Activity Recognition using Context-Aware Infrastructure Ontology in Smart Home Domain

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***Abstract*—Nowadays, activity recognition has been proposed in several researches. It is attractive to improve the ability of the activity recognition system because existing research on activity recognition systems still have an error in an ambiguous cases. In this paper, we introduce the novel technique to improve the activity recognition system in smart home domain. We propose the three contributions in this research. Firstly, we design the context-aware infrastructure ontology for modelling the user's context in the smart home. The innovative data, human posture, is added into the user's context for reducing the ambiguous cases. Secondly, we propose the concepts to distinguish the activities by object-based and location-based concepts. We also present the description logic (DL) rules for making the human activity decision based on our proposed concepts. Lastly, We conduct the Ontology Based Activity Recognition (OBAR) system for two purposes: to recognize the human activity, and to search the semantic information in the system, called semantic ontology search (SOS) system. The results show the system can recognize the human activity correctly and also reduce the ambiguous case.**

***Index Terms*—Activity recognition, Context-aware infrastructure ontology, Ontology based activity recognition, Semantic ontology search**

I. INTRODUCTION

The proportion of people, who have old age, increases gradually every day because of the growing of technology. High technology helps human do medical treatment and doctor diagnose diseases easier. However, most of old people still suffer from living alone in home without any health supporter because they are disability to take care of them. Thus, several healthcare systems have been introduced to help the doctor such as diagnosis, medical and disease prevention treatment, and prevent the diseases. Nevertheless, symptomatic information that the doctor receives from the patient at that time may not enough for diagnosis because the doctor will obtain the patient's condition, when the patient feels sick. Accordingly, the doctor cannot know real causes of disease. Therefore, human activity recognition system is very important for healthcare system to recognize what activity the patient does in each day.

At present, Home Sensor Network (HSN) is developed under Smart Home (SH) concept [1]. The SH concept gathers several technologies to produce the ambient intelligence in home i.e. Wireless Sensor Network (WSN), data communication, or security. HSN technique uses various kinds of sensors to build into the home appliance or furniture such as sofa, chair, or electric stove. The HSN data is executed according to simple condition. For example, [2] proposed the activity recognition system based on how long user spends time on each home appliance. However, they still have many problems that these systems are unable to justify what is the current user activity. For example, when sensors on TV and electric stove are activated at the same time, the system cannot know now the user is interacting with either TV or electric stove. Moreover, user normally has individual pattern to perform each activity depending on lifestyle, time, or location. It is a challenge to recognize the human activity more accurate.

From above problems, we identify the three contributions in this paper and setup a target in 13 activities, illustrated in table I. Firstly, we propose the context-awareness in home, which is home sensor, human location, time, and human posture for activity recognition. This approach addresses the difficulty by explicit the huge information from the various kinds of sensors

TABLE I
TARGET ACTIVITIES IN THIS RESEARCH

Target activities	
- Sitting & relaxing	- Wash dish
- Sitting on the toilet	- Take a bath
- Watching TV	- Cooking
- Working on computer	- Make a drink
- Eating or drinking	- Sweep the floor
- Sleeping	- Scrub the floor
- Lying down & relaxing	

through the context-aware infrastructure ontology. Our ontology can model each activity by the location, human posture, sensor, and so on. Secondly, object-based and location-based concepts are developed for making a decision. Some activities rely on the object. For instance "sweep the floor" activity can happen for all room in home. On the other hand, occurrence of some activities depends on the location. For instance, usually user cooks in a kitchen, takes a bath in a bathroom, or sleeps in a bedroom. We also present a description logic (DL) rules based on above two concepts for making a decision. Finally, we develop the Ontology Based Activity Recognition (OBAR) system by NECTEC's recommender management framework [3]. We apply the recommendation framework to the activity recognition. OBAR system can recognize the activity based on user's context. Moreover, OBAR system also expand into the semantic ontology search (SOS) system using a shared conceptualization between classes in ontology. Our OBAR system exhibit the result of human activity in each time accurately.

This paper is organized as follows: in section II, we briefly describe background and related works. Section III explains our system architecture. The context-aware infrastructure ontology is introduced in section IV. Next, we describes object-based and location-based concepts, which are used in the description logic rules. Section VI addresses the OBAR system for activity recognition and semantic search in SOS system. After that, in section VII, we show the experiment and resultant of activity recognition. Finally, conclusion and future works are in section VIII.

