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Behavioural Modelling for Ambient Assisted Living

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October 2017

Declaration

This is to certify that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

University of Minho, **26/ 10 / 2017**

Name: **Samih Eisa Suliman Abdalla**

Signature: ____

Acknowledgement

First of all, I would like to express my sincere thanks to my advisor, Professor Adriano Moreira, who has provided me immense help, support, guidance, and encouragement. I thank him for everything I have learned from him.

I am also grateful to Centro de Computação Gráfica (CCG) for hosting my research work and to all of my colleagues, specially João Peixoto and Professor Filipe Meneses for their help and support.

I also wish to thank my friends Dr. Mansoor Hak, Gassan Abujumra, and Nasir Taha for their encouragement and support.

Special thanks to my family members for their patience and their unconditional support.

Resumo

A mudança incomum na rotina diária ao nível da mobilidade de um idoso em sua casa, pode ser um sinal ou sintoma precoce para a possibilidade de vir a desenvolver um problema de saúde. O recurso a diferentes sensores pode ser um meio para complementar os sistemas de cuidados de saúde tradicionais, de forma a obter uma visão mais detalhada da mobilidade diária do individuo em sua casa, enquanto realiza as suas tarefas diárias.

Acreditamos, que os dados recolhidos a partir de sensores de baixo custo, como sensores de presença e ocupação, podem ser utilizados para fornecer evidências sobre os hábitos diários de mobilidade dos idosos que vivem sozinhos em casa e detetar desta forma mudanças nas suas rotinas. Neste trabalho, validamos esta hipótese, desenvolvendo um sistema que aprende automaticamente as transições diárias entre divisões da habitação e hábitos de estadia em cada uma dessas divisões em cada momento do dia e consequentemente gera alarmes sempre que os desvios são detetados.

Apresentamos neste trabalho um algoritmo que processa os fluxos de dados dos diferentes sensores e identifica características que descrevem a rotina diária de mobilidade de um idoso que vive sozinho em casa. Para isso foi definido um conjunto de dimensões baseadas nos dados extraídos dos sensores, como parte do nosso *Behaviour Monitoring System* (BMS). Fomos capazes de detetar com um atraso mínimo os comportamentos incomuns e ao mesmo tempo, durações de confirmação da deteção elevadas, de tal modo suficientes para um conjunto comum de situações anormais.

Apresentamos e avaliamos o BMS com dados sintetizados, produzidos por um gerador de dados desenvolvido para este efeito e projetado para simular diferentes perfis de mobilidade de indivíduos em casa, e também com dados reais obtidos de trabalhos de investigação anteriores. Os resultados indicam que o BMS deteta várias mudanças de

mobilidade que podem ser sintomas para problemas de saúde comuns. O sistema proposto é uma abordagem útil para a aprendizagem dos hábitos de mobilidade em ambientes domésticos, com potencial para detetar alterações comportamentais que ocorrem devido a problemas de saúde, e assim encorajar a monitorização dos comportamentos e dos cuidados de saúde dos idosos.

Abstract

Unusual changes in the regular daily mobility routine of an elderly at home can be an indicator or early symptoms for developing a health problem. Sensor technology can be utilised to complement the traditional healthcare systems to gain a more detailed view of the daily mobility of a person at home when performing everyday tasks. We hypothesise that data collected from low-cost sensors such as presence and occupancy sensors can be analysed to provide insights on the daily mobility habits of the elderly living alone at home and to detect routine changes. We validate this hypothesis by designing a system that automatically learns the daily room-to-room transitions and stays habits in each room at each time of the day and generates alarm notifications when deviations are detected.

We present an algorithm to process the sensor data streams and compute features that describe the daily mobility routine of an elderly living alone at home. This was done by defining a set of sensor-driven dimensions extracted from the sensor data as part of our Behaviour Monitoring System (BMS). We are able to achieve low detection delay with confirmation time that is high enough to convey the detection of a set of common abnormal situations.

We illustrate and evaluate BMS with synthetic data, generated by a developed data generator that was designed to mimic different users' mobility profiles at home, and also with real-life dataset collected from prior research work. Results indicate BMS detects several mobility changes that can be symptoms of common health problems. The proposed system is a useful approach for learning the mobility habits at home environments, with the potential to detect behaviour changes that occur due to health problems, and therefore, motivating progress toward behaviour monitoring and elder's care.

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List of Abbreviations

AA	Intra-room Activity
AAL	Ambient Assisted Living
ACT	Anomaly Confirmation Time
ADD	Anomaly Detection Delay
ADLs	Activities of Daily Living
AE	Inter-room Activity
AG	Global Activity
BSM	Behaviour Monitoring System
CCG	Centro de Computação Gráfica
CRF	Conditional Random Fields
CS	Intra-room Continuous Stay
EMG	Electromyography
FN	False Negative
FP	False Positive
GPS	Global Positioning System
HMM	Hidden Markov Model
IID	Independent and Identically Distributed
PIR	Passive Infrared
RSSI	Received Signal Strength Indicator
SVM	Support Vector Machine
UART	Universal Asynchronous Receiver/Transmitter
UWB	Ultra-Wide-Band

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Chapter 1. **Introduction**

The world's ageing population is growing rapidly. In Europe alone, the number of adults age 65 and older is expected to increase from 17.1% to 30% by the year 2060 [1] while in the United State the number will double in the next 20 years [2]. This trend has tremendous implications on nearly all sectors of society, including healthcare and medical services. As the populations become increasingly aged, healthcare costs are expected to increase putting more pressure on the families and governments. Medical and social studies show that the majority of the elderly people prefer to live independently in their own homes, in spite of their health conditions [2][3], which makes them more vulnerable to unsafe situations such as falls or unsafe movements. Solutions to this problem currently take great advantage of the advent of modern communications and electronic advances, particularly the advancement in sensing and smart home technologies, to enable the monitoring of the Activity of Daily Living (ADLs) such as sleeping, walking, showering, dressing, taking medicine, cooking, functional mobility, etc. This allows the healthcare providers to continuously monitor the functional status of the elderly, increase their ability to live independently and allow for early detection of diseases [4].

Older adults usually exhibit high regularities in their daily life routines. They tend to follow specific patterns when performing their daily activities at home. This includes their daily room-to-room transitions and stays habits in each room or place at home. Long-term history logs of this information unveil valuable knowledge about their daily mobility patterns. If uncovered, these patterns can be utilised to model their daily mobility behaviour and then identify any significant shift or unusual mobility habit that does not conform to a normal routine and may be an early symptom of a health problem [2][4]. For instance, a change in a person’s sleeping habits (e.g. prolonged or less sleeping time) can be a symptom of anxiety, depression or early indication for developing Alzheimer’s disease.

In this research work, we are interested in detecting unusual changes in the regular mobility behaviour of the independently living older adults by monitoring their daily navigations between rooms at home. In this thesis, we describe how we approach this goal by designing a system that automatically learns the daily room-to-room transitions and stays habits in each room at each time of the day and generates alarm notifications when deviations are detected. We hypothesise that the relationship between the changes in behaviour can be observed using data collected from smart home sensors. Hence, our system uses Passive Infrared (PIR) motion sensors as primary input to track the mobility of the monitored person and also is designed to be agnostic of the users’ daily mobility profiles. No explicit annotation or laborious labelling is required to manually configure the mobility profile of the monitored person or to train the underlying behavioural model. We validate the developed system on synthetic data as well as on real-life data that represents the daily behaviour of an elderly person living alone at home.

1.1. Motivation

Many elderlies nowadays live independently in their own homes and for whom frequent accidents that may occur and require medical attention are often detected too late. For instance, in Portugal during winter 2011 the social media reported some cases of elderly people found dead in their homes several weeks after passing away. These cases raised large social awareness for the effect of such dangerous events and also directed the community’s attention to the importance of monitoring the elderly at their homes to detect those kinds of abnormal situations and provide timely responses. The solution, importantly, should take into account the elderly’s preferences and requirements and also should respect the existing settings that they have at home with no extra effort or expenses to ensure the adoption of the solution among a large sector of people.

1.2. Problem Statement

The problem of detecting unusual changes in the daily behaviour of an elderly person who lives independently at home has been investigated widely in the literature [5]. Solutions typically are sensor-based systems that require the use of wearable and non-wearable sensors to track the daily behaviours and provide responses when deviations are detected. These solutions usually require the intervention of the resident user, for instance, by pushing a button on a pendant or on a wrist watch, or by monitoring the resident using camera-based sensors installed at different locations at home. However, prior research studies [6] show that wearable and camera-based sensors are not very appreciated by the elderly people due to inconvenience, computational complexity, and privacy issues. The elderly might not feel comfortable wearing sensors all the time and may forget to wear them on some occasions, or may feel losing their privacy when monitored by cameras at home. This reduces the usefulness of these sensors for continuous behaviour monitoring. Even though some recent research studies include the sensors into the people clothes [7] or utilise the capability of smart watches [8] for behaviour monitoring, these works are still limited and not affordable for everyone, besides the limitations of the sensors' battery energy. Moreover, most of the existing systems entail an explicit annotation or labelling process to be made offline in order to manually configure the typical behaviour of the monitored persons before use, which increases the required installation time of these systems and prevents them from being adaptive to small shifts in behaviour that do not necessarily should be considered unusual behaviour (e.g. seasonal changes).

In this research, we aim at reducing the required user intervention in the monitoring system by relying only on sensors that can be included in the surrounding home environment and do not require too much attention. Therefore, our system uses Passive Infrared (PIR) motion sensors as primary input to track the mobility of the monitored person. PIR sensors are relatively cheap, easy to install and maintain, nonintrusive and are aligned with the privacy requirement of the elders and also are increasingly being adopted and installed in many buildings and houses for security and intrusion detection. Thus, our system will be readily installed at low cost and effort and also will not require personal data to be transmitted to external or cloud-based servers; the data will be processed locally at home, respecting the privacy requirement of the elders. Furthermore, it will avoid any kind of labelling or explicit annotation to pre-configure the users' mobility profiles. The system is capable of learning the daily mobility behaviour automatically from sensor observations and detect anomalous behaviours in quasi-real time, in contrast to most of the existing approaches in which the anomaly detection is provided on a daily basis.

1.3. Objectives

The main objectives of our research work can be articulated as follows:

- To further study the problem of behavioural modelling and anomaly detection in the Ambient Assisted Living (AAL) domain.
- To define a comprehensive framework that uses sensor observations obtained from low-cost sensors (e.g. Passive Infrared (PIR) motion sensors) to learn and understand the daily behaviour patterns of an elderly person living alone at home using the location context history.
- To identify a set of abnormal or unusual behaviours that may happen to the elderly and have a high correlation with the deviations in the daily mobility routine at home.
- To detect and recognise the basic activities that lead to the previously defined unusual behaviours (e.g. abnormal movement transitions, the absence of movement inside the house for a certain threshold time period, and leaving or entering the house at an unusual time).
- To detect diseases symptoms at early stages and help healthcare professionals in the long-term diagnosis of some of the mobility-related diseases such as anxiety, depression or early stage of Alzheimer’s disease.
- To reduce the number of false alerts generated by the monitoring system to the minimum and provide detection of abnormal situations in the least delay near to quasi-real time.
- To identify suitable performance metrics to evaluate the developed monitoring system.
- To define an evaluation methodology to validate the viability of the proposed system through realistic use cases and usage scenarios.

1.4. Method

The research method that we followed can be described as follows:

- First, we started by performing a research study to identify the requirements and metrics for indoor location and tracking for Ambient Assisted Living (AAL). The study was conducted on the most common techniques and technologies for indoor localisation and their suitability for in-house monitoring of older adults. The results were published in [9].
- We studied the available technologies for sensors communication inside the home in preparation for the real deployment of the monitoring system.
- We conducted an empirical experiment to evaluate the use of ZigBee technology for indoor localisation and collected results to estimate how good this technology is for tracking the mobility behaviour of the monitored persons. The results are included in Chapter 3.
- We performed a review study on the recent literature on the topic of human behaviour modelling, exploring most of the current approaches for modelling human behaviour from sensor data streams.
- We identified and designed the layout of the behaviour learning algorithm and the complete system's architecture.
- We developed the system as well as a data generator to produce synthetic data that simulates the typical daily behaviour of an elderly person living alone at home. The data generator was designed to generate data for users with different daily mobility profiles to ensure the diversity and realism of the generated data. The details of the developed data generator are provided in Appendix A.
- We then identified a set of abnormal behaviours and their relationship with some of the most common health declines that may happen to older people at home.
- We developed the anomaly detection module of the system and adapted its parameters experimentally before validating the whole system using the synthetic data and also real-life data collected from well-known smart home projects for activity recognition.

1.5. Contributions

The major contributions of this thesis include:

- The introduction of a system's architecture for in-house monitoring that utilises Passive Infrared (PIR) motion sensors to track the mobility of the older people at home environments.
- The development of an algorithm that automatically maps the raw sensors data of the monitoring system into meaningful movement patterns that describe the daily mobility behaviour of the monitored elderly person.
- The algorithm is designed as part of the learning module in the system to extract relevant dimensions from the raw sensors data using an unsupervised method with no prior knowledge or explicit data labelling that describes the typical daily mobility profile of the monitored elderly person (i.e. agnostic of the user's daily mobility profile).
- The algorithm uses a time-based sliding window to interpret and process the sensory data streams and can adjust its internal behaviour model in real time as new observations become available, achieving the goal of providing online learning method.
- The algorithm also can adapt its internal model to slight shifts in behaviour such as seasonal changes and to different people having very different daily behaviours, such as someone usually sleeping all morning or staying outside the house during the nights (e.g. sleeping at relatives' home).
- The developed system uses location context information (room-to-room transitions and stays habits) to build the underlying behavioural model. This gives the system the ability to be agnostic of the type of sensors used to acquire the location knowledge of the monitored person.
- The system provides abnormal alarm notifications in quasi-real time, in contrast to most of the existing behaviour models, and also reduces the rate of wrong detection and false alert notifications.
- We developed a data generator to simulate the mobility behaviour of the elderly people at home with an ability to generate different user mobility profiles and also to inject artificial anomalous behaviours.

- We designed and performed an evaluation method on synthetic data and real-life dataset and compared the obtained results with some approaches from the state-of-the-art.

1.6. The Structure of the thesis

The remainder of this thesis is organised as follows:

- **Chapter 2: Behaviour Monitoring for Ambient Assisted Living:** This chapter gives a background on the subject of the thesis. It provides an overview on the topic of human behaviour monitoring at home environments and introduces the most common techniques and technologies used for human behaviour monitoring. Moreover, it presents the most common approaches for modelling human behaviour from sensor data as well as detecting behavioural changes. We conclude the chapter by presenting a list of challenges and issues associated with the development of human behaviour monitoring systems for AAL and elders' care.
- **Chapter 3: Indoor Location for Ambient Assisted Living:** In this chapter, we present the results and description of a prototype experiment that we performed to evaluate the use of ZigBee technology for indoor localisation. We also present the results of a review study that we performed to identify the requirements and metrics for indoor location and tracking for Ambient Assisted Living.
- **Chapter 4: Behaviour Monitoring System (BMS):** In this chapter, we describe the developed Behaviour Monitoring System (BMS). The description includes the overall architecture of the system, the defined modules, and a presentation of the behaviour modelling method.
- **Chapter 5: Validation Approach:** An approach to validate the developed Behaviour Monitoring System (BMS) is presented in this chapter. It includes the description of the datasets used in the experiments and the definition of the performance metrics used to evaluate the system. We also present the description of the types of abnormal behaviours that we are targeting in this research work.

- **Chapter 6: results and discussion:** In this chapter, we present the obtained results of the performed experiments and give thorough discussions on them. The results are presented with respect to the defined performance metrics (Chapter 5) and the system's modules.
- **Chapter 7: Conclusion:** This chapter concludes the thesis. It gives an overall summary of the thesis as well as its limitations and possible directions for future research.
- **Appendices:** The appendices include the descriptions of the developed Behaviour Monitoring System (BMS) and the Synthetic Data Generator as well as an extended presentation of the obtained results.

Chapter 2. **Behaviour Monitoring for Ambient Assisted Living**

Behaviour monitoring for Ambient Assisted Living (AAL) is an active research area with wide range of techniques and technologies currently being investigated. Monitoring human behaviour is not a trivial task. In fact, there is no single approach that claims to cover all aspects of human behaviour monitoring. However, with the recent advent of sensing and communication technologies, many innovative approaches have emerged and quite promising results have been achieved. In this chapter, a brief description on the topic of human behaviour monitoring is given, with more focus on technologies used for behaviour monitoring for Ambient Assisted Living (AAL) in smart home environments.

