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Description	

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High Performance Activity Recognition Framework for Ambient Assisted Living in the Home Network Environment

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SUMMARY Activity recognition has recently been playing an important role in several research domains, especially within the healthcare system. It is important for physicians to know what their patients do in daily life. Nevertheless, existing research work has failed to adequately identify human activity because of the variety of human lifestyles. To address this shortcoming, we propose the high performance activity recognition framework by introducing a new user context and activity location in the activity log (AL^2). In this paper, the user's context is comprised by context-aware infrastructure and human posture. We propose a context sensor network to collect information from the surrounding home environment. We also propose a range-based algorithm to classify human posture for combination with the traditional user's context. For recognition process, ontology-based activity recognition (OBAR) is developed. The ontology concept is the main approach that uses to define the semantic information and model human activity in OBAR. We also introduce a new activity log ontology, called AL^2 for investigating activities that occur at the user's location at that time. Through experimental studies, the results reveal that the proposed context-aware activity recognition engine architecture can achieve an average accuracy of 96.60%.

key words: *activity recognition, context sensor network, human posture, range-based algorithm, ontology-based activity recognition, activity's location in activity log*

1. Introduction

Nowadays, concern about healthcare has become an essential aspect in daily life, not just for the elderly but also for young people. Until now, the trend of healthcare systems has become more popular than in the past, especially in the smart home domain [1]. A home health care (HHC) system [2] has been proposed to help people achieve better health at home. The HHC system assists residents by providing in-home nursing assistance. In this system, basic health information is collected from the home user. However, basic health information alone might not be enough for diagnosis of disease in some cases. It is difficult to accurately assess an individual's health condition because each person has a different lifestyle. Consequently, a human activity recognition system has been proposed to capture what humans do on a daily basis. The results obtained from such a human activity recognition system are relevant for several purposes, including healthcare systems. This kind of information can aid in physician diagnoses, enabling them to make more accurate recommendations on how to prevent disease.

When considering activity recognition in the smart home domain, there is a huge amount of information affecting recognition accuracy. Existing research has attempted to classify human activity based on surrounding information in the home. However, most of the research encounters a low recognition accuracy due to various kinds of problems. For example, the system can sometimes indicate several possible resultant activities, called the "ambiguous activity problem" [3] when several objects are being used at the same time. Moreover, each human has their own way of performing each activity. One activity can be performed in a different order depending on the person. Due to these problems, low accuracy results appear in the activity recognition system and it cannot be used for processing by the intelligence system to enhance quality of life and support people in their daily activities in the home.

In what follows, we aim to develop the high performance activity recognition system by introducing two pieces of information: a new user's context and activity's location in the activity log (AL^2). Moreover, this research proposes not only the high performance in classification, but also yields reliable and reasonable results. In this research, target activities are selected based on the location in home. We focus on target activities that users often perform at home, examples of which are shown in Table 1. The recognition results can be used in further processing. For example, the existing HHC systems cannot recognize "Diarrhea" because the symptom of "Diarrhea" does not appear in the basic

Table 1 Target activities in this research.

Target activities	
A_1 = Sitting on the toilet	A_9 = Working on a computer
A_2 = Taking a bath	A_{10} = Watching TV
A_3 = Lying down & relaxing	A_{11} = Reading a book
A_4 = Sleeping	A_{12} = Scrubbing the floor
A_5 = Making coffee	A_{13} = Sweeping the floor
A_6 = Cooking	A_{14} = Others
A_7 = Eating or drinking	
A_8 = Washing dishes	

Note: A_1 and A_2 are bathroom activities, A_3 is a living room activity, A_4 is a bedroom activity, A_5–A_8 are kitchen activities, and A_9–A_{14} are location-agnostic activities.

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health information. Nevertheless, the HHC system can predict this illness from the "Sitting on the toilet" activity. If the home user tends to perform the "Sitting on the toilet" often in short period of time, the system might predict that the user has some problems with "Diarrhea". Consequently, the system can provide a health recommendation service to the user for checking and preventing this problem. To achieve our goal, we design the context-aware activity recognition engine (CARE) architecture as the human activity framework for classifying human activity in the smart home environment. According to this CARE architecture, several techniques are developed. First is Context Sensor Network (CSN). We introduce a new set of data obtained through real measurements in the smart home. The aggregation of sensing techniques is identified for collection of the appropriate information for activity recognition. Second is posture classification. We propose a new algorithm, called a range-based algorithm, to classify human posture data, and results of this are combined with the original user's context for classifying the human activity. Last, Ontology-Based Activity Recognition (OBAR) is proposed. The ontology concept is the main approach in the development of activity recognition in this research. The ontology concept is used to define the surrounding information in the home. We also present a new term of activity log ontology, called AL^2. The AL^2 can help the OBAR analyzes the results more reasonable.

The remainder of this paper is organized as follows. In Sect. 2, we briefly describe the background and related works. Section 3 provides an overview of the CARE architecture. Then, we describe the process of collecting data using several techniques. Next, we present two components for organizing system information. In Sect. 6, OBAR is presented. Next, we briefly introduce the semantic ontology search system for retrieving both semantic and human activity information. After that, we analyze the sensing data to identify which are the most important. In Sect. 9, we evaluate the performance and analyze the advantage of our proposed idea. Then, we discuss the results of our proposed activity recognition system. Finally, a conclusion and ideas for future work are presented in the last section.

2. Background and Related Works

In the past, improving the ability of an activity recognition system has been a challenging task because of difficulties in terms of activity. For instance, individuals have a high degree of freedom in performing each activity and have unique lifestyles, habits, and abilities. Currently, the process for developing activity recognition falls into two parts: sensing and recognition.

2.1 Sensing

For the sensing part, its main responsibility is to collect the necessary information. Implementing activity recognition requires a different type of data depending on the recognition technique. This section will review two main approaches used for sensing data. First, the visual sensing approach has been used in the computer vision area for several years. A visual sensing device, such as a high-resolution camera, is mainly used for collecting image or video files. The image processing technique plays an important role to extract the essential information from the video recording. For example, a pose recognition algorithm has been proposed using a 3D camera [4]. This applies the depth information to distinguish between human and object. However, single viewpoint-based surveillance might not suitable in large areas because of the angle and position of the camera. Thus, a distributed camera network has been proposed to detect human action in large area [5]. Nevertheless, a visual sensing approach has limitations in certain circumstances. For example, it is difficult to identify which object is being used by the user. The system also cannot classify specific activities such as "Watching TV," "Cooking," or "Taking a bath." Moreover, privacy is also a major problem in using this approach, especially in the home domain. Using a camera for continuous monitoring of human activity in home can be considered invasive and an intrusion of privacy. People might be annoyed or even feel threatened by revealing such aspects of their personal life.

