Title	ホームネットワーク環境における生活環境に注目した活動認識フレームワーク
Author(s)	Wongpatikaseree, Konlakorn
Citation	
Issue Date	2013-09
Type	Thesis or Dissertation
Text version	ETD
URL	http://hdl.handle.net/10119/11557
Rights	
Description	Supervisor:丹　康雄，情報科学研究科，博士

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

Konlakorn Wongpatikaseree

Japan Advanced Institute of Science and Technology

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

by

Konlakorn Wongpatikaseree

Submitted to
Japan Advanced Institute of Science and Technology
in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy

Supervisor: Professor Yasuo Tan

School of Information Science
Japan Advanced Institute of Science and Technology

September 2013

Dedication

To my respected parents, my beloved wife.

Abstract

Until now there has been continued growth in the size of the aging population living at home alone and suffering from physical disabilities. To this effect, many kinds of research are being developed for a system that can improve the quality of life of elderly or needy people in the ambient assisted living (AAL) environment, especially in the home domain. Nevertheless, the information, used in current research works, might not be enough in some circumstances. Other information might help improve the ability of the current research with human activity information being one of them. Thus, this research proposes a high performance activity framework for obtaining more reliable, reasonable, and accurate results.

Consequently, this dissertation describes a "High Performance Activity Recognition Framework for Ambient Assisted Living in the Home Network Environment." The main goal of this study is to develop a high performance activity recognition framework for home application based on the results of this research.

To achieve the goal of this dissertation, Context-aware Activity Recognition Engine (CARE) architecture is designed as a human activity framework. The application requiring human activity information can be built on top of the CARE architecture, i.e. the healthcare system, semantic ontology search system, home security system, etc. The CARE architecture consists of six layers each combining several technologies and techniques.

For building the practical architecture, this research proposes a context sensor network (CSN) in the real environment to collect the surrounding information in the home; including human information. The proposed CSN integrates several sensing techniques for obtaining the data and several communication networks for its transmission. Moreover, posture classification is also presented in this research with a novel range-based algorithm for classifying human posture. All the information will be conformed to the new user's context, and sent to the proposed activity recognition system.

Ontology-Based Activity Recognition (OBAR) is introduced in this research for classifying the human activity based on the new user's context. The ontology approach is selected to define semantic information in the smart home and also to model human activ-

ity. The OBAR system is different from other existing activity recognition in terms of the new user's context and history information. The original idea of using an ontology concept does not support temporal reasoning. However, the OBAR system is implemented together with the external program to keep track of temporal reasoning. Moreover, a new term of activity log introduces the activity's location in activity log (AL^2). The history of activity occurring at the current user's location will be investigated. It improves the results more reasonably and reliably. Through experimental studies, the results reveal that the proposed CARE architecture can achieve an average accuracy of 96.60 %.

Since the proposed research can produce reliable, reasonable, and accurate results of activity recognition, several home applications in the research domain can become more efficient by utilizing the results of this research. For example, the activity information can be used in the healthcare domain for analyzing or recognizing a disease. In the provision of home service delivery, current research systems are dependent on the current situation. However, if the system knows the user's habits based on routine activity, it can prepare the home service automatically.

Acknowledgments

I would like to convey my gratitude to my principal advisor, Professor Dr. Yasuo Tan, who encouraged and advised me with ideas for my dissertation from beginning to end. I am delighted and grateful to be able to work under the excellent supervision of Professor Dr. Yasuo Tan. He provided me with unlimited support and cooperation. He gave me the opportunity to carry on my research at JAIST in Japan under The Graduate Research Program (GRP) scholarship. Without his help, I would not have been able to finish this research.

I gratefully acknowledge the generous support and cooperation of Associate Professor Dr. Azman Osman Lim, who is my sub-supervisor. He provided many valuable comments and intellectual support to my research. He helped me to realize how fun it is to undertake scientific research in Japan. I gained excellent knowledge on the production of a good publication from my sub-supervisor.

I am deeply grateful to my minor research supervisor Professor Dr. Mitsuru Ikeda, who has provided me with the ontology knowledge during my minor research work. Being a novice to ontology knowledge, he gave some helpful guidelines, discussions and suggestions throughout my research. He taught me not only academically, but also showed me the way to carry out the research. I still remember his talk "You do not need to do complicated research, but you have to make a research contribution." I would like to thank, Dr. Hideaki Kanai, Associate Professor in the School of Knowledge Science of JAIST, for his help. He gave me a great chance to conduct my first experiment in his research facility, "AwareRium".

I would like to express special thanks to my professors in Thailand. Assistant Professor Dr. Cholwich Nattee, Associate Professor Dr. Thanaruk Theeramunkong, Dr. Thepchai Supnithi, Dr. Marut Buranarach, Dr. Ananlada Chotimongkol, and Dr. Denduan Pradubsuwan. All of them have supported me absolutely throughout my Bachelor degree, and also inspired me to study Doctoral degree in Japan.

I devote my sincere thanks and appreciation to Mr. Marios Sioutis, Mr. Junsoo Kim, Mr. Yoshi Makino, Ms. Wai Wai Shein, and Mr. Zhengguo Yang, and all the members of "Tan & Lim Lab" for their support and cooperation. Working with them has helped me to discover fun and enjoyment during my stay at JAIST. I am also grateful to my friends: Mr. Chaianun Damrongrat, Mr.Kobkrit Viriyayudhakorn, Mr. Apimuk Muengkasem, and all my Thai friends who helped to make the three years fly by.

I would like to thank my parents, Mr. Siri Wongpatikaseree and Ms. Chantana Udompuksa, who kindly support me in all I do. Moreover, I am fortunate to have my beloved wife, Ms. Arunee Ratikan, whose kind support, encouragement and love always inspired and motivated me during the tensions and frustrations of my life.

Last but not least, my sincere thanks to all the JAIST staff and those who have cooperated with me. They have always been very helpful with any problems I have had during my stay in Japan.

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Chapter 1

Introduction

1.1 Introduction

For the last 50 years [1], the world's population has multiplied more rapidly than ever before, and is projected to grow even more rapidly in the future. From the statistics, the world population was 2.5 billion in 1950, 6.5 billion in 2005, and could reach more than 9 billion in 2050. The exponential growth poses problems for almost every country. Each government faces the difficult task of dealing with the population in their country. Meanwhile, the growth of high technology, especially in medicine, is one of the important and emerging factors that increases the average age of the population. The proportion of people who are over 60 years old is increasing faster than any other age group. For example, nearly 25 million Japanese are over 65 years old and approximately 20,000 citizens are over 100 years old. The World Health Organization [2] estimates that the original shape of the population will have inverted to an up-side-down pyramid by 2025, with people aged 80 and above accounting for the largest population group.

Improving the quality of life is attracting growing attention contributing to intensive thrusts from the latest technological development and application demands. The Ambient Assisted Living (AAL) environment is one of the areas that most researchers are aiming to develop to assist and support independent living and ageing in place. The basic idea of AAL is to provide assistant technologies for enhancing quality of life and supporting people in their daily activities. There are a number of ways that devices in the AAL environment and connected to ICT technology can help to improve the quality of life and health of the elderly. For example, Panasonic [3] has introduced EW-NK63, a device used for measuring the calories consumed each day. Omron [4] has presented a Heart Scan device for monitoring and recording the ECG information. Based on these example technologies, users can monitor the condition of their own health, and the physician can utilize this data to recognize diseases. Nonetheless, the assistant technologies in the AAL environment are not only limited to medical services. A verities services can provide more comfort in everyday life, higher security in the living environment, or automatic home service and energy saving.

Nowadays, the concept of the AAL environment is also expanded to include the smart home domain. The smart home has emerged as one of the mainstream approaches to support technology-driven independent living for elderly and disabled persons. The smart home concept [5, 6] is combined with several technologies i.e. wireless sensor network (WSN), data communication, and security to produce ambient intelligence in the home. Figure 1.1 shows an example of the next generation smart home network.

Based on Figure 1.1, powerful and scalable user context can be obtained based on the AAL environment in the smart home. Diversity of sensors is embedded into the object in the home to obtain context-aware infrastructure information. The context-aware infrastructure information in the smart home is useful in several home systems. For example, knowing how long the home user sleeps at night [8] is considered relevant information for the homecare system, furthermore, realizing the difference between the user's sleep time and the status of door is useful for the home security system.

According to the ability of the AAL environment in the smart home, the activity recognition system plays an important role in realizing the information in the AAL environment and providing the relevant information back to the home application for supporting the independent living and ageing in place. Currently, activity recognition systems aim to capture what humans do on a daily basis [9, 10]. However, realizing the information from activity recognition in supporting the smart home based AAL environment rarely appears

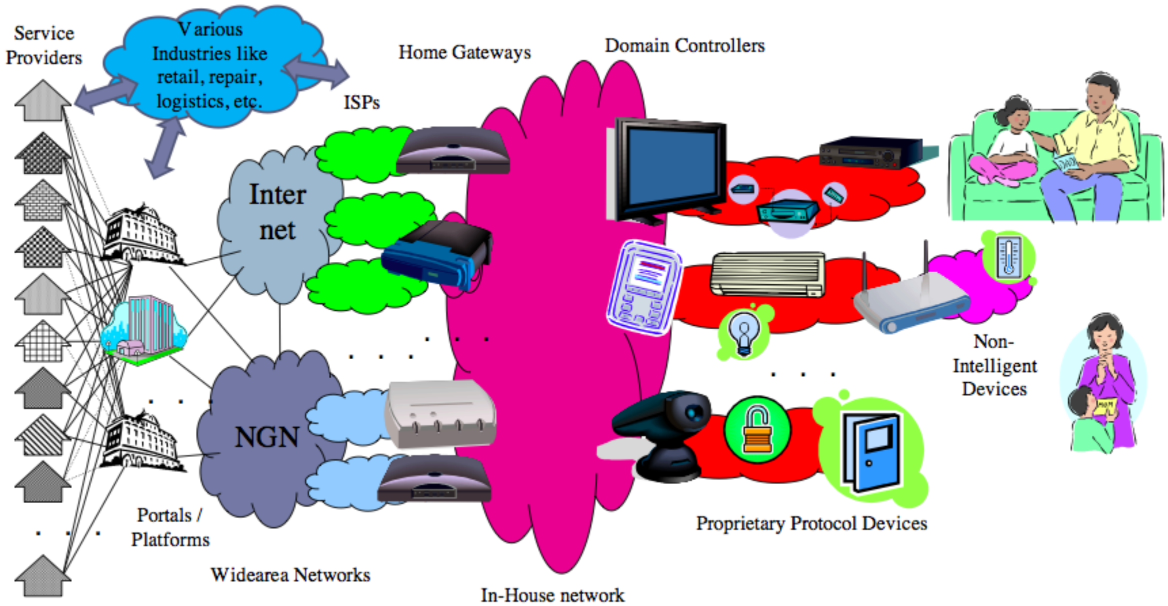


Figure 1.1: Next generation smart home network [7]

in current research. Moreover, constructing the activity recognition is not an easy task. It is difficult to accurately assess an individual activity pattern because each person has a different lifestyle. Therefore, the development of the high-performance activity recognition framework for realizing the application in the smart home domain presents a number of challenging tasks.

1.2 Statement of problems

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 cannot classify human activity 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 this sense, the high-performance activity recognition framework is required for addressing the existing problems. In this section, summarization of the problems of existing research is illustrated as follows:

1. Although the human activity information is useful for several purposes in the smart home domain, it is not easy to achieve reliable results from the activity recognition system. Existing research work has failed to adequately identify human activity because of the variety of human lifestyles.

2. Based on the current research [8, 65, 66, 71], the basic context aware information (user's location, object activation, and time) is used to conform the user's context for the activity recognition system. The system provides only a common term of primitive activity and might not be realistic in some circumstances. For instance, 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. Context-aware information, especially object activation information, can lead to an ambiguous problem. For example, when several objects are being used at the same time the activity recognition system generates several possible resultant activities. The system cannot know which one is the correct answer. This research refers to this problem as the "ambiguous activity problem".

4. Data collection directly affects the accuracy of activity recognition. Most of the existing research relies on data collected from subjects under an artificial laboratory setting. It is not realistic in a real situation. Thus, data collection in the real home environment is relevant in proving the accuracy of the proposed activity recognition.

1.3 Research objectives

As exploratory research, the main purpose of this study is to develop the high-performance activity recognition framework and realize the applications in the smart home based on the results of the activity recognition framework. Hence, in pursuing this purpose, four objectives are introduced to answer the current problems as follows:

1. The proposed research should have an artificial intelligence module to collect the necessary context aware information in order to conform to a new type of user context in the activity recognition system.

2. The architecture of the system must be well designed to achieve a high performance activity recognition system. Moreover, the proposed activity system should have the ability to reduce the "ambiguous activity problem".

3. The proposed activity recognition should be a practical system. The activity recognition has to demonstrate its operation in real scenarios with volunteer users. Thus, system verification will be introduced to the real environment.

4. Reusability of the recognition results with the applications in the smart home is presented in this research.

1.4 Research methodologies and originalities

To achieve the above objectives of this research, there are two main research methodologies: a context-aware activity recognition engine (CARE) architecture, and an ontology-based activity recognition (OBAR). These are described as follows:

1. **Context-aware Activity Recognition Engine (CARE) Architecture:**

   Designing the CARE architecture is the relevant process that needs to be considered carefully. The CARE architecture is proposed as a human activity recognition framework in the smart home domain. It consists of six layers, each combining several technologies and techniques. For data collection in the CARE architecture, not all of the surrounding information in the home affects the system, therefore, it is necessary to focus on the relevant information to be used in the activity recognition system. Context sensor network (CSN) is introduced in the CARE architecture to obtain the surrounding information from the home and individual. Moreover, posture classification is also proposed to collect novel information of human posture, in order to conform to a new user's context.

The originality of this research methodology is that the proposed CARE architecture can provide the semantic information in the smart home and human activity information based on the new user's context, which is obtained through the CSN and the posture classification. Compared with the traditional activity recognition system, the new user's context shows the ability to reduce the "ambiguous activity problem" more successfully than in the existing system, which uses the common user's context.

2. **Ontology-Based Activity Recognition (OBAR):** The ontology concept OBAR is the main approach in the development of activity recognition in this research. The OBAR is introduced as a sub-system in the CARE architecture. The OBAR addresses the difficulty in explicitly handling huge amounts of information from a diversity of sensors. Moreover, the ontology concept is used to define the surrounding information in the home and from the individual. Based on the proposed OBAR, the information history is also described in the activity log ontology. A new term in the activity log, called the activity location (AL^2) is proposed in this research.

   The originality of OBAR is a system that can handle an extra large amount of observing data and limit the training process. The advantage of the ontology concept also appears in the OBAR. For example, the OBAR creates the activity model as a standard model. This means the activity model is not specific to the person. It is totally different to other methods in that the activity model will be specific only to the person who trains the data. Furthermore, the OBAR also shows high-performance activity recognition with the new user's context and AL^2. The AL^2 shows this advantage overcomes the existing research, which utilizes the common activity log in activity recognition. The research on the OBAR exhibits not only high performance in classification, but also yields reliable and reasonable results.

1.5 Chapter Organization

This dissertation is organized into nine chapters as shown in Figure 1.2. Chapter 1 provides the introduction of this dissertation, statement of problems, research objectives, research methodologies and originalities of this research. Then, Chapter 2 describes a review of the existing research in the area of ambient assisted living and activity recognition. Chapter 3 provides an explanation of the CARE architecture. Next, the process of CSN, which is used for collecting data; is described in Chapter 4. After that, a new algorithm in posture classification is presented in Chapter 5. This dissertation then presents data organization and describes the process in OBAR in Chapter 5. Chapter 6 shows the evaluation of the impact of the description logic rule used in the OBAR, and also presents the performance of the proposed activity recognition system. Chapter 8 exhibits possible applications which realize the results from the OBAR. Finally, the conclusion and ideas for future research are presented in Chapter 9.

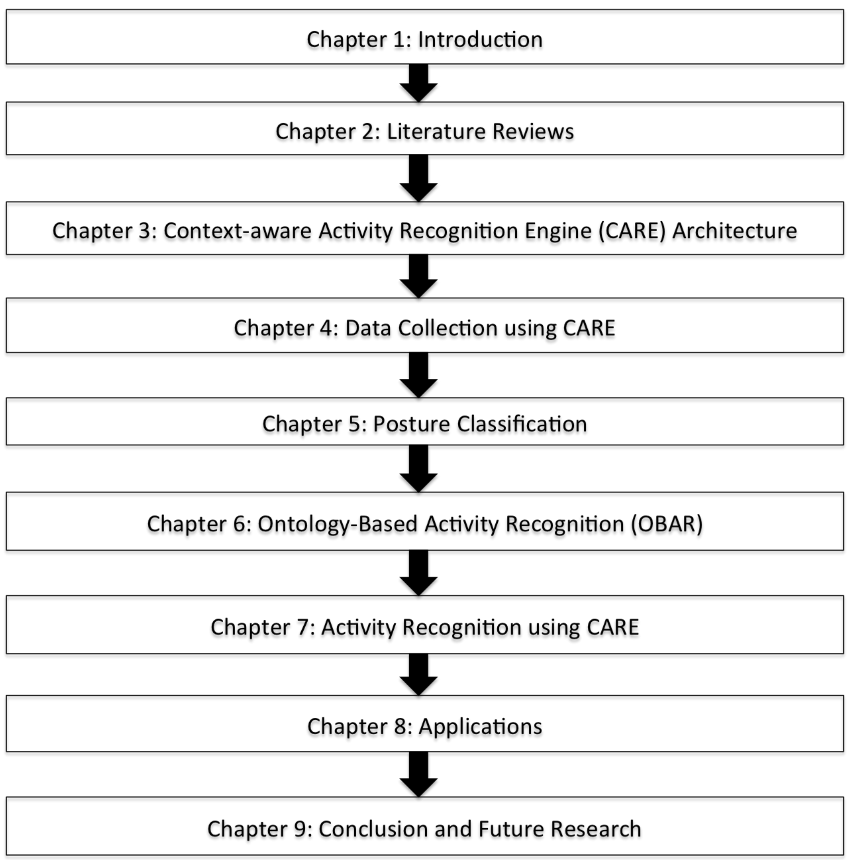


Figure 1.2: Organization of this dissertation

Chapter 2

Literature Reviews

2.1 Introduction

Until now, the smart environment [11] has become popular with the realization of development technology. Together with the concept of Ambient Assisted Living (AAL), it can provide an interactive environment for improving the quality of life in place. The trend of AAL has expanded into several situations for various purposes. For example, the AAL system in hospitals is proposed for the purpose of healthcare, or the AAL in the smart home is introduced to help the elderly improve their quality of life. In this sense, the AAL system integrates several system concepts for living assistance; and the activity recognition system can improve the ability AAL. The activity recognition system has been explored in different environments, such as homes, hospitals, and factories. In this research, the smart home domain is considered to implement the activity recognition system. The increasing capabilities of generating massive amounts of sensor data related to the smart home environment could provide novel advanced activities of daily living (ADL) for several purposes in the AAL environment.

However, obtaining reliable and accurate results from the activity recognition system is not an easy task. There are several factors that affect recognition accuracy. Accordingly , to build high performance activity recognition for ambient assisted living (AAL), background knowledge in both the AAL system and activity recognition system is required. In this chapter, the main work reviewed from previous and current work relates to both the AAL system and the activity recognition system.

2.2 Ambient Assisted Living (AAL) System

AAL is an intelligent system of assistance that aims to improve the quality of life of the elderly or other needy people. AAL systems are seamlessly embedded in the preferred living environment. The systems are capable of gathering environmental and personal information and reasoning with it. They also acquire knowledge of their surroundings with ambient intelligent technologies. The ambient intelligence technologies are widely developed in this domain and aim to construct a safe environment for assisted people and help maintain independent living. Consequently, the AAL system can provide an interactive environment for people based on ubiquitous sensing, environment interaction, and context-awareness.

Accordingly the AAL environment can be extended to incorporate a wide domain, such as hospitals, homes, or companies. Figure 2.1 shows the multifaceted AAL environment, presented in research by O'Grady et al. [12]. The home network environment is the main area of focus. Thus, in this section, research on the home-based AAL system will be reviewed.

2.2.1 Home-based AAL System

The definition of the home-based AAL system is to integrate two basic concepts; the smart home and the AAL. The smart home concept embeds the ambient intelligence technologies for sensing, reasoning, or controlling the environment in a person's daily life. Meanwhile, the concept of the AAL uses information and communication technologies (ICT) to provide individual support in a person's preferred living environment. For example, Martin et al. [13] developed the wireless sensor networks (WSN) in the AAL environment to support the provision of future AAL service.

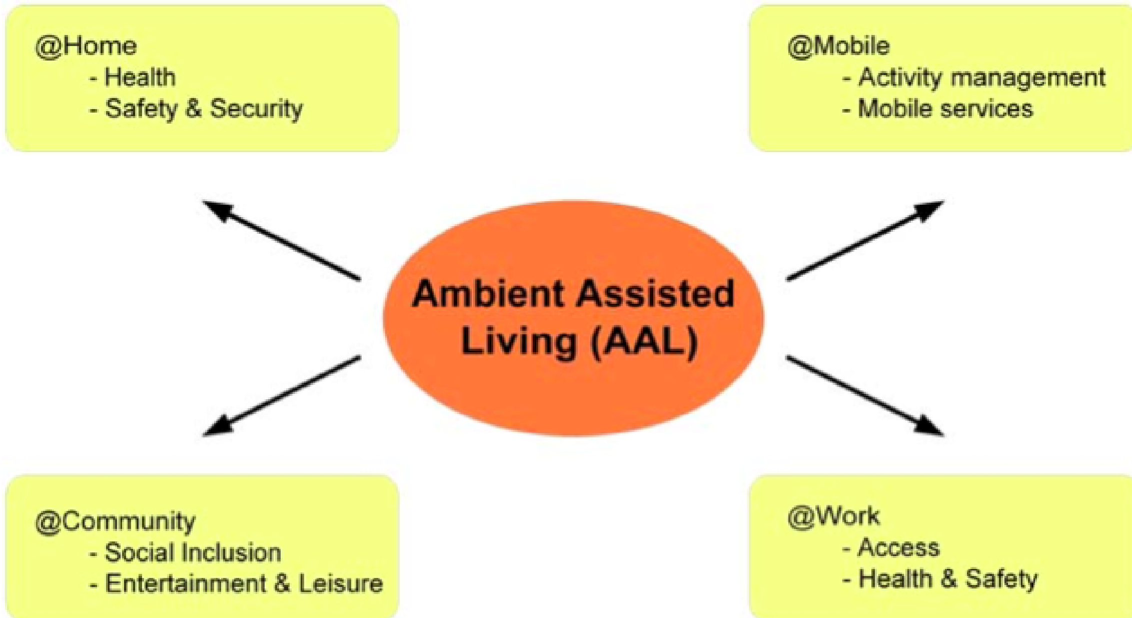


Figure 2.1: The example areas of AAL environment [12]

The definition of the home-based AAL system varies depending on the research, but its final goal is the same. The following is a good description of the home-based AAL system, proposed by Steg et al. [14]

"AAL aims to prolong the time people can live in a decent way in their own home by increasing their autonomy and self-confidence, the discharge of activities of daily living, to monitor and care for the elderly or ill person, to enhance security and save resources"

Recently, research on the home-based AAL system has become more popular. Several research studies propose novel architecture for processing the information in the AAL environment. Spanoudakis et al. [15] applied technological solutions in the HERA system for addressing the needs of the elderly suffering from moderate and mild Alzheimer's Disease. Near Field Communication (NFC) technology has also been developed in research of the home-based AAL system for identifying human location [16]. Human location is used to assist when taking care of people who have a problem with Alzheimer's. Reichman et al. [17] described the general architecture of the ambient assisted living system. The conceptual description of the home-based AAL system is shown in Figure 2.2 with three main components. It starts in the physical world. The system gains context-awareness information when humans interact with objects or the environment. For example, home users turn on the "Air-condition", and the room temperature changes when the "Air-condition" is turned on. This kind of information is based on the observation of the ambient intelligent technology or sensor. The system will then process the data and send the results back to the actuator for the provision of services to the home user or controlling objects in the home environment.

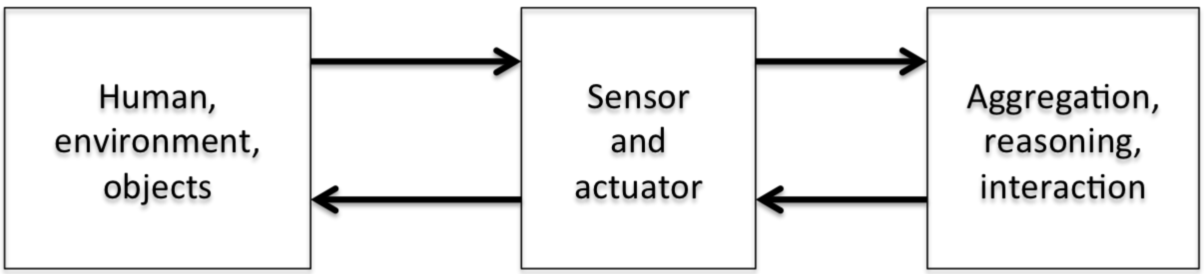


Figure 2.2: Conceptual description of the home-based AAL system

With the concept of the home-based AAL system, there are several technologies and techniques applied to each part. The following is a detailed description of each part of the home-based AAL system.

1. **Human, Environment, Objects**

   Before providing services or controlling objects in the home, the context-aware information in the home is necessary for later processing stages. In the evolution of homes in the 21^{st} century the concept of ubiquity has been explored for presence-aware home control. The context-aware information in the home-based AAL system can provide various kinds of information, depending on the purpose of the research domain. For example, for the purpose of smart home automation, Beak, et al. [18] proposed an intelligent home care system based on a sensor platform to acquire environment data from the home. The context-aware information is used in the home appliance control system for managing the optimal performance of devices at home.

Considering in detail of the context-aware information, this can be divided into three types. Firstly, the human information obtained from the home user. For example, human activity information can be used for predicting or monitoring elderly people in the home. Virone et al. [19] proposed activity prediction for in-home activity monitoring. They used various housing contexts in the home such as an assisted living (AL) facility for a better understanding of behavior. Other human information can also be obtained directly from the user's body. For example, the user's health information (body temperature, blood pressure, or ECG) can be used for the home health care (HHC) system. Kang et al. [20] proposed a remote health monitoring and self-check health system. The physician can monitor the patient's health information (heart rate, blood pressure, or body temperature) to anticipate or detect health risks.

Secondly, comes home environment information. Monitoring home environment information is also useful for the home-based AAL system because it can be used for analysis purposes. For instance, the system observes the current room temperature, and adjusts the room temperature according to the occupants' comfort. Other home environment information, such as smoke emission can be used in the home security system, or an ambient brightness system can perceive brightness information and control the light in each room for energy saving.

Lastly, there is object interaction information. This information is mainly used in the home-based AAL system for the provision of home service to the user. It is a simple idea to detect the object that the home user is using at that time, and provide a home service based on the activated object. For example, if the system detects that the home theatre is being used by the user, the system might provide an entertainment service to the home user by reducing the brightness in the room and controlling the proper room temperature. In the same way the system is able to perceive that the user is sleeping by detecting the use of the bed. The system might provide a security service by preventing theft.

2. **Sensor and Actuator**

Based on the information from the first part, sensor and actuator play an important role in collecting the data to interact with the physical world. For observing the data, there are several types of sensors, presented in existing research. Hui Wang et al. [21] proposed the information-based sensor tasking WBAN in u-Health systems. They aim to prevent stroke disease by gaining health information obtained from portable healthcare devices (e.g. ECGs, EEGs, Blood pressure, Body Temperature, Pulse), shown in Figure 2.3. ature, Pulse), shown in Figure 2.3.

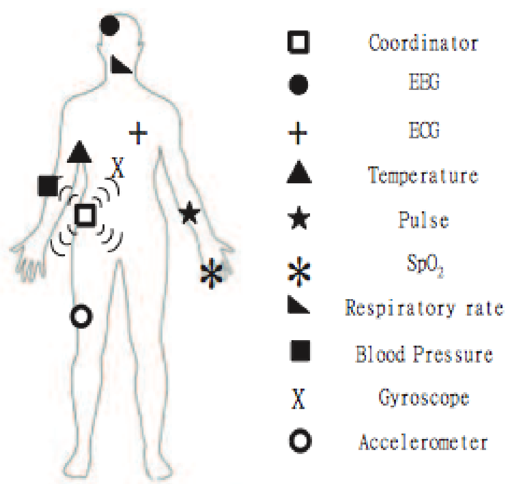


Figure 2.3: The example devices in [21]

To monitor the user's health information in the AAL environment, the novel health care device is also presented in Lopez et al. [22]. They developed electronic textiles (e-textiles) for measuring physiological data. The advantage of e-textiles is not only for monitoring the patient's health, but also their comfort. It does not disturb the user when using the e-textiles [23, 24]. For observing other information in the home, Rowe et al. [25] introduced a micro-climate for a personal tracking application in the indoor environment. Human location can be used for tracking elderly people or taking care of individuals with Alzheimer's. Kovacshazy et al. [26] detected human motion through the passive infrared (PIR) motion sensors in the AAL environment. The collected information can be used in the security application by monitoring movement in the observed area, and also used for tracking the activity of elderly people in the home. Wei Wei et al. [27] proposed a home temperature control (HTC) system. They designed a PID controller for temperature control in the cyber-physical home system. Air-conditioners and windows are controlled by both PID hybrid controllers.

Using video cameras is one option to observe the information in the home-based AAL system. Poh et al. [28] presented a methodology for contactless measurement of cardiac pulse rate using a video camera. NaitCharif et al. [29] used an overhead camera to recognize human activity and investigate whether or not human activity is a good indicator for health. Foroughi et al. [30] presented an eigenspace-based approach for human fall detection through the video camera.

3. **Aggregation, Reasoning, Interaction**

After obtaining the context-aware information from the sensor, the responsibility of this part is to process the collected data. Normally, there are three main steps to this. First is the aggregation step. The context-aware information is gathered into the system. For example, for the purpose of healthcare, electronic health records have been introduced for several years. There are three kinds of electronic records widely used today: electronic medical records (EMR) [31], electronic health records (EHR) [32], and personal health records (PHR) [33]. These electronic health records are important in helping the patient monitor their own health information. Moreover, the benefits of the electronic health records are also presented to improve the accuracy of diagnoses and health outcomes, increase patient participation in their care and reduce healthcare costs. In a different way , human activity information can be collected into the activity log for learning the model in the activity recognition system.