2.1. Monitoring Activities of Daily Livings (ADLs)

An important concept in Ambient Assisted Living (AAL) is the monitoring of the Activities of Daily Living (ADLs) [4]. Most of the existing AAL systems for elders' care exploit the activity that is being performed by the elderly at home as a means for inferring or assessing the functional health status of the elderly. An elderly remains in a good health as long as he carries on his activities as usual with no significate deviations from the normal daily routine. The ADLs at home environment can be categorised into two main categories: basic ADLs (e.g. personal hygiene, bathing, feeding, dressing, and functional mobility) and instrumented ADLs (e.g. cooking and housework) [5]. ADLs monitoring of older adults allows healthcare providers to continuously monitor the functional status of the elderly, increases their ability to live independently, and allows for early detection of diseases such as

Alzheimer's [10][11], dementia [12][13][14] and urinary tract infection [15]. ADLs also can be used to learn daily behaviour patterns such as sleeping habits [16] or daily movement patterns [17].

However, monitoring ADLs at home environments faces many challenges that need to be considered. Issues related to the types of sensors used for capturing the ADLs and the data processing and algorithms used for ADLs classification and recognition as well as the people's preferences and privacy concerns are some of these challenges. In section 2.4 we discuss the challenges in more detail.

2.1.1. Sensing Technologies

In general, there are two main categories of sensors used for human behaviour monitoring: wearable and non-wearable sensors. Wearable sensors are usually attached to the human body or clothes whereas non-wearable sensors are usually embedded into the surrounding home environment [4]. The two kinds of sensors have been used extensively in various systems for behaviour monitoring and remote healthcare assisted living [18][19][20].

2.1.1.1. Wearable sensors

Wearable sensors used for activity recognition and ADLs classification vary depending on the nature of the required application. As mentioned, they are usually attached to the human body or clothes or can be part of or make use of devices that people usually carry with them, such as wristwatches or cell phones. However, accelerometers are the most commonly used wearable sensors with a variety of applications and usage scenarios. Accelerometers are used to identify the location of a person and differentiate motions (e.g. running, walking, walk upstairs, cycling, etc.) [21] or to detect falls using acceleration data from wristwatches [22] or to classify posture of a person by monitoring the tilt of certain parts of the body using the acceleration due to gravity [5]. Moreover, accelerometers are combined with gyroscopes to obtained orientation information [23] and also with tilt switches in a wrist-worn unit sensor [24] to capture the user's behaviour rhythms in day-to-day activities as a way to improve long-term activity recognition. Figure 2-1 shows examples of wearable accelerometers.

Figure 2-1: Wearable Accelerometers [25]

Smartphones are also considered wearable sensors. They are equipped with multiple kinds of sensors that provide a wealth of information for different applications (e.g. global positioning system (GPS), cameras, microphones, light, temperature, magnetic compasses, gyroscopes, and accelerometers). In [26], a framework that exploits the rich contextual information from smartphones (e.g. location, time, apps, call logs, and internal state) is presented. The framework uses the data collected from smartphone sensors to predict our next destination and which app we will be using in the next ten minutes. In [27], cell phone accelerometers are used for recognising activities such as walking, running, and jogging.

Other kinds of wearable sensors also have been used for ADLs monitoring such as magnetic sensors [28] for monitoring activities and use of portable devices, RFID sensors for detecting interactions with objects in smart homes and recognizing activities like cooking, washing dishes [29], teeth brushing and watching TV [30], and inertial sensors [31] for providing assessment of patient progress after an injury or stroke in ecological rehabilitation environments.

Wearable sensors are also used to monitor clinical measurements or vital signs, such as pulse rate, body humidity and temperature, respiration rate, and blood pressure, which indicate the state of a patient’s essential body functions. These measurements allow a much more in-depth evaluation on the person’s behaviours. For example, the detection of the heart rate and the use of Electromyography (EMG) sensors can be indicators for the overall activity level and physical fitness of the body and also can be used for the classification of the performed activities (e.g. in fitness applications). Moreover, monitoring changes in vital signs also can lead to early detection of health-related issues and, as a result, minimise the health-related risks and discover diseases earlier [32]. Sensors that embedded into human clothes also have emerged lately for monitoring vital signs, and many applications are being developed that facilitate the diagnosis of some diseases using these sensors [7].

However, the power consumption requirement and the convenience of constantly wearing wearable sensors are the major challenges that face the use of these sensors for long-term human behaviour monitoring.

2.1.1.2. Non-wearable sensors

Non-wearable sensors also are being used for ADLs monitoring [33][34][35]. Infrared (IR) sensors are the most commonly used non-wearable sensors. They are used for detecting presence, motion or locating people at home. Passive Infrared (PIR) sensors detect infrared radiation that is emitted by objects in their field of view [25], as shown in Figure 2-2. In [14], PIR sensors were used for managing dementia and depression diseases. The collected data from PIR sensors were used for the early detection of changes in activity level which was used to reduce the advancements of these diseases and lead to early interventions.

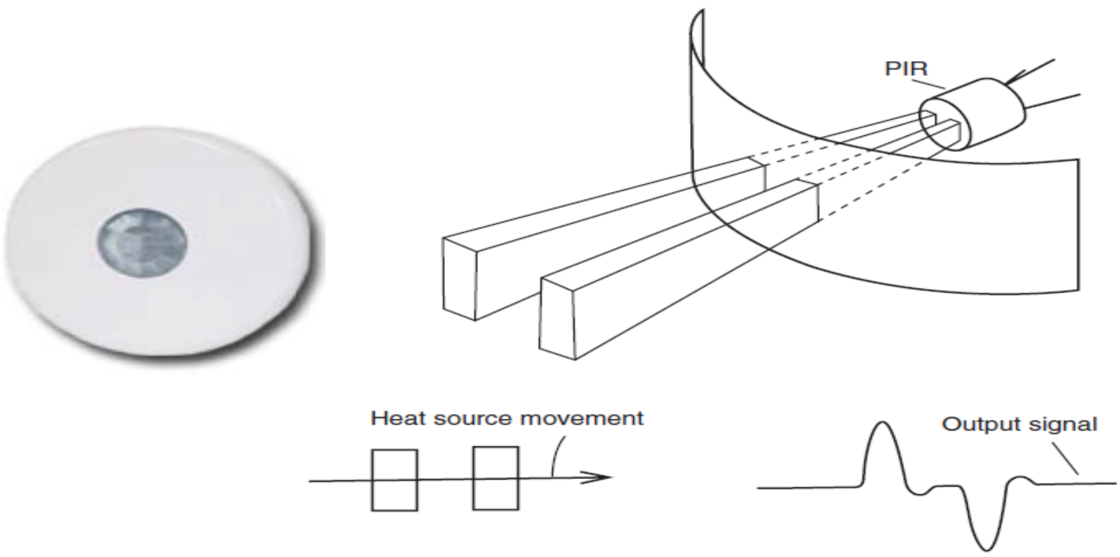


Figure 2-2: PIR Infrared Sensor [25]

Other non-wearable sensors are also being used for ADLs monitoring such as Ultrasonic sensors [36], pressure sensors [37], vibration sensors [38], video-based sensors, low-resolution thermal sensors [39], wattmeter sensors [40], water flow sensors [41], magnetic door switches [42] , and audio or sound sensors [43].

Table 2-1 presents a comparison on some of the properties of sensing technologies used for ADLs monitoring.

Table 2-1: Sensing Technologies - Properties Comparison

Property	**PIR**	**Camera**	**Smartphone**	**Smartwatch**
Location detection	Low	High	High	High
Presence detection	Medium	High	High	High
Tracking	Single user	Multi-users	Multi-users	Multi-users
Resolution	Single bit (on/off)	High	High	High
Cost	Low	High	High	High
Privacy Concern	Low	High	Low	Low
Battery life	High	NA	Medium	Low
Require data Processing	Medium	High	High	High
Localization accuracy	Low (Room-level)	High	High	High

2.1.2. Activity Classification

The existing studies towards the goal of human behaviour monitoring typically focus on the recognition of activities of daily living (ADLs) [44][45]. Various machine learning algorithms, signal processing techniques and statistical (heuristic) approaches have been used. The main steps that involved in this process are shown in Figure 2-3. In this section, we are more concerned about the activity classification step.

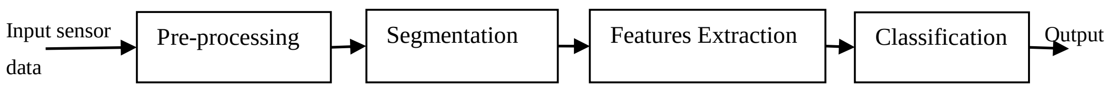


Figure 2-3: Steps for Activity Classification (adapted from [44]**)**

Many data mining and machine learning algorithms are used for ADLs classification: Support Vector Machines (SVM) [46][47], random forest [48], decision trees [28], fuzzy logic [49], Bayesian methods [50], and neural networks [47]. However, most of these classical machine learning algorithms assume that the input data for the classification step is independent and identically distributed (IID). This assumption does not hold in the case of human behaviour modelling and recognition, what a person is doing at the moment is not independent of what he was doing just before. Hence, more advanced models are required to handle the case when IID does not hold. In [4], two main categories that consider the dependency assumption are defined: generative approaches (e.g. Hidden Markov Model (HMM) [51]) and discriminative approaches (e.g. Conditional Random Field (CRF) [22]). Many algorithms from these two categories have been used widely and successfully in many behaviour modelling and ADLs classification applications. However, a previous intensive supervised training stage is required to estimate their models, which in turns may lead to human bias when labelling and annotating the activities.

Statistical (heuristic) approaches are also being used for human behaviour monitoring [33][52]. A system that examines the activity rhythms at home using a statistical predictive algorithm is presented in [33] to evaluate the behaviour of a resident individual while performing the daily activity routine. In some cases, simple statistics (heuristics) measures are used as features for a second-level activity classification algorithm, as implemented in [53], where heuristic measures like means and variances were used as features for neural network models to detect and classify motion activities.

2.2. Monitoring Location Context

The location of a person is essential for measuring the activity and assessing the overall behaviour of the person. The location includes both indoor and outdoor locations. In this section, we present some of the prior research works that used the location context for human behaviour monitoring.

2.2.1. Indoor location

The indoor location of a person at home gives useful information that can be used to build behavioural models for their everyday life. The movements of people inside the home correlate to their daily physical activities and performance of the activities of daily living. For example, frequent visits to the bathroom at night during sleeping time can be an indicator for significant sleep disorder or nocturia disease and may be a sign of developing urinary tract infections disease [54]. These kinds of unusual sleep disorder can be detected by a localisation system that continuously monitors the location of a person at home. In [15], an integrated sensors network of Passive Infrared (PIR) motion sensors, bed and chair sensors, was used in apartments of volunteer residents at an ageing in place retirement community. The sensors were used for detecting pulse, respiration rate and bed restlessness which, in turn, were used for detecting urinary tract infections. PIR motion sensors also were used in [55] to determine the location of an older adult in a smart home environment and to infer the Activities of Daily Living (ADLs) such as sleeping, preparing meals, going out, toileting, and brushing. In [56], a Ultra-Wide-Band (UWB) location system (UBISENSE) was used for monitoring the elderly people suffering from dementia. The system relied on small tags to provides accurate indoor localisation. In [57], an ultrasonic indoor location tracking system also was used for enabling location-aware pervasive services to monitor the older adults at home.

In the following chapter (section 3.2), we present an evaluation study that we conducted to review the current techniques and technologies for indoor localisation.

2.2.2. Outdoor Location

The outdoor mobility of the elderly is also important for evaluating their quality of life when going outside. Elderlies who have physical mobility limitations tend to have a lower quality of life and involvement in social communities [58]. In [59], a disorientation detection method that detects outliers in a person GPS mobility trajectories is presented. A survey for mining GPS data for mobility patterns is presented in [60].

In this thesis, we mainly focus on behaviour monitoring at the home environment, and therefore, we will not dive further into behaviour monitoring using outdoor location. We do, however, consider in the modelling of daily habits the time periods when the persons leave their homes.

2.3. Detection of Abnormal Behaviour

Abnormal behaviour refers to finding unexpected behaviour that does not conform to usual behavioural routine [61]. This topic has been investigated widely and applied in many domains and application scenarios. The detection of abnormal human behaviour depends on the way of defining the human behaviour. Activity recognition is the main approach for detecting abnormal human behaviour [44]. The deviations in the activities of daily living (ADLs) are considered the most common way of defining abnormalities in the human behaviour. By monitoring the performed daily activities of a person for a certain time, one can learn and build a model of normal behaviour and then detect deviations. In [52], an abnormal human behaviour was defined as an increase or decrease in the daily physical activity, defined as any body movement produced by skeletal muscles that result in energy expenditure. The deviation or change in the physical activity level, according to historical data, was used as early symptoms of health problems.

In general, the abnormalities in the human behaviour are mainly related to the detection of falls [62][63], inactive periods [64][65], abnormal living patterns [66], long-term behaviour changes [32], or abnormal events such as sleeping disorder [67].

2.3.1. Detection of abnormal long period of inactivity

One of the most abnormal behaviour that might happen to the elderly living alone is that of an elderly being immobilised or inactive for a long period of time due to falls, and not being able to get up and request an assistance. Some of the current solution to this problem use camera-based systems or include worn devices where the elderly can push a button to ask for a help in the case of emergency. Other works use smart home sensors to continually monitor the elderly and generate alarms that indicate the detection of long periods of inactivity. In [65], an algorithm was developed to automatically construct individual models of normal activity within the home using motion sensor data. The algorithm is based on learning the inactivity duration from the motion data over the past weeks and months. It was designed to generate alert anytime a new inactivity period occurs which is longer than a threshold value that indicates the normal inactivity periods. The system has four configurable parameters that determine the size of the alert threshold over daily 48 intervals. The algorithm's parameters have been optimized experimentally to meet the performance objective of one or fewer alerts per week with slightly higher rate during the early weeks of learning. However, the algorithm requires robust determination of when the senior resident is away from home to avoid giving normal inactivity for the period outside home, and therefore, it uses different code to model when the senior is away from home. Figure 2-4 shows an example of a normal inactivity data learned by the developed algorithm in [65] with the alert line showing the threshold for detecting the abnormal inactivity periods.

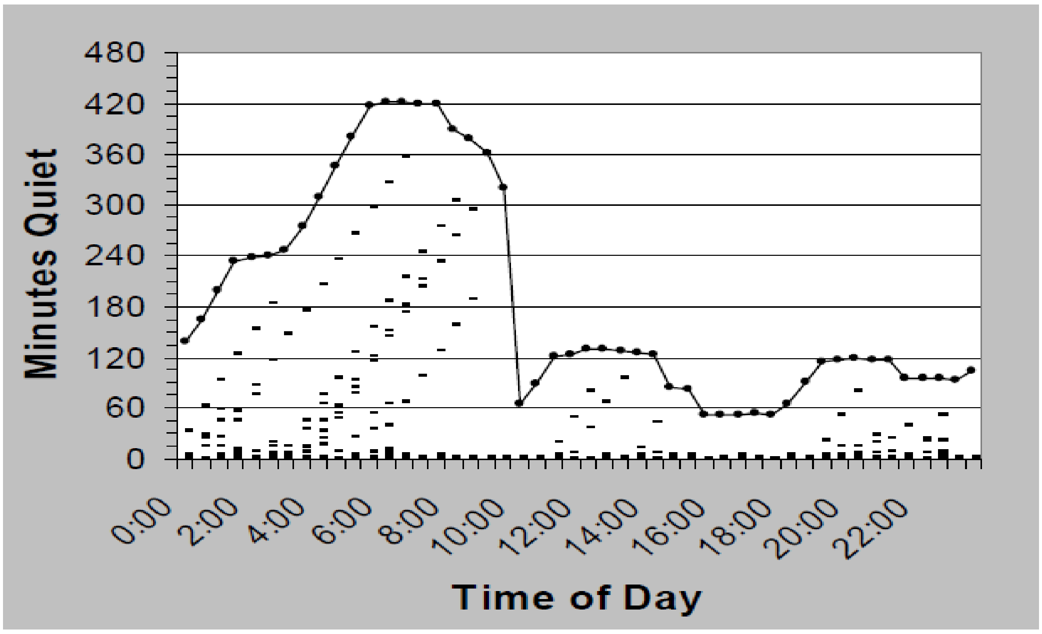


Figure 2-4: Inactivity data with alert line [65]

This work was further extended in [64] where three statistical and adaptive models were designed for detecting abnormal periods of inactivity using data obtained from unobtrusive PIR sensors. The authors applied a user-centric approach that addresses the requirements and concerns of the elderly users and their caregivers. The developed algorithm calculates the inactivity profile of a person on a daily basis and measures the difference with predefined inactivity profile so that days with large differences are considered abnormal. The algorithm inspects information obtained from the PIR sensors at half-hour interval over 24 hours and uses percentile information to compute an alert threshold for the acceptable elapsed inactivity for these 48 daily intervals. It represents periods of inactivity by considering two commonly used distributions: Pareto distribution and hyper-exponential distributions. These distributions enabled them to use outlier anomaly detection techniques. In addition, they performed an evaluation on two real-life datasets CASAS Smart home (the Aruba) [68] and GT4 [64].