Second, the sensor network approach is a network of diverse sensors. The system entails collecting various kinds of information from the sensors, and can divide the data sensing into two techniques based on sensor placement, the most popular of which is the use of a body sensor network (BSN). In this technique, wearable sensors are attached to an individual's body. For example, accelerometer sensors are used to capture human movement by calculating the acceleration signal in three dimensions [6]. The second technique makes use of a home sensor network (HSN) for detecting which object is being used in the home facility by embedded sensors in the home facilities. The system recognizes human activities by monitoring what home facility is being used and how long the user spends in that facility [7]. Radio-frequency identification (RFID) technology is also used in this technique to find the user's location or to observe which object is being used.

2.2 Recognition

Having obtained sensing data, one can then recognize human activity by classification. Numerous intelligent techniques have been developed to recognize human activity. Probabilistic analysis methods, involving hidden Markov model (HMMs) [8], C4.5 decision tree [9], or support vector machine (SVMs) [10], are often used to determine the results of classification. However, the main problem with using a probabilistic analysis method is that it requires a large data set for creating the activity models. Furthermore, the activity model for each person is not exactly the same because of lifestyle differences, so personalized activity models rely on the, person who trains the data. Consequently, this approach suffers from the problems of scalability and re-usability.

Because of problems, the ontology concept has been adopted for defining semantic context information for explicitly and formally specifying shared conceptualization by knowledge engineering [11]. Domain knowledge can be modeled by using semantic information at a level of abstraction. In this sense, the ontology concept can prevent an overlarge amount of observing data and limit the training process. Riboni et al. [12] proposed a combination of ontological and statistical reasoning for context-aware activity recognition. The basic context environment (user's location, activated object, and time) is conformed as the user's context for activity recognition. However, the method provides only a common term of primitive activity and might not be realistic in some circumstances. For example, in most research protocols recognize the "Sleeping" activity when a sensor attached to the bed is activated. Nevertheless, this is not always true because there are other possible activities (e.g., the user might sit on the bed and watch TV).

3. CARE Architecture Overview

To carry out the goal of this paper, the CARE architecture is designed as the human activity framework. Thus, the application that requires the human activity information and the semantic information can build on top of the CARE architecture. Figure 1 depicts the high-level CARE architecture. For sensing data in this architecture (Sect. 4), the proposed CSN is placed at the beginning of the architecture to collect the data from the home environment, including human information. Ambient intelligence technologies are attached and embedded into the home facilities. The advantage of the CARE architecture is also shown in the posture classification. The novel information such as human posture is investigate in order to create a new user's context for classification of human activity. Based on the huge amount of data (Sect. 5), good organization is important for handling the enormous amount of information in the smart home. A data manager is proposed to normalize and transform the data before storing it into the system repository, while the system repository is responsible for controlling all the data in this proposed architecture. To process the data, OBAR is proposed for creating the knowledge base and activity model (Sect. 6). Finally, the results of activity recognition and semantic information can be retrieved through the semantic ontology search system (Sect. 7).

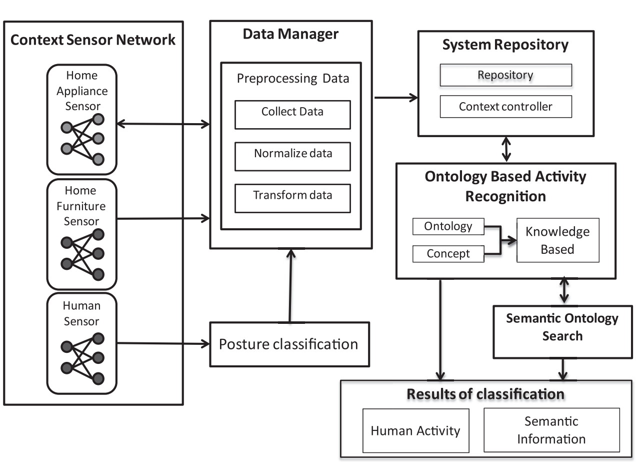


Fig. 1 CARE architecture.

4. Data Collection

4.1 Context Sensor Network

To obtain the relevant information in a real environment, a CSN with a diversity of sensors and network protocols is proposed. To obtain a large number of data for classifying human activity in the smart home, both a BSN and an HSN are integrated into the CSN for observing object usage and human information. There are three kinds of sensor networks in the CSN, described in the following.

4.1.1 Home Appliance Sensor Network

To capture home appliance usage, a variety of sensors, such as power consumption sensors and water-flow sensors, are built into the smart home. Most electrical home appliances can be detected by measuring the change of electric current from the power consumption sensor. A water-flow sensor is also embedded in the smart home for monitoring the use of water fixtures such as "Sink," "Shower," and "Flushing." In our research, there are two protocols for sending the requested command to each sensor: ECHONET [13] and UPnP [14]. The ECHONET is an international home network protocol standard used to control, monitor, and gather information from equipment and sensors. UPnP is responsible for sending request commands and receiving data from the home appliance sensor. The interval time is set to five seconds for sending the requested command.

4.1.2 Home Furniture Sensor Network

Apart from home appliances, we have to consider use of other items in the home environment, such as "Sofa," "Chair," or "Bed." Information from these kinds of objects can be combined with the home appliance information to indicate the performance of specific activities. For example, if the "Computer" object is turned on, this does not necessarily mean the user is performing the "Working on a computer" activity. Normally, a user tends to sit on a "Chair" for "Working on a computer." In this sense, a pressure sensor, a gyro sensor, and a magnetic sensor are deployed and attached to the home furniture. For example, a pressure sensor is attached to the sofa to detect whether or not a human is sitting on the sofa.

However, we cannot use ECHONET and UPnP protocols to communicate with the home furniture sensors because most of the home furniture items are not in the international home network protocol standard. Thus, in the setup of the experimental environment, ZigBee protocol is emulated for communication within the home furniture sensor network. This network has two basic parts: a sensor node and a coordinator. For the sensor node, the Arduino Fio microcontroller board is connected to a pressure sensor, a gyro sensor, and a magnetic sensor via an external board. For the coordinator, the Arduino Ethernet is developed to connect with the XBee shield. At this stage, the coordinator node will collect data from the sensor node via the ZigBee protocol and transmit it to the server via an Ethernet cable.

