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Framework for activity sensing in smart home

TESIS DOCTORAL

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- 陈寅恪

*Dedicated to my dear parents and husband
& our coming baby*

Abstract

The ability to accurately identify the different activities of daily living (ADLs) is considered as one of the basis to foster new technological solutions inside the home, including services to prolong independent living of the elderly. However, the automated detection of activities is a challenging research area. Existing activity monitoring systems suffer from some practical limitations, such as acceptance, due to privacy issues, as well as technical limitations, such as the complexity of activity recognition, imbalanced data classes or lack of common and suitable representations of the context information.

This Thesis proposes a framework for sensing activities in smart home. The main novelty of this research work lies in the application of different approaches simultaneously to obtain a more accurate and proper detection of activities in real environments. The final framework that represents the mixture of the aforementioned approaches includes the contributions described in the following. Firstly, a characterization of the main activities considered in smart home scenarios is proposed which are targeted to older people's independent living. Secondly, it is proposed to use an ensemble of heterogeneous classifiers to recognize twelve activities, including very short-duration transitional activities usually discarded in most of the previous works. We also specify a novel segmentation method that dynamically detects the appropriate starting position of windows from accelerometer data, for the purposes of activity recognition. Thirdly, a human activity ontology is presented to support explicit and flexible representation of reasoning based on activity context information. This ontology has been developed by following the NeON methodology and it is linked with existing technologies capable to handle real-life aspects such as time, space, relations between activities, etc. Finally, we propose a three-layered context-aware architecture for building and rapid prototyping of context-aware systems tailored to activity monitoring in Smart Home. This architecture provides support for the inclusion of new functionalities including low-level data

collecting, discovering of devices, information interpreting and high-level context knowledge managing.

Keywords: Smart Home, Healthcare, Ubiquitous Computing, Ambient Intelligence, Activity Recognition, Ontology, Context awareness.

Resumen

La habilidad de identificar de forma precisa las distintas actividades de la vida diaria (ADL, Activity of Daily Life) es considerada como una de las bases que potencian el desarrollo de nuevas soluciones tecnológicas dentro del hogar, incluyendo los servicios para prolongar la vida independiente de las personas de edad avanzada. Sin embargo la detección automática de actividades es un área que aún está en las fases iniciales de investigación. Los sistemas de monitorización de actividades existentes sufren de limitaciones prácticas como la aceptación de los sensores por parte de los usuarios debido a la pérdida de privacidad, y limitaciones tecnológicas como el reconocimiento de actividades complejas, datos no preparados para poder ser procesados adecuadamente o la falta de esquemas de representación de información de contexto comunes y adecuados

Esta tesis presenta un marco de trabajo para la detección de actividades en el hogar digital. La principal novedad de la tesis radica en la aplicación de distintas aproximaciones de forma simultánea para obtener una detección de actividades más precisa y acorde a escenarios reales. El marco de trabajo final, que da forma a la combinación de aproximaciones comentadas anteriormente, incluye las siguientes contribuciones. En primer lugar se propone una caracterización de las principales actividades existentes en los escenarios manejados en la literatura relacionada con hogar digital, enfocando el estudio en la mejora de la vida independiente de las personas mayores. En segundo lugar se propone el uso de un ensamblado de clasificadores heterogéneos para reconocer un total de doce actividades entre las que existen actividades de transición, caracterizadas por ser de muy corta duración y quedar comúnmente excluidas de muchos trabajos de investigación. El clasificador propuesto además incluye un método de detección automática de la posición inicial de las ventanas que enmarcan la actividad. En tercer lugar se presenta una ontología que permita la representación explícita y flexible de razonamiento basado en la información del contexto de las actividades. Esta ontología se ha desarrollado mediante el método NeON y está enlazada

con otras ontologías capaces de manejar conceptos como el espacio, el tiempo, etc. Finalmente se propone una arquitectura de gestión de contexto en tres capas que permite el prototipado rápido de sistemas dependientes del contexto orientados a la detección de actividades en el hogar digital. La arquitectura provee soporte para la inclusión de nuevas funcionalidades incluyendo la recolección de datos de bajo nivel, el descubrimiento, la interpretación de la información y la gestión de conocimiento de contexto de alto nivel.

Palabras clave: Hogar Digital, Cuidado de la Salud, Computación Ubicua, Inteligencia Ambiental, Reconocimiento de actividades, Ontologías, gestión del contexto.

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List of publications

The elderly's independent living in smart homes: A characterization of activities and sensing infrastructure survey to facilitate services development

By Qin Ni, Ana Belén García Hernando and Iván Pau de la Cruz
Sensors. 15(5). 11312-11362. 2015.

A foundational ontology-based model for human activity representation in smart homes

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A Context-aware System Infrastructure for Monitoring Activities of Daily Living in Smart Home

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Chapter 1 Introduction

1.1 Motivation

In the last decades, recent advances in sensing, computing, networking and ambient intelligence technologies have contributed to a rapid emergence of smart environments and novel ideas aiming to satisfy people's needs. Among these, smart home, which exploits information collected from the users and their environment, has gained a lot of attention for the promotion of enhanced quality of life within home.

Smart home research is motivated, among others, by the significant increase of worldwide aging population. In fact, approximately 2 billion people will be aged 60 or older in 2050 [1], and the proportion of the EU27 elderly population aged 65 or older will be increased to 30% in 2060 [2]. This results in many specific health care issues and society challenges. Older adults suffer or may suffer with higher probability from both age-related diseases, such as Parkinson's, cardiovascular and Alzheimer's diseases, for which there is currently no cure, and physical limitations that constrain them to live at their own home independently. Health costs tend to rise since a large amount of professionals, experts and caregivers have to be trained to work with an aging population. It would be very resource-consuming to maintain all these patients in medical centres for an uncertain nursing period of time. Moreover, there are research studies showing that 89% of the investigated older adults prefer to live independently in their own homes [3]. As one interesting element of the solution, smart home technologies could enable to accommodate in-home healthcare services and personalized assistance, helping to enhance quality of life and to maintain independent living for the

elderly, as well as to reduce healthcare costs in general. Additionally, user comfort is benefited by a continuous and unobtrusive monitoring and context awareness services.

Most of the current work of research in this area is mainly related to activity recognition. Activity recognition is a multidisciplinary research field that connects with mobile computing [4], human computer interaction [5], context-aware computing [6], ambient assistive living [7] [8] and artificial intelligence [9] [10]. Activity recognition, particularly the recognition of Activities of Daily Living (ADLs) and ambulatory activities, is an important component in smart home applications for elderly healthcare. One goal of activity recognition is to offer context awareness that allows smart home applications to better understand the user's demands and adapt to their circumstances to provide personalized services. Monitoring daily activities enables a wide range of applications and services to support healthcare issues for the older adults such as the detection of health emergencies, early disease detection, professional advice on routine lifestyle, health status monitoring and help in treatment prescription.

Performing automated activity recognition in smart home using sensor data is a challenging issue. Apart from several practical limitations such as the location of sensors and privacy issues, it also faces a number of technical challenges that directly impact the activity recognition systems in smart home. An additional category of challenges is the diversity inherent to human activities. Some human activities are quite complex to detect either because they are composed of many lower level actions, or because these actions may be performed differently by different people or at different times. Most research on this field is more focused on recognizing what activity is taking place rather than evaluating how correctly it is being executed and other qualitative information.

The formal representation of heterogeneous sensor data is another research open issue in activity recognition. Raw data collected from sensors in smart environments are heterogeneous in format, structure and semantics, especially when multimodal sensors and different types of sensors are used to obtain it. This lack of formalisation makes it difficult to share and reuse these datasets. Activity monitoring of multiple users is also clearly more

challenging than for a single user. In current research, sensor data is collected and analysed from a single user activity in smart home. However, in real life scenarios, activities can be performed by multiple users concurrently and there may be interaction between them. Not only multiple users, but also multiple sensors pose research challenges. Even if the physical sensors are already available, to process different sensor data in order to provide sufficient accuracy for activity monitoring is still an open research issue. There also exist other challenges, including high-level and long-term activity monitoring, real world data collection, imbalanced and overlapping data classes and consideration of human factors.

In this thesis, we explore the diversity of main activities and sensors in smart home by considering their specific characteristics and utilize both knowledge-driven approaches and data-driven approaches to represent the human activities and perform activity recognition of static activities, dynamic activities as well as short-duration transitions between them, while addressing some the above challenges. We aim to provide a clear understanding of activities, sensors and related processing methods in order to realize the functionalities needed to perform all the recognition stages, ranging from low-level data acquisition by sensors up to high-level data integration and inference of knowledge. This Thesis is motivated by the search of answers to the following set of research questions: What activities can be monitored for the elderly wellbeing, and in general for population wellbeing inside home? How to identify and exploit the suitable sensors to monitor these activities? How to represent the context information that is meaningful for the recognition of activities in a formalized way? What sensor data processing methods and machine learning algorithms are suitable for efficient human activity recognition?

1.2 Summary of the contributions

The main contributions of this PhD Thesis are presented as follows:

- We provide a characterization of main activities and sensors related with our specific domain. The characterization of activities includes a taxonomy of main activities,

activity conceptualization and activity context representation formalization. On its side, the characterization of sensors considers the sensor platforms and an extensive analysis of the various sensors that can be used to monitor activities. These characterizations of main activities and sensors help researchers to select proper methods for the success of smart home applications.

- As part of the data-driven contributions, we propose a heterogeneous ensemble approach by combining various base classifiers to improve the activity recognition performance. It is constructed by a combination of three elements: a feature selection method to select only discriminative and relevant features, a class distribution rebalance method to improve the classification accuracy of transitional activities and an ensemble classification model that combines various base classifiers using a majority voting combination function. We demonstrate improvements on the detection of transitional activities while maintaining high accuracy on the classification of static and dynamic activities.
- We generate an available dataset that consists of raw accelerometer data and activity labels gathered from a group of 10 participants in a real home setting scenario for over ten hours. We design an experiment protocol to collect data of static, dynamic and transitional activities by using three small, low-cost and non-intrusive accelerometers placed on wrist, chest and ankle of the participants.
- Still in the data-driven domain, we also propose a novel accelerometer data segmentation based on change state point detection in the data stream. In order to identify locations within an input data stream that exhibit sudden changes, we develop a novel algorithm to detect the changing points from the data stream online, which consists of two stages: the change point within a processing window is identified in the first phase and the hypothesis that the most likely change point was significant is proved or disproved in the second stage. The main advantage of this algorithm is that it does not require previous knowledge of the underlying distribution, has a small memory footprint and a relatively low computational cost.

- Moving on to knowledge-driven approaches, we specify a human activity ontology based on foundational ontologies to model the attachment of the sensor data and context knowledge to the abstraction level representation. An extensive exploration of the various perspectives on contexts that are currently used to describe the human activity is conducted to emphasize the key factors for multiple levels of context representation. We also demonstrate a proof-of-concept implementation and evaluation of the proposed model with a specific scenario in smart home domain. The adoption of the concepts and statements from widely reused ontologies promotes a high degree of interoperability and reusability within smart home applications.
- We propose a three-layered context-aware architecture for monitoring activities of daily living in smart home. This potentially includes formal languages to describe activities and variables, methods for software and hardware setups, communication and services. This architecture provides for the inclusion of functionalities that range from low-level data collection to high-level context knowledge extraction. The implementation to realize the architecture makes use of Microsoft's Lab of Things (LoT) platform.

1.3 Structure of the Thesis dissertation

This PhD Thesis dissertation is structured in a total of seven chapters (see Figure 1.1). A summary and a brief description of each of the remaining chapters follows:

- *Chapter 2. Background and literature review*

This chapter presents a brief historical overview of the smart home concept and reviews the current literature on the subject of smart home projects worldwide and smart home applications in the healthcare field. Besides, the relevant work related to context-aware systems, data-driven approaches and knowledge-driven approaches for activity recognition is summarized in this chapter.

Chapter 1. Introduction

- *Chapter 3. Hypothesis and objectives*

After having presented the current state of the art, chapter 3 concretes the research hypotheses and objectives that guide the rest of the work performed in this Thesis. It also frames all the contributions into a proposed smart home activity recognition development framework.

- *Chapter 4. Characterization of activities and sensors*

This chapter starts by providing a taxonomy of main activities in smart home and proposes a conceptualization of both activities of daily living and the representation of their related context information. This conceptualization has been devised to be of practical use for the target applications that we consider, that is, applications that benefit from the precise detection of ADLs with the purpose of enhance inhabitant's quality of life in home. Based on this work, we also give a summary of sensors that can be used to detect these activities together with the analysis of their advantages and disadvantages.

- *Chapter 5. Materials and methodology*

This chapter details both the data-driven and knowledge-driven methodologies followed during the production of the results. Regarding the data-driven approach, the experiment design for the data collection, and all the methodological aspects considered for the classification of static, dynamic and transitional activities are detailed. As per the knowledge-driven approach, the NeOn methodology for the construction of ontology networks is chosen to generate the ontology for home activities description.

- *Chapter 6. Results of the research*

This chapter is dedicated to the description and discussion of the results obtained by the experimentation and implementation of our proposed contributions. Two complete data-driven proposals are assessed, namely the use of an ensemble of heterogeneous classifiers at the classification phase, and the segmentation of accelerometer data based on the detection of state change points. We complete the framework by describing our main knowledge-driven

proposal, which is the definition and evaluation of an ontology to formalize human activities in smart home. Finally, we provide with a first approach to a three-layered context-aware architecture for monitoring ADLs in home.

- Chapter 7. Conclusions

This chapter summarizes both the achievement of the individual objectives as well as the overall achievement of this Thesis work. In addition, it also presents the updated discussion on our initial hypotheses under the light of the results attained by this research work.

Figure 1.1. Structure of the PhD Thesis dissertation.

Chapter 2 Background and literature review

2.1 Concept of smart home: definitions

Smart home, also known as intelligent home, aware home or adaptive home, is an application of pervasive computing. There is no exact definition of smart home and it is often related to similar systems, such as e-health, assistive technology or telemedicine.

An early concept of smart home was formalized by Lutolf [11], who stated that “the smart home concept is the integration of different services within a home by using a common communication system. It assures an economic, secure and comfortable operation of the home and includes a high degree of intelligent functionality and flexibility.” In this paper, the smart home concept included technical services and applications from the following areas: security and safety, energy management, comfort control, communication services and audio/visual entertainment. Thus this definition focused on home automation terminology rather than home intelligence. Home intelligence was included in the smart home concept by Berlo et al. [12]. In their paper, the smart home was defined as “a home or working environment, which includes the technology to allow the devices and systems to be controlled automatically”.

Another elaborated definition of smart home concept was proposed by Intertek [13]. In this paper, the smart home concept was defined as “a dwelling incorporating a communication network that connects key electrical applications and services and allows them to be remotely controlled monitored or accessed”. This definition focused on home intelligence, including

internal network and intelligent control, and emphasised on remote access via home automation, which linked the devices within the home to services/systems outside the home.

Aldrich [14] defined smart home as “a residence equipped with computing and information technology which anticipates and responds to the needs of the occupants, working to promote their comfort, convenience, security and entertainment through the management of technology within the home and connections to the world beyond.” This smart home concept started to focus on domestic technology and moved the “smart home” closer to realisation from science understanding.

More recently, Satpathy [15] proposed a concept of smart home more centered on assisting the residents to live independently and comfortably with the help of mechanical and digital devices. In this paper, the smart home concept was defined as “a home which is smart enough to assist the inhabitants to live independently and comfortably with the help of technology (...). In a smart home, all the mechanical and digital devices are interconnected to form a network, which can communicate with each other and with the user to create an interactive space”. This definition considers both home intelligence and services, such as those promoting independent living, and is very aligned with the understanding of smart home that we use throughout our research work.

2.2 Review of smart home projects

The numerous research advancements achieved in smart home area have improved access to healthcare services for the elderly. Various projects have been developed throughout the World to prolong the independent living for this population segment. In this section, we conduct an investigation on the most significant smart home projects that aim at enhancing assisted living for older people in the recent past.

The smart home projects fully simulate the smart home environment including the deployment of a wide range of sensors. A chronological order is chosen for this presentation,

in order to give a clearer picture on how the expectations and research issues related to smart home have evolved with time. In the earliest projects presented, the main issues discussed were related to physical and logical connectivity of devices. This kind of projects evolved to multidisciplinary approaches very focused on improving the usability of the interaction of devices with the inhabitants. This form of interaction demanded technologies with a high grade of abstraction such as those related to Artificial Intelligence which, in turn, fostered the evolution to more natural and personalized interaction approaches. In addition, these technologies introduced the capacity of managing uncertainty, a common issue in smart home solutions. In recent years the projects have no longer been focused on the smart home as a final objective but rather as an enabling technology to achieve other purposes such as independent living for seniors. Table 2.1 summarizes some significant smart home projects in different world regions.

Table 2.1. Summary of some significant smart home projects.

Area	Smart home projects
North America	GatorTech [16], Adaptive House [17], Smart Medical Home [18], MavHome [19], Aware Home [20], House_n [21], PlaceLab [22], CASAS [23],
Europe	SWEET-HOME [24], ComHOME [25], PROSAFE [26], ENABLE [27], HIS [28], USEFIL [29], Smarter and Safer Home [30]
Asia	WTH [31], SELF [32], CoreLab [33], Ubiquitous Home [33]

Many smart home projects have been conducted in North America. GatorTech [16] was an early smart home project carried out at University of Florida to assist older and disabled adults in maintaining good quality of life and prolong their independent living in their own homes. In this project, a comprehensive house is deployed that integrated a number of environmental sensors and devices including: video cameras for detecting inhabitants' activity and controlling other devices, location tracking transceivers for detecting inhabitants' location, movement and orientation, pressure sensors for detecting falls and reporting emergency situations, a smart bed for monitoring sleep patterns, a smart mirror for displaying

Chapter 2. Background and literature review

critical messages and reminders and smart displays for presenting entertainment information that the inhabitant can follow from room to room. Additionally, healthcare technologies were added to provide diabetes management. The researchers proposed a six-layered architecture for GatorTech consisting of physical layer, sensor platform layer, service layer, knowledge layer, context management layer and application layer. GatorTech was a good example of what would become the next-generation smart home research.

The University of Colorado developed an “Adaptive House” [17], which aimed to explore the automatically programmable home environment. The Adaptive House was equipped with a variety of sensors to monitor room temperature, water heat, light and sound levels as well as control sensors for temperature, heating, lighting and so on. With these equipment, the system was able to detect the activities performed by the inhabitants, such as opening the window and turning on the light. In addition, a neural network was utilized in this system to learn the patterns and predict activities automatically.

The University of Rochester developed a Smart Medical Home for future health [18]. This project had a five-room house equipped with infrared sensors, vital signs sensors, video cameras and computers. The integrated technologies allowed to advice on medication management and dietary adherence, detect disease of inhabitants, provide memory assistance, and lower burdens for caregivers. The applications that were foreseen in this project included sleeping observation, behavioural pattern recognition and gait monitoring.

MavHome [19] was conducted at the University of Texas at Arlington. It combined a set of multidisciplinary technologies including mobile computing, multimedia technology, artificial intelligence and robotics. The architecture of MavHome consisted of four abstract layers: physical layer, communication layer, information layer and decision layer. The researchers implemented an active LeZi algorithm to predict future actions and calculate the probability of previous actions based on a Markov model. This algorithm enabled to make accurate decisions, but limited to predictions of only one habitant’s behaviour.

The Georgia Institute of Technology developed a smart home project named “Aware Home” [20]. It was a two-story single-family house in the Broadband Institute’s Residential Lab, equipped with cameras, microphones, a wireless network allowing high-speed communication between the devices deployed house-wide, and a radio-locating system allowing tagged objects tracking. This project was primarily designed for older adults with cognitive impairment. Ubiquitous computing was utilized to detect potential crises and recognize behaviour trends for the older adults with declining memory, something that can help maintain the older adults in their homes as long as possible. Based on different stages of development, a variety of applications were carried out associated with Aware Home, such as an intercom system which enabled the user to speak to others by saying their name via voice recognition, a software which produced family albums from video pictures collected automatically in the home area and a tracking system which identified people by using their footsteps. Additionally, biomedical healthcare technology was developed to provide a diabetes management service Mobile Access to health information was utilized to record activities on blood sugar via a glucose meter that could be connected to the mobile phone via Bluetooth.

The Massachusetts Institute of Technology developed House_n [21], a collaborative and multi-disciplinary smart home project, designed to create suitable environments for people of all ages and develop algorithms to interpret data collected from sensors. This project focused on how the design of the home and its related technologies, products and services should evolve to better meet the opportunities and challenges of the future. The researchers investigated methods for merging new technologies with user-concerned design. PlaceLab [22] is a part of House_n project to monitor vital signs, activities performed by the inhabitants and energy expenditure via ubiquitous sensors and wearable systems.

CASAS smart home project [23], developed at Washington State University in 2007, is a multi-disciplinary research project focused on creating an intelligent home environment by using unobtrusive sensors and actuators. The research areas included in CASAS are assistive technology, artificial intelligence, machine learning and activity recognition. The researchers

developed a frequent and periodic activity miner (FPAM) algorithm that constructed a hierarchical activity model by utilizing temporal and structural regularities to identify frequent and periodic activity patterns. This same team developed in its recent research the “smart home in a box” [34], a lightweight smart home design that is easy to install and provides smart home capabilities out of the box with no customization or training needed. These capabilities included activity recognition, which provided real time activity labelling as sensor events arrive in a stream, and activity discovery for unlabelled data by using an unsupervised learning algorithm.

In Europe, SWEET-HOME [24] was a French national supported research project that aimed to design a new smart home system based on audio technology. This project had three main goals: providing an audio-based interaction technology that lets the users have full control over their home environment, detecting distress situations and easing the social inclusion of the elderly and frail population. An interesting research direction of their smart home system was the context-aware decision process, which used a dedicated Markov Logic Network approach to enhance the ability of coping with uncertain events inferred from real sensor data [35].

ComHOME [25] was conducted in The Interactive Institute, Sweden. This smart home project was a full-scale model made of a number of scenario-like room setups. ComHOME was equipped with audio sensors that enable voice control and voice-mediated communication. Different aspects of home-based activity were investigated, such as distance work and communication. The researchers also explored the technology that may have impact on these aspects of home-based activity.

PROSAFE was a smart home project conducted in France [26]. This project was designed to support autonomous living. The infrared sensors installed in the ceiling of the apartment allowed monitoring the mobility and activity of the inhabitant. These sensors connected to a network to provide automatic activity recognition and possible falls to accommodate patients with Alzheimer’s disease. An abnormal behaviour can be identified and interpreted as an

emergent accident based on the collected sensor data, then as a result, the emergency sound alarm can be generated.

ENABLE project [27] was conducted in Netherlands. The apartment was equipped with only two types of devices: cooker and night light. This project aimed to evaluate psychological impact of assistive technologies rather than technical impact on patients with mild or moderate dementia. It turned out that a good relationship between caregivers and evaluators is critical for a long-term evaluation. The assistive services for patients with other types of disease were excluded in this design.

HIS [28] was another smart home project in France. This project was designed to ensure medical security and quality of life for patients who need home based medical monitoring through the use of technologies and clinical evaluation. The apartment was equipped with intelligent sensors for longevity effectiveness. Location sensors were installed in each room to monitor patient's successive daily activity phases within the home environment, infrared sensors were used for activity assessment, weight and vital sign sensors were connected via a home network for data processing. HIS enabled automatic measurements at three levels: the circadian activity, the vegetative state and some state variables specific of certain organs involved in precise diseases. Based on these automatic measurements, a mean value with confidence limits of activity variables was established in normal behaviour permitting to detect for example a sudden abnormal activity such as a fall, which enabled to define a canonical domain within which the patient's activity was qualified to be "predictable".

A recent smart home project is "Unobtrusive Smart Environments for Independent Living" (USEFIL), a European FP7 project which started in 2011. It aims to provide advanced and affordable health-care assistance in a smart home environment, adopting a three-layer architecture and an unobtrusive sensor network to support a Decision Support System (DSS) for providing inputs to monitoring apps by user-friendly interaction [29]. A limited set of sensors and devices, such as a wrist wearable unit, a camera, a microphone and a Kinect sensor, are used in a SH setting to identify the basic physical activities (lying, sitting, walking, standing, cycling, running, ascending and descending stairs) of elderly people [36]. A low

cost off-the-self system and open source platforms are developed to facilitate the generation of applications addressing the gap between advanced technologies and aging population.

Zhang and Karunanithi [30] proposed a Smarter and Safer Home solution at the Australian e-Health Research Centre, CSIRO, to enhance elderly people's quality of life. To achieve this, a number of environmental sensors are placed in various locations within smart home, acting as non-intrusive monitoring devices for identifying human behaviours. Based on this project, Zhang et al. [37] proposed a Smart Assistive Living (SAL) platform to enable elderly people to remain at their homes independently as long as possible. Sensors placed in smart home are expected to provide a continuous data stream to a server. Extracting and analysing these data using machine learning mechanisms are helpful to perform diagnosis and decision making by clinical experts and health caregivers.

Several smart home projects have been developed in Asia. The Welfare Techno-Houses (WTH) was conducted by The Japanese Ministry of International Trade and Industry in Japan [31]. These experimental houses were built to secure a measure of independence for the older adults and disabled people in order to improve the quality of their daily living. In the houses, the rooms were equipped with infrared sensors, the doors and windows were equipped with magnetic switches and the bathrooms were equipped with automated biomedical devices. These sensors and devices were utilized to collect data for the inhabitant's activity and vital signs. Particularly, the sleeping and toilet activities of the habitant were meticulously monitored.

Another group of Japanese researchers developed an intelligent environment called SELF [32], which enabled a habitant to maintain health via self-communication. In SELF, a number of distributed sensors that embedded invisibly in the home area were used to extract physiological parameters in order to observe a habitant's behaviour. A model room was set up by the researchers, equipped with a bed with pressure sensors, a ceiling lighting dome with a microphone and a washstand with a display. Based on these, a self-assessment system was developed to evaluate respiration and sleep disorders.

CoreLab was a prototype of smart home built at National Taiwan University [33]. CoreLab was equipped with integrated component named ambient intelligence compliant objectives (AICOs), used for different purposes such as contact detection, location detection and motion detection. The researchers developed a location-aware activity recognition system based on Naïve Bayes classification model, and this system enabled to recognize activities of a single inhabitant at high confidence levels.

Yamazaki conducted the Ubiquitous Home project [33], which aimed to support context aware services in smart home domain by connecting sensors, devices and appliances across a home network. The Ubiquitous Home project served as a real-life test bed for setting up context-aware services. The sensor system monitored human activities via a variety of sensors and devices. Video cameras installed in room were used to identify and follow the user, and microphones were used to collect complete audio data. Pressure sensors in the floor were used to track the inhabitants' movements and locate furniture. Active and passive radio-frequency identification (RFID) receivers installed on the ceiling and at the entrance of the door were used to identify the inhabitants. A network robot served as an intermediary between the inhabitants and the house to perform certain home services.