II. BACKGROUND AND RELATED WORKS

Until now, activity recognition systems have been proposed from several years. Several researches introduced the way to recognize the activity in several techniques. However we can divide into two main approaches. First is sensor-based approach. Second is ontology-based approach.

For the sensor-based approach, there are two principle techniques: Body Sensor Network (BSN) and Home Sensor Network (HSN), for activity recognition. The concept of the BSN technique [4] [5], is to attach the sensor on the body part of user in order to collect the various kinds of information such as vital sign, energy, or correlation of acceleration data. However, the drawback of this technique is the data is not enough for recognition in some cases. For instance, although single data from accelerometer sensor can recognize some activities such as walking, sitting, or running, it cannot classify more specific activities, if human interact with object as "Watching TV" activity. Philipose, et al. [6] proposed an RFID-detecting glove to detect the activities from the interacted object. Even though, it can solve the problem of unknown object, what user is interacting, it is inconvenient for user to wear the glove all the time. Consequently, HSN has been proposed [7]. The advantage of this HSN technique is that there is no need to attach any sensors on human body. The system recognizes the human activities by monitoring what the home appliance is in use and how long user spends time on appliances. Nonetheless, several sensors are required in the HSN technique to built in the home facility such as toilet, TV, and bed.

The ontology-based approach used the knowledge engineering to define a semantic of context information to explicit and formal specification of a shared conceptualization [8]. OWL web ontology language [9] has been exhibited in several researches to build the activity ontology model and classified the activity based on context data. Riboni, et al. [10], proposed the solution to classify the activity based on the OWL-DL. They focused on the location information because the current symbolic location of a user can give useful hints about which activities s/he can or cannot perform. Moreover, they also link the concepts of symbolic location and artifact by "hasArtifact" concepts. Nonetheless, it is not support for the artifact which has dynamic location such as broom, mop, or chair. In this paper, we are not use only the location information but also combination between location and object information. In these sense, object will has the location itself. The system realize the object's location although the object's location is changed.

Generally, the most common ontology-based approach for activity recognition consists of a specific semantic data from observation of smart home domain such as time, user's location, or object [11] [12]. Although, the existing researches introduced the activity recognition