4.1.3 Human Sensor Network

Normally, simply using the home environment data might not be sufficient to conform to the user's context for the activity recognition system. Thus, a human sensor network is used to observe human information such as the location of the individual. Infrared sensors are deployed in each room in the experimental environment to detect the human location. The current location of the user can give useful hints about which activities the individual is able to perform in their current location.

Nevertheless, using information concerning object activation and human location still has limitations because sometimes, human location does not hint at any specific activity if several objects are being used at the same location. Recently, further human information has been introduced for classifying human activity, and the effective combination between human posture data and home sensor data is discussed in [15]. Therefore, in our proposed system, we address posture classification to perceive human posture data for improving the ability of activity recognition system.

4.2 Posture Classification

Generally, posture classification and activity recognition are very closely related research areas. Posture classification mainly focuses on the position of the body parts (with little regard for movement), such as "Standing," "Sitting," or "Lying down." Activity recognition, in contrast, considers human actions or occurrences, such as "Watching TV," "Walking," or "Cooking." From observation, we believe that each human activity is composed of human postures. Nonetheless, implementing a posture classification scheme is not an easy task. Achieving high accuracy in activity recognition does not necessarily mean we will get high performance in posture classification. For example, Lee et al. [16] used triaxial accelerometers to classify human activity. They achieved high performance in dynamic activity classification of 90.65%, whereas performance in static activity classification drops to 83%. Errors can easily be found in static activity because the signals are quite stable. One cannot extract the necessary information from a stable signal.

To address this problem, we propose a new range-based algorithm [17], to improve the accuracy when the human undergoes little movement. In this algorithm, we focus on three human postures: "Standing," "Sitting," and "Lying down." The idea for this algorithm comes from the hypothesis "Each human posture has a different physical pattern." This means that the relationship between the body parts can conform to a specific human posture. In this paper, we used three ultrasonic sensors attached to the shoulder, hip, and knee to perform the range-based algorithm. The reason to use the wearable sensor in the posture classification is that we cannot recognize the human posture based on only the context-aware information. For example, using the "Sofa", it does not necessary mean the user is performing the "Sitting" posture. It is possible that the user is "Lying down" on the "Sofa". Thus, the information from the human body sensor is necessary to recognize the accurate results. Figure 2 shows the ranges between body parts that are extracted from the height data. The range between body parts will change along the y axis depending on the postures. For example, "Standing" and "Sitting" postures have different ranges between shoulder and knee, whereas a "Lying down" posture has little difference in range values between body parts. To classify the human posture, four modules are proposed in the range-based algorithm: binary decision tree, finite state machine, adaptive posture window scheme, and posture pattern recognition [17].

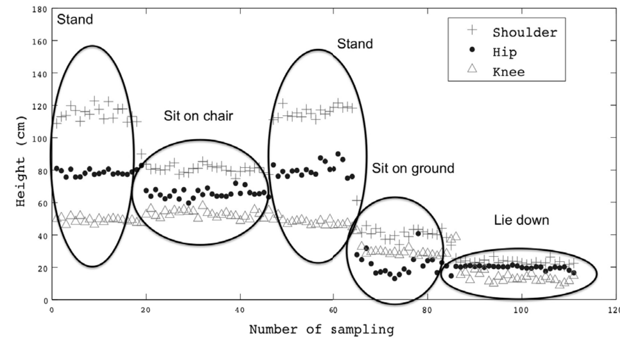


Fig. 2 Ranges between body parts in each posture.

This algorithm shows high performance when the actor has little movement. In the static posture experiment, the range-based algorithm can classify correctly 100% of the time, and in the consequent postures experiment, the range-based algorithm also achieves a high percentage (around 98%). One important aspect that makes for good results is the relation between body parts. We did not use the height data for each body part; the correlation between body parts was considered for deciding the human posture. In existing systems, an accelerometer sensor is mainly used to classify the human posture. It needs to extract the essential parameter from the oscillation signals. However, feature extraction cannot be used very well if the signal input is a stable signal. In contrast, the range-based algorithm does not require a feature extraction technique to extract the parameter; it needs only the measured sensor ranges.

5. Data Organization

Organizing the huge amount of data in a smart home is a complicated task because there are several information components for the system to consider. Moreover The system cannot always obtain absolutely perfect data from the sensor. There can be missing data and noise problems associated with hardware. In this section, we present a practical metrics as following.

5.1 Data Manager

After the system obtains the data from the CSN and posture classification, the data is sent to the “Preprocessing Data” module for normalization. The raw data are normalized by a supply missing data function or an eliminating noisy data function. For the supply missing data function, the system will find suitable data or possible data to make the information complete. For example, for detecting human location, an infrared sensor is used to detect the object in its field of view. Nonetheless, the system cannot recognize human location if the user is stationary or only moves a little. In this case, the supply missing data function will retrieve the last location instead of the current location. For the eliminate data function, a threshold technique is adopted for filtering the noise in some circumstances. For example, even though an electrical device is turned off (but still plugged in), the power consumption sensor still perceives data from the electrical device. Thus, a lower boundary is set for deletion and removal of this kind of noise.

5.2 System Repository

The system repository is a vital part in controlling data flow in the system. Figure 3 illustrates the flow of data between the system repository and OBAR. There are two modules in this part: a repository and a context controller. The repository is introduced as the database in the CARE architecture. It collects the results from the data manager and also retains the temporal reasoning of the OBAR system. The context controller performs three main data-processing tasks.

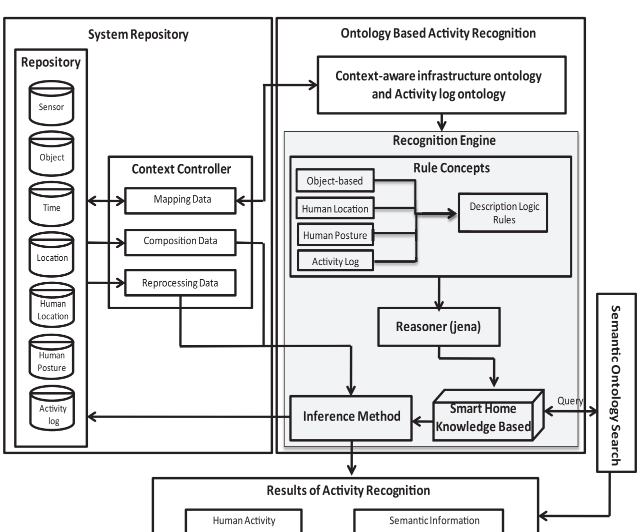


Fig. 3 Flow of OBAR.