The second step is reasoning. There are several techniques used for processing the data in the AAL environment. Xu et al. [34] proposed a Complex Event Processing (CEP) based on semantic technologies to detect typical situations in real-time.

The ontology concept is also presented to express the users' preferences in order to personalize the system behavior, and also discover an interconnection of devices [35]. Meanwhile, the artificial intelligence (AI) domain is developed in the AAL environment. Artificial neural networks (ANNs) are used to compute the time offsets of the controller in a heating system [36]. A rule-based engine is also developed in an ambient home care system (AHCS) in order to enable context-aware medication prompting [37]. In other research methodology areas, a computer vision approach is one methodology that uses the image processing technique for computing the image information in the AAL environment. Cardinaux et al. [38] proposed a taxonomic scheme in the computer vision approach for action recognition in the AAL environment. They define the actions by individual posture features (e.g. bending over, lying, squatting, etc.) or by individual ambulatory information (motion tracking). Following the same direction, Ovejero et al. [39] reviewed the image algorithms used for AAL services.

After processing the data and obtaining the results, interaction with the physical world is the last step of this part. Normally, the home-based AAL system will interact in two ways. Firstly, it sends an interaction command to control the object for a specific purpose, namely automation technology. For example, air-conditioners and windows are controlled by the system in order to adjust the room temperature [27]. Lee et al. [40] proposed a bundle of context-aware information in home services. The system analyzes the context-aware information in the home to control an object which may not be in use that time. For example, the system will turn off some devices in the living room while the user is cooking in the kitchen. Secondly, it provides a service to the home user in the healthcare domain. For example, Park et al. [41] proposed the development of the u-Wellbeing Support System. Medical staff can diagnose a health condition from the patient's vital signs collected from the wireless devices through the u-Wellbeing Support System. The doctor can then maintain the user's wellbeing by offering a healthy meal and an exercise-recommendation service. In addition to wellbeing, a diet recommendation service has been proposed to support those at risk of obesity. Basic information such as vital signs, family history of disease and food intake is considered to provide a diet recommendation service to the user [42].

2.2.2 Current Approaches in Home-based AAL system

As a traditional purpose of the home-based AAL system, several research studies have proposed applications that focus on the healthcare domain. Nevertheless, the ability of the home-based AAL system is not limited to merely healthcare. Recently, more and more projects are beginning to extend the concept of the home-based AAL system. Current applications in the home-based AAL system are capable of gathering environmental and personal information and reasoning on it. Below is a list of research domains applicable for the home-based AAL system.

1. **Home Automation**

   The idea is such that the AAL environment plays an important role in application development in home automation. Applications in this domain aim to provide services to the home user according to their situation, location, time, and so on. These services are performed by many kinds of home appliances in the user's home. Zamora-Izquierdo [43] presented the DOMOSEC platform that covers a home automation solution. This platform has an ability to control appliances in the home. For example, they control an automatic window opener and air-conditioner by adjusting the desired temperature, or open and close the blinds according to the desired light intensity. Mynatt et al. [44] developed a wireless device that enables users to control different services within the smart home environment, such as closing the blinds, locking the door, and so on. Tiberkak et al. [45] proposed an automated policy-based system. The policy is used not only for controlling the household appliance, but also the management of each room.

2. **Home Security**

   Detecting an abnormal situation in the home environment, or anticipating an unexpected situation is the main concept of the application in the home security domain. Lee et al. [46] proposed the network-based fire-detection system in the smart home environment. A fire detector such as a smoke detector, heat detector, gas detector, etc. and actuators (e.g., guide light, fire wall, sprinkler, smoke ventilator, etc.) are connected to the home network. With the recent ongoing developments in home security, a combination of home automation and security is presented in the smart-home base AAL system. Balasubramanian et al. [47] introduced the remote control technique in home automation and security systems. The home user can switch on certain lamps to give the impression to others that the home user is inside, even if they are not.

3. **Home Healthcare**

   For the purpose of the healthcare domain, several research studies aim to provide several kinds of services to the home user for optimum health at home. A home healthcare (HHC) system has been proposed to help people achieve this [48]. The concept of HHC is illustrated in Figure 2.4, consisting of three main parts. Firstly, the system collects the personal health information of the home user and summarizes their daily health situation. The physician then makes a diagnosis based on that summary. Finally, doctor will give recommendations to the home user for prevention or treatment.

   With the user's health information, certain is research presents the ambient technology used for sensing that health information from the home user. Various kinds of health information have been collected. For example, Goh et al [49] has implemented home-based patient monitoring used for recognizing cardiac arrhythmias based on ECG data. The mobile health monitoring system (MHMS) architecture has been designed to monitor the heart rate from a RFID ring-type pulse sensor [50].

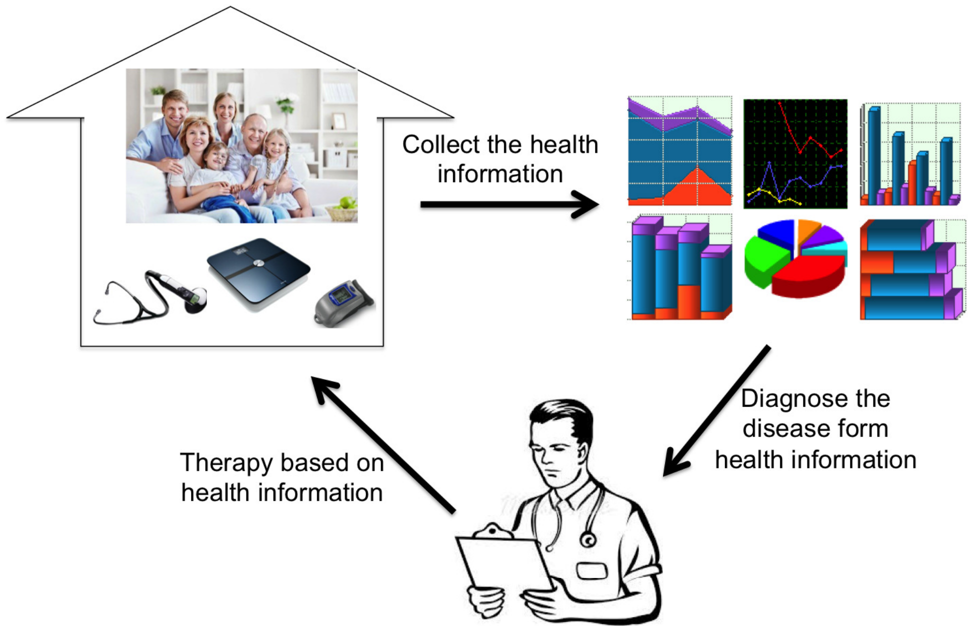


Figure 2.4: The basic concept of HHC

This section concludes with a description of the background knowledge of the AAL system from past present. The AAL system is an intelligent system of assistance that focuses on enhancing the quality of life of elderly or otherwise needy persons in the preferred living environment. Several research studies have developed the AAL system in different environments, but the most popular and challenging is the home environment. The home-based AAL system has been proposed according to the concepts of the smart home and the AAL. The home-based AAL environment is the same as the common AAL system, but mainly focuses on the home environment. The conceptual home-based AAL system has three main parts. The first is the physical world. The system will sense the data from both the home environment and the individual. The second part is the sensor and actuator. This is a part of ICT technology included in the concept of the AAL system. Diversity of sensors is deployed in the home facility, home environment, and also attached to the human body. The latter step has a duty to process the collected data. All of the data is aggregated, computed, and interacted later.

The direction of the application in the home-based AAL system has been extended to several research domains. There are two main forms of information often used for implementing the application: the context-aware information and the user's health information.

Information such as object activation, human information, room temperature, and so on, are gathered to conform with the context-aware information. The context-aware information can be used for analyzing the current situation in the home, and the application can control the home appliance based on the analyzed context-aware information. Meanwhile, the user's health information is applied in relation to the healthcare domain. The system can detect abnormal signs from the user's health information and alert the home user or physician to enable checking of the health condition.

Nevertheless, merely the context-aware information and user's health information may not be sufficient for applications in the home-based AAL system in certain circumstances. For example, when several objects are being used at the same time the system is unable to make a decision as to which home service is appropriate for the home user, or using only health information may be suitable for analyzing symptoms of a disease. Other information might help improve the ability of the current applications. Human activity information is one that can be used to analyze the current situation in the home. For instance, if the system knows the home user is performing the "Watching TV" activity, it should provide a home entertainment service On the other hand, if the system perceives the user to have a high daily food intake, the system can send a health service to the home user to prevent an obesity problem. Therefore, an explanation of the background knowledge in the field of activity recognition systems will be provided in the next section.

2.3 Activity Recognition System

As the results obtained from such a human activity recognition system are relevant for several purposes, the activity recognition system has been developed in several research domains such as surveillance-based security, pervasive computing, context-aware computing and ambient assisted living, to name but a few. For example, in surveillance-based security, the system should be in the security mode, when recognizing that the home user is sleeping. In context-aware computing, the system can provide a suitable home service to the user if the system perceives current user activity. For example, if the system knows the home user is cooking, it should serve the home service that relates to the "Cooking" activity. Furthermore, other useful information can be generated from the activity information such as daily life (ADL) [51], human behavior [52], or healthcare information [53]. These kinds of information are useful for analysis in several ways.

Nonetheless, implementing activity recognition is not an easy task. There are several factors that can affect the system. Among existing research efforts in this area, several ways to recognize daily physical activity have emerged. 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, have unique lifestyles, habits, and abilities. Thus, each activity can be carried out in a different sequential order. For example, to make coffee, some individuals turn on the kettle first, whereas some prepare the cup of coffee and milk first. Such phenomena can occur depending on individual lifestyles. Currently, the process for developing activity recognition falls into two parts: sensing and recognition.

2.3.1 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 for the activity recognition system.

1. **Visual Sensing Approach**

   The visual sensing approach has been used in the computer vision area for several years [54, 55]. This approach is suitable for the long term monitoring of people because it is not affected by the life of the battery and does not need to attach any sensor to the human body. However, implementing activity recognition based on the visual sensing approach is not an easy task since people are free to move throughout the area of interest in any direction they like. In addition, it is hard to detect the transition state from one activity to another. For example, the "Cooking" and "Washing dishes" activities have the same human posture and location. Thus, the system cannot classify the correct activity.

Based on this approach, a visual sensing device, such as a high-resolution camera, is mainly used for collecting images or video files. The image processing technique plays an important role in this approach to extract essential information from the video recording to classify human activity. Single viewpoint-based surveillance has been developed in some activity recognition research. A pose recognition algorithm has been proposed using a 3D camera [56]. This applies the depth of information to track the location of the individual in the image, and classifies the human poses by using the pose recognition algorithm. Wallhoff et al. [57] proposed activity recognition with depth of information. Various kinds of techniques (person counting, face detection, and gesture recognition) are included in his research.

However, single viewpoint-based surveillance might not be suitable in large areas because of the angle and position of the camera. A distributed camera network has been proposed, not only to detect human action [58], but also to detect the appearance and determine traveling times of individuals in an area [59]. They separated the individual activities into four different classes: normal, break-in, stay, and sudden appearance/disappearance. This information is necessary to monitor the elderly, who live alone in the home. 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. In addition, the system cannot classify specific activities such as "watching TV," "working on a computer," or "sweeping the floor." 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 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.

2. **Sensor Network Approach**

   Research in activity recognition has found the sensor network approach to be the most popular. In this approach, a network of diverse sensors is used on the objects, including the human body. The system entails collecting various kinds of information from the sensors. Thus, this approach can recognize human action through the information from the sensors directly. Based on the sensor network approach, it can divide the data sensing into two techniques based on sensor placement.

First is the body sensor network (BSN) technique. Portable sensors are attached to an individual's body in order to collect body movement information. There are several types of sensors used in the BSN technique. For example, accelerometer sensors are used to capture human movement by calculating the acceleration signal in three dimensions [60, 61]. Although the results of current activity recognition based on the BSN technique show a high performance; it is not realistic in some circumstances. Most of the existing works rely on data collected from subjects under artificially constrained laboratory settings to validate recognition results [62], whereas the performance of application, which collects data in natural or out-of-lab settings, is dropped [63]. Therefore, the BSN technique presents the following number of challenges:

- The real environment is essential to verify activity recognition systems on data collected under realistic circumstances because laboratory environments may artificially constrict, simplify, or influence subject activity patterns.

- The number of activities are limited when using only as body sensors. The system cannot know which object is being used by user.

- The size of the sensor and battery is the main problem that deters the user from wearing the sensor device. It is also difficult to attach sensors to every part of the body.

- It is difficult to discern human activity when the person does not move at all or very little, which leads to undetectable signals for identifying the posture.

Many recent research works, including this research, have studied activity recognition as part of context awareness. The second technique is a home sensor network (HSN) technique for detecting which object is being used. The concept of HSN is different from the BSN in terms of type of sensor, type of data and sensor placement. The sensor placement of the HSN technique is changed from the body part of an individual to the home facilities. Thus, the HSN technique does not need to attach any sensors to the human body. The context information or object activation information describes the situation or status of the user or device. Radio-frequency identification (RFID) technology [64, 65] is also used in this technique to find the user's location or to observe which object is being used. Zhang et al. [66] proposed a system that recognizes human activity by monitoring what home appliance is being used and for how long. Nevertheless, the HSN technique still encounters the following problems:

- Several sensors are required in the HSN technique to be built into the home facility such as in the toilet, TV, and bed, to detect what home facility is being used.

- Results from the use of the HSN technique can sometimes indicate several possible activities when several home facilities are being used at the same time, this is called the "ambiguous activity problem" [67].

2.3.2 Recognition

Having obtained sensing data, one can then recognize human activity by classification. Numerous intelligent techniques have been proposed to recognize human activity. Existing research and recognition methods can be grouped into two approaches.

1. **Data-driven Approach**

   The data-driven approach learns the activity model from a large-scale dataset of information based on probabilistic or statistical classifiers. The advantages of this approach are the capabilities of handling uncertainty and temporal information. Current research on the activity recognition system has focused on this approach. Several training and learning processes have been found in the activity recognition system. Hidden Markov Models (HMMs), naive bayesian, or Support Vector Machines (SVMs) are the example techniques that are often used to determine the results of classification. HMMs is a popular technique that is widely used in activity recognition. HMMs is a kind of stochastic state transit model, which treats discrete time sequences as the output of a Markov process whose states cannot be directly observed. He et al. [68] proposed a real-time activity classification framework based on the HMMs. The human activity series is considered as a Markov process, and activities are considered as states. In addition, in his framework, the Baum-Welch Algorithm is used to train the parameters of the model and the Viterbi algorithm is used to estimate the most probable hidden states. In the computer vision area, Chen et al. [69] proposed the HMM for activity recognition using star skeleton. Star skeleton is a fast skeletonization technique connecting the centroid of the target object to contour extremes. An action comprises a series of star skeletons over time and is transformed into a feature vector sequence for the HMM model. Nevertheless, the limitation of the HMMs technique means it is incapable of capturing transitive dependencies of the observations due to its strict independence assumptions.

Other probabilistic analysis methods are also presented in previous works. In the Bao et al study [70], 20 activities were classified with the accelerometer sensors. In his research, the combination between decision tree classifiers and the nearest neighbor (NN) is the best technique, which achieved over 80%, compared with decision table, instance-based learning (IBL), and naive bayes. In the work by He et al. [71], autoregressive coefficients were extracted from tri-axial accelerometer data. These essential coefficients are used as the input features of the SVM classifier. Four activities (running, still, jumping, and walking) are classified based on SVM with an average accuracy of 92.25%.

Even though the data-driven approach has a strong point of generating personalized activity, this approach still has limitations. The main problem is that the learning and training process requires a large data set for creating the activity model. If the dataset is too small, it can lead to the "cold start" problem. The "cold start" problem occurs when new information has just entered the system, and there is not enough information to find similarities. Furthermore, the training 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.

2. **Knowledge-driven Approach**

   The basic idea of the knowledge-driven approach is to use logical formalisms to formalize and create domain knowledge theories, including axioms and a plan (i.e. activity plan) library [72]. The concept of this approach is different to the data-driven approach because the knowledge-driven approach is more semantically clear in modeling and representation and elegant in inference and reasoning. In addition, the data collection does not affect the activity model in the knowledge-driven approach, but in the data-driven approach, the data collection has an influence on the activity model. However, handling uncertainty and temporal information is a weak point of this approach.

   The ontology concept is one of the knowledge-driven approaches, which consists of hierarchically organized concepts and the relationship between them. Normally, ontology is used to explain and define the object appearing in the domain of interest. The ontology concept has been adopted for defining semantic context information for explicitly and formally specifying shared conceptualization by knowledge engineering [73]. Domain knowledge can be modeled by using semantic information at a level of abstraction to prevent an over-large amount of observing data and limit the training process. To date, there are some ontology development tools such as protégé [74], Hozo [75], which provide support for creating various kinds of ontologies.

   The popular ontological language, the Web Ontology Language (OWL) [76] has been used to build activity ontologies, and to recognize activities based on context data. Naturally, ontology uses Description Logic (DL) [77] to express the knowledge for representing and reasoning with conceptual knowledge. 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. Therefore, the conceptual level of activity class is described by a number of properties while these properties infer to the types of objects that are used to perform the activity. Figure 2.5 shows the example of activity ontology, which is centered on the Activity class.

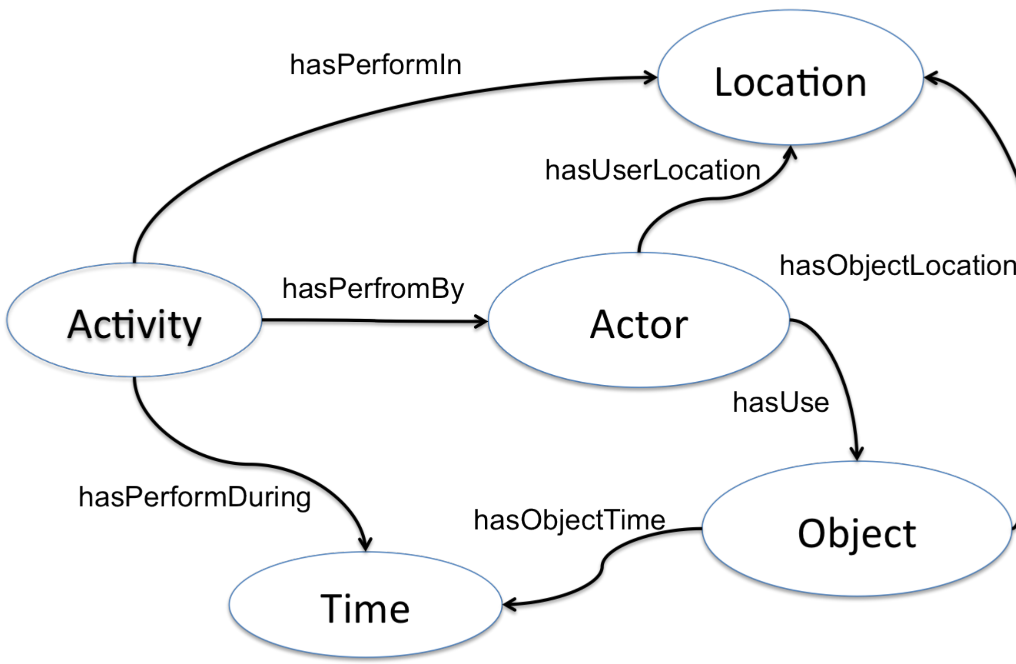


Figure 2.5: The example of the activity ontology

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. Chen et al. [78] proposed an ontology for analyzing social interaction in a nursing home using video. They design and refine the ontology based on knowledge gained from 80 hours of video recorded in the public spaces of a nursing home. Riboni et al. [79] proposed a combination of ontological and statistical reasoning for context-aware activity recognition. The basic context environment (user location, activated object, and time) is conformed as the user's context for activity recognition. Khattak et al [80] proposed the manipulation of recognized activities using Context-aware Activity Manipulation Engine (CAME). Within the CAME, ontology is used to define the higher level activity of a set of activities in a series, whereas the location information, time and profile information of the subject are linked in the low level activities.

2.4 Conclusion

This chapter describes a detailed review of two previous proposals in the AAL system and activity recognition system. The purpose of the AAL system is to build the AAL environment with the ICT technologies with the aim of supporting and improving the life quality of the elderly or otherwise needy people in their preferred living environment. In the same direction as the AAL system, the home-based AAL system was proposed with the same purpose of the AAL system, but focused specifically on the home area. There are several technologies and techniques applied in the home-based AAL system. However, the information currently used in the home-based AAL system might not be realistic in some circumstances. It requires other information to help improve the ability of the system, and activity information is one of them.

Consequently, the background knowledge of the activity recognition system was provided in section 2.3. The activity recognition system has been proposed for capturing what humans are doing. The results of the activity recognition system are useful in several research domains. Nonetheless, to implement the activity recognition system is not an easy task. Most of the research suffers from the problem of the variety of human lifestyles. Until now, the existing activity recognition research work have presented only a common term of primitive activity and might not be realistic in some circumstances. For example, 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). Consequently, the activity recognition system still needs to improve to support various kinds of problems, especially “ambiguous activity problems”. Thus, the following chapter of this dissertation will describe the proposed idea for studying human behavior to provide a health service based on the high-performance activity recognition system.

Chapter 3

Context-aware Activity Recognition Engine (CARE) Architecture

3.1 Introduction

The main aim of this chapter is to introduce the context-aware activity recognition engine (CARE) architecture, which is the core of this research. The proposed CARE architecture has the principal task of improving the ability of the activity recognition system, and providing results that are more accurate, more reasonable, and more reliable in the real environment.

The challenging tasks when designing the CARE architecture are presented. Firstly, when considering the smart home environment, how to observe enough necessary information for activity recognition. Secondly, how to handle the "ambiguous activity problem", which easily occurs when the home user uses several objects at the same time. Thirdly, which intelligent approach is appropriate for recognizing human activity in this research. Lastly, because each individual has their own lifestyle; improving the performance of the activity recognition system has to be observed.

Consequently, the CARE architecture is designed for recognition of human activity based on both human and context-aware information in the home. Several techniques are applied in the CARE architecture. For example, BSN and HSN techniques are developed to collect information from the individual and their surroundings in the smart home. To classify human activity, this proposed architecture focuses on target activities that users often perform at home, examples of which are shown in Table 3.1.

Table 3.1: 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.

3.2 A Layered Architecture of CARE Architecture

The CARE architecture is proposed as the human activity framework consisting of six layers as shown in Figure 3.1. The physical layer consists of hardware such as sensors, home appliances, or network components. This layer provides the context-aware and human information in the smart home The data layer has the responsibility of storing and organizing the data obtained from the physical layer. The semantic layer or the ontology concept is the main approach used for defining the activity model in the CARE architecture. The ontology model will be converted into the RDF (Resource Description Framework) file and linked to the data in the platform infrastructure layer via ontology application management (OAM) framework [81]. After that, the intelligent technique is built in the processing layer for recognizing human activity based on the knowledge converted in the platform infrastructure layer. Lastly, the application can be implemented on top of this architecture and application layer. The application can gain information from the human activity and semantic information in the smart home for several purposes such as the activity recognition system, semantic ontology search, or human behavior analysis system.

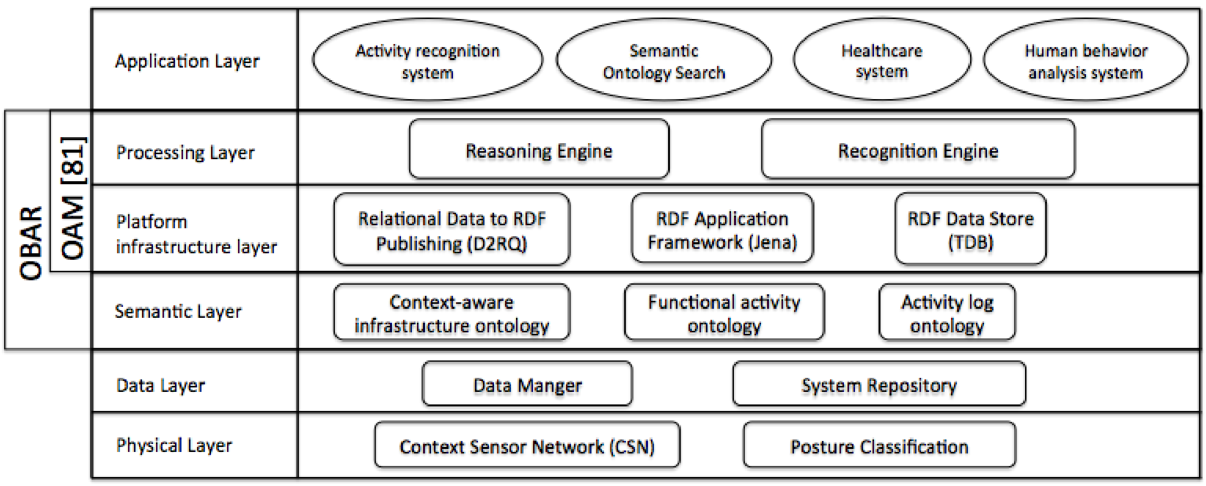


Figure 3.1: A layered architecture of the CARE architecture

3.3 CARE Architecture Overview

Figure 3.2 depicts the high-level CARE architecture. For sensing data in the CARE architecture, the proposed CSN is placed at the beginning of the architecture to monitor the data from the home environment, including human information. A variety of sensors are attached and embedded into the home facilities; for instance, a pressure sensor is attached to the “Sofa”, a gyro sensor is placed on the “Coffee Container”, or a power-consumption sensor is built-into the “Outlets”. Nevertheless, the CARE architecture is not only designed for collecting the context-aware information in the home, but also human information. The human information, such as the location of the individual, is also observed by the infrared sensors. In addition, the advantage of the CARE architecture is that it collects novel information such as human posture in order to create a new user’s context for classification of human activity. Nevertheless, there are no sensors that can directly detect human posture, a posture classification scheme is proposed based on a range-based algorithm for classifying human posture from sensors placed on the individual.

Based on the huge amount of data, good organization is important for handling the enormous amount of information in the smart home. A data manager and system repository are proposed to organize the data in the smart home. The data manager is proposed to normalize and transform the data before storing it into the repository, while the system repository is responsible for controlling all the data in this proposed architecture. Therefore, a context controller is presented in the system repository to associate the data in the repository and Ontology-Based Activity Recognition (OBAR) system.

In this research, the ontology approach is selected to implement the activity recognition system. Three ontology models, i.e. context-aware infrastructure ontology, functional activity ontology, and activity log ontology, are proposed in OBAR for creating the smart home knowledge base and activity model for classifying human activity. In the OBAR system, several techniques are proposed for improving the ability of activity recognition, and also to make the results more reliable, reasonable, and accurate. The advantage of the ontology concept is also presented in the semantic ontology search application. The results of activity recognition and semantic information can be retrieved through the semantic ontology search application. The semantic ontology search application shows the ability of the ontology approach via shared conceptualization.

3.4 Contributions of CARE architecture

According to this CARE architecture, four contributions are presented as follows:

1. **Context Sensor Network (CSN)**

   The CARE architecture introduces 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.

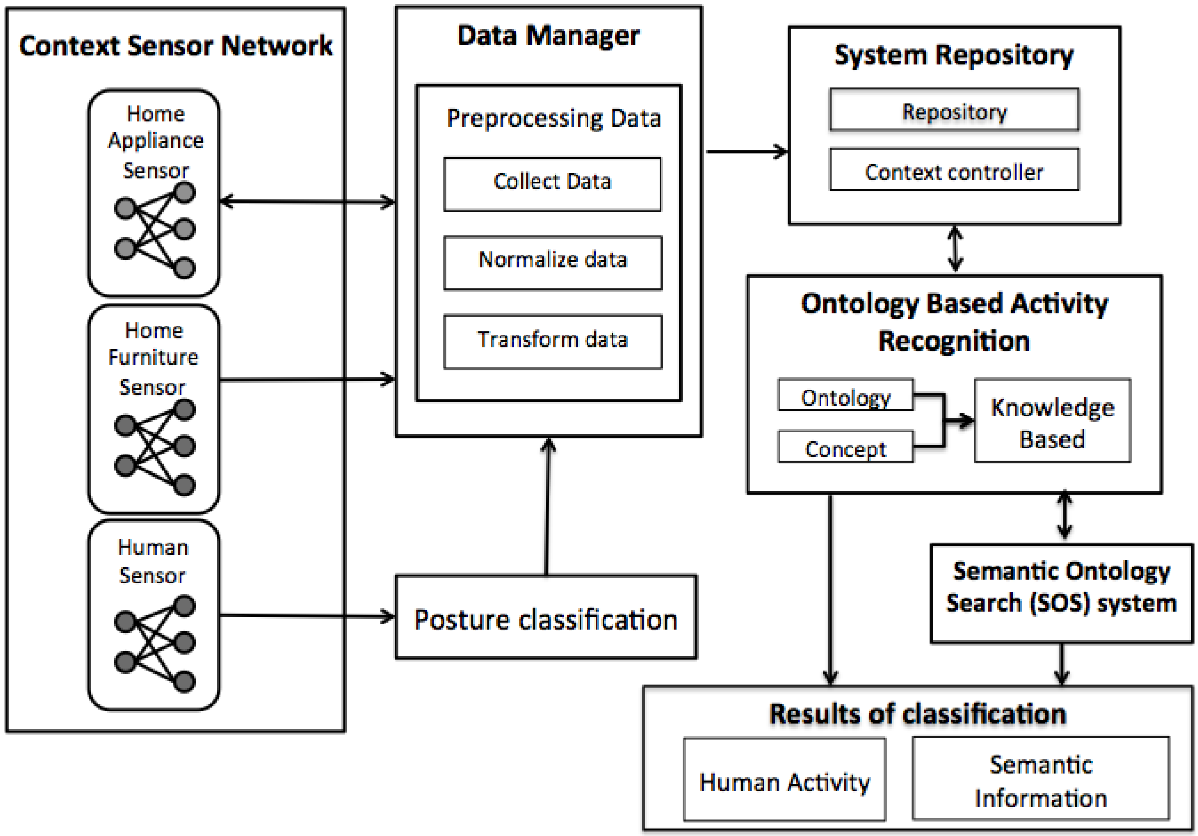


Figure 3.2: CARE architecture

2. **Posture Classification**

   In a new user's context, a novel information, human posture, is added into the user's context since the human posture information can distinguish some activity cases. However, there is no sensor that can observe the human posture information directly, so in this research, the posture classification is presented. The posture classification is implemented in this research as a sub-system of activity recognition. A new range-based algorithm is proposed to classify human posture data to conform to a new user's context by combining human posture and the traditional user's context.