Several of these smart home projects provided a large amount of datasets, some of which are publicly available and can be used by researchers to conduct further studies. Among the publicly available datasets listed in the "Home Dataset"¹, those collected by MIT, the University of Amsterdam and the Washington State University are widely used in Smart Home research. Moreover, the dataset provided by MIT [22] was, to the best of our knowledge, by far the largest dataset collected from a real-world environment with more than 900 sensor inputs, including those coming from motion, switch and RFID sensors. In addition to data from embedded sensors, the dataset provided by [38] contained acceleration and gesture data. The benchmark dataset described in [39] was also widely used and contains data collected from a set of nine inertial sensors attached to different parts of the body. Concretely, there was motion data related to 33 fitness activities recorded from 17 volunteers.

¹ List of home datasets. <<http://boxlab.wikispaces.com/List+of+Home+Datasets>>, Accessed: April 2016.

2.3 Smart home applications for healthcare

Smart home technology is commonly used for healthcare applications that utilize an infrastructure equipped with a variety of sensor and devices. The purpose is to study the elderly's activity and behaviour within the smart home environment. These applications have been conducted that convey different functions, considerations and utilities according to researcher interests and user requirements. There is not a single way of classifying the SH applications that may enhance older adults' quality of life and health status. This section summarizes some of the most significant recent work found in the literature in terms of four categories of services: health monitoring, daily activities monitoring and prediction, anomaly detection and automatic planning and reminding based on various research objectives and service expectations. Figure 2.1 shows this categorization of smart home applications according to different purposes. We also note that these are not mutually exclusive categories: the same application may contain ingredients that fit into more than one of them.

Figure 2.1. Categorization of smart home applications.

2.3.1 Health monitoring

On occasions the older adults need specific monitoring of either vital signs or daily activities in order to assess if a medical condition is being correctly controlled. Other possible aims of

this is to detect early when an illness is developing or to react quickly when a sudden change in medical parameters occur. In the following we summarize information from some projects focused on this type of functionality and related with specific diseases such as diabetes and stroke patients.

Pulkkinen et al. [40] described a platform for monitoring daily activities by using different types of sensors for elderly people with diabetes at home. It helped detecting if the patients were following the recommended exercise and diet routines. Data obtained from the sensors for a long period of time can be used to distinguish the user's life patterns, helping doctors to design treatment plans and, after that, providing the patient with automatic notifications.

Chatterjee et al. [41] built an in-home activity monitoring system to detect the daily routine of elderly people also with diabetes by using environmental sensors and body wearable sensors. Daily messages based on previous behaviours and a tailored health newsletter that summarized biological parameters and blood glucose level prediction were sent to the users and caregivers to determine the health status.

Chiang et al. [42] developed a set of wireless sensor network devices to support physical therapy to be carried out by elderly stroke patients at smart home environments. Stroke patients usually had to repeat specific movements or postures during their rehabilitation, as indicated by the physiatrist. Thus the system described by Chiang et al. was aimed at measuring both static postures and dynamic movements, to record them as routines.

As an example of vital signs monitoring, Sardini and Serpelloni [43] developed a T-Shirt with embedded sensors to take measurements that include heart rate, respiratory rate and body temperature of the patient. The acquired data can be wirelessly sent to caregivers and then analysed continuously by healthcare experts to perform proper evaluation and assess sudden changes in the health status of the patient.

Apart from health monitoring systems developed in laboratory environments, some commercially available solutions also exist. Those solutions have a broader scope in healthcare management but are usually less integrated with the home. To mention a few,

Genesis by Honeywell, TeleStation by Philips, HeathBuddy by Bosch and HealthGuide by Intel fall into this category.

2.3.2 Daily activities monitoring and prediction

Many elderly people who live alone also suffer from other age-related diseases such as depression and diabetes, and the activities of these patients can be influenced by their diseases. For example, patients with depression could exhibit infrequent leaving the house, less talking, sleeping disorder and less eating, whereas patients with diabetes could perform frequent drinking, eating, sleeping and toileting. Being capable of detecting these patterns can help in diagnosing these illnesses.

In the literature different approaches can be found when dealing with activities detection: detection of activities as the main objective, detection of changes in routines as signs of possible risks or diagnosis of specific diseases based on activity patterns. Some significant examples of each of these approaches are discussed in the following.

Chernbumroong et al. [44] proposed a practical multi-sensor activity recognition system for monitoring daily life activities including brushing, exercising, feeding, ironing, reading, scrubbing, walking, walking stairs, washing, watching and wiping by using seven types of sensors attached to the body.

Suryadevara et al. [45] developed an intelligent home monitoring system to detect behaviour changes and forecast the behaviour of elderly people. A variety of environmental embedded sensors, such as motion sensors, power sensors, temperature sensors and humidity sensors, were used to gather activity and ambience data which can be fused via specific decision support algorithms to extract activities of daily living. These estimated activities can be correlated with recorded health information to predict health decline and emergent health situations.

Lara et al. [46] proposed Centinela, a system that continuously monitors five activities (walking, running, sitting, ascending and descending) by using a single sensing device and a

mobile phone. The system consisted of a portable and unobtrusive data collection platform to provide real-time human activity monitoring. The mobile application they implemented was based on acceleration and physiological signals to recognize physical activities automatically.

Han et al. [47] proposed a four layers healthcare framework to predict the risk of depression and diabetes by monitoring long-term disease related activity and generating long-term activity patterns. When the symptoms of these diseases appeared in people with irregular activity patterns, the information would be sent to doctors and caregivers for early detection and prevention of the depression and diabetes.

2.3.3 Anomaly detection

Anomaly detection aims to identify uncommon patterns in a dataset, that is, patterns which do not conform to the notion of normal behaviour [48]. To detect them, techniques based on rule-based approaches, temporal relation discovery approaches and similarity-based approaches may be used. The identification of anomaly patterns, especially in daily activities monitoring systems, can be significantly valuable for experts to make decisions or diagnoses in emergency situations. It can also be used to provide elderly people with memory impairments with reminders or audio signals if an anomalous behaviour is being detected.

As an important subset of the detection of anomalous situations we find fall detection applications. Older adults are more prone to falls, and their consequences are in general more serious than for younger people. This is the reason why it is possible to encounter a good number of proposals specifically focused in fall detection for the elderly, as an important issue to facilitate their independence at home.

In [49], Phua et al. proposed an Erroneous-Plan Recognition (EPR) to detect faults in the daily activities of elderly people with dementia, by using sensors deployed in SH to monitor daily activities. When an error was detected, timely audio or visual prompts were sent to the dementia patients to replace some of their diminished memory and enhance their problem-

solving abilities. Similar works about anomaly detection for dementia patients can be found in [50], [51] and [52].

Ordóñez et al. [53] developed an automated behaviour analysis system for elderly people who live alone at home. They capture measurements from various sensors, detected the activities of each user, and were capable of detecting anomalous behaviour that reflects changes in health status, by learning standard behaviour patterns. Gjoreski et al. [54] proposed a system to monitor user's daily activity by combining two accelerometers and an electrocardiogram (ECG) sensor. Measured acceleration data can be analysed in conjunction with the ECG signals to detect anomalies in the user's behaviour and heart-related problems.

Regarding fall detection systems, Wu and Xue [55] developed a portable pre-impact fall detection and injury prevention system with inertial sensors. By using the inertial frame velocity profile of the body, they distinguished falls from non-fall activities as well as identify early falls by using a threshold detection algorithm. The designed pre-impact detection device was embedded into a wearable belt that can be worn by the older adult when they were performing daily activities. This system had been proved to increase the confidence of independent living for elderly people.

Rimminen et al. [56] also proposed a fall detection system by using a near-field imaging floor sensor and pattern recognition. The shape, size and magnitude of the patterns were used for classification, and the result shows good performance on fall detection even on unclear falls (ending up sitting or on one's knees) and a good tolerance of daily activities.

Zhuang et al. [57] described a fall detection system to distinguish noise coming from falls from other noise in smart home environment. In their system they only used a far-field microphone to identify various sounds. Then a Gaussian Mixture Models (GMM) supervector was used to model each fall or noise segment by applying Euclidean distance to measure the pairwise difference between audio segments. A Support Vector Machine built on a GMM supervector kernel was used to classify audio segments into falls and various types of noise.

More generally, although also usable for detecting falls, Ghasemzadeh et al. [58] introduced a physiological monitoring system, which collected acceleration and muscle activity signals to assess standing balance. They used machine learning algorithms and statistical techniques to infer relevant information from the correspondence between the accelerometer and the electromyogram (EMG) sensors measurements.

2.3.4 Automatic planning and reminding

Patterns obtained from daily routines can be very useful for helping elderly people who suffer from any kind of cognition decline. Reasoning over these patterns allows to provide automatic planning, which enables to schedule daily living and offer reminders of the things that should be done. The reminding issue is related to when to remind and what to remind, for example, guidance when the person does not remember the steps to follow to complete an activity).

Chaminda et al. [59] proposed a smart reminder system for reminding older adults with memory impairment of the forgotten complex activities in smart home environment. Reminders of forgotten activities were predicted according to the inhabitant's current location, current behavior patterns and past activity patterns. Wearable sensors were used to acquire data to generate these activity patterns. A similar system was proposed in [60].

Pollack et al. [61] described Autominder, a cognitive orthotic system that intended to help the older adults with mild or moderate memory impairment adapt to cognitive decline and continue the satisfactory performance of routine activities. This goal was achieved by providing adaptive and personalized reminders of activities of daily living. A number of artificial intelligent techniques were utilized to model an inhabitant's daily plans, track the execution of these plans by reasoning about the observable behaviour of the inhabitant and make decisions about whether and when it is most appropriate to issue reminders.

Chu et al. [62] presented a model of interactive activity recognition and promoting, which aimed to ensure the inhabitant to adhere to a daily schedule by providing prompts about when

to begin or end activities, creating logs of the inhabitant's activities and minimizing interruptions to the inhabitant. This model was built upon a hierarchical partially observed Markov decision process. Both prompts and information-seeking actions were considered in this model and the responses from the inhabitant were used to identify states and improve the model.

Kamar et al. [63] presented a research on methods for context-sensitive reminding to show promise for effective reminder systems. A set of probabilistic models that learned from collected data were employed to obtain effective reminding from a set of outcomes, which included the probability that a certain piece of information would not be remembered, the relevance of the forgotten information in the current or forthcoming setting and the cost of transmitting the reminder to a habitant within the current context. A decision-theoretic approach was utilized to distinguish reminders that were beneficial for a habitant's performance from the ones that were not.

2.4 Activity recognition in smart home

2.4.1 Context-aware systems

In order to provide adequate services, some systems and applications should be aware of the contextual information of the environment and adapt automatically to its changes. These systems are known as context-aware system. Context plays a critical role in many systems since it provides any information that can be used to present the state of an entity [64]. Entities consist of people, places, objects, applications or devices within a smart environment. In summary, a context-aware system extracts, interprets and uses context information and adapt its functionality to the current context of the environment in which it runs [65].

Context was defined by Dey [64] as “any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications

themselves”. Zimmermann et al. [66] extended this definition with five categories of context information: individuality context, time context, location context, activity context and relations context. This enriched the information representation of context. Based on this, the context-aware system used context to provide relevant information and services adapted to the user’s task. In order to deal with the diverse characteristics of activities, the context-aware infrastructure can be used independently of the hardware platform, operating system and programming language to support a greater range of devices and applications [67].

Figure 2.2. Abstract layer architecture for context-aware systems [68].

Figure 2.2 depicts the abstract layer architecture of context-aware systems in general based on current literature [68]. This abstract layer architecture consists of five layers: concepts and research layer that involves theories and foundations to construct context-aware systems; network infrastructure layer that provide protocols and management to dynamically adapt to changes in context and connect entities based on network; middleware layer involves tools to gather context information, process it and derive meaningful actions from it; application layer involves providing appropriate services to the user; user interface layer involves providing suitable interface between handheld devices and the users. In the following, we summarize the significant specific architectures of context-aware systems that have been defined in the current literature.

Wang et al. [69] proposed Semantic Space, a pervasive computing infrastructure that exploits semantic web technologies to support explicit representation, expressive querying and flexible reasoning of contexts in smart environments. The Semantic Space consisted of five collaborating components: the context wrapper that obtains raw context information from hardware sensors and devices and transforms it into context markups; the context aggregator that discovers the context wrapper, registers it in the service directory and obtains context markups from it; the context knowledge base that provides persistent context knowledge storage; the context query engine that provides an abstract interface for applications to extract the desired contexts from the context knowledge base; and the context reasoner that infers abstract, high-level contexts from basic sensed contexts.

Chen et al. [70] proposed CoBrA, an agent-based infrastructure that provided context modelling, knowledge sharing, context reasoning and privacy protection support for pervasive context-aware systems. Central to the proposed infrastructure was the presence of an intelligent agent called context broker. The context broker was a specialized server entity and can be used to maintain a shared model of context on behalf of a community of agents and devices in the environment. The design of the context broker consisted of four functional components: context knowledge base, context reasoning engine, context acquisition module and policy management module.

Gu et al. [71] introduced SOCAM, a service-oriented architecture support for the building and rapid prototyping of context-aware mobile services in pervasive computing environments. The purposes of SOCAM were to present context information to mobile users, trigger behaviours on the occurrence of a set of contexts and adapt to presentation of services to mobile users. The SOCAM converted various physical spaces where contexts were acquired from into a semantic space where contexts can be easily shared and accessed by context-aware services by using five components: context providers, context interpreter, context database, service location services and context-aware mobile services.

Khedr et al. [72] proposed ACAI, an innovative agent-based context aware infrastructure equipped with capabilities to maintain spontaneous applications both locally and across

different domains. ACAI allowed context information to be collected, processed, inferred and disseminated to the spontaneous applications. This purpose was achieved via a three-layered architecture: the sensing layer to capture and acquire context information about the elements in the environment, the context service layer to represent context in a well-structured model and provide context-based services, and the application layer to provide the interface between mobile users and applications.

Even though context-aware systems have been included in the research literature, much research has just focused on the concept or deployed in limited spaces, such as laboratories, smart home pilots and hospitals, rather than fully implemented in real-world scenarios. One challenge of the context-aware infrastructure is to exploit the changing environment with a new class of applications that are aware of the context in which they run and then react to changes in the environment [73].

Another important challenge is the overcoming of the technical specificities of the scenarios being studied up to now, needed to reach to a sufficiently reusable and extendable solution. The addition of new devices or their change in a specific solution usually requires great amounts of tailoring to that specific architecture, being it difficult to compare, merge and share results among different proposals. In this line, some initiatives, among them Microsoft's Lab of Things², aim at reaching to an homogeneous and easier way of coping with heterogeneity in sensing and actuating infrastructures, getting nearer to the deployment of extensible and normalized Internet of Things environments.

2.4.2 Data-driven based activity recognition

The data collected from sensors form the basis to construct a behaviour model to recognize the monitored activities. Machine learning methods have been extensively adopted to achieve high accuracy on the activity recognition task. There are mainly three categories of machine learning methods for activity recognition: probabilistic models, rule-based models and

² Microsoft Research. Lab of Things. <<http://www.lab-of-things.com/>>. Accessed: April 2016.

geometric models. In the following, we summarize some significant work in these three categories.

Probabilistic models attempt to provide a complete description of the data space and have great flexibility on controlling different variables. Naïve Bayes model is probably the simplest probabilistic model [74] [75] [76] [8]; it adopts a probabilistic function to model the dependence between variables and activity labels and then it identifies the most likely activity. The Naïve Bayes model assumes independence among the variables in the data space, and the probabilistic function is typically expressed as a simple one-dimensional normal distribution. The Naïve Bayes model is easy to implement and yields high accuracy when given with large amounts of samples in data space. However, it logically yields bad performance when the monitored activities are highly related with each other and it lacks the ability to model temporal information in data space.

In terms of modelling temporal information in data space, the Hidden Markov model (HMM) is the most commonly used probabilistic model, which builds a model for each activity in parallel in order to identify the most likely activity that fits the current behaviour of the user. In HMM, a set of hidden states are coupled in a stochastic Markov chain, chain that is used to describe the probability of transitions between two hidden states. Lee et al. [77] proposed a two-step hierarchical HMM to recognize what they call five actions (standing, walking, walking upstairs, walking downstairs and running) and three activities (shopping, taking bus and moving by walk), from data collected by a smart phone. Similar work can be found in [78] [79] [79] [80]. The HMM has as an advantage the capability of modelling sensor failure probability and dealing with noise in data space. However, it suffers from two limitations: first, it cannot capture long range dependences of the variables due to its first-order assumption; second, it is hard to recognize all possible sequences of a particular activity, especially if this activity is performed in several different ways by the user. Multiple Behaviour HMM (MBHMM) [81] and Condition Random Fields (CRF) [82] were proposed to address the second limitation.

The decision tree (DT) and the random Forest (RF) are two commonly used *rule-based models* in activity recognition. The DT is a hierarchical method. It constructs a binary decision structure that consists of a set of nodes, a binary decision being made according to the input features and rules at each node. Maurer et al. [75] adopted decision trees to represent logical descriptions of activities from complex sensor data collected by a wearable sensor platform called eWatch. Cluitmans et al. [83] used binary decision trees as an effective online classifier for activity recognition using wireless sensors and a PDA. Their model showed an overall accuracy of 86.6% on classifying five everyday activities: lying, sitting/standing, walking, running and cycling. Moreover, the results showed that the decision tree exhibited low computational cost and low battery consumption. In summary, The DT provides a simple and visual representation, fast detection of the target activities, and it allows the addition of new possible variables in data space. However, if many values in data space are uncertain, the computational cost of DT becomes relatively high.

The RF is a collection of decision trees and provides an output that depends on the different results from the individual trees. Each decision tree is constructed by learning from a subset of the data space chosen randomly, then the outputs obtained from these decision trees are averaged to determine the final output. Ellis et al. [84] developed two predictive RF models to predict the activity type and estimate the energy expenditure by using the data collected from two accelerometers placed on wrist and hip. They obtained an average accuracy of 92.3% from the data collected by the accelerometer placed on the hip and an average accuracy of 87.5% from the data collected by the accelerometer placed on the wrist. The RF runs efficiently on large data spaces and it can maintain accuracy when there exists a large proportion of missing data.

Geometric models consider the boundaries that can be used directly to classify the activities rather than representing the description of activities. Compared to probabilistic models, geometric models do not require enough data to learn a complete probabilistic representation of activities. The nearest neighbour (NN) is probably the simplest geometric model. It compares a new sequence with the template sequence in training set and chooses the most

closely matching sequence. A generalization of this algorithm is KNN, for which the K nearest matching training sequences are considered and then the class is decided by the majority vote of them. Some work that used KNN for activity recognition can be found in [85] [86] [87] [88]. The NN model is robust to noisy sensor data stream and effective if there is a large amount of training data. However, it needs to determine the number of nearest neighbours, and since it is a distance-based learning model, the computational cost is quite high and the storage requirement is large in order to compute the distance of each instance to all training samples.

Support vector machine (SVM) is another popular geometric model. It aims to find out the optimal separated decision hyperplanes between classes. The SVM is commonly used to differentiate falls from other activities. Fleury et al. [89] used SVM to construct a model to recognize seven activities: hygiene, toilet use, eating, resting, sleeping, communication and dressing/undressing. The data used as input for the SVM model was collected by several types of sensors deployed at home such as infrared sensors, door contacts, temperature sensors and microphones. The cross validation test gave interesting preliminary results with a good classification rate of 75% for a polynomial kernel and 86% for a Gaussian kernel with adapted parameters. Ortiz et al. [90] proposed a transition-aware human activity recognition system architecture for the recognition of physical activities using smartphones. They adopted SVM combined with a heuristic filtering approach to deal with transitions, such as sit-to-stand, sit-to-lie and stand-to-lie, in two different ways: learning transitions directly and considering transitions as unknown activities. Their model showed good performance on recognizing very short duration transitional activities. Compared to NN, SVM models have advantages on dealing with over-fitting problem and the learning result from SVM is more robust; the SVM works well when there are fewer training samples in data space. However, by using SVM, the classification problem should be formulated as a two-class classification and the learning phase normally takes longer time.

The artificial neural network (ANN) is a flexible geometric model in which a mathematical function is configured to present the relationships between the inputs and outputs. It can be

used to get the outputs from any set of given inputs after training. The ANN is widely used in human movement studies. Lubina et al. [91] used ANN to recognize seven ambulatory activities (sitting, standing, walking, walking upstairs, walking downstairs, standing up and sitting down) from simple features derived from signals collected by five accelerometers placed on five different parts of the body. Their model showed a high accuracy of 97% for discriminating sitting and walking, 89% for standing, 75% for walking the stairs, and relatively low accuracies of 56% for standing up and 38% for sitting down. Ermes et al. [92] trained a neural network to infer seven activities: rowing, biking, playing football, walking, running, sitting and hiking, from data collected by an accelerometer and a temperature sensor. In their research, the neural network model showed good noise tolerance and low computational requirements to detect human activities in a real-time scenario. However, the ANN suffers from difficulties in training when there are no local optima and adaptation latency to changes in data space.

2.4.3 Knowledge-driven based activity recognition

Knowledge-driven approaches model activities by using knowledge engineering methods and representation formalisms. Among the various knowledge-driven approaches, the ontology-based approach has gained increasing attention due to its powerful representation capabilities and reasoning methods for handling heterogeneous and imprecise sensor data. Generally, the expressive needs in context modelling related to activity detection include the ability to represent user-related information, hierarchical structure of environmental context and complex relationships among context instances (e.g. using temporal restrictions). Ontology-based modelling can be utilized as a symbolic context representation method for describing knowledge about the context.

Ontology formation is firstly defined by Paul James as “formations of social relations understood as dominant ways of living. Temporal, spatial, corporeal, epistemological and performative relations are taken to be central to understanding a dominant formation. That is, a particular ontological formation is based on how ontological categories of time, space,

embodiment, knowing and performing are lived—objectively and subjectively” [93]. The formalized vocabulary provided by an ontology can be used to define the concepts and properties, which facilitates knowledge sharing and reusing. Various ontology languages have been developed to describe these concepts and the relationships between them, such as Resources Description Framework (RDF) and Ontology Web Language (OWL). These Description Logic-based markup languages allow information to be read and processed by machines.

From the definition of an ontology we can assume that many common sense aspects have been included in the various ontologies defined so far for different domains. These common sense aspects would stem from the profound knowledge provided by groups of experts in every specific real-life area that was being formalized. The potential of reusing these already accepted representations of phenomena among different domains is very positive, since they help in coping with the variability that a certain real-life entity or action may present when surrounded by different environmental or personal contexts.

In current literature, various ontologies are proposed to model and represent context knowledge in smart environments. Vallerand et al. [94] proposed an ontology model of contextual information aimed at the deployment of software services into the most suitable devices. To do so, they took into account user profiles (focusing on their interaction capabilities, built around the notion of interaction modalities, and preferences), device profiles, software profiles and environment topology. In [95], a novel ontology was integrated into an adaptation framework for situation-based and self-adaptive applications in smart environments. This ontology was embodied to model context, security, performance management and dynamic models for performing run-time reasoning and adaption. Even if the authors mentioned the possibility of representing activities, they did not center their description on this objective. Daoutis et al. [96] considered contextual information including different sensors, but they heavily centered on visual perceptions obtained by cameras. Their purpose was to allow natural communication between robotic systems and humans. They obtained a representation of the objects located in home together with their properties, as far

as they were significant for the human-robot interactions. All these ontologies use specific concepts and statements tailored to concrete application areas. Because of this concreteness, they lack the ability of facilitating knowledge sharing and interoperability among various smart environments applications in an open and extensible manner.

There exist a number of ontologies widely accepted and reusable for modelling the related context knowledge across different applications. COBRA-ONT [97] was an ontology to describe the attributes and relationships related to people, space and activities. SOUPA [98] defined not only core concepts that describe information in common scenarios (e.g. person, time and space), but also extended concepts for narrower domains (e.g. home, office and entertainment). Event Model F [99] is an ontology that supports a comprehensive representation of the participant, mereological, causal and correlative relationships between events. These ontologies provide common knowledge concepts and statements, which facilitate knowledge sharing and interoperability.

Regarding the specific domain knowledge that we deal with in this research work, Chen et al. [100] proposed seven ontologies to model semantic data in a smart home, related to physical equipment, activity, space, actor, medical information, software components and time. Okeyo et al. [101] extended existing ontology-based approaches by combining ontological and temporal knowledge representation formalisms to provide a powerful representation capability for composite activities modelling. Horst et al. [102] proposed an ontology approach to bridge the gap between raw sensor data and high-level services in independent living applications by using a method of structuring knowledge and reasoning. The main contribution of their approach was the usage of generalized events, which makes modelling context more generic and simplifies context structuring and management. These works just summarized are more focused on activities modelling, as this Thesis is. However, they do not take user profiles into consideration during the inference process, while users are in fact the focus point in most smart home applications.

Several contributions have been made for modelling user profiles. Chen et al. [103] modelled smart home domain knowledge at two levels of abstraction, generic activity knowledge and

user profile (the specific way to perform an activity). Skillen et al. [104] proposed a user profile ontology to provide the personalization for context-aware assistive services, the rules were created by SWRL and used alongside the user profile for the purposes of application personalization. Martin et al. [105] combined ontologies that represent information based on a user profile along with machine learning techniques to infer user preferences automatically. The proposed profile used two types of information: static information, such as name and age, and environmental user preferences that are configurable by the user. These user preferences allow the development of context-aware applications for the home environments that adjust proactively taking into account both user preferences and the particular situation.

Chapter 3 Hypotheses and objectives

The theoretical analysis of current literature made in the previous chapter has risen some current needs in the area of the detection of activities. This chapter describes the needs on which the thesis will be focused. Subsequently, and based on the identified needs, both the hypotheses and the objectives will be formulated. Finally the scope for the research will be specified.

3.1 Research needs

The research performed in this Thesis has focused on solving four main needs (as shown in Table 3.1).

3.2 Hypotheses

After having exposed the needs that motivate our work, this section presents the hypotheses assumed during the research. In the area of digital home, one of the largest sources of uncertainty is the type of technology to be applied. Therefore, most of the hypotheses relate to the appropriateness of technologies or methods to accomplish the objectives that we will set out later.

Chapter 3. Hypotheses and objectives

Table 3.1. Description of the needs considered in this research.

Need	Description
Proper characterization of the existing initiatives and challenges in the area	Although there are numerous research papers in the area of activity detection, there are not enough compiled works to facilitate the identification of trends and specific challenges to solve. This causes difficulties in the development of innovative solutions that solve aspects not covered by other research.
Integration of the existing approaches in a unique conceptual framework for activity detection	Activity detection has been addressed from several approaches. Most of these approaches can be classified as being either data-driven or knowledge-driven. Even within these two approaches multiple variants have been performed seeking to obtain a sufficiently fine detection. To get a more complete approach it is necessary to integrate these two approaches and get the best of each, providing developers with a proper development framework.
Improvement of the detection of transitional activities within the home	Human activities are quite varied. Most of the literature has focused on detecting well known activities that are maintained over a relatively long period of time (either static or dynamic). However transitional activities, which occur on changes of activity, have not been adequately addressed. This is largely due to the difficulty associated with the lack of precise definition and the shortage of samples available for these activities, due to their short duration in time. It is necessary to create a suitable method to characterize this type of activities and that allows their detection, something that would add also to the more precise detection of the overall sequence of users' activities.
Management of the uncertainty caused in the detection of activities in real settings	The activities that people carry out in their daily lives are usually not as well characterized as those in an experiment. In real environments it is necessary to take into account common sense aspects such as the time spent performing an activity, the changing of the location where the activity usually happens or the performing of an activity that has strong relations with other activities. All this generates uncertainty that hinder the development of real solutions based on activity detection. Therefore it is necessary to use models capable of handling common sense issues to adequately manage these sources of uncertainty.

