to RT Ontology. We use Jena framework to implement this module.

Noisy text data in the corpus may affect RT Ontology learning by resulting in irrelevant candidate tasks. To deal with this problem, we employ the weighting value of each path in the object-task map as the integer feature of each entity and individual in RT Ontology. As for each object in RT Ontology we get the same number of 2000 queries from search engines, this weighting value may represent the relatedness of different tasks for each object. Higher weighting value may indicates more common task.

D. RT Ontology Evolution

Typically, for each service robotic system, the RT Ontology learning process is activated one time during the system set up. However, after setting up the system, RT Ontology needs to have an evolution mechanism to reflect and adapt to the dynamic of environment and human activities. There are some scenarios that require RT Ontology evolution:

- When new object is tagged and installed into the system.
- When there are changes in human's action pattern or preference.

At the initial phase of RT Ontology development, we

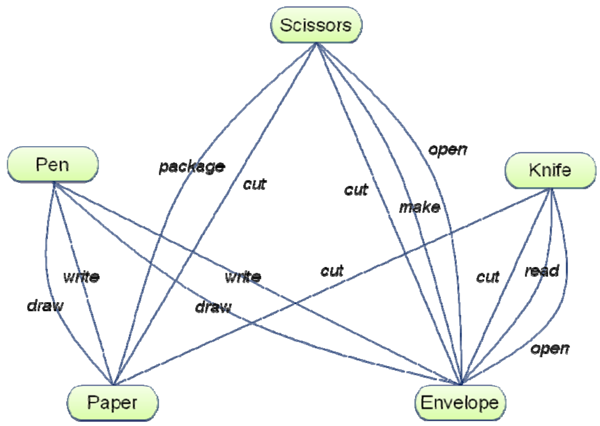

Fig. 6. Example task map.

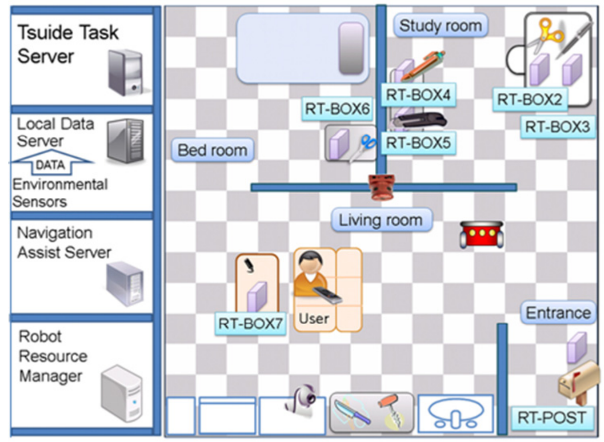

Fig. 7. Layout of experiment environment

implement two ontology evolution mechanisms.

1) Adaptation to changes in environment

In order to install new objects into the system, these objects must be tagged and registered with the Local Database Server (LDS). After registering, the list of tagged object in LDS will be updated and RT Ontology learning process is activated to add more information about the new objects. Therefore Tsuide-Task server is able work with the new object immediately without manually RT Ontology annotation.

2) Adaptation to changes in human action pattern

In the initial phase of RT Ontology development, we employ a simple method using the weighting value in RT Ontology to realize the adaptation of RT Ontology with human action pattern.

In RT Ontology, each object will be associated with multiple tasks; each task is assigned with one weighting value to represent the relatedness of the task with corresponding object. This weighting value can be changed to reflect user's preference.

Using the UUC device, user can select one object in the environment and activate the "delivery" task. Based on RT Ontology and weighting value, UUC can make recommendation about tsuide-objects and let user selects the suitable object. The weighting value for each tsuide-object will be increased after it is selected.

V. Experiments

A. Experiment environment

Experiments are conducted in a laboratory room which imitates the real living environment in an area of 50 m^2, including bed room, living room and study room. A sensor network has been installed inside this area for human and environment monitoring. RFID tags are embedded under the carpet for robot navigation. Fig. 7 shows the layout of experiment environment.

To enable human-robot interfacing, we developed the UUC device adopting augmented reality concept. It can render a virtual map of the room with object's image and location in real time as user walks around. Fig. 8 shows our UUC device. User can select main task and tsuide-tasks directly via the touch screen.

B. Experiment scenarios

Experiments are conducted to verify the effectiveness of our proposed ontology learning method in a service robotic system. Two test cases were considered.

Case 1: System setup. We tag 16 common objects and register them with LDS. Then the RT Ontology creation module is activated to create a brand new RT Ontology and the Tsuide-Task server is associated with the new ontology. Finally we try to test the output RT Ontology by activating the delivery task with different objects.

Case 2: New object installation. After the system is set up successfully with RT Ontology, when user requests the envelope from mail box, robot is able to provide a pair of scissors as the tsuide-task. Then a new cutter is installed into the workspace by tagging and registering with LDS. In this case, RT Ontology learning module should be activated and the system should be able to provide new services related to the cutter.

C. Experiment result

Case 1: The RT Ontology with 16 objects was automatically built. These objects include pen, scissors, knife, paper, envelope, lunchbox, chopsticks, tea, coffee, tape, glue, eye-glasses, newspaper, book, telephone,

Fig. 8. Ubiquitous User Communicator

phonebook.

We test the output RT Ontology by activating two “object delivery” tasks with different main objects.

- *First test:* Request newspaper as the main object. Tsuide-Task server automatically proposes eye-glasses as tsuide-object.
- *Second test:* Request the envelope as the main object. Tsuide-Task server proposes scissors as tsuide object.

Case 2: After the installation of the new cutter, our system successfully recognizes and activates the new cutter’s service. RT Ontology sets cutter as a tool for cutting and it may be used as an alternation for the scissors. If user requests the envelope while the scissors is not available, the cutter will provided with the envelope as the tsuide object.

VI. Conclusion

In this paper, we present our method for multi-layer RT Ontology automatic learning from textual data with corpus gathered from search engines. The proposed automatic development method helps to reduce much of labor work for manually RT Ontology creation. Experiment results also showed the improved adaptability and robustness of current RT service generation system adopting our methods.

The paper introduced the initial achievement in the research of RT Ontology automatic development. Future works will focus on the improvement and evaluation of RT Ontology. Other data sources such as life log system should be considered for RT Ontology creation to reduce the noise data. The evolution process could be improved as well with human preference learning based on RT Ontology encoded activities.

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