3. **Ontology-Based Activity Recognition (OBAR)**

   OBAR addresses the difficulty in explicitly handling huge amounts of information from a diversity of sensors in the smart home. Context-aware infrastructure ontology is presented to model the surrounding environment in the smart home. This research also presents a new term in the activity log, called activity location (AL^2). AL^2 is used to find the relationship between the activities occurring in the user's location at that time.

4. **The Human Information**

   Because the CARE architecture can produce results from human activities and semantic information in the smart home, the application, which requires human information, can be implement on top of the CARE architecture.

3.5 Conclusion

This chapter describes the overview of the CARE architecture. The main purpose of the CARE architecture is to improve the ability of the activity recognition system based on real environmental data. To achieve this purpose, several techniques have been developed in the CARE architecture. The remaining chapters in this dissertation will report on the contributions of this CARE architecture.

The data collection section (Chapter 4) exhibits the way to obtain the context-information in the smart home through sensors. Posture classification is also presented in the data collection for acquiring human posture through a new range based algorithm. After data collection, data organization and processing in the OBAR system (Chapter 5) are demonstrated for the classification of human activity. The ontology approach is applied in the OBAR system for reducing and preventing the existing problems.

Chapter 4

Data Collection using CSN

4.1 Introduction

Collecting the data is one of the challenging tasks in this research, since the data collection directly affects recognition accuracy. Even though there is a huge amount information in the smart home, not all of it is essential for the activity recognition system. For example, information from the "Air-condition" object is useful for providing a comfortable room temperature, but is not necessary for the activity recognition system because it cannot infer any human activity (based on the temperature information). Whereas interaction with the "Chair" object seems needless for home applications, but it can be used with other information for inference to the human activity. For example using the "Chair" object and the "Computer" object at the same time can infer a "Working on the computer" activity. Consequently, this chapter presents the techniques for collecting the data in the smart home based on the proposed CSN.

4.2 Context Sensor Network (CSN)

To obtain the relevant information in a real environment, a CSN with a diversity of sensors and network protocols is proposed. The CSN is a sensor network that is typically used for collecting the context-aware data in the smart home. For this research, iHouse [82] was selected as an experimental smart home environment. The iHouse is designed for the development of the next-generation home network system. Two floors measuring 107.76

m^2 ,more than 250 sensors and home appliances are connected through Energy Conservation and the Home care Network (ECHONET), Universal Plug and Play (UPnP), and Zigbee. A photograph of iHouse is presented in Figure 4.1.

Figure 4.1: The smart home, iHouse, used for the real activity recognition experiment

To obtain a large amount of data for classifying human activity in the smart home, both a BSN and a HSN are integrated into the CSN for observing object usage and human information. There are three kinds of sensor networks in the CSN: a home appliance sensor network, a home furniture sensor network, and a human sensor network. These are described in the following sections:

4.2.1 Home Appliance Sensor Network

The principal task of a home appliance sensor network is to capture home appliance usage. A variety of sensors, such as power consumption sensors and water-flow sensors, are built into the iHouse. Most electrical home appliances can be detected by measuring the change of the electric current from the power consumption sensor. For example, the system can detect “TV” usage by measuring the changed voltage. A water-flow sensor is also embedded in the iHouse for monitoring the use of water fixtures such as “Sink”, “Shower”, and “Flushing”. The home appliance sensor network measures not only the home appliance usage, but also environmental information. For example, the temperature sensor and the brightness sensor are also installed in the iHouse.

This kind of information is relevant for classifying a specific activity such as “Watching TV”, “Working on the computer”, and “Cooking”. For example, the system can detect the user might be performing the “Cooking” activity when it recognizes “Electric stove” is being used, or it might classify the activity as “Taking a bath” if the water-flow sensor detects the flow of water from the “Shower” object. It overcomes the BSN technique because data from the body sensors only is not enough to recognize which object is being used.

In this research, to transfer the data in the home appliance sensor network, there are two protocols for sending the requested command to each sensor: ECHONET [83] and UPnP [84]. The ECHONET is an international home network protocol standard used to control, monitor, and gather information from equipment, and sensors that are usually found in the home. The devices range from various types of simple sensors to more complicated devices such as air conditioning, or a refrigerator. UPnP is a set of networking protocols that permits networked devices to seamlessly discover each other’s presence on the network. Figure 4.2 illustrates the network system of the home appliance sensor network in iHouse.

This sensor network procedure begins by sending the UPnP requested command (id and command) to the sub-gateway (SGW). Since the UPnP has device discovering ability, it maps the UPnP requested command with the SGW. The SGW has the responsibility of converting the UPnP command into an ECHONET command, based on the ECHONET specification [85]. The SGW then sends the ECHONET command based on the ECHONET id (device ip address and object id (EOJ)) to the device. After that, the device will respond to the command and return the data to the SGW in order to convert to the UPnP command again. After the system obtains the data, the interval time is set to five seconds for sending the new UPnP request command for the next round. Figure 4.3 presents a flowchart of this sensor network.

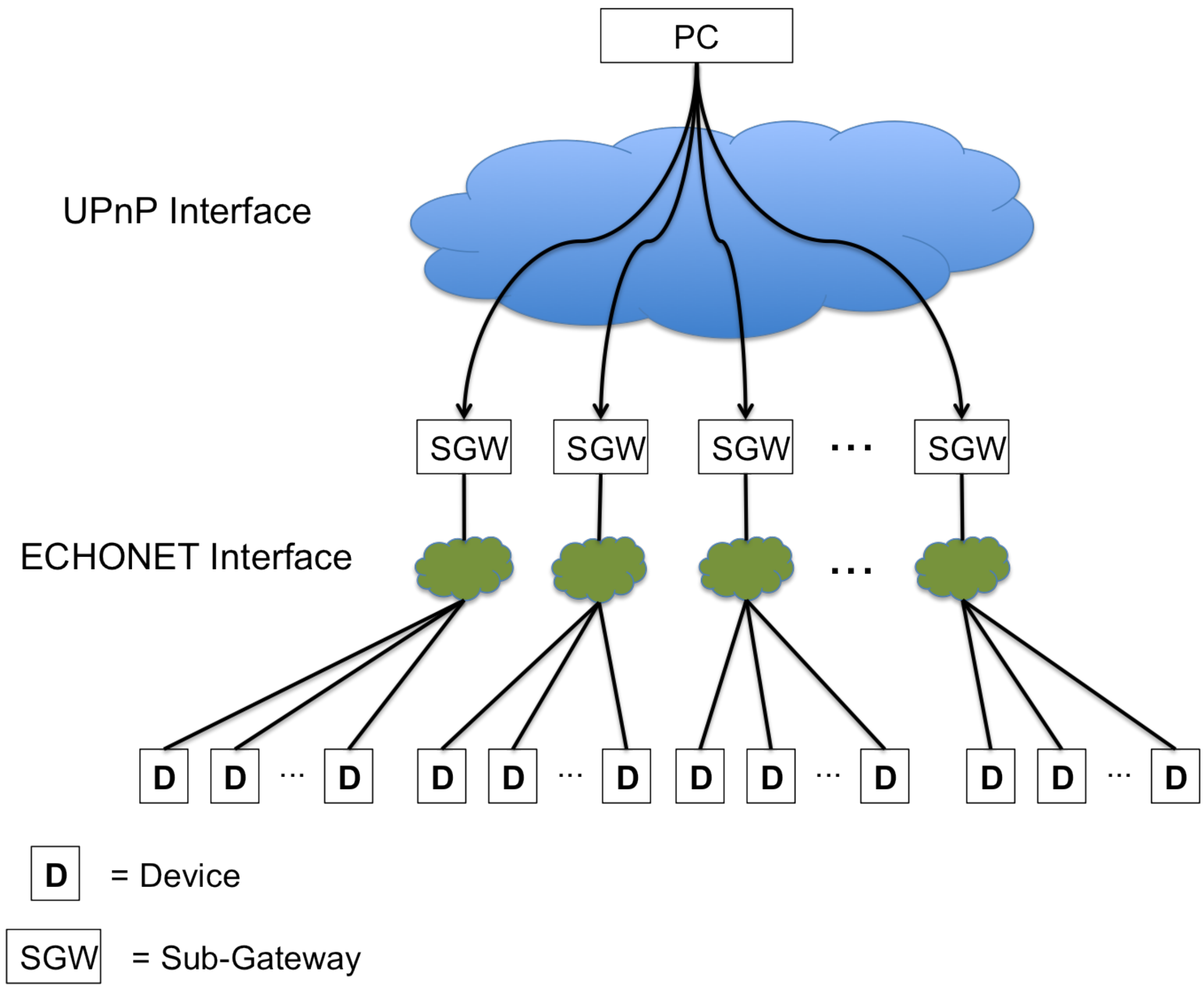


Figure 4.2: Procedure of network communication of the home appliance sensor network

4.2.2 Home Furniture Sensor Network

Apart from home appliances, the network still has to consider the use of other items in the home environment, such as “Sofa”, “Chair”, or “Bed”. Normally, the objects in this sensor network can be divided into two types. First, is the direct-purpose object. This means that the object usage information can be used to infer only one human activity. For example, usually, the individual uses the “Broom” object only for the “Sweeping the floor” activity. Second is the multi-purpose object. There is some furniture in the home that is used for several purposes. For example, the individual uses the “Sofa” object for sitting and watching TV, or lying down on the “Sofa” to relax.

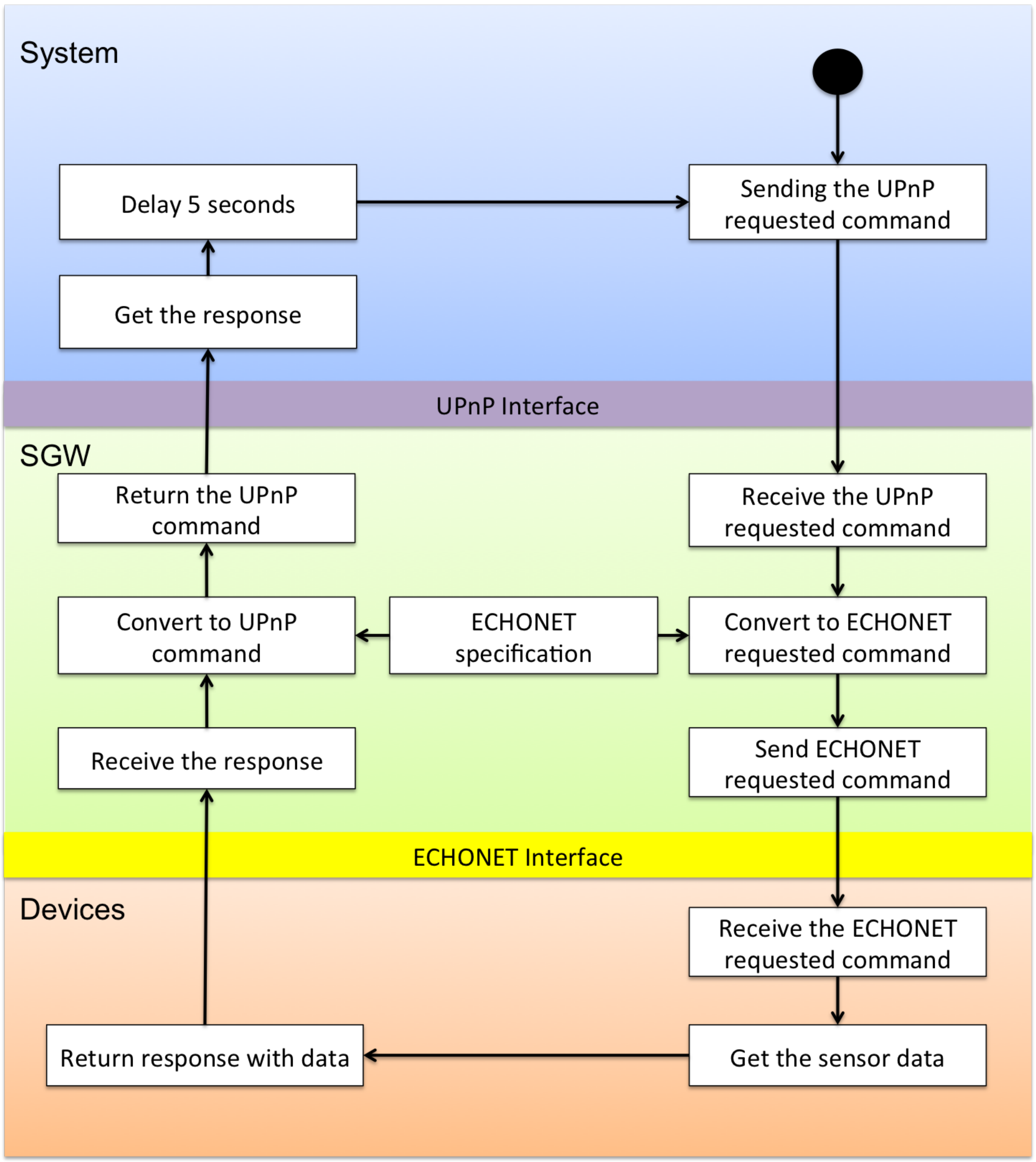


Figure 4.3: Flowchart of the procedure in the home appliance sensor network

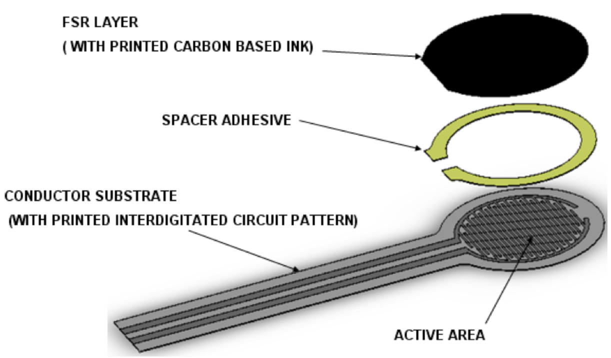
Furthermore, the information from these kinds of objects can be combined with the home appliance information to indicate the performance of specific activities. For example, if the "Computer" object is turned on, this does not necessarily mean the user is performing the "Working on a computer" activity. Maybe, the user turns on the "Computer" and does other things. However, normally, a user tends to sit on a "Chair" for "Working on a computer", so the system can integrate the information with the home furniture sensor network and the home appliance sensor network to conform to the user's context. In this research, three types of sensors (a force sensor, a gyro sensor, and a magnetic sensor) are attached and deployed to the home furniture.

- **Force sensor**

  The pressure sensor or force sensor is currently introduced as a transducer to convert an input mechanical force into an electrical output signal. Figure 4.4a shows the basic force sensor construction. In the research, the force sensor is mainly attached to an object operated by using mechanical force. For example, a force sensor is attached to the "Sofa" for detecting whether or not a human is sitting on it. In this research, the force sensor models 402 and 408 from Interlink Electronics, Inc. [86] are chosen to be attached to the home furniture in the iHouse such as "Sofa", "Chair", or "Bed", as shown in the example in Figure 4.4b.

- **Gyro sensor**

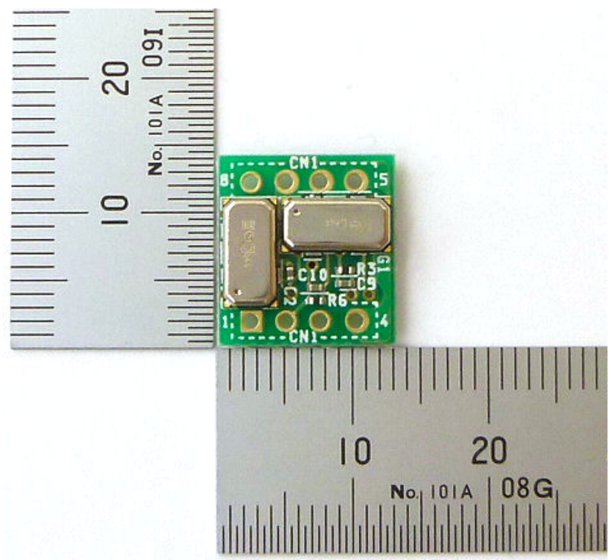
  The gyro sensor is normally used all around us, in items such as mobiles, robots, or digital cameras. The gyro sensor can sense angular velocity, rotational motion, or changes in orientation, so it can complement data from the accelerometer to smooth out a great deal of the movement readings. Figure 4.5a shows the size of the gyro sensor used in this research. The target objects of the gyro sensor are the objects that have movement ability such as a "Broom", "Mop", or "Coffee Container". Figure 4.5b illustrates the example object, which is attached to the gyro sensor.



(a) The example force sensor construction

(b) The "Sofa" with force sensors

Figure 4.4: The force sensor



(a) The example of gyro sensor in this research

(b) The "Coffee Container" with gyro sensor

Figure 4.5: The gyro sensor

- **Magnetic sensor**

  The magnetic sensor or contact switch sensor is a well-known sensor that is used for detecting the "Open" and "Close" status of the object. The concept of the magnetic sensor will sense the "Open" status when there is no connection between the two wires, whereas the "Close" status will occur if the range of the magnet is less than its threshold. The magnetic sensor is usually used to detect the status of the door, but in this research, the magnetic sensor is attached to an object which has an “Open” and “Close” function such as “Cupboard”, illustrated in Figure 4.6. Although the use of “Cupboard” might not infer human activity directly, it can conform to the user’s context for analyzing the human activity. For example, detecting the “Cupboard” in the kitchen, the system can perceive that the home user might take kitchenware from the “Cupboard” to perform the “Cooking” activity.

Figure 4.6: The “Cupboard” with magnetic sensor

However, in this sensor network, it cannot use UPnP and ECHONET protocols to communicate with the home furniture sensors in the same way as the home appliance sensor network because most of the home furniture items are not in the international home network protocol standard. Thus, in the setup of the experimental environment, the Zigbee protocol is emulated for communication within the home furniture sensor network. The network system in the home furniture sensor network is designed and shown in Figure 4.7.

There are two basic modules in this sensor network: sensor node and coordinator. For installation, the Arduino board [87] is selected for sensing the data. For the sensor node, the Arudino Fio is selected as a microcontroller board (ATmega328P). The Arduino Fio is connected to a pressure sensor, a gyro sensor, and a magnetic sensor via an external board, shown in Figure 4.8. The Arduino Fio also allows the developer to program it wirelessly, over a pair of XBee radios. Therefore, the Zigbee protocol is used for transmitting

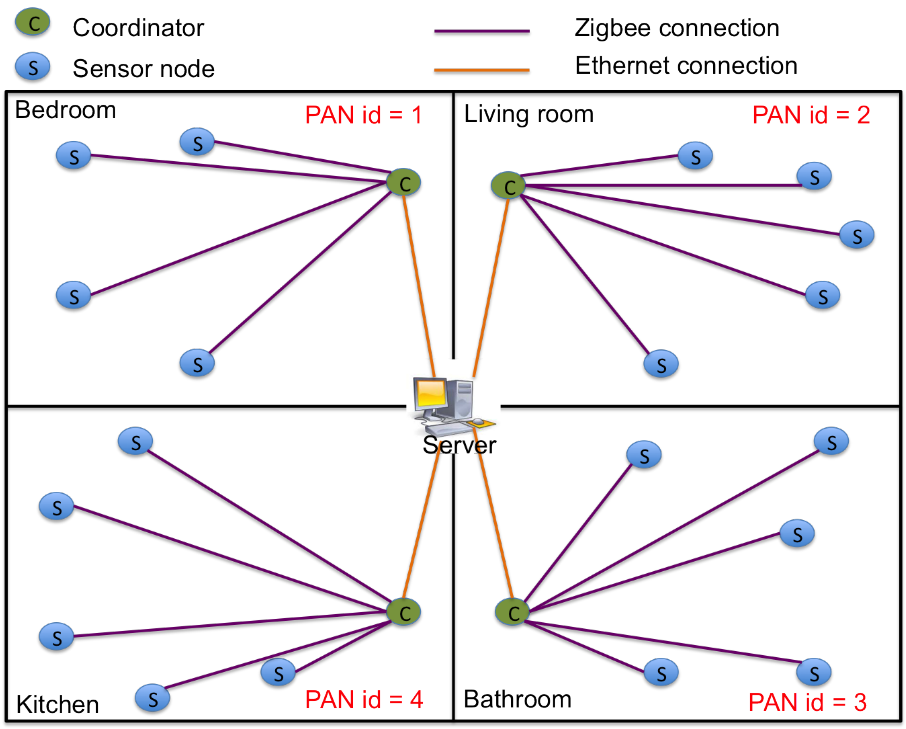


Figure 4.7: The network system in home furniture sensor network

the data between the home furniture sensor and coordinator. For the coordinator, the Arduino Ethernet is developed to connect with the XBee shield. The XBee shield allows an Arduino board to communicate wirelessly using Zigbee. 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. Each coordinator node will be placed on the corner of each room. Therefore, the system will perceive where the data is coming from based on the "Coordinator id" and "Sensor id".

To deploy the sensor nodes in the iHouse, it has to consider the power consumption in the sensor node, since usually the home user does not want to frequently change the battery. Thus, this section also introduces a way of reducing the power consumption in the home furniture sensor network. Table 4.1 shows the power consumption of the Arduino Fio, the XBee, and the gyro sensor.

In Table 4.1, although the Arduino Fio consumes little power, when adding the XBee module into the Arduino Fio for transmitting the data, the power consumption is in-

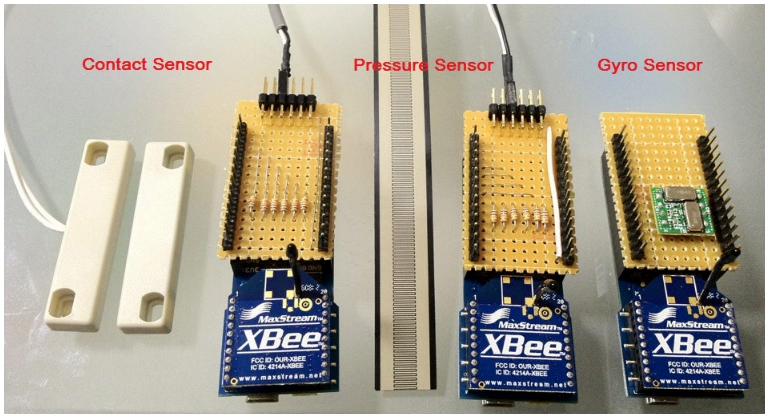


Figure 4.8: The Arduino Fio with external board and sensor

Table 4.1: Power consumption of three devices

Devices	Power consumption (mAh)
Arduino Fio	≈ 3
Arduino Fio + XBee	≈ 57
Arduino Fio + XBee + gyro sensor	≈ 64

creased from 3 mAh to 57 mAh. For a small sized battery (850 mAh), if the sensor node consumes 64 mAh, battery life should be about 13 hours. This means that the home user has to change the battery twice a day. Therefore, this research aims to save the power consumption by activating the XBee module only when the sensor is activated. Figure 4.9 presents the finite state machine (FSM) of the sensor node.

Based on Figure 4.9, when XBee is disabled, the power consumption is reduced to 10 mAh. Assume the sensor node is activated one hour per day. In one day, the sensor node will consume power of 294 mAh per day. For a small sized battery, the batter life can be increased by up to almost three days or 70 hours. Consequently, power consumption is reduced by 530%. In the experimental setup, where four triple-A batteries are used for each sensor node it can extend the battery for life up to one month.

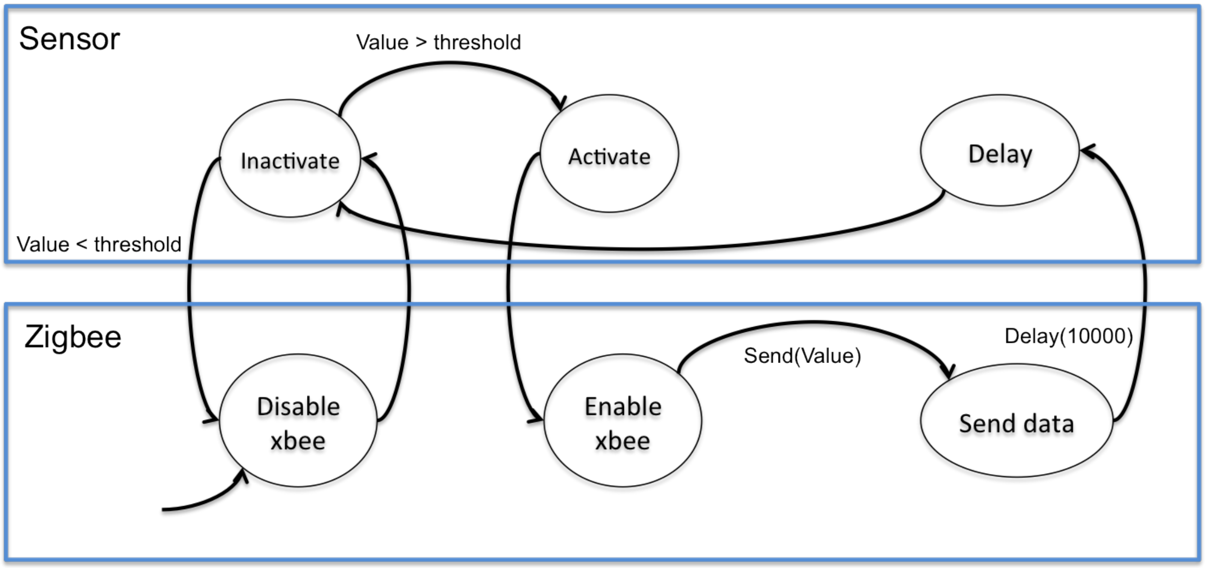


Figure 4.9: Finite state machine of the sensor node.

4.2.3 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. Using only home environment data can lead to the "ambiguous activity problem". For example, only object activation information is considered when implementing the activity recognition system, it cannot guarantee a sufficiently high level of accuracy when several objects are being used. It can make the system generate several possible resultant activities. Thus, a human sensor network is used to observe human information such as the location of the individual. In this research in order to reduce possible resultant activities, infrared sensors are deployed in each room in the iHouse to detect the human location, as illustrated in Figure 4.10, and the network system is designed in the same way as the home appliance sensor network. The current location of the user is relevant to activity recognition because it can give useful hints about which activities the individual is able to perform in their current location.

(a) First floor (b) Second floor

Figure 4.10: The infrared sensor in iHouse

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. Recently, further information has been introduced for classifying human activity, and the effective combination between human posture data and the home sensor is discussed in [88]. Here is one proposed example scenario:

"The home user takes a book from the shelf and then sits on the bed in the bedroom and reads the book."

From the above scenario, most activity recognition systems will classify this situation as a "Sleeping" activity since the sensor which attaches to the Bed object is activated, and the location of the home user is in the bedroom. However, it is not always true if you consider Figure 4.11. There are other possible activities that the user might perform rather than the "Sleeping" activity.

Therefore, to obtain human posture information in the CARE architecture, posture classification is proposed to classify the human posture based on a new algorithm, described in more detail in the next Chapter.

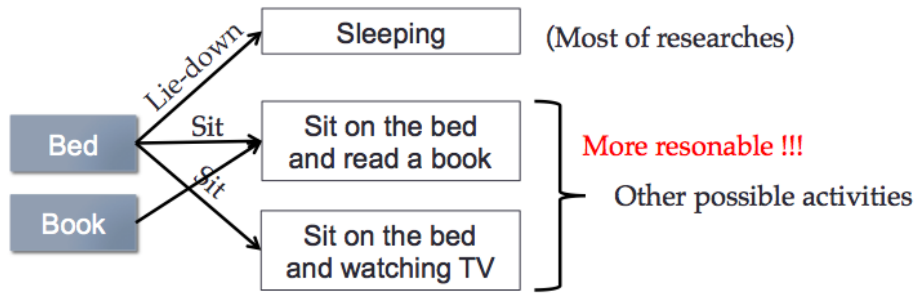


Figure 4.11: Example scenario in [88]

4.3 Conclusion

This chapter introduces details of part of the data collection in the CARE architecture. The CSN was described in this chapter. The surroundings and human and information were observed in the real environment, iHouse, by the proposed CSN. The CSN was composed of three sensor networks, namely, the home appliance sensor network, the home furniture sensor network, and the human sensor network. The first two sensor networks are used to monitor the object usage in the iHouse, while the human sensor network is used to observe the human location in the iHouse. Based on the proposed CSN, a diversity of sensors were installed in the real environment, and several protocols were developed for transmitting the data between the sensor and the server.

Nonetheless, the information merely from the CSN might not be sufficient to classify human activity. It still needs further information in order to improve the ability of activity recognition. Thus, in the next Chapter of this dissertation, posture classification will be introduced as one technique for data collection in CARE architecture. The results from the posture classification will be used to conform to the new user's context in this research.

Chapter 5

Posture Classification

5.1 Introduction

According to findings in this dissertation, there are improvements in the high-performance activity recognition framework with the new user's context. In a new user's context, human posture information is added for the purpose of reducing the "ambiguous activity problem". The human posture information is useful for the activity recognition system because normally, each human activity will consist of several pieces of information, one of them being human posture information. For example, the "Cooking" activity has a "Stand" posture, the "Sleeping" activity has a "Lie-down" posture, or the posture when "Watching TV" can be the "Lie-down" posture or "Sit" posture. Consequently, it can distinguish the activities of different human postures. In this chapter, posture classification is presented to obtain human posture information. A new algorithm is also proposed in posture classification for solving problems in existing research studies.

5.2 Posture classification

Generally, posture classification and activity recognition are very closely related areas for research. 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, each human activity is composed of human posture information. 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. [89] 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, this research proposes a new range-based algorithm [90], to improve the accuracy of reduced human movement. This algorithm focuses on three human postures: "Standing", "Sitting", and "Lying-down", and also accidents such as "Falling-down". After observing the postures in real human daily actions, the idea for this algorithm comes from the hypothesis "Each human posture has a different physical pattern", as shown from the example in Figure 5.1. This means that the relationship between the body parts can conform to a specific human posture. The concept of this algorithm is to determine the relationship of body parts, and extract the postures from the range of those body parts. Three sensors are attached to the shoulder, hip, and knee to perform the range-based algorithm, and four modules are proposed: binary decision tree, finite state machine, adaptive posture window scheme, and posture pattern recognition.