- *Hypothesis 1. Activity detection must be addressed considering that neither the environment (sensors and actuators in a home) nor residents may have predefined behaviours.*

Many of the approaches described above address the problem of detecting activities from a data-driven or knowledge-driven approach. Having chosen the approach (data- or knowledge-driven), the behaviour of all the actors of the house is defined. Thus, if a data-driven

approach is chosen, the network of sensors and actuators are defined taking into account not only the activities to detect but also the temporal and spatial sequence of these activities. In the case of a knowledge-driven approach the model of the activities determines specific schemes for the data aggregation of the devices. In both cases applied separately the translation to real-life environments has proven unsuccessful. In this Thesis both approaches are assumed. On the one hand, the accurate detection of three types of activities (static, dynamic and transitional) from data obtained by sensing devices will be performed by following a data-driven approach. On the other hand, a knowledge-driven approach will be applied to manage the problem of lack of information for the activity detection due to changes in the behaviour of devices or inhabitants.

- *Hypothesis 2. The technologies aligned with the concept of Internet of Things can result in architectures capable of collecting context information with the adaptability and flexibility demanded by the home environment.*

One of the fundamental aspects for the detection of activities is the architecture of devices deployed at home. Due to the peculiarities, both technical and behavioural, of each sensor, it is common that architectures deployed at home are presented as closed solutions where new sensors must be designed specifically for that architecture. The adoption of mature technologies from the computer networks field to develop open architectures has resulted again into the creation of closed architectures because of the lack of semantic interoperability. This deficiency in the deployment of open architectures hinders the research of innovative Smart Home solutions, especially in real-life environments. The current movement of Internet of Things, addressing the open architecture issues from a semantic approach, will foster the adoption of open architectures also in smart home.

- *Hypothesis 3. The machine learning techniques allow the detection of complex activities, such as interrelated or transitional activities, that are difficult to model through logical rules.*

The number of events related to an activity and the order or frequency of these are highly variable in domestic environments. This implies huge difficulties for reaching to a logical modelling of activities from the raw data obtained by the devices. To face this challenge, machine learning methods have been used to process and aggregate the device data and events associated with the activity of a particular inhabitant. Furthermore, a suitable choice of learning algorithms and classification enable not only a more accurate detection of common activities but also an increase of the success of transitional activities detection.

- *Hypothesis 4. The ontologies are an appropriate tool for the management of real activities due to their capability to model common sense knowledge.*

The ontology technologies were designed to model, execute and share real-world scenes in a way that is readable and understandable by machines. One of the main difficulties in the detection and management of activities in a home is that, given their variability, they are difficult to be represented in a formalized manner. This causes that the existing models meet in practice with a high level of uncertainty inherent in real environments. Ontologies provide greater capacity than many other semantic modelling technologies to handle real world uncertainty. This flexibility allows, for example, consideration of issues that relate to the common sense of human beings: the possibility that an activity is only partially carried out, different durations when performing the activity, activities that have dependencies or relationships with other activities, etc. In addition, most of these common sense issues have been previously modelled and validated by pre-existing ontologies so that they can be incorporated into the current activity models. This is possible because ontologies also have a great capacity for abstraction and can be linked in networks of ontologies. All these features make ontologies appropriate tools for high-level management of activities at home.

3.3 Objectives

This section describes the objectives that guide the development of this thesis according to the needs identified and the hypotheses formulated. These objectives have been divided into main objective and specific objectives.

3.3.1 Main Objective

This objective frames the Thesis work within a broad social and academic vision, allowing the understanding of the main motivation that has driven this work.

The main objective is to improve the detection of activities in the context of the smart home by the definition and characterization of a development framework to facilitate the implementation and deployment of real applications in these environments.

3.3.2 Overview of the development framework

This Thesis defines a development framework as a set of processes that developers should carry out to obtain suitable and proficient results. Figure 3.1 shows an overview, based on the needs and hypotheses previously presented, of the proposed development framework for the detection of activities. The home events are initially collected and then processed by a home architecture. This architecture also allows the execution of two different processes to perform the activity detection. First a data-driven detection process, which transforms the data received by the sensors into activities. After this process, atomic (or simple) activities are obtained. Subsequently, a knowledge-driven process manages the previously detected activities taking into account both the other activities and the general context of the home and its inhabitants. This knowledge-driven process will enhance the activity detection obtaining results closer to the actual behaviour of the inhabitant.

Figure 3.1. Overview of the development framework.

3.3.3 Specific objectives

The Specific objectives in this thesis are described as follows:

- *Specific objective 1. To understand the current research status in the area of detection activities for smart home environments.*

This requires a detailed analysis of the knowledge settled in the area, the technologies that have been used together with their applicability strengths and limitations, the existing trends and the major challenges still to be addressed. This objective has to be tackled from the beginning of the doctoral work so that it will influence the precise formulation of the hypotheses and objectives. An adequate knowledge of this state-of-the-art statues will facilitate to set up the contributions of the Thesis through the definition of appropriate targets and to minimize the technological risks associated with the hypotheses.

- *Specific objective 2. To develop a method to detect activities from the data obtained by sensors.*

Detection must be carried out for static, dynamic and transitional activities, aiming for good classification precisions on the three of them. Transitional activities tend to be an issue due to the short duration in time, which translates into the availability of fewer samples. In addition, the developed method should be adaptable to different types of sensors and uses thereof, either automatically or by training processes.

- *Specific objective 3. To develop a network of ontologies that facilitates the management of the activities previously detected.*

The ontology should include temporal and spatial concepts that are common in real environments. It must also be able to adequately model the relationships among the execution of activities.

- *Specific objective 4. To draft an open architecture for data acquisition in the smart home with the purpose of detecting activities of daily living.*

This architecture will be based on emerging technologies related to the concept of Internet of Things. In addition, the ability of these technologies to model the context of the home and its resilience to adapt to the characteristics of each household will be evaluated.

3.4 Scope

The objectives presented above represent all stages, according to the author of the Thesis, needed to improve the current research state of activity detection at home. However, since the research must be framed in a limited period of time to be effective, the scope of the fulfilment of these objectives has been restricted.

The main restriction in the objectives is that no experiment of the whole system working together has been made. Although each process of the framework is well characterized, a

final experiment with all the processes working for detection could lead to a more global approach and more robust evidences. However, a complete experiment would imply the involvement of real users. The research conducted does not have the necessary resources to carry out such experiments and, since its inception, these whole system experiments were considered out of reach.

Nevertheless, both the author and her supervisors consider that this restriction on the scope of the thesis will not significantly affect the validity of the results and contributions of the Thesis. Even if a joint test of all the proposed processes has not been made, we do have validated each of them separately. Since processes have been defined in a sufficiently decoupled manner as they have quantifiable and measurable inputs and outputs, it can be considered that the results and conclusions obtained separately are an important indication of overall performance.

Finally, it is noteworthy that although most of the proposed processes are equally valid for activity detection in smart home in general, when it has been necessary to specify a concrete set of activities among the huge amount of possibilities, we have given priority to activities that could be significant to enhance the quality of life and to prolong the independent living of the elderly. Whenever any assumption on this has been made, we have adequately noted it down.

Chapter 4 Characterization of activities and sensors

4.1 Characterization of activities

There are various possible definitions of activities performed by the inhabitants in smart home that can be adequate for adapting to different system requirements. A clear understanding of the target activities and their specific characteristics is critical for proper sensor selection and system design. Besides, a proper analysis of activities could facilitate the deployment of applications for supporting healthcare services and foster independent living. On the other hand, the relevant context information, such as related objects and location, may contribute to the activity modelling. In this section, we classify the smart home activities into three categories and describe these significant activities especially for the older adults. Next we summarize the conceptualization of activities, including their diversity, their relationships with other activities as well as with the relevant context information. This leads to the formalization of activities contextual information, for which we have investigated the specific techniques and languages for representing this information in detail in current literature.

4.1.1 Taxonomy of activities

There exist various activities in smart home which reflect the living state of the inhabitant. In this sub-section, we only focus on the activities related to healthcare, wellbeing and independence in SH environments, with special emphasis on the elderly population.

Activities of Daily Life (ADLs) are defined as “the things we normally do in daily living including any daily activity we perform for self-care such as feeding ourselves, bathing, dressing, grooming work, homemaking and leisure”³ by the medical community. ADLs are used in smart home as an umbrella term encompassing self-care and domestic activities or tasks that the user undertakes routinely. Thus the ability performing ADLs at home without assistance from other people can be considered as a reference for the estimation of the independent living level of the older adults [89]. Katz and Lawton define a range of ADLs [106] and Instrumental ADLs (IADLs) [107]. According to their definitions, the ADLs can be subdivided into personal self-care activities, or basic ADLs (BADLs), and domestic activities, or instrumental ADLs (IADLs). BADLs refer to the necessary self-care activities, such as bathing, dressing, eating and drinking, functional mobility, using toilet and grooming. IADLs are not activities necessary but let an individual live independently in a community: shopping, housekeeping, managing money, preparing food, taking medication, using telephone and transportation.

Ambulatory activities are related to either specific motions or postures of the person. These activities can be subdivided into stationary activities, transitional activities and dynamic activities. Stationary activities describe a posture such as sitting, standing or lying. Transitional activities refer to the change from a stationary state to either another stationary state or a dynamic state, or vice versa, such as sit-to-stand, stand-to-sit, stand-to-walk and sit-to-lie. Dynamic activities include a set of simple dynamic actions such as walking, running, cycling and jogging. Ambulatory activity monitoring is very useful for detecting the physical activity level, promoting health (e.g. doing exercise) and detecting hazardous situations such as falling. Additionally, ambulatory activities can be useful for estimating the psychological wellbeing of older adults. For example, Tartarisco et al. [108] propose a system for prolonged stress monitoring during normal activity performance in a smart home environment. They

³ MedicineNet, Inc. “Definition of ADLs (activities of daily living)”. 2016. <<http://www.medicinenet.com/script/main/art.asp?articlekey=2152>> [Access: April 2016]

Chapter 4. Characterization of activities and sensors

evaluate the individual immediate stress level by analyzing both the ambulatory activity frequency and the heart rate when the individual performs these ambulatory activities.

Table 4.1. Taxonomy of activities significant for the older adults in smart home.

Type	Activity	Description of how the activity relates to the elderly independent living
Basic ADLs	Bathing	Performs sponge bathing, tub bathing or showering without assistance
	Brushing teeth	Brushes one's teeth without assistance (including the use of toothbrush and toothpaste)
	Dressing	Puts on and off clothes and shoes without assistance (except for tying shoes)
	Using toilet	Goes to toilet, uses it, dresses and returns without assistance (may use cane or walker)
	Eating and drinking	Feeds oneself and drinks without assistance (including the use of cutlery)
	Sleeping	Sleeps on a bed in the bedroom without assistance
Instrumental ADLs	Preparing meals	Chooses material and food in the kitchen, prepares meals autonomously without assistance
	Preparing drinks	Chooses the type of drinks, prepares drinks with sugar or milk
	Resting	Reads a book, listens to music, operates and watches TV without assistance during leisure time
	Housekeeping	Keeps house clean (sweeps floor with broom, washes dishes and glasses in kitchen, etc.) and does housework (such as ironing) without assistance
	Using a telephone	Picks up the telephone, dials the number, has a conversation or answers a call without assistance
	Taking medicine	Takes the prescribed medicines appropriately and timely without assistance
Ambulatory Activities	Walking	Walks from one place to another, walks up or down the stairs without assistance
	Doing exercise	Does exercise such as running and cycling without assistance
	Transitional activities	Performs transitional movements (such as sit-to-stand, sit-to-lie, stand-to-sit, lie-to-sit) in and out of bed or chair without assistance
	Stationary activities	Sits in the sofa, stands for a period of time (may use cane or walker), lies in bed or sofa

By taking into consideration the contribution included in the research referenced above, we have compiled a summary of activities including basic, instrumental and ambulatory activities. The classification and detailed description of the activities that are significant for

the elderly well-being and independent living in SH is included in Table 4.1. This taxonomy establishes a first basis for the activities definition that is aimed at decoupling the specification of sensors and processing techniques from the final high level description of the service. Depending on the application specific goals, some activities will be more interesting to be detected than others. For instance, a healthcare application for elderly people may concern about the user's movements and fall detection but an assistance application for elderly people with cognitive decline would be more focused on the sequences of activities that the user performs.

4.1.2 Activity conceptualization

There exist a major gap between the basic data generation for the activities presented in Table 4.1 and the potential understanding of the user's behaviours, in order to provide with the necessary personalized assistance. The main reason is the diversity of activities characteristics. Indeed, the activities are performed in smart home by the older adults in different ways and most of them have some relationships with other activities and environment context (e.g. location and related object).

In this subsection, we present the characteristics related to activities conceptualization, then a formalization of activities that can be understandable by computers is proposed.

The aforementioned characteristics can be mainly classified into four categories:

- *Variability of activities*

The user may perform activities in different manners. Firstly, most activities involve a number of actions. In [101], the authors distinguish the ADLs in smart home from the actions, in order to define the human behaviour at different complexity levels and durations. An action is an atomic activity that is performed by a single subject and lasts for a relatively short time. Some examples of actions are “open the microwave”, “put dishes into the dishwasher” and “close the door”. An ADL is usually defined as a more complex behaviour performed by either a single user or multiple users and which lasts for a longer period of time

than an action. Thus the ordering of the actions of an activity depends on the user's preferences. Secondly, the time and duration of activities may also change based on users' preferences. For example, some users shower in the morning, while others shower in the evening. Although the way of performing the activities usually follows fixed patterns, there do not exist strict constraints on their duration and sequence. The specific and preferred ways of performing activities by the user are described by user profiles, which can be used for personalized assistance services. The diverse lifestyles, preferences and habits provide prior personal details about the activities, which lead to a large number of activities variants, thus the activity model should have the ability to capture these variants in a flexible way.

- *Specialization of activities*

Activities can be categorized at multiple levels of granularity. Specialized activities include only a single activity and cannot be split into any child activities. More general activities may consist of several kinds of simple activities. Those complex activities with specialized sub-activities are called coarse-grained activities. The specialized sub-activities with no child activities are called fine-grained activities. Generally, a coarse-grained activity may be specialized into two or more fine-grained activities. For example, "preparing drinks" may have as its child activities: "preparing hot drink" and "preparing cold drink", whereas "preparing hot drink" can be further broken down into its child activities: "preparing tea", "preparing hot milk" and "preparing coffee". Usually a "is-a" or "part-of" relationship is used to link coarse-grained activities and fine-grained activities. Meditskos et al. [109] define the specialization of activities into others. As an example, in their activity pattern, the activity "night sleep" is defined as the overall night sleep activity of a person and the activity "out of bed" is detected when the person gets out of bed. With the addition of context description and activity type interpretation, an "out of bed" activity can be further specialized as a "bed exit" activity, which refers to the "out of bed" activity when it occurs during the "night sleep".

- *Composition of activities*

Most complex ADLs are composed of an ordered succession of simpler activities. For instance, “sleeping” may consist of: “opening the door”, “going to bed”, and “turning off the light” (as shown in Figure 4.1a). The ordering of the simple activities may depend on an individual’s preferences or habits, thus leading to several variants of an activity. Furthermore, activities may have time-related connections to each other, to form a composite activity. At this respect we may distinguish three situations: sequential activities, concurrent activities and interleaved activities. Figure 4.1 shows graphically these temporal relationships.

In terms of time interval, the so-called Allen relations [110] are commonly used to describe temporal links between activities: (1) Sequential activities are described by associating their time intervals using the before/after and meet/metby relations. The before/after relation is found when one activity is performed either before or after another activity, and the two associated time intervals have a gap between them. For example, “opening tab” occurs before “washing dishes” and “closing tab” occurs after “washing dishes”. On the other side, the meet/metby relation indicates that the two associated time intervals do not have a gap between them. (2) Concurrent activities occur at the same time, thus they share the same time intervals either fully or partially. There are nine options in this case: the overlaps/overlappedby relation indicates that the two intervals have a common shared sub-interval, and one interval starts or finishes before the other; the contains/during relation is found when the interval of a composite activity encloses the interval of its composing activities; the starts/startedby and finishes/finishedby relations relate to the case of two activities that have either the same start time or finish time but one of them has a longer interval length than the other; the equals relation indicates that two activities occur in parallel and thus they start and finish at the same time [47]. Concurrent activities take place either when one user performs two different activities simultaneously or when multiple users perform activities at the same time. For example, one user can perform “watching TV” and “using the computer” at the same time, or two users can perform “drinking tea” together. (3) Interleaved activities have time intervals that “preempt” each other, which indicates that a long and complex activity has a long time

interval that contains the shorter one. The during/contains relation is also used to describe interleaved activities, but with a different meaning to the concurrent activities, since in this case the two interleaved activities are not part of the same coarse-grained activity. For example, the user may use the telephone or drink water at intervals that occur during the activity “prepare meals”.

Figure 4.1. Diagrams showing different relationships between activities: (a) composite activities; (b) sequential activities; (c) concurrent activities; (d) interleaved activities.

- *Context of activities*

Besides the variants and relationships between activities, the context of activities also plays a critical role in activity modelling since it is useful to capture activity diversity. Context is defined as “any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves” in [64]. Zimmermann *et al.* [66] extend this definition with five categories of context information: individuality context, time context, location context, activity context and relations context. This enriches the information representation of context.

Within a smart home environment, the inhabitant perform activities in a diversity of spatial, object and temporal contexts. The spatial context refers to location information, such as bedroom, kitchen and dining room. For those activities which usually take place in specific spaces, spatial context greatly contributes to the representation of the activities. For example, “preparing meals” only takes place in the kitchen and “taking a shower” only occurs in the bathroom. On its side, the object context refers to any object found in a smart home and related to an activity, either a person or a physical object. For example, if the TV set is the object, it can be inferred that we are dealing with “watching TV” activity, whereas having the broom as the object can lead to assume the “sweeping the floor” activity. Spatial context and object context are commonly used to describe and distinguish activities. Moreover, the location can help to discard some objects outside the target place. The temporal context is another key instrument for activity description, since the user may perform an activity at different times but some activities only occur at specific times of the day. It indicates the time or duration of an activity. For example, the activity “preparing breakfast” usually occurs in the morning, “preparing dinner” usually occurs in the evening and “taking shower” normally occurs once or twice a day: after waking up and/or before going to bed.

Beside the above-described commonly used context information, there are some other context information that are useful for activities characterization, including temperature, humidity and human posture. Wongpatikaseree et al. [111] use “human posture” to help improve the accuracy of the definition of the ADLs in the smart home environment. For example, currently, most of the intelligent activities monitoring systems detect “sleeping” when bed pressure sensors are triggered. However, there is a considerable uncertainty in the “sleeping” recognition defined this way, since the sensors may be triggered by the user while sleeping but also while sitting on the bed. As a consequence, human posture such as “standing”, “sitting” and “lying down” can help to recognize the activity more accurately. Figure 4.2 (modified from an original figure of [112]) depicts the conceptual description of activities characterization in smart home. Our modification consist on adding a new general relationship between activities called “relatedTo”, which allows for relations additional to “sub-“, “super-“ and “typeOf”; for instance, it would allow to specify temporal relationships

between different activities such as the ones described earlier under the “Composition of activities” epigraph.

Figure 4.2. Conceptual description of an activity characterization (modified from an original of [103]).

As shown in Figure 4.2, each node, such as actor, time and location, is called a class that can denote a type of activity. These classes can be described with a number of properties. A property of an activity is specified with its domain and range, and it is used to link two classes. For example, the property “performedBy” can link classes “Activity” and “Actor”. The domain includes all classes and the range refers to all instances of the classes that can be assigned to the corresponding property. This way, the activity can be related to other activities or conceptual entities. Properties like conditions and effects represent the causal and functional relationships, which are used for inference during activity level reasoning.

4.1.3 Formalization of activities conceptual information

Due to the heterogeneity of sensor records from different sources in smart home, the contextual information related to activities is not standardly formalized. This heterogeneity hinders interoperability, and the different context representations need separate process approaches to do further reasoning and analysis, which is not efficient for the data exchange and reusability within smart home community. The standard formalization forms the basis for

context management to facilitate expressive representation, semantic sharing and interoperability of heterogeneous computational entities, which is critical to facilitate effective designs and implementations of smart home applications and infrastructures. Figure 4.3 shows an example of three datasets collected from real world smart home environments ([113], [114] and [115]). In this sub-section, we present the most relevant approaches on activity context representation formalism found in current literature (summarized in Table 4.2). Among them, we will discuss ontologies in detail since they provide with the most powerful and complex models for activity representation.

Timestamp	Sensor	Value	sensor ID	date / time	reading
2009-08-24 20:23:43.054643	Kitchen_Stove	ON	12048146000000B2	2008-02-12 10:50:45.673225	ON
2009-08-24 20:23:56.086543	WorkArea1_Computer	ON	12D27E46000000D	2008-02-12 10:50:48.903745	ON
2009-08-24 20:23:57.002937	Kitchen_Fridge	ON	12048146000000B2	2008-02-12 10:50:49.339849	OFF
2009-08-24 20:24:19.034964	WorkArea1	ON			
2009-08-24 20:24:21.061429	WorkArea1	ON			
2009-08-24 20:24:22.078563	Kitchen_Door	ON			

Activity	sensor ID	day	activation time	deactivation time	duration (sec)	room (opt)	object type (opt)
Preparing breakfast	PDA	12/1/02	08:23:01		10 min		
	23	12/1/02	08:23:03	08:23:07	4	kitchen	drawer
	18	12/1/02	08:23:09	08:23:17	8	kitchen	cabinet
	89	12/1/02	08:24:49	08:24:59	10	kitchen	fridge door

Figure 4.3. Example of three datasets collected from real world smart home environments.

- *Key-value modelling*

Key-value modelling is almost the earliest and simplest approach in literature for contextual information modelling. This modelling is based on the simplest data structure for describing the activities based on flexible units of sensor data representation. A list of simple key-value pairs is used to define the set of attributes and corresponding value mappings as a single record. Composite Capability/Preference Profile (CC/PP) [116] is the first W3C standard context modelling approach based on a key-value-based formalism. This specification uses Resource Description Framework (RDF) language and includes elementary constraints and relationships between context types. Particularly, the key-value modelling provides

contextual information in a format that is easy to manage. However, it is not expressive enough to capture more sophisticated context data such as relationships, dependencies, time stamping and quality of the context information. Another major limitation is its lack of support for reasoning on context uncertainty or higher context abstractions.

Table 4.2. Context representation: options for its formalization.

Type	References	Advantages	Disadvantages
Key-value modelling	Aiello et al. [117] CC/PP [116]	Key-value pairs are easy to manage	Limited capacities in capturing sophisticated context types
Markup scheme modelling	McDonald et al. [118] Gonçalves et al. [119]	Allow defining interaction patterns	Lack of design criteria, only available in a limited scale
Graphical modelling	Rialle et al. [120] Henricksen et al. [121]	More comprehensive support for capturing imperfect and historical information	Flat information model, limited in supporting interoperability within context-aware systems
Object-oriented modelling	Zhang et al. [122]	Good performance in object related activity context representation	Limitation of interoperability
Logic-based modelling	Bruno et al. [123] Chen et al. [124]	Clear and elegant semantics in describing contextual information	Unable to represent uncertain context and inflexibility to represent user's habits
Ontology-based modelling	Okeyo et al. [101] Ye et al. [125] Perich et al. [126] Chen et al. [103]	Represent context in terms of heterogeneity, interoperability, and usability with user friendly interface	Require well-built knowledge engineering skills, limited ability in dealing with uncertain and changing context

- *Markup scheme modelling*

Markup scheme modelling allows to define hierarchical data structures. It consists of markup tags with attributes and content and includes a variety of markup languages including XML.

For instance, McDonald et al. [118] propose homeML, an XML-based format, as a solution for the heterogeneous nature of data records, in order to support data exchange and storage within smart home environments. They have also developed the homeML suite as an online tool to support data exchange and reuse. Markup scheme modelling approaches allow to define interaction patterns and dependencies under the consideration of contextual information, but they suffer from scalability and interoperability problems due to the lack of common design criteria, which are only available in very limited scales.

- *Graphical modelling*

Graphical modelling includes diagrammatical representation of contextual information at design phase. Unified Modelling Language (UML) is a well-known modelling instrument and the UML diagrams can be treated as strong graphical components. Rialle et al. [120] use UML context model as the standardization of telemonitoring systems representation to present the components of the system. UML models show advantages in capturing information about the static structure and dynamic behaviour of a system, but have limitations in providing precise semantics and supporting reasoning on human behaviours. Henriksen et al. [121] develop Context Modelling Language (CML) to provide graphical notions of different types of contextual information. It allows to categorize fact types (which describe types of information) in accordance with their persistence and source. The CML model has several strengths including capturing different classifications of facts, quality metadata, conflicting assertions, dependencies among various fact types and histories on the fact types. However, CML emphasizes the development of appropriate context representations for particular applications, and does not prioritize interoperability with other context-aware systems.

- *Object-oriented modelling*

Object-oriented modelling encapsulates on an object the context information and uses a set of object oriented programming principles to represent it, hence the other components of context are hidden. This approach serves to link a target activity with most of the objects with which

there is interaction. For example, the activity “watching TV” is usually related to object “TV” and the activity “sleeping” is usually related to object “bed”. Zhang et al. [122] adopt a general object-oriented context model to be used in a context-aware smart home system. In their context model, the information is structured around a set of entities, each describing a physical or conceptual object such as a person or an activity. These contextual entities are linked to their attributes and other entities by relationships. For example, a user (e.g., Ray), that is a contextual entity, may be related to an object (e.g., BedRoom), that is a contextual entity or a datatype value, by means of a verb (e.g., locatedIn). Object-oriented models take advantage of object-oriented features to encapsulate context processing and representation through well-defined interfaces. However, not all smart home services and applications adapt well to an object-oriented modelling, and there is a need of further work in terms of context semantics.

- *Logic-based modelling*

Logic-based modelling makes use of rules by which context can be derived from facts. Commonly, there are conditions defined by which a fact could be logically inferred from a set of other facts. Bouchard et al. [123] propose a logical framework to represent the contextual information gathered in a smart home using a variety of sensors. Their approach is based on description logic (DL) to overcome the problem of intra-dependencies among context items. DL is used to formalize actions, entities and variables states in smart home environments by creating a hierarchy of contextual information for the specific domain. The logical model consists of a set of conceptual and assertive objects to define the current state of the environment. When new inputs are received from hardware sensors, an agent updates the state of the environment and creates an action structure, representing the changes that happened to the environment. This approach is a highly developed logical theory of actions that is able to describe dynamically environment state changing in sorted first-order logic. In addition, it has the capability of incorporating a temporal dimension during the description process. This model has clear and elegant semantics in describing contextual information and could serve as a proper way to represent facts, expressions and rules to do further inference

and derive new facts from existing action observations. Nevertheless, this model has among its limitations its incapability of representing context information uncertainty and its inflexibility to represent multiple users' activity habits.