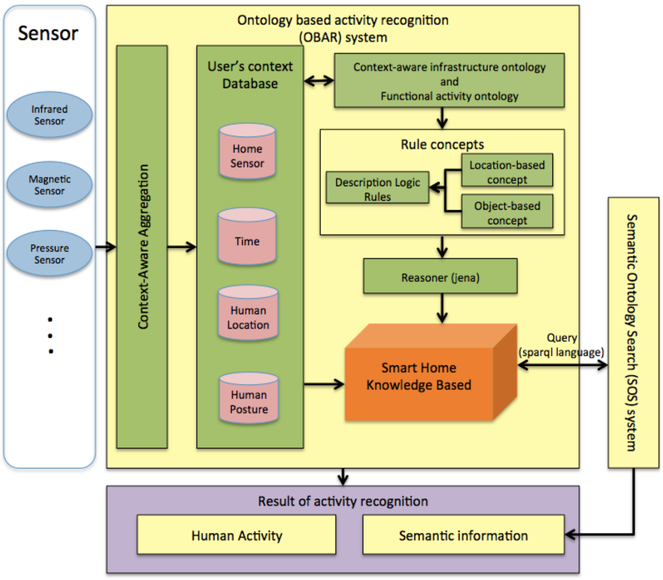

Fig. 1. Architecture of Ontology Based Activity Recognition system

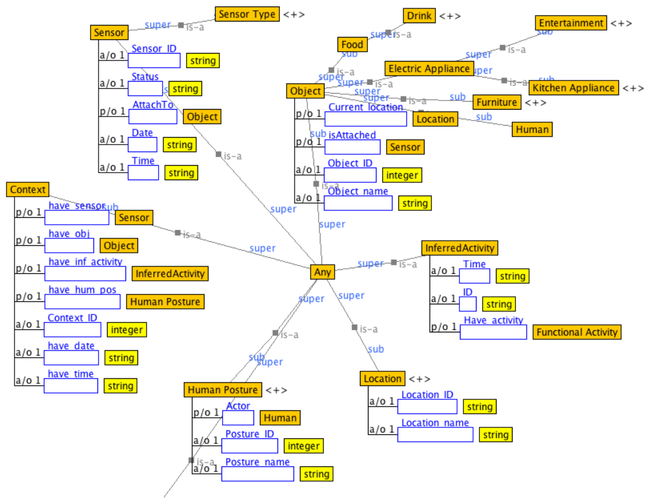

Fig. 2. Context-Aware Infrastructure ontology

based on ontology approach, it still needs to improve recognition's ability in some ambiguous cases [13]. For example, Personal Computer (PC) is turned on while sensors at sofa and chair are activated and user's location is in living room. There are three possible activities; "Working on computer", "Sitting & relaxing" or "Lying down & relaxing". For our approach, we include the body posture data into the user's context for reducing the ambiguous cases in activity recognition system.

III. The System Architecture

From our proposed, we aim to implement the ontology based activity recognition (OBAR) system using context-aware infrastructure ontology and object-based and location-based concepts. The system architecture is illustrated in Fig. 1. For the SH domain, we can observe the huge data in SH from various kind of sensors. For example, infrared sensors are used to detect the position of user. The human posture can obtain by ultrasonic sensor. All of observation data from sensors, called user's context, will collect into the database. Based on user's context, the context-aware infrastructure ontology can be designed by Hozo application [14]. Hozo is an environment for building/using ontologies based on a fundamental consideration of "Role" and "Relationship". For the OBAR system, we use the description logic rules to explict the human activity based on two concepts: object-based and location-based concepts. Reasoner's Jena API [15] is used to compile the DL rules before store a new activity instance into the SH knowledge based. SH knowledge based can be used to two purposes: to recognize the human activity, and to search the semantic information through the semantic ontology search (SOS) system.

IV. Context-Aware Infrastructure Ontology

Generally, people perform the activities depending on lifestyle of each people. Context-aware information in SH is a meaningful data for analysing the human activities in home. We can obtain the context-aware information through various kind of sensor and we can perform this information as the user's context for recognition the human activity.

Fig. 2 presents the semantic of each class and relationship between classes through the ontology. There are two principle properties using in this ontology: data property and object property. The data property is used to identify an "attribute-of" of each class. The object property is used to define a "part-of" relationship between two classes. In our design, we have seven classes, which can be divided into two ontologies. The main ontology is context-aware infrastructure ontology. Second is functional activity ontology. For context-aware infrastructure ontology, it consists of six classes, which are: *Location* class: to define a location's name in smart home, *Sensor* class: to identify the sensor type and to check the usage of human, *Object* class: to describe a type of object in smart home, *Human posture* class: to recognize the human posture in each period of time, *Context* class: to gather the user's context data for activity recognition, and *InferredActivity* class: to map between *Context* class and *Functional Activity* class.

Considering in the relationship between classes, "AttachTo" is a "part-of" property of the *Sensor* class (e.g., pressure sensor, gyro sensor, infrared sensor) that links to the *Object* class (e.g., sofa, groom, bed). On the other hand, *Object* class also has an invert function with *Sensor* class, "isAttached" property. Moreover, "Current_location" is also a "part-of" property of *Object* class that links to the *Location* class (e.g., living room, kitchen, bed room). For this reason, we can infer what object is using and where the object's location is by these semantic data. For example, "Sensor id = 1" is activating. We can get various kinds of semantic data from this knowledge. First, we can know which object is using based on "AttachTo" property. In the same way, object's location can be realized from "Current_location" property in *Object* class. In our design, we also give a "human" is a one sub-class in *Object* class. Thus, we can perceive the human location by "Current_location" property in *Object* class.

Generally, it is not an easy task for knowing the lifestyle of human in home. Since each human has the different way to perform the activity. Some activity events are occurred in specific time for each day. Hence, time can be used to distinguish the activity in specific detail. For example, we can know the "Eating & drinking" activity, which is for breakfast, launch, or dinner based on time. In addition, it is very important for further analysis i.e. healthcare system needs to know the time when patient have a meal in each day. Thus, if we know the lifestyle of human in home, we can predict, which activity will occur in specific time. For instant, human take a bath twice a day, after wake up and before sleeping. The system can predict the "take a bath" activity, if user wake up in the morning and go to the bathroom.