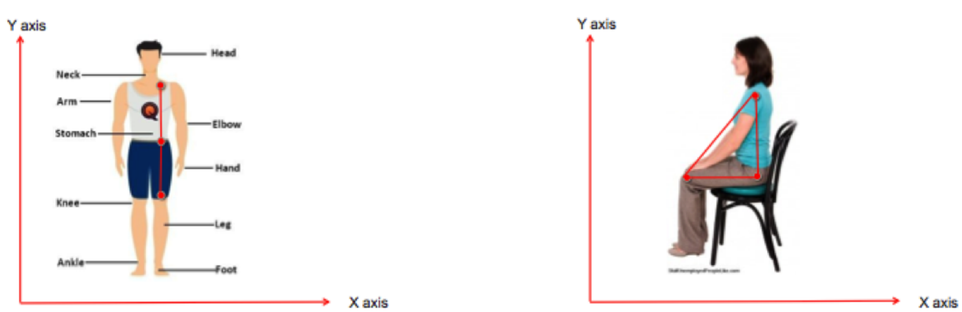


Figure 5.1: Physical patterns of "Standing" and "Sitting"

1. **Binary Decision Tree**

   A binary decision tree is applied to distinguish human posture. It consists of five nodes: three leaf nodes representing human posture and two parent nodes denoting the binary decision, using a threshold technique to distinguish human posture. The *Threshold value* is defined by the proportion range between the body parts. Figure 5.2 presents the binary simple decision tree. T_1 is defined by the range value between the hip and knee, and the range value between the knee and shoulder is determined as the threshold value in T_2. If the range value between the hip and knee is higher than T1, the posture will be "Stand", or if the range value between the knee and shoulder is higher than T_2 , the posture will be "Sit".

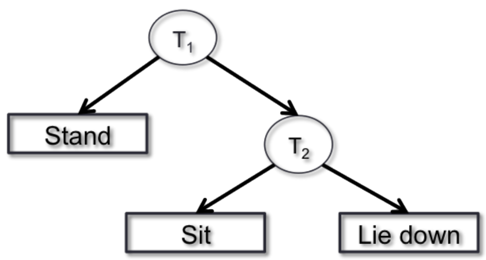


Figure 5.2: Binary decision tree of the range-based algorithm

2. **Finite State Machine (FSM)**

   FSM is used to handle the posture states, and indicate current user posture. In this research, the FSM is applied to define two posture states. The first, *"posture state"* is only one fundamental posture. Secondly, *"changing posture state"* is the transition from one posture to another posture as presented in Figure 5.3.

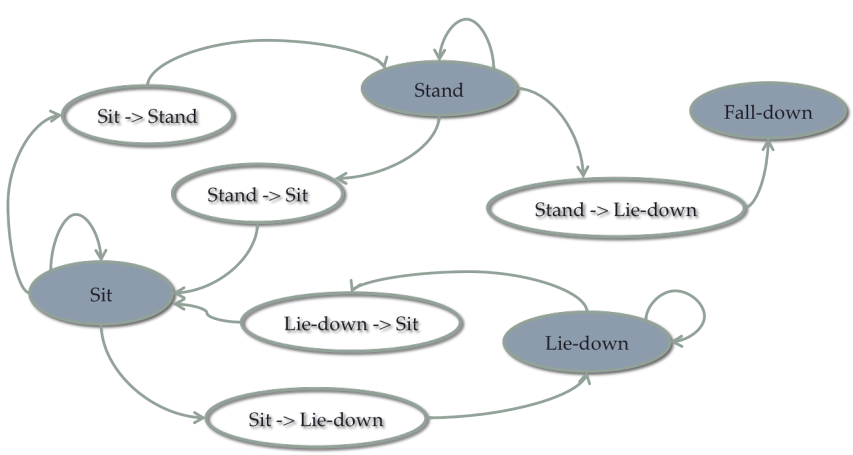


Figure 5.3: FSM of the range-based algorithm

Figure 5.3 illustrates the FSM of this system. It consists of nine states: five *"changing posture state"* and four *"posture state"*. The *"posture state"* can be divided into two types: human postures (sit, stand, lie-down) and accidents (fall-down). In the *"changing posture state"*, it does not have the "Lie-down→Stand' state because in real human behavior, when a human changes posture from lying-down to standing, they will be in a sitting posture before standing. Consequently, the "Stand→Lie-down" state can be defined as "fall-down" because it does not perform the sitting posture before lying-down.

3. **Adaptive Posture Window Scheme**

   Because the computation this posture classification is in real-time, the outcomes of the classification change rapidly. The adaptive posture window is adopted to identify current posture. The adaptive posture window starts with a subsequence posture in the time series. The subsequence posture in the adaptive posture window is the *"posture state"*. Therefore, time computation (TC) is defined in equation 5.1 below:

$$TC = Window_{size} \times Time\ sampling \tag{5.1}$$

   $Window_{size}$ is the size of the adaptive posture window, which is dependent on the environment such as speed in changing posture and so on. $Time\ sampling$ is the interval time for each *"posture state"*. In this research, the size of adaptive posture window fitted depends on posture speed because when humans change posture, the change in posture speed is not the same. The status of each particular individual also affects the speed of changing posture such as the elderly, children, or an average adult person. For this reason, the adaptive posture window scheme is implemented in order to improve the posture classification accuracy and reliability.

4. **Posture Pattern Recognition (PPR)**

   In the adaptive posture window scheme, three fundamental patterns can be obtained: *majority pattern*, *equal pattern*, and *minority pattern*. Two methods are used; a *ratio method* and a *transition weight method* to recognize the resultant state, defined as the current state in the FSM. The ratio method is used to justify the posture patterns. The posture patterns are recognized by counting the number of *"posture state"* in the adaptive posture window. The *majority pattern* is recognized if the number of *"posture state"* is more than half the size of the adaptive posture window, when the resultant state will correspond to human posture as shown in Nos.1 and 2 in Table 5.1. However, if there are at least two postures with the same number, the system will classify this as an *equal pattern* and the resting condition will be a *minority pattern*.

Table 5.1: The example of posture patterns with a size of adaptive posture window of 4

No	Posture window	Pattern	Transition weight	Resultant state
1	Stand-Stand-Stand-Stand	Majority	-	Stand
2	Stand-Sit-Stand-Stand	Majority	-	Stand
3	Stand-Stand-Sit-Sit	Equal	2	Stand→Sit
4	Stand-Sit-Stand-Sit	Equal	6	Sit
5	Sit-Lie-down-Stand-Stand	Minority	3	Sit→Stand
6	Stand-Stand-Sit-Lie-down	Minority	5	Stand

For the *majority pattern*, the *transition weight method* does not need to be used because this pattern can infer the exact posture itself. Nevertheless, *equal pattern* and *minority pattern* need the *transition weight method* to decide the resultant state. PPR will take the transition weight (TW) value in the transition between two postures in the adaptive posture window as +1, +2, +3, and so on for the postures between first and second, second and third, third and fourth, and so on, respectively. The TW value will be added when the posture changes. The threshold technique is also combined with the TW method. The threshold of the TW method will change depending on the size of the adaptive posture window. Figure 5.4 shows the flowchart for deciding the resultant state, when the size of posture window is 4.

This research also introduces another algorithm for classification of human posture, which is a height-based algorithm in order to compare it with the range-based algorithm. The idea of the height-based algorithm is to attach a sensor to the user's shoulder to

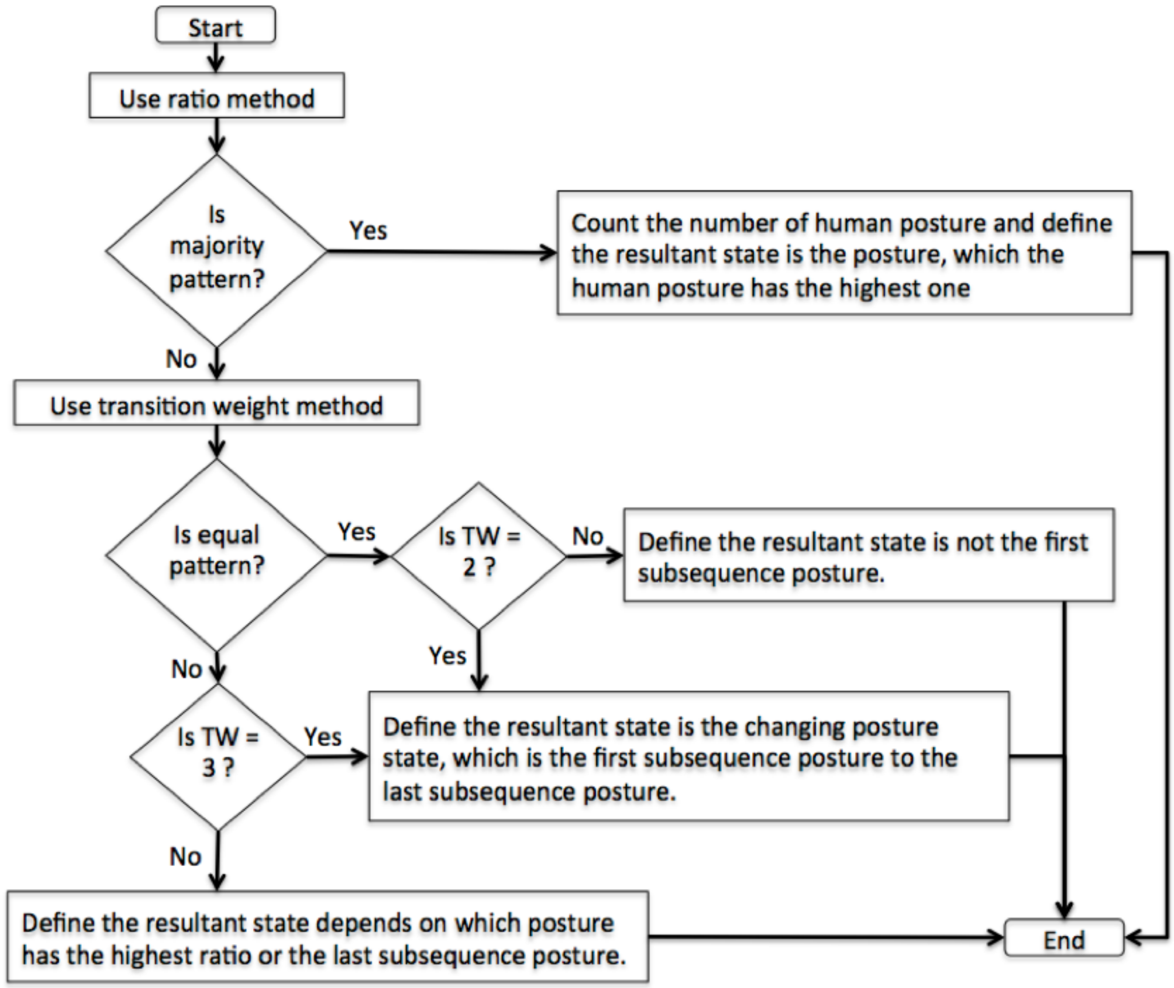


Figure 5.4: Flowchart for PPR when the size of the adaptive posture window is 4

classify human posture. The decision tree of the height-based algorithm is similar to the range-based algorithm, but it has a different threshold value. The threshold value in the height-based algorithm is defined by the shoulder height of the user. Meanwhile, the adaptive posture window, posture pattern recognition, and FSM are the same as in the range-based algorithm.

5.3 Experiments and results of posture classification

The proposed range-based algorithm and the height-based algorithm are designed and installed in AwareRium [91], a room in an experimental environment to investigate various support systems, as shown in Figure 5.5a. The room size is 50 m2 (4.5 m $\times$ 11 m). Ultrasonic technology is the main technology in the AwareRium, which consists of two main devices: the ultrasonic receiver and ultrasonic tag. The ultrasonic receivers are embedded in the walls of the room but not the floor, and connected with a LAN cable. Meanwhile, the size of the ultrasonic tag is small, 45×52×168 mm, and weighs 60 grams, as illustrated in Figure 5.5b.

The comparison procedure is shown in Figure 5.6. Accuracy in these experiments is defined as the ratio between the correct number of *"posture state"* and *"changing posture state"* and the total number of resultant states in this experiment.

(a) AwareRium (b) Ultrasonic tags

Figure 5.5: Experimental setup for posture classification

To evaluate this algorithm, the experiment is divided into four. The first experiment aims to examine the adaptive posture window scheme. The size of the adaptive posture window is adjusted depending on the speed of the changing posture. The size of the adaptive posture window changes from 3 to 6 *"posture states"*. In the first experiment, time sampling is defined as 0.2 seconds. The test subject of this experiment is an average adult person, and the results are shown in Figure 5.7.

After several experiments, the optimum size of the adaptive posture window is four. This size of the adaptive posture window achieved the highest accuracy in the environmental scenario, and was performed by two subjects; one male and one female (ages ranging between 25 and26 years, height between 164cm and 174cm). However, other sizes

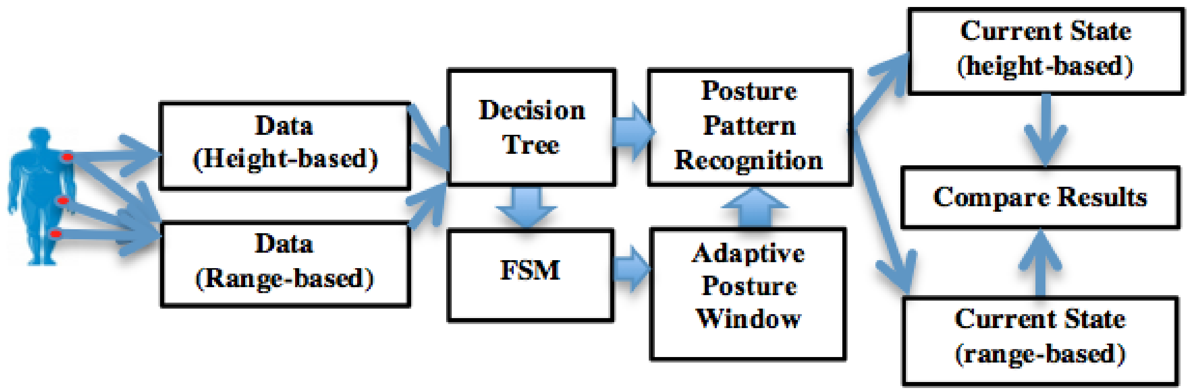


Figure 5.6: Procedure of comparison between the range-based algorithm and the height-based algorithm

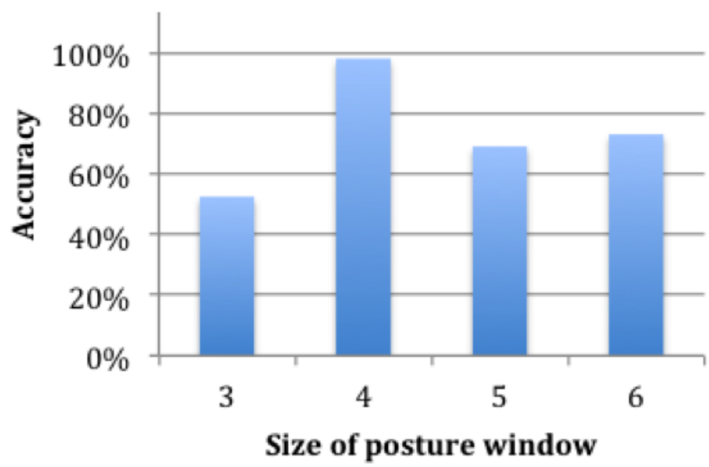


Figure 5.7: The difference between the size of posture window and accuracy

can also be used in different circumstances. For example, the size of an adaptive posture window of 6 is suitable for elderly people. Because the time computation of this size is around 1.2 seconds, the inside the adaptive posture window six subsequent postures will be collected. It is quite easy to find the current posture if the individuals change their posture very slowly like in the elderly. On the other hand, if people change posture very quickly, as with children, various kinds of posture states will be held inside the window. It is extremely hard to decide the current posture. Thus, a small size of adaptive posture window is suitable for those moving quickly.

The second experiment verifies the problem when a user is merely moving. A static posture experiment was proposed. Each test set has only one posture. This means that the user performs only a single posture in one period of time. The test subject performs each posture in five minutes and five times per test set. This experiment also designs the height of the object for the test subject; sitting or lying-down. The results of the second experiment are shown in Table 5.2.

Table 5.2: Accuracy of the height-based algorithm and range-based algorithm in the static posture experiment

Posture	Height-based algorithm	Range-based algorithm
Stand	100 %	100 %
Sit *	100 %	100 %
Sit **	0 %	100 %
Lie-down ***	100 %	100 %
Lie-down ****	0 %	100 %

Note: * Object that the user is sitting on is lower than hip height.

* Object that the user is sitting on is higher than hip height.

** Objects height that the user lying on is lower than 15 cm.

*** Objects height that the user lying on is higher than 15 cm.

From the second experiment, the height-based algorithm obtains poor results in some circumstances because the results of the height-based algorithm are based on only the shoulder height of the test subject which causes a major problem. For example, if the test subject sits on a table where its height is higher than hip height, it means the shoulder height of the test subject is equal to or higher than shoulder height inthe standing posture. Thus, the system will classify this posture as a standing posture. On the other hand, the range-based algorithm does not have this kind of problem because the relationship between the body parts is investigated. The result of the range-based algorithm also shows a high accuracy even though there is less human movement.

The third experiment focuses on the consequence posture experiment by looking at the *"changing posture state"* in FSM. The consequence posture scenario is setup as "Lie-down→Stand→Sit→Stand→Lie-down→Sit→Stand", and performed 10 times. These consequence posture scenarios can cover all states in FSM. Table 5.3 shows the accuracy in the consequence postures experiment.

Table 5.3: Accuracy of the consequence postures experiment

Consequence postures	Hight-based algorithm	Range-based algorithm
Lie-down→Stand→Sit→Stand→ Lie-down→Sit→Stand	86 %	98 %

According to the results of the consequence posture experiment, the main error of both algorithms occurs in the state of "Lie-down→Sit", shown in Figure 5.8, since the sitting posture in this experiment means sitting on a chair. Considering real human behavior, the order of the posture should be "Lie-down → Sit(ground) → Stand → Sit(chair)". The height-based algorithm often classifies the state only as "Lie-down→Sit(ground)" which is incorrect, whereas the range-based algorithm uses three types of data, making classification more precise. It has a slight error when it moves very quickly. In addition, the results of the second and third experiments show that the posture in the height-based algorithm is not flexible when compared to the range-based algorithm. For example, the "Standing" posture in the height-based algorithm refers to standing up straight, and the user could not bend down, whereas the user could do both in the range-based algorithm.

In the last experiment, fall-down detection, it is extremely important for monitoring unexpected situations, especially with elderly people who live alone in the home. Fall-down is defined as a backward fall-down. In this experiment, fall-down is examined by detecting the *"changing posture state"* of "Stand→Lie-down". Table 5.4 shows the accuracy of the correct classification for fall-down detection in five instances.

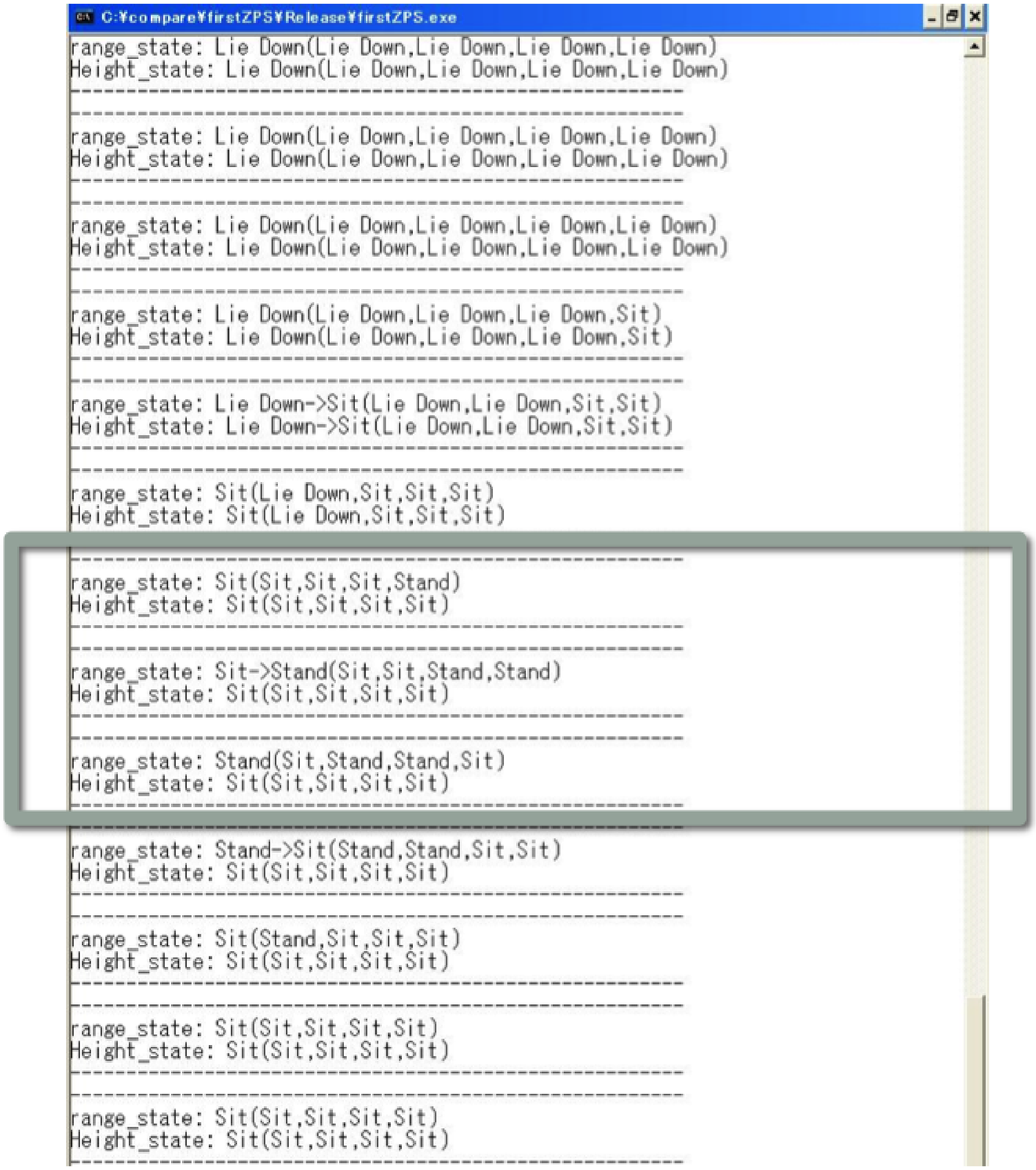


Figure 5.8: The error in "Lie-down→Sit" state

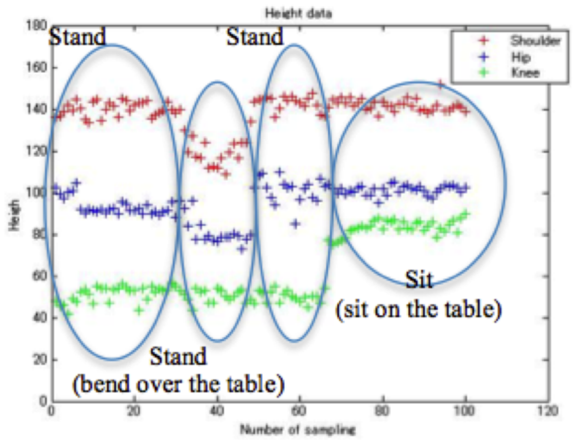
Table 5.4: Accuracy of the fall-down detection experiment

Algorithm	Accuracy of fall-down detection
Height-based algorithm	80 %
Range-based algorithm	100 %

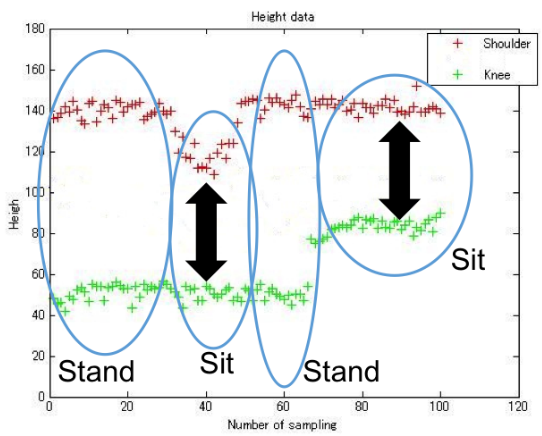
5.4 Discussion

Although the range-based algorithm uses a simple concept to classify human posture in home, the results are efficient. The postures in the range-based algorithm are more flexible than in the height-based algorithm. One thing that makes the posture more flexible is the number of sensors. The number of sensors affects recognition accuracy. For example, when a user is bending over a table, shoulder height reduces the threshold. In this situation, merely one sensor (height-based algorithm) might not be suitable for classification because only shoulder height is used in classification. If two sensors are used with the range-based algorithm (attached to the shoulder and knee), the same problem still remains. Although it can recognize human posture in normal situations, from complex posture such as sitting on a chair or bending over a table, the range between shoulder and knee is slightly different as illustrated in Figure 5.9b. Nonetheless, for the proposed range-based algorithm using three sensors, it still classifies the "Stand" posture when the subject bends over the table, and recognizes the "Sit" posture when the subject sits on the table, as illustrated in Figure 5.9a. Thus, the results illustrate that the important thing when classifying postures with this algorithm is the relationship of the body parts. Moreover, this algorithm is applicable because it does not depend on any type of sensor. If the developer has sensors that have the ability to measure the distance between those sensors, the range-based algorithm can work well.

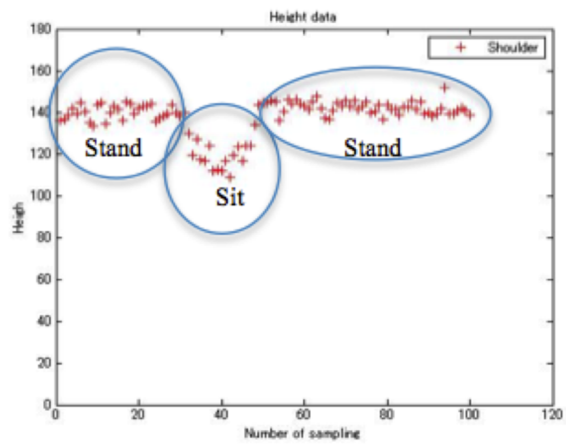
From the results in the posture classification experiments, the range-based algorithm demonstrates the simple technique for classification, but achieves a higher accuracy when compared with existing techniques. The majority of existing research provides good accuracy in dynamic activity, but results in static activity or posture classification, are quite low. One thing that makes the results between the proposed technique and existing techniques different is the type of data. In the proposed experiments, ultrasonic sensors are used to collect the height data. This data can be used for extracting the range between body parts, and ultrasonic sensors provide stable and accurate data. On the contrary, existing techniques use the accelerometer sensor where the output of the sensor is a raw signal. It needs some feature extraction to gain the necessary variables. Lee et al [89] is a good example of research which explains the problem with the accelerometer sensor.



(a) Range-based algorithm with three sensors



(b) Range-based algorithm with two sensors



(c) Height-based algorithm with one sensor

Figure 5.9: Compares the results when there are a different number of sensors

They obtained high performance in dynamic activity classification of 90.65 %, while performance in static activity classification drops to 83 %. In their work, errors can easily be found in static activity because signals are quite stable. It is different in terms of magnitude in each axis. Feature extraction cannot be used very well if the signal input is a stable signal. On the other hand, signals in the dynamic activity have oscillations. It is easy to extract the value from the oscillation signals. In conclusion, the accelerometer might not be so accurate for posture classification.

5.5 Conclusion

This chapter has described the range-based algorithm to classify human posture and to detect fall-down accidents. The range-based algorithm is used to measure the distance between body parts, and then extracts the relationship range between body parts to classify human posture. Moreover, the adaptive posture window scheme has also been developed to select the appropriate size of the adaptive posture window, regardless of the speed of the changing posture. From experiments, the test subject is an average adult person performing all postures normally, at average speed. The system adopts the size of the posture window to 4 for posture classification. The advantages of the proposed algorithm are high accuracy, high reliability, and real-time operation. Nevertheless, this proposed algorithm can distinguish only human postures ("Stand", "Sit", and "Lie-down"). It still needs more techniques for classification in certain cases. In the next Chapter, the results of this posture classification will be used for improving the proposed activity classification.

Chapter 6

Ontology-Based Activity Recognition (OBAR)

6.1 Introduction

In this chapter, before going into the process of activity recognition, the data organization (section 6.2) presents ways to process the data through two modules: data manager, and system repository. These two modules attempt to normalize the raw data and to conform the data to control it in the system.

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 [92], so this poses a problem when classified data is insufficient.

The OBAR system (section 6.3) is proposed as belonging to the ontology concept. The context-aware infrastructure in the home is defined in terms of the ontology model. The aim of this OBAR system is to improve the ability of activity recognition by using a new semantic user context and activity log in the ontology. Our proposed method exhibits not only high classification performance but also yields reliable and reasonable results.

6.2 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. The system cannot always obtain absolutely perfect data from the sensor. There can be missing data and noise problems associated with hardware. This section will present practical metrics, a data manager and system repository to organize the data in the system [93].

6.2.1 Data Manager

According to CSN and posture classification, there are several pieces of environmental data in the home that the system has to obtain because certain object activation and human information in the home can infer human activity. Thus, a large amount of data is collected into the system. It is not only the amount of data in the smart home which affects the system, but also its quality. Although the system can obtain the data from a diversity of sensors, it still suffers from missing data or noise from the sensors. There are particular problems with data when dealing with hardware. Therefore, the data manager component aims to normalize data before sending it to the system repository.

After the system obtains the data from the CSN and posture classification, the data is sent to the "Preprocessing Data" module for normalization. There are two main techniques to normalize raw data from the data collection section. Firstly, the supply of missing data function is developed to solve the missing data problem. The system will find suitable data or possible data to make the information complete. For example, for detecting human location, an infrared (IR) sensor is used to measure the IR light radiating from 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 missing data supply function will retrieve the last location instead of the current location.

context id	context date	context time	sensor id	posture name	last activity name	last object name	location name	activated object name	resultant activity
669	20121129	30	13,15,5,6	Sit	Working on computer,Lying down & relaxing	Computer,Chair	Living Room,Bathroom	Human,Chair,Shower,Computer	Working on computer
670	20121129	31	13,15,5	Sit	Working on computer,Lying down & relaxing	Computer,Chair,Shower	Living Room	Human,Chair,Computer	Working on computer
671	20121129	32	13,15,5	Sit	Working on computer,Lying down & relaxing	Computer,Chair,Shower	Living Room	Human,Chair,Computer	Working on computer
672	20121129	33	13,15,5	Sit	Working on computer,Lying down & relaxing	Chair,Computer	Living Room	Human,Chair,Computer	Working on computer
673	20121129	34	13,15,5	Sit	Working on computer,Lying down & relaxing	Computer,Chair	Living Room	Human,Chair,Computer	Working on computer

Figure 6.1: The data error from the shower sensor

Secondly, eliminating data function is the relevant function to reduce unexpected data or noise from the sensor. The unexpected data problem can easily change the recognition result. In this research, 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. Moreover, the human location information can be used to eliminate noise from the sensor. Figure 6.1 is a good example of expressing the advantage when using the human location information in this module. Although the "Shower" object is the necessary object to infer the "Taking a bath" activity, it cannot guarantee that the user is "Taking a bath" now. If we consider the other information in the user's context 669, it is impossible that the user performs the "Taking a bath" activity in the living room.