- **Mapping Data** The ontology model will perceive the data in the repository through this step. This task has duty to map between the properties and concepts in the ontology model and the data structure in the repository via an ontology application management framework [18]. After this process, the system will generate the results as a resource description framework (RDF) file, a standard model for interchange on the Web. Then, the results of mapping will be stored in the smart home knowledge-based for further processing.
- **Composing Data** The data in the repository are formed to the user's context. We compose data every minute for one user's context. In the user's context, the system can perceive various kinds of semantic information such as object activated, sensor status, human posture, human location, and so on. OBAR will classify human activity based on these user contexts, described the semantic information in more detail in Sect. 6.
- **Reprocessing Data** The advantage of our proposed method is that we can utilize historical information inferring human activity in the next classification. An external Java program is implemented for capturing the temporal reasoning. It collects classification results and sends these to the inference method for the next classification. Lack of information for classification can be resolved with this task.

6. Ontology-Based Activity Recognition

Normally, using the ontology concept in activity recognition is not a new approach. Several research groups have applied the ontology concept in activity recognition systems. However, the limitations of existing research still leave room for improvement; for instance, common semantic information (object activation and human location) is used for activity recognition. Certain research does not support temporal reasoning [19], so this poses a problem when classified data is insufficient. Because of these problems, in this research, we aim to improve the ability of activity recognition by using a new semantic user's context and AL^2. There are two parts for OBAR: ontology modeling and a recognition engine.

6.1 Ontology Modeling

In this research, there are two main ontology models in the smart home domain: a context-aware infrastructure ontology, used to define the semantic environment information in the smart home domain, and an activity log ontology, which is used to track the history of activities and activated objects.

6.1.1 Context-Aware Infrastructure Ontology

Classifying human activity is a complicated task because each activity can be carried out in different sequential order depending on individual lifestyles. This means that one human does not need to perform an activity in the same

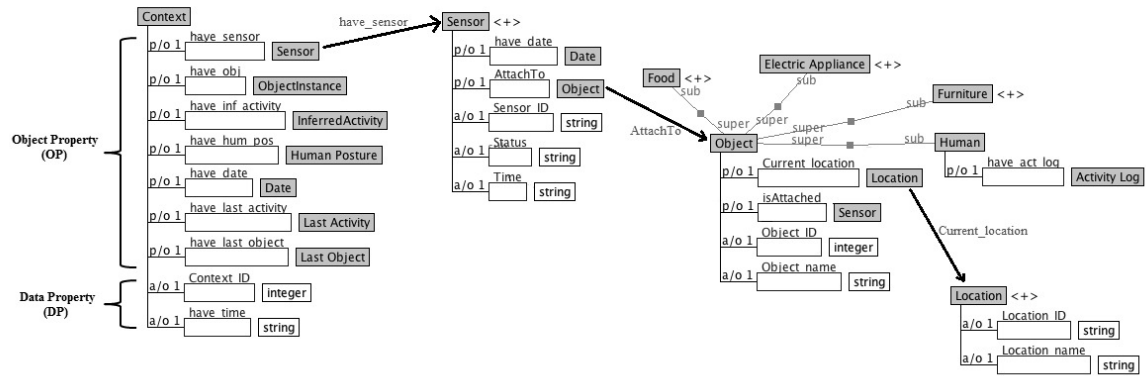


Fig. 4 Example of context-aware infrastructure ontology.

way as another. Consideration of each activity event takes place under location information and surrounding environment context in the smart home. The location information can be human's location, the object's location, or the activity's location, while the surrounding environment context comprises sensors, time, home appliances, furniture, and so on. To handle the huge semantic context, we design a context-aware infrastructure ontology to elicit the semantic context in the smart home.

The context-aware infrastructure ontology in this research is designed based on the Hozo application [20]. Hozo is an ontology development tool for building and using ontologies based on a fundamental consideration of "Role" and "Relationship." Superclass and subclass relationships are also utilized in our ontology for definition of the environmental context in the smart home. For example, the *Electric appliance* class and *Furniture* class are subclasses of the *Object* class. Thus, all properties in the superclass will be inherited to the subclass. Properties in our ontology model can be divided into two principle properties: Object Property (OP) and Data Property (DP). The OP describes a "part of" relationship between two classes, whereas the DP identifies an "attribute of" each class. Figure 4 depicts a good example of DP and OP properties in the context-aware infrastructure ontology. The *Context* class is a relevant class that relates location information and surrounding entities such as sensor, object, and human posture. For example, from Fig. 4, the "have_sensor" property in the *Context* class can infer to the *Sensor* class. Then the *Sensor* class is inherently linked to the *Object* class through the "AttachTo" property, while the "Current_location" property in the *Object* class links to the *Location* class. Consequently, the "have_sensor" property can infer three kinds of semantic data: sensor information (activated time, status, or sensor id), object information (object type, object name, or object id), and location information (location id and location name).

Nonetheless, existing research has revealed limitations when using common semantic information. There are several possible resultant activities when several sensors are activated at the same time. The system cannot know which resultant activity is correct. We refer to this problem as the "ambiguous activity problem" Therefore, the context-aware infrastructure ontology is designed not only information regarding location and surrounding entities, but human posture information is also integrated into the *Context* class through the "have_hum_pos" property. This information is very useful for distinguishing ambiguous resultant activities in some circumstances. For example, when a pressure sensor attached to the bed is activated, most research protocols will classify this context as a "Sleeping" activity. However, it is not always true because it could indicate "Sitting on the bed and watching TV" or "Sitting on the bed and reading a book." In this sense, human posture data from the posture classification proposed in Sect. 4.2 becomes the relevant information for reducing the possible resultant activities. It can make the system more accurate and reliable.

6.1.2 Activity Log in the Ontology Model

Normally, there is a few researches that applied the activity log in the ontology model in activity recognition system because the original idea of using an ontological model is used for definition the object appearing in the domain of interest, so it does not support temporal reasoning. This means that snapshot data from the sensors is used as input data of activity recognition. An interval time for receiving data is set depending on the experimental environment, so that the system will identify the activity only when the interval time is reached. However, the concept of snapshot data might not suitable for activity recognition because it can lack recognition information in some cases. For example, the "Sink" object in the kitchen can be used for several purposes, such as "Washing hands" or "Washing dishes." Thus, the system cannot decide which activity is correct, if it uses only data from one period of time. However, if the system knows the user performed an "Eating and drinking" or a "cooking" activity before using the "Sink," then the "Washing dishes" activity will have a high probability in this context.