Our approach, we also include the *Human posture* class into the context-aware infrastructure ontology. Since the existing researches used the context data, which received through several sensors, it has a traditional problem when several objects or sensors are activated at the same time. We cannot know, which object is interacted by the user. As a result, the system has several possible activities at the same time. We define this problem as "*ambiguous activity problem*". Nonetheless, this paper attempt to solve and reduce the ambiguous activity problem by adding the human posture data into the user's context. For example, most of systems classify the "Sleeping" activity when sensor, which is attached on the bed, is activated. However we cannot always justify the activity as "Sleeping" because s/he may sit on the bed and read a book or sit on the bed and watching TV. Consequently, human posture data become a one of necessary information that SH domain should have to have for activity recognition. To achieve the human posture data, [16] proposed the range-based algorithm for human posture classification in home. Range between body part of human is investigated in order to distinguish the human posture such as "Standing", "Sitting", and "Lying down".

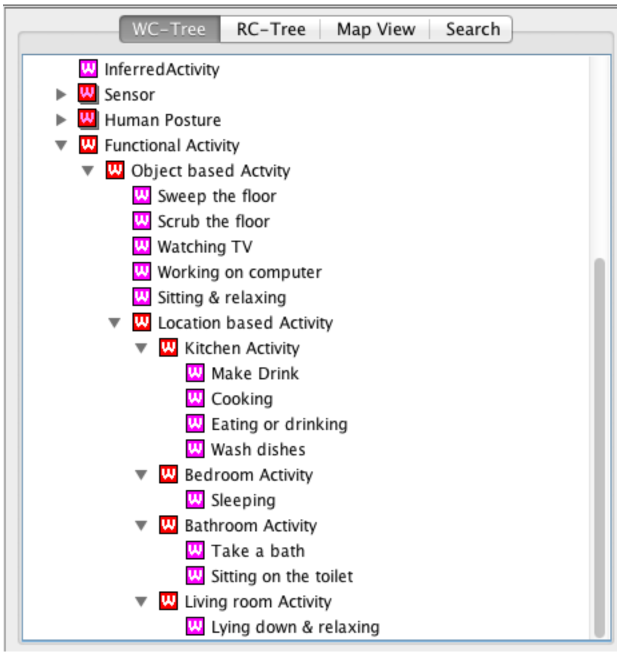

Fig. 3. Functional activity class

The functional activity ontology is designed for definition of the activities. The super class, *Functional Activity* class, is mapped to the *Context* class through *InferredActivity* class. The *Functional Activity* class is represented in hierarchy and shown in Fig. 3. In our design, we use the data from *Context* class to recognize the activities based on two concepts: object-based concept and location-based concepts.

V. Object-based and Location-based Concepts

For activity recognition, the object-based and location-based concepts have proposed in this paper. Fig. 3 illustrates the *Object-based activity* class and *Location-based activity* class in functional activity ontology. For the object-based concept, activity event occurs, when human uses the object to do something such as watching TV, working on computer, or sleeping in the bed. Usually, there are two purposes for using object: direct purpose and multi-purpose. Direct purpose means the object that can be inferred to only one activity. For example, broom is used only for sweeping the floor in home. TV is used for watching the TV program. Multi-purpose means the object that can be indicated to many activities. For example, human use chair for several proposes: sitting on the chair for working on computer, and sitting on the chair for having a meal. Although, the system can classify more specific activity through this concept, it produce a lot of the ambiguous activities when objects are activated at the same time.

Therefore, the location-based concept is proposed to recognize the activity, which occurs in specific location. For example, cooking activity has to be performed at kitchen, or taking a bath activity is done at bathroom only. This is a useful concept because it can cut-off some objects that are activated outside interesting areas. Furthermore, the location-based concept is also limit the activity should not out of interesting area. However the disadvantage of this concept is that it cannot work well for activity, which can be done in any location. For instance, the user performs the sweep and scrub the floor activity at all room in the home.

To process these two concepts, the aggregate data from database is served into the system. Then, the DL rules are created by modeling and linking between an activity instances and inferred activity instance. At this point, we can create the new data for SH knowledge base from the DL rules. The DL rules are designed into an object-based rule and a combination of object-based and location-based rule. The scheme of object-based rule, we focus on two user's context: object and human posture.