6.2.2 System Repository

To control the data in CARE architecture, the system repository plays a vital role in controlling data flow in the system. Figure 6.2 illustrates the flow of data between the system

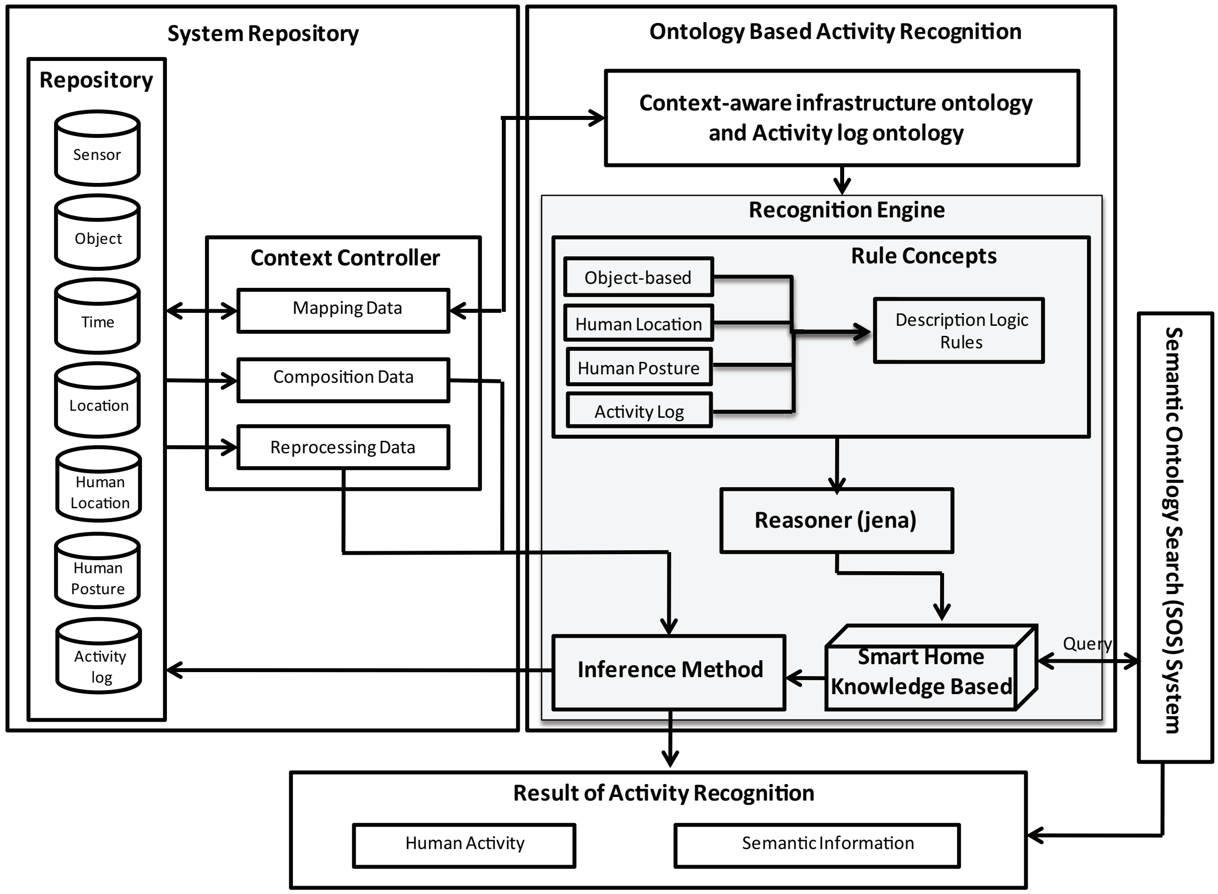


Figure 6.2: Data flow between the system repository and OBAR

repository and OBAR. There are two modules in this section: a repository and a context controller. The repository is used as the database in the CARE architecture. It collects the data that is normalized by the data manager and also retains the temporal reasoning of the OBAR system. The context controller performs three main data-processing tasks.

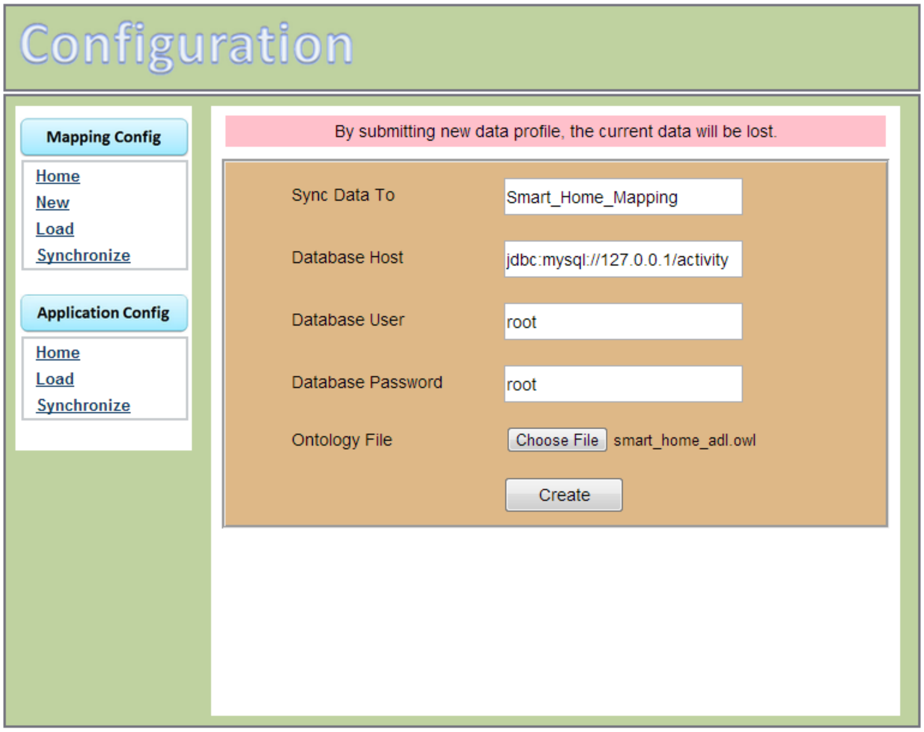
1. **Mapping Data**

   Based on the CARE architecture, the ontology concept is used to elicit huge amount of information from a variety of sensors. In this research, three ontology models are described in the abstract level, whereas 23 database tables are designed in the repository. The ontology application management (OAM) framework [81], an application development platform for implementing a semantic web application, is adopted to map between the properties and concepts in the ontology model and the data in the repository. The ontology model class will perceive the data in the database through this step.

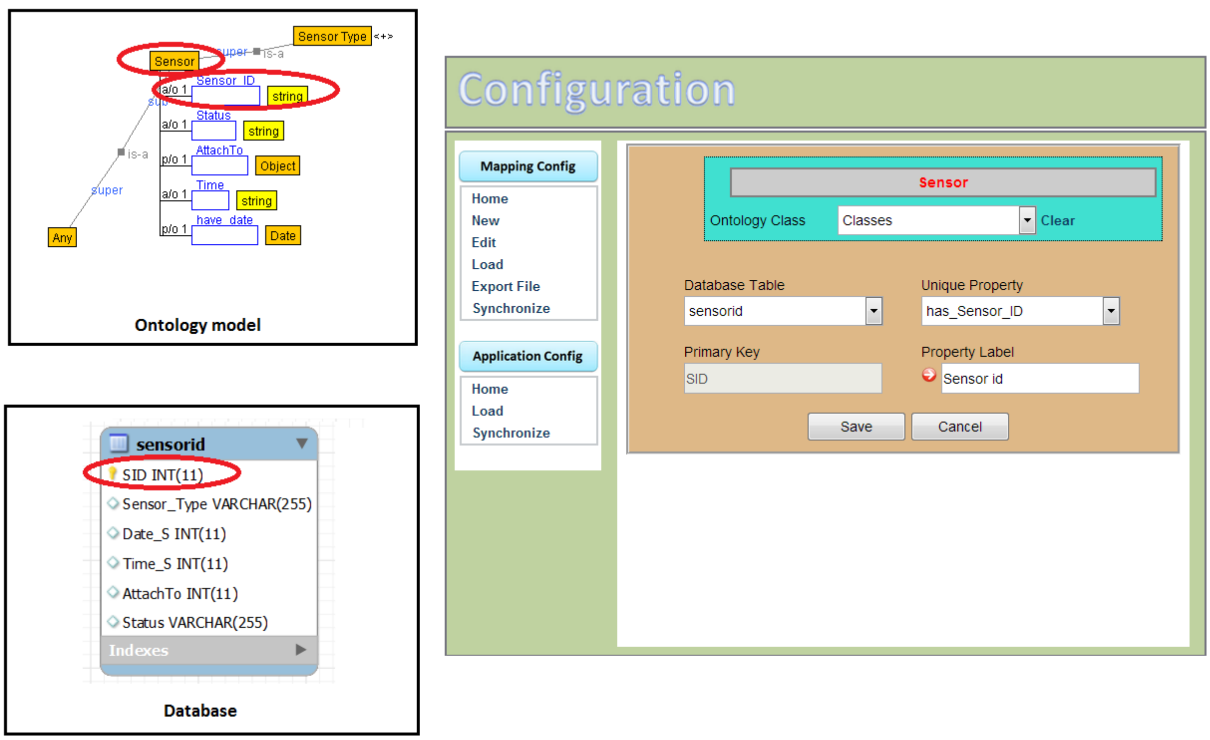
Nevertheless, the ontology model and the relational database cannot map directly. There are certain steps for mapping the data. Firstly, the ontology model has to export to OWL (Web Ontology Language), and then map the OWL with the database through the OAM framework. According to the OAM framework, it provides the interface for configuration between the database and the OWL as shown in Figure 6.3a. After that, the relationship between the ontology class and the table in the database (Class-Table Mapping) is created as shown in Figure 6.3b. From the example, the *Sensor* class is associated with the primary key of a *sensorid* table.

The next step is Property-Column Mapping. The properties in each class and column in the database table are linked through the OAM interface, as shown in Figure 6.4. Our research can be divided into two properties: Data Property and Object Property, which are described in more detail in the next section. Figure 6.4a shows the datatype property mapping process, which links the *sensor_name* property in the *Sensor* class with the *sensor_name* column in the table *sensorid*. Meanwhile, Figure 6.4b presents the object property mapping process which maps between the *AttachTo* property in the *Sensor* class and *object_id* column in the table *objectid*.

After the Mapping Data process is finished, the system will generate the results as a resource description framework (RDF), a standard model for data interchange on the Web, for easy use when applied to semantic web technology. In this research, the results of mapping will be stored in the smart home knowledge-base for further processing.

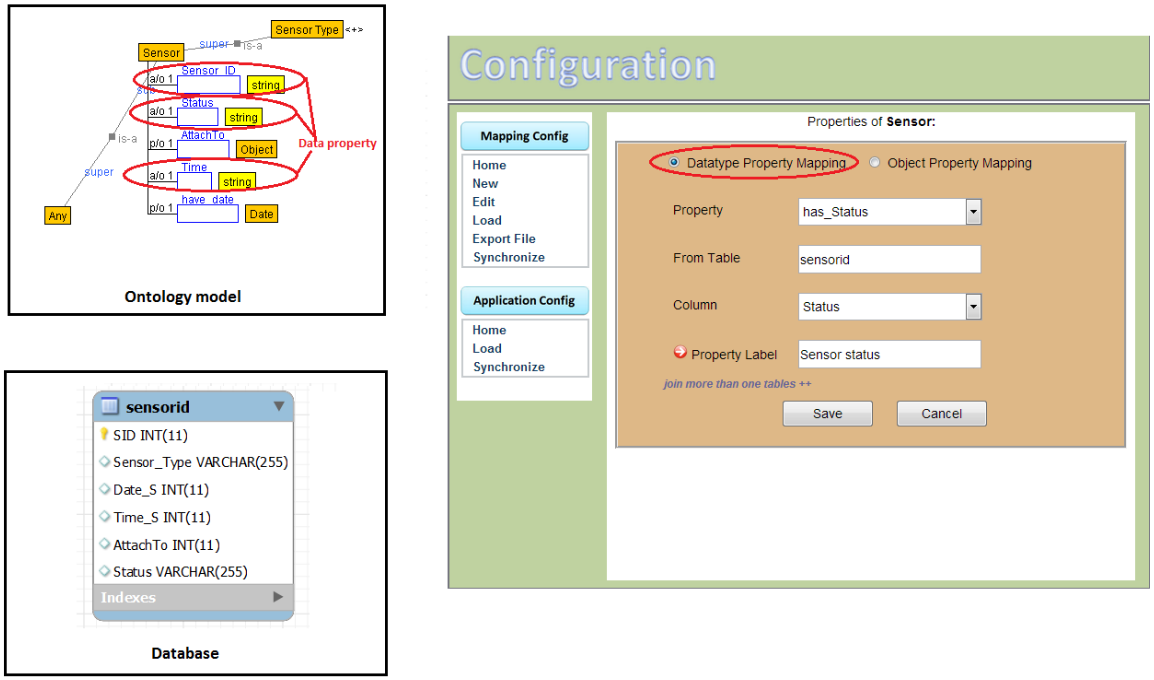


(a) Configuration page

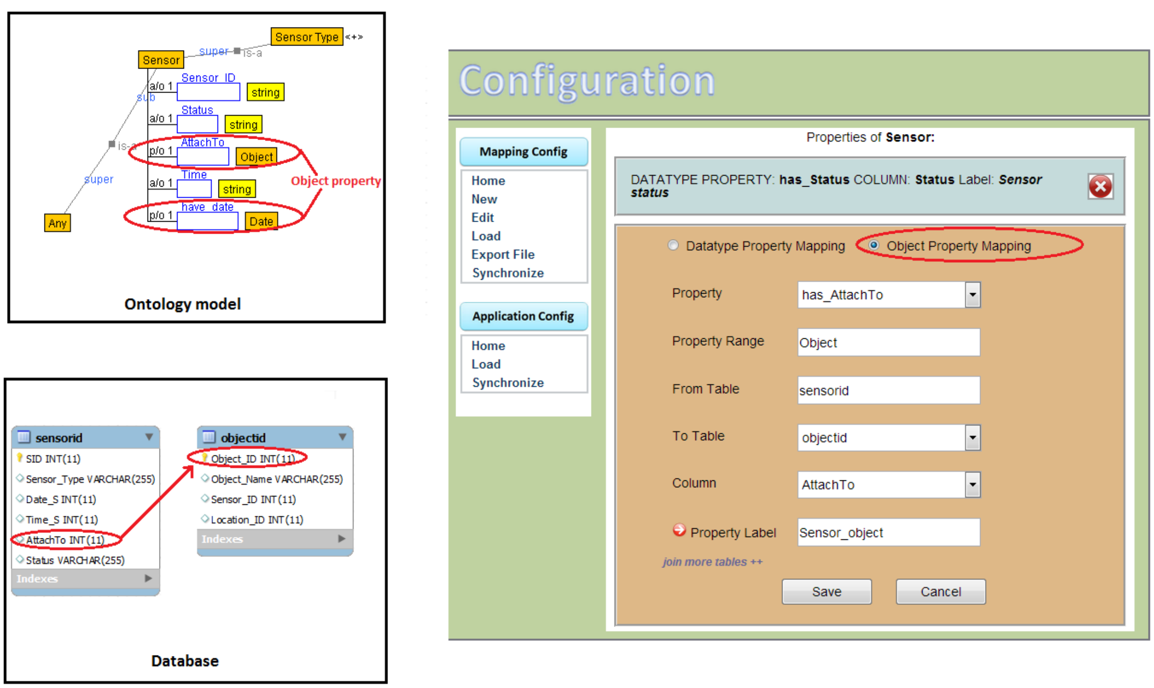


(b) Class-Table Mapping

Figure 6.3: Mapping data process with OAM framework (1)



(a) Datatype property mapping



(b) Object property mapping

Figure 6.4: Mapping data process with OAM framework (2)

2. **Composing Data**

The main task of the compositing data is gathering the necessary information in the repository to the user context. In one user context, the system can perceive various kinds of semantic information such as object activation, human location, or time. The human posture information is also included in the user context. The user context in this research is designed based on the EER diagram of context-aware information as shown in Figure 6.5.

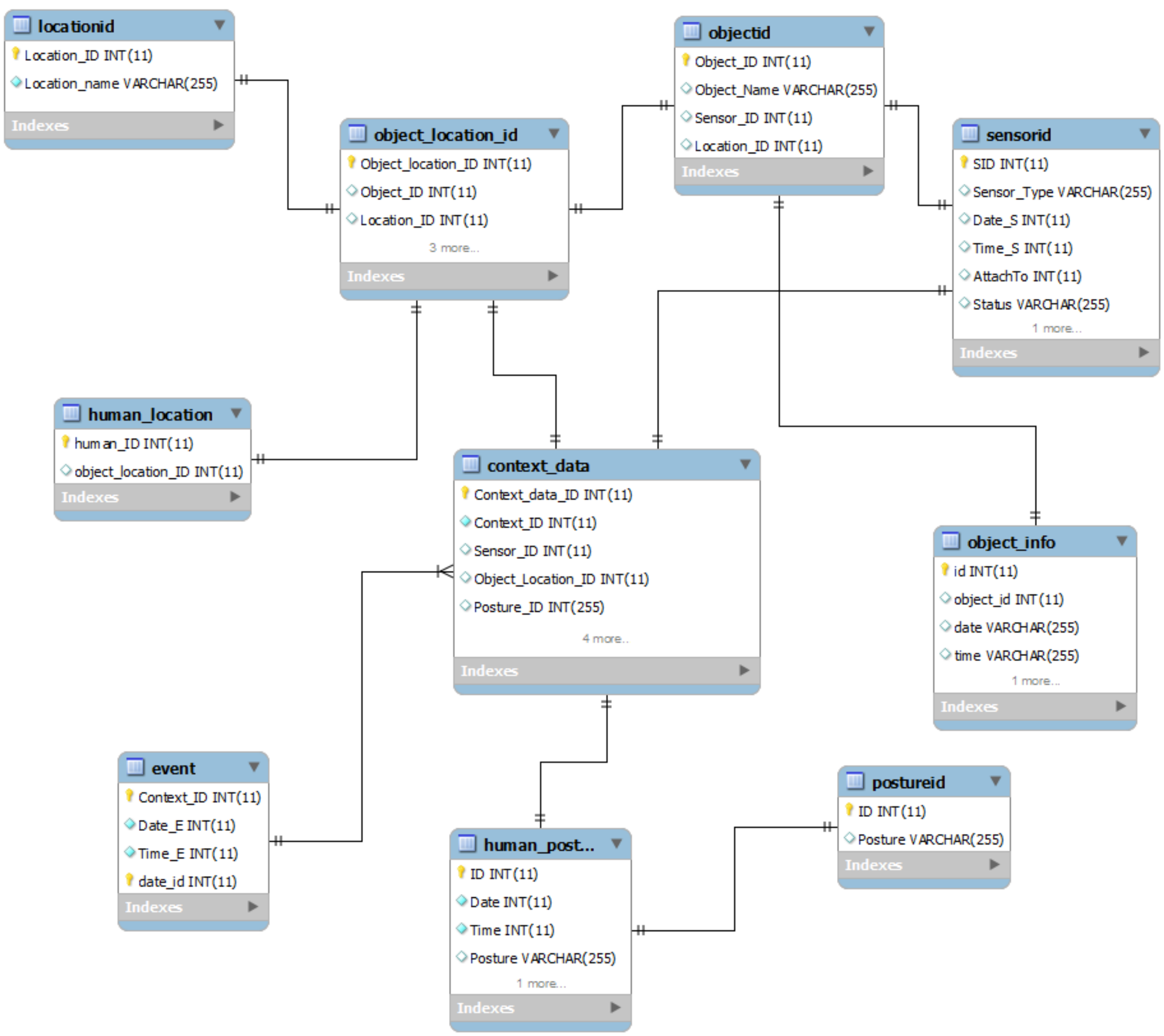


Figure 6.5: EER diagram of context-aware information

Based on the designed EER diagram of context-aware information in Figure 6.5, there are two types of relationships that link the tables. The first is the "one-to-one" relationship, which means that they are single-valued in both directions. A "one-to-one" relationship might be better explained with an example of a table *objectid* and table *sensorid*. Consider that in the sensor networks of the CSN, each object is attached by one sensor type. Thus, each sensor id will refer to only one object. The second is the "one-to-many" relationship, denotes that one entity is multi-valued with another. For example, one event id in a table *event* can have several context data ids in the table *context_data*.

3. **Reprocessing Data**

   According to the original idea of using an ontology concept, it does not support temporal reasoning, so the input data will be snapshot input data. Consequently, the system cannot guarantee the correctness of the results when using the snapshot input data. Therefore, in this task, an external Java program is implemented for capturing temporal reasoning from OBAR. It collects classified and semantic results, and then, updates the knowledge in the smart home knowledge-base with the new data. After that, the composing data task will conform to the current user's context and temporal reasoning and send to the inference method for the next classification.

   The temporal reasoning of the activity information in this task can be used to conform the activity of daily living (ADL) for analyzing human behavior. Therefore, the temporal reasoning of the context-aware information is tracked and combined with the current user's context for solving the problem of snapshot input data.

6.3 Ontology-Based Activity Recognition (OBAR)

There are two parts to the implementation of the OBAR: ontology modeling and a recognition engine.

6.3.1 Ontology Modeling

In this research, there are three main ontology models for the classification of human activity. The first is a context-aware infrastructure ontology, used to define the semantic environmental information in the smar home domain. The second is a functional activity ontology, designed for definition of the target activities in this research. The last is an activity log ontology, which is used to track the history of activities and activated objects.

1. **Context-Aware Infrastructure Ontology**

   Classifying human activity is a complicated task because each activity can be carried out in a different sequential order depending on individual lifestyles. This means that one human does not need to perform an activity in the same way as another; for instance, to perform "Making coffee", some subjects turn on the kettle first, whereas some prepare the cup with coffee and milk first. Consideration of each activity event takes place under the location information and surrounding environment context in the smart home. The information can be human 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, a context-aware infrastructure ontology is designed to elicit the semantic context in the smart home.

   The context-aware infrastructure ontology shown in Figure 6.6., in this research is designed based on the Hozo application [75]. Hozo is an environment for building and using ontologies based on the 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 (*Object* class) will be inherited by the subclass *Electric appliance, Furniture* classes).

   According to Figure 6.6, ten classes were designed in the context-aware infrastructure ontology, namely: *Location* class: to define a location in the smart home.

Sensor class: to identify the sensor type and to check the usage of an object. *Object* class: to describe a type of object in the smart home. *Human posture* class: to recognize human posture in each period of time. *ObjectInstance* class: to identify the object instance with location. *Context* class: to gather the user's context data for activity recognition. *InferredActivity* class: to map between the *Context* class and *Functional Activity* class in Functional activity ontology. *Activity Log* class: to capture the history of activities and object activation information. *ADL* class: to form the activities that the user performs in one day. *Date* class: to identify the date of the information.

Considering the relationship between classes, our ontology can be divided into two principal properties: Object Property (OP) and Data Property (DP). The OP describes a "part of" the relationship between the two classes, whereas the DP identifies an "attribute of" each class. Figure 6.7 depicts a good example of DP and OP properties in the *Context* class. The *Context* is a relevant class that relates location information and surrounding entities such as sensor, object, and human posture. For example, from Figure 6.7, the "have sensor" property in the *Context* class can infer 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 in the *Context* class can infer three kinds of semantic data: sensor information (activation time, status, or sensor id), object information (object type, object name, or object id), and location information (location id and location name). For example, if the system perceives "Sensor id = 1" is activated, the system can obtain various kinds of semantic data from this knowledge. Firstly, the system can ascertain that the "Sofa" object is being used by "Attach To" property in the *Sensor* class. In the same way, the system knows the "Sofa" is in the living room from the "Current Location" property in the *Object* class. Furthermore, In this design, human is defined as one subclass in the *Object* class. Therefore, the system can perceive the human location by the "Current Location" property in the *Object* class in the same way as the object in the smart home.

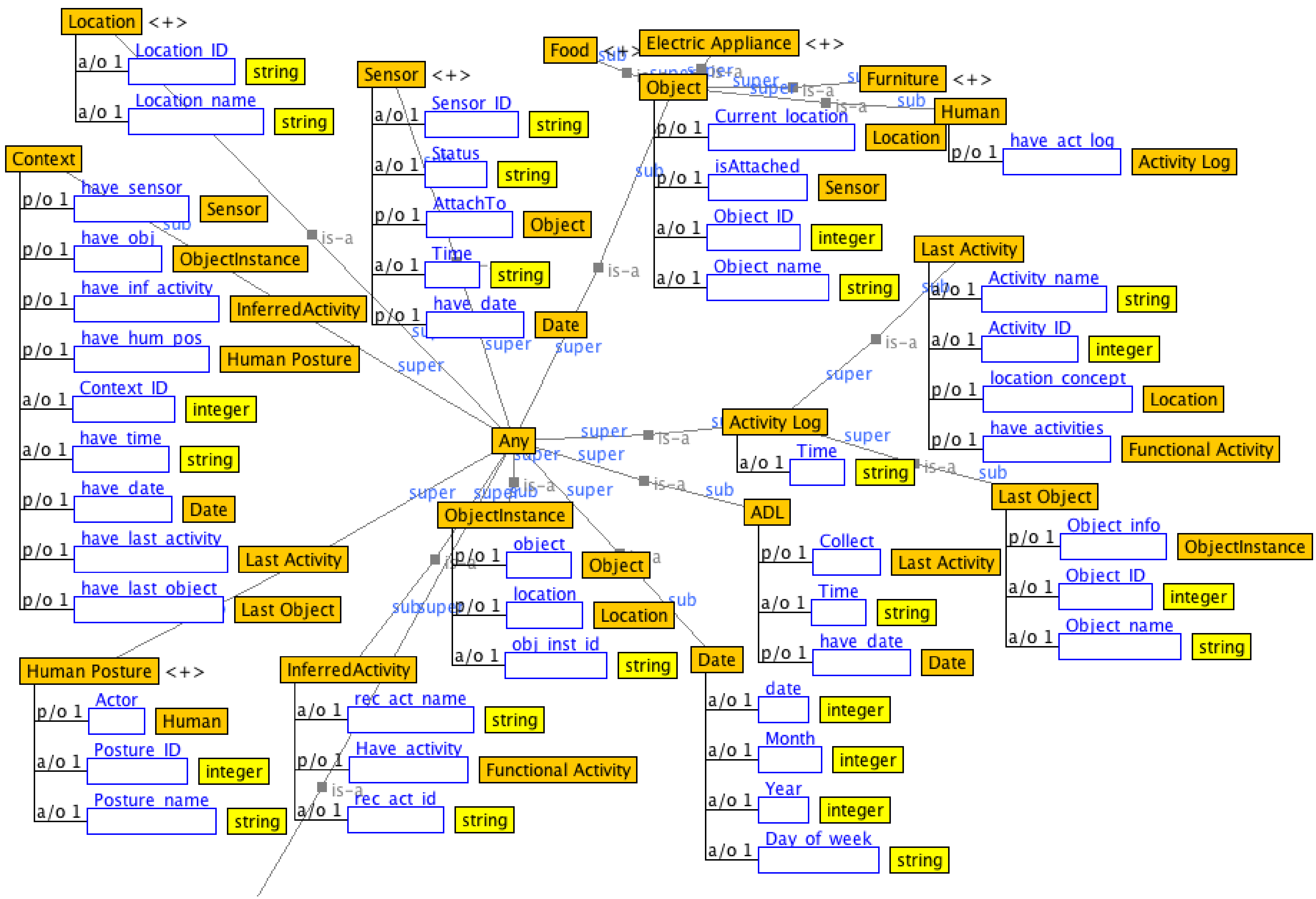


Figure 6.6: The context-aware infrastructure ontology

Nonetheless, existing research has revealed limitations when using common semantic information for classification. Naeem et al. [94] proposed that the recognition system, considers only the usage of an everyday object to classify human activity. However, there are various possible resultant activities when several sensors are activated at the same time. The system cannot decide on the correct resultant activity. This research refers to this problem as the "ambiguous activity problem" Therefore, the context-aware infrastructure ontology, designs 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 section 5 becomes the relevant information for reducing the possible resultant activities. It can make the system more accurate and reliable.

Furthermore, each context is identified by the time information. It provides relevant information to analyze human activity. Because some activity events occur at a specific time each day; time can be used to distinguish the activity in specific

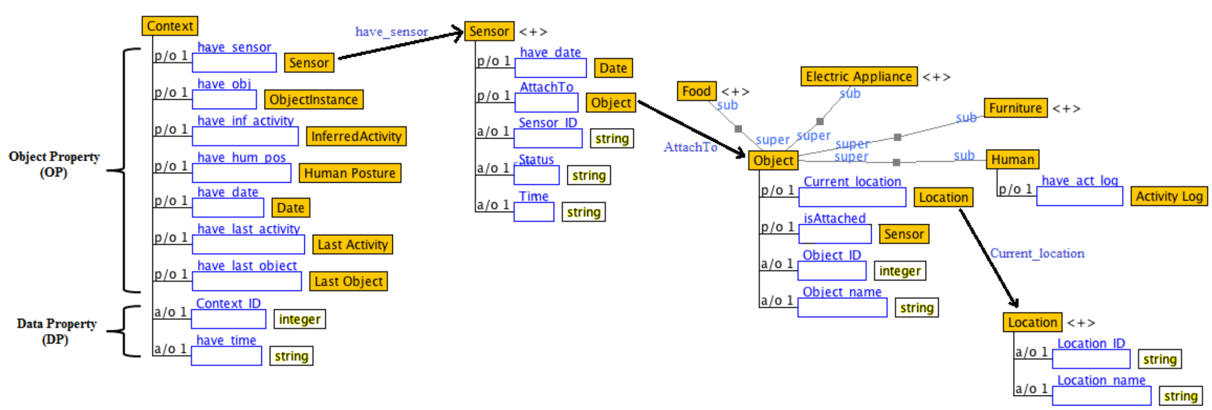


Figure 6.7: The relationship in the *Context* class, *Sensor* class, *Object* class, and *Location* class

detail. For example, the system can ascertain the "Eating and drinking" activity for breakfast, lunch, or dinner based on time. In addition, it is very important for further analysis, i.e. the healthcare system needs to know the time when the patient has a meal each day. Thus, if the system knows the lifestyle of an individual in the home, it can predict the activity occurring at a specific time. For instance, a human takes a bath twice a day, after waking up and before sleeping. The system can predict the "taking a bath" activity if the user wakes up in the morning and goes to the bathroom at night.