- *Ontology modelling*

Ontology modelling provides a semantic contextual information representation of activities. Ontology modelling is particularly interesting to represent activity contextual information since it provides a representation of concepts in a hierarchal manner that has been explicitly agreed upon. Ontology-based markup languages provide a portable specification together with reasoning mechanisms. The core elements in the formalism are concepts, instances and relationships. SOUPA (Standard Ontology for Ubiquitous and Pervasive Applications) [126] is one of the most comprehensive ontologies to provide formal and well-structured semantics for context information programming. It contains representation of generic domain knowledge (such as agents, events, space and time) in different scenarios as well as particular concepts in narrower domains (such as home and office environments). Ye et al. [125] propose a reusable formal ontology model to describe an intelligent environment context focusing on the interactions between the user and the context. Their context ontology model consists of four components: object, location, sensor and activity. The structural properties of the activities are represented by the other three concepts (object, location and sensors). Additionally, they specify two types of time conditions: occurring time and duration. For example, the activity "prepare breakfast" should occur in the morning (6am to 12am) and the activity "take shower" should not last more than 5 minutes. Chen et al. [103] propose a formal ADL ontology model to establish links between activities and contextual information through activity-based properties. They use web ontology language (OWL) for ontological modelling and representation. OWL is a formalized markup language theoretically based on the well-developed knowledge representation formalism of DL. It is primarily designed to represent contextual information about classes of objects and inter-relationships between them. The main feature of the ontology proposed by these authors (Chen et al.) is that it can model domain knowledge at two levels of abstraction: the conceptual level, in which an

activity class is described by a number of properties according to generic activity knowledge; and the specific level, in which the special way a user performs an activity can be modelled as an instance. A similar work can be found in [101]. Ontology-based representations approaches show clear advantages for context knowledge sharing among different entities by using OWL formalisms. They also work well as a solution for capturing sensor information in terms of heterogeneity, interoperability and usability with user-friendly graphic tools (e.g. protégé [127]). However, there are current limitations of this domain ontology models that must be tackled: they require solid knowledge engineering skills; they do not support time-related reasoning, they are normally computationally expensive in context reasoning; and they have limited ability to deal with uncertain and changing context of objects.

4.2 Characterization of sensors

This subsection describes the distributed hardware components used by the activity monitoring system. We focus on the most commonly used sensors for monitoring different activities in recent research and analyse their advantages and disadvantages.

4.2.1 Sensor platform

The fundamental hardware building block of an activity monitoring system is the sensor platform. It is critical to select the appropriate sensors and communication protocol for target activities. As described in Figure 4.4, a sensor platform mainly consists of the sensing interface, the microcontroller, the communication interface and the storage memory. The sensing interface represents a variety of sensors and devices for use at home environment, such as contact switches, pressure sensors and accelerometers. These sensors and devices provide the older adults and their healthcare providers insight into physical activities states and physiological health states, which are critical to detection and diagnosis. The microcontroller is the core processing unit. The communication protocol is usually based on one of four basic communication standards, namely Wifi, Zigbee, Bluetooth and USB. The sensors and devices are capable of connecting with external devices, such as computers,

smartphones or personal digital assistants, via the communication interface. Among them, the wired USB interface is used to connect sensors and devices to a computer. Zigbee and Bluetooth are short range wireless communication technologies and enable the sensors and devices to connect to nearby external devices. The long range communication protocol WiFi enables sensors and devices to communicate with cloud computing services. Finally, the storage memory is used to store the measures from the sensors and devices.

Figure 4.4. Activity monitoring sensor platform.

4.2.2 Sensors and equipment

In order to gather the context information about human activities, there are a variety of sensor and devices that are either deployed within smart home environment or worn by the user. There are mainly two categories of sensors for activity monitoring: environmental sensors and wearable sensors. Environmental sensors are used to detect context related to human activities that deal with specific objects or are performed in specific areas, whereas wearable sensors are used for monitoring ambulatory activities and physiological signals. The main characteristics of these sensors are summarized in Table 4.3.

4.2.2.1 Environmental sensors

Diverse sensors can be deployed in different home areas or attached on a range of objects to monitor activities in smart home. There are two categories of environmental sensors for activity monitoring: audio/visual-based monitoring and sensor-based monitoring. The audio/visual-based monitoring adopts audio and visual sensing devices, such as microphones and cameras, to monitor the inhabitants' movements and environmental changes. The sensor-based monitoring involves sensors embedded in the smart home environment.

Video cameras are low-cost devices that can provide a sequence of images, which is directly used to detect human actions and environmental states. Since they are capable of capturing clear information about the users, such as the number of people, they have high potential for multiple-users' activity monitoring. However, they face important difficulties including privacy issues, high computational expense and environment dependency. Microphones can provide accurate information about users' communications and sounds in specific locations, but they also present shortcomings including the high computational costs associated to the audio processing algorithms necessary to distinguish different sounds. Both video cameras and microphones pose privacy threats, since they can potentially record private conversations, thus the acceptance of audio/visual-based monitoring by the users is relatively low. This is especially true for the elderly and that is the reason why we will not elaborate further on audio and video sensors.

Radio-Frequency Identification (RFID) is commonly used for user-object interaction detecting and personal identification. Due to the unique identification, RFID is well suited for tracking multiple-users' location and interactions. Fujinami et al. [128] insert RFID tags into slippers to track the long-term daily life activities of the elderly with dementia in a group home in Japan. Philipose et al. [129] develop a system to monitor activities in a home environment by using RFID tags attached to objects. In this system, the activity information is presented with a probabilistic sequence of the used objects. RFID has as obvious advantages its small size and low cost. However, the problem of reliability and stability, especially when reading through liquid and metals, is one limitation of RFID.

Chapter 4. Characterization of activities and sensors

Table 4.3. Sensors in smart home: summary of main characteristics relevant to activity detection. The two last rows correspond to wearable sensors. All the rest are environmental sensors.

Sensor	Measurement	Data format	Advantages	Disadvantages
Video cameras	Human actions/ environmental state	Image, video	Precise information	Privacy issues, computational expense, acceptability issues
Microphones	Voice detection, other sounds	Audio	Certain and rich information about sound	Implementation difficulty and high computational cost, potential acceptability issues
Simple binary sensors	User-object interaction detection/ movements and location identification	Categorical	Low-cost, low-maintenance, easy to install and replace, inexpensive, less privacy-sensitive, minimal computation requirements	Provide simple and limited information for composite and multi-user activity monitoring
RFID	Object and user identification	Categorical	Small size and low cost	Reader collision and tag collision, range limited
Temperature sensors/ light sensors/ humidity sensors/ other similar ambient properties	Environmental parameters	Time series	Intuitive monitoring of environment and objects	Limited information for activity monitoring
Wearable inertial sensors	Acceleration/ orientation	Time series	Compact size, low cost, non-intrusiveness, high accuracy, unique identification of users, user's location easily tracked.	Cumbersome and uncomfortable feeling, cannot provide sufficient context information
Wearable vital signs sensors	Vital signs	Analog signal	Sensitive to slight change in vital signs monitoring, more accurate in emergency situation detecting	Reliability constraints, Security issues and uncomfortable feeling for long-time skin attachment

The other environmental sensors, such as light sensors, temperature sensors, humidity sensors or power sensors, have been also deployed and used in smart home environments to help in the detection of activities. Light sensors are used to measure the intensity of light in a specific location. Temperature sensors are used to measure the temperature of the objects and their surrounding environment. Humidity sensors are used to detect the air humidity in a specific area. Power sensors are used to detect the usage of electric devices. These sensors can perform intuitive monitoring of environment and objects, but on their own they only can provide very limited information for activity monitoring.

4.2.2.2 Wearable sensors

Wearable sensor-based activity monitoring has gained particular attention recently. Due to the small size of wearable sensors, they can be embedded into belts, clothes, glasses, wristwatches, shoes and mobile devices and attached to human body either directly or indirectly to provide a continuous flow of information. There are mainly two categories of wearable sensors: inertial sensors and vital sign sensors.

Wearable inertial sensors can give accurate descriptive features of user's movement and body posture. Accelerometers are probably the most frequently used sensors for ambulatory activity monitoring. They can measure the value of acceleration along a sensitive axis and are particularly effective in monitoring activities related to body motion such as doing exercise, walking, standing, sitting, or walking upstairs and downstairs. Data collected from accelerometers has four attributes or dimensions: time, acceleration on x-axis, acceleration on y-axis and acceleration on z-axis. Together, they provide information to identify human movements depending on frequency and tilt, which are critical to assess the posture. Recent researches carry out experiments placing accelerometers on different body parts, such as wrist, chest and ankle, for identifying the optimal activity monitoring performance. A summary of different placements of accelerometers found in recent research and experiments is given in Table 4.4. Gyroscopes are used to sense the rate of orientation change in terms of angular and velocity. In most studies, gyroscopes are generally used combined with the

accelerometers in the field of ambulatory activities monitoring. Due to their small size and relatively low cost, wearable inertial sensors can be used for long-time continuous activities monitoring and emergency situation recognition such as fall detection. However, the wearable inertial sensors also suffer from some limitations. Due to the long-time attachment on the body, which may lead to uncomfortable feeling, there exist practical issue of the acceptability and willingness to use the wearable inertial sensor by the user. Additionally, wearable inertial sensors provide only information about body movements, it is a challenge to provide information about the activities involve the environment changes.

Vital signs sensors, also known as biosensors, can provide bio-measurements, such as heart rate, blood pressure and skin temperature, which are critical for elderly people's health condition monitoring during the execution of activities. The commonly used vital signs sensors include Electroencephalography (EEG) sensor, Electrooculography (EOG) sensor, Electromyography (EMG) sensor and Electrocardiography (ECG) sensor. EEG sensors measure the electrical activity of brain, which is useful for detecting sleep state, panic disorder, and sudden unexplained nocturnal death syndrome. EOG sensors measure the electrical ocular activity, which is used to provide information on the state of the user by detecting eye movements: rapid eye movements would indicate that the person is awake, and slowly rolling eye movements would indicate that the user is in the state of transition from being awake to sleeping. EMG sensors measure the electrical activity of muscle, Muscle activity may occur in different parts of the body. For instance, a more intense activity of chin muscles may represent chewing or drinking. ECG sensors measure the electrical activity of the heart, which gives indications of arrhythmias. Other used vital signs sensors include: pressure sensors for monitoring blood pressure, which shows immediate changes of user's health state such as nose bleeding; CO₂ gas sensors for monitoring respiration, which involves measuring airflow though nose and mouth; thermal sensors for monitoring body temperature, which can be used to detect fever; Galvanic Skin Response (GSR) for monitoring skin sweating, which is a good indicator of sport and housework activities.

Chapter 4. Characterization of activities and sensors

Table 4.4. Different placements of accelerometers on human body for activity monitoring.

References	Number of sensors	Placements	Activities
Gjoreski et al. [130] (2011)	1 to 3 accelerometers	Chest, left thigh, right ankle	Standing, sitting, lying, going down, standing up, sitting on the ground, on all fours
Jiang et al. [131] (2011)	4 accelerometers	Left forearm, right forearm, left shank and right shank	Standing straight, sitting on a chair, lying on a bed, walking, jogging, cycling, walking on an elliptical machine, running on an elliptical machine, rowing and weight lifting.
Jennifer et al. [132] (2011)	1 accelerometer	Smartphone	Walking, jogging, upstairs, downstairs, standing, sitting
Zhu and Sheng [133] (2011)	1 accelerometer	Right thigh	Sitting, standing, lying, walking, sit-to-stand, stand-to-sit, lie-to-sit, sit-to-lie
Siirtola et al. [134] (2012)	1 accelerometer	Smartphone placed in trousers' front pocket	Walking, cycling, sitting, standing, driving a car
Hemalatha and Vaidehi [135] (2013)	1 accelerometer	Chest	Standing, walking, sitting, lying, fall
Mannini et al. [136] (2013)	1 accelerometer	Wrist/ankle	26 daily activities
Zheng et al. [137] (2013)	1 accelerometer	Wrist/hip/waist pocket	Lying, sitting, standing, walking, running, dancing, jogging, upstairs, downstairs, skipping
Muaaz et al. [138] (2014)	1 accelerometer	Waist, right-hand side of the hip	Walking
Gao et al. [139] (2014)	4 accelerometers	Chest, left under-arm, waist and thigh	Lying, sitting, standing, flat walking and up & down stairs, lie-to-stand, stand-to-lie, sit-to-stand, stand-to-sit

Vital signs sensors, similarly to wearable inertial sensors, have as advantages their low cost, low error, low-intrusiveness and high accuracy. Besides, they are very sensitive to slight changes of physiological signals, and thus they can support non-invasive alternatives for continuous healthcare monitoring in smart home environments. The disadvantages of biosensors include reliability constraints and uncomfortable feeling for long time skin attaching.

Generally, in terms of mobile computing, wearable sensors are gaining more attention than environmental sensors, especially since wearable technology has experienced a rapid development. However, it is clear that wearable sensors are not sufficient for monitoring complex activities that involve similar physical movements (e.g. make coffee and make tea) nor for detecting multiple interactions with the environment. In terms of environmental-aware applications, environmental sensors show stronger ability for monitoring activities than wearable sensors.

Chapter 5 Materials and methodology

5.1 Data-driven materials and methodology

We have designed, deployed, executed and assessed the results of a set of experiments related to the recognition of three types of activities, namely stationary activities, dynamic activities and transitional activities. These basic activities form part of those activities that are necessary to take care of oneself and commonly occur in real daily life.

The experiments are based on a contextual sensing infrastructure that is solely composed of three accelerometers placed on different body parts of each test participant, and they follow a data-driven methodology that will be described in this section. The results of the experiments will be detailed in next chapter.

The aims of the experiment will be assessed through the following objectives:

- To assess usability and acceptability of wearable inertial sensors in the tested individuals.
- To assess the impact of accelerometers and the placements of accelerometers on physical and daily activity recognition in tested individuals.
- To assess the performance of data processing methods and machine learning algorithms on the activity recognition accuracy.

We will elaborate through the components of the materials and methods we have used by following this structure:

- First, we specify the experiment design and the data collection and annotation tasks that we have followed, which provide next phases with the set of raw and annotated sensor readings sequence.
- The next logical step is the data processing stage that includes an ordered set of mechanisms leading to a final decision on the activity to which each data segment most likely belongs. We will provide with the rationale behind each data processing stage adapted to accelerometer data treatment, discussing the current proposals found in research literature.
- After having presented in a general way the data collection & processing methodologies, we will describe the methodology we have followed to define and assess the two contributions we propose on the classifying and data segmentation phases respectively.

5.1.1 Experiment design, data collection and data annotation

To reach to a precise and useful global data classification system that is capable of identifying the three types of activities we aim for, it is crucial to start with a correct design and deployment of the data collection and annotation phases. The data collected has to contain the necessary features and has to be correctly annotated in order to train the posterior classification phases.

5.1.1.1 Experiment design

Of the types of activities we want to recognize, static activities, such as standing and sleeping, and dynamic activities, such as walking and running, are not limited by duration. However, transitional activities, such as stand-to-sit and sit-to-stand, commonly have a limited duration, and are characterized by start and end times which usually vary slightly from one person to another [140]. Taking this into account, the experiment is designed so that static and dynamic

activities can be executed continuously during a period of time, whereas transitional activities are executed repeatedly to get separate samples.

We plan to recognize twelve activities: standing, sleeping, watching TV, walking, running, sweeping, stand-to-sit, sit-to-stand, stand-to-walk, walk-to-stand, lie-to-sit and sit-to-lie (see Table 5.2 below). A summary of the experiment setup to collect the data related to these twelve activities is shown in Table 5.1.

Table 5.1. Experiment setup.

Sensors	Three accelerometers in SHIMMER3 platforms ⁴ (the calibration time has to be taken into consideration)
Placement	Right wrist, chest and right ankle
Sampling rate	102.4 Hz
Mode	In the controlled laboratory environment, the subjects perform the activities by following verbal guiding instructions
Data collection and analysis devices	Android phone and windows PC
Software	ShimmerCapture/Matlab/Consensys
Communication Protocol	Bluetooth
Test participants	10 adults (3 females and 7 males)

- *Sensing devices*

The SHIMMER wireless sensor platform (Shimmer 3, Realtime Techniques, Dublin, Ireland), developed by Intel Digital Health Advanced Technology Group, was used to record the raw data for the investigation. It is a compact, wearable sensing platform with an integrated three-axis accelerometer, which runs on the TinyOS operating system. It contains an on-board tri-axial accelerometer, with a configurable sampling rate up to 1 kHz and an amplitude range up to $\pm 6g$ [141]. Sensor data from this tri-axial accelerometer is transmitted via Bluetooth to a PC. The selection of this platform is justified by its sufficiently small size and weight

⁴ <http://www.shimmersensing.com/shop/shimmer3>

(53mm*32mm*25mm in size and 22g in weight), so that it can be comfortably worn by the participants and is well suited for long-term wearable activity monitoring applications.

SHIMMER is a research prototype experimental device and thus it has not been fully tested to be launched as a commercial product meeting all medical class regulatory approved standards. Consequently, there are some risks associated with the design and manufacturing that are assumed when using the device in close proximity of the body of a test subject. To counteract these risks, the device has been electrically isolated from the subject's body during the course of the study.

- *Participants*

Ten healthy adults (3 females and 7 males) with no known neuromuscular, musculoskeletal, or cardiovascular pathology were recruited to participate in this study from the University of Ulster. To reassure the individual regarding confidentiality, it was made explicitly clear in the participant information sheet and again when collecting consent from the participant that no identifiable information would be collected. Each participant was assigned with an ID number on entry to the trial in order to ensure confidentiality.

The participants were asked to perform the 12 activities according to the experiment protocol in a controlled laboratory environment. A tri-axial accelerometer was attached at each participant's right wrist, chest and right ankle by using a custom belt. These placements were selected as it is unobtrusive and comfortable for the wearer and is one of the most common locations to place accelerometers in physical activity monitoring. Previous research has shown sensors on the wrist provided reasonably good rates of precision and recall for some fine grain activities [142].

- *Experiment protocol*

The experiment protocol consisted of asking participants to perform a guided sequence of twelve scenarios corresponding to the physical activities, by using voice instructions. Table 5.2 shows the classification and description of the twelve activities into the three considered

types. Participants were told what activity to perform but not specifically how to perform it, thus this experiment protocol allowed for natural participant variability in how activities are performed. For stationary activities, each participant was asked to perform standing still, sleeping on the sofa and watching TV. Participants can choose the posture that they find comfortable, small movements such as changing lying posture during sleeping and changing sitting posture during watching TV were allowed. For dynamic activities, each participant was asked to perform walking on a treadmill with the preferred speed, running on the treadmill with the preferred speed and sweeping with a vacuum cleaner around the home area. All stationary and dynamic activities were performed for 5 minutes each. For transitional activities, each participant was asked to perform the three pairs of activities (stand-to-walk-to-stand, stand-to-sit-to-stand and sit-to-lie-to-sit), being each pair performed for 45s, then repeated 15 times. The protocol took approximately 1 hour for each participant to complete.

Table 5.2. Description of the monitored activities in experiment.

Type	Activities	Description
Stationary Activities	Standing	Standing still for 5 minutes.
	Sleeping	Sleeping on the sofa for 5 minutes, small movements such as changing the lying posture are allowed.
	Watching TV	Watching TV while sitting on the sofa in whatever posture the participant feels comfortable for 5 minutes, changing sitting posture is allowed.
Dynamic Activities	Walking	Walking on treadmill with a set speed for 5 minutes.
	Running	Running on the treadmill for 5 minutes.
	Sweeping	Sweeping with the vacuum cleaner in the home area for 5 minutes.
Transitional Activities	Stand-to-sit	Standing still for 15s and then sitting on the sofa, repeat 15 times.
	Sit-to-stand	Sitting on the sofa for 10s and then standing up, repeat 15 times.
	Stand-to-walk	Performing the “stand-to-walk-to-stand”, standing still for 15s then start to walk, keep walking for 15s, then standing still for 15s, repeat 15 times
	Walk-to-stand	
	Lie-to-sit	Lying on the sofa for 15s and then sitting on the sofa, repeat 15 times.
	Sit-to-lie	Sitting on the sofa for 15s and then lying down, repeat 15 times.

5.1.1.2 Data collection

Data were collected in the smart home located in Ulster University. Prior to data collection, the device was calibrated when placed in orthogonal orientations using standard calibration techniques as described in [143]. Raw acceleration data were collected with a sampling rate of 102.4 Hz and an amplitude range of $\pm 2.0g$ (g is the gravitational acceleration and equals 9.8 m/s^2). Consistent sampling allowed both time domain and frequency domain signal analysis. Previous studies have demonstrated that human movements can be captured and modelled by signals below 18 Hz [144]. Thus a sampling rate of 102.4 Hz was considered to be more than sufficient for capturing transitional activities as well as activities of daily living. The sensed data of each participant were first stored in the memory card embedded into the SHIMMER wireless sensor platform, then exported to a separate spreadsheet file in a notebook computer for later offline analysis. In this research, we only used the data collected from the accelerometer placed at right wrist. The format of the collected data was {timestamp, acceleration-X, acceleration-Y, acceleration-Z}.

Figure 5.1. An example of the acceleration data along three axis captured during a walking activity.

Figure 5.1 shows an example of the acceleration data captured along X, Y and Z axis during a walking activity. As a result of the complete data collection phase execution, a dataset of over ten hours, containing 4,020,288 raw data instances, was acquired.

Figure 5.2. Collected accelerometer data for twelve identified activities.

5.1.1.3 Data annotation

The collected data were annotated during the activities execution by using the information of voice instructions, then labelled with start time and stop time of a manually observed activity. Given the short duration of the transitional activities and the potential for a delay in the participant performing the activity after having given the verbal command, the following

labelling procedure was undertaken for transitional activities. The duration of transitional activities has been proven to be from 1.45 seconds to 3.49 seconds [145]. Taking the different reaction times of participants into consideration, 4s was used to label the transitional activities in order to be sure to cover the whole transitional phase. Figure 5.2 shows collected accelerometer data corresponding to the twelve identified activities. Consequently, 2160 seconds of stably collected accelerometer raw data were labelled with the twelve activities that were being performed at each time. These labelled data is useful to calculate training parameters or testing feature vectors later.

5.1.2 Accelerometer data processing methodological options

According to the current literature, a generic data-driven methodology for accelerometer-based activity recognition is composed of five key issues:

1. *How to preprocess the acquired sensor signals?* This issue mainly deals with filtering, such as low-pass filtering and high-pass filtering, to remove noise contained in the raw signals. In addition, the sample acquisition frequency should be taken into consideration to be able to obtain the interesting part of the signal.
2. *How to divide the signal stream into smaller segments?* It is more adequate to extract meaningful features from signal segments than from single data records. Thus the selection of the segmentation method, which divides the signal stream into smaller segments, depends on the characteristics of the signals.
3. *How to generate the proper features that can adequately describe the characteristics of the signals?* The segmented data should be transformed into proper features, which capture the main characteristics of the signals. Commonly used features are defined on the time domain, frequency domain and discrete domain.
4. *How to select the most meaningful features?* Not all the features are necessary or significant to be used for activity modelling. In order to select the set of most relevant and least redundant features, the proper feature selection methods should be used.

5. Which machine learning technique can be applied to model the activity? Reliable models of activity recognition are needed to learn the complex relationships between the features and performance classes. The selection of the adequate machine learning technique is important to build activity models.

Figure 5.3. The typical procedure of activity recognition that consists of data preprocessing, data segmentation, feature extraction, feature selection and machine learning techniques.

This methodology translates into a typical activity recognition procedure consisting on a sequence of stages, namely: data preprocessing, data segmentation, feature extraction, feature selection and machine learning techniques for classification (as shown in Figure 5.3). On occasions, an additional stage is necessary if the class distribution imbalance problem is present. In this case a class distribution rebalancing task has to be introduced just before the classification. The input data to the complete activity recognition procedure consists of signal streams that have been collected using accelerometers worn on the body and annotated.

In the following subsections, we introduce the main methods used in current research literature for each aforementioned stage, up to the class distribution rebalancing.

5.1.2.1 Data preprocessing

Raw data gathered from sensors has a certain degree of erroneous, noisy and redundant information caused by discharged batteries, failures in sensor readings and intermittent communication loss typical of wireless sensor networks. To compensate for these effects, data cleaning is necessary. This set of techniques is used to smooth out raw data by filtering out artifacts and removing unwanted information and noise, in order to only keep the characteristics of signals that carry relevant information. To do so, several filters are used which have to be in accordance with the characteristics of the sensor.

The 3D acceleration data collected from any accelerometer contains a constant component due to gravity. The effect of gravity should be eliminated in order to obtain the real acceleration experimented by the device. Khan et al. [146] apply a low-pass filter to isolate the constant gravity acceleration in the time series dataset collected from accelerometers. Wang et al. [147] compare the noise reduction performance of four filters (median filter, Kalman filter, low-pass filter and discrete wavelet package shrinkage) on the acceleration signals captured by a nine-axis wireless body sensor network platform. The results show that, in terms of signal-to-noise ratio (SNR) and correlation coefficient (R) between filtered and reference signals, the Kalman filter exhibits the greatest figures, followed by the median filter and the discrete wavelet package shrinkage, the low-pass filter being the one with the worst performance due to the waveform delay it causes. The authors also found that window length has great impact on the real-time performance of the median filter and the inappropriate choose of filter order and cut-off frequency would lead to large waveform delay of low-pass filters.

5.1.2.2 Data segmentation

Data from sensors usually comes as a continuous flow of raw data. This is because sensors will basically provide instant measurements of the monitored phenomenon, either when requested or at periodic intervals. One of the main challenges related to sensory data preprocessing is to achieve a proper division of this raw and continuous data flow into smaller blocks of information that ideally contain one activity each. This is the purpose of segmentation methods. The proper selection and parameterization of segmentation techniques has great potential impact on the success of feature extraction and inference algorithms, directly resulting in the accuracy of activity monitoring and recognition.

The sliding window segmentation approach is one of the most widely used segmentation techniques for activity monitoring [148]. By using this approach, the continuous sensor data flow obtained by accelerometers are divided into windows with either static or dynamic sizes. In the former case, the fixed window size can be based on equal time intervals. Two segmentation algorithms are of particular interest in current literature: Fixed-size Non-overlapping Sliding Window (FNSW) and Fixed-size Overlapping Sliding Window (FOSW) [149] [150]. FNSW is a simple segmentation approach without any data overlap, thus the amount of windows can be exactly calculated. However since this algorithm works with a fixed window size, the data associated with a particular event such as a fall could be split in different windows, resulting in important loss of information. FOSW includes data overlap between adjacent windows, and the different overlapping percentages can be referred to as window shifts. Authors of [151] set up an experiment to compare the classification accuracy of FOSW with different window overlap values (0%, 25%, 50%, 75% and 90%) applied to acceleration data for recognizing ambulatory activities. Their work determined that the optimal segmentation approach was FOSW with 90% of window overlap and 12 s of window size, reaching a classification accuracy of 98.38%. Dynamic sliding window approach enables varying window sizes based on different sensor features (such as sensor state change or location change of consecutive sensor data) and/or on typical activity duration. Noor et al. [152] proposed a dynamic sliding window method to segment the data obtained by a single

accelerometer for monitoring static, dynamic and transitional activities. The window size could be dynamically adjusted by using signal information to determine the most effective segmentation. Krishnan et al. [153] proposed and evaluated a combination of static and dynamic sliding window sizes. They improved the sliding window approach with three modifications, oriented to calculate the size of the window to be used at each moment depending on the sensor data, the environment and the monitored activity, to capture the relationship between sensor events within a window and between multiple windows.