Example 1: From the observation data, the user can use the broom only for sweeping the floor. Thus, we can apply the object-based rule for classifying the "Sweep the floor" activity. The rule of "Sweep the floor" activity is defined and shown in a term of natural language for understanding as below.

$$\begin{aligned} Sweep\ the\ floor \sqsubseteq\ & Functional\ Activity \\ & \sqcap\ use(Object.Furniture(Broom)) \\ & \sqcap\ HumanPosture(Stand) \end{aligned}$$

The above definition, the "Sweep the floor" activity event occurs, when the broom is used and human posture is stand. Based on the target activities in table I, there are five activities that can be classified by object-based rule, which are "Sweep the floor", "Scrub the floor", "Sitting & relaxing", "Watching TV", and "Working on computer". However above example rule is represented in natural language. The system cannot understand from this rule. In our system, we implement the rules by Jena language. Fig. 4 shows the rule written by Jena syntax for "Sweep the floor" activity.

```
Linking_InferredActivity_instance_id_1_to_Context_0: (?x rdf:type ns:
        Context) (?x ns:has_have_obj ?y0) (?y0 rdf:type ns:Broom) (?x ns
        :has_have_hum_pos ?y1) (?y1 rdf:type ns:Stand) -> (?x ns:
        has_have_inf_activity ns:InferredActivity_instance_id_1) (?x ns:
        has_rule_name '
        Linking_InferredActivity_instance_id_1_to_Context_0')
```

Fig. 4. Example rule for "Sweep the floor" activity in Jena syntax

For the combination of the object-based and location-based rule, We add the location information, including both human location and object's location, into the user's context.

Example 2: Let's consider the kitchen location. There are several possible activities that the user can perform in the kitchen such as "Cooking", "Washing a dish", "making a drink", and "Eating & drinking". Therefore, the system will focus only on these four of activities and ignore other activated objects, which are not placed in the kitchen. The example below indicate the rule for "Cooking" activity in the natural language.

$$\begin{aligned} & Cooking \sqsubseteq Functional\ Activity \\ & \sqcap\ use(Object.Electric\ Appliance(Electric\ Stove)) \\ & \sqcap\ Object.Human.Current\_location(kitchen) \\ & \sqcap\ HumanPosture(Stand) \end{aligned}$$

The rest of target activities such as "Sleeping", "Taking a bath", or "Sitting on the toilet", have to use the combination of the object-based and location-based for making a decision because these activities have the static location. This rule is also programmed in Jena as shown in Fig. 5.

```
Linking_InferredActivity_instance_id_2_to_Context_0: (?x rdf:type ns:
        Context) (?x ns:has_have_obj ?y0) (?y0 rdf:type ns:Electric
        stove) (?x ns:has_have_hum_pos ?y1) (?y1 rdf:type ns:Stand) ->
        (?x ns:has_have_inf_activity ns:InferredActivity_instance_id_2)
        (?x ns:has_rule_name '
        Linking_InferredActivity_instance_id_2_to_Context_0')
```

Fig. 5. Example rule for "Cooking" activity in Jena syntax

VI. ONTOLOGY BASED ACTIVITY RECOGNITION SYSTEM

The ontology based activity recognition (OBAR) system composes of three sub-components. Firstly, the database is used to collect the data from various kinds of sensors. Sencondly, the ontology is defined a semantic of user's context and functional activity. Finally, the DL rules make the activity decision based on user's context. The OBAR system is developed belonging to NECTEC's Recommender Management Framework. This framework is a tool for implementing the ontology application. Jena API is also used to expand this framework. To achieve the OBAR system, there are two main steps: mapping step and setting up rules step.

To manage the database through this framework, D2RQ [17] is used to transform the relational database into resource description framework (RDF). RDF is a standard model for data interchange on the web. First step, we have to map between tables in database and classes in ontology file via NECTECs recommender management framework. Class in the ontology will perceive the data in database through this step. The relationship between two entities can be a many-many relationship. For instance, *event* table consists of event_id, time, activate object_id, and location_id. Several objects can activate at one time, and one object can be activated in different time depending on usage. Data property and object property are also mapped in this step. The data property map between table column in the database and "attribute-of" property in the ontology. The object property is a "part-of" relationship between two classes in the ontology, so we use a foreign key to connect between two tables, shown in Fig. 6.