2. **Functional Activity Ontology**

   The functional activity ontology is designed for the definition of each activity. The superclass, *Functional Activity* class, is mapped to the *Context* class through the *InferredActivity* class in the context-aware infrastructure ontology. The *Functional Activity* class is represented in the hierarchy and shown in Figure 6.8. The data from the *Context* class is used to recognize the activities based on two concepts: the object based concept and location based concept.

   For the object based concept, the activity event occurs, when the individual uses the object to do something such as watching TV, working on the computer, or sleeping in the bed. Usually, the object can be divided into two types based on the purpose of usage: the direct purpose object and the multi-purpose object. A direct purpose object means an object that can only be inferred to one activity. For example, the "Broom" is used only for "Sweeping the floor" in the home. The "TV" is used for "Watching TV". A multi-purpose object means an object that can be used for many activities. For example, a human uses a "Chair" for several proposes: sitting on a chair for working on the computer, or sitting on a chair to have a meal. Although, the system can classify more specific activity through this concept, it produces a lot of ambiguous activities when the objects are activated at the same time.

   Therefore, the location based concept is proposed to recognize the activity occurring in a specific location. For example, the "Cooking" activity has to be performed in

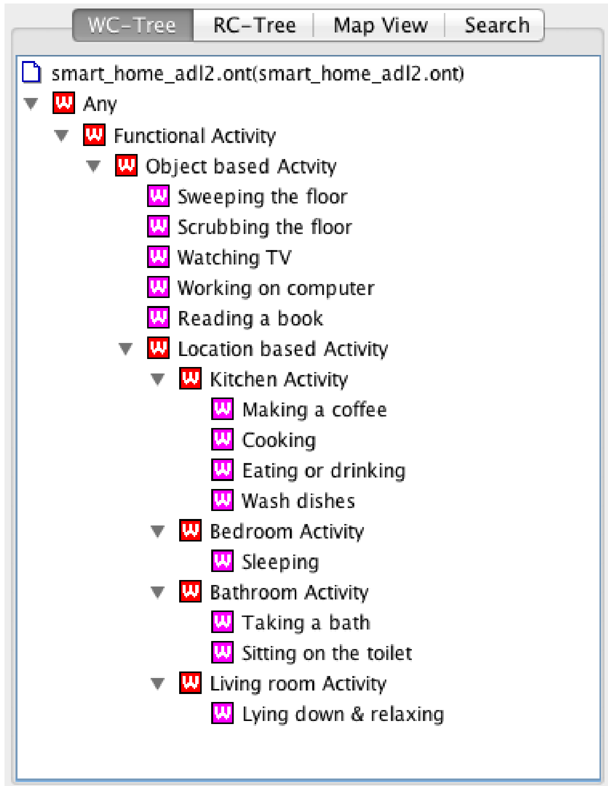


Figure 6.8: Functional activity ontology

the kitchen, or the "Taking a bath" activity is done in the bathroom only. This is a useful concept because it can disregard some objects that are activated outside the interest areas. Furthermore, the location-based concept also limits the activity that should not be out of the interest area, and also hints the human activity that the user will perform based on the current human location. However, the disadvantage of this concept is that it cannot work well for activities which can be done in any location. For instance, the user performs the "Sweeping the floor" and "Scrubbing the floor" activities in every room of the home.

3. **Activity Log Ontology**

The original idea of using an ontological model in activity recognition does not support temporal reasoning. This means that snapshot data from the sensors is used as input data for 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 information might not be 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” activity 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 Figure 6.9, is proposed in our ontology model to aggregate the sequential history of activities and object activations. Information in the *Activity Log* class is relevant for activity recognition because the system cannot guarantee accuracy when used only as data at a specific point in time. In this dissertation, the activity log is proposed for collecting the history of the object activations and activities. The history of the 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 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, this research proposes 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 location for computing the current user’s context [95]. For example, if the system knows that the current location of the individual is the kitchen, the activities the performed in the kitchen will be considered in the system for classifying the current activity. The relationship between activities in the same place is investigated. For example, the “Wash dishes” activity will occur if, and only if, the “Cooking”, “Eating and Drinking” activities occur beforehand. Hence, the system can ignore those activities performed out of the current user’s location.

AL^2 produces more reliable results compared with those of existing research efforts (for additional detail see the results in Chapter 6). For the activity log ontology model, the location information in the *Activity log* class can be referred to through the "location concept" property. Based on Figure 6.9, the *Last Activity* class can infer the activity performed by the user from the "have activities" property, and each activity location will be tagged by using the "location concept" property.

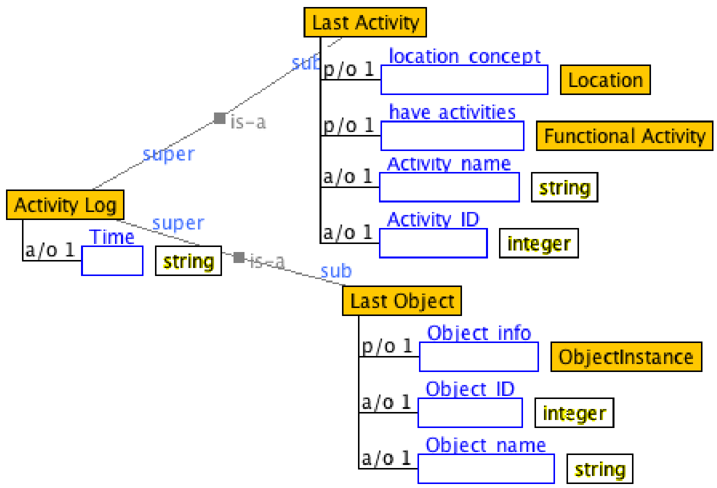


Figure 6.9: Activity log in the ontology model

6.4 Recognition Engine

Normally, ontological models do not have the ability to recognize human activity. Usually, OWL, 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). In this research, the OBAR system is built upon the DL and reasoning mechanisms as presented in Figure 6.2.

For inference of human activity, the DL rules are created by modeling and linking activity instances and inferred activity instances. There are four factors to be considered when creating the DL rules. 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, such as “Watching TV”, “Working on a computer”, or “Sweeping the floor”. Secondly, the human location factor is used to scoop the possible activity for the object being used at the same current user location. Thirdly, the human posture factor is used to reduce the possible resultant activities. It can be used to distinguish some activities; for example, when the “Sofa” is being used, the system can classify the user as sitting on the sofa and “Watching TV” or lying down on the sofa for “Lying down & relaxing” by human posture information. Lastly, the activity log factor is used to enhance the relationship between the history of the user context and their current context. The following example indicates the DL rule for the “Washing dishes” activity:

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

Although, the above example DL rule is represented in general terms, the system cannot understand this rule. Therefore, a built-in reasoner (Jena) [96] is implemented to compute the DL rules for the new data and storing them in the smart home knowledge base. The following Figure 6.10 shows the example rule for the “Washing dishes” activity in Jena syntax.

After generating the DL rules in Jena syntax, an *InferredActivity* class instance is created to link it with the DL rules. Figure 6.11 illustrates the instance of the “Washing dishes” activity in Jena syntax.

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.

```
[Linking_InferredActivity_instance_id_98_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0)  (?y0 rdf:type
     ns:Sink) (?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11)  (?y11 rdf
    :type ns:Human) (?x00 ns:has_location ?y12) (?y12 rdf:type ns:Kitchen)
    (?x ns:has_have_hum_pos ?y2) (?y2 rdf:type ns:Stand) (?x ns:
    has_have_last_activity ?y13) (?y13 ns:has_have_activities ?y14) (?y14
    rdf:type ns:Eating_or_drinking) -> (?x ns:has_have_inf_activity ns:
    InferredActivity_instance_id_98) (?x ns:has_rule_name '
    Linking_InferredActivity_instance_id_98_to_Context_0')]
```

Figure 6.10: Example rule for the "Washing dishes" activity in Jena syntax

```
[InferredActivity_instance_id_98: (?x1 rdf:type ns:Functional_Activity) (?
    x1 ns:has_name ?y0) regex(?y0 '(.)*Wash_dishes(.*)') -> (ns:
    InferredActivity_instance_id_98 ns:has_Have_activity ?x1) (ns:
    InferredActivity_instance_id_98 ns:has_rec_act_name 'Wash_dishes') (ns:
    InferredActivity_instance_id_98 ns:has_rec_act_id 'uid_98') (ns:
    InferredActivity_instance_id_98 rdf:type ns:InferredActivity) (ns:
    InferredActivity_instance_id_98 ns:has_rule_name '
    InferredActivity_instance_id_98')]
```

Figure 6.11: Example activity instance of the "Washing dishes" activity in Jena syntax

6.5 Conclusion

In this chapter, data organization is proposed for preprocessing the raw data received from the data collection. A data manager and system repository are proposed. The data manager has responsibility for normalizing the raw data while the duty of the system repository is to control all data between the repository and the OBAR system. The OAM framework is developed in this research for synchronization between the repository and the ontology model.

Activity recognition is established based on the ontology of OBAR. The ontology approach is selected for the OBAR since the ontology concept is advantageous compared to other approaches. Firstly, the ontology model defines the interesting domain in the abstract level, so it does not need a large training set to learn the activity model. Hence, it can prevent the "cold start" problem when lacking recognition information. Secondly, the ontology concept can produce the standard activity model, so it does not need to train the activity model for a specific person, the same as the probabilistic approach.

To develop the OBAR system with the ontology approach, three ontology models are proposed; the context-aware infrastructure ontology, functional activity ontology, and activity log ontology. The OBAR system utilizes the advantages of the ontology concept through these three ontology models. A new user context and the AL^2 have been proposed in this research to improve the ability of activity recognition. The well-known DL rules are also created based on the observation of real human behavior. The four factors, i.e. object activation, human location, human posture and the activity log are used to create the DL rules for recognition of human activity.

Chapter 7

Activity Recognition using CARE

7.1 Introduction

Although existing activity recognition research achievements have recognized human activity, most of them use the common term of user's context. This leads to several problems with the system. Due to the huge amount of information in the smart home, the common term of user's context cannot be used as in existing research for recognizing human activity because there are several factors affecting the performance of the activity recognition system.

To avoid the above problem, this chapter presents the impact of the description rule (section 7.2) used in our proposed OBAR system. Then, section 7.3 expresses how this research is setup in the environment for evaluating the performance of OBAR. After that, section 7.4 presents the performance of the OBAR system based on the data obtained from the CARE architecture. Section 7.5 explains the advantage of the OBAR system, and the results of the OBAR system will be discussed in section 7.6. Finally, this chapter concludes with the performance of our proposed OBAR system in section 7.7.

7.2 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, this section 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 the activity log (AL).

In this section, the experiment analyzes each factor by measuring the classification performance of each activity. The factors are divided 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, the innovative human posture information is added to the third group (OB+HL+HP). Finally, all factors are considered in the last group (OB+HL+HP+AL). All four groups have the same environment, input data, and test subjects. The performance of each group is shown in Figure 7.1, and Table 7.1 presenting a comparison between the accuracy of each activity in the first group with the other groups.

In the results, all four test groups are examined in the OBAR system for the classification of human activity. Below is an analysis of the results of the impact of sensing data (factors) obtained from the CARE architecture:

- **Object-based** although using the object-based factor offers the lowest percentage of recognition, it is the most relevant information for classification of human activity because if the system does not know which object is being used, the system cannot classify the specific activity such as "Watching TV," "Working on a computer," or "Sweeping the floor." Nevertheless, the system will generate several possible resultant activities if it utilizes object-only information. It can lead to the "ambiguous activity problem" when several objects are being used, and is the main reason for the low accuracy in the first group. Hence, most research tends to combine object-based information with other information as shown in the second group (OB + HL).

Table 7.1: 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)

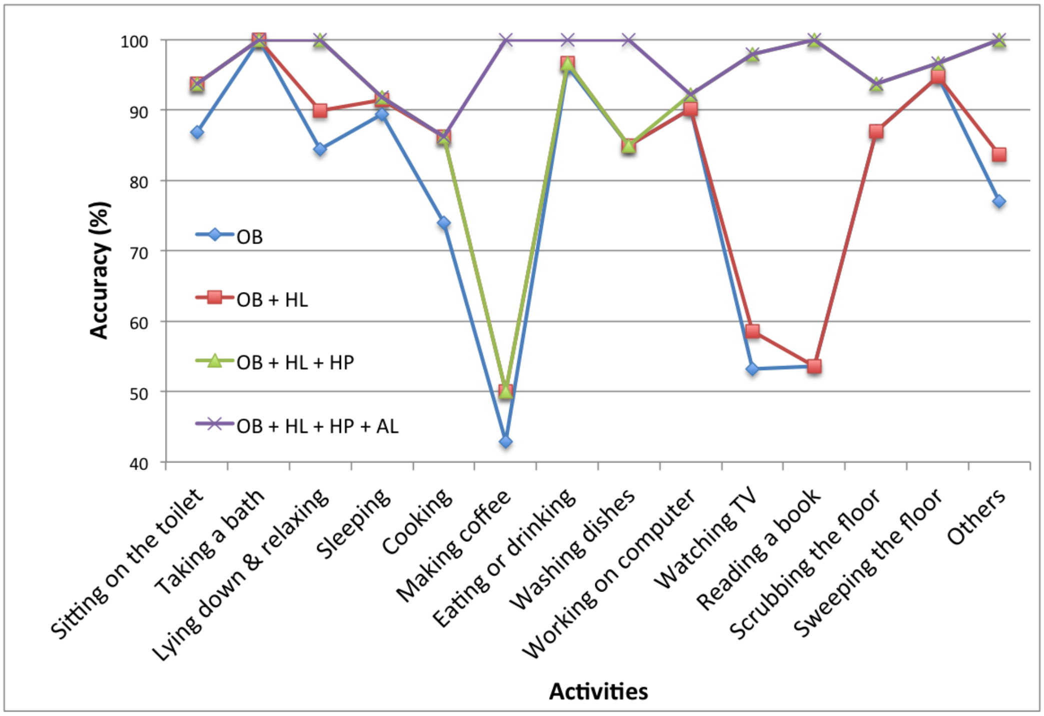


Figure 7.1: Recognition accuracy for each activity

- **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 human activity in this situation as "Sleeping." However, if the system knows that the user is in kitchen, it 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 context human posture, in the third group provides an average improvement of 12.01% when compared to the first group. The concept of using human posture is to distinguish activities that have different postures. For example, "Watching TV" is an outstanding example of an explanation of the major point of human posture in activity recognition. If the system considers "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 the location of the activity in the activity log (AL^2), which tracks the activity that the user performed at their current location. From these two techniques, the results demonstrate the highest accuracy when adding the activity log factor. Table 7.1 shows, the advantage of these two points. Firstly, the history of object activation 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 section 7.5.

7.3 Environment Setup

According to the CARE architecture, the real environment data is collected through the diversity of sensors based on the proposed CSN. Meanwhile, the OBAR and semantic ontology search systems are implemented and installed on the server in the iHouse. For this research, 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 UPnP, ECHONET and Zigbee. This experiment was performed using six test subjects (three males and three females) whose ages ranged from 24 to 31. They were asked to perform any activity in the iHouse without instruction. The evaluation of this setup, is divided into two parts. The first measures the performance of our activity recognition based on proposed ideas (section 7.4). The second analyzes the advantage of our proposed ideas from the results of the semantic ontology search system (section 7.5).

7.4 Performance Evaluation

As described in Chapter 6, one advantage of using the ontology concept in the OBAR is that it does not need a large training set or process. Thus, in this experiment, six test subjects demonstrate the activities in the iHouse. In each minute or single user context, a subject is either performing A_1–A_{13}, or others (A_{14}). 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 7.2 shows the recognition accuracy of each activity.

In total, 1,140 user contexts are performed by six test subjects. 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 specifically 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 cases. 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, poor results appeared because of an asynchronous sensor delay and the interval time in classification. In this experiment, for sensing data if the sensor is activated, it will be delayed for one minute when sensing new data. Meanwhile, the interval time for classification is fixed to

Table 7.2: 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 %		

one minute. In this sense, one might have a situation where the subject already changes activity, but the system still uses the old information to classify human activity.

The average accuracy obtained in this research also exceeds that of existing research (as shown in Figure 7.2). Bao et al. [70] presents activity recognition using a probabilistic method. Accelerometer sensors are used for detecting human activities. The average recognition accuracy of his research is 83.90% for 20 activities and 89.67% for home activities (seven activities). The limitation of this research is the lack of information for classification because the information used was only from body sensors. Thus, it leads to low performance for classification of specific activities such as "Watching TV" or "Reading a book." Chen et al. [99] demonstrated activity recognition using the ontology concept. This mainly focused on object activation data for classification. However, there are several problems when one tries to classify human activity based on only a single type of information. For example, the "ambiguous activity problem" arises when several objects are being used, or the system might classify incorrectly if there is sensor noise in the system.

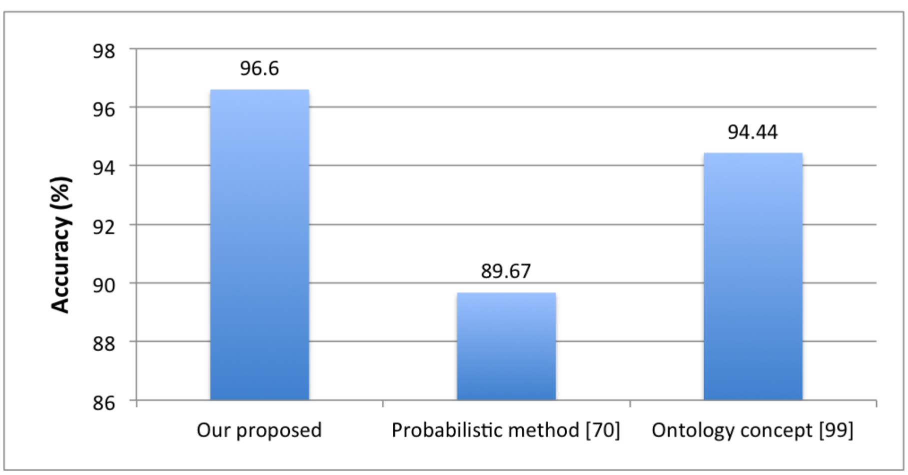


Figure 7.2: Comparison of the activity recognition accuracy rate in existing research results

7.5 Findings

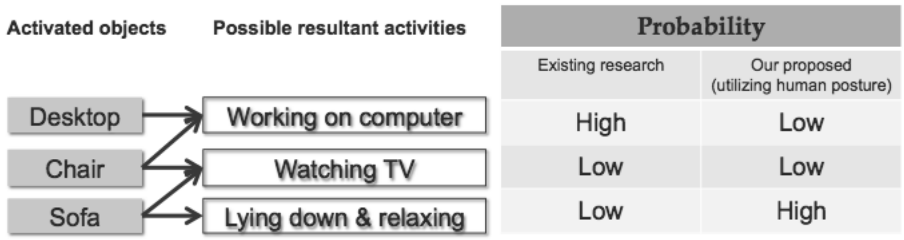
This section will analyze the advantage of our proposed activity recognition from the results of a semantic ontology search application. Behind the results, two benefits were found when using human posture information and AL^2 in OBAR, described as follows:

7.5.1 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, this research has used posture classification, and the results 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 a test subject in our experiment:

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

From the above situation, the context information can be analyzed as shown in Fig. 7.3. The system can perceive the user's context as identifying the location as the living room, and there are three activated objects: the "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 between the remaining activities. Normally, if the system does not have human posture information, then "Working on a computer" will be the resultant activity. Nevertheless, in this context, the system recognizes 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 subject may be "Lying down & relaxing" on the sofa. Figure 7.3b shows the results from the semantic ontology search application, and the context id 702 and 703 are illustrated in the results of the classification based on the above reasons.



(a) Analysis of the ambiguous context

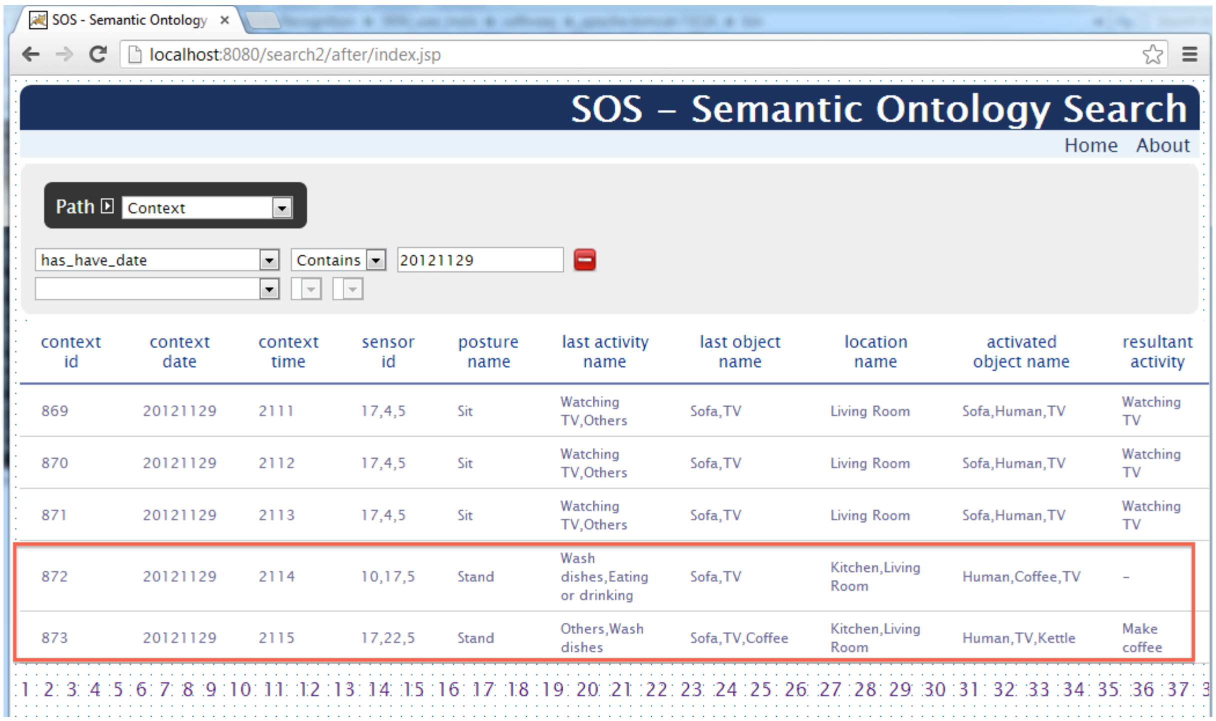
(b) Results of the semantic ontology search application

Figure 7.3: Ambiguous activity problem

7.5.2 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 7.1 is an outstanding result. Moreover, the context id 872-873 in Figure 7.4 shows evidence that the activity log can solve the problem of snapshot input data. The interval time in this experiment is set to one minute, but it is possible that the test subject 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% (Table 7.1) the interval time can, of course, be expanded, but if it too long, then it may lead to the system having a lot of activated object information for classification. Consequently, the system can indicate several possible resultant activities.

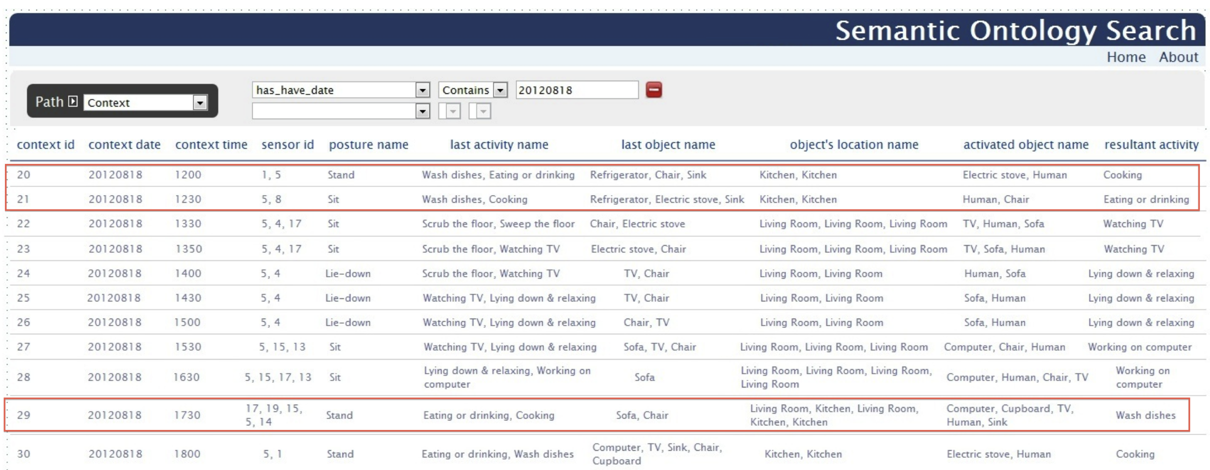


context id	context date	context time	sensor id	posture name	last activity name	last object name	location name	activated object name	resultant activity
869	20121129	2111	17,4,5	Sit	Watching TV,Others	Sofa,TV	Living Room	Sofa,Human,TV	Watching TV
870	20121129	2112	17,4,5	Sit	Watching TV,Others	Sofa,TV	Living Room	Sofa,Human,TV	Watching TV
871	20121129	2113	17,4,5	Sit	Watching TV,Others	Sofa,TV	Living Room	Sofa,Human,TV	Watching TV
872	20121129	2114	10,17,5	Stand	Wash dishes,Eating or drinking	Sofa,TV	Kitchen,Living Room	Human,Coffee,TV	-
873	20121129	2115	17,22,5	Stand	Others,Wash dishes	Sofa,TV,Coffee	Kitchen,Living Room	Human,TV,Kettle	Make coffee

Figure 7.4: Limitation of snapshot input data is solved in context id 872-873

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. This section aims to compare the performance of two methods: one using only a common activity log to classify the activity, and another where the AL^2 technique is applied.

Context_id 29 in Figure 7.5 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 an 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 the user performed in the current location (context_id 20 = “Cooking” and context_id 21 = “Eating or drinking”) to classify the resultant activity in context id_id 29 as “Washing dishes.” Of course, the resultant activity in context id_id 29 can be something else, but “Washing dishes” has a high probability factor because the system uses temporal reasoning for “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 7.2, especially for activities in the kitchen. The OBAR system can achieve high accuracy in sequential activities: “Cooking” or “Making coffee” → “Eating & drinking” → “Washing dishes.”



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

Figure 7.5: The results of the semantic ontology search application, AL^2 is used in Context_id 29

7.6 Discussion

The analyzed results in section 7.2 show how each factor is important. Although the object-based factor achieved the lowest performance, it is an independent parameter while the remaining factors are dependent parameters. The independent factor means activity recognition can classify human activity based on only the independent factor, whereas the dependent parameter has to combine other information to classify human activity. For example, merely human location cannot classify the activity, but it can improve the accuracy of activity recognition if combined with an object-based factor. In the same way, the human posture factor can recognize only basic activity (i.e. "Stand", "Sit", or "Lie-down"), it needs other information to classify more specific activities.

The overall results in this chapter 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 system achieves high activity recognition performance, it still needs additional techniques for improved 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 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 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 concept of AL^2 exhibits good performance when compared to existing research [100] when recent activities are used to recognize current activity. However, the system cannot know the exact number of recent activities that it should consider. For example, existing research could establish a rule that the "Washing dishes" activity should occur immediately after the "Eating or drinking" activity, but this is not always the true because it depends the lifestyle of the individual. One subject might be "Eating or drinking" and carrying out other activities before "Washing dishes". Thus, tracking the last activity the user performed at their current location is the relevant method of finding the relationship between activities.

7.7 Conclusion

This chapter presents experiments and results of the research in the activity recognition system, especially the OBAR system. The environmental data in the home and human information are analyzed to find the system requirement of the activity recognition system. The accuracy of activity recognition in section 7.2 shows the improvement when the new information (HP+AL) is added to the user context. The OB factor shows the lowest performance in this experiment, but the OB factor is the most relevant for activity recognition systems to use for the classification of human activity.

For measuring the performance of the OBAR system, the real data obtained from the real environment based on the CARE architecture, is used in the OBAR system for classification. 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 utilizing only the OB factor. The results from the posture classification proposed in the previous chapter are relevant for activity classification and can be used to reduce the "ambiguous activity problem" because each activity comprises human posture, and some human activities have a different human posture. In this sense the human posture information can be used to distinguish some activities. For the AL^2, the activities, performed in the same location, are considered for deciding the current activity. The experimental results indicate the importance of the location-based concept. The location information, system scans the recent activities only in the area of interest. It helps the system to classify human activity more reasonably.

According to the CARE architecture, the results of the OBAR system are sent and collected into the repository in order to conform to the ADL information. Moreover, not merely human activity information is saved in the repository, but also the environmental information used by to perform the activity. All results in the CARE architecture analyzed to provide recommendations for a health service based on human behavior in the next chapter.

Chapter 8

Applications

8.1 Introduction

At present, activity recognition systems have been developed together with several applications in different domains. For example, for the home security domain; activity recognition technologies can help the system to address the threat of terrorism. In the AAL system, the results of the activity recognition system can be used to decide the appropriate home service for the user, based on current activity. Nevertheless, these applications might not work if there are no reliable results from activity recognition.

So far, this dissertation has discussed details of proposed high performance activity recognition systems, such as CARE architecture, data collection using CSN, posture classification, and OBAR. This chapter will look into possible applications for utilizing the results from the proposed high performance activity recognition. This chapter specifically provides six example applications in different research areas; semantic ontology search, home healthcare (HHC), home security, human behavior schedule system, home service schedule system, and smart power management system.

8.2 Semantic Ontology Search

The semantic ontology search application [97], is a search engine typically used for retrieving the history of semantic information in a smart home based on the ontology concept.

The semantic information of object interaction, time, sensor status, and so on can be monitored through this application. The semantic ontology search is different to the traditional search application, which uses the database as a center for data. A RDF file is used in this application. 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. The advantages of using RDF are also its reusability and application by other parties dealing with large amounts of data.