Table 5.3. A range of different window sizes used in current literature.

Reference	Sensors	Monitored activities	Window size	Classification accuracy
Kwapisz et al. [132]	1 accelerometer	Walking, jogging, ascending stairs, descending stairs, sitting and standing	10s	91.7%
Siirtola et al. [134]	1 accelerometer	walking, running, cycling, driving a car, sitting and standing	7s	95.8%
Jiang et al. [131]	4 accelerometers	Standing, sitting, lying, walking, jogging, cycling, running, rowing, weight lifting	6s	95.1%
Chernbumroong et al. [154]	1 accelerometer, temperature sensor, altimeter	Feeding, brushing teeth, dressing, walking, walking upstairs, walking downstairs, sleeping, washing dishes, ironing, sweeping, watching TV	3.88s	90.2%
Ortiz et al. [90]	1 accelerometer	Standing, sitting, lying, walking, walking downstairs and walking upstairs, stand-to-sit, sit-to-stand, sit-to-lie, lie-to-sit, stand-to-lie, and lie-to-stand	2.56s	92.2%
Gao et al. [139]	1 accelerometer	Lying, sitting, standing, walking, lying-standing, standing-lying, sitting-standing, and standing-sitting.	1s	92.8%

One challenge in sliding window segmentation approach is to optimize the window size by considering both short and long duration activities. In current literature, a wide range of window sizes are adopted depending on the different monitored activities (see Table 5.3). Fida et al. [155] presented the impact of window size on the recognition of both short duration, such as sitting, standing and transitions between activities, and long duration activities, such as walking. They found that 1.5 s window size represented the best trade-off value for recognition among activities. Banos et al. [156] evaluated the effect of different window sizes on 33 different fitness exercises recognition with a non-overlapping sliding windowing approach. These window sizes ranged from 0.25 s to 7 s in steps of 0.25 s. As a result they proved that short windows normally resulted in better recognition performance, and the interval 1 s to 2 s exhibits the best trade-off between recognition speed and accuracy from a global perspective. In general the sliding window-based approach is appropriate for data streams that are continuously obtained by sensors over a relatively long period of time. Furthermore, it requires less computational complexity than other methods. Nevertheless, the selection of the optimal value for the time interval is a critical issue. Too small an interval may split one activity into two adjacent windows, especially for a long duration activity such as cooking, resulting in a lack of sufficient information to arrive to an accurate classification. On the other hand, a too wide interval may gather two or more activities into the same segment and add extra noise for further data processing. Thus, one of the novel proposals that we will describe later consists on dynamically detecting changes in a user's activity and subsequently utilizing these transitions in activity as window starting positions. For activities with durations greater than the window length this approach helps to ensure that each window only contains sensor values for a single activity.

Activity-based segmentation consists in dividing the sensory data stream by identifying the start and end points of each activity. As a consequence, the main issue to be tackled for these methods is the correct identification of those boundary instants. Various methods are proposed in the literature to identify the beginning and ending points of activities. Yoshizawa et al. [157] proposed a method to identify these limits, distinguishing between static activities (such as standing and sitting) and movement-related ones (such as walking and running). In

their approach, a threshold was set for detecting the changing points of static activities, and the analysis of variations in the frequency domain was used for determining the beginning and ending points of movement-related activities. A similar work can be read in [158], where the authors proposed a model based on wavelet decomposition to separate into segments the continuous data records collected from an accelerometer. This model detected frequency changes for the location of three walking activities' limits (walking, ascending stairs and descending stairs). Another method to identify the beginning and ending points of an activity was achieved by asking the user to give explicit feedback. In [159], volunteers in the experiments were asked to stand still for a few seconds between two activities to identify these transition points. A similar method was used in [160], where the subjects were asked to set the beginning and ending points of daily life activities such as cooking and cleaning through a smart phone interface. Obviously, this method was only feasible in laboratory environments. Moreover, the participants performed the activities following instructions from experts, thus leading to potentially artificial behaviours (i.e. not totally equal to the ones that would be observed in real life).

5.1.2.3 Feature extraction

The next step consists on extracting the features that best represent the activity characteristics from each segment. A wide range of features which characterize segments of data stream have been used in previous activity recognition studies. By using these features, the data stream is transformed into a set of features vectors, which contain proper information and can be used as the inputs to classification schemes. In this sub-section, we present the different features used in activity recognition in three categories: time domain features, frequency domain features and discrete domain features. Table 5.4 summarizes the main features that can be extracted in each of these three domains.

The time domain features are typically mathematical and statistical indicators that are directly derived from a segment of data stream. Among time domain features, the mean is the most common for almost all sensor types due to its low computational cost and minimum memory

requirements. It can be used to identify the human posture, such as standing, sitting and lying, and discriminate static from dynamic activities. The standard deviation, which represents the stability of a signal around its mean, is frequently used as the basic metric for classifiers or threshold-based algorithms. The median, on its side, is very useful to replace missing values from a sequence of discrete measurements. The range is defined as the difference between maximum and minimum sample values, and it is typically used to discriminate walking from running. Other time domain features include root mean square (RMS), correlation, difference, and angular velocity.

Table 5.4. Taxonomy of extracted features in three domains.

Domain	Extracted features
Time domain	Mean, Median, Average, Variance, Standard Deviation, Minimum, Maximum, Range, Root Mean Square (RMS), Correlation, Cross-Correlation, Zero-Correlation, Integration, Differences, Velocity, Signal magnitude area (SMA), Signal vector magnitude (SVM), Zero-crossing.
Frequency domain	Wavelet Transformation, Fourier Transform (DC component, Key Coefficients, Coefficients sum, Dominant frequency, Spectrum Energy, Spectrum Entropy, Spectrum centroid, Skewness, Kurtosis)
Discrete domain	Euclidean-based Distances, Dynamic Time Warping, Levenshtein Edit Distance

Frequency domain features focus on the repetitive nature and the periodic structure of a sensor signal, which usually relates to specific activities such as walking or running. Wavelet transformation is mainly used to detect the transition between different activities due to its ability to capture sudden changes in signals, especially in acceleration ones. The Fourier transform can be computed for a time-based discrete signal over a specific window length by using algorithms such as the Fast Fourier Transform (FFT) and the Fast Time Frequency Transform (FTFT). The output of a FFT provides information on the amplitudes of the frequency components and energy distribution of the signal. The mainly used frequency domain features include spectral energy, entropy, Skewness, and Kurtosis.

Discrete domain features are used to map sensor signals into strings of discrete symbols. They can be used to represent both time and frequency characteristics of the signal. These features allow the signal to be decomposed into a set of coefficients, each coefficient containing information on a specific frequency band, thus they can represent the signal between temporal changes in frequency content along the entire length. Euclidean-based Distances, Dynamic Time Warping and Levenshtein Edit Distance are key approaches used to evaluate string similarity for classifying human activities and modelling behavioural patterns.

5.1.2.4 Feature selection

Different users may perform one activity in diverse ways, which may lead to variability of the extracted features. On the other side, there may exist features that are almost irrelevant or redundant for the purpose of activity detection. Extracting the feature combinations that are most reliable for a specific activity recognition purpose can positively affect system performance, and this is the aim of the feature selection methods.

There are several benefits of applying a feature selection method. Firstly, it can reduce the dimensionality of feature inputs, leading to the reduction of computational expense needed for the machine learning algorithms. Secondly, less features result in simpler models, which are more robust and have less variability on datasets. Simpler models vary less relying on the particularities of a single samples, such as outliers and noise. Thirdly, if the dataset can be represented with fewer features without loss of information, better ideas can be produced from the visual analysis to define the structure and determine the outliers.

In current literature, a number of feature selection methods have been used according to the different characteristics of extracted features. These feature selection methods choose the features mainly in two ways: ranking and selecting. Feature ranking adopts a metric to rank the features then the features which do not satisfy an adequate score are eliminated. The Information Gain method and Relief-F method are the most commonly used ranking feature selection methods. Ranking feature selection method benefit from their scalability, simplicity

and efficient computation. Selecting methods search for the optimal subset that consists of possible features. Maurer et al. [161] used Correlation-based Feature Selection (CFS) on an accelerometer dataset. This method is convenient since it is built in WEKA⁵, an open source tool widely used for machine learning. Optimal features are selected under the assumption that these features are highly correlated with the given class and loosely correlated between different classes. Some other methods, including SVM-Based Feature Selection, Sequential Forward Floating Search, and Forward-Backward Sequential Search, are also used to select the most relevant features from a high dimensional feature vector. The main advantage of selecting methods is that they consider the relations between the features, since they look for optimal subsets of features instead of scoring each feature individually as ranking methods do.

5.1.2.5 Class distribution rebalance

There is an important issue related to datasets obtained from smart environments which may highly impact on further data analysis and classification accuracy. This problem is called class imbalance (i.e. classes which exhibit much more samples than others, causing uncompensation in training). In our case, this problem is very likely to be present since the much shorter duration of transitional activities causes that much less samples are captured associated to them than to dynamic activities.

It is widely accepted that a dataset containing less than 10% of minority class samples is considered as an imbalanced dataset [162]. The under-representation of minority classes compared to the majority classes may restrict the performance of classifiers on the dataset, since the machine learning algorithms aim to optimize the classification accuracy for the whole set of available samples and not considering those that belong to minority classes leads to their incorrect classification. Sometimes the correct classification of the minority classes samples is very important for real-life scenarios.

⁵ <http://www.cs.waikato.ac.nz/ml/weka/>

The resampling technique is the most commonly used technique for addressing the dataset imbalance problem. It rebalances the class distribution by increasing the samples of minority classes or reducing the samples of majority classes. Goodwin et al. [163] use an under-sampling technique to deal with the unknown classes in an acceleration dataset. In their experiment the majority class consists of not labelled motor movement samples, and under-sampling is performed on them to balance the dataset by discarding a proportion of the samples in this class.

Figure 5.4. The conceptual scheme of the proposed ensemble classification approach.

5.1.3 Ensemble classification methodology

This proposal consists on testing the benefits that the application of an ensemble of heterogeneous classifiers to a balanced dataset containing samples from the 12 considered activities has on the classification accuracy of the whole data-driven activity detection procedure. We observed from the review of previous literature that current ADL detection proposals do not cope equally well for all types of activities (static, dynamic and transitional), and consequently our objective was to find an activity detection method that would exhibit good performance numbers for all of them. The procedure described in this section has been performed during the research stay that the PhD. student has made at the Smart Environment Research Group of University of Ulster. Figure 5.4 shows the conceptual scheme of the proposed ensemble classification approach.

The raw signal data are preprocessed to remove the unwanted noise and separate the body acceleration from gravity acceleration. Then the continuous signals are segmented into windows; for each window in the dataset 77 features are extracted by the feature extraction process. Based on this, the feature selection method is used to select the optimal feature subset by choosing relevant features and removing redundant ones. A resampling technique is applied to rebalance the class distribution in the dataset. After this, the heterogeneous ensemble classification model proposed herein is built by using a majority voting function to combine the results of the base classifiers. The computational procedure of the proposed approach is illustrated in Figure 5.5.

Regarding the concrete tools utilized, the acquired acceleration signals from the wrist accelerometer are analysed using custom MATLAB programs (MathWorks, Natick, MA) and the classification task is implemented using Weka. In the following we detail the concrete methods utilized for each phase of the procedure.

Require:
X: Raw acceleration dataset
Y: Raw activity label array
f1(): Low-pass Butterworth filter with 20Hz cut-off frequency
f2(): Median filter
f3(): High-pass Butterworth filter with 0.3Hz cut-off frequency
buffer(): Segmentation function
 $\alpha()$: Feature extraction function
 $\beta()$: Windows discarding function
 $\mu()$: Feature selection function
resampling(): SMOTE with a 1200% boosting oversampling

procedure SignalPreprocessing(X)
filteredX = f2(f1(X)); // remove the noise
BX = f3(filteredX); // get the body acceleration
GX = X – BX; //get gravity acceleration
return BX, GX
end procedure

procedure ObtainFeature(BX, GX, Y)
(SBX, SGX, SY) = buffer(BX, GX, Y); // segment signal into 256 samples
frames with 50% overlapping
A = α (BX,GX); //extract time and frequency domain features
B = mean (Y);
(A', B') = β (A,B); // discard the windows that contain multiple activities
(Asub, Bsub) = μ (A', B'); // select feature subset
return (Asub, Bsub)
end procedure

procedure Classification (Asub, Bsub)
(x, y) = resampling(Asub, Bsub); //get balanced features samples
Split (x, y) into training set Ttraining and testing set Ttesting ; //use 10-fold
cross validation
for n = 1 to 10 do
/***Traning***/
for all (xi, yi) $\in$ Ttraining do
Build heterogeneous ensemble model C;
end
/***Testing***/
for all (xj, yj) $\in$ Ttesting do
Apply (xj, yj) on ensemble model C;
end
end
return classification accuracy
end procedure

Figure 5.5. Pseudo code of computational procedure of the proposed ensemble approach.

5.1.3.1 Data preprocessing

Generally, acceleration data collected in real-world scenarios contain noise. This noise may be introduced by either external vibration not produced by the body itself, or by movement of the sensor against the body due to loose coupling. Since essentially all measured body motions are contained within frequency components below 20 Hz [164], a third-order low-pass Butterworth filter with cutoff frequency at 20 Hz is used to remove high frequency noise and smooth the graphs. After that, the acceleration data is filtered by a third-order median filter to remove abnormal noise spikes and solve the signal delay problem caused by the low-pass Butterworth filter. Figure 5.6 gives an example of raw accelerometer data and data filtered by the third-order low-pass Butterworth filter and third-order median filter.

Figure 5.6. Raw (blue) and filtered (orange) accelerometer data.

Additionally, the acceleration data collected from the accelerometer is decomposed into body acceleration (BA) component and gravity acceleration (GA) component. The BA component caused by the body movement can be used to distinguish motional activities from the static activities. The GA component caused by the gravity can be used to estimate the posture orientation of a participant when performing the activities. In order to separate the two components of the filtered signal, a third-order high-pass Butterworth filter with cutoff frequency at 0.3 Hz is firstly applied to extract the BA component from the filtered signal,

then the GA component is obtained as the difference between the filtered signal and the BA component. Figure 5.7 gives an example of body acceleration component and gravity acceleration component extracted from the filtered accelerometer data.

Figure 5.7. BA (orange) and GA (yellow) components extracted from the filtered accelerometer data (blue).

5.1.3.2 Data segmentation

In order to test the ensemble classifier proposal we have chosen a simple Fixed-size Overlapping Sliding Window segmentation method, and we will later discard all windows that contain data from more than one activity.

After the preprocessing phase, the dataset, consisting of the BA and GA components and the activity labels, is divided into windows of 256 samples each with 50% overlap between two consecutive windows. Therefore, each classification task made about the activity is performed on windows with a duration of 2.5 seconds (recall from the description of the experiment design that the sampling rate is 102.4 Hz, thus each 256-sample window lasts for 2.5 seconds).

Figure 5.8. Feature extraction procedure performed on the segmented accelerometer data.

5.1.3.3 Feature extraction and selection

After segmentation, a feature vector consisting of both time-domain features as well as frequency-domain features is calculated on each windowed data. The extracted features are obtained by processing the acceleration values of X-, Y-, and Z-axes of both BA component and GA component. The signal magnitude vector (SMV) is also used to extract features. The SMV provides a measure of the degree of body movement intensity, which can be calculated by using the tri-axial acceleration values [165]. The formula is as follows:

$$SMV_t = \sqrt{x_t^2 + y_t^2 + z_t^2} \quad (5.1)$$

Where x_t, y_t, z_t refer to the acceleration values of X-, Y-, and Z-axis, respectively, at the sampling time t .

A total of 77 features are calculated on each window, as shown in Figure 5.8.

Table 5.5. Features extracted in time and frequency domains.

Features domain	Features	Formulation	Data values	Number of features
Time-domain features	Mean	$\frac{1}{n} \sum_{i=1}^n x_i$		
	Root mean squared (RMS)	$\sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2}$	BA-X, BA-Y,	40
	Standard deviation (STD)	$\sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2}$	BA-Z, GA-X,	
	Median absolute deviation (MAD)	$median(x_i - median_j(x_j))$	GA-Y, GA-Z,	
	Range	$\max_i(x) - \min_j(x)$	BASMV, GASMV	
	Signal magnitude area (SMA)	$\frac{1}{n} \sum_{i=1}^n x_i + y_i + z_i $	BA, GA, BASMV, GASMV	4
Frequency-domain features	Correlation coefficient	$cov(x, y) / \sigma_x \sigma_y$	BA-XY, BA-YZ, BA-XZ, GA-XY, GA-YZ, GA-XZ,	6
	Tilt angle (TA)	$\tan^{-1}(x / \sqrt{y^2 + z^2}) * 180 / \pi$	BA-X, BA-Y, BA-Z	3
	Spectral energy	$\frac{1}{n} \sum_{i=1}^n x_i^2$		
	Spectral entropy	$\sum_{i=1}^n (c_i \log(c_i)), c_i = s_i / \sum_{j=1}^n s_j$		
	Skewness	$E\left[\left(\frac{x - \bar{x}}{\sigma}\right)^3\right]$	BA-X, BA-Y,	24
Frequency-domain features	Kurtosis	$E[(x - \bar{x})^4] / E[(x - \bar{x})^2]^2$	BA-Z, BASMV	
	Largest frequency component	$\arg \max_i(x_i)$		
	Frequency signal weighted average	$\sum_{i=1}^n (ix_i) / \sum_{j=1}^n x_j$		

Commonly used time-domain statistical features, such as mean, root mean squared, standard deviation and correlation coefficient are included in this work [166]. Additionally, also the signal magnitude area (SMA) and tilt angle are considered in our study. The SMA computes the energy expenditure in activities by using the sum of the area encompassed by the magnitude of three-axis acceleration, therefore it can be used to distinguish a resting state from a dynamic activity. The tilt angle provides the information to determine the orientation of the participant, which is useful for transitional activities classification. On the other hand, the extracted frequency-domain features include spectral energy, spectral entropy, skewness, kurtosis, largest frequency component and signal weighted average. The list of 77 features used in our study as well as their formulations is summarized in Table 5.5.

There exists the situation that more than one activity label fall into the same segmented window. When dealing with multiple activities within a window, this window was discarded. Figure 5.9 shows the diagram of discarding a window that contains multiple activities. As a result, the remaining dataset contained 15,178 windows consisting of their extracted features and activity labels.

As per the feature selection methods, we have considered three: Information Gain (InfoGain), correlation-based feature selection (CFS) with Genetic search (GS) algorithm and ReliefF. We chose these three statistical methods because they rely on general data characteristics rather than on learning algorithms, while some other methods require the use of predetermined classifiers and their performance quite depends on the classifiers. Since our proposed ensemble approach is based on the usage of several heterogeneous classifiers, the methods that rely on the specific classifiers that have to be used are not suitable for us.

Figure 5.9. Discarding a window that contains multiple activities.

5.1.3.4 Class distribution rebalance

Having an imbalanced number of activity instances may lead to over-fitting, leading to inconsistencies in the activity recognition model. In order to deal with the class imbalance in the dataset, a resampling technique is integrated to rebalance the class distribution. Previous works have reported that randomly over-sampling methods would result in over-fitting problem whereas under-sampling methods would lead to the loss of useful information [167]. Thus, we utilize SMOTE (Synthetic Minority Over-sampling Technique) boosting method to improve the representation of classes with less number of instances, which generates synthetic instances along the segments adding any of the k minority class to their nearest neighbours. With an oversampling rate of 1200% boosting to increase the samples of the minority class, 15,517 new samples of the minority class are synthesized to create balanced sample numbers with the majority class. Figure 5.10 shows the class distribution change in the dataset by using SMOTE technique.

Figure 5.10. Class distribution in the dataset: (a) original unbalanced class distribution; (b) class distribution after performing rebalance by using SMOTE.

5.1.3.5 Ensemble construction

We create the ensemble classifier model for activity recognition by following two steps. The first step is to generate a diverse and accurate set of base classifiers by comparing the performance of various single classifiers. In this study, we consider six common used classifiers: random forest (RF), k-nearest neighbors (KNN), decision tree (J48), artificial neural network (MLP), Naïve Bayes (NB) and support vector machine (SVM) [168]. These six classifiers belong to different classifier types, which have different internal representations and may be biased in different ways. The different outputs of the base classifiers represent the extent to which they disagree about the probability distribution for the test data. This diversity would lead to disagreements with each other over the data instances covering a range of feature space.

The second step is to combine the models into a heterogeneous set of base classifiers using combination functions. The combination functions intend to make the best use of the information obtained from the base classifiers for the purpose of making class labels predictions as accurately as possible. There are two general categories of combination functions: fusion and selection. Since the output of the selection function typically depends on the characteristics of the instance whose class is being predicted, which is not suitable in this study, we have chosen a majority voting function [169], a fusion function, to combine the outputs of base classifiers. In majority voting, the outputs from base classifiers are used as votes on the predicted class, and the prediction with the most votes is outputted as the final predicted class of the ensemble classifier. The majority voting function is defined as follows:

$$C(x) = \operatorname{argmax} \sum_{C_i(x)=y} 1 \quad (5.2)$$

As a result of these two steps, 4 base classifiers (2 RF, 1 KNN and 1 J48) are selected to generate the ensemble. The predictions of these four classifiers, which are the results of 3 algorithms applied on balanced class distribution dataset, are finally voted to get the final classification result.

5.1.4 Data segmentation methodology based on change point detection

In this section we describe the methodology followed for a second data-driven contribution we propose. In this case we aim to improve the data segmentation stage of the activity identification procedure by detecting state change points in the accelerometer dataset. We describe in the following subsections the hypothesis generation and verification procedures followed for this proposal [170]. Then we introduce the classification procedure followed that uses the proposed segmentation method. The procedure described in this section has been performed during the research stay that the PhD. student has made at the Smart Environment Research Group of University of Ulster.

5.1.4.1 Motivation

One of the main challenges related to accelerometer data segmentation is to achieve a proper division of this raw and continuous data flow into the set of individual segments most suitable for the activity recognition [148] [155]. Each segment is treated as an instance of a specific activity. Segmenting this continuous data flow is a difficult task. On one hand, the user performs consecutive activities probably interleaved with each other rather than clearly separated by pauses. On the other hand, the exact boundaries of an activity are difficult to define. Existing literature has highlighted the sliding-window based segmentation approach for dividing the accelerometer data flow. However, identifying the optimal window size is challenging in this approach. Additionally, since the different types of activities have diverse durations, transitional activities are usually discarded in most works due to their generally low incidence and very short durations [90].

The overall objective of state change detection is to identify locations within an input data stream that exhibit sudden changes in metrics such as mean or variance thus representing a change point in time series data. Change point detection algorithms can be either online or offline. The aim of online change detection algorithms is to complete the processing of a set of data points before the next set arrives, with the number of new data points in successive sets influenced by the target application and available computational resources. In the offline

case, data is firstly collected and then analysed to detect change points with less emphasis on computational resource requirements. Online change detection algorithms are sequential, fast and minimise false alarms; on the other hand, offline change detection algorithms seek to identify all possible change points in order to attain higher levels of sensitivity (true positives) and specificity (true negatives).

5.1.4.2 Hypothesis generation and verification

In the context of this work the aim of change detection is to identify transitions in a user's activity to determine the starting position of windows that are to be utilized in window-based activity classification. We propose to autonomously detect changes in an input data stream such as accelerometer data as follows: consider a data stream of length q consisting of data points $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_q$. Each data point $\mathbf{x}$ is a b -element vector where b is the number of sensor observations for each variable. The data stream may contain points from multiple distributions, for example $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_{k-1}$ may have distribution D_1 whilst $\mathbf{x}_k, \mathbf{x}_{k+1}, \dots, \mathbf{x}_q$ may have distribution D_2 . It is therefore the overall aim of the algorithm to identify the position in the data stream of change points k ($1 \leq k \leq q$)

This methodology follows a hypothesis-and-verification principle: in the hypothesis step a point is detected within the window under consideration which maximises the test statistic. In the second stage the hypothesis that a detected change point is significant is verified.

- *Hypothesis generation*

In the hypothesis generation stage we pass an analysis window of length n over the data stream assuming that there is a maximum of one change point per window. The movement of the window over the data stream may be distinct, in which case the start of a new window (other than the first) is at position $m + cn + 1$ where m is the padding size and c is the number of previous windows. Alternatively, a sliding window version of the algorithm may be executed with the start position incremented by a predetermined number of data points. For ease of notation we denote the data points within a window as $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n$ regardless of

their actual position within the data stream. Following Jain and Wang [171] we pad either side of the window with m data points such that the analysis window contains data points $\mathbf{x}_{1-m}, \dots, \mathbf{x}_{n+m}$ therefore containing a total of $n + 2m$ data points. This padding ensures sufficient data to compute summary statistics at the window extremities and is particularly crucial when executing a distinct window version of the algorithm; however, results in a minimum latency of m data points.

Within each window we slide an index variable, $l, 1 < l \leq n$ subsequently computing summary statistics of the component distributions separated at l . Specifically, we compute the means, $\bar{\mathbf{f}}_1(l)$ and $\bar{\mathbf{f}}_2(l)$, which contain the mean of observations, in addition to variance-covariance matrices, $\mathbf{S}_1(l)$ and $\mathbf{S}_2(l)$, which contain the variance of observations in the diagonals and their covariance in the off-diagonals. To ensure that the change detection algorithm can operate in online scenarios we compute $\bar{\mathbf{f}}_1(l)$, $\bar{\mathbf{f}}_2(l)$ and $\mathbf{S}_1(l)$, $\mathbf{S}_2(l)$ recursively. Thus as index l increments to position $l + 1$ the summary statistics are calculated as follows:

$$\bar{\mathbf{f}}_1(l + 1) = \frac{m+l-1}{m+l} \bar{\mathbf{f}}_1(l) + \frac{f(\mathbf{x}_{l+1})}{m+l} \quad (5.3)$$

$$\bar{\mathbf{f}}_2(l + 1) = \frac{n+m-l+1}{n+m-l} \bar{\mathbf{f}}_2(l) - \frac{f(\mathbf{x}_{l+1})}{n+m-l} \quad (5.4)$$

$$\mathbf{S}_1(l + 1) = \frac{m+l-1}{m+l} \mathbf{S}_1(l) + \frac{1}{m+l-1} \mathbf{X} [\mathbf{x}_{l+1} - \bar{\mathbf{f}}_1(l + 1)]' [\mathbf{x}_{l+1} - \bar{\mathbf{f}}_1(l + 1)] \quad (5.5)$$

$$\mathbf{S}_2(l + 1) = \frac{n+m-l+1}{n+m-l} \mathbf{S}_2(l) - \frac{1}{n+m-l} \mathbf{X} [\mathbf{x}_{l+1} - \bar{\mathbf{f}}_2(l + 1)]' [\mathbf{x}_{l+1} - \bar{\mathbf{f}}_2(l + 1)] \quad (5.6)$$

where $f(\mathbf{x}_{l+1})$ is the value of the datastream at position $l + 1$. Having calculated summary statistics before and after l we proceed to compute the F statistic at position l , F_l as follows:

$$F_l = \frac{n_1 + n_2 - b - 1}{b(n_1 + n_2 - 2)} T^2 \quad (5.7)$$

where $n_1 = m + l - 1, n_2 = n + m - l + 1, b$ is the number of variables and T^2 is the Hotelling T-squared statistic calculated as [32],

$$T^2 = (\bar{\mathbf{f}}_1 - \bar{\mathbf{f}}_2)' \left\{ \mathbf{S}_p \left(\frac{1}{n_1} + \frac{1}{n_2} \right) \right\}^{-1} (\bar{\mathbf{f}}_1 - \bar{\mathbf{f}}_2) \quad (5.8)$$

where $\mathbf{S}_p$ is the pooled variance-covariance matrix,

$$\mathbf{S}_p = \frac{(n_1-1)\mathbf{S}_1 + (n_2-1)\mathbf{S}_2}{n_1 + n_2 - 2} \quad (5.9)$$

Under the null hypothesis (i.e. equal distributions) and assuming Gaussian distributions this has an F distribution [172]. We choose the point l which maximises F_l as the most likely change point within a window and proceed to the hypothesis verification phase.