An *Activity log* class, illustrated in Fig. 5, is proposed in our ontology model to aggregate a sequential history of activities and object activations. Information in the *Activity log* class is relevant for activity recognition because we cannot guarantee the accuracy when used only as data at a specific time point. In this paper, we present the activity log

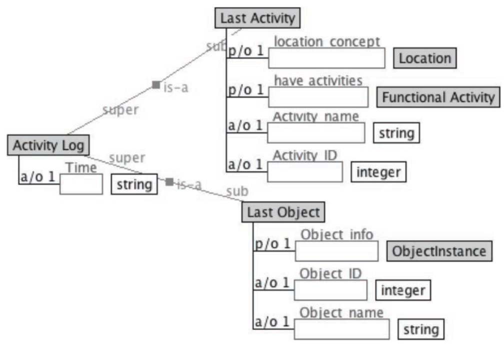


Fig. 5 Activity log in the ontology model.

for collecting the history of the object activations and activities. The history of object activations is defined in the *Last Object* class and can be inferred through the "Object_info" property. This information is very important in solving the traditional problem of lack of recognition information. For example, the system perceives that the "Kettle" object is being used, although the system cannot classify any resultant activities in this context. Nevertheless, if the system knows that the object is used just before a "Coffee container," the system might recognize the current activity as "Making coffee." For the history of activities, we propose a new activity log term, AL^2. It is different from the traditional activity log because AL^2 will retrieve activities that the user performed at the current user's location for computing the current user's context [21]. For example, if the system knows that the current location of the individual is the kitchen, the activities that user performed in the kitchen will be considered in the system for classifying the current activity. AL^2 produces more reliable results compared with those of existing research efforts (for additional detail see Sect. 9.3.2). Based on Fig. 5, the *Last Activity* class can infer the activity performed by the user from the "have_activities" property, and each activity will be tagged by the location by using the "location_concept" property.

6.2 Recognition Engine

The popular ontological language, OWL (Web Ontology Language), has been used to build activity ontologies, and to recognize activities based on context data. Naturally, ontological models do not have the ability to recognize human activity. Description Logic (DL) is widely used to express knowledge of an interesting domain. The DL is established to support inference and reasoning and for describing the domain in terms of concepts (classes) and roles (properties and relationships). Benefits of using DL in ontology application are clear & unambiguous syntax, precise mathematical semantics, automatic reasoning, and placement of a concept in the hierarchy can be done automatically. In the activity recognition area, the rationale of a logical approach is to exploit logical knowledge representation for activity, sensor data modeling and to use logical reasoning to perform activity recognition. There are four factors to be considered in this research. Firstly, the object is the main factor that most current research uses to create the DL rules because the majority of activities in a smart home involve an object. Secondly, the human location factor is used to scoop the possible activities for the object being used at the same current user location. Thirdly, the human posture factor is used to reduce the possible resultant activities. Lastly, the activity log factor is used to enhance the relationship between the history user context and the current context. The following example indicates the DL rule for the "Wash dishes" activity:

$$
\begin{aligned}
&Washing\ dishes \sqsubseteq Functional\ Activity\\
&\sqsubseteq Kitchen\ Activity\\
&\sqcap\ use(Object.Furniture(Sink))\\
&\sqcap\ Object.Human.Current\_location(kitchen)\\
&\sqcap\ HumanPosture(Stand)\\
&\sqcap\ LastActivity.Kitchen\ Activity(Eating\ or\ drinking)
\end{aligned}
$$

However, the example DL rule is represented in natural language. We need some reasoners to translate from DL rules in natural language to DL rules in machine language. Thus, a built-in reasoner (Jena) [22] is implemented for computing the DL rules for the new data and storing them in the smart home knowledge-base. Then, an Inferred Activity class instance is created to link it with the DL rules. At this stage, the smart home knowledge-base has the DL rules for deciding upon the activity and instances of activity. If an input context reaches the system and is consistent with the rule linked with the instance of activities, the system will infer the activity as a result of recognition.

7. Semantic Ontology Search

Because the OBAR uses the ontology concept as its core, of of the advantages of the ontology concept is that it can provide explicit specifications of a shared conceptualization. In this sense, all semantic information defined in the above section can be used for describing the surrounding context in a smart home. In this paper, the semantic ontology search system [22] is implemented on top of the CARE architecture for utilizing the knowledge from the OBAR. The semantic ontology search system is a search engine typically used for retrieving the history of semantic information in a smart home based on the ontology concept. This system allows the users to set the search configuration based on the classes and properties in the ontology models. This system is different to the traditional search application, which uses the database as a center for data. A RDF file is used in this system. The RDF file is a standard model for data interchange on the web. The RDF is not strictly an XML format or traditional database. It is not just about metadata, but structured information is presented in RDF. Moreover, the language query, SPARQL, is used to query the data from the smart home knowledge-based. For the user interface of the semantic ontology search system, the user can retrieve all semantic data in the smart home based on the class in the context-aware infrastructure ontology (object, sensor, or context) or the property in each

Table 2 Recognition performance for each factor.

Activity	OB	OB + HL		OB + HL + HP		OB + HL + HP + AL	
	Acc_1	Acc_2	$\triangle Acc_2 Acc_1$	Acc_3	$\triangle Acc_3 Acc_1$	Acc_4	$\triangle Acc_4 Acc_1$
Sitting on the toilet	86.88	93.75	(+6.87)	93.75	(+6.87)	93.75	(+6.87)
Taking a bath	100	100	(0)	100	(0)	100	(0)
Lying down & relaxing	84.41	89.89	(+5.48)	100	(+15.59)	100	(+15.59)
Sleeping	89.42	91.46	(+2.04)	91.86	(+2.44)	91.86	(+2.44)
Making coffee	42.86	50	(+7.14)	50	(+7.14)	100	(+57.14)
Cooking	74.02	86.21	(+12.19)	86.21	(+12.19)	86.21	(+12.19)
Eating or drinking	96.2	96.67	(+0.47)	96.67	(+0.47)	100	(+3.8)
Washing dishes	85	85	(0)	85	(0)	100	(+15)
Working on a computer	90.1	90.16	(+0.06)	92.25	(+2.09)	92.25	(+2.09)
Watching TV	53.19	58.59	(+5.4)	97.94	(+44.75)	97.94	(+44.75)
Reading a book	53.57	53.57	(0)	100	(+46.43)	100	(+46.43)
Scrubbing the floor	86.95	86.95	(0)	93.75	(+6.8)	93.75	(+6.8)
Sweeping the floor	94.73	94.73	(0)	96.67	(+1.94)	96.67	(+1.94)
Others	77	83.6	(+6.6)	100	(+23)	100	(+23)
Average accuracy	79.6	82.9	(+3.3)	91.72	(+12.01)	96.6	(+16.89)

class (date, time, or sensor status), shown for the example of a user interface of a semantic ontology search in Sect. 9.