Furthermore, because the semantic ontology search application uses the ontology concept as its core, one 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 ontology models can be used for describing the surrounding context in a smart home, including human activity information. In this research, the OAM framework [81] is used not only for the data-mapping process in the system repository, but also in the search process. This framework allows the developer to set the search configuration based on the classes and properties in the ontology model. The language query, SPARQL, is used to query the data from the RDF file in a smart home knowledge base.

For the user interface, the semantic ontology search application provides a form-based interface [98]. The user can select a class in the ontology to search for its instance data and define some search property conditions. Moreover, the semantic ontology search application also provides the comparison equator for making the property condition.

Consequently, 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 properties in each class (date, time, or sensor status). Moreover, the results of activity recognition are also added into the semantic ontology search application when searching the context data as shown in Figure 8.1.

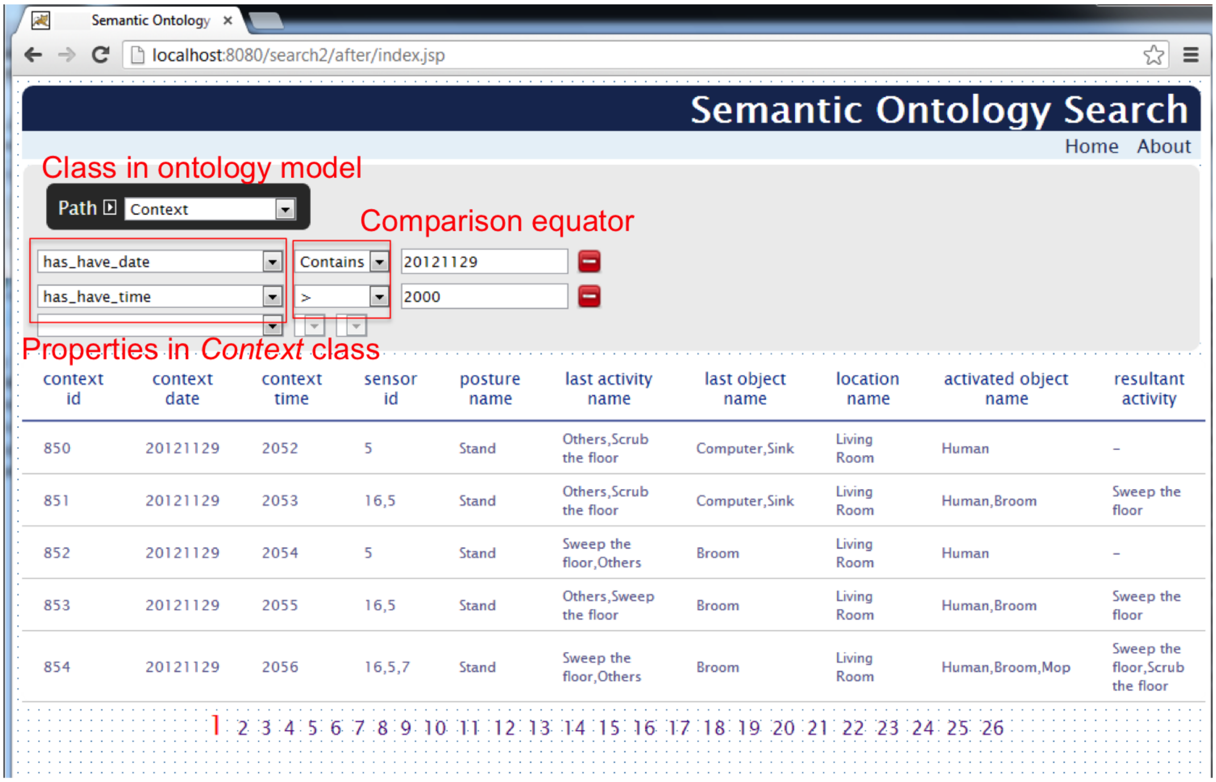


Figure 8.1: The example of semantic ontology search application

8.3 Home Healthcare (HHC)

Recently, a home healthcare (HHC) system has been proposed for taking care of individuals at home to achieve better health. There are several research studies proposing systems which attempt to provide a health recommendation service to the home user. Most of the existing research tends to collect only user health conditions through intelligent wearable devices based on various kinds of techniques, which recognize disease based on only the user's health condition. However, there is little research on providing appropriate health recommendation services in the home, based on human behavior. It is a challenging task for the system to decide a suitable health recommendation service for the home user.

Essentially, when considering the HHC system, health information is most important to the physician when diagnosing illness or disease because some can be diagnosed directly from relevant health information. For example, for hypertension, the HHC system can provide a health recommendation service to the home easily if the HHC system detects an abnormal signal from the blood pressure monitor.

Nevertheless, the existing HHC system cannot perceive the real cause an illness or disease because only health signals are used in diagnosis. There are several types of data available for consideration such as user location, user action, or object activation. Consequently, human activity is one of the essential pieces of information to help the HHC system to recognize a disease or illness. Hence, in this research, high performance activity recognition was proposed and provided good results. The results from the OBAR system, using the CARE architecture, will be used for analyzing and presenting to the home user and the physician to aid diagnosis.

8.3.1 Activity Information Analysis

Normally, to recognize disease or illness, health information is the main information used by a physician or the healthcare system in diagnosis. However, in some cases, the real cause of the disease or illness does not appear in the health information. Therefore, activity information plays an important role in recognizing the cause. In this research, the human behavior analysis system provides activity information of various types, as shown in Figure 8.2.

The above figure shows a summary of the activity information. The ADL information is displayed with data and time on the left-hand side of both pictures. The home user, physician, or healthcare system can monitor the ADL information, and perceive what a home user does each day to analyze the cause of disease or illness.

In Figure 8.2, the results from the OBAR are summarized and drawn on a pie chart. It shows the percentage of activities the home user performs in one period of time (depending on the input time). This kind of information is very useful for ascertaining the cause of an illness or disease. For example, the existing HHC systems cannot recognize “Diarrhea” because the symptom of “Diarrhea” does not appear in the basic health information. Nevertheless, the human behavior analysis application can predict this illness from the “Sitting on the toilet” activity. If the home user tends to perform the “Sitting

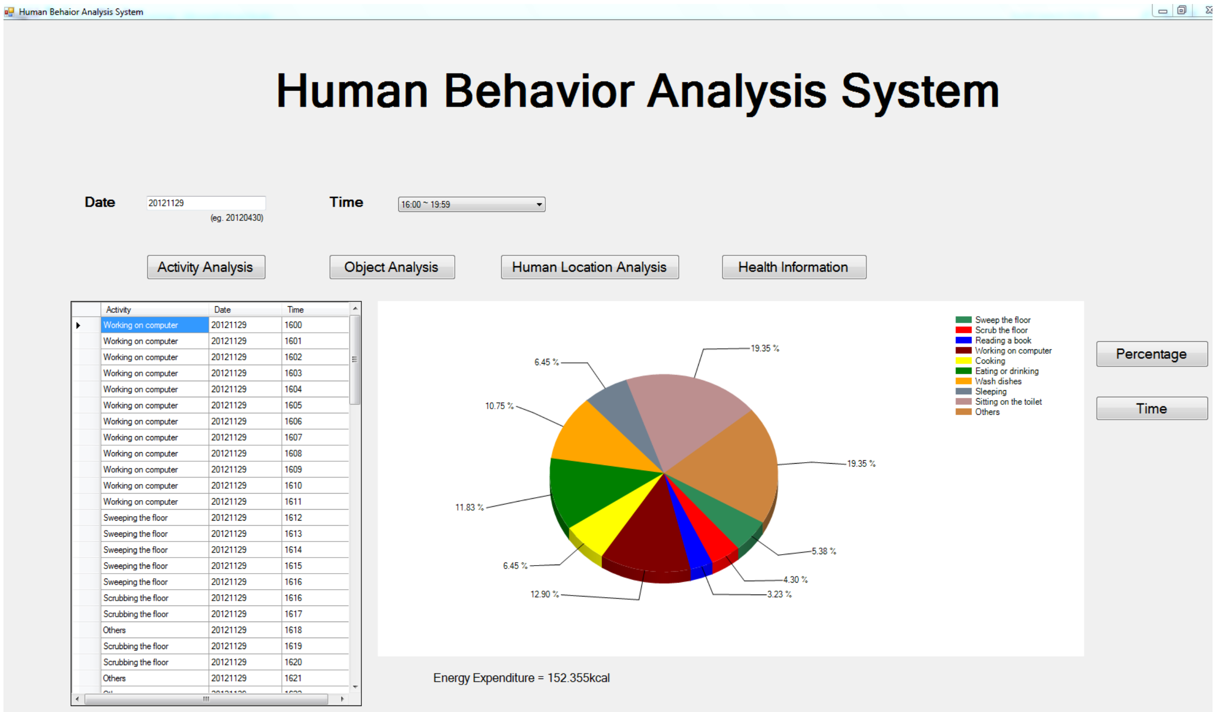


Figure 8.2: The activity information in human behavior analysis system

on the toilet" often, 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.

Consider for example obesity. This is considered a serious condition since it is one of the main causes of diseases such as diabetes, heart disease, and cancer. Of course, it is easy to diagnose obesity from body weight, but the reason for obesity is not dependent only on body weight. The daily habits of the user can also affect obesity. In this research, the human behavior analysis application also provides energy expenditure information based on the activities the user performs each day. Energy expenditure is calculated based on Metabolic Equivalents (METS) values. The METS value is most frequently used in calorie counting to compute the energy consumed during each activity. The METS values for 14 activities are obtained from [101] and shown in Table 8.1.

The formula for energy expenditure in this research is defined by the American College

Table 8.1: METS values in 14 activities

Activities	METS values
Sweeping the floor	3.3
Scrubbing the floor	3.5
Reading a book	1.3
Watching TV	1.0
Working on computer	1.5
Making a coffee	2.0
Cooking	3.3
Eating or drinking	1.5
Washing dishes	3.3
Sleeping	0.9
Taking a bath	2.0
Sitting on the toilet	1.0
Lying down & relaxing	1.0
Others	1.0

of Sports Medicine (ACSM), illustrated in Eq. 8.1.

$$Energy\ Expenditure\ (kcal) = 1.05 \times METS \times Duration\ (hour) \times Weight\ (kg) \quad (8.1)$$

Based on the energy expenditure provided by the human behavior analysis application, the system can perceive how many calories are burned in one day based on the activities that the user performed. Thus, if the home user tends to perform low calorie activities frequently, the system may indicate to the healthcare service that an exercise service be provided to the home user to prevent the obesity problem.

8.3.2 Object Interaction Analysis

The results of the CARE architecture indicate not only the activity information, but also all semantic information in the home. The object activation information is one result of the CARE architecture. Normally, object information is used to recognize human activity.

In this research, the human behavior analysis application provides the object interaction information for analysis in the healthcare domain. Figure 8.3 shows the information of object activation provided by the human behavior analysis application.

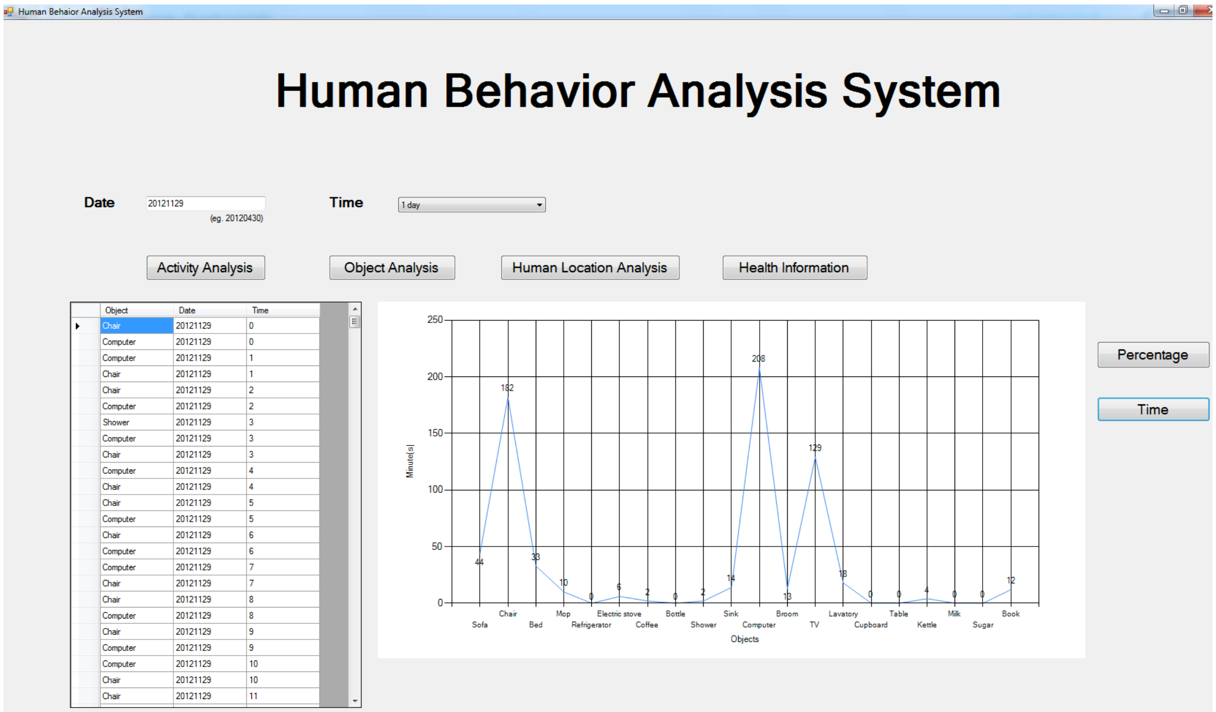


Figure 8.3: The object interaction information in the human behavior analysis system

The object interaction information based on Figure 8.3 can be analyzed in several by from detecting the duration of “Bed” usage. The sleeping time is important for indicating whether or not the home user has adequate sleep. Monitoring the use of the “Sugar Container” can help the home user, with “Diabetes”, to help control their blood sugar level.

However, analyzing only the object interaction information for the healthcare domain might not be enough because some objects in the home, are turned on by the user such as the home appliances, but does are not used. For example, the user might turn on the “TV” in the living room while cooking in the kitchen. Thus, the object interaction information might be useful when combined with other information such as activity information, or location information.

Normally, the object interaction information is linked to the activity information because the object interaction information can be used for classifying the human activity. Thus, the combination of the object interaction information and activity information will improve its ability to analyze illness. For example, the existing healthcare system cannot detect the cause of a “Tension-type headache” problem. However, the human behavior analysis system can show the information. The “Computer” is often used for a long time in one day, so the system can predict that the use of the “Computer” might lead to a “Tension-type headache” problem. Nevertheless, the the “Computer” object is activated frequently. It does not mean the user pays attention to the “Computer” object all the time. The home user might turn on the “Computer” and do other things. In this case, the activity information will help the system to analyze the problem more accurately.

8.3.3 Human Location Analysis

The location information is also provided in the human behavior analysis system. The location information is very useful for an individual who lives alone at home and has Alzheimer’s disease. Sometimes there can be a situation where the person has regular lapses in memory and forgets what/where the activity is that they were supposed to be doing.

Caring for a person with Alzheimer’s at home can be difficult. The location information can help people in the early stages of Alzheimer’s disease. The system can give the health service a “Quiz exercise” for asking when the person moves from one place to another. For instance, the system might ask or remind the person to checking the gas system when they leave the kitchen.

Furthermore, location information does not only refer to human location, but the location of an also object. Object location information can support the system in providing the object finding service when the home user has trouble remembering where the object is. This kind of service can help the home user in terms of memory function.

8.4 Home Security

Normally, the application in the domain of home security is aimed at detecting unexpected situations through the sensors. A diversity of sensors is embedded in the home environment. For example, fire detectors are attached to the ceiling of each room to detect a fire in the home. Research on fire-detection systems in the home has been proposed for several years, but few use the context-aware information to help in fire-detection.

In fact, the context-aware information cannot be used to infer a fire in the home, but it can help to improve the ability of the fire-detection system. The information can identify "How many people are in the home, where is the fire in the home", "Where is the home user?", or "What is home user doing" All this information might be useful for the fire fighter to help the person in the home. Since, the CARE architecture provides semantic information in the smart home via ontology models, proposed in section 6, the fire-detection system can retrieve this information through the CARE architecture.

Meanwhile, the application in the home security domain is not limited just to the fire-detection system, but also the anti-theft system. The anti-theft system is proposed in the home area for preventing entry of an unauthorized person. Usually, a surveillance camera is in the home security domain to identify an unauthorized person. However, the use of a camera might lead to a privacy problem when deployed in the home environment. Thus, the sensor-based technique is proposed for solving the privacy problem by attaching o sensors to the door and windows in the home. The anti-theft system will sound an alarm when the status of sensors attached to a door or window change.

However, the limitation of current research on anti-theft systems is recognizing when the system should be in safety mode. The system cannot operate in the safety mode if the home user does not turn on the system. Therefore, human activity information might help this kind of problem. For example, if the anti- theft system perceives the home user to be sleeping, the system should change the operation into the safety mode by itself, and avoid entry by an unauthorized person by checking the sensor's status. The CARE architecture also provides information for checking the sensor's status, based on the context-aware infrastructure ontology. Thus, the anti-theft system can check the sensor's status, based on information, provided from the CARE architecture.

8.5 Human Behavior Schedule System

Nowadays, to create an activity for daily living (ADL) information is a challenging task since the current activity recognition systems suffer several problems when people have different lifestyles. It needs a high performance activity recognition system to classify reliable results in order to conform to the ADL information. As the purpose of this research is to develop high performance activity recognition, this research has used the CARE architecture as a human activity framework. The application requires activity information, which can be built on top the CARE architecture. The results of the proposed activity recognition are more reliable, reasonable, and accurate. Thus, this section aims to use the results from the proposed activity recognition to learn the ADL information and generate a human behavior schedule for each home user. Figure 8.4 shows the procedure of the human behavior schedule system using the results from the CARE architecture.

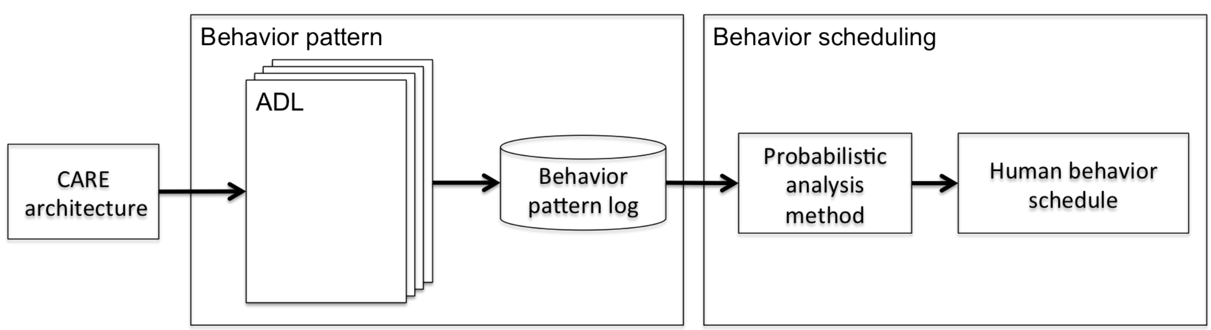


Figure 8.4: Human behavior schedule system

In order to estimate the behavior of the subject automatically, there are two main steps: behavior pattern and behavior scheduling. For the first step, a history of daily human activity is used to create a sample case of ADL information. The sequential activities in the sample case of the ADL information are paired. For example, sequential activities $\{A_1, A_2, A_3\}$ are matched into patterns as following: $P_1 : \{A_1 \rightarrow A_2\}$, $P_2 : \{A_2 \rightarrow A_3\}$, and $P_3 : \{A_1 \rightarrow A_3\}$. The system then counts the numbers in each pattern and filters out using the threshold technique. As a result, the behavior pattern will be generated in the system as shown in Figure 8.5, and collected into the behavior pattern log.

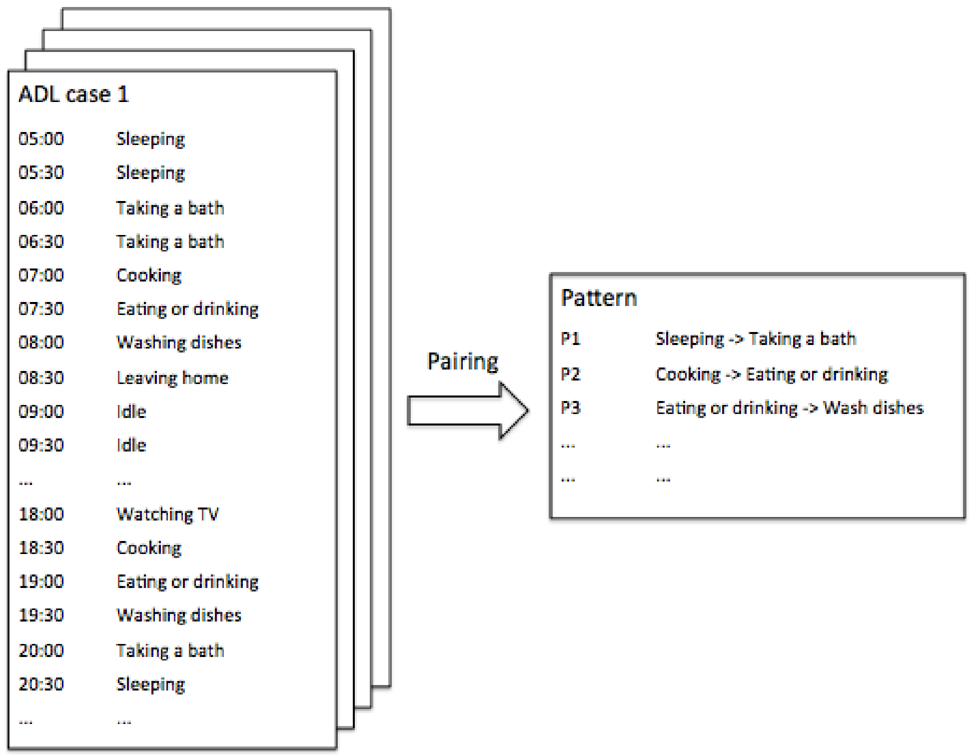


Figure 8.5: Creating the human behavior patterns

After getting the behavior pattern, the next step is behaivor scheduling. The behavior patterns will be trained by the probabilistic analysis method. The probabilistic analysis methods, involving the hidden Markov model (HMM), Bayesian network, or Support Vector Machines (SVMs), are considered to train behavior patterns for producing the activity prediction and human behavior schedule for each day. Based on the human behavior schedule, the system can understand the user's habits, and can then prepare the appropriate service to the home user ahead of time. For example, if the system knows from the human behavior schedule that the user usually wakes up at 5:30 am, and performs the "take a bath" activity at 6:00 am, the system will prepare the "hot-water" service before 6:00 am. It overcomes the existing research providing a home service depending on the situation.

8.6 Home Service Schedule System

Currently, providing a service in the home environment is dependent on the use of the object at that time. So, the system will find the appropriate home service if, and only if, the system detects the object is used by the home user. For example, the system will provide a temperature service to control the temperature in the bedroom when the home user turns on the air-conditioning at night. However, the system can provide a temperature service automatically, if the system knows the daily routines of the home user. Thus, it is not an easy task to provide an appropriate home service to the home user, if using only information about the home surroundings. In the following section the home service schedule system aims to use human activity information to decide the appropriate home service at any given time. As presented in this research, using only the object activation information, it can hint at several needs of the home user (ambiguous problem), but the human activity information can be specific to the purpose of what the home user wants to do at that time.

According to the previous section, the human behavior schedule system has introduced a system that can predict and schedule human behavior each day. In this section, the home service schedule system attempts to change from the individual home service (home service depending on the situation) to a schedule of the home service by mapping the home services depending on the human behavior schedule. Nevertheless, mapping between the home service and human activity is a complicated task because sometimes one activity can infer several home services, and between the home services, it can have conflict functions with each other. For instance, the "Curtain", "Air-condition", and "Light" objects have conflict functions in terms of brightness and temperature. The "Curtain" can give brightness to the room, but the sunshine also increases the room temperature. Meanwhile, the "Air-condition" attempts to keep the room temperature close to the desired level, and the "Light" tries to provide suitable brightness in the room.

To handle this problem, Figure 8.6 illustrates the procedure of the home service schedule system. The ontology concept is developed in this system for defining the home services. The domain knowledge of the home service is created based on the home service ontology. Meanwhile, the inference method has the responsibility of mapping between human activity information and the home service in the home service knowledge base, and responses to the results as a home service. Lastly, the system conforms the results of inference for creating the home service schedule.

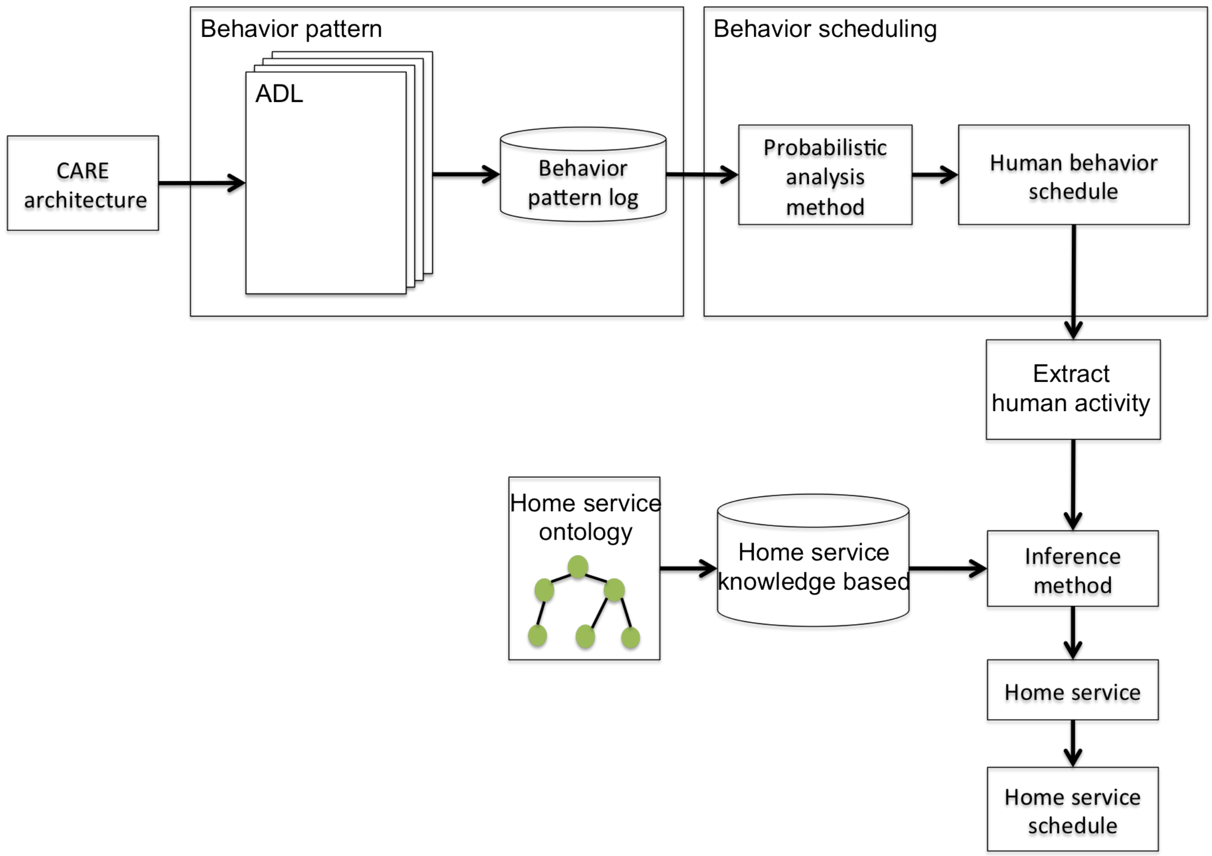


Figure 8.6: Home service schedule system

8.7 Smart Power Management System

The human activity information is not used only for service delivery, but also home power management. The concept of a smart grid has been presented in the smart home in the past few years [102] for measuring and controlling power consumption in the home. However, the existing systems measure power consumption case by case or merely monitor the duration time of device usage. Although, there is a smart meter device [103] with the responsibility for monitoring the power consumption of each device, it does not give any explanation as to the real cause when there is high power consumption on a particular day.

Moreover it is hard to manage the power plan for cost saving purposes. Therefore, the proposed smart power management system has the ability to predict the time and nature of the activity that the home user will perform. So, the system can control and manage power consumption efficiently. Then, the system can prepare a secondary power from renewable energy such as solar and wind power, for use each day based on the power plan.

The smart power management system can utilize the results from the human behavior schedule and the home service schedule to create a smart power management system in the home network. Although smart grid technology has been introduced and shows the benefit of technology in the home network, it still needs more techniques to improve power management. In my proposed ideas, the human behavior schedule and home service schedule are analyzed to model the power plan in the home network. This model can show the real cause of power usage in the home. It is better than the existing systems, which observes the power usage of each device directly. Based on the power plan, the home automation concept can be used to control the home appliance. The system can shut down the home appliance which the user might not be using at the time. For example, the system detects the lights are switched on in the living room and bedroom, while the user is cooking in the kitchen, the system switches off the lights to save energy.

8.8 Conclusion

This chapter presented the power of the human activity and semantic information in the smart home, provided by the proposed CARE architecture. To implement the application together with the activity recognition system, reliable results of the activity recognition system are necessary because they can easily change the analyzed results in the application. For example, in healthcare, if the system attempts to recognize a disease based on activity recognition, high performance activity recognition is required.

The previous sections in this chapter show possible example applications in different area domains. Firstly, the semantic ontology search application uses ontology as a core concept. The semantic information in the smart home and human activity information can be searched through the semantic ontology search application. Secondly, the home healthcare (HHC) system describes the application in the healthcare domain. The HHC mainly used the activity information to analyze and recognize the illness. Thirdly, human activity information is utilized in the home security domain. The example scenario presented the advantage of the system when using human activity information. Next, the human behavior schedule system was presented to predict human activity, and to formulate the individual activity information into the human behavior schedule. This information is useful for several purposes, one of which is described in the home service schedule system at section 8.6. The home service schedule system maps between the human behavior schedule and home service knowledge, base to generate the home service schedule. The home service schedule can be used in order to prepare a home service for the user automatically. Lastly, the smart power management system introduces a way of reducing power consumption, and show how to generate a power plan based on the activity and home service information.