- *Hypothesis verification*

An hypothesis verification stage is executed to prove or disprove the null hypothesis that a significant change did not occur at point l . Firstly, we compute the probability of finding an F value lower than that calculated in Equation 5 resulting in d . The F Cumulative Distribution Function is utilized for this phase with b and $n_1 + n_2 - b$ degrees of freedom. The test's p -value is then computed as,

$$p = 1 - d \quad (5.10)$$

As multiple statistical tests are being simultaneously performed within the window it is necessary to adjust our confidence value, α to reflect the confidence for the entire window and not a single, isolated value. We therefore use a Bonferroni correction [173] to compute an adjusted threshold t as:

$$t = \frac{\alpha}{n} \quad (5.11)$$

with the null hypothesis rejected (i.e. a significant change did occur at l) if $p < t$.

5.1.4.3 Classification procedure: differences with the ensemble classification methodology

As shown in Figure 5.11, the complete activity detection procedure we follow to assess the segmentation method proposal is very similar in structure to the one we used for the heterogeneous classifiers ensemble. There are some differences that will be highlighted below, especially the following: the filtered data is segmented into windows based on the proposed two-step segmentation method; the class distribution rebalance considers additional methods; and the classification task is conducted by machine learning techniques.

Figure 5.11. Conceptual scheme of the activity recognition framework based on the proposed segmentation method.

- *Data segmentation*

Our main objective is to map a set of accelerometer data samples with a corresponding activity label to the most accurate extent. To do so, we adopt a two-step approach as shown in Figure 5.12. During step 1, the hypothesis-and-verification procedure is applied to the data samples $x_1, x_2, \dots, x_q$ in the accelerometer dataset collected from smart home, as has already been described. This results in a set of change point indices, $C_1, C_2, \dots, C_n$, $n \leq q$. Formally, the data samples $x_1, x_2, \dots, x_q$ are divided into segments $S_1, S_2, \dots, S_n$, $n \leq q$, where segment S_i contains the following data samples: $[x_{c_i}, \dots, x_{c_{i+1}-1}]$.

In order to reduce the information loss, in step 2 each segment S_i is further divided into windows of 256 samples (2.5 seconds windows), each with a 50% overlap between two consecutive windows, represented by $w_1, w_2, \dots, w_N$. The rest of the classification procedures will be performed on these windows.

For each window w_i defined in segment S_i , a feature extraction and selection phases are executed the same way as described previously for the ensemble classification procedure. When dealing with multiple activities or less than 256 samples within a window, this window is discarded. Then a set of feature vectors x_i and their corresponding activity labels y_i are fed into a classifier as the training data and testing data.

Figure 5.12. Proposed two-phased segmentation method based on change point detection.

Figure 5.13. Class distribution in the dataset: (a) the unbalanced class distribution; (b) the class distribution rebalanced by using SMOTE, (c) the class distribution rebalanced by using combination of over-sampling and under-sampling techniques with a 2:1 ratio, (d) the class distribution rebalanced by using combination of over-sampling and under-sampling techniques with a 3:1 ratio.

- *Class distribution rebalance*

We have modified the class distribution rebalance for this experiment with respect to the method used in the ensemble classifiers one by adding more options. Inspired by the work demonstrated in [174] [175], which suggested the SMOTE technique that generates synthetic instances along the windows adding any of the k minority class to their nearest neighbours, and a combination of over-sampling technique on the minority class and under-sampling technique on the majority class, we utilize three different resampling techniques on the dataset: SMOTE boosting method, for which the percentage of data to create for the six

transitional activities classes with less number of instances was set to 200%, and the combination of over-sampling and under-sampling techniques with a 2:1 ratio and 3:1 ratio of the majority class samples to minority class samples. These parameters have shown as optimum within previous works for rebalancing datasets [174] [175]. The performance of each activity class obtained from the three techniques (SMOTE, 2:1 ratio, 3:1 ratio) are then compared to determine the optimal balanced class distribution. Figure 5.13 shows the class distribution in the dataset by using SMOTE technique and the combination of over-sampling and under-sampling techniques with 2:1 and 3:1 ratios.

- *Classification techniques*

For the classification phase, we have considered six commonly used classifiers: random forest (RF), k-nearest neighbors (KNN), decision tree (J48), artificial neural network (MLP), Naïve Bayes (NB) and support vector machine (SVM) [168]. These six classifiers belong to different classifier types, which have different internal representations and may be biased in different ways.

5.2 Knowledge-driven materials and methodology

The knowledge-driven approach mainly adopts ontologies to model the activities and their related context information. Compared to the data-driven approach, it is more sensitive to the environmental and user contexts. In this section, we describe design motivation and principles that guided us to represent the activities and related context information in order to obtain the proposed ontology approach. After the investigation of various knowledge engineering methodologies, we have decided to follow the NeOn ontology engineering methodology [176]. NeOn highlights some key aspects, such as scenario specification, scope and purpose definition, requirements analysis and ontology evaluation. We analyse the activity and context information representation based on these key aspects.

5.2.1 *Ontology design Motivation*

In smart home domain, human activity can be explored from several subdomains which contain a collection of information sources. We highlight three main entities: user, environment and ADL. These three elements can be considered as the core of the proposed ontology.

5.2.1.1 User modelling

The user in smart home applications refers to the owner of context and ADL information. We consider three categories of users:

- The older adult who uses the sensors and performs their activities, which provides the information to the system,
- The health expert who analyses the elderly's state by using the information provided, and
- The caregiver who provides assistance if necessary.

Of the different users, we mostly focus on the older adult. The relevant information for user modelling contains both static and dynamic contexts: A user's static context represent the information that does not, or rarely change in time, such as the user's name, age, gender and the role that the user plays. Conversely, the dynamic context refers to the changing information, for example, the current location of a user, their heart rate and the specific way that the person performs an activity. These dynamic contexts could be modelled as user profile and preference to express the user's state, and further used for providing personalized services.

5.2.1.2 Environment modelling

In smart home, the user performs activity in a diversity of environment contexts, which mainly include: spatial contexts, temporal contexts and measurement contexts [103]. Spatial

contexts contain information on the locations (e.g. bathroom, kitchen, bedroom) and the physical objects (e.g. stove, telephone, television). Temporal contexts deal with time and duration. Measurement contexts contain the state changes or digital records from the sensors, such as the state changes from the motion sensor in the dining room, the temperature in the room and the heart rate from the ECG sensor. The contexts are highly correlated with the description of user and ADL. For instance, the presence of the user in bedroom is detected by the state changes of motion sensor and the activity “preparing breakfast” occurs in the kitchen in the morning. These contexts are captured via multiple and heterogeneous sensors deployed in smart home, hence, the sensor modelling is the core element in the SH context modelling.

5.2.1.3 ADL modelling

The modelling of Activities of Daily Life can be greatly benefited from considering both users’ and environmental contexts. Not only this, but also the inclusion of knowledge regarding the temporal and specialization / composition relations between different activities can help in their detection. That is why we aim to specify the ADL in our knowledge-driven approach based on the characterization of activities presented previously on chapter 4.

5.2.2 Scenario

The activity monitoring use case for the elderly constitutes an example of the smart home applications, for which we consider the following scenario:

Maria is an old woman with Parkinson disease who lives alone in a smart home, Carlos is her health expert and Juan, who is the caregiver, is her son. Maria’s house is already equipped with different embedded sensors such as motion detection sensors, RFID and temperature sensors. She has also some wearable sensors attached such as an accelerometer and ECG sensor. When she performs her daily activities, the data generated by these sensors, which indicate Maria’s personal information and environmental information, are sent to Carlos and Juan by standard communication means. Carlos and Juan want to know what Maria does

The main specific goal is to create an ontology that is capable of representing information related to user, context, activity and relationships among them. For this purpose, the NeON methodology is chosen due to its flexibility and adaptability to diverse development scenarios. The NeON methodology is a scenario-based methodology that addresses the definition and formalization of ontologies. It provides clear guidelines for every task in the development

phase, and focuses particularly on reusing/reengineering the existing knowledge resources. Moreover, the NeON toolkit (<http://neon-toolkit.org/>) is also provided to support the technological availability.

According to NeOn methodology, a set of 9 scenarios are taken into consideration to collaboratively construct ontologies and ontology networks (as shown in Figure 5.14) [177]:

- *Scenario 1: From specification to implementation.* This scenario builds ontologies and ontology networks from scratch, being the core activities specification, conceptualization and implementation.
- *Scenario 2: Reusing and reengineering non-ontological resources.* This scenario builds ontologies and ontology networks in two forms: reusing non-ontological resources and reengineering non-ontological resources. The core activities of reusing non-ontological resources include: search of non-ontological resources, assess the set of candidate non-ontological resources and select the most appropriate non-ontological resources. The core activities of reengineering non-ontological resources include: non-ontological resource reverse engineering, non-ontological resource transformation and ontology forward engineering.
- *Scenario 3: Reusing ontological resources.* There exist a large amount of ontological resources that are available on ontology repositories. The main activities of this scenario include: ontology search, ontology assessment, ontology comparison, ontology selection and ontology integration.
- *Scenario 4: Reusing and reengineering ontological resources.* Some ontologies can be useful but not exactly as they are; they should be modified to serve the intended purpose. The core activities of reusing ontological resources are the same as scenario 3. The core activities of reengineering ontological resources include: ontological resource reverse engineering, ontological resource restructuring and ontological resource forward engineering.
- *Scenario 5: Reusing and merging ontological resources.* The core activities of this scenario include ontology aligning, which aims to gather a set of alignments from

different ontological resources in the same domain, and ontology merging, which aims to obtain a new ontological resource from the overlapping of other ontological resources.

- *Scenario 6: Reusing, merging and reengineering ontological resources.* The new ontological resource obtained from scenario 5 is possibly not useful exactly as it is and should be modified to satisfy the intended purpose. The main activities of this scenario include: ontological resource reuse process, ontology aligning/merging and ontological resource re-engineering process.
- *Scenario 7: Reusing ontology design patterns.* This scenario deals with the problems regarding the way in which certain knowledge should be modelled. Some ontology design patterns can be used directly to model certain knowledge.
- *Scenario 8: Restructuring ontological resources.* The ontology and ontology network should be corrected and reorganized in order to cover the requirements. The core activities of this scenario include: ontology modularization, ontology pruning, ontology enrichment, ontology extension and ontology specialization.
- *Scenario 9: Localizing ontological resources.* The core activities of this scenario include: selecting the most appropriate linguistic assets, selecting ontology labels to be localized, obtaining ontology label translations, evaluating label translations and updating the ontology.

The scenario 1 is a basic and mandatory scenario that can be combined with the rest. These nine scenarios can be combined in flexible ways while any combination should include scenario 1.

The development process based on NeON methodology defines the following tasks to be accomplished: (1) identification of purpose, scope and intended users of the ontology that have drove its development and implementation language, (2) analysis of ontology requirements, including non-functional requirements and functional requirements and (3) grouping the requirements with competency questions. In the following subsections we elaborate on how we have fulfilled these methodological tasks for our ontology definition.

5.2.4 Ontology purpose and scope

A proper modelling of the entities and their associations in the form of ontology facilitates collaboration among diverse smart home applications. The smart home applications need to extract useful context information to express the performed activities and their relationships from the heterogeneous sensor observations and context knowledge. There are several goals that a human activity ontology should achieve. Firstly, the related contextual information should be represented as a whole, e.g. the information on sensor measurements and their sensing time and location, the user information, as well as physical objects attached to the sensors; Secondly, the different types of activities, their related context interpretation and their complex temporal relationships should be supported; Thirdly, the ontology should be designed with interoperability and reusability in mind to achieve a better degree of knowledge sharing within different smart home applications.

It is important to define as well what concepts should be included in this model and what others should be excluded from it. The ontology is proposed to model concepts used by activity monitoring applications, it mainly focuses on the representation of user information, related context information and ADL information. The represented information could be viewed as a reference for the health experts to make decision on healthcare services, however, the concepts specific of the activity recognition method and healthcare service, such as the prediction of future activities, the generation of activity reminders for users and the details of human computer interaction, are not included in this model. Moreover, considering that ADL is a concept defined for smart home, the concepts related to users, context and activities in external locations (such as the office or the hospital) are excluded from this model.

5.2.5 Ontology implementation language

In order to specify the formal and explicit conceptualization of user, environmental and ADL models, the ontology language to be used should have well defined syntax and semantics. Moreover, sufficient expressive power and efficient reasoning support are needed. The Web

Ontology Language (OWL), a Description Logic (DL) based markup language, meets these requirements and can be used to implement the human activity ontology.

OWL is defined by the World Wide Web Consortium (W3C) for the Semantic Web. It enables to formally specify the context data semantics to support the exchange of the context data among heterogeneous entities and to allow its processing by computers. OWL-DL is a sublanguage of OWL designed to offer the maximum expressive power while maintaining computational completeness and efficient reasoning support. OWL-DL covers all OWL language constructs and adopts description logics, whose concepts form the foundation of OWL. The conceptual ontology is constructed based on classes, properties and individuals. As the implementation tool we have chosen Protégé (<http://protege.stanford.edu/>), developed by Stanford University, which handles concepts strongly related to OWL-DL.

Due to the inability of OWL to express complex rule formations, the Semantic Web Rule Language (SWRL) is used to define rules and add them to the OWL-based ontology. SWRL-based rules are constructed from an antecedent and a consequent, and can be used together with OWL constructors to ensure decidability, soundness and completeness in reasoning. SWRL uses constructs, such as equivalent, disjoint and subsumption relations, to check class consistency and assert inter-ontology relationships. After the SWRL rules are created, they may be used for inference and reasoning by using a reasoning tool (such as Pellet).

5.2.6 Ontology design requirements and competency questions

For ontology requirements, we consider four elements as the core of the ontology, namely what, who, when and where. In the following, we derive non-functional requirements as well as functional requirements based on existing smart environment ontologies and the specific scenario proposed in this study.

5.2.6.1 Non-functional requirements

Non-functional requirements refer to the ontological principles that work as the guidelines of how the human activity model needs to be designed in order to be applicable among various applications. According to NeON methodology, the ontological model needs to be carried out following four principles:

- *Interoperability*. In order to establish a common understanding in a particular domain that can be applicable among various smart home systems, a mechanism is needed to ensure interoperability with respect to both the syntax and the semantics.
- *Modularity*. The ontological model needs to capture different structural knowledge, an adequate modular structure of the model could decrease the complexity of the system and simplify the development phase.
- *Reusability*. The different systems or modules concern different aspects of activities, thus the ontological model needs to support the reuse of its modules, which can be imported by different domains.
- *Extensibility*. The ontological model needs to be extensible for developing new functions and anticipating the use of shared vocabularies.

5.2.6.2 Functional requirements and grouping into competency questions

Functional requirements aim at specific domain functions. Although we have already gone through several issues related to the functionality and concepts of the ontology, the following overview of functional requirements facilitates the understanding of the competency questions included later in this section.

- *The human activity model must support user modelling*. The information about a user, not only the static information (such as the name and the role in the application) but also the dynamic information (such as the location of the user and the performed

activity), should be described by the ontology. For example, in the scenario, Maria plays the role of the actor of an activity, her heart rate is recorded and she has the preference of watching TV in the dining room with lights off.

- *The human activity model must support SH context modelling.* To establish the sources of information, sensors are critical for providing data and linking it to other entities. For example, in the scenario, the motion sensor links the data to the place within smart home, the accelerometer links it to the user who wears it, and the RFID sensor links it to the physical object with which the user interacts.
- *The human activity model must support activity modelling.* The sensor observations collected from various sensors deployed in smart home should be mapped in order to model the activity information. In the scenario, the triggering of the pressure sensor attached to the bed indicates the activity “sleeping” is performed by the user.
- *The human activity model must represent the activity pattern of the user.* The concerned information of a user can be added as an interpretation of an activity to express the activity pattern of a user. In the scenario, the heart rate record when Maria is sleeping is concerned.
- *The human activity model must represent the temporal relations between activities.* The representation of the temporal entities (e.g. activity valid time and duration) and processing of temporal relations between activities (e.g. an activity occurs before another activity) should be supported.

Based on these functional requirements, the competency questions are categorized into five groups:

- *CQG1. Competency questions about user modelling.* (What is the personal data of the user? What role does the user play? What is the user’s profile? What are the user’s preferences?)
- *CQG2. Competency questions about SH context modelling.* (What sensor is deployed in smart home? What is the sensor observation? Where is the sensor located? What physical object is the sensor attached to? Whom is the sensor attached to?)

- *CQG3. Competency questions about activity modelling.* (Who performs the activity? Where does the activity occur? What physical object is related to the activity? Does the occurrence of an activity have any constraints? What are the time characteristics of the activity?)
- *CQG4. Competency questions regarding ADL pattern modelling.* (What information can be added as an interpretation to an activity pattern? What type is this activity in the given activity pattern?)
- *CQG5. Competency questions regarding the activities' temporal relations modelling.* (Is there any temporal relation between activities? What kind of temporal relation is it?)

Chapter 6 Results of the research

In this chapter we describe and discuss the experimental and technological results obtained during this Thesis' research work. We begin with the two data-driven contributions that aim to rise the performance of the detection of activities belonging to any of the three identified types (i.e. static, dynamic and transitional activities), namely: the proposed heterogeneous ensemble classification model, and the novel data segmentation method. After this, we move on to the specification of the ontology defined to describe activities of daily living in smart home, which constitutes a knowledge-driven contribution to the complete smart home architecture. We finalise this chapter by discussing the global framework for the context-aware smart home architecture, which has followed some of the driving principles of the Internet of Things.

6.1 Ensemble classification model

In this section, we present the comparative results of applying different feature selection methods, a resampling method (with respect to no resampling) and various learning algorithms on the dataset. The main performance measures used for the comparisons, such as accuracy, sensitivity and specificity, are based on the numbers of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) obtained by executing the various specified algorithms in Weka.

6.1.1 Performance of feature selection methods

The optimal feature subset selected by a feature selection method should contain the most relevant and discriminative features, and its size should be as small as possible to reduce the complexity of the subsequent learning process. We have compared the effectiveness of three feature selection methods, namely InfoGain, CFS with GS and ReliefF, by following 10-fold cross validation experiments on their performance. Two of them (the two that are feature ranking methods) were tested with two different numbers of extracted features each, giving a total of five selected feature subsets (FS) as follows: FS1 using InfoGain with 75 selected features; FS2 using ReliefF with 40 selected features; FS3 using CFS and GS algorithm with 36 selected features; FS4 using InfoGain with 36 selected features; and FS5 using ReliefF with 36 selected features.

This comparison has been made in two different groups: Each group consisted of three feature subsets: FS1, FS2 and FS3 belonged to group 1, whereas FS3, FS4 and FS5 belonged to group 2. The performance using all features was used as baseline for comparison. It should be noted that both InfoGain and ReliefF are ranking methods and thus all features are first ranked based on different criteria and then compared with a threshold, while the feature subset was picked directly by CFS and GS algorithm since it is a feature selection method.

The average 10-fold cross validation performance of the aforementioned five feature subsets is shown in Table 6.1. The decision tree (J48) was used here as learning algorithm for classification. We used three measures to validate the performance of three feature selection methods: accuracy (defined as $(TP+TN)/(TP+TN+FP+FN)$), sensitivity (defined as $TP/(TP+FN)$), and specificity (defined as $TN/(TN+FP)$).

In group 1, the top 75 ranked features by InfoGain yielded an accuracy of 89.21% and a sensitivity of 0.892. The top 40 ranked features by ReliefF produced an accuracy of 89.32% and a sensitivity of 0.893. The CFS and GS algorithm directly selects a feature subset that contains 36 features and provided the highest values for both accuracy (89.34%) and sensitivity (0.893) among three feature subsets. All three feature subsets yielded a specificity

as high as 0.990. Compared to the performance of using all features, the classifiers with less features, in contrast, produced higher accuracy and sensitivity. This is probably due to the fact that some features are irrelevant and redundant, and their high correlation with other features would affect the performance. The feature selection methods selected only informative and relevant features that contributed to improve the performance of the classifier.

Table 6.1. Comparison of the performance on five feature subsets by three feature selection methods.

Feature subset	No. of features	Accuracy	Sensitivity	Specificity
All features	77	88.98%	0.890	0.990
FS1: InfoGain	75	89.21%	0.892	0.990
FS2: ReliefF	40	89.32%	0.893	0.990
FS3: CFS+GS	36	89.34%	0.893	0.990
FS4: InfoGain	36	88.40%	0.884	0.989
FS5: ReliefF	36	89.11%	0.891	0.990

Table 6.2. Features selected by CFS and GS algorithms.

Feature domain	Selected features
Time-domain	Mean-BA-X, STD-BA-X, MAD-BA-X, MAD-BA-X, SMA-BA, TA-BA-X, TA-BA-Y, TA-BA-Y, Mean-GA-X, Mean-GA-Y, Mean-GA-Z, RMS-GA-X, RMS-GA-Y, RMS-GA-Z, MAD-GA-Z, Range-GA-Y, Range-GA-Z, SMA-GA, Mean-BASMV, RMS- BASMV, SMA-BASMV, RMS-GASMV, STD-GASMV, MAD-GASMV, Range-GASMV, SMA-GASMV
Frequency-domain	Spectral Entropy-BA-Z, Skewness-BA-X, Skewness-BA-Y, Kurtosis-BA-Y, Largest frequency component-BA-X, Frequency signal weighted average-BA-Y, Frequency signal weighted average-BA-Y, Spectral Entropy-BASMV, Skewness-BASMV, Kurtosis-BASMV

To determine the optimal feature subset, the performance of the three feature subsets with the same number of features (36) extracted by three feature selection methods were compared (group 2). With this decreased number of selected features, InfoGain only produced an accuracy of 88.40%, even lower than the baseline accuracy of 88.98%. Similarly, both the accuracy and sensitivity obtained by ReliefF with the top 36 ranked features were reduced as compared to group 1 results. Among the classifiers with different sizes of feature subsets, the classifier combined with the CFS and GS algorithms yielded the highest accuracy and best

performance. Therefore, the CFS and GS algorithms was used as the feature selection method to reduce the feature vector dimensions as well as to improve the classifier performance. The 36 picked features by the CFS and GS algorithms are given in Table 6.2. These selected features were used as input to various learning algorithms in further experiments.

6.1.2 Performance assessment of base classifiers and selection of the most appropriate for the ensemble model

In order to choose the efficient base classifiers for the construction of an ensemble, we investigated and compared various classification algorithms: RF, KNN, J48, MLP, NB and SVM. The preliminary activity classification performance of these six different algorithms on a balanced dataset with the selected features previously specified is summarized in Table 6.3. The data were processed using average 10-fold cross validation during training and testing phases.

For the performance comparison, besides the accuracy, sensitivity and specificity, we also introduced the following measures: mean absolute error (MAE), relative absolute error (RAE), F-measure and receiver operating characteristic (ROC) area. The mean absolute error (MAE) is a quantity used to measure how close or far the predictions are to the eventual outcomes [178]. The definition of MAE is given by

$$MAE = \frac{1}{n} \sum_{i=1,n} |y - y'| \quad (6.1)$$

The relative absolute error (RAE), also related to how close or far the predictions are from the eventual outcomes, represents the error as a percentage of how good of a predictor the simple average of the values is. The definition of RAE is given by

$$RAE = \sum_{i=1,n} |y - y'| / \sum_{i=1,n} |\bar{y} - y| \quad (6.2)$$

Where y is the actual value, y' is the predicted value and n is the number of samples. A value of 0 value corresponds to the ideal case both in MAE and RAE. F-measure is defined as $2 * \text{Precision} * \text{Recall} / (\text{Precision} + \text{Recall})$, where Recall is the same as Sensitivity and Precision

is defined as $TP/(TP+FP)$. The receiver operating characteristic (ROC) curve is a graphic plot of the true positive rate against the false positive rate at various threshold settings. Therefore the area under the ROC curve can be used to illustrate the performance of a classifier.

Table 6.3. Comparison of the performance of different learning algorithms.

Algorithms	Accuracy	MAE	RAE	Sensitivity	Specificity	F-measure	ROC Area
Random forest (RF)	96.90%	0.025	16.01%	0.969	0.997	0.969	0.999
K-nearest neighbors (KNN)	95.64%	0.007	4.80%	0.956	0.996	0.956	0.976
Decision tree (J48)	89.34%	0.019	12.41%	0.893	0.990	0.893	0.953
Artificial neural network (MLP)	85.97%	0.028	18.09%	0.860	0.987	0.859	0.976
Naïve Bayes (NB)	63.21%	0.063	41.27%	0.632	0.967	0.616	0.933
Support vector machine (SVM)	31.86%	0.114	74.33%	0.681	0.938	0.319	0.628

Among the six classifiers, RF, KNN and J48 showed superior performance in the evaluation metrics. Specially, RF contributed the highest accuracy of 96.90%. It also achieved the best performance in terms of sensitivity, specificity, F-measure and ROC area measures (0.969, 0.997, 0.969 and 0.999, respectively). This is probably because RF combined multiple decision trees with various discriminative rules, which can handle the multi-class data characteristics. Thus we used RF as the baseline classifier here. Compared to RF, the KNN yielded lower MAE and RAE measurements of 0.007 and 4.80%, respectively. This implies that KNN produced closer predictions to the eventual outcomes. J48 also contributed lower MAE (0.019) and RAE (12.41%) values than RF, thus KNN and J48 may perform better in the classification of specific activity classes. In comparison to the performance of RF, the classification results of MLP, NB and SVM were not very good. The accuracy obtained by MLP was 85.97% and SVM only reached to 31.86% of accuracy. Therefore, we considered RF, KNN and J48 as the possible ensemble members.