8. Impact of Description Logic Rule

To recognize human activity in the home, there are several factors that affect recognition accuracy. Thus, before commencing verification of the activity recognition system, we will analyze each factor to ascertain its importance. There are four factors in this research: object-based (OB), human location (HL), human posture (HP), and activity log (AL).

In this section, the experiment analyzes each factor by measuring the classification performance of each activity. We divided the factors into four groups. The first two groups are widely used in existing research: object-based (OB) and a combination of object-based and human location (OB+HL). Then, we add the innovative human posture information, to the third group (OB+HL+HP). Finally, we consider all factors in the last group (OB+HL+HP+AL). All four groups have the same environment, input data, and test subjects. Table 2 presenting a comparison between the accuracy of each activity in the first group with the other groups. From the results, we can analyze the impact of sensing data (factors) as follows:

- **Object-based** Although using the object-based factor offers the lowest percentage of recognition, it is the most relevant information for classifying human activity because if the system does not know which object is being used, it cannot classify the specific activity such as "Watching TV," "Working on a computer," or "Sweeping the floor." Nevertheless, object-only information can lead to the "ambiguous activity problem" when several objects are being used, which is the main reason for the low accuracy of the first group.
- **Human Location** In absolute terms, human location information cannot be used to distinguish between the different types of human activity. Nevertheless, it is useful when combined with other factors, such as the object-based factor. The combination in the second group exhibits improved accuracy. It can help the system to reduce sensor noise in some cases. For example, if there is error data indicating that the sensor attached to the bed is activated, the system will classify the human activity in this situation as "Sleeping." However, if the system knows that the user is in kitchen, the system can ignore the data coming from outside the kitchen. In contrast, for "Scrubbing the floor" and "Sweeping the floor" activities, no improvement is possible because the activity can be performed in any room, so location information is of no value.
- **Human Posture** Inclusion of the new user's context, human posture, in the third group provides an average improvement of 12.01% when compared to the first group. The idea of using human posture is to distinguish activities that have different postures. For example, "Watching TV" is an outstanding example to explain the strong point of human posture in activity recognition. If we consider "Watching TV" and "Lying down & relaxing" activities, both of them occur when the "Sofa" object is being used. However, in these two activities, human posture can be different: "Watching TV" (sitting or lying down), "Lying down & relaxing" (lying down). Thus, the system can distinguish these two activities easily. However, human posture information does not work well if the activities involve the same posture. For example, the system cannot distinguish between "Washing dishes" and "Cooking" by human posture, so the same results will appear as for the second group.
- **Activity Log** There are two techniques in the AL to capture the history of the user's context. The first is the common AL technique that captures the history of object activation. The second is AL^2, which tracks the activity that user performed at their current location. From these two techniques, the results demonstrate highest accuracy when adding the activity log factor. From Table 2, we can see the advantage of these two points. Firstly, the history of object activa-

tion is used to solve the snapshot data problem. The "Making coffee" activity illustrates the improved accuracy (57.14%) when compared to the first group. Secondly, the relationship between activities performed at the same location is considered. The improvement in accuracy for kitchen activities shows the advantage over other groups for a sequence of activities at the same location. This experiment will be explained in more detail in Sect. 9.3.2.

9. Performance Evaluation

9.1 Experimental Setup

All modules in CARE architecture were designed and installed in iHouse [23], excepted the posture classification. Posture classification was demonstrated in AwareRium [24], a room in an experimental environment to investigate various support systems. Ultrasonic technology is the main technology in the AwareRium. Meanwhile, the iHouse was selected as an experimental smart home environment. The iHouse is designed to aid the development of the next-generation home network systems. Two floors with 107.76 m^2, more than 250 sensors, and home appliances are connected through ECHONET, UPnP, and ZigBee. A photograph of iHouse is presented in Fig. 6. This activity experiment was performed using six actors (three males and three females) whose ages ranged from 24 to 31. The experiment is divided into six sections, and each actor performs each section individually. In addition, because the reality of the experiment is the one of the important factor that makes the recognition accuracy change, all of actors were asked to perform any activities in the iHouse without instruction. Thus, the actors were free to perform any activities during the experiment. The context-aware information in this experiment will be collected through CSN, excepted the human posture. Only the posture information is observed by visual inspection in iHouse. In this section, we divide the evaluation into two parts. The first measures the performance of our activity recognition based on our proposed ideas. The second analyzes the advantage of our proposed ideas from the results of the semantic ontology search system.

9.2 Performance Evaluation

As described in Sect. 2, one advantage of using the ontology concept in the OBAR is that it does not need a large training set or training process. Thus, in this experiment, six actors demonstrate the activities in iHouse. In each minute or single user's context, an actor is either performing A_1–A_{13}, or doing others (A_{14}). All of data such as object activation, human location, human posture, or activity log will be gathered into one user's context. The metric used for evaluation is recognition accuracy, defined by the number of correctly recognized activities against the total number of each activity. The number of correctly recognized activities can be observed by visual inspection, and the correct activity can be inputted into the system. Table 3 shows the recognition accuracy of each activity.

In total, 1,140 user contexts are performed by six actors. The overall classification accuracy reaches 96.60%. Most activities are recognized correctly, except for the "Cooking" activity. In fact, the "Cooking" activity can be divided into three stages: "Preparing food for cooking," "Cooking," and "Preparing food for eating." The "Cooking" stage is not a problem for classification because the DL rules are designed to support "Cooking." However, for the "Preparing food for cooking" and "Preparing food for eating" stages, the system cannot perceive when the user will start cooking or finish cooking. Therefore, the system will classify before and after "Cooking" activities as "Others."

Strange results also appear in certain circumstances. For example, poor results are shown to distinguish "Taking a bath" from "Working on a computer." Although these two activities are very different in terms of human location and activated objects, we get incorrect results because of asynchronous sensor delay and the interval time in classification. In this experiment, for sensing data, if the sensor is activated, it will be delayed one minute for sensing new data. Meanwhile, the interval time for classification is fixed to one minute. In this sense, one might have a situation in which the actor already changes activity, but the system still uses the old information to classify human activity.