For the setting up rules step, all designed DL rules in section V will be converted into the Jena syntax. Built-in reasoner will compute the rules for the new data and store in the SH knowledge base. Then, instance of *InferredActivity* class is created in order to link with rules. Fig. 7 illustrates the instance of "Sweep the floor" activity in Jena syntax. At this stage, we have rules for decision the activity and instances of activity. If an input context comes to the system and is consistent with the rule, which is linked with the instance of activity, the system will infer to the activity as the result of recognition.

VII. EXPERIMENT AND RESULTS

Accordingly, the OBAR system is implemented based on semantic web service. System can execute both server and client sides. As described in introduction section, there are two main objectives of the OBAR system. First is to recognize the human activity in smart home domain. Second is to search the semantic information such as user's context and human activities based on time.

To achieve the first objective of OBAR system, the system gains the data from the database, which is the

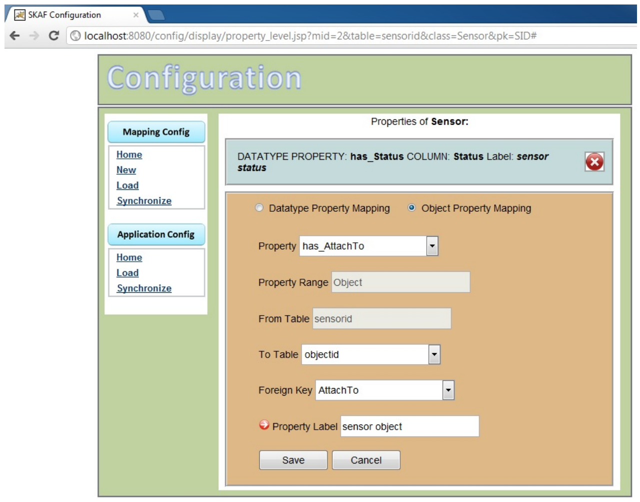

Fig. 6. Object property mapping

```
[InferredActivity_instance_id_1: (?x1 rdf:type ns:Functional_Activity
    ) (?x1 ns:has_name ?y0) regex(?y0 '(.)*Sweep_the_floor(.*)') ->
    (ns:InferredActivity_instance_id_1 ns:has_Have_activity ?x1) (ns
    :InferredActivity_instance_id_1 ns:has_Time 'morning') (ns:
    InferredActivity_instance_id_1 ns:has_ID 'uid_1') (ns:
    InferredActivity_instance_id_1 rdf:type ns:InferredActivity) (ns
    :InferredActivity_instance_id_1 ns:has_rule_name '
    InferredActivity_instance_id_1')]
```

Fig. 7. Instance of "Sweep the floor" activity in Jena syntax

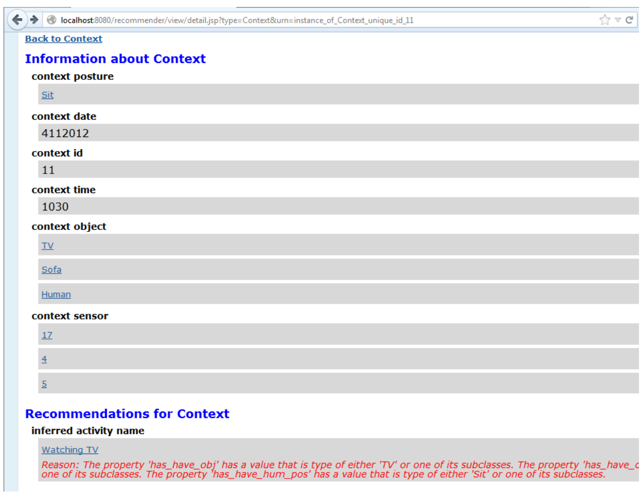

Fig. 8. Result of activity recognition at 10.30 AM.