To determine the best classification performance for each activity, we analysed the confusion matrices produced by RF, KNN and J48. Table 6.4 contains the confusion matrices of each activity obtained by the three classification algorithms. These confusion matrices reveal that

the RF model often misclassified walking class into sweeping (79 instances), stand-to-walk (95 instances), walk-to-stand (24 instances) and sit-to-lie (22 instances). Standing class was frequently confused with walk-to-stand (50 instances). Sweeping class was sometimes misclassified as walking (25 instances). Probably the reason is that these activities shared similar movements. (In the table 6.4, A1 stands for Standing, A2 stands for Sleeping, A3 stands for Watching TV, A4 stands for Walking, A5 stands for Running, A6 stands for Sweeping, A7 stands for Stand-to-sit, A8 stands for Sit-to-stand, A9 stands for Stand-to-walk, A10 stands for Walk-to-stand, A11 stands for Lie-to-sit, A12 stands for Sit-to-lie).

We have also found that these three classifiers make quite different misclassifications. For example, J48 misclassified less walking class into sit-to-lie class (10 instances) than that from RF (22 instances). J48 also contributed less misclassified instances of sleeping and watching TV than RF. Similarly, KNN contributed less misclassified instances of several activities.

These results illustrated that each single classifier cannot perform best in all evaluation measures, only on a subset of them. Thus combining the three classifiers may contribute to a better classification performance. Based on this, we selected RF, KNN and J48 as ensemble members due to their excellent performance in evaluation measures. These three classifiers had their own strengths on classifying different activities, they also provided different disagreements with each other, and these disagreements were to be overcome by majority voting to obtain a final prediction. As a result, we got an ensemble model with 4 heterogeneous classifiers (2 RF, 1KNN and 1J48). This combination including two RF is the one that yielded the best results. The two RF are parametrized differently since the set of randomly chosen samples to do the training varies every time.

Table 6.4. The confusion matrices of the twelve activities obtained by selected learning algorithms.

Random Forest (RF)												
	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
A1	2290	0	3	0	0	16	0	6	9	50	2	3
A2	5	2348	0	0	0	6	7	2	1	1	4	5
A3	0	0	2302	2	0	3	8	3	4	10	11	28
A4	0	1	0	2071	1	79	9	17	95	24	8	22
A5	0	0	0	4	2270	7	0	0	2	0	0	0
A6	2	0	0	25	2	2233	11	17	17	18	10	6
A7	0	0	0	1	0	1	2279	31	4	9	2	0
A8	0	0	1	0	0	1	18	2350	1	6	0	2
A9	1	0	0	24	0	14	7	2	2331	27	8	4
A10	4	0	2	7	0	6	3	17	46	2289	3	2
A11	0	3	0	0	0	0	5	3	0	2	2338	15
A12	0	1	0	0	0	0	1	2	0	0	26	2375
k-Nearest Neighbors (KNN)												
	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
A1	2264	2	6	9	0	10	0	6	23	56	3	0
A2	1	2353	10	1	0	2	5	0	0	0	1	6
A3	1	3	2330	6	0	0	6	3	1	2	8	11
A4	2	0	3	2151	0	39	9	11	71	25	6	10
A5	0	0	0	4	2276	3	0	0	0	0	0	0
A6	3	0	0	60	1	2179	15	17	40	15	7	4
A7	0	0	0	3	0	8	2240	61	3	7	2	3
A8	1	1	0	0	0	2	46	2316	1	8	4	0
A9	11	0	1	40	1	19	7	10	2225	99	5	0
A10	100	4	3	13	0	4	4	13	115	2120	1	2
A11	0	6	0	0	0	0	8	1	1	6	2310	34
A12	0	3	5	0	0	0	3	3	0	0	37	2354
Decision Tree (J48)												
	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
A1	2281	0	2	4	0	20	4	9	8	47	1	3
A2	1	2332	6	0	0	5	6	1	2	10	4	12
A3	1	6	2279	6	0	8	13	7	1	20	13	17
A4	5	2	6	1962	5	75	8	20	172	47	15	10
A5	0	0	0	4	2266	8	1	0	4	0	0	0
A6	16	4	4	79	6	2056	28	37	55	35	11	10
A7	1	11	12	11	0	20	2022	161	18	26	21	24
A8	4	3	5	21	0	22	148	2061	35	42	19	19
A9	7	1	3	144	2	63	23	30	1995	129	9	12
A10	40	17	20	51	1	33	35	51	145	1959	19	8
A11	1	7	17	16	0	10	27	15	10	15	2034	214
A12	5	13	17	16	2	7	26	22	5	8	199	2085

6.1.3 Performance comparison between our ensemble model and the use of imbalanced and all-features datasets

We evaluated the classification performance of the ensemble constructed with 2 RF, 1 KNN and 1 J48 by applying it on the balanced feature subset. Table 6.5 presented the sensitivity, results showed high sensitivity and specificity (sensitivity was between 0.893 and 0.995, specificity was between 0.993 and 1.000) on each activity class, which indicates that the ensemble model performed good both in true positive and true negative rates. The ensemble model performed extremely well in identifying running with the highest F-measure (0.997).

Activities such as sleeping, watching TV, lie-to-sit and sit-to-lie were also identified very well. Compared to the isolated classifiers, the ensemble model provided 97.00% accuracy, higher than the 96.90% accuracy obtained by RF, which was the highest accuracy among the various single classifiers. This shows that the ensemble model is a high-performance method to achieve higher accuracy than the single classifiers.

Table 6.5. Performance of heterogeneous ensemble model with selected features.

	A1	A2	A3	A4	A5	A6
Sensitivity	0.965	0.987	0.972	0.893	0.995	0.956
Specificity	1.000	1.000	1.000	0.998	1.000	0.995
F-measure	0.980	0.992	0.984	0.930	0.997	0.950
	A7	A8	A9	A10	A11	A12
Sensitivity	0.979	0.988	0.964	0.962	0.989	0.989
Specificity	0.998	0.996	0.993	0.995	0.997	0.997
F-measure	0.976	0.975	0.946	0.952	0.981	0.977

A1 = Standing, A2 = Sleeping, A3 = Watching TV, A4 = Walking, A5 = Running, A6 = Sweeping, A7 = Stand-to-sit, A8 = Sit-to-stand, A9 = Stand-to-walk, A10 = Walk-to-stand, A11 = Lie-to-sit, A12 = Sit-to-lie.

To evaluate the performance of the ensemble classifier model, we derived and compared its performance under three different circumstances, which we have identified as EM1, EM2 and EM3. EM1 was derived on the raw data without applying any resampling technique and with all features as the input. EM2 also maintained all features although trained on balanced data

after performing the resampling techniques. The difference between EM1 and EM2 was the class distribution in dataset. EM3 was derived on the balanced data and using the 36 features selected by CFS and GS algorithms. The difference between EM2 and EM3 was the number of used features.

Table 6.6. Performance of different ensemble models generated by 10-fold cross validation.

Dataset	Accuracy	Sensitivity	Specificity	F-measure	ROC Area
EM1: Imbalanced data with all features	95.14%	0.951	0.993	0.946	0.972
EM2: Balanced data with all features	96.01%	0.960	0.996	0.960	0.978
EM3: Balanced data with 36 selected features	97.00%	0.970	0.997	0.970	0.984

Table 6.6 presents the performance of EM1, EM2 and EM3 in terms of accuracy, sensitivity, specificity, F-measure and ROC area. Comparing the performance of EM1 and EM2, the accuracy was significantly increased from 95.14% to 96.01%. The sensitivity of EM2 was increased to 0.960, which was higher than that of EM1 (0.951). Even though the accuracy of EM1 was still relatively high, many instances of transitional activities were misclassified, this can be shown by the sensitivity of EM1. This is because learning algorithms assume that positive and negative classes are balanced in datasets, and thus usually maximize the overall accuracy exhibiting a bias toward the majority class. To address the poor performance on minority classes, we applied SMOTE with an oversampling rate of 1200% boosting to balance the dataset. Figure 6.1 depicts the sensitivity of EM1, EM2 and EM3 on each class. It is clear from that figure that after rebalancing the dataset, the sensitivity of EM2 and EM3 on transitional activity classes was significantly increased and balanced with that of the static activity and dynamic activity classes. By applying the feature selection method to obtain a feature subset that contains only discriminative and relevant features, compared to EM2, the performance of EM3 was improved from 96.01% to 97.00% in terms of accuracy, from 0.960 to 0.970 in terms of sensitivity, from 0.996 to 0.997 in terms of specificity, from 0.960 to 0.970 in terms of F-measure and from 0.978 to 0.984 in terms of ROC area.

The results showed that not only combining the heterogeneous base classifiers outputs by majority voting, but also rebalancing the class distribution by resampling technique as well as selecting informative and relevant features by feature selection method, contribute to significantly improve the performance of activity recognition. Also, we have succeeded in our objective of being capable of identify with similar performance metrics the transitional activities and not only static and dynamic activities.

Figure 6.1. Comparison of sensitivity of twelve activities between EM1, EM2 and EM3.

6.2 Proposed segmentation method

In this section, we present and discuss the results obtained from the proposed segmentation approach, feature selection methods, several resampling techniques and learning algorithms applied on the dataset. Analogously to the previous set of experiments, in order to precisely assess the performance evaluation and model comparison, several performance measurements such as accuracy, sensitivity, specificity and F-measure are used.

6.2.1 Performance improvement of proposed segmentation method

The results from the 10-fold cross validation of the performance obtained by the proposed segmentation approach based on change point detection, together with that of non-

overlapping segmentation approach and 50% overlapping segmentation approach on the dataset are included in Table 6.7. Both non-overlapping segmentation approach and 50% overlapping segmentation approach adopted 2.56 s as the window size. Here, the decision tree (J48) was used as machine learning classifier for the classification phase. The overall accuracy of non-overlapping segmentation approach, 50% overlapping segmentation approach and change point based segmentation approach were 90.50%, 92.40% and 93.11%, respectively. 50% overlapping segmentation approach generally performed well in classifying static and dynamic activities but performed worse when classifying transitional activities. This is probably due to the short duration of transitional activities, causing that more windows in the 50% overlapping segmentation approach contain samples of more than one activity rather than a single transitional activity, resulting in misclassification of this type of activities.

Table 6.7. Performance evaluation for the proposed segmentation approach based on change point detection.

	Accuracy	Sensitivity	Specificity	F-measure
Non-overlapping segmentation	90.50%	90.5%	99.0%	0.904
50% overlapping segmentation	92.40%	92.4%	99.2%	0.923
Change point based segmentation	93.11%	93.1%	99.0%	0.930

The results indicated that change point based segmentation approach contributed better performance in terms of either overall classification accuracy or the specific classification accuracy of transitional activities. This is because change point based segmentation approach reorganized windows better and more effectively. However, compared to static and dynamic activities, change point based segmentation approach still performed relatively bad in classifying transitional activities. This lead us to adopt in the next experiments feature selection methods and resampling techniques to enhance the performance on transitional activities classification.

6.2.2 Performance improvement of feature selection

We have followed a similar approach as the one explained to assess the performance of feature selection methods in previous section (6.1.1). On this occasion, the five feature subsets are the following: FS1 using InfoGain with 60 selected features, FS2 using ReliefF with 70 selected features, FS3 using CFS and BFS algorithm with 21 selected features, FS4 using InfoGain with 21 selected features, and FS5 using ReliefF with 21 selected features. These were also grouped into two groups, each one consisting of three feature subsets: FS1, FS2 and FS3 belonged to group 1; FS3, FS4 and FS5 belonged to group 2. The performance using all features was used as baseline for comparison. The average 10-fold cross validation performance of the five feature subsets is shown in Table 6.8. The decision tree (J48) was used here as machine learning classifier for classification.

Table 6.8. Comparison of the performance obtained by three feature selection methods.

	No. of features	Accuracy	Sensitivity	Specificity
All features	77	93.11%	93.1%	99.0%
FS1: InfoGain	60	93.36%	93.4%	99.0%
FS2: ReliefF	70	93.44%	93.4%	99.0%
FS3: CFS+BFS	21	93.51%	93.5%	99.0%
FS4: InfoGain	21	91.80%	91.8%	98.7%
FS5: ReliefF	21	93.06%	93.1%	99.0%

In group 1, The CFS and BFS algorithms directly selected a feature subset (FS3) that contained 21 features and provided the highest accuracy of 93.51% and the highest sensitivity of 93.5% of the three feature subsets. Compared to the performance of using all features, the classifier produced higher accuracy and sensitivity with only 21 features, a similar effect as that observed in 6.1.1.

To determine the optimal feature subset, the performance of the three feature subsets with the same number of features (21) by the three feature selection methods were compared (i.e. the performance of feature subsets of group 2). The top 21 ranked features by InfoGain only produced an accuracy of 91.80%, even lower than the baseline accuracy of 93.11%. Similarly, both the accuracy and sensitivity with the top 21 ranked features by ReliefF decreased.

Among the five different feature subsets, the CFS and BFS algorithms yielded the highest accuracy and the best performance. Therefore, the CFS + BFS algorithm was used as the feature selection method to reduce the feature vector dimensions as well as to improve the classifier performance. The 21 picked features by the CFS and BFS algorithm are given in Table 6.9.

Table 6.9. The 21 features selected by CFS and BFS algorithm.

Feature Domain	Feature Number	Selected Feature name (Axis applied to)
Time Domain	1	STD- (BA-X)
	2	MAD (BA-X)
	3	Correlation (BA-XY)
	4	Tilt (BA-X)
	5	Tilt (BA-Y)
	6	Tilt (BA-Z)
	7	Mean (GA-Y)
	8	Mean (GA-Z)
	9	RMS (GA-X)
	10	RMS (GA-Y)
	11	Correlation (GA-XZ)
	12	SMA (GA)
	13	Mean (BA-SMV)
	14	MAD (BA-SMV)
	15	STD (GA-SMV)
Frequency Domain	16	Kurtosis (BA-X)
	17	Kurtosis (BA-Y)
	18	Kurtosis (BA-Z)
	19	Largest frequency component (BA-X)
	20	Largest frequency component (BA-Y)
	21	Frequency signal weighted average (BASMV)

6.2.3 Performance improvement of class distribution re-balancing

We evaluated the classification performance of the decision tree (J48) classifier on the segmented dataset by using three different resampling techniques: SMOTE, combination of over-sampling and under-sampling with 2:1 ratio and combination of over-sampling and under-sampling with 3:1 ratio. The classification performance of the imbalanced dataset was used as baseline. Besides the overall classification accuracy, we additionally used True Positive (TP) rate (i.e. Sensitivity), False Positive (FP) rate (defined as $FP/(TN+FP)$), i.e. 1-Specificity) and ROC area as the performance measurements to capture classification performance for both majority and minority classes.

Table 6.10. Classification performance by using three resampling techniques.

	Accuracy	TP	FP	ROC area
Imbalanced dataset	93.11%	0.931	0.010	0.965
SMOTE	93.24%	0.932	0.009	0.967
Combination with 2:1 ratio	83.13%	0.831	0.015	0.923
Combination with 3:1 ratio	85.15%	0.852	0.013	0.928

As shown in Table 6.10, among the performance obtained from three resampling techniques, SMOTE yielded the highest accuracy of 93.24%, TP rate of 0.932 and ROC area of 0.967, and also the lowest FP rate of 0.009. The results also illustrated that compared to the dataset without resampling techniques, SMOTE contributed better classification performance in terms of both majority and minority classes.

Figure 6.2 depicts the sensitivity exhibited by the three resampling techniques on each activity class. Compared to the performance without using resampling technique (the baseline), all three resampling techniques increased the sensitivity of transitional activity classes that were more even with the static and dynamic activity classes. Among them, the sensitivity of static activities and dynamic activities decreased by using combination with 2:1 ratio and combination with 3:1 ratio. However, SMOTE contributed more or less the same sensitivity for static and dynamic activities as the baseline while it also increased the

sensitivity of the six transitional activities. The classification performance for sit-to-lie and lie-to-sit transitional activities was especially benefited by using SMOTE.

Figure 6.2. Comparison of sensitivity of the classification of twelve activities by applying three resampling techniques.

6.2.4 Model selection

In order to choose the most efficient classifier for the classification phase, we investigated and compared various classification algorithms, namely: RF, KNN, J48, MLP, NB and SVM. The preliminary activity classification performance of these six different algorithms on a balanced dataset with selected features is summarized in Table 6.11. The data were processed using average 10-fold cross validation during training phase and testing phase.

Among the six classifiers, the classification results of KNN, NB and SVM were significantly lower than the rest. RF showed its superior performance in all the considered evaluation metrics, contributing the highest accuracy of 95.72%, which is even higher than the highest accuracy obtained from [155]. It also achieved the best performance in terms of sensitivity, specificity, F-measure and ROC area measures (95.7%, 99.3%, 0.954 and 0.998, respectively). This is probably because RF combined multiple decision tree with various discriminative rules, being better at handling the multi-class data characteristics. Compared to RF, J48 and MLP contributed slightly lower classification accuracy of 93.15% and 93.00%, respectively. Therefore, it was decided to use only RF in this study.

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Table 6.11. Classification performance by using different classifiers on balanced dataset with selected features.

Algorithms	Accuracy	Sensitivity	Specificity	F-measure	ROC Area
Random forest (RF)	95.72%	95.7%	99.3%	0.954	0.998
K-nearest neighbors (KNN)	87.31%	87.3%	99.1%	0.891	0.932
Decision tree (J48)	93.15%	93.1%	99.1%	0.931	0.969
Artificial neural network (MLP)	93.00%	93.0%	99.0%	0.926	0.972
Naïve Bayes (NB)	84.56%	84.6%	98.1%	0.852	0.969
Support vector machine (SVM)	63.63%	63.6%	95.0%	0.613	0.793

Table 6.12. . Confusion matrix obtained by using RF on balanced dataset with selected features.

Classified as	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
A1	1833	0	10	3	0	16	0	0	0	5	0	0
A2	0	1950	34	16	1	11	0	0	0	0	1	2
A3	1	10	2064	8	0	5	3	0	0	1	2	4
A4	1	4	27	2175	0	54	3	5	0	2	1	1
A5	1	7	7	12	2252	6	0	0	0	0	0	0
A6	11	0	5	46	1	1533	0	2	2	2	2	0
A7	2	0	2	0	0	6	81	1	0	1	0	0
A8	0	0	2	1	0	7	0	139	0	2	2	0
A9	4	0	2	88	0	8	0	1	31	10	0	1
A10	25	0	12	25	0	12	1	4	3	81	1	2
A11	0	1	0	0	0	0	0	0	0	0	206	0
A12	0	0	0	0	1	0	0	0	0	0	1	241

A1 = Standing, A2 = Sleeping, A3 = Watching TV, A4 = Walking, A5 = Running, A6 = Sweeping, A7 = Stand-to-sit, A8 = Sit-to-stand, A9 = Stand-to-walk, A10 = Walk-to-stand, A11 = Lie-to-sit, A12 = Sit-to-lie.

Table 6.12 shows the confusion matrix of each activity class obtained by using RF on the balanced dataset with selected features. The model performed extremely well in classifying sit-to-lie and lie-to sit activities (A12 and A11). Activities such as standing, watching TV and running were also classified correctly very well. However, the model did not perform well in stand-to-walk and walk-to-stand activities (A9 and A10). The confusion matrix illustrates that the stand-to-walk class was most often classified as walking class (A4, a total of 88 instances of this misclassification), whereas the walk-to-stand class was confused many times

with standing class (A1, 25 instances) or walking class (A4, 25 instances). This is because these activities shared quite similar movements and the transition duration was quite short. Walking class (A4) was also frequently misclassified as sweeping class (A6, 54 instances) by the model. The combination of multimodal sensor data from additional sensors such as gyroscope or magnetometer data could be useful in further discriminating between these very similar activities.

6.3 *Ontology to represent human activities*

As the first contribution to the knowledge-based approach to classify activities in smart home, a research was conducted on existing formalized foundational ontologies. Based on this, the human activity model has been proposed to interlink a set of ontologies and describe the different subdomains needed for context knowledge modelling. The human activity model was developed by importing the existing foundational ontologies and extending statements on them according to the objectives to be met.

6.3.1 *Reusing existing ontologies*

After the analysis of relevant ontologies related to the requirements of user and activity modelling domains, it was not possible to find a single ontology that fully covered all the aforementioned requirements. However, there existed relevant ontologies and ontology design patterns which could be partly reused for the construction of the human activity model. Moreover, an upper-level ontology was adopted, which allowed to model generic concepts that can be specialized for the proposed ontology, fostering this way better interoperability and reusability characteristics of the human activity model.

6.3.1.1 *Upper-level ontology*

The DOLCE Ultralite ontology (DUL) was chosen as the upper ontology. It serves as a broadly reusable and formalized ontology and contains common sense concepts, which

enabled interoperability and reusability of our own proposed ontology. Moreover, many ontology-based frameworks have been built on it or aligned with it.

The DUL ontology provides a set of upper level concepts to foster interoperability among many middle and lower level ontologies. The highest level concept of the DUL ontology is *dul:Entity*. Under the umbrella of this concept, four disjoint classes are defined: *dul:Event*, *dul:Object*, *dul:Abstract* and *dul:Quality*. The class *dul:Event* represents enduring entities that unfold over time (e.g. an event that takes time to complete). The class *dul:Object* represents enduring entities that unfold over space (e.g. living things as well as non-living things). The class *dul:Quality* represents the characteristics of the instances of *dul:Event* and *dul:Object*. Finally, the class *dul:Abstract* represents value spaces (e.g. the time interval of an event).

6.3.1.2 Ontology statements

For the user modelling, the Friend of a Friend (FOAF, <http://xmlns.com/foaf/spec/>) ontology enabled us to model generic information about a user, such as the name, age and profile. However, it did not support the role and user preferences modelling. Hence, the vocabulary of Semantically Interlinked Online Communities core ontology (SIOC, <http://www.w3.org/Submission/sioc-spec/>) was reused to model the role that the user plays. The RECommendation Ontology (RECO, <http://ontologies.ezweb.morfeoproject.org/reco/spec>) offers a vocabulary to express user preferences, and thus it can be reused to model the user's preferences when performing an activity. For sensor modelling, the Sensor and Sensor Network (SSN, <http://purl.oclc.org/NET/ssnx/ssn>) ontology was reused to model sensors deployed in smart home. This ontology was created by the W3C Semantic Sensor Network Incubator Group (SSN-XG, <http://www.w3.org/2005/Incubator/ssn/wiki>), and associates sensing devices with their observations and measurements. The SWRL Temporal ontology (<http://protege.cim3.net/cgi-bin/wiki.pl?SWRLTemporalOntology>) was also reused to model temporal context. It defines a set of built-ins that can be used as SWRL rules to represent

temporal information. The place ontology design pattern (ODP, <http://ontologydesignpatterns.org/wiki/Submissions:Place>) and the vocabulary inherited from the DUL ontology were reused to model spatial context in home areas. The Simple Event Model (SEM) [99] was reused to represent domain activity concepts and the Mereology pattern of Event Model F [179] was reused to model the activity state as well as the relative temporal relations between activities.

Figure 6.3. Conceptual modules of the human activity model.

Figure 6.3 describes the conceptual modules of the human activity model we propose. This model consists of a set of modules, which can be classified into application ontologies, domain ontologies and general ontologies, based on the subject of their conceptualization identified in [180]. Application ontologies are built for certain applications. In our case, the human activity ontology can be provided with possible extensions for certain application scenarios. Domain ontologies, on their side, model common concepts and aspects for a certain domain, which could be reused for more specific scenarios. In our proposal, domain activity, physical object, sensor and ADL pattern ontologies were classified in this category. General ontologies are applicable to universal and domain-independent areas that can be reused across various domains of knowledge. In this sense, temporal, place and user

ontologies were classified into this category. It is worth to mention that the more general an ontology is, the fewer possibilities exist for its direct usability but the more possibilities exist for its reusability among heterogeneous applications.

6.3.2 Core concepts

The concept of *ha:Entity* was defined as the top-level concept of the human activity ontology. It consists of the following core concepts: *ha:User* is used to model the users, their roles and preferences; *ha:Sensor* is used to model sensor devices and their measurements; *ha:Place* is used to represent the house areas; *ha:PhysicalObject* represents the household objects; *ha:Temporal* models the temporal information; *ha:Activity* represents the activities being monitored in smart home; *ha:ADLSituation*, *ha:ADLDescription* and *ha:Concept* were used to model the ADL pattern of a user. The detailed description of each of these core concepts is presented in the following subsections.

6.3.2.1 User

The user ontology is proposed to model the information of intended users of smart home applications. The function of this ontology is two-fold: (1) to describe the static information (e.g. name and age) of an individual and identify the role that the individual plays (e.g. Maria plays the “activity actor” role); and (2) to present the profiles and activity preferences of the individual (e.g. Maria’s heart rate is recorded in her profile and she prefers watching TV in the dining room with light off). Since the roles, profiles and activity preferences can be completely different for different individuals, it is necessary for the user ontology to capture this inherent complexity of the relations between individuals and the smart home applications.

The concept of *ha:User* has been modelled to be equivalent to *foaf:Agent*, *sioc:User* and *reco:Agent*. It was aligned with the DUL ontology as an equivalent class of *dul:Agent*. The vocabulary of the FOAF ontology was reused to represent the users’ static information and their profiles. The individual involved in smart home applications is modelled as an instance of *foaf:Person*. The properties *foaf:name*, *foaf:age* and *foaf:gender* were used to express a

user's name, age and gender, respectively. The user profile was described by the *ha:Profile* class (equivalent to *foaf:PersonalProfileDocument*) and represented the user in different contexts, where context was widely interpreted. The relations between *ha:Profile* and *foaf:Person* were established by means of the property *ha:profiles*. The role that a *foaf:Person* plays has been modelled as an instance of the *sioc:Role* class to represent a collection of individuals, and the corresponding property *ha:plays* links up the instances of *foaf:Person* and *sioc:Role*. The vocabulary of RECO ontology was added to represent the preferences of a particular user. The perception of activities occurring in the real scenarios heavily relies on the point view of the actor. The particular way that an actor prefers to perform an activity has been defined by *reco:Preference*, and linked to *foaf:Person* via the *ha:hasPreference* property.

6.3.2.2 Sensor

The input of smart home system is a stream of time-stamped values produced by heterogonous sensors, which are either deployed in the environments or attached on the users to observe significant variables. In smart homes, data collected from different sensors usually have heterogeneous formats. For example, a contact sensor provides a two-state binary value while an accelerometer offers 3-D coordinates. The lack of a formalized representation of these data would lead to weak interoperability and reusability within different systems. The basic idea of sensor measurements modelling is annotating heterogonous sensor data with formalized semantic, which could provide a mechanism to manage the perceived sensor data by creating semantic content in order to increase interoperability as well as to provide contextual information.

The conceptualizations of sensor measurements module relating to sensing and observations have been reused from the SSN ontology. SSN was a remarkable work for the formal representation of sensor capabilities, properties, observation and measurement processes through high-level specifications. This ontology was developed by following the principle of minimal ontological commitments, and it introduced a minimal set of classes and relations

entered around the notions of *ssn:Sensor* and *ssn:Observation* to make it reusable for various application domains. The *ssn:Sensor* class was defined as an entity that observes and transforms incoming stimuli into another, often digital, representation through the object property *ssn:detects*. The *ssn:Observation* of sensor was defined as a subclass of *dul:Situation*, which is a social object that satisfies some descriptions. It placed related classes, including sensor (*ssn:observedBy*), property (*ssn:observedProperty*) and observation value (*ssn:hasValue*) in an interpretative context.