In both works, the period of inactivity was used as a proxy for detecting abnormal behaviour. However, in the two works the inactivity is detected on a daily basis or half-hourly, not in real time (high detection delay) and they focus only on one type of anomaly “long inactivity”.

These two works share some similar objectives with us. The use of simple unobtrusive sensors (PIR) for learning the human behaviour and detecting abnormal behaviour (inactivity periods in this case), the performance evaluation metrics used to assess their systems as well as the dataset used for validation (the Aruba). However, the main distinct difference from our work is that the performance of the developed statistical models in these works depends on prior assumptions about the data distribution of the inactivity periods (the normal behaviour). In [64], the authors showed that the exponential distribution, which is widely used for modelling the time between events, is not suitable for modelling periods of inactivity. This is because the distribution has a longer tail than exponential distribution. Therefore, they investigated the use of Pareto and hyper-exponential distributions. In our model, we do not have any prior assumption on the data distributions of the normal movement behaviour of the monitored person, and therefore, our model reduces the modelling settings and provides a more seamless behaviour learning approach.

2.4. Challenges and Issues

Figure 2-5 illustrates a taxonomy for some of the challenges and issues related to the development of behaviour monitoring systems for Ambient Assisted Living (AAL). These challenges are inspired by prior research studies [4][69][70] and learned while covering the state of the art materials. The hierarchy classification categorises the challenges and their sub-challenges and then in this section, we present their respective descriptions and emphasis on the challenges that have been addressed in our system.

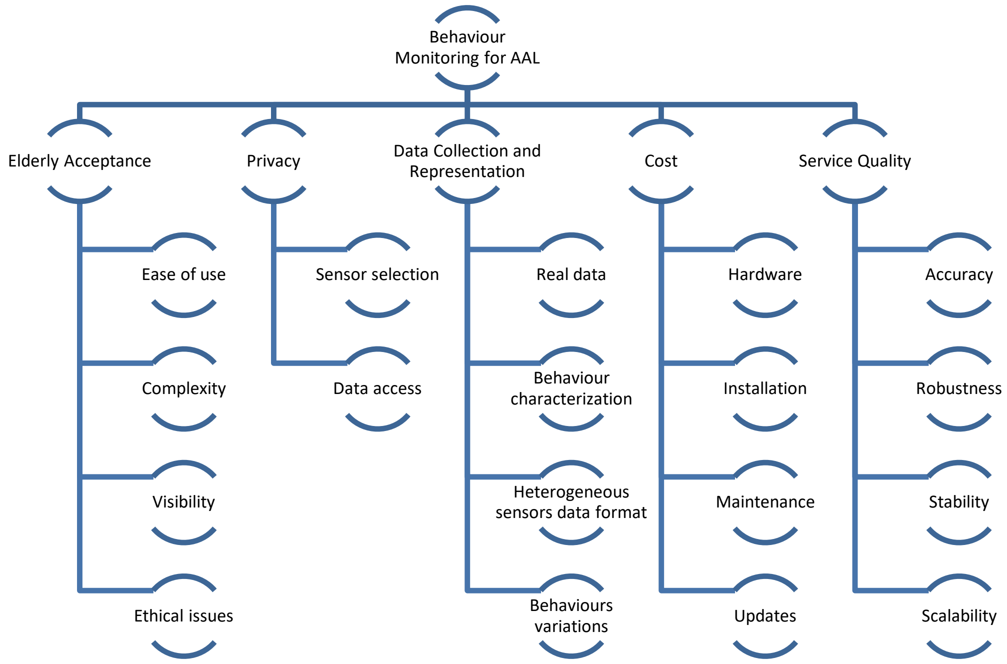


Figure 2-5: Behaviour Monitoring for AAL - Challenges and Issues

2.4.1. Elderly Acceptance

Providing a monitoring service for the elderly poses many challenges. Elderlies, especially unhealthy elderlies, have some limitations in performing tasks. Any service intended for them should pay more attention to the ease of use requirement, avoiding any kinds of complexity or interference that may overwhelm the elderly and reduce their autonomy and independence (ethical issues). This is translated into the selection of sensor modalities used for measuring and monitoring the behaviour, complexity of the system's settings and assumptions, and service's transparency and visibility. Social studies [3][71][72] give insights on the real requirements of the elderly and caregivers and also provide solid foundations to support the development of monitoring services for the elderly and help to reduce the lack of confidence in the services.

2.4.2. Data Collection and Representation

The characterization and representation of a behaviour are fundamental for the behaviour monitoring systems. The clear definition of the required behaviour leads to meaningful features extraction and model's definition and helps to handle behaviours variances. The main challenge here is related to the lack of descriptive knowledge and standards to define the human behaviour in terms of features, heterogeneous sensor data formats, and modelling approaches. Each of the existing systems for behaviour monitoring has their own individual definitions of the behaviour, their own design goals, and modelling approaches, which make the evaluation and comparison of these systems more difficult. Moreover, performing real-world experiments to validate these systems is really difficult. Many studies have been validated using synthetic data only [32], or real data collected for short periods of time in very controlled settings. In addition, the anomalous behaviours, in general, are rarely to happen and we may need a long time of monitoring to detect cases of abnormal behaviours to validate the developed systems.

2.4.3. Privacy

The privacy issue is a major concern for human behaviour monitoring. The type of sensors used for measuring the behaviour is crucial for the acceptance of the monitoring service. The trade-off between the privacy and the quality of monitoring is always existing, however, the advancement in sensing technologies may provide some compromises. For instance, a monitoring system based on camera sensors is not much appreciated, but currently, we have seen considerable advancement in this trend (e.g. the use of low-resolution cameras or images) which may help to reduce the privacy concerns.

Moreover, the right to access the collected data from the monitoring system is also important to decide the authorised recipients of the monitoring data as well as the allowed data granularity for the recipients.

2.4.4. Cost

The costs of the sensing technologies used for measuring the human behaviour, their installation, calibration, maintenance, and updates costs have to hit the lowest prices to ensure the wide adoption and deployment of the behaviour monitoring systems among a larger sector of people.

2.4.5. Service Quality

The quality of the human behaviour monitoring service is represented in terms of its accuracy, robustness, adaptability, and scalability. The accuracy of detecting and differentiating the behaviour, despite the complexity of the monitored behaviours and the different ways of performing the same behaviour, is still a challenge for many behaviour monitoring systems. Moreover, the adaptability of changing behaviour over time as well as the robustness of the monitoring service with respect to context changes (e.g. handling visitors, caregiver visits and pets' existence at home while monitoring the elderly). The scalability of the monitoring service to cover large sector of people is also criteria to evaluate the quality of the service.

Chapter 3. **Indoor Location for Ambient Assisted Living**

There is a wide variety of approaches available that exploit indoor location as a measure for human behaviour monitoring in Ambient Assisted Living (AAL). The location of a person together with the time of the day, for instance, can be an indicator of the activity being performed by a person, and therefore can be used to monitor his daily behaviour and routine. In this chapter, we present, briefly, the description of a prototype study that we performed to evaluate the use of ZigBee technology for indoor localisation. The prototype was designed as an initial step towards the real deployment of the proposed behaviour monitoring system. The location context is a fundamental element of the system, and therefore, this prototype study plays an important role to identify the main challenges that face the deployment of the proposed system in real-life settings. In this chapter, we briefly describe the prototype, the ZigBee hardware components, the developed software for ZigBee modules, the developed indoor location system, and the obtained localisation results. This is followed by a summary of a review study that we conducted to identify the real requirements and metrics for location and tracking for AAL. We combined our findings from the prototype and the review study to emphasis on the wide gap among the real requirements of AAL applications and the capabilities of the existing indoor location technologies. The results of the review study were published in [9].

3.1. ZigBee Prototype

ZigBee technology is being used widely as one of the promising technologies that support Ambient Assisted Living (AAL) at home environment. In this section, we present the description of the prototype study that we performed to evaluate the use of ZigBee technology for indoor localisation and the obtained localisation results.

3.1.1. Prototype Description

A ZigBee network that consists of multiple ZigBee devices was designed and deployed in a home-like building to tracked the indoor location of a single person who usually navigates between the rooms in the building. The layout of the testbed environment is shown in Figure 3-1. All of the prototype's experiments were carried out on the 1st Floor of CCG building at the University of Minho, Portugal. The building consists of multiple rooms and places, as shown in the figure.

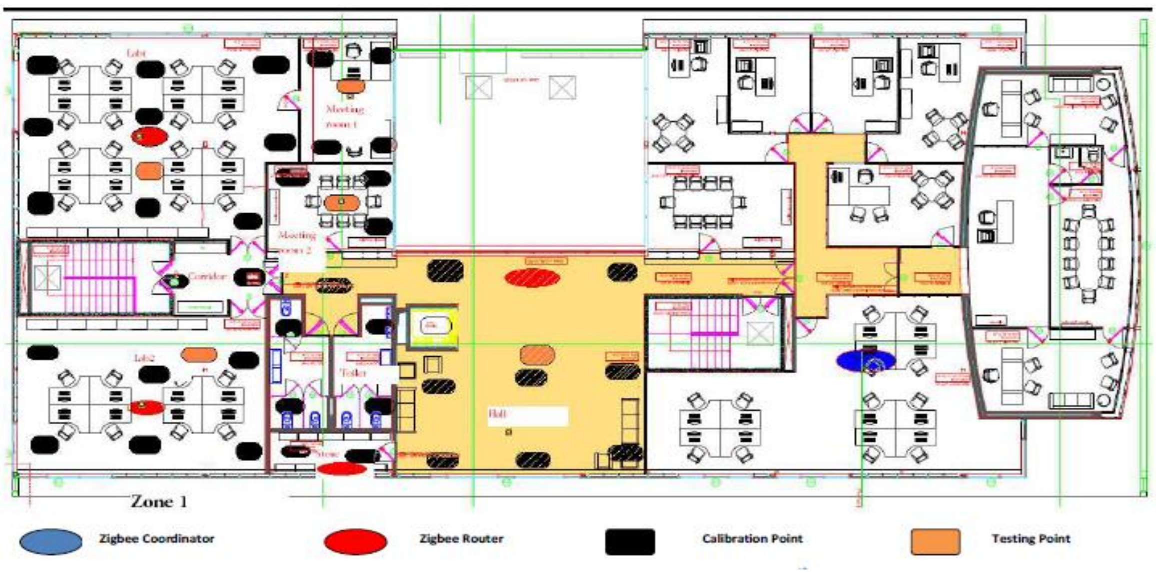


Figure 3-1:Experiment testbed

The general localisation principle of the ZigBee prototype is based on the fingerprinting approach [73]; a location technique that relies on measuring the wireless signal strength level of the ZigBee network at predefined locations and storing this information in a database as an offline radio map for the positioning area (i.e. the building). This map is used later on during an online phase to locate the persons in real time. Thus, the localisation method of the prototype consists of two main phases: calibration (or training) phase and testing (or positioning) phase.

3.1.2. Hardware Configuration Profiles

The prototype was developed based on CC2530 ZigBee System-On-chip Development kits from Texas Instruments, as shown in Figure 3-2.

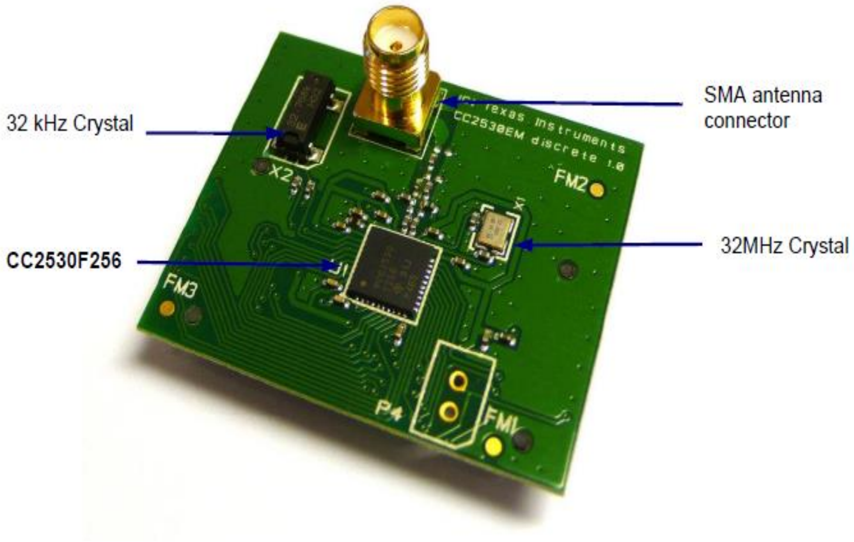


Figure 3-2: CC2530 ZigBee Evaluation Module

The developed System-On-Chip of the ZigBee evaluation module has three different configuration profiles: coordinator, router, and end node device. Figure 3-3 illustrates the program flow, functionality and interactions of these configuration profiles.

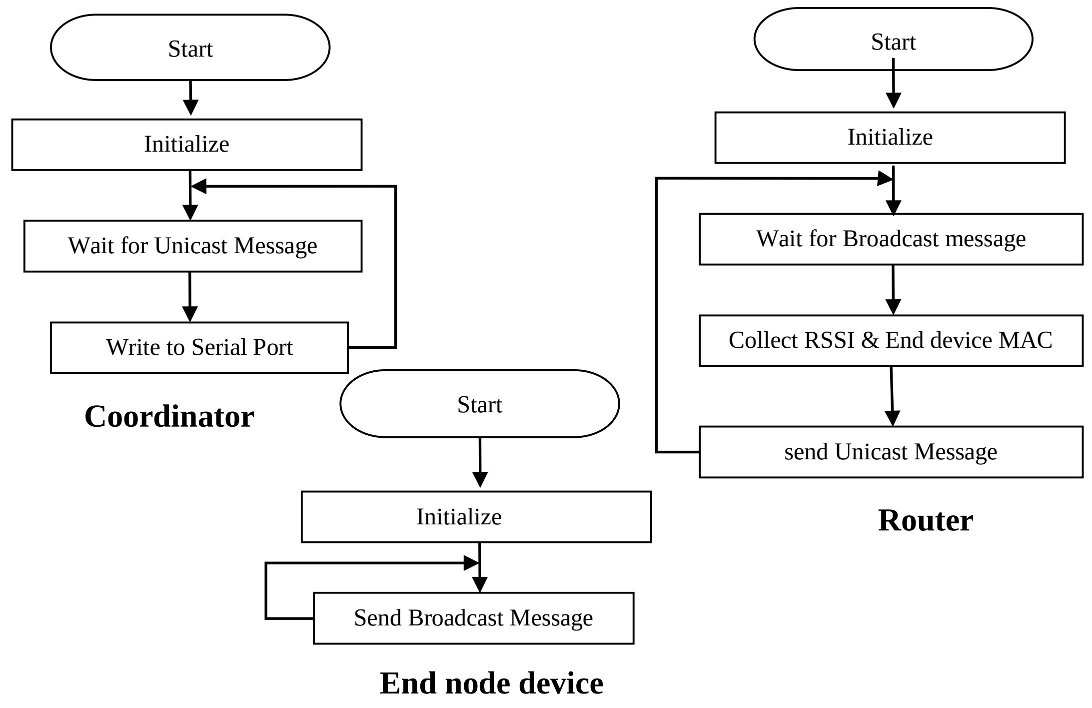


Figure 3-3: Configuration Profiles and Program Flow

- **Coordinators**: The coordinator is the master communication node of the ZigBee network. It receives unicast messages from ZigBee routers and transfers this information to the indoor location software running on a PC computer.
- **Router**: The router measures the Received Signal Strength Indicator (RSSI) and then forwards the received messages to the coordinator together with the measured RSSI value.
- **End node**: This profile represents the tracked person. It sends periodic broadcast messages to all nearby routers.

3.1.3. Indoor Localisation Method

To perform the localisation, we configured one module as ZigBee end node device to represent the tracked person during the prototype. This device was periodically sending broadcast messages to three ZigBee routers. The routers were configured and mounted at known places in the building to represent the location references. By exchanging messages between the ZigBee routers and the ZigBee end node device, the Received Signal Strength Indicator (RSSI) values near the ZigBee end node device were measured and transferred to the network coordinator node (ZigBee Coordinator). Then the coordinator transferred the received data to an indoor location software, running on a PC computer, to perform the localisation. As mentioned, the fingerprinting localisation is performed in two phases.