The average accuracy obtained in this research is also compared with other methods. The same kind of data is trained and tested using probabilistic methods, which are K-Nearest Neighbor (KNN), SVM, C4.5 decision tree, and Naive bayes classifiers. Weka Machine Learning Algorithms Toolkit [25] is used for measuring the recognition

Fig. 6 The iHouse used for the real activity recognition experiment.

Table 3 Accuracy of OBAR.

Activity	Accuracy (%)	Other possible resultant activities
A_1 = Sitting on the toilet	93.75	A_9 (2.08%), A_{14} (4.17%)
A_2 = Taking a bath	100	—
A_3 = Lying down & relaxing	100	—
A_4 = Sleeping	91.86	A_{11} (3.49%), A_{14} (4.65%)
A_5 = Making coffee	100	—
A_6 = Cooking	86.21	A_{14} (13.79%)
A_7 = Eating or drinking	100	—
A_8 = Washing dishes	100	—
A_9 = Working on a computer	92.25	A_{10} (6.90%), A_2 (0.42%), A_{14} (0.43%)
A_{10} = Watching TV	97.94	A_{14} (2.06%)
A_{11} = Reading a book	100	—
A_{12} = Scrubbing the floor	93.75	A_{14} (6.25%)
A_{13} = Sweeping the floor	96.67	A_{14} (3.33%)
A_{14} = Others	100	—
Average accuracy: 96.60 %		

Table 4 Comparison between proposed method and other methods.

Methods	Our proposed	KNN	SVM	C4.5 Decision Tree	Naive Bayes
Accuracy	96.60%	95.72%	94.70%	90.93%	94.06%

accuracy of four algorithms. Table 4 illustrates the results of classification in each algorithm. Our proposed method got the highest accuracy when compared with others. The advantage of the proposed method can recognize the ambiguous situation and the historical information, which will be explained in the next section.

9.3 Findings

In this section, we will analyze the advantage of our proposed activity recognition from the results of a semantic ontology search system. Behind the results, two benefits were found when using human posture information and AL^2.

9.3.1 Ambiguous Activity Problem

In the traditional method, the "ambiguous activity problem" usually arises when there are several possible resultant activities in one classification. In this sense, the common semantic information might not be enough for classification. Therefore, we have conducted posture classification, and the results from posture classification are gathered in the user context for classification in OBAR. Actually, in our experiment, there are several ambiguous situations. Here is one example situation from an actor in our experiment:

"In the living room, an actor is sitting on a chair and using the desktop. Then, the actor puts something on the chair and lies down on the sofa."

From the above situation, the system can perceive the user's context as identify the human's location as the living room, and there are three activated objects: "Chair," "Desktop," and "Sofa." Each object can infer different activities, and there are three possible resultant activities in this context: "Watching TV," "Working on a computer," and "Lying down & relaxing." With certainty, the system can ignore the "Watching TV" activity because the "TV" object is not being used. However, the system cannot distinguish the remaining activities. Normally, if we do not have human posture information, then "Working on a computer" will be the resultant activity. Nevertheless, in this context, we know the human posture as "Lying down." It is unlikely that the user is lying down on the chair and working on the desktop. In this case, the system classifies the possibility that the actor may be "Lying down & relaxing" on the sofa.

9.3.2 Effect of Activity Log

There are two major advantages when using the activity log in OBAR. Firstly, it can resolve the snapshot input data problem. Secondly, AL^2 makes the system results more reasonable and reliable when analyzing the relationship of activities that occurring in the same place.

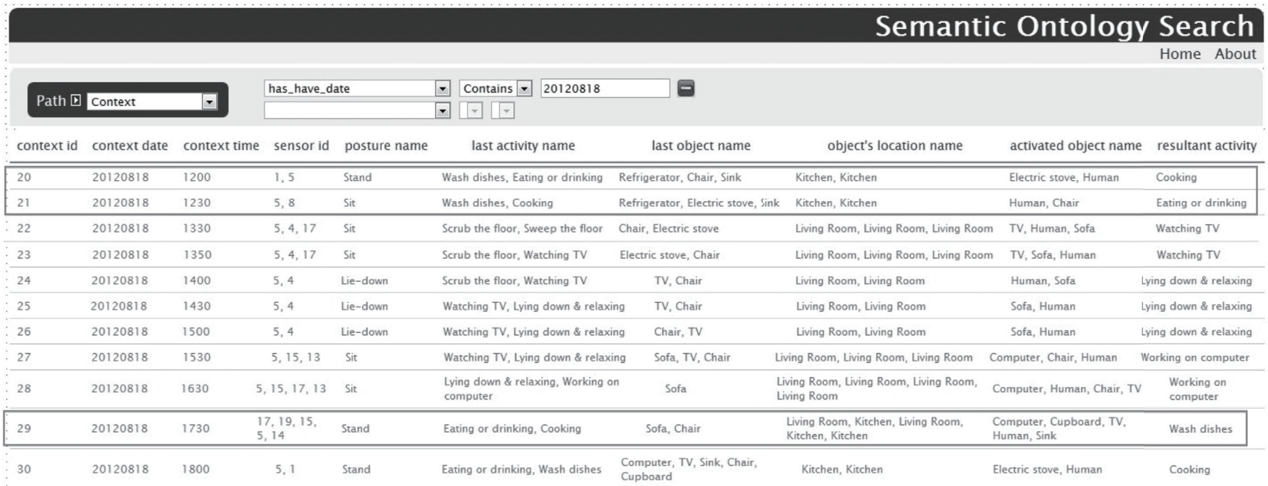
Owing to the limitation of snapshot input data, the activity log is developed to help the system classify human activity correctly when lacking input data. The accuracy of the "Making coffee" activity, illustrated in Table 2, is the best example for explaining how important the activity log is in OBAR. The interval time in this experiment is set to one minute, but it is possible that the actor will perform the "Making coffee" activity for longer than one minute. In this case, merely one user context is not sufficient for classification, so the classification accuracy drops to 42%. We can, of course, expand the interval time, but if the interval time is too long, then the previous activated objects might lead the system to have a lot of activated object information in the next classification. Consequently, the system might indicate several possible resultant activities.

Nonetheless, using the activity log to keep track of activity history is not an easy task because the system cannot recognize which previous activities should be considered with the current activity. Therefore, this research improves the activity log capability by introducing AL^2. Relationships between activities occurring in the same place are considered. We compare the performance of two methods: one using only a common activity log to classify the activity and another in which the AL^2 technique is applied.