Chapter 9

Conclusion and Future Research

9.1 Conclusion

Now is in a position to return back to our original research objectives in Chapter 1. The main purpose of this research is to develop the high performance activity recognition framework and realize its applications in the smart home based on the results of the activity recognition framework. The following is the conclusion of the achievements of this dissertation.

With the increase in world population, the demand for a system that can improve the life quality of elderly or needy people is increasing, especially in the smart home domain. Many kinds of research studies and projects are being performed to construct an AAL environment to support people in the home. Nonetheless, the information, used in current research might not be enough in some circumstances. Other information might help improve the ability of current research. Human activity information can be used in further analysis. Thus, this research aims to propose a high performance activity framework to obtain more reliable, reasonable, and accurate results.

Consequently, the CARE architecture was designed in this research with the purpose of improving the ability of the activity recognition system based on the real environment. The CARE architecture was proposed as the human activity framework, consisting of six layers. Several techniques were developed in each layer. For example, in the physical layer, CSN and human posture classification were proposed to collect the context-aware and human information in the smart home. On top of the CARE architecture, several applications utilizing the human activity and semantic context-aware information in the smart home can be implemented, such as the activity recognition system, semantic ontology search application or human behavior schedule system.

Based on the designed CARE architecture, the CSN was proposed and described in Chapter 4. The CSN is a sensor network typically used for collecting the context-aware data in the smart home. Three sensor networks were proposed in the CSN and installed in the iHouse. Firstly, there are two sensor networks; the home appliance sensor network and the home furniture sensor network. A diversity of sensors were built into the home facility such as "Sofa", "Outlet", or "TV". In this two sensor network the main focus is on object usage in the smart home. Therefore, the human sensor network was proposed for observing human information, such as human location in the smart home. Moreover, several communication networks were developed within these three sensor networks: UPnP, ECHONET, and Zigbee.

Not only was the CSN proposed for data collection part, but also for human posture classification. A novel range-based algorithm, was proposed for the classification of three human postures ("Stand", "Sit", and "Lie-down") and one unexpected situation ("Fall-down"). The range between the body parts is investigated based on the hypothesis: "Each human posture has a different physical pattern," so the relationship between the body parts can conform to a specific human posture. Various techniques such as the binary decision tree, FSM, the adaptive posture window scheme, and the posture pattern recognition were developed in the range-based algorithm. The results of the proposed algorithm are highly accurate when compared with other research. The average results for the static posture are 100 % and 98% in consequence posture. Meanwhile, the accuracy of the fall-down detection experiment also reached 100 %. The range-based algorithm also solved the problem of little human movement. It overcomes the limitation of existing research. These kinds of results are truly useful for activity recognition because when considering each activity, human posture is one of a subset of activities, meaning some activities can be distinguished by human posture information.

To organize the huge amount of data in the smart home, the data manager and the system repository take responsibility for organizing the data. Because the system cannot guarantee perfect data from the sensors, the data manager was developed for normalizing the data to produce appropriate data using two methods: supplying missing data and eliminating data. Meanwhile, the system repository exhibited a vital role to control the large amount of data in the system. It was developed to belong to the OAM framework [81]. Processes of mapping data, composing data, and reprocessing data were proposed in the system repository for synchronization between the repository and OBAR system.

For further originality in this dissertation, the OBAR system was implemented with the ontology concept. Three ontology models were designed in the OBAR system: context-aware infrastructure ontology, functional activity ontology, and activity log ontology. The proposed OBAR system has an advantage in terms of scalability because it describes at the abstract level, so it does not need a training process. Furthermore, the OBAR system also gains benefit from the semantic web technology - standards for distributing data sharing and processing as shown in the semantic ontology search system. It means the smart home knowledge base is not created for a specific home, but other homes can utilize the smart home knowledge base by sending the context-aware data to the server, and the server will generate results back to the home. Moreover, the advantage of ontology also appears in the OBAR system. For example, the reusability of knowledge can make the results more reasonable and reliable or the knowledge maintenance easier because the knowledge and programming are separated.

The OBAR system proposed two pieces of information to improve the ability of activity recognition: the new user's context and AL^2. For the new user's context, human posture information is added into the user's context to reduce the "ambiguous activity problem". The average recognition accuracy reaches 91.72 % when the new user's context is used. It improves 12.01 % when compared with the system using only the object activation information. Meanwhile, the AL^2 was introduced to find the relationship between activities occurring at the same location. The history of activities at the current user's location is investigated with the current activity for classification. Consequently, the average performance accuracy of OBAR when using 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.

To complete the purpose of this research, the results of the proposed activity recognition system are used in several applications in different research domains. The semantic ontology search application is one example application implemented on top of the CARE architecture. The home user can retrieve the history information of human activity and semantic information in the smart home based on the proposed ontology models. In the HHC system, the activity information is used to analyze and recognize illness. In the service delivery domain, the human behavior schedule system and home service schedule system have been proposed in order to provide the service automatically. The activity information is the main information used for creating both the human behavior schedule and home service schedule.

According to these discoveries, all of the research objectives were achieved. The human activity information obtained from the real environment can be observed from the high performance activity recognition (OBAR system). The proposed architecture is a practical system conforming the user's context from the real environment, while the application in the home can realize results from the high performance activity recognition system. The life quality of the home user might improve, based on the proposals of this study in demonstrating the experiment.

9.2 Future Research

Even though this research has been conducted using the CARE architecture to produce reliable, reasonable and accurate results, more effort is still needed to improve this research. The smart home knowledge can be placed at the center of further processing in future research. Figure 9.1 illustrates the future research model, based on the results of the proposed research.

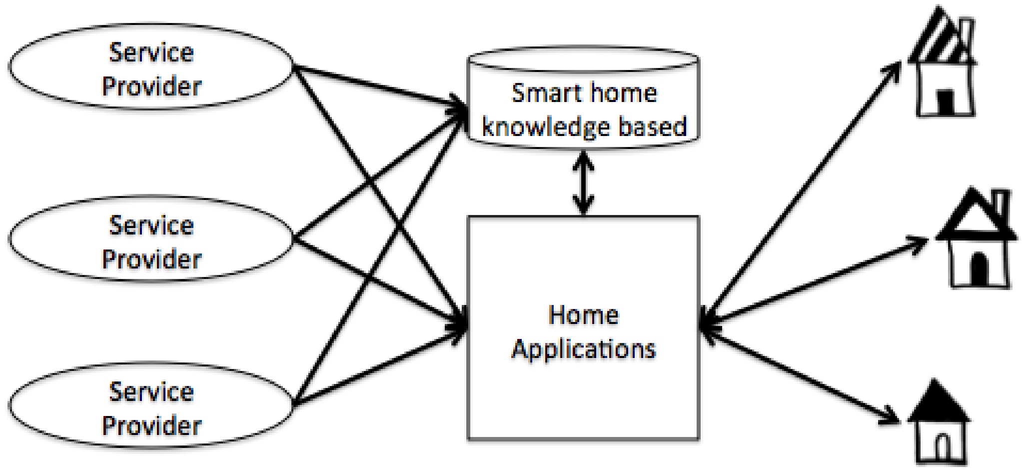


Figure 9.1: Future research model

Due to the limitation of this research, the activity model is limited only to 14 home activities. It still needs to improve the system for classification of more specific activities. According to the OBAR system, the activity model and context-aware infrastructure model were designed based on the ontology concept. The concept of reusability can be used in future research. Service providers can add their activity models into the smart home knowledge base to classify more specific activities. In this sense, this research shows the starting point of a standard activity recognition system to classify more and more activities in the future.

With the advantage of the ontology concept, the ontology model has the ability to share conceptualization by knowledge engineering, so the context-aware infrastructure ontology can be linked to other ontology models. For example, service providers provide the home service ontology used to define the service in the home. This kind of home service has to be linked with the infrastructure in the smart home. Thus, the context-aware infrastructure ontology and the home service ontology can be shared conceptually with each other, and provide the knowledge to home applications. At this stage, the smart home knowledge base proposed in this research illustrates that it is not limited to only the activity recognition domain. It can be used in several ways as described in section 8.

From the Figure 9.1, the home applications can be provided by the service providers, and those home applications can utilize the smart home knowledge base for processing their purposes. As the results of this research show, the information on human activity and semantic information in the smart home can be used to help improve the ability of the current home applications. Moreover, from the future research model, the more the smart home knowledge base can be extended to other research areas, the more home applications can be implemented within the range of the smart home knowledge base.

Appendices

Appendix A

List of Description Logics Rules

A list of description logic rules for the target activities are shows as follows:

"Sitting on the toilet" activity

```
[Linking_InferredActivity_instance_id_14_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0) (?y0 rdf:type
    ns:Lavatory) (?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11) (?y11
    rdf:type ns:Human) (?x00 ns:has_location ?y12) (?y12 rdf:type ns:
    Bathroom) (?x ns:has_have_hum_pos ?y1) (?y1 rdf:type ns:Sit) -> (?x ns:
    has_have_inf_activity ns:InferredActivity_instance_id_14) (?x ns:
    has_rule_name 'Linking_InferredActivity_instance_id_14_to_Context_0')]
```

Figure A.1: Rule for "Sitting on the toilet" activity in Jena syntax

```
[InferredActivity_instance_id_14: (?x1 rdf:type ns:Functional_Activity) (?
    x1 ns:has_name ?y0) regex(?y0 '(.)*Sitting_on_the_toilet(.*)') -> (ns:
    InferredActivity_instance_id_14 ns:has_Have_activity ?x1) (ns:
    InferredActivity_instance_id_14 ns:has_rec_act_name 'Sitting_on_the_
    toilet') (ns:InferredActivity_instance_id_14 ns:has_rec_act_id 'uid_14')
      (ns:InferredActivity_instance_id_14 rdf:type ns:InferredActivity) (ns
    :InferredActivity_instance_id_14 ns:has_rule_name '
    InferredActivity_instance_id_14')]
```

Figure A.2: Activity instance of "Sitting on the toilet" activity in Jena syntax

"Taking a bath" activity

```
[Linking_InferredActivity_instance_id_11_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0) (?y0 rdf:type
    ns:Shower) (?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11) (?y11 rdf
    :type ns:Human) (?x00 ns:has_location ?y12) (?y12 rdf:type ns:Bathroom)
    -> (?x ns:has_have_inf_activity ns:InferredActivity_instance_id_11) (?x
    ns:has_rule_name 'Linking_InferredActivity_instance_id_11_to_Context_0')
    ]
```

Figure A.3: Rule for "Taking a bath" activity in Jena syntax

```
[InferredActivity_instance_id_11: (?x1 rdf:type ns:Functional_Activity) (?
   x1 ns:has_name ?y0) regex(?y0 '(.)*Take_a_bath(.*)') -> (ns:
   InferredActivity_instance_id_11 ns:has_Have_activity ?x1) (ns:
   InferredActivity_instance_id_11 ns:has_rec_act_name 'Take_a_bath') (ns:
   InferredActivity_instance_id_11 ns:has_rec_act_id 'uid_11') (ns:
   InferredActivity_instance_id_11 rdf:type ns:InferredActivity) (ns:
   InferredActivity_instance_id_11 ns:has_rule_name '
   InferredActivity_instance_id_11')]
```

Figure A.4: Activity instance of "Taking a bath" activity in Jena syntax

"Lying down & relaxing" activity

```
[Linking_InferredActivity_instance_id_13_to_Context_0: (?x rdf:type ns:
   Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0) (?y0 rdf:type
   ns:Sofa) (?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11) (?y11 rdf:
   type ns:Human) (?x ns:has_have_hum_pos ?y1) (?y1 rdf:type ns:Lie-down)
   -> (?x ns:has_have_inf_activity ns:InferredActivity_instance_id_13) (?x
   ns:has_rule_name 'Linking_InferredActivity_instance_id_13_to_Context_0')
   ]
```

Figure A.5: Rule for "Lying down & relaxing" activity in Jena syntax

```
[InferredActivity_instance_id_13: (?x1 rdf:type ns:Functional_Activity) (?
    x1 ns:has_name ?y0) regex(?y0 '(.)*Lying_down(.*)') -> (ns:
    InferredActivity_instance_id_13 ns:has_Have_activity ?x1) (ns:
    InferredActivity_instance_id_13 ns:has_rec_act_name 'Lying_down_&_
    relaxing') (ns:InferredActivity_instance_id_13 ns:has_rec_act_id 'uid_13
    ') (ns:InferredActivity_instance_id_13 rdf:type ns:InferredActivity) (ns
    :InferredActivity_instance_id_13 ns:has_rule_name '
    InferredActivity_instance_id_13')]
```

Figure A.6: Activity instance of “Lying down & relaxing” activity in Jena syntax

“Sleeping” activity

```
[Linking_InferredActivity_instance_id_10_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0) (?y0 rdf:type
    ns:Bed) (?x ns:has_have_hum_pos ?y1) (?y1 rdf:type ns:Lie-down) (?x ns:
    has_have_obj ?x00) (?x00 ns:has_object ?y11) (?y11 rdf:type ns:Human) (?
    x00 ns:has_location ?y12) (?y12 rdf:type ns:Bedroom) -> (?x ns:
    has_have_inf_activity ns:InferredActivity_instance_id_10) (?x ns:
    has_rule_name 'Linking_InferredActivity_instance_id_10_to_Context_0')]
```

Figure A.7: Rule for “Sleeping” activity in Jena syntax

```
[InferredActivity_instance_id_10: (?x1 rdf:type ns:Functional_Activity) (?
   x1 ns:has_name ?y0) regex(?y0 '(.)*Sleeping(.*)') -> (ns:
   InferredActivity_instance_id_10 ns:has_Have_activity ?x1)  (ns:
   InferredActivity_instance_id_10 ns:has_rec_act_name 'Sleeping') (ns:
   InferredActivity_instance_id_10 ns:has_rec_act_id 'uid_10')  (ns:
   InferredActivity_instance_id_10 rdf:type ns:InferredActivity)  (ns:
   InferredActivity_instance_id_10 ns:has_rule_name '
   InferredActivity_instance_id_10')]
```

Figure A.8: Activity instance of “Sleeping” activity in Jena syntax

“Making coffee” activity

```
[Linking_InferredActivity_instance_id_96_to_Context_1: (?x rdf:type ns:
   Context) (?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11)  (?y11 rdf:
   type ns:Human) (?x00 ns:has_location ?y12) (?y12 rdf:type ns:Kitchen) (?
   x ns:has_have_obj ?x01) (?x01 ns:has_object ?y21)  (?y21 rdf:type ns:
   Coffee) (?x ns:has_have_obj ?x02) (?x02 ns:has_object ?y31)  (?y31 rdf:
   type ns:Kettle)-> (?x ns:has_have_inf_activity ns:
   InferredActivity_instance_id_96) (?x ns:has_rule_name '
   Linking_InferredActivity_instance_id_96_to_Context_1')]
```

Figure A.9: Rule for “Making coffee” activity in Jena syntax (1)

```
[Linking_InferredActivity_instance_id_96_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11)  (?y11 rdf:
    type ns:Human) (?x00 ns:has_location ?y12) (?y12 rdf:type ns:Kitchen) (?
    x ns:has_have_last_object ?y15) (?y15 ns:has_Object_info ?y15x) (?y15x
    ns:has_object ?y16) (?y16 rdf:type ns:Kettle) (?x ns:
    has_have_last_object ?y17) (?y17 ns:has_Object_info ?y17x) (?y17x ns:
    has_object ?y18) (?y18 rdf:type ns:Coffee) -> (?x ns:
    has_have_inf_activity ns:InferredActivity_instance_id_96) (?x ns:
    has_rule_name 'Linking_InferredActivity_instance_id_96_to_Context_0')]
```

Figure A.10: Rule for "Making coffee" activity in Jena syntax (2)

```
[InferredActivity_instance_id_96: (?x1 rdf:type ns:Functional_Activity) (?
    x1 ns:has_name ?y0) regex(?y0 '(.)*Make_coffee(.*)') -> (ns:
    InferredActivity_instance_id_96 ns:has_Have_activity ?x1) (ns:
    InferredActivity_instance_id_96 ns:has_rec_act_name 'Make_coffee') (ns:
    InferredActivity_instance_id_96 ns:has_rec_act_id 'uid_96') (ns:
    InferredActivity_instance_id_96 rdf:type ns:InferredActivity) (ns:
    InferredActivity_instance_id_96 ns:has_rule_name '
    InferredActivity_instance_id_96')]
```

Figure A.11: Activity instance of "Making coffee" activity in Jena syntax

“Cooking” activity

```
[Linking_InferredActivity_instance_id_99_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0) (?y0 rdf:type
    ns:Electric_Stove) (?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11)
    (?y11 rdf:type ns:Human) (?x00 ns:has_location ?y12) (?y12 rdf:type ns:
    Kitchen) (?x ns:has_have_hum_pos ?y2) (?y2 rdf:type ns:Stand) -> (?x ns
    :has_have_inf_activity ns:InferredActivity_instance_id_99) (?x ns:
    has_rule_name 'Linking_InferredActivity_instance_id_99_to_Context_0')]
```

Figure A.12: Rule for “Cooking” activity in Jena syntax

```
[InferredActivity_instance_id_99: (?x1 rdf:type ns:Functional_Activity) (?
    x1 ns:has_name ?y0) regex(?y0 '(.)*Cooking(.*)') -> (ns:
    InferredActivity_instance_id_99 ns:has_Have_activity ?x1) (ns:
    InferredActivity_instance_id_99 ns:has_rec_act_name 'Cooking') (ns:
    InferredActivity_instance_id_99 ns:has_rec_act_id 'uid_99') (ns:
    InferredActivity_instance_id_99 rdf:type ns:InferredActivity) (ns:
    InferredActivity_instance_id_99 ns:has_rule_name '
    InferredActivity_instance_id_99')]
```

Figure A.13: Activity instance of “Cooking” activity in Jena syntax

“Eating or drinking” activity

```
[Linking_InferredActivity_instance_id_97_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0)  (?y0 rdf:type
     ns:Chair) (?x0 ns:has_location ?y02) (?y02 rdf:type ns:Kitchen) (?x ns:
    has_have_obj ?x00) (?x00 ns:has_object ?y11)  (?y11 rdf:type ns:Human)
    (?x00 ns:has_location ?y12) (?y12 rdf:type ns:Kitchen) (?x ns:
    has_have_hum_pos ?y2) (?y2 rdf:type ns:Sit) (?x ns:
    has_have_last_activity ?y13) (?y13 ns:has_have_activities ?y14) (?y14
    rdf:type ns:Make_Drink) -> (?x ns:has_have_inf_activity ns:
    InferredActivity_instance_id_97) (?x ns:has_rule_name '
    Linking_InferredActivity_instance_id_97_to_Context_0')]
```

Figure A.14: Rule for “Eating or drinking” activity in Jena syntax (1)

```
[Linking_InferredActivity_instance_id_97_to_Context_1: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0)  (?y0 rdf:type
     ns:Chair) (?x0 ns:has_location ?y02) (?y02 rdf:type ns:Kitchen) (?x ns:
    has_have_obj ?x00) (?x00 ns:has_object ?y11)  (?y11 rdf:type ns:Human)
    (?x00 ns:has_location ?y12) (?y12 rdf:type ns:Kitchen) (?x ns:
    has_have_hum_pos ?y2) (?y2 rdf:type ns:Sit) (?x ns:
    has_have_last_activity ?y13) (?y13 ns:has_have_activities ?y14) (?y14
    rdf:type ns:Cooking) -> (?x ns:has_have_inf_activity ns:
    InferredActivity_instance_id_97) (?x ns:has_rule_name '
    Linking_InferredActivity_instance_id_97_to_Context_1')]
```

Figure A.15: Rule for “Eating or drinking” activity in Jena syntax (2)

```
[Linking_InferredActivity_instance_id_97_to_Context_2: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0)  (?y0 rdf:type
     ns:Chair) (?x0 ns:has_location ?y02) (?y02 rdf:type ns:Kitchen) (?x ns:
    has_have_obj ?x00) (?x00 ns:has_object ?y11)  (?y11 rdf:type ns:Human)
    (?x00 ns:has_location ?y12) (?y12 rdf:type ns:Kitchen) (?x ns:
    has_have_hum_pos ?y2) (?y2 rdf:type ns:Sit) (?x ns:
    has_have_last_activity ?y13) (?y13 ns:has_have_activities ?y14) (?y14
    rdf:type ns:Making_a_coffee) -> (?x ns:has_have_inf_activity ns:
    InferredActivity_instance_id_97) (?x ns:has_rule_name '
    Linking_InferredActivity_instance_id_97_to_Context_2')]
```

Figure A.16: Rule for “Eating or drinking” activity in Jena syntax (3)

```
[InferredActivity_instance_id_97: (?x1 rdf:type ns:Functional_Activity) (?
    x1 ns:has_name ?y0) regex(?y0 '(.)*Eating_or_drinking(.*)') -> (ns:
    InferredActivity_instance_id_97 ns:has_Have_activity ?x1) (ns:
    InferredActivity_instance_id_97 ns:has_rec_act_name 'Eating_or_drinking'
    ) (ns:InferredActivity_instance_id_97 ns:has_rec_act_id 'uid_97') (ns:
    InferredActivity_instance_id_97 rdf:type ns:InferredActivity) (ns:
    InferredActivity_instance_id_97 ns:has_rule_name '
    InferredActivity_instance_id_97')]
```

Figure A.17: Activity instance of “Eating or drinking” activity in Jena syntax

“Washing dishes” activity

```
[Linking_InferredActivity_instance_id_98_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0)  (?y0 rdf:type
     ns:Sink) (?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11)  (?y11 rdf
    :type ns:Human) (?x00 ns:has_location ?y12) (?y12 rdf:type ns:Kitchen)
    (?x ns:has_have_hum_pos ?y2) (?y2 rdf:type ns:Stand) (?x ns:
    has_have_last_activity ?y13) (?y13 ns:has_have_activities ?y14) (?y14
    rdf:type ns:Eating_or_drinking) -> (?x ns:has_have_inf_activity ns:
    InferredActivity_instance_id_98) (?x ns:has_rule_name '
    Linking_InferredActivity_instance_id_98_to_Context_0')]
```

Figure A.18: Rule for “Washing dishes” activity in Jena syntax

```
[InferredActivity_instance_id_98: (?x1 rdf:type ns:Functional_Activity) (?
    x1 ns:has_name ?y0) regex(?y0 '(.)*Wash_dishes(.*)') -> (ns:
    InferredActivity_instance_id_98 ns:has_Have_activity ?x1) (ns:
    InferredActivity_instance_id_98 ns:has_rec_act_name 'Wash_dishes') (ns:
    InferredActivity_instance_id_98 ns:has_rec_act_id 'uid_98') (ns:
    InferredActivity_instance_id_98 rdf:type ns:InferredActivity) (ns:
    InferredActivity_instance_id_98 ns:has_rule_name '
    InferredActivity_instance_id_98')]
```

Figure A.19: Activity instance of “Washing dishes” activity in Jena syntax

“Working on a computer” activity

```
[Linking_InferredActivity_instance_id_17_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0) (?y0 rdf:type
    ns:Computer) (?x ns:has_have_obj ?y1x) (?y1x ns:has_object ?y1) (?y1 rdf
    :type ns:Chair) (?y1x ns:has_location ?y02) (?y02 rdf:type ns:Livingroom
    )(?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11) (?y11 rdf:type ns:
    Human) (?x00 ns:has_location ?y12) (?y12 rdf:type ns:Livingroom)(?x ns:
    has_have_hum_pos ?y2) (?y2 rdf:type ns:Sit) -> (?x ns:
    has_have_inf_activity ns:InferredActivity_instance_id_17) (?x ns:
    has_rule_name 'Linking_InferredActivity_instance_id_17_to_Context_0')]
```

Figure A.20: Rule for “Working on a computer” activity in Jena syntax

```
[InferredActivity_instance_id_17: (?x1 rdf:type ns:Functional_Activity) (?
    x1 ns:has_name ?y0) regex(?y0 '(.)*Working_on_computer(.*)') -> (ns:
    InferredActivity_instance_id_17 ns:has_Have_activity ?x1) (ns:
    InferredActivity_instance_id_17 ns:has_rec_act_name 'Working_on_computer
    ') (ns:InferredActivity_instance_id_17 ns:has_rec_act_id 'uid_17') (ns:
    InferredActivity_instance_id_17 rdf:type ns:InferredActivity)  (ns:
    InferredActivity_instance_id_17 ns:has_rule_name '
    InferredActivity_instance_id_17')]
```

Figure A.21: Activity instance of “Working on a computer” activity in Jena syntax

“Watching TV” activity

```
[Linking_InferredActivity_instance_id_7_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0)  (?y0 rdf:type
     ns:TV) (?x ns:has_have_obj ?y1x) (?y1x ns:has_object ?y1) (?y1 rdf:type
     ns:Sofa) (?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11) (?y11 rdf:
    type ns:Human) (?x ns:has_have_hum_pos ?y2) (?y2 rdf:type ns:Lie-down)
    -> (?x ns:has_have_inf_activity ns:InferredActivity_instance_id_7) (?x
    ns:has_rule_name 'Linking_InferredActivity_instance_id_7_to_Context_0')
    ]
```

Figure A.22: Rule for “Watching TV” activity in Jena syntax (1)

```
[Linking_InferredActivity_instance_id_9_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0)  (?y0 rdf:type
     ns:TV) (?x ns:has_have_obj ?y1x) (?y1x ns:has_object ?y1) (?y1 rdf:type
     ns:Sofa) (?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11) (?y11 rdf:
    type ns:Human) (?x ns:has_have_hum_pos ?y2) (?y2 rdf:type ns:Sit) -> (?x
     ns:has_have_inf_activity ns:InferredActivity_instance_id_9) (?x ns:
    has_rule_name 'Linking_InferredActivity_instance_id_9_to_Context_0')]
```

Figure A.23: Rule for “Watching TV” activity in Jena syntax (2)

```
[InferredActivity_instance_id_7: (?x1 rdf:type ns:Functional_Activity) (?x1
    ns:has_name ?y0) regex(?y0, '(.)*Watching_TV(.*)') -> (ns:
   InferredActivity_instance_id_7 ns:has_Have_activity ?x1) (ns:
   InferredActivity_instance_id_7 ns:has_rec_act_name 'Watching_TV') (ns:
   InferredActivity_instance_id_7 ns:has_rec_act_id 'uid_7') (ns:
   InferredActivity_instance_id_7 rdf:type ns:InferredActivity) (ns:
   InferredActivity_instance_id_7 ns:has_rule_name '
   InferredActivity_instance_id_7')]
```

Figure A.24: Activity instance of "Watching TV" activity in Jena syntax (1)

```
[InferredActivity_instance_id_9: (?x1 rdf:type ns:Functional_Activity) (?x1
    ns:has_name ?y0) regex(?y0 '(.)*Watching_TV(.*)') -> (ns:
   InferredActivity_instance_id_9 ns:has_Have_activity ?x1) (ns:
   InferredActivity_instance_id_9 ns:has_rec_act_name 'Watching_TV') (ns:
   InferredActivity_instance_id_9 ns:has_rec_act_id 'uid_9') (ns:
   InferredActivity_instance_id_9 rdf:type ns:InferredActivity) (ns:
   InferredActivity_instance_id_9 ns:has_rule_name '
   InferredActivity_instance_id_9')]
```

Figure A.25: Activity instance of "Watching TV" activity in Jena syntax (2)

"Reading a book" activity

```
[Linking_InferredActivity_instance_id_16_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0) (?y0 rdf:type
    ns:Book) (?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11) (?y11 rdf:
    type ns:Human) (?x ns:has_have_hum_pos ?y1) (?y1 rdf:type ns:Sit) -> (?x
     ns:has_have_inf_activity ns:InferredActivity_instance_id_16) (?x ns:
    has_rule_name 'Linking_InferredActivity_instance_id_16_to_Context_0')]
```

Figure A.26: Rule for "Reading a book" activity in Jena syntax

```
[InferredActivity_instance_id_16: (?x1 rdf:type ns:Functional_Activity) (?
    x1 ns:has_name ?y0) regex(?y0 '(.)*Reading␣a␣book(.*)') -> (ns:
    InferredActivity_instance_id_16 ns:has_Have_activity ?x1) (ns:
    InferredActivity_instance_id_16 ns:has_rec_act_name 'Reading␣a␣Book') (
    ns:InferredActivity_instance_id_16 ns:has_rec_act_id 'uid_16') (ns:
    InferredActivity_instance_id_16 rdf:type ns:InferredActivity) (ns:
    InferredActivity_instance_id_16 ns:has_rule_name '
    InferredActivity_instance_id_16')]
```

Figure A.27: Activity instance of "Reading a book" activity in Jena syntax

“Scrubbing the floor” activity

```
[Linking_InferredActivity_instance_id_15_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0) (?y0 rdf:type
    ns:Mop) (?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11) (?y11 rdf:
    type ns:Human) (?x ns:has_have_hum_pos ?y1) (?y1 rdf:type ns:Stand) ->
    (?x ns:has_have_inf_activity ns:InferredActivity_instance_id_15) (?x ns:
    has_rule_name 'Linking_InferredActivity_instance_id_15_to_Context_0')]
```

Figure A.28: Rule for “Scrubbing the floor” activity in Jena syntax

```
[InferredActivity_instance_id_15: (?x1 rdf:type ns:Functional_Activity) (?
    x1 ns:has_name ?y0) regex(?y0 '(.)*Scrub_the_floor(.*)') -> (ns:
    InferredActivity_instance_id_15 ns:has_Have_activity ?x1) (ns:
    InferredActivity_instance_id_15 ns:has_rec_act_name 'Scrub_the_floor') (
    ns:InferredActivity_instance_id_15 ns:has_rec_act_id 'uid_15') (ns:
    InferredActivity_instance_id_15 rdf:type ns:InferredActivity) (ns:
    InferredActivity_instance_id_15 ns:has_rule_name '
    InferredActivity_instance_id_15')]
```

Figure A.29: Activity instance of “Scrubbing the floor” activity in Jena syntax

“Sweeping the floor” activity

```
[Linking_InferredActivity_instance_id_1_to_Context_0: (?x rdf:type ns:
    Context) (?x ns:has_have_obj ?x0) (?x0 ns:has_object ?y0)  (?y0 rdf:type
     ns:Broom) (?x ns:has_have_obj ?x00) (?x00 ns:has_object ?y11) (?y11 rdf
    :type ns:Human) (?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')]
```

Figure A.30: Rule for “Sweeping the floor” activity in Jena syntax

```
[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_rec_act_name 'Sweep_the_floor') (
    ns:InferredActivity_instance_id_1 ns:has_rec_act_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')]
```

Figure A.31: Activity instance of “Sweeping the floor” activity in Jena syntax

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