3.1.3.1. Calibration Phase

In the calibration phase, we built a positioning radio map (fingerprints) for the testbed building by defining first a set of calibration points as reference points. At each point, we estimated the signal strength level of the ZigBee network. The locations of the defined calibration points are denoted by BLACK rectangles on the testbed layout, as shown in Figure 3-1. The ZigBee end node device was mounted on a calibration car with a height of 1.0 meter. Using the calibration car, we moved to each calibration point and recorded the RSSI values from the ZigBee routers in range and stored this information in a database together with the corresponding names of the rooms in which the points were defined. This step constructed the offline positioning radio map for the testbed building.

3.1.3.2. Testing Phase

In the online testing phase, we measured the RSSI values at several testing points that were randomly distributed. The locations of the testing points are denoted by dark orange rectangles in the testbed layout, as shown in Figure 3-1. At each point, the current collected RSSI values were compared against the stored fingerprints values in the offline radio map and the best match (nearest point) was selected as the estimated location of the tracked end node device. The prototype uses the Euclidean distance algorithm to calculate the distances between the testing points and the fingerprints. The tracked end node device was located at room-level granularity and the room's name, where the device was located, was provided as final output.

3.1.4. Experiments and Results

Table 3-1 presents the experiments settings of the prototype and Table 3-2 presents the obtained localisation results. We performed three experiments with three different sampling times at each testing point (5, 2, 1 minutes). The sampling time here represents the time interval between the broadcast messages sent by the ZigBee end node. In the three experiments, we obtained 80%, 50%, and 60% correct results, respectively. The results show that the localisation capability of ZigBee network still needs more improvement, especially when it is used for AAL systems.

Table 3-1:Experiment Settings

# Calibration Points	39 (Figure 3-1)
# Testing Points	10
Time Interval (sampling) at each point	5, 2, 1 min
Location Algorithm	Euclidean and KNN
Location Resolution	Room-level

Table 3-2: ZigBee Prototype - Experiments results

Point	Actual Location	Estimated (5 min)	Result	Estimated (2 min)	Result	Estimated (1 min)	Result
1	Hall	Hall	Correct	Lab2	Incorrect	Lab2	Incorrect
2	Hall	Hall	Correct	Store	Incorrect	Hall	Correct
3	Store	Store	Correct	Hall	Incorrect	Hall	Incorrect
4	Toilet	Toilet	Correct	Hall	Incorrect	Toilet	Correct
5	Corridor	Room1	Incorrect	Corridor	Correct	Room1	Incorrect
6	Corridor	Corridor	Correct	Corridor	Correct	Corridor	Correct
7	Lab1	Lab1	Correct	Lab1	Correct	Lab1	Correct
8	Room1	Room1	Correct	Lab1	Incorrect	Room2	Incorrect
9	Lab1	Lab1	Correct	Lab1	Correct	Lab1	Correct
10	Lab2	Toilet	Incorrect	Lab2	Correct	Lab2	Correct

3.1.5. Network Performance

ZigBee network performance also has been experimentally evaluated in terms of the number of messages sent and received.

3.1.5.1. Experiment Description

In this experiment, we performed five tests in which the ZigBee end node device was configured to send periodic broadcast messages every 2, 3, 5, 10, 15 seconds in each test respectively. The reason was to specify the most relevant sending time in which the ZigBee network reaches its best performance.

The main goal of this analysis was to estimate the percentage of the transmitted messages (by the end node device) that were actually received by the ZigBee routers. Ideally, when the ZigBee end node device sends a broadcast message, all nearby routers, who successively receive the broadcast, should generate a unicast message and send it to the coordinator node. A unicast message includes unique timestamp coming from the broadcast received by the router. By calculating the number of received messages at the coordinator, we estimated the percentage of the successfully received broadcasts. The main steps of this analysis experiment can be summarised as follow:

- The ZigBee end node device sends periodic broadcast messages to the nearby ZigBee routers every configurable time interval. In the experiments, we tested several time intervals (2,3,5,10,15 seconds).
- The ZigBee routers receive the broadcasts, measure RSSI from the received broadcasts, and then send unicast messages to the ZigBee network coordinator. The unicast messages contain the measured RSSI, timestamp of the broadcast, and MAC address of the ZigBee router and the ZigBee end node device.
- The ZigBee coordinator, in turn, receives the unicast messages and then transfers the received information to the connected PC via serial port.
- The application on the PC was customised to receive the unicast messages during an adjustable time interval (5, 2, 1 minutes). The application user has the option to set the preferable period for receiving the messages (in seconds, minutes, or hours).

3.1.5.2. Results and Discussion

Table 3-3 presents the obtained results of the experiments. As shown, there are two columns provided for each receiving time interval to show the comparison of the actually received messages compared to the expected messages in the ideal case. As mentioned, the application on the PC was configured to receive the messages from the coordinator within several time intervals (5, 2, and 1 minutes). Within each receiving time interval, we performed 5 different tests. The results are shown in the table.

Table 3-3: Network Performance results

	5 min		**2 min**		**1 min**	
	Actual	**Ideal**	**Actual**	**Ideal**	**Actual**	**Ideal**
2 seconds	0	150	0	60	0	30
3 seconds	0	00	0	40	0	20
5 seconds	39	60	11	24	5	12
10 seconds	30	30	12	12	6	6
15 seconds	20	20	8	8	4	4

As shown in the table, the results show poor network performance in the cases where the sending time between broadcast messages was less than 5 seconds. The network was totally unreliable, all broadcast messages have been lost during the transmission. However, as the sending time of the broadcast increased, the network performance improved. We believe that the reason for the poor performance when using shorter sending time might be because of the time required for writing the received messages on the serial port (UART port). This UART delay makes the coordinator fully occupied and therefore no transmission will be received from other ZigBee routers.

3.1.6. Conclusion

Developing an indoor location system based on fingerprinting technique and ZigBee technology is still a challenge. Based on the obtained results from the ZigBee prototype, the localisation accuracy is not as good as it should be, especially if the localisation service will be used for critical applications like healthcare and assisted living. Moreover, the network transmission behaviour was not fully reliable as many messages have been lost during the network performance experiments. Additional experiments with different settings are required to confirm the results and the use of ZigBee technology for indoor localisation.

3.2. Requirements and Metrics for Indoor Location

Indoor location and tracking technologies are becoming fundamental components for Ambient Assisted Living (AAL) and, as a result, diverse technologies are being used for indoor location such as Passive Infrared (PIR) [74], Ultrasound [75], Radio Frequency (RF) [76][77][78], and computer-vision (camera-based) technologies [79]. These technologies have different physical, operational, performance, and cost characteristics that make them available for different kind of operational scenarios. In [9], we set out the general requirements for indoor location and tracking services for AAL. The definition of the requirements was based on a conceptual view for a typical AAL application scenario. From the scenario, we defined the requirements and also defined a set of metrics to be used as evaluation criteria. We also used the defined metrics to evaluate two of the existing technologies for indoor localisation.

3.2.1. Requirements

Figure 3-4 illustrates a conceptual view of a typical AAL system. The system is designed to monitor the daily behaviour of an elderly person living alone at home. As shown in the figure, the system consists of multiple interactive layers that are combined together to give the intended functionality of the system. In the subsequent sections, we provide the identified requirements for indoor location for AAL based on this conceptual view.

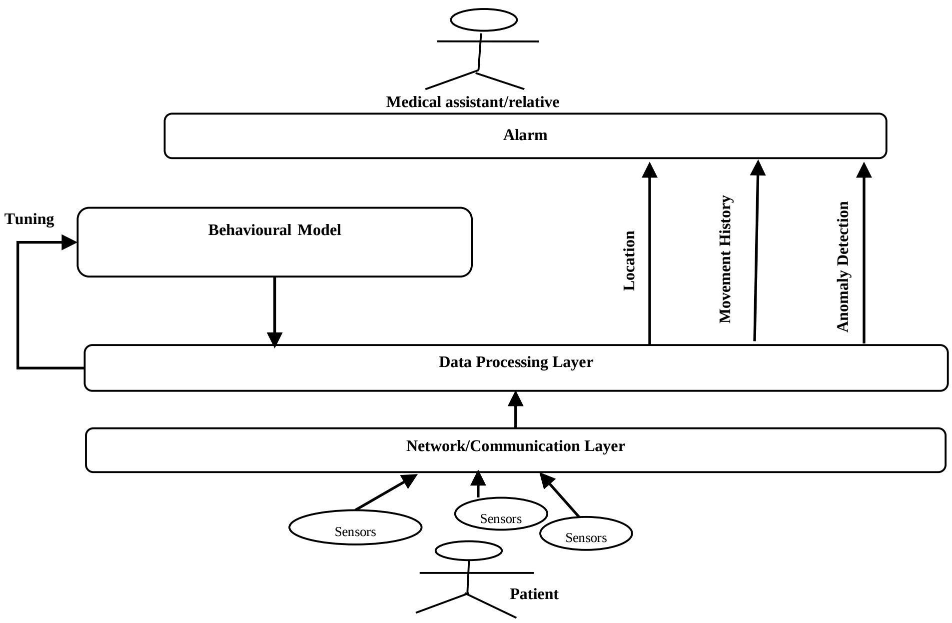


Figure 3-4: Conceptual view for a typical AAL system

3.2.1.1. Functional Requirements

The functional requirements include all the tasks and functions that the service is required to perform such as track, locate, and detect the presence of the people indoors with unique personal identification. They also include the detection of unusual or abnormal events e.g. falls or death and the ability to provide the final output in human-interpreted format. Moreover, they also include the capability of sending the data to remote servers at remote healthcare units for early interventions and timely responses as well as increasing the safety feeling of the monitored people.

3.2.1.2. Non-Functional Requirements

The non-functional requirements specify the criteria that can be used to judge the operation of the service such as providing enough localisation coverage, resilience to a power outage at homes, and the use of standards and normative definitions for information exchange and also ensuring privacy.

3.2.1.3. Interface Requirements

The interface requirements cover all the requirements related to the service's user interfaces and the monitoring software used for indoor location and tracking. They include the ability to provide a user-friendly interface, visualised views of the service’s output, and different data granularity views.

3.2.1.4. Performance requirements

The performance requirements are related to the performance of the service such as responsiveness (real time responses), the ability to provide the required location resolution, minimise localisation error and increase accuracy, avoid interferences with other home’s devices, automatic fault detection and reliability, availability and scalability.

3.2.1.5. Product Requirements

The product requirements include all the requirements that are related to the deliverable version of the service such as reduce the cost of installation, deployment, and maintenance, provide means for tackling the service’s performance, facilities information exchange for easy integration and interoperability, use of standards and norms, power efficient and eco-friendliness, and also provide information security.

3.2.2. Metrics

The introduced requirements in the previous section provide a means to categorise the general requirements of indoor location service for AAL systems. In this section, we combined our findings from the requirements with some prior research works [80] [81] to defined a set of evaluation benchmarking to be used by the indoor location services' developers and practitioners to evaluate their services. The defined metrics in this section provide a clear evaluation framework that maps between the desired (target) value and the minimum and acceptable value for each requirement. Table 3-4 lists the evaluation metrics.

Table 3-4: Metrics for Indoor Location for AAL

Metric	**Target**	**Threshold**
Service Response time	Within seconds	Less than 5 minutes
Precision	Room-level	Room-level
Coverage Scope	Inside house and areas nearby	Inside house
Service Output format	Symbolic (Bedroom, Kitchen)	Symbolic (Bedroom, Kitchen)
Person Identifier	Required	Required
Presence/Absence indicator	Required	Required
Location Update Interval	Adjustable	Every 5 minutes
Location Sampling rate/sec	1 sample every 5 second	1 sample every minute
Service Calibration	Self-Calibration	Self-Calibration
Service Remote Communication	Fast connection to support remote instructions	Fast connection to support remote instructions
Remote Communication Cost	Less than Internet Cost	Same as Internet Cost
Resilience to Power Outage	Required	Required
Interference avoidance	No Interference	No Interference
Automatic Fault Detection	Required	Required
Battery lifetime	more than 1 year	6 months
# Location Reference Nodes	One per house	Two per house
Use of Wearable tags	No/Simple tags	Easy to carry and wear
Installation Complexity	Low	Low
Remote/Local Computation	Local	Remote
User's Movement History	Required	Required
# Tracked Persons	Multiple	Multiple
User acceptance	Required	Required

Use of behavioural models for abnormality detection	Required	Required
Service Cost	Cheap	Cheap

Target: desired value Threshold: minimum acceptable value

3.2.3. Evaluation

In this section, as an example, we use the previously defined metrics to evaluate two of the indoor location technologies. We present how the metrics can be used to assess and identify the gaps between the real requirements of AAL systems and the existing indoor location technologies (WiFi Fingerprinting and Ultrasound-based). We selected these technologies due to their wide use in many localisation systems and also because other technologies might end up being too intrusive and not acceptable by the users (e.g. camera-based), or too expensive to build and deploy (e.g. UWB-based). First, we briefly introduce the two technologies and then provide the evaluation results.

3.2.3.1. WiFi Fingerprinting

WiFi fingerprinting is a location technique that uses the existing WiFi network infrastructure at home/building to provide indoor localisation service for various location-aware applications such as social networking, personal tracking, inventory control, entertainment augmented reality, and healthcare monitoring applications [82]. The technique has gained more attention in the last years due to the popularity and low price of WiFi devices. It estimates the locations of the tracked objects based on the Received Signal Strength Indicator (RSSI) collected from WiFi Access Points. Hence, it does not require additional hardware than what already exists at home. In this technique, there are two main phases: the offline phase (training) and the online phase (positioning) [83]. In the offline phase, the signal strength collected from several WiFi access points in the range are recorded and stored in a database along with the known coordinates of the user's device. In the online phase, the current recorded RSSI values at an unknown location are compared to those stored in the fingerprint database and the closest match is returned as the estimated location of the user's device.

The main challenge of this technique is that any change of the environment such as adding or removing furniture at home/building requires an update on the recorded fingerprint database. However, the integration with another type of sensors such as cameras or motion sensors can be used to reduce the need for frequent updates on the recorded fingerprints. Ekahau [84] and Microsoft RADAR [73] are some of the location systems that use WiFi fingerprinting for indoor localisation.

3.2.3.2. Ultrasound-based

Location services based on ultrasound consist of a set of ceiling-mounted receivers that detect ultrasound signals from tags, transmitted at user-defined time intervals, to calculate distances using time-of-flight. This technique has the potential to provide good accuracy and the fundamental devices are cheap. However, the synchronisation of the location sensors and the high installation complexity are the major challenges of this technology. Location systems that use ultrasound include Active bat [85], Cricket [86], and Dolphin [87].

3.2.3.3. Evaluation results

Table 3-5 illustrates the evaluation results of the two technologies. In the table "+" depicts that the technology has satisfied the corresponding metric while "-" depicts unsatisfied. For each evaluation metric, there is a pair of values, represented as (target, threshold) respectively, to compare the technology against the defined values for each metric.

Table 3-5: Evolution of Indoor Location techniques

Metric	WiFi Fingerprinting	Ultrasound-based
Response time	(+,+)	(+,+)
Precision	(+,+)	(+,+)
Coverage Scope	(-,+)	(-,+)
Service Output Format	(+,+)	(+,+)
Person Identifier	(+,+)	(+,+)
Presence/Absence indicator	(-,-)	(-,-)
Location Update Interval	(+,+)	(+,+)
Location Sampling rate/sec	(+,+)	(+,+)
Service Calibration	(-,-)	(+,+)
Service Remote Communication	(+,+)	(+,+)
Remote Communication Cost	(-,+)	(-,+)
Resilience to Power Outage	(-,-)	(-,-)
Interference avoidance	(-,-)	(+,+)
Automatic Fault Detection	(-,-)	(-,-)

Battery life time	(-,-)	(-,-)
# Location Reference nodes	(-,-)	(-,-)
Use of Wearable tags	(-,-)	(-,-)
Installation Complexity	(-,-)	(-,-)
Remote/Local Computation	(+,+)	(+,+)
User's Movement History	(+,+)	(+,+)
# Tracked Persons	(+,+)	(+,+)
User acceptance	(-,-)	(-,-)
Use of behavioural models for abnormality	(-,-)	(-,-)
Service Cost	(-,-)	(-,-)

3.2.4. Conclusion

As illustrated in Table 3-5, the two location technologies used in the comparison are not designed to fully comply with all the requirements of AAL. For instance, the coverage scope requirement is not fully supported by both technologies unless additional location sensors are being deployed (e.g. additional WiFi access points and ultrasound receivers). Moreover, WiFi fingerprinting requires additional effort to calibrate the neighbourhood areas, in order to provide the required coverage, which means an extra deployment complexity. The ideal location service for AAL should provide the service with less effort and a minimum number of location sensors. In addition, the resilience for a power outage is also not considered by both technologies. The power outage is mostly occurring in houses and residential environments, especially in rural areas. The two technologies do not provide a reasonable solution for this requirement. Furthermore, the installation complexity of the two technologies is high. A location service for AAL has to be easy to install in terms of time, cost, and effort. Moreover, the automatic fault detection and handling the anomalies and outliers in the location data are not fully supported by the two technologies.