Context_id 29 in Fig. 7 is an outstanding example for helping to explain the strong point of AL^2. If one considers the column "resultant activity" in context_id 24-28, the resultant activities are "Working on a computer" and "Lying down & relaxing." There are no relationships between these two activities and context_id 29. A system using only a common activity log will not have any supporting reason for classifying that user as performing "Washing dishes" in context_id 29, whereas a system using AL^2 will retrieve the last activities that user performed in the current location (context_id 20 = "Cooking" and context_id 21 = "Eating or drinking") to classify the resultant activity of context_id 29 as "Washing dishes." Of course, the resultant activity in context_id 29 can be something else, but "Washing dishes" has a high probability factor because we have temporal reasoning as "Cooking" and "Eating or drinking" to verify this result. Another piece of evidence that shows the improvement when using AL^2 is the accuracy in Table 3, especially for activities in the kitchen. The OBAR can achieve high accuracy in sequential activities: "Cooking" or "Making coffee" → "Eating & drinking" → "Washing dishes."

10. Discussion

The overall results in Sect. 9 show the advantage of our proposed activity recognition when combining human posture and context-aware infrastructure ontology and utilizing the activity log in the ontology model. Although the OBAR achieves high activity recognition performance, it still needs additional techniques to improve the classification. For instance, there are several steps when performing the "Cooking" activity. The system cannot know what time to start cooking. Thus, a back-propagation technique is needed to



context id	context date	context time	sensor id	posture name	last activity name	last object name	object's location name	activated object name	resultant activity
20	20120818	1200	1, 5	Stand	Wash dishes, Eating or drinking	Refrigerator, Chair, Sink	Kitchen, Kitchen	Electric stove, Human	Cooking
21	20120818	1230	5, 8	Sit	Wash dishes, Cooking	Refrigerator, Electric stove, Sink	Kitchen, Kitchen	Human, Chair	Eating or drinking
22	20120818	1330	5, 4, 17	Sit	Scrub the floor, Sweep the floor	Chair, Electric stove	Living Room, Living Room, Living Room	TV, Human, Sofa	Watching TV
23	20120818	1350	5, 4, 17	Sit	Scrub the floor, Watching TV	Electric stove, Chair	Living Room, Living Room, Living Room	TV, Sofa, Human	Watching TV
24	20120818	1400	5, 4	Lie-down	Scrub the floor, Watching TV	TV, Chair	Living Room, Living Room	Human, Sofa	Lying down & relaxing
25	20120818	1430	5, 4	Lie-down	Watching TV, Lying down & relaxing	TV, Chair	Living Room, Living Room	Sofa, Human	Lying down & relaxing
26	20120818	1500	5, 4	Lie-down	Watching TV, Lying down & relaxing	Chair, TV	Living Room, Living Room	Sofa, Human	Lying down & relaxing
27	20120818	1530	5, 15, 13	Sit	Watching TV, Lying down & relaxing	Sofa, TV, Chair	Living Room, Living Room, Living Room	Computer, Chair, Human	Working on computer
28	20120818	1630	5, 15, 17, 13	Sit	Lying down & relaxing, Working on computer	Sofa	Living Room, Living Room, Living Room, Living Room	Computer, Human, Chair, TV	Working on computer
29	20120818	1730	17, 19, 15, 5, 14	Stand	Eating or drinking, Cooking	Sofa, Chair	Living Room, Kitchen, Living Room, Kitchen, Kitchen	Computer, Cupboard, TV, Human, Sink	Wash dishes
30	20120818	1800	5, 1	Stand	Eating or drinking, Wash dishes	Computer, TV, Sink, Chair, Cupboard	Kitchen, Kitchen	Electric stove, Human	Cooking

Fig. 7 Semantic ontology search system results on August 18, 2012.

detect the "Preparing food for cooking" step. If the system can detect the "Cooking" step, then it can use current information to recompute the previous step. Consequently, the accuracy of the "Cooking" activity might improve by using a back-propagation technique.

Although the new information regarding, human posture, in the user's context can help resolve the "ambiguous activity problem," not all ambiguous activity cases can be resolved by human posture. Human posture works well in activities in which different postures are involved. For example, the "Working on a computer" activity and the "Lying-down & relaxing" activity are different in terms of activated object and human posture, whereas "Sweeping the floor" and "Scrubbing the floor" are different only in terms of the main activated object ("Broom" and "Mop"), but the posture is the same ("Standing"). Human posture cannot be used to distinguish these two activities.

The idea of AL^2 exhibits good performance when compared to existing research [26] when recent activities are used to recognize current activity. However, we cannot know the exact number of recent activities that it should consider. For example, existing research could establish a rule that the "Wash dishes" activity should occur immediately after the "Eating or drinking" activity, but this is not always true because it depends on human lifestyle. One actor might be "Eating or drinking" and carrying out other activities before "Wash dishes." Thus, tracking the last activity that user performed at their current user's location is the relevant method of finding the relationship between activities.

11. Conclusion and Future Work

In this paper, we proposed the high performance activity recognition framework, which utilized two pieces of information: the new user's context and AL^2. To achieve our goals, we implemented the CARE architecture, which consists of several relevant components. Based on the CARE architecture, we have designed a CSN for collecting the real environment information in a smart home. Following the CSN, we have developed a diversity of sensors and network protocols for deployment in iHouse. We also proposed a new range-based algorithm for posture classification. The ranges between body parts are investigated for classifying human posture. The results from posture classification are relevant for activity classification and can be used to help resolve the "ambiguous activity problem." Then, in OBAR, the context-aware infrastructure ontology was designed for defining information in a smart home and modeling human activity. The proposed ontology has an advantage in terms of scalability because it describes at the abstract level, so it does not need a training process. Moreover, we also created the activity log ontology for solving the problem of snapshot data. The re-usability of knowledge can make the results more reasonable and reliable. In addition, AL^2 is introduced to find the relationship between activities that occur at the same location. The history of activities at the current user's location is investigated with the current activity for classification. Furthermore, the OBAR also gained benefit from the semantic web technology as shown in the semantic ontology search system, constructed for retrieving the semantic information via shared conceptualization. Consequently, the average performance accuracy of OBAR when adding two kinds of factors (HP and AL) reaches 96.60%. This is an improvement of over 16% compared with activity recognition that utilizes only the OB factor.

Although the experiment in this research was tested by six persons and the system achieved the high accuracy, the experimental environment was set up for the individual classification. Thus, the intelligence technologies should be included in the experiment for identifying each individual's information. For example, the RFID technology can be attached on the object and the person for identifying the object, which is being used by whom. Moreover, we plan to use the results of this research for further processing. For example, the activities performed each day will be used to examine human behavior. We can then analyze human behavior for providing appropriate services such as healthcare or home service.

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