One limitation of the existing SSN ontology is that it cannot support the association among context entities. In order to overcome this limitation, new properties have been defined to extend the sensor and associate it with features of interest and properties. The *ha:locatedIn* property was used to assert that a sensor is deployed in a specific house area. The *ha:attachedTo* property was used to associate the sensor to the user or physical object to which it is attached.

6.3.2.3 Place

The specific place in the smart home, such as the dining room, bathroom, kitchen, and bedroom, could be used to characterize the location of a sensor, user or situation. In this sense, the place ontology is proposed based on the place ontology design pattern to model knowledge about generic locations within smart home. The Place ontology design pattern was implemented in DUL and the relevant DUL statements, a *dul:Place* was something that had at least one *dul:isLocationOf* property (its inverse property is *ha:hasPlace*). Furthermore, The place ontology can be linked with SSN ontology through *ha:hasObservedPlace*, which is defined as a subclass of *ssn:hasProperty*, to express the observed location of sensor.

6.3.2.4 Physical object

The physical object ontology reused the concept of object module from the DUL ontology to describe the knowledge of household objects that are involved in an activity; for instance, the activity “take medicine” occurs with the usage of medicine box. Moreover, the vocabulary

extracted from [181] was also reused to classify the household objects into two categories: fixed and moveable. The fixed physical objects include fixtures and fittings (e.g. bed, door, stove) and the moveable ones refer to the physical objects that have changeable locations (e.g. telephone, chair). Such a categorization facilitates to keep track of an entity. The instance of *dul:PhysicalObject* class can be linked to the place ontology through the *dul:hasLocation* property to express the location of the household object (e.g. the stove is located in the kitchen). In addition, recall that the property *ha:attachedTo* (its inverse property is *ha:hasSensor*) is used to assert that a sensor is attached to a household object (e.g. a RFID sensor can be attached to a cup).

6.3.2.5 Temporal

The SWRL temporal ontology was reused as a principled temporal model to enforce a consistent representation of temporal content and properties. This ontology provides a vocabulary for describing complex interval-based temporal information, as well as the formal underpinning with a library of SWRL built-ins to perform temporal operations.

Figure 6.4. The concepts of SWRL temporal ontology.

As shown in Figure 6.4, an activity's valid-time is represented by using the class *swrlto:ValidTime* (equivalent to *dul:TimeInterval*) via the property *swrlto:hasValidTime*. The *swrlto:ValidInstant* and *swrlto:ValidPeriod* were donated as two subclasses of

swrlto:ValidTime to describe the corresponding instants and intervals respectively. An instance of *swrlto:ValidPeriod* represents an extent of time; it links *xsd:Date Time* via two properties: *swrlto:hasStart* and *swrlto:hasFinish*. The instance of *swrlto:ValidInstant* is, intuitively, point-like in the sense that it contains no interior points; it links *xsd:Date Time* via the *ha:hasInstant* property (equivalent to *swrlto:hasTime*). Generally, an instant can be treated as an interval where the start and finish times are the same. The granularity of time (e.g. year, month, day, hour, minute, etc.) is represented by using the *swrlto:Granularity* class (a subclass of *dul:Unit of measure*) to specify the accuracy of the temporal information. Durations are represented by the class *swrlto:Duration*, which has a functional integer property, *swrlto:hasCount*, and a functional granularity property with a range of *swrlto:Granulairty*.

The SWRL temporal ontology can be linked with the *ssn:Observation* class of SSN ontology though *ssn:observationSamplingTime* and *ssn:observationResultTime*, to express the significant information about sensor observation times.

6.3.2.6 Activity

The ADL model has been specified with the related contextual information in mind, e.g. occurring time, place, and related objects. A domain ontology has served as the core vocabulary for the basic activity contextual information representation. We have chosen the Simple Event Model (SEM) as the basis of the ADL domain ontology. SEM was built on DOLCE+DnS Ultralite ontology. Our model takes main aspects (e.g. actor, place, time) of an activity into consideration and allows the user to integrate external ontologies, such as the temporal ontology, for further description of an activity.

The proposed activity domain ontology (depicted in Figure 6.5) has been constructed as a core vocabulary, which enables to drive the derivation of composite activities from the contextual information. Based on SEM, the ADL is represented as an instance of the *ha:Activity* class (equivalent to *sem:Event*). A *ha:Activity* instance is matched with one or more instances of the context entities in order to present a specific activity with its

environment. The user who performs the activity is defined as an individual of the *sem:actor* class by using the *sem:hasActor* property. The place where an activity occurs is represented by using the *sem:hasPlace* property. The semantics of composite activities correlation can be represented by the use of *ha:hasSubActivity* (equivalent to *sem:hasSubEvent*) property. Additionally, the concept *ha:PhysicalObject* has been added to the SEM ontology to represent the household object relevant to the activity; the association between one *ha:PhysicalObject* and one *ha:Activity* is implemented by using the *ha:hasPhysicalObject* property (e.g. the household object “broom” is related to the activity “sweeping the floor”). The *ha:hasConstraint* property was also added to specify the activity with *ssn:Property*. For example, the human posture can be viewed as a sensor property to specify an activity presenting an ambiguity problem that can be solved by determining the posture of the individual. As an example, if the pressure sensor attached to the bed in the bedroom is triggered, there are two possible activities: sleeping in the bed or sitting on the bed to read a newspaper; in this case, the addition of posture “lying down” or “sitting” can identify the activity that is being carried out in a more precise manner.

Figure 6.5. Conceptual ADL domain ontology.

6.3.2.7 ADL pattern

The functional requirements of the human activity ontology have been represented by specialized instantiations of the description and situation (DnS) ontology pattern of the DUL ontology. The DnS pattern enables to have formally precise representations of various contextualized views on the instances of the *dul:Event* class, which can be used to describe the *n*-ary relations among multiple individuals of *dul:Event* and *dul:Object*. Based on DnS, the proposed ADL pattern implements the relations of situations and descriptions with individuals of the *ha:Activity* (a subclass of *dul:Event*) and *ha:ActivityType* (a subclass of *dul:Concept*) classes. As shown in Figure 6.6, the monitoring result is expressed by a *ha:ADLSituation* that *dul:satisfies* a *ha:ADLDescription*. The classes *ha:ADLSituation* and *ha:ADLDescription* are aligned with the DUL ontology to be equivalent classes of *dul:Situation* and *dul:Description*, respectively. The *ha:ADLSituation* includes context information related to the activity being described. The *ha:ADLDescription* serves as the corresponding descriptive context on a set of entities to create views on a *ha:ADLSituation*. The concept *ha:ActivityType* classifies the *ha:Activity* class and describes the interpretation of an activity in *ha:ADLSituation*.

Some vocabulary in the mereology pattern of Event Model F has been reused to construct an extension of the ADL pattern in order to express temporal relationships among activities. The mereology pattern considers the interrelationships as compositions of activities and enables to express their temporal relations by using temporal inference.

As can also be observed in Figure 6.6, the instances of *ha:Activity* from the domain activity ontology are included in *F:CompositionSituation*, which satisfies a *F:CompositionDescription*. The *F:Composite* and *F:Component* classes are defined as subclasses of *ha:ActivityType* to express the composed activity and its constitutive activities, respectively. Activities that play *F:Component* roles can be further qualified by temporal constraints to describe the temporal relations among these activities, and such temporal constraints are formally expressed by instances of the *F:TemporalConstraint* class (a subclass of *F:CompositionConstraint*) that is defined by the *F:CompositionDescription* class.

Figure 6.6. Conceptual ADL pattern.

Table 6.13. Thirteen temporal relations between activities and their corresponding time intervals (x and y are temporal intervals).

Relation	Diagram example	Inverse
x before y		y after x
x meets y		y metBy x
x overlaps y		y overlappedBy x
x starts y		y startedBy x
x during y		y contains x
x finishes y		y finishedBy x
x equals y		

Allen's Time Calculus can be integrated into this ADL pattern to support temporal inferences. Table 6.13 details Allen's temporal relations of activities [110], which position any pair of intervals by comparing their starting and ending time points to support qualitative temporal knowledge representation. In terms of the relationship between their temporal intervals, activities and their relations can be modelled as sequential activities, concurrent activities and interleaved activities.

- *Sequential activities*: In this case one activity is performed either before or after another one. The before/after and meets/metBy of Allen relations are used to associate sequential activities and their temporal intervals. The before/after relation indicates that there is a time gap between the two intervals, whereas the meets/metBy relation could be views as a specification of the before/after relation with a zero-length gap between the two intervals.
- *Concurrent activities*: Concurrent activities occur at the same time, thus they share either fully or partially their time intervals. There are nine relations used to model concurrent activities: overlaps/overlappedBy, starts/startedBy, during/contains, finishes/finishedBy and equals. The overlaps/overlappedBy relation is used to model activities that have partially shared temporal intervals but do not share neither the same start nor the same end points. The starts/startedBy relation indicates that two intervals have the same start time but one is longer than the other. The finishes/finishedBy relation is similar to the previous one, but with coinciding end times. The during/contains relation is used to represent that the interval of a composite activity encloses the interval of one of its composing activities. Finally, the equals relation is only used when two activities have the exact same timespans.
- *Interleaved activities*: Interleaved activities have time intervals that “preempt” each other, which indicates that an activity may occur within a long and complex activity, the longer interval containing the shorter one. The during/contains relation is also used to describe interleaved activities, but differently from the case of concurrent activities, in this case the activity with the shorter interval is not a component of the other.

6.3.3 Implementation and evaluation

In this section, we describe the proof-of-concept implementation we have performed of the ontology that represents human activities, together with its evaluation for a specific scenario.

6.3.3.1 Formalization

The proposed human activity ontology was constructed by using Protégé ontology editor and represented in OWL2. OWL2 is a semantic web ontology language based on DL. It contains a set of constructors for specifying conceptual structures and relationships (e.g. equivalent, disjoint and subsumption) as well as supporting inference and reasoning. Figure 6.7 presents a hierarchical fragment of key classes within the human activity ontology.

Figure 6.7. A snapshot of classes in human activity ontology.

This human activity ontology enables to model knowledge at two levels of abstraction. One is related to obtaining raw data and generating the related contextual information from context entities. The other deals with deducing the high-level activity-concerned information from the

raw data and contextual information. The sensor devices deployed in smart home environments capture the detailed signals of an activity when triggered. These data are received and stored for further processing. Moreover, the ontology enriches these signals by adding semantic metadata to the raw sensor data. Then semantic contexts as well as sensor data are potentially generated to gain the high-level context for smart home applications.

Due to the inability of OWL to express complex rule formations, the Semantic Web Rule Language (SWRL) was used to add rule capabilities to OWL-based ontologies. SWRL-based rules are made up of an antecedent and a consequent each [182], and these rules can be used together with OWL constructors to ensure the decidability, soundness and completeness in reasoning. After the SWRL rules are created, they can be used for inference and reasoning by using a reasoning tool (e.g. Pellet, <https://github.com/complexible/pellet>). Three example rules by using the syntax of SWRL temporal ontology built-ins are described as follows.

Example rule 1: $hasValidPeriod(?X, ?pX) \wedge hasValidPeriod(?Y, ?pY) \wedge hasFinish(?pX, ?fX) \wedge hasStart(?pY, ?sY) \wedge before(?fX, ?sY) \square before(?pX, ?pY)$

Example rule 1 states that, if Activity X has an interval pX, activity Y has an interval pY, and the finish time of pX occurs before the start time of pY, then the fact “pX is before pY” is inferred according to composite activity analysis on Allen’s Time Calculus. That is, it is inferred that activity X and activity Y take place sequentially and activity X takes place before activity Y.

Example rule 2: $hasValidPeriod(?X, ?pX) \wedge hasValidPeriod(?Y, ?pY) \wedge hasValidPeriod(?Z, ?pZ) \wedge before(?pX, ?pY) \wedge before(?pY, ?pZ) \square before(?pX, ?pZ)$

Example rule 2 states that, if the interval of X is before the interval of Y, and the interval of Y is before the interval of Z, then the fact “the interval of X is before the interval of Z” is inferred.

Example rule 3: $hasValidPeriod(?X, ?pX) \wedge hasValidPeriod(?Y, ?pY) \wedge hasStart(?pX, ?sX) \wedge hasFinish(?pX, ?fX) \wedge hasStart(?pY, ?sY) \wedge hasFinish(?pY, ?fY) \wedge before(?sX, ?sY) \wedge before(?fY, ?fX) \sqsupset during(?pY, ?pX), isComponentFor(?Y, ?X)$

Example rule 3 derives the during interval relation by using the start and finish points of two given activities. It asserts that the activity Y, which has a shorter time interval that is totally included into that of X, is a component activity of activity X.

6.3.3.2 Scenario with ontology extensions

To evaluate the proposed human activity ontology, this section describes a proof of concept tailored to smart home domain. The specified scenario presented in section 5.2.2 is revisited to provide an overview on how to represent the user and activity information with concepts and properties.

In terms of user aspects, Maria, Carlos and Juan were created as individuals of the *foaf:Person* class, and played (via the property *ha:plays*) the roles of actor, health expert and caregiver, respectively. In terms of SH context aspects, the accelerometer, ECG, RFID, motion sensor, pressure sensor, temperature sensor and light sensor were created as individuals of the *ssn:Sensor* class. Bedroom was created as an individual of the *ha:Place* class. Bed, medicine box and cup were created as individuals of the *ha:PhysicalObject* class. Regarding activities, “sleep”, “take medicine” and “use cup” were created as individuals of the *ha:activity* class. Take the activity “sleep”, for example. It is defined as “an Actor: Maria uses bed in bedroom for 8 hours”, this description can be expressed with the following OWL axioms:

$Sleep \sqsubseteq Activity \sqcap hasActor(Maria) \sqcap hasPhysicalObject(Bed) \sqcap hasPlace(Bedroom) \sqcap hasDuration(8[int]hour)$

Additionally, in the scenario, two health features (heart rate and posture) and two environmental features (temperature and light) were monitored to help understand Maria’s state when she performed activities in home areas. As shown in Figure 6.8, two modules,

namely *PhysiologicalState* and *EnvironmentalState*, were added as extensions of human activity ontology to provide additional health and environment information in terms of a specific type of property. The concept of *PhysiologicalState* consists of two subclasses: *HeartRate* and *Posture*. The concept of *EnvironmentalState* consists also of two subclasses: *Temperature* and *Light*. These two modules were added as subclasses of *ssn:Property*, and their values represent the observations of the corresponding sensors (in this case, Electrocardiogram sensor (ECG) and Accelerometer for health information; temperature sensor and light sensor for environment information).

Figure 6.8. Extended modules for features related to *PhysiologicalState* and *EnvironmentalState*.

6.4 Context-aware system architecture

All the previous results are integrated into our proposed three-layered context-aware architecture for monitoring ADLs in Smart Home (see Figure 6.9). This architecture allows for the inclusion of the necessary functions to represent in a meaningful manner the context in which those ADLs take place, and includes the definition of an upper-level ontology to facilitate reasoning and sharing. Besides, we have implemented a platform in an initial state, built in part over LoT (Microsoft's Lab of Things), to realize and validate the architectural model by following some of the extensibility and normalization principles of what is called the Internet of Things. In fact, the adoption of LoT platform eases the connection of sensors and devices and facilitates the sharing of results and data with the smart home community.

Figure 6.9. Three-layered architecture overview for ADLs sensing and characterization in smart home.

6.4.1 System architecture description

The proposed context-aware system infrastructure aims to collect and manage the context data from heterogeneous sources, then process it to obtain the required context information suitable to target applications and cloud storage. The layered architecture is depicted in Figure 6.9. We define the following three layers in the architecture:

- *The context sensing layer*, where context is sensed and collected through the heterogeneous sensors and devices embedded in the smart home environment or worn by the user. This layer provides the sensor-based information that constitutes the input of the data-driven domain as we have defined in our smart home development framework (chapter 3).
- *The context management layer*, where the captured data coming from the context sensing layer is preprocessed, interpreted by the context ontology model and inferred by the context reasoner. This layer is decomposed in two stages in our framework (see chapter 3): the data-driven phase is capable of detecting simple or almost-atomic activities, whereas the knowledge-driven phase leverages the use of ontologies to represent contextual information and activities relations with powerful semantics and high levels of reusability.

- *The application layer*, which serves as an interface for the users to access the context information provided by the context management layer in a manner that is meaningful for them. At this level composite activities and inferred inhabitants' behaviour can be deduced and processed to provide users with the full end user functionality.

Each layer's core components together with their detailed functionalities are presented in the following subsections.

6.4.1.1 The context sensing layer

The context sensing layer consists of both physical hardware (e.g. environmental sensors, accelerometers and door switches), and network components. This layer is responsible for obtaining raw context information from various sources.

This layer contains two core modules: the device connectivity module and the device functionality module. The device connectivity module deals with the discovery and association of sensors and devices to make them available to the platform. Devices and sensors are in general capable of connecting through multiple paradigms, such as WiFi, Bluetooth or proprietary protocols. Once discovered, a handle to the device is passed to the device functionality module.

The device functionality module takes the handles provided by the device connectivity module and turns them into high-level APIs that are independent of the low-level details of sensors and devices. It basically constitutes a driver. Then the captured contexts, such as temperature from embedded sensors and door status from door switches, are handled to the context management layer.

6.4.1.2 The context management layer

The context management layer works on low-level context sensing information to provide context abstraction for higher-level context manipulation. It consists of three collaborating components: (1) the data preprocessing component preprocesses the data collected from the

context sensing layer to build a context knowledge base. (2) The Context ontology model abstracts ADL-related contexts from heterogeneous sources and converts them to formalized representations in order to facilitate interoperability and reusability. (3) The context reasoner provides logic reasoning services (e.g. deriving high-level contexts from low-level ones) for ADL-related contexts processing via the reasoning engine. In the following, we describe the functionalities of each of these components.

- *Data preprocessing component.* In general, different sensors are needed simultaneously to correctly identify the different activities, and each of them may provide its measurements (i.e., the raw data) in a different format. Raw data by itself is therefore of little (or no) use for the activity detection algorithms. The preprocessing of this data is a must in order to obtain useful and significant information for the application. This preprocessing includes methods related to data cleaning, transformation, segmentation and dimensionality reduction, with the objective of converting data into the proper formats. For example, the filtering method is commonly used to eliminate the constant component due to gravity in 3D acceleration data.
- *Context ontology model.* This component provides semantic capabilities by using ontology engineering to model ADL-related context information, such as user, location, interacting objects and time. The context ontology model aims to provide a homogeneous view over the heterogeneous data in order to enable data sharing, reuse and multiple applications integration. This context information is stored in the context database. The ADLs ontology we have designed allows the markup of heterogeneous data to generate semantic content, related to both activity modelling and context representation.
- *Context reasoner.* The context reasoner is built upon the context representation and the functionalities of the context ontology model. Its purpose is to extract and define the abstract context information that cannot be directly detected by sensors and devices (e.g. what is the user doing? where is the user located?), in order to provide advanced processing services. This is achieved by using the reasoning engine,

supporting the inference of high-level contexts from their corresponding basic contexts, in a process that depends on the availability of collected data as well as the system requirements.

6.4.1.3 The application layer

The application layer makes use of the different levels of context information that are provided by the context sensing layer and the context management layer. The user interface is placed between the users and the interpreted context information, relieving the former from the requirement to directly deal with context management. The ADLs monitoring application provides insight about the elderly's health status to the caregivers/experts and facilitates the provision of assistance when necessary. All collected and processed data can be uploaded to a cloud storage (e.g. Azure) for sharing and further research by the research community.

6.4.2 Initial Implementation and result

We adopted the LoT research platform, developed by Microsoft, as a base to construct our system infrastructure for monitoring ADLs in smart home. The LoT research platform is built upon the top of HomeOS [183], which provides a standard user interface to configure the so-called Home Hub, enable remote access from web browser and ease the tasks of managing in-home hardware and writing applications. The LoT platform ran HomeOS on a dedicated computer, the Home Hub, which was utilized to interact with the in-home sensors and devices and host the target applications. This platform also provided a common framework to write and execute applications by utilizing the functionalities of the deployed sensors and devices, providing field deployments with a set of capabilities including uploading application data obtained in home to cloud storage, remote monitoring of system health, and remote updating of applications if needed [184].

Regarding the context-sensing layer, in our experiment we used Arduino Uno boards to connect with sensors deployed in smart home. The so-called scout was responsible of locating connected devices and make them available to the platform (serving as the device

connectivity module). We have written an Arduino scout to discover the Arduino device on its serial port; once the Arduino device was found, the scout handed over the target device to the device functionality module.

Regarding the device functionality module, the driver implemented was responsible of facilitating the communication between the Arduino device and the Home Hub. The driver exposed the functionalities of the Arduino device by using a service abstraction called role, which contained a set of operations that can be invoked. We have written the Arduino driver to allow for the request and reception of data from the connected sensors.

Figure 6.10. Screenshots of user interface for device discovery, installation and data display.

To perform an initial validation of our approach, we have developed an example device with an Arduino Uno board and an associated LoT application supporting a temperature sensor to measure the temperature and a passive infrared (PIR) sensor to detect motion and presence of humans. The open-source Arduino Software (IDE) was used to write code and upload it to the Arduino board, whose main functions were sending commands from the Home Hub and

receiving the data collected from the temperature sensor and PIR sensor. The Arduino scout and driver have been written in C#.

As we can see from Figure 6.10, when the Arduino scout ran through the DashBoard of the Home Hub, the Arduino device called “HomeOSArduinoDevice_001” could be found and added in the “Add Devices” page (as shown in figure 6.10(a)). Then, the Arduino driver exposed the functionality of the device in order for the Arduino application to communicate with the device (as shown in figure 6.10(b)). We also preprocessed the analog output of the PIR sensor. When the PIR sensor was triggered, the output was transformed into “presence”, and when the PIR sensor was not triggered, the output was transformed into “absence” (as shown in figure 6.10(c)), which indicated the user’s presence or absence in the home area where the PIR was located. This contextual information was susceptible to be further used by our ADLs ontology model.

Chapter 7 Conclusion

7.1 Objective achievements and contributions

Each of the specific objectives we defined in chapter 3 has led to the development of one of the results presented in the previous chapter. Besides, these results are original contributions to the existing methods, knowledge and technologies in the area of the activity detection. In the following we discuss, for each of the specific objectives, the degree of accomplishment and the contributions to which it that has given rise.

Figure 7.1. Specific objective and contributions.

Specific objective 1. Understanding the current advances and trends in the activity detection area.

This objective has been carried out leading to a publication in a high-impact journal [185]. This publication presents the current state of activity detection specifically tailored to elderly people at home. In addition, it identifies detected challenges that should be faced for the next years.

Specific objective 2. Method to detect all types of activities from raw sensor data.

This objective has been achieved by defining new setups for accurate detection of all types of activities (including short-termed transitional activities) with data captured by only a few sensors. This work has led to the writing of a paper that has been already sent for its consideration by a high-impact journal and is, at the time of writing this dissertation, under the process of peer-reviewing. Moreover, the design and execution of the corresponding experiment has produced a dataset containing circa 10 hours of curated data, millions of samples in total, captured by three accelerometers placed on each of 10 collaborating people. We plan to publish this dataset in UC Irvine Machine Learning Repository⁶ for its possible reuse by the scientific community. This dataset has been used for the production of one of the Thesis results, concretely by extracting the data of one of the accelerometers, the way it is described in the results chapter.

Specific objective 3. Network of ontologies to ease the high-level management of activities in real environments.

The ontology developed in this objective can be linked with other ontologies forming a network of ontologies capable to handle common sense issues of real environments. Although the ontology has not been tested in a real environment, the development has followed a well-known methodology that includes validation tests. Besides, a summary of the specific methodology application, the final formalization of the ontology and the validation

⁶ UC Irvine Machine Learning Repository, <http://archive.ics.uci.edu/ml/>, April, 2016.

tests have been published in a high-impact journal [186]. Consequently, the author considers that this objective has been achieved.

Specific objective 4. Open architecture for context data gathering.

This objective has been achieved through the implementation of a context-aware architecture using Microsoft's Lab-of-Things framework. Most of the previous assumptions about open architectures have been successfully addressed obtaining an adaptable and flexible architecture. The final architecture and validation tests have been published on [187].

7.2 Overall achievement

The author considers that all specific objectives have been adequately achieved. However, although the technologies developed have been specifically designed to address the difficulties related to real environments, we acknowledge that more assessment experiments are necessary to complete the validation of the system in such environments. While each technological result is conveniently decoupled through the definition of clear semantic interfaces (at detection or management levels), it is possible that the final ensemble of all modules shows previously undetected issues. This can be especially important in the case of the proposed open architecture since is the backbone for the rest of the modules.

To continue with the research presented in this Thesis, the author recommends the creation of a complete solution for Smart Home activity detection as a composition of all the technological results obtained in this work. Once developed, this solution should be employed to carry out a set of experiments designed to evaluate the performance of the complete solution in a real home as well as the performance of each of the modules to detect possible mismatches.

It should be emphasized that in all experiments the assumption has been that the same person carries out all activities. This is consistent with the fact that the application domain is aimed at improving the capacity of independent life for the elderly living alone at home. However it

is important to note that the possibility that the detected activities are performed by different persons is real even if the person lives alone in their home (e.g. they may receive the visit of familiars). The definition of strategies to manage this situation is beyond the scope of this Thesis.

7.3 Discussion on hypotheses

Hypothesis 1. Mixed approach to face the activity detection.

The approach based on the combination of both data-driven and knowledge-driven methods has enabled a suitable addressing of most of the challenges raised when considering real environments. The complexity of those environments has been divided in low-level complexity, more related with the type of activity to be detected through sensors, and high-level complexity, aligned with the interrelation among activities. This division of concepts has facilitated to tackle the technical difficulties of these environments.

Hypothesis 2. Architecture based on Internet-of-Thing concepts.

The definition of adaptable architectures capable to gather context information from a real environment, such as the home, has been a challenge from the beginning of the research associated to the smart home. The decision of adopting Internet-of-Things based solutions, such as the Lab-of-Things development environment, has lightened the decisions about technologies. Thus the technology risks associated with these decisions have also been reduced. In addition, this approach has not limited the scope and objectives of the Thesis and thus the author considers that this hypothesis has been validated.

Hypothesis 3. Machine learning for low-level activity detection.

The application of machine learning methods has led to obtaining a technological result which presents accurate detection of activities with few devices. Even though it is possible that the performance of other technologies is better for this kind of detection, the maturity, flexibility and adaptability of machine learning methods and technologies leads us to

conclude that they can be considered as proper technologies for the detection of activities in real environments.

Hypothesis 4. Ontologies to address high-level activity management.

The management of the detected activities in a home should take into account aspects related to human common sense. This includes the consideration of issues related with space, time or relations among different activities. The ontology presented as a result of this Thesis has been integrated in a network of ontologies that includes models to handle the aforementioned aspects, as has been described in the results chapter. Thus, the author of this Thesis considers that this hypothesis has also been validated.

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