From the conducted review and evaluation results we conclude that the existing indoor location technologies are not quite adequate for Ambient Assisted Living (AAL). There is a gap between the real requirements and the available technologies. The defined requirements and metrics in this section can contribute to the definition of a generic evaluation framework. This framework can be used to evaluate the potential AAL location services and also can be used as guidelines for technological developments and system design. Additional evaluation and comparison studies are required to completely define all the requirements.

Chapter 4. **Behaviour Monitoring System (BMS)**

In this chapter, we present the overall description of our system and also provide details for each of its components. For simplicity, we base the description of our proposal on the use of simple PIR sensors installed in all rooms of a house. However, a similar approach can be used with other types of sensors/technologies that are able to detect the presence of a person in a room.

4.1. System Architecture

The general architecture of our system is graphically represented in Figure 4-1. A set of sensors is placed at different locations to collect information about a person's daily mobility routine at the home environment. The collected data from the sensors is forwarded (**1**) to a home gateway installed inside the house that continuously processes and interprets the data locally, learns the normal routine of the person (Learning Module and Model) and then provides alarm notifications (**6**) when unusual deviations from the normal routine are detected (Detection Module).

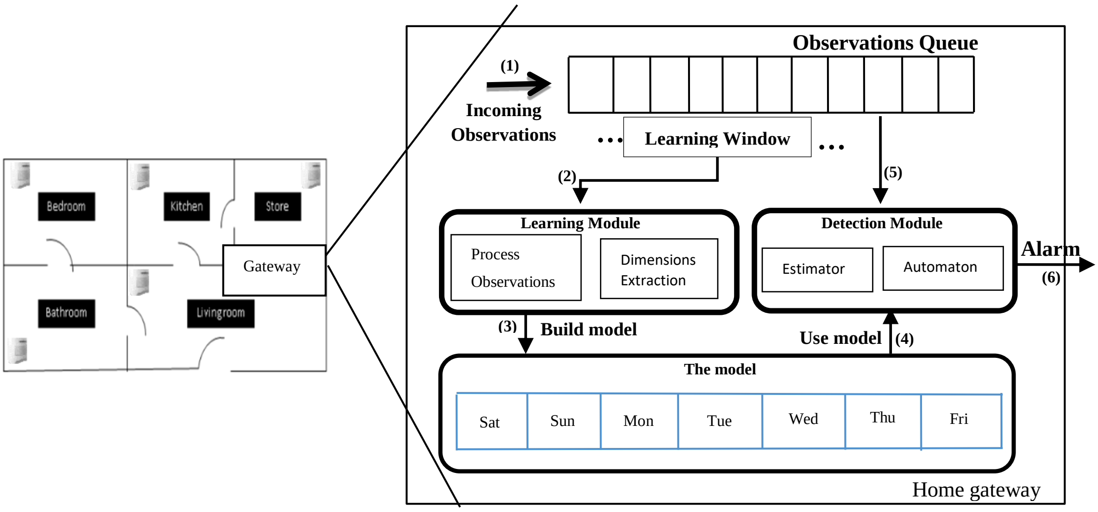


Figure 4-1: BMS system architecture

In the following subsections, we describe our approach of using the collected observations from those affordable PIR sensors to learn a model for the normal mobility routine of the monitored person and then show how this model can be used to detect abnormalities.

4.2. Learning Module

The deployed PIR sensors in the home environment transmit signals when motion is detected. These sensor observations are logged in the home gateway and stored in a queue buffer for processing. An observation *o* is defined in the form *o* = <*ts, sensor_id*>, where *ts* denotes a timestamp indicating the time of detection, and *sensor_id* denotes the identification of the sensor that detected the motion. Examples of the sensor observations are presented in Table 4-1. Each sensor is assumed to be installed in a particular room in the house, and each room must have at least one sensor covering its serving area. The operation of the system relies on the detection of the monitored person within the range of these sensors with room-level localisation accuracy.

Table 4-1:Examples of sensor observations

Timestamp	Sensor ID
06/04/2016-00:00:00	M001
06/04/2016-00:06:05	M001
06/04/2016-00:08:18	M002
06/04/2016-01:10:20	M002
06/04/2016-01:15:30	M002

We hypothesise that a long-term sequence of these observations encodes the mobility routine of the monitored person, and therefore it can be used to build a model that represents the mobility behaviour of that person during normal days. The role of the learning module in our system is to continuously process and interpret the incoming sensor observations and use them to build a realistic model that summarises the mobility behaviour of the monitored person at each location in the house during the hours of the day. The learning module uses a time-based sliding window to process the observations from the queue buffer sequentially. The size of the learning window is pre-configured (e.g. a month) to indicate the sufficient context history to tune the model. The learning window is shifted every week to update the model on a weekly basis. Every time the model is updated, the oldest observations are removed from consideration, while the most recent observations are added. This feature allows the learning process to be performed in an online manner, considering the most recent observations, and also allows the model to adapt to slight shifts in behaviour that are not genuine anomalies (e.g. seasonal changes).

4.2.1. Concepts and Terminology

In this section, we summarise and list the important concepts and terminology used in the learning modules and employed by the model in the next section.

4.2.1.1. Observation

An observation is defined as a sensor event that perceives the state of an individual at home. It is represented in the form $o = \langle ts, sensor\_id \rangle$, where *ts* denotes the timestamp of sensor activation, and *sensor_id* denotes the identification of the sensor that detects the motion event.

4.2.1.2. Stay

A stay is defined as the amount of time a person spent in a particular room at a certain time. It represents the elapsed time between any pair of consecutive sensor activations (observations).

4.2.1.3. Transition

A Transition is assumed to be instantaneous and is detected based on an observation whenever the sensor associated to o_i is different from the sensor associated to o_{i-1}.

4.2.1.4. Transition Probability

The estimated probability of moving between any pair of rooms at home. It is calculated with respect to the stay time and movement frequencies between rooms in each day within each time interval.

4.2.1.5. Stay Probability

The estimated probability of staying in a particular room in the house in a particular moment, the same as self-transition probability. It is calculated with respect to the stay time in the room in each day within each time interval.

4.3. The Model

To model the daily mobility behaviour, we define the concept of *Stay* to indicate the amount of time a person spent in a particular room and time. As mentioned, a *Stay* is obtained from any pair of consecutive observations (o_{i-1}, o_i). It is defined as the time elapsed between o_{i-1} and o_i at the room associated to o_{i-1}. The *Stay* concept is fundamental for the learning module to estimate the dimensions of the underlying behavioural model.

The underlying behavioural model of the system, as shown in Figure 4-1, is represented by a data structure that separates the mobility behaviour of the monitored person in each day of the week to capture the weekly behaviour. Furthermore, each day is subdivided into equal intervals (e.g. 1-hour interval) to capture the daily behaviour. This flexible structure differentiates our work from others where the same behaviour is assumed for all the weekdays. In each interval the mobility profile of the monitored person is represented by a state transition model, as shown in Figure 4-2. The states represent the rooms or places in the home while the connections between states represent the possible transitions or movements. This representation is used to model the spatial transition dependencies between the rooms with respect to the layout of the user's home. As illustrated in Figure 4-2, there are no transitions between rooms that are not directly linked (e.g. one cannot go directly from the bedroom to the kitchen without going through the living room). By observing the daily movements from sensor observations and then applying the right learning method we can build a reliable model for the daily mobility behaviour of the monitored person and use that model to detect abnormalities. The model can be formulated as $Model^d(t, \Delta t)$ to denote the model of the weekday d within the time interval from t to $t+\Delta t$, $d = \{Sunday, \ldots, Saturday\}$. For example, if

$\Delta \boldsymbol{t}$=1 hour then there will be 24 time intervals and models in each day: *Model*^{Sunday}*(0-1]*, *Model*^{Sunday}*(1-2],…,Model*^{Saturday}*(23-24]*.

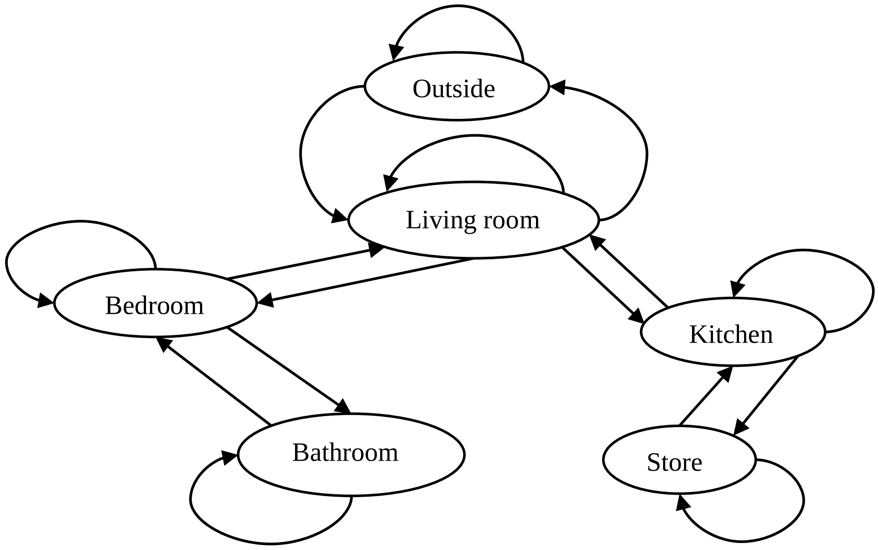


Figure 4-2: Room-to-room state transition model

A model for a given time interval is defined by a set of dimensions, each dimension has its own unique meaning and contribution in describing the person's behaviour. The following subsections describe these dimensions. It is worth mentioning that our model considers the person to be staying at the location reported by an observation until a new observation indicates the presence at a different location. This is consistent with the use of PIR sensors in a real house. Usually, these sensors turn off for a few seconds after they are triggered to save battery power.

4.3.1. Transition Matrix

This is the fundamental dimension of the behavioural model. It is a direct and personalised representation of the daily stay and room-to-room transition behaviour of the monitored person. It shows how likely the monitored person is to be found in each room during the different hours of each day of the week, considering the differences in every person's habits. Each possible transition in the state model (Figure 4-2) has an associated probability $P^{i,j}$ representing the estimated probability of that transition. All transition probabilities between rooms for a given time interval, including self-transitions, are represented in a 2D matrix. The role of the learning module here is to compute the entries of the transition matrix by processing the entire observations in the learning window, computing the stay durations between any pair of consecutive observations, calculating the total stay time at each room within each time interval, and finally computing the transition probabilities. These steps are implemented as follows. In the examples below, and without loss of generality, we consider Δt =1 hour.

Step 1: Compute a stay duration

A pair of consecutive observations (o_1=<ts_1, *sensor_id*>, o_2=<ts_2, *sensor_id*>) represents a stay(s) in the model. The duration of this stay is calculated as the time elapsed between these two observations (ts_2 - ts_1). It may happen that a single stay overlaps with multiple intervals. In this case, we distribute the period among them according to their contributions in the total stay period. For example, a stay duration of 1 hour and 30 minutes that starts at ts_1= 04:00 and ends at ts_2=05:30 is distributed among two intervals. In this case, 1 hour will be assigned to the interval (4-5], and the remaining 30 minutes to the interval (5-6].

Step 2: Compute total stay time

The total stay time $TS^i(t, \Delta t)$ at a room within a given time interval is given by:

$$TS^i(t, \Delta t) = \sum_{k=1}^{ns^i} s_k^i(t, \Delta t) \tag{1}$$

where $s_k^i(t, \Delta t)$ denotes the k^{th} stay at room i, and ns^i denotes the number of stays at room i, within the time interval from t to $t + \Delta t$.

Step 3: Compute self-transition, or stay, probability

The self-transition probability $P^{i,i}(t, \Delta t)$ at a room within a given time interval represents the probability of finding the person at that room (i) within the given time interval (from t to $t + \Delta t$), and is given by:

$$P^{i,i}(t, \Delta t) = \frac{TS^i(t, \Delta t)}{\sum_{j=1}^{r} TS^j(t, \Delta t)} = \frac{TS^i(t, \Delta t)}{\Delta t} \tag{2}$$

where r denotes the number of rooms in the house, including a virtual room for outside of the house.

Step 4: Compute transition probability

The transition probability $P^{i,j}(t, \Delta t)$ within a given time interval (from t to $t + \Delta t$) represents the probability of observing a person's movement from room i to room j within that interval. Given that:

$$\sum_{j=1}^{r} P^{i,j}(t, \Delta t) = 1$$

$P^{i,j}(t, \Delta t)$ is given by:

$$P^{i,j}(t, \Delta t) = \left[1 - P^{i,i}(t, \Delta t)\right] \times \frac{M^{i,j}(t, \Delta t)}{\sum_{k=1\ k\neq i}^{r} M^{i,k}(t, \Delta t)} \tag{3}$$

where $j \neq i$ and $M^{i,j}(t, \Delta t)$ denotes the number of transitions from room i to room j within the time interval from t to $t + \Delta t$.

The following is an example of a complete transition matrix for the six-rooms home in Figure 4-1. The entries of the matrix indicate the estimated room-to-room transition probabilities in the model for a given time interval.

	Bedroom	*Bathroom*	*Livingroom*	*Kitchen*	*Store*	*Outside*
Bedroom	0.1	0.3	0.4	0.2	0	0
Bathroom	0.3	0.7	0	0	0	0
Livingroom	0.2	0	0.3	0.2	0	0.3
Kitchen	0	0	0.3	0.5	0.2	0
Store	0	0	0	0.9	0.1	0
Outside	0	0	0.8	0	0	0.2

The estimated values of the matrix indicate how probable the person tends to stay or navigate between the rooms of the house. The matrix is not symmetric so that $M^{i,j} \neq M^{j,i}$ and 0 probability indicates no transition was detected.

4.3.2. Global Activity (AG)

This is an accumulative dimension to count the total number of observations received within an interval, no matter the rooms in which the sensors were triggered, normalised to the length of the time interval. It models the level of activity within the house, as more activities (movements) translate into more sensors being triggered. The following equation (equ.4) is used to compute this dimension.

$$AG(t, \Delta t) = \frac{1}{\Delta t} \times \#\big(O(t, \Delta t)\big) \tag{4}$$

where $\#(O(t, \Delta t))$ denotes the cardinality of the received observations within the time interval from t to $t + \Delta t$.

4.3.3. Inter-room Activity (AE)

The Inter-room Activity dimension represents the total number of times the sensors were triggered to indicate transitions within an interval, excluding self-transitions. It represents how often a person moves between rooms within a given time interval. This is different from the Global Activity because it captures the transitions among different rooms, while the Global Activity dimension captures the activities that might be between different rooms or within a single room. The following equation (equ.5) is used to compute this dimension.

$$AE(t, \Delta t) = \frac{1}{\Delta t} \times \# \left(M(t, \Delta t)\right) - \sum_{i=1}^{r} \# \left(M^{i,i}(t, \Delta t)\right) \qquad (5)$$

where $\#(M(t, \Delta t))$ denotes the cardinality of all the transitions within the time interval from t to $t + \Delta t$ and $\#(M^{i,i}(t, \Delta t))$ denotes the cardinality of the self-transitions in room i.

4.3.4. Intra-room Activity (AA)

The Intra-room Activity dimension represents the total number of self-transitions in a room within an interval, computed as the total number of received observations in a room within an interval. This dimension shows how active the person was in each room. The Intra-room Activity is given by:

$$AA^{i}(t, \Delta t) = \frac{1}{\Delta t} \times \# \left(O^{i}(t, \Delta t)\right) \qquad (6)$$

where $\#(O^{i}(t, \Delta t))$ denotes the cardinality of the received observations at room i within the time interval from t to $t + \Delta t$.

4.3.5. Intra-room Continuous Stay (CS)

This dimension is used to estimate the longest continuous stay at each room in each day of the week. A continuous stay is defined by a sequence of consecutive stays, or a single long stay, that occurs in the same room with no interrupting stay in different rooms. The dimension is given by:

$$CS^{i} = \sum_{k=1}^{u} d(s_{k}^{i}) \qquad (7)$$

where $d(s_k^i)$ denotes the duration of the k^{th} stay at room i and u denotes the number of the consecutive stays in room i. In the model, each day has a list of continuous stays for each room.

4.4. The Learning Algorithm

As mentioned before, the learning module updates the behavioural model on a weekly basis, processes all observations in the learning window and updates the model's dimensions of each time interval. The following is the description of the learning algorithm.

Algorithm 1: Model Learning algorithm

```
1: Input:   O ← {o1, o2, o3, …} incoming observations
2: Params: w ←  learning window size
3:           t ←  real-time, t0 = start time
4:           n ←  0
5: While (true) {
6: wait-until (t >= t0 +w+ n * one_week)
7: Ow ← O (t0 + n * one_week, t0 +w + n * one_week)
8: o_previous ←  Ow [1]
9: For i=2 to w do
10:   o_current ←  Ow [i]
11:   S[i-1]  ← compute_stay (o_previous, o_current)
12:   M[i-1]  ← compute_transition (o_previous, o_current)
13:  o_previous ← o_current
14: End for
15: update_model(Ow,S,M)
16: n ←  n+1
17: }
```

The learning module continuously accepts incoming observations and waits for a period of one week (line 6:) before updating the model. Then iterates over the entire observations in the learning window to compute the stays (line 11:) and the transitions (line 12:) before estimating the transition probabilities and updating the model (line 15:). Updating the model means computing the values of the different dimensions of the model for each time interval for each day of the week, as described in the previous section.

4.5. Detection Module

The detection module is a separate process that runs continuously in real time, and asynchronously from the learning module to produce outputs at regular intervals (e.g. every one minute). This module consists of two main components: the estimator and the automaton. The estimator computes the location likelihood for the detected location of the monitored person and provides classified binary abnormality state. The structure of the detection module is illustrated in Figure 4-3.

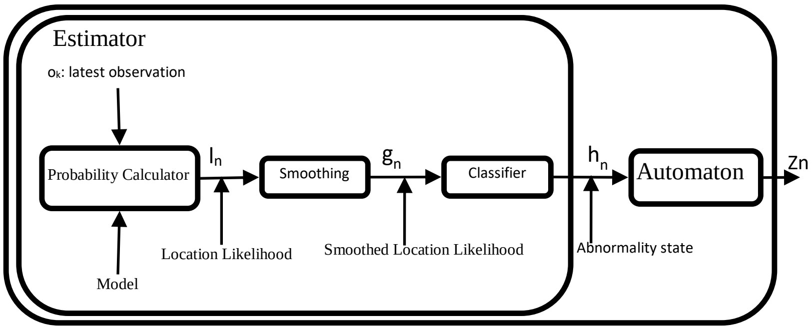


Figure 4-3: Detection Module - Internal structure

4.5.1. The Estimator

In every running cycle of the detection module, the estimator takes the most recent received observation in the queue buffer o_k and compares the current stay at the room reported in that observation to what is expected based on the behavioural model created from past observations. This comparison is based on estimating how probable it is to observe the person in that room during this interval and day of the week. For example, consider that, on a Monday at 4:25 am, the latest observation o_k reported the person as being in the bedroom. Given the behavioural model for the current time interval, the probability of finding the person in that room is 0.97 (equ.2) and, therefore, the observed behaviour was expected with high probability. We call this probability the Location Likelihood l_n.

A simplistic way for detecting abnormal behaviour is obtained by just comparing the estimated Location Likelihood l_n with a fixed threshold. All estimates higher than the threshold indicate no significant change in the mobility routine, while any drop below the threshold indicates a presence at an abnormal location given the current time and weekday. However, through experimentation, we found that this simple approach is affected by spurious observations and leads to poor performance. Moreover, the fixed threshold approach is also affected by the fact that, in some cases, the most probable location has a probability much lower than 1. Therefore, a more elaborated method is required to improve the reliability of the detection. To deal with this, we added a normalisation step in the probability calculator. The estimated Location Likelihood l_n is normalised by the probability of the most probable location of the current time interval before being passed through a low-pass filter to smooth out the results and generate smoothed Location Likelihood g_n and then finally applying the threshold classifier.

Figure 4-4 illustrates an example of the generated estimator's results. It shows the process of applying the smoothing step on the normalised estimated Location Likelihood l_n to smooth out the generated signal and reduce the rate of false alarms (whenever the location likelihood drops below the threshold). The example in the figure shows the estimated results of a normal day so that the estimated Location Likelihood l_n should always be high (near to 1.0) and any low value is considered a false estimate. As shown in the figure, the smoothing step may reduce the rate of false estimates, however, it does not eliminate them all. The smoothed Location Likelihood g_n afterwards is passed through the threshold classifier to generate the classified abnormality state results h_n, as shown in the figure.

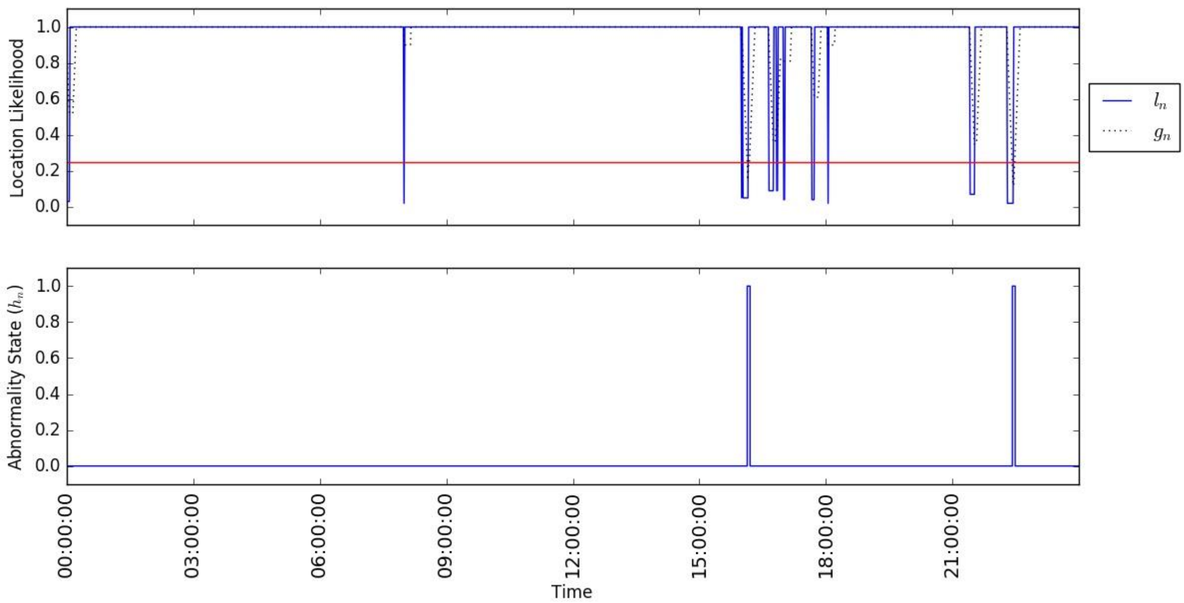


Figure 4-4: Sample of the estimator's results

Figure 4-5 illustrates the temporal relationship between the incoming observations and the generated abnormality states h_n by the estimator. As illustrated in the figure, the estimator keeps generating abnormality states, on a regular basis, while the observations are arriving, randomly, based on the person's movement. This way we transform the outputs of the estimator into periodic time series to simplify the detection of the abnormal changes.

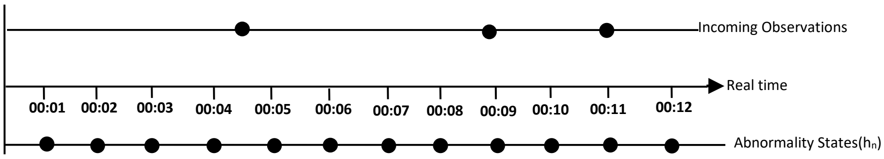


Figure 4-5: Temporal relationship (incoming observations and estimated abnormality state)

4.5.2. The Automaton

The estimator generates binary classifications (0=normal or 1=abnormal) based on the evaluation of the detected location of the monitored person. However, binary outputs are not very informative feedback to show the real state of the subject and might be misleading and not realistic in some cases. Therefore, it is more convenient to define the final output of the detection module in terms of states, giving more descriptive and detailed explanation of the decisions made. For this, we defined an automaton with three states {Normal, Potential Abnormal, and Abnormal} to interpret the detection results. Figure 4-6 illustrates the states of the automaton. The state of the automaton is updated at a regular pace defined by the output (h_n) of the estimator, including one timer that is reset, incremented or decremented.

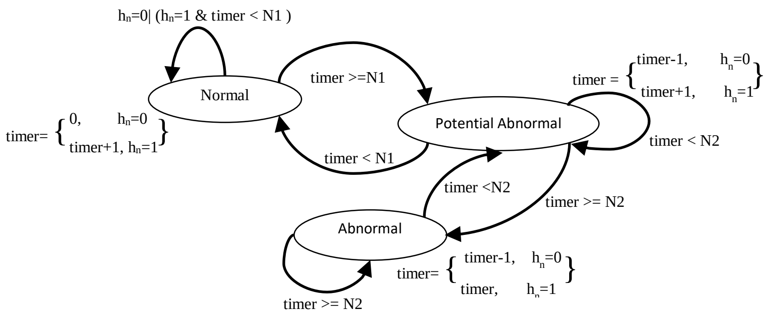


Figure 4-6: Detection Module - Automaton

The normal state represents the case in which the detection module doesn't detect any significant deviation or shift in the daily routine of the monitored person. The automaton is kept in this state as long as the output of the estimator reports a normal behaviour (h_n=0), or while abnormal outputs (h_n=1) do not hold for more than the normal timeout *N1*. This way, short glitches of abnormal outputs followed by normal outputs are filtered out, and thus reducing the rate of false alarms. The "Potential Abnormal" state represents the cases in which the estimator reports a sequence of abnormal behaviours longer than *N1* (meaning that it might not be a glitch anymore), and therefore more attention must be given to the situation. The automaton changes to the "Abnormal" state if the estimator keeps reporting an abnormal state for a long time (t >= *N2*). The difference between the states "Normal" and "Potential Abnormal" is that the timer is not reset after the first normal output of the detection module (h_n=0). The transition to "Abnormal" state can be done only in case the detection timer exceeds the abnormal timeout (*N2*), indicating the confirmation of the detected abnormal state. Upon each decision, the detection timer gets updated according to the rules of each state. The transition constraints between states are shown in the state diagram, explaining the rules and conditions that govern each transition. Applying such state machine simplifies the final decision of the detection module, gives more flexibility and also reduces the false positive detection rate.

We performed an optimisation experiment to tune the different parameters of the detection module in order to select the optimal values with respect to the performance metrics in Chapter 5. The results of this optimisation experiment are presented in chapter 6.

4.5.3. Anomaly Classification

To give more semantic to the final output of the detection module, we added a rule-based anomaly classification step into the detection module. It is an attempt to give names or classes to the possible abnormal behaviours that may occur to the elderly at home. This step helps to correlate the detected abnormal behaviour with some symptoms of the possible diseases and health declines. We know that it is not trivial to identify all of the abnormal behaviours (anomalies) that may happen to the elderly at home environment. Hence, we limited our system to a specific set of abnormal behaviours (Chapter 5), each anomalous behaviour is related to some well-known health declines. We defined the rules to incorporate the output of the automaton with other dimensions of the behavioural model in order to enhance the detection results and provide a classification for the detected anomalies. The following flow chart shows the details of this process. The included other dimensions of the model are shown in the flow chart diagram in Figure 4-7.

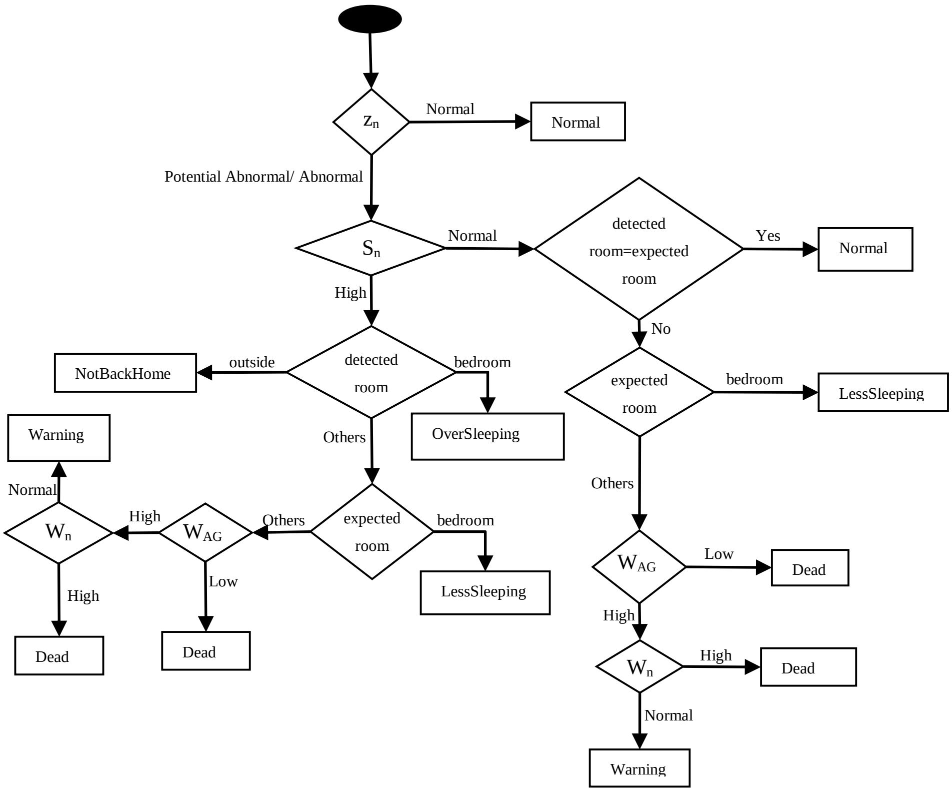


Figure 4-7: Rule-based Anomaly Classification

In the above flow diagram, the following symbols and names are used:

- Z_n: represents the automaton's output (Normal, Potential Abnormal, Abnormal).
- S_n: represents the classification of the detected longest continuous stay (Normal or High). The detected longest stay is "Normal" if its value is less than the expected longest stay value from the model; otherwise, it is "High".
- Detected room: represents the room where the person was detected.
- Expected room: represents the room where the person is expected to be according to the model.
- W_{AG}: represents the weighted Global Activity. It is computed based on the current and previous time intervals from the model (see equ.8).
- W_n: represents the classification of the weighted Global Activity (W_{AG}). The individual classification of the W_{AG} and the sampled global activity (S_{AG}) at the current time. The table below (Table 4-2) shows the matching matrix used to come up with the final classification for W_n. The sign ✓ means Normal and ✗ means Abnormal. The values in the matrix are based on how closed W_{AG} and S_{AG} are to the max Global activity from the model.

$$W_{AG} = \frac{minutes}{\Delta t} \times AG_{model(current\ interval)} + \frac{\Delta t - minutes}{\Delta t} \times AG_{model(previou\ interval)} \tag{8}$$

where minutes denotes the elapsed time in the current time interval (in minutes) and $\Delta \boldsymbol{t}$ denotes the length of the time interval (e.g. 60 minutes).

Table 4-2: Weighted Global Activity Classification

$S_{AG}\backslash W_{AG}$	Very High	High	Medium	Low	Very Low
Very High	✓	✓	✗	✗	✗
High	✓	✓	✓	✗	✗
Medium	✗	✓	✓	✓	✗
Low	✗	✗	✓	✓	✓
Very Low	✗	✗	✗	✓	✓

The use of the abnormal behaviour classification step in the detection module provides a way to transform the final output of the detection module into meaningful states that the caregivers and healthcare providers can easily understand and react upon.

In the following chapters, we present how the BMS system is been evaluated, by presenting first the validation approach that we designed to evaluate the system and then the conducted experiments and the obtained results.

Chapter 5. **Validation Approach**

One of the most challenging steps in developing a human behaviour monitoring system is its validation. Designing real-life experiments to validate a behaviour monitoring system is difficult and needs more efforts. In this chapter, we present an attempt to provide a more realistic validation approach for the developed system depending on generated synthetic data and real-life datasets collected from other research projects.

The chapter includes the description of the datasets, analysis of the user profiles of each dataset as well as the description of the used assumptions and possible abnormal behaviours (anomalies). Moreover, we present the description of the identified performance metrics used to evaluate the system.

5.1. Datasets

Two different types of datasets have been used for validation, named Synthetic and the Aruba datasets.

5.1.1. Synthetic

A synthetic data generator was developed to simulate the daily transition and stay behaviours of a monitored person in a home environment. The layout of the home is shown in Figure 4-1, with a virtual “outside” room to model the periods when the person goes outside of the home. We simulated three different periods of the day with different behaviours: sleeping at the bedroom, begin out of the home, and staying in the living room. The data generator runs repeatedly for a predefined period (e.g. 4 months) and generates observations every 1 to 10 minutes, uniformly distributed in time. For the day segments in which the person is sleeping or outside home, the data generator is designed to generate fewer observations with longer time between each pair of observations (1 to 8 hours) in order to simulate those behaviours in a more realistic way. Examples of the generated synthetic sensor observations are shown in Table 5-1 and the detailed description of the data generator is provided in Appendix A.

Table 5-1: Synthetic - Examples of sensor observations

Timestamp	Room
06/04/2016-00:00:00	Bedroom
06/04/2016-00:06:05	Bedroom
06/04/2016-00:08:18	Outside
06/04/2016-10:10:20	Outside
06/04/2016-01:15:30	Living room

The normal daily behaviours of the monitored person in the data generator are defined as a user profile, represented in a matrix format. The following are the descriptions of the user profiles that we considered in our experiments with the synthetic data.

5.1.1.1. User Profile A - “morning” person

This profile describes the daily transition and stays behaviour for a “morning” person who follows a normal daily routine similar to the large majority of the people. This person usually gets up at 8:00 in the morning, goes outside home at around 9:00 am and comes back home in the middle of the day around 16:00 afternoon. As a daily habit, he spends most of the evening in the living room watching TV before going to bed at midnight. Therefore, the day of this person is divided into three main segments: the first segment for the night and early morning in hours (0, 8], in which the person spends most of the time in the bedroom; the second segment in the middle of the day in hours (8-16], which is mostly spent outside; the last segment in the evening and night time, in hours (16-24], which is mostly spent at the living room. This information was used to approximate stay probabilities for observing the person in each room within the three defined segments of the day. The approximated probabilities are shown in the following matrix. As shown, we assigned highest probabilities to the rooms that the person usually navigates to, according to his/her profile.

$$\begin{bmatrix} \boldsymbol{interval/room} & \boldsymbol{Bedroom} & \boldsymbol{Bathroom} & \boldsymbol{Livingroom} & \boldsymbol{Kitchen} & \boldsymbol{Store} & \boldsymbol{Outside} \\ \mathbf{0-8} & 0.96 & 0.01 & 0.03 & 0 & 0 & 0 \\ \mathbf{8-16} & 0.1 & 0 & 0 & 0 & 0 & 0.9 \\ \mathbf{16-24} & 0.02 & 0 & 0.95 & 0 & 0 & 0.03 \end{bmatrix}$$

5.1.1.2. User Profile B - "nightly" person

Unlike the previous, this user profile describes the daily behaviour for a "nightly" person who usually spends the entire night outside the house and sleeps during the day. The idea here is to have an extremely different user behaviour than the previous profile to show the model's ability to learn different behaviour profiles and detect anomalies based on the user's learned behaviour. The person of this profile usually sleeps during the day in hours between 8:00 to 16:00 in the afternoon and then spends most of his time after waking up in the living room watching TV or doing some domestic work before going outside at midnight and coming back home around 8:00 in the morning. The approximated stay probabilities during the day for this profile are shown in the following matrix. We assigned highest probabilities to the rooms that the person usually navigates to, according to his/her profile. Table 5-2 presents a summary of the synthetic dataset.

$$\begin{bmatrix} \boldsymbol{interval/room} & \boldsymbol{Bedroom} & \boldsymbol{Bathroom} & \boldsymbol{Livingroom} & \boldsymbol{Kitchen} & \boldsymbol{Store} & \boldsymbol{Outside} \\ \mathbf{0-8} & 0.1 & 0 & 0 & 0 & 0 & 0.9 \\ \mathbf{8-16} & 0.96 & 0.01 & 0.03 & 0 & 0 & 0 \\ \mathbf{16-24} & 0.02 & 0 & 0.95 & 0 & 0 & 0.03 \end{bmatrix}$$

Table 5-2: The Synthetic dataset - Summary

# resident	1
# rooms	6
Length (months)	3
#PIR sensors	6
# Observations	26103[1]

5.1.2. The Aruba

The Aruba dataset is collected from the CASAS Smart Home Project at Washington State University (WSU), the source can be found here (http://casas.wsu.edu/datasets/). The dataset contains sensor data that was collected in a home of a volunteer adult woman. The home was equipped with three kinds of sensors: PIR motion sensors (M), door closure sensors

[1] This is the number of observations for a particular run of the data generator, for a period of 3 months.

(D), and temperature sensors (T). Figure 5-1 shows the home's layout. For our experiments, we consider only PIR motion sensors. The locations of the sensors are represented by black circles in the figure. Table 5-3 lists samples of the sensor observations.

Table 5-3: The Aruba - Examples of Sensor Observations

Date	Time	SensorID	Status
2010-11-04	00:03:50.209589	M003	ON
2010-11-04	00:03:57.399391	M003	OFF
2010-11-04	02:32:33.351906	M003	ON
2010-11-04	02:32:38.895958	M003	OFF
2010-11-04	04:14:33.203704	M002	ON
2010-11-04	04:14:37.15509	M002	OFF

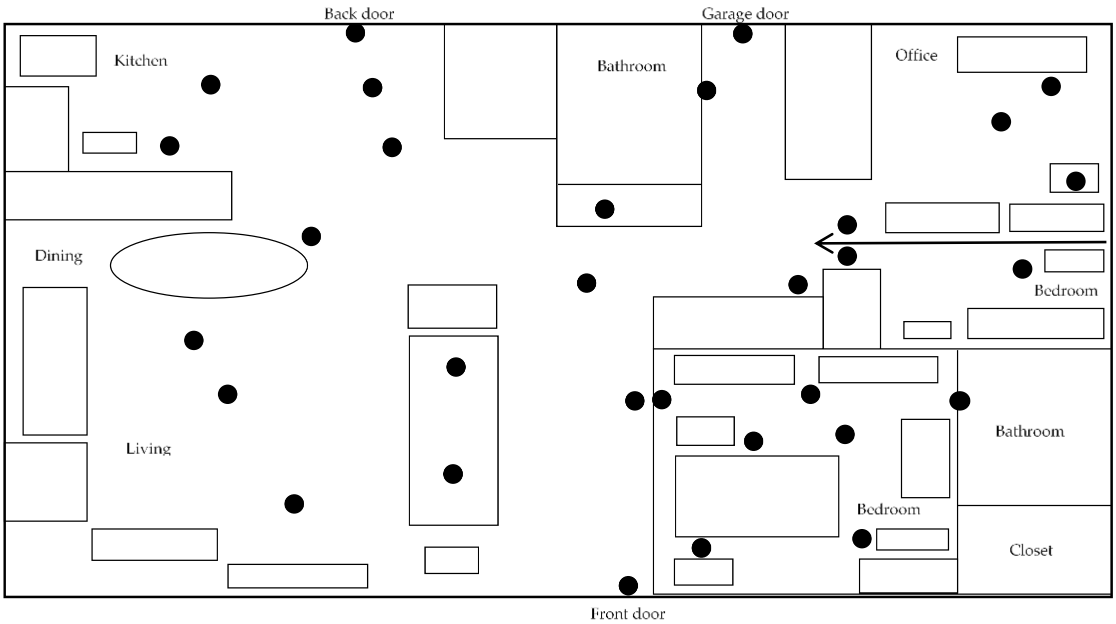


Figure 5-1: The Aruba Home Layout (adapted from [68] **)**

5.1.2.1. Pre-processing

As shown in Table 5-3, the Aruba dataset consists of sensor observations collected from PIR sensors that are distributed in a home of an adult woman to monitor her daily activities. The dataset was annotated to include the performed activities during the period of the experiment. The data includes the activities and their occurring frequencies. Moreover, from the description of the dataset, it has been mentioned that the monitored woman received regular visits from her children and grandchildren during the experiment period. However, there is no ground truth data to specify or annotate those visit days.

Firstly, we grouped the observations of the PIR motion sensors by room. Instead of using the original sensor IDs, as shown in Table 5-3. We map the IDs onto labels corresponding to the rooms in which the sensors reside with respect to the layout of the home. As shown in Figure 5-1, multiple sensors cover the serving area in each room. Figure 5-2 illustrates the distribution of the daily generated sensors' observations. The illustrated results in the figure show the daily number of observations (blue) and their daily differences (red) as well as the daily density distribution plot (histogram).

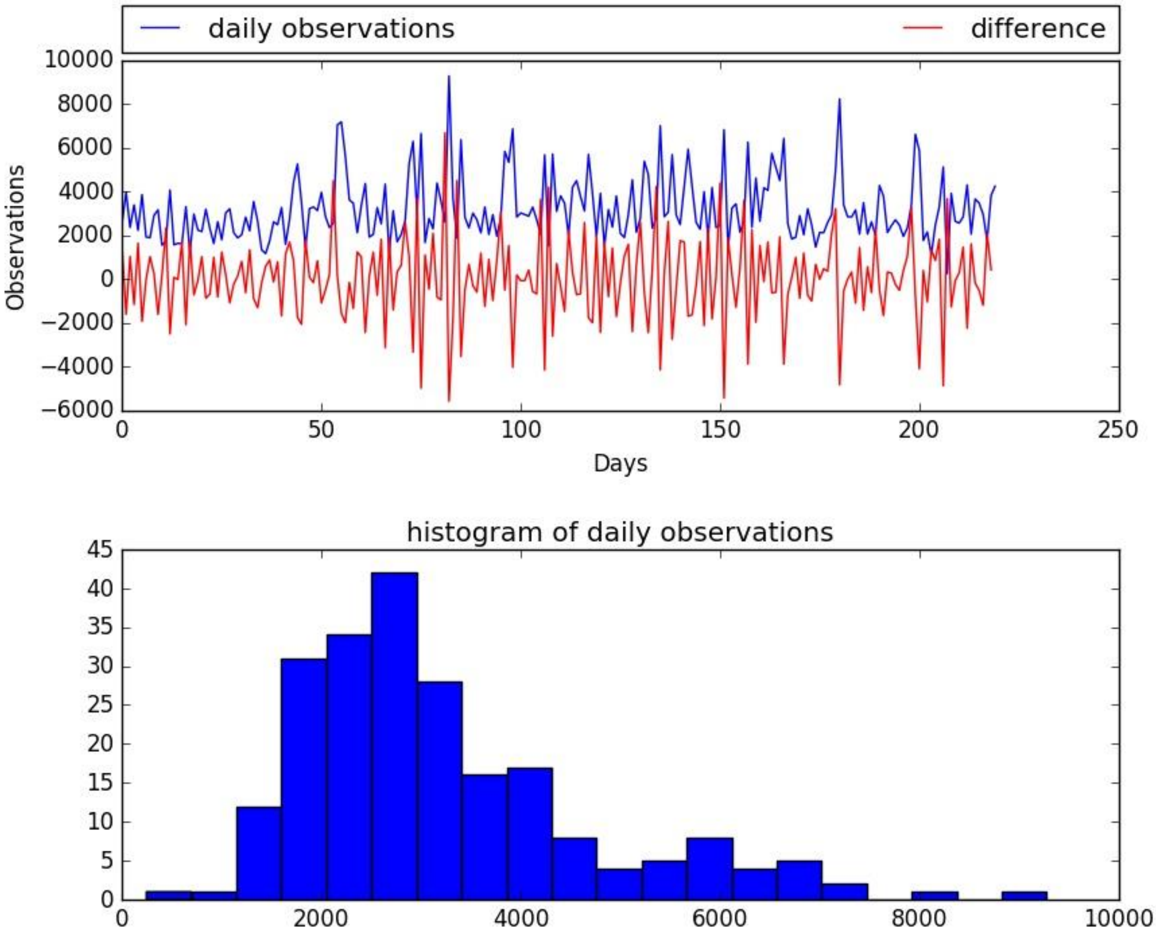


Figure 5-2: Line and density plots of distribution of daily observations in the Aruba

Another view of the Aruba dataset is shown in Figure 5-3. The results illustrate the distribution of the daily activities performed by the monitored woman. We counted the number of the performed activities in each day based on the annotated ground truth data of the activities. The illustrated results show the daily number of activities (blue) and their daily differences (red) as well as the daily density distribution plot (histogram).

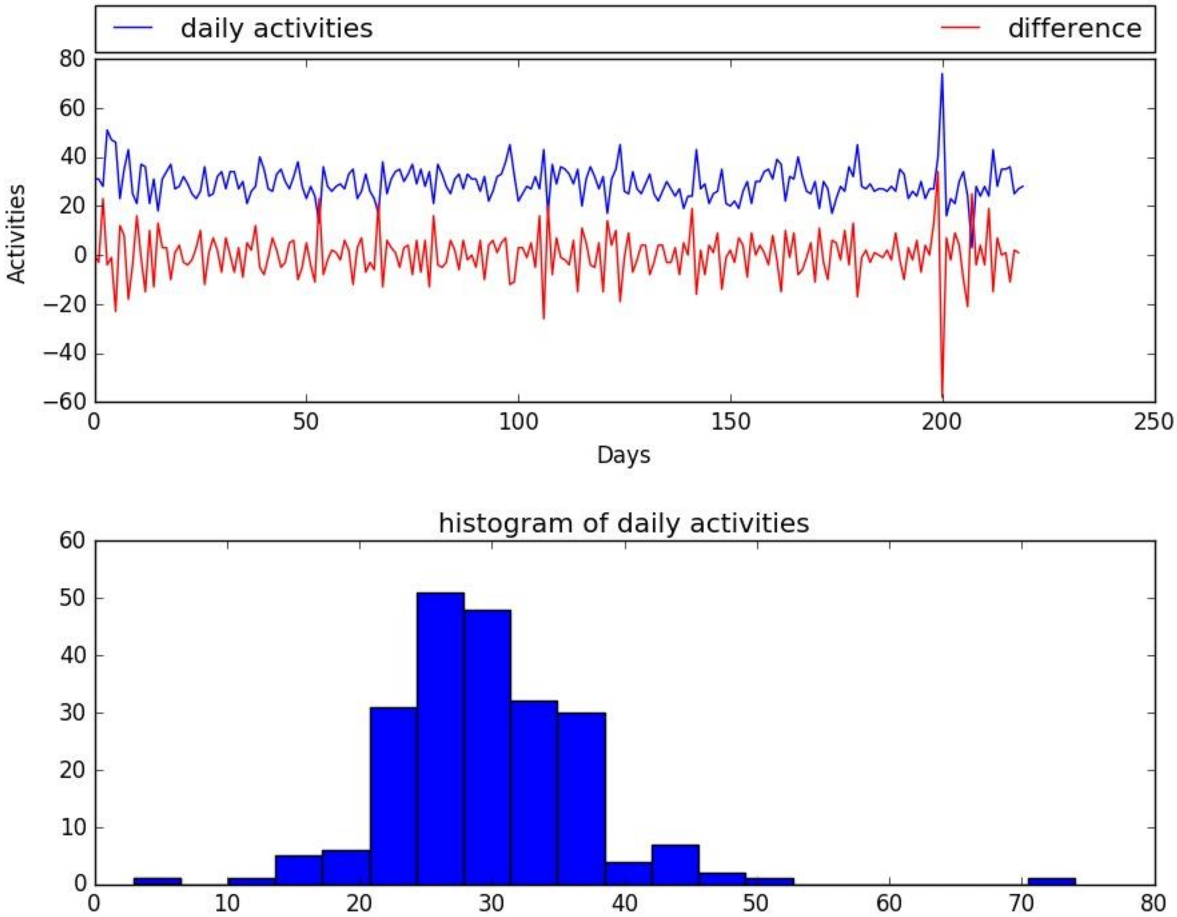


Figure 5-3: Line and density plots of distribution of daily activities in the Aruba

To exclude the visits days from the Aruba dataset, we considered the obtained results of the daily observations and activities to come up with a simple criterion. We assume that the visit days most probably have a high number of daily sensors observations and also a high number of activities compared to the majority of the days. Based on this assumption we managed to exclude about 48 days from the dataset which, most probably, represent the days with a high number of observations and activities that were probably generated by multiple persons.

Table 5-4: The Aruba dataset - Summary

# resident	1
# rooms	10
Length (months)	7 (220 days)
#PIR sensors	31
# Observations	798061
# removed visit days	48

5.1.2.2. Similarity of daily routine

Figure 5-4 illustrates the estimated similarity of the performed activities by the monitored woman during the experiment period. The similarity was computed on the sequence of the performed activities in each day against other days in order to capture the daily activity routine of the monitored woman.

First, we constructed a sequence of the daily activities for each day from the Aruba dataset using the ground truth data of the annotated activities. The daily sequence represents the daily behaviour of the monitored woman. We hypothesise that a person with similar daily routine has a relatively similar sequence of daily activities, and therefore, we computed a similarity measure in range (0,1) between the sequence of activities for each day against other days using the edit distance algorithm for string matching. For each day we constructed a string sequence separated by a (",") to represent the daily activity sequence ("sleeping, bathing, cooking….").

The obtained similarity results are shown in Figure 5-4. As shown in the figure, there is low similarity observed between the days. The yellow diagonal illustrates the computed self-similarity of the days with high similarity while the blue lines represent the days of different activity routines with a high number of observed activities and observations.

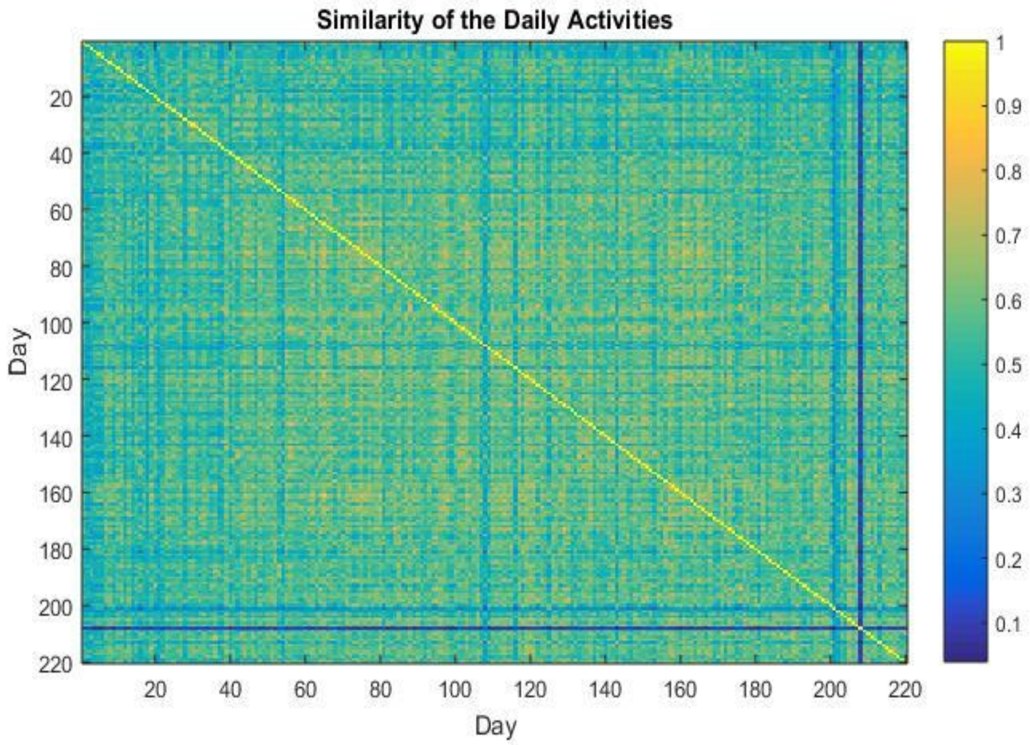


Figure 5-4: Aruba - Similarity of the daily activities

Moreover, we also computed the average start and end times for each activity, as shown in Table 5-5. This was done to give an idea of how the normal day of the monitored woman looked like during the days of the experiment. As shown from the results in the table, it is quite difficult to conclude a stable daily routine for the monitored woman in the Aruba dataset based on this information.

Table 5-5: The Aruba - average start and end time of the activities

Activity	Start Time(mean)	End Time (mean)
Bed_to_Toilet	04:41:55	04:44:39
Eating	13:06:53	13:17:07
Enter_Home	14:18:14	14:18:12
Housekeeping	13:07:01	13:27:44
Leave_Home	12:33:37	12:33:43
Meal_Preparation	13:02:57	13:12:21
Relax	15:46:52	15:40:27
Respirate	11:35:30	11:44:04
Sleeping	09:19:29	06:17:32
Wash_Dishes	15:26:11	15:36:03
Work	13:24:06	13:41:11

5.2. Abnormal Behaviours (anomalies)

An elderly person may have different kinds of anomalous behaviour while performing the daily routine and it is not trivial to anticipate all of them in advance. Thus, we limited ourselves to a finite set of abnormal behaviours to be detected by the system. The generic type of anomalies that we are targeting in our system is the “Unusual stay” anomaly which can be translated into an unusual stay at the unusual location and/or time of the day that do not conform to the normal routine of the monitored persons. Following the intuition that an elderly person usually follows a specific daily pattern when performing daily activities and that routine may change only when the person is having or experiencing some kind of health problems. Our system aims at detecting those kind of changes and to correlate them with the most possible health declines a person might have when living alone at home. In Table 5-6 we list the set of abnormal behaviour for our system together with their descriptions and associated health declines.

Table 5-6:Possible Abnormal Behaviours

Anomaly	Description	Applied Semantic in model
Oversleeping	An extended prolonged stay at bedroom has been detected, (e.g. the entire morning as well as part of the afternoon) due to mobility problems, stroke or death	Longer stay at bedroom; longer than usual. This implies: • None or low Global Activity • None Inter-room Activity • Longer stay at bedroom
LessSleeping	The inhabitant has been detected awake during sleeping time, having sleepless time due to anxiety or may be developing Alzheimer's diseases.	Detected motion at one of the rooms, not a bedroom, during the usual sleeping time. This implies: • Relatively higher Global activity; higher than usual • May include some inter-room Activity
NotBackHome	The inhabitant has not been at home for a long time, longer than the usual duration of being outside. The person may be having trouble coming back home or get lost or wondering outdoors.	Person stayed outside longer than usual. This implies: • No Global Activity • No Inter-room Activity • Longer stay outside
Dead	Unusual stay has been detected for a relatively extended prolonged time due to death	Longer stay at one of the rooms, not bedroom nor outside, longer than usual. This implies: • No Global activities • No inter-room activities • Unusual stay at unusual room
Warning	An inactivity period has been detected that is not long enough to indicate "Dead" state. This could be an indicator for unsafe situations or mobility problems such as unsteadiness while walking, difficulty getting in and out of a chair/bed.	Intermediate state if the conditions of the "Dead" state are not fully satisfied. This implies: • Unusual stay at unusual room, not bedroom nor outside • A few weighted Global activities

5.3. Assumptions

We put some assumptions to be considered during the behavioural modelling and experiments:

- We assume that a monitored person is an elderly person who lives alone at home and has relatively regular daily mobility routine.
- No visits from relatives or caregivers are expected during the experiment period.
- The transition time between rooms is zero; no transition time is required to complete the movement from one room to another.
- Only a single anomaly is expected to happen during an experiment.
- The final output of the detection module can easily be transmitted to caregivers via the Internet or a web service and how to send the notifications is considered a simple technological problem and is not considered in this work.

5.4. Performance Metrics

To assess the performance of the developed system, we define a set of evaluation metrics to be used as performance metrics. They are graphically illustrated in Figure 5-5 and described as follows:

- The Anomaly Detection Delay (ADD): it is a measure of the delay time since the anomaly actually started until before the detection module starts correctly detecting it; it is the delay before real alerts.
- The Anomaly Confirmation Time (ACT): it represents the amount of time the system keeps reporting an anomaly after it has been detected (a too short ACT might be understood by caregivers or relatives as a false alarm).
- An average number of False Positive alerts (FP): it indicates the rates of wrong detections. The detection module raises alerts for none anomalous cases.

In addition to the above explicit evaluation metrics, the performance of the system is also assessed by considering the following metrics:

- The sensitivity of learning window size: it shows the effect of the learning window size on the detection results. The learning window indicates the sufficient context history to build mature models that minimises false alerts while generating timely true alarms.

- Anomaly Classification: A confusion matrix that shows the correctly classified anomalies, considering the set of identified anomalies.

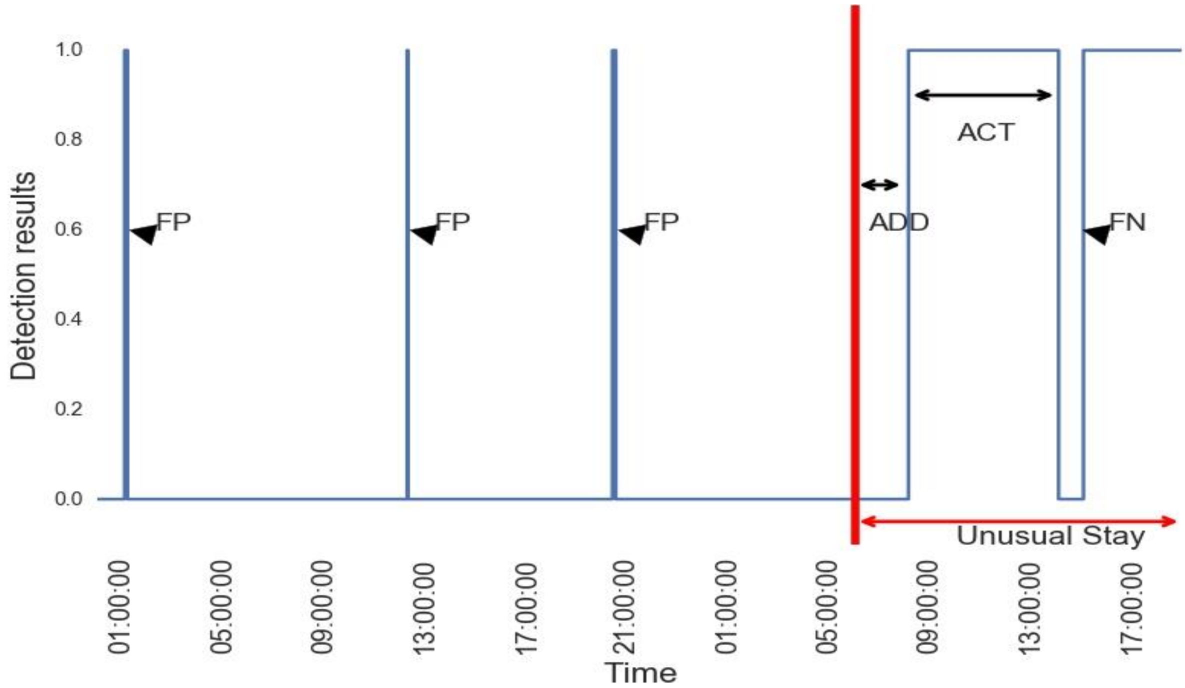


Figure 5-5: Performance metrics (FP: false positive, FN: false negative detection)

Ideally, for a detection system to be reliable, it should generate true alarms with the shortest anomaly detection delay (ADD) and longest anomaly confirmation time (ACT), enough to convey the alarm notifications while minimising the number of false alerts and provide correct anomaly classification.

Chapter 6. **Results and Discussions**

This chapter presents the obtained results of the conducted experiments. The results are presented with regard to the performance metrics and the individual modules of the system. Thorough discussions on the obtained results are also provided in this chapter. More detailed results can be found in Appendix C.

6.1. Experiments Settings

In the experiments, we employed one-month learning window to process the sensors' observations and to build the underlying behaviour model. The entire set of observations in the learning window is used to compute the dimensions of the model. The testing was done on observations beyond the first month of data (i.e. post-learning period). Artificial anomalies (abnormal behaviours) were injected into the datasets (Chapter 5) to simulate the behaviour deviations. Each anomaly was injected, individually, into the datasets to evaluate the performance of the system in each abnormal behaviour, separately. Table 6-1 presents the experiments settings and the optimised parameters of the learning and the detection modules.

Table 6-1: Experiments settings

Parameter	**Value**
Learning window size	4 weeks (1 month)
Model update	weekly
Learning window shift	1 week
Detection sampling period	1 minute
Estimator smoothing window size	10 minutes

Classifier threshold	[0,1]
sNormal timeout (N1)	5 minutes
Abnormal timeout (N2)	10 minutes

Table 6-2 presents the injected abnormal behaviours in the different datasets used in the experiments. The table provides a description of the abnormal behaviour and how it was implemented in each dataset.

Table 6-2: Injected Abnormal behaviours in the datasets

Anomaly\Dataset	Profile A	Profile B	Aruba
OverSleeping	Prolong sleeping at "bedroom" extended to all afternoon, hours (8-19]	Prolong sleeping at "bedroom" extended to all afternoon, hours (16-23]	Prolong sleeping at "Bedroom1" extended to all afternoon up to hour 19
LessSleeping	Being "outside" during sleeping time in hour (0-8]	Being in "kitchen" during sleeping time in hours (8-16]	Being "Outside" in sleeping time in hours (0-6)
NotBackHome	Stay longer "outside" in hours (16-23)	Stay longer "outside" in hours (8-23)	Going "Outside" and not coming back in hours (7-23)
Dead	Long stay at "store" in hours (8-23)	Long stay at "store" in hours (8-23)	Long stay at "office" in hours (7-23)

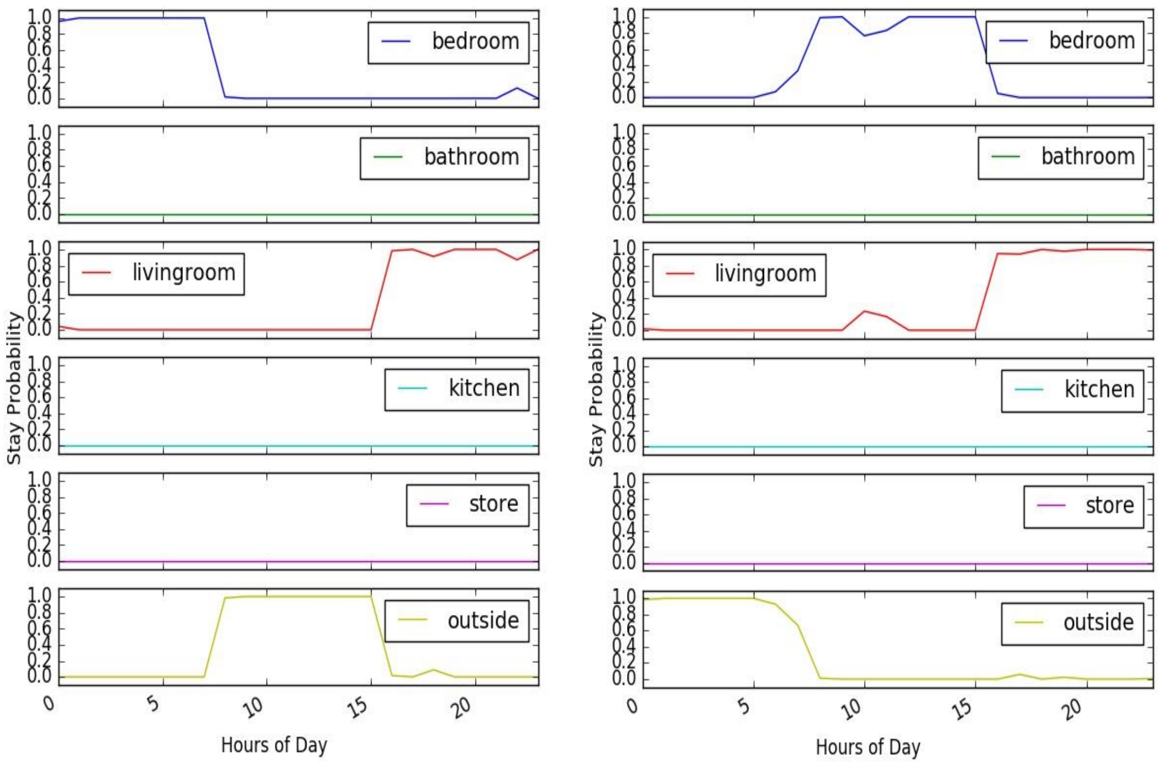
6.2. The Learning Module

The quality of the learning module or, particularly, the learned behavioural model is determined by how well it describes the behaviour of the monitored person and the interpretation it provides to better distinguish between normal and abnormal behaviour. The intuition of the learning module is based on the idea of giving high probability estimates for normal behaviours (usual routines) and low estimates for abnormal behaviours (unusual routines). Hence, we expect the learning module to build a model for the normal routine that gives high stay probability estimates in the rooms in which the person usually spends most of his time, during the hours of the day, and low estimates anywhere else.

6.2.1. Learning normal routine

Figure 6-1 illustrates an example of the obtained results of the learning module for a normal day for the two user profiles (Profile A and Profile B) of the synthetic dataset. The results are presented in a stacked plot to show the comparison of the learned stay probability estimates in all rooms during the hours of the day.

As shown in the figure and based on the given user's profile, the three simulated behaviours of the person in the two user profiles are correctly estimated and high stay probability estimates are given to the rooms where the person usually performs his daily normal routine. The learning module was successfully able to learn the normal daily behaviour of the monitored person during each hour of the day, each data point in the figures represents, for the given time of the day, the learned stay probability from the model (equ.2). As shown, the day is clearly segmented into three segments and high stay probability estimates are assigned to the rooms where the user was active during the hours of the day.



(a) (b)

Figure 6-1: Learned stay probability for user (a) Profile A (b) Profile B

Additionally, the correctness of the learning module can also be illustrated by showing the estimated stay transition matrix dimension of the model for the different hours of the day.

The following are the learned stay transition matrices for