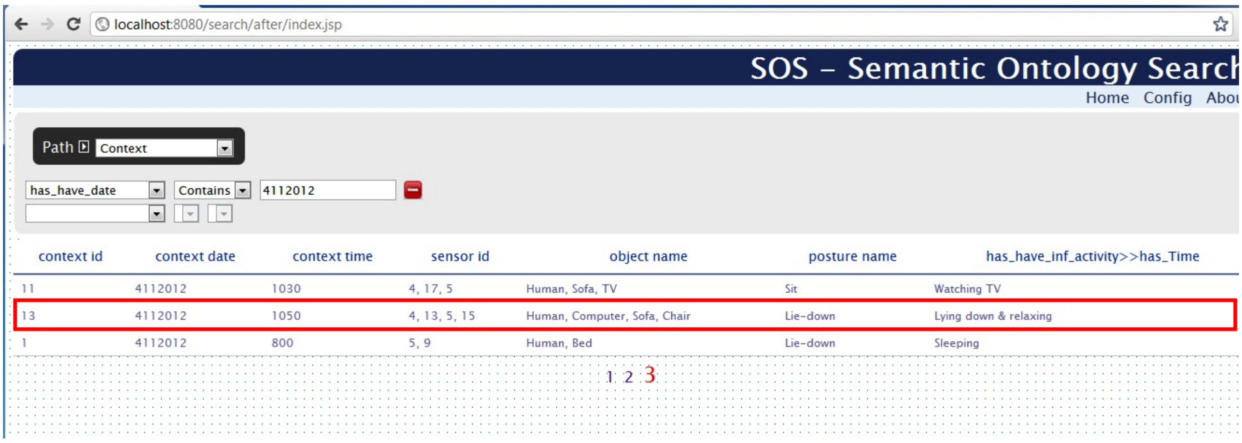

Fig. 9. Result of SOS system at 11th April 2012

user's context. User's context comes from *Context* class in context-aware infrastructure ontology. In Fig. 2, the *Context* class consists of several object properties such as *Sensor* class, *Object* class, and *Human posture* class. This *Context* class can cover all of semantic data, including location information. Therefore, the data in *Context* class is suitable for the input data for the OBAR system. *InferredActivity* class is also used for linking between the *Context* class and the *Functional Activity* class.

We investigated the experiment by using the input data in one day, which is performed by only one home user. This input is fetched into the database every five minutes. Fig. 8 illustrates the example result for activity recognition at 10.30 AM.

From the Fig. 8, the result is shown in two parts: information about context, and recommendations for context. For the information about context, the human posture, date, time, activated object, and so on are displayed in first part. The detail information is also provided when the user clicks on the hyperlink link.

The recommendation context part or activity recognition part shows the resultant activity from information in context part. This part cooperates together between the DL rules and user's context. Not only the result is presented in this part, but also the reason for choosing the activity is also provided.

For the second objective of OBAR system, the semantic ontology search (SOS) is implemented for searching the semantic information. SPARQL, the language query, is used to query the data from RDF file. In the SOS, we can retrieve the data by date, time, object, and so on. Fig. 9 shows the result when we input the date = 4112012 (11th April 2012) into the SOS system. The result in SOS system displays the id of context, date, time, id of sensor, the activate object, posture name, and activity.

From the Fig. 9, context id 13 exhibit the ambiguous case when several object are activated at the same time. Even though the computer object is being used, the resultant activity is not the "Working on computer". If we consider in the human posture, it is less possible that user lying down on the chair, while working on the computer. Therefore, we predict this possibility that human may "lying down & relaxing" on the sofa.

VIII. Conclusion and Future Works

This paper introduced the novel context-aware infrastructure ontology in smart home domain for activity recognition. We aim to propose three goals in this paper. First is a model of the ontology for activity recognition in SH, which consists of the user's context such as human posture, human location, sensor and so on. The result from this ontology showed the advantage overcome the existing system when we add the specific information, human posture data, into the ontology. Second, we present the object-based and location-based concepts to distinguish the activities. We also introduce the description logic (DL) rules for decision the human activities. Third is ontology based activity recognition (OBAR) system. OBAR system is developed based on first two goals. The outputs of OBAR system show the resultant activity based on user's context. Some of ambiguous cases are also solved in the OBAR system. Moreover, the OBAR system is not only used to recognize the human activity, but also used to search the semantic information e.g. object, sensor, or human activity by SOS system. The SOS system presents the ability of ontology concept via the shared conceptualization.

Although the system can recognize the human activity, it still needs to improve the complex rules for more specific activities. We also plan to use the human activity data to further processing, such as gathering the human activities in one day to conform an activity of daily living (ADL). Then, we plan to used the ADL for analyzing the human behavior or lifestyle of human.

ACKNOWLEDGMENT

The authors gratefully acknowledge the NECTEC's Recommender Management Framework from National Electronics and Computer Technology Center (NECTEC) for implementing the system of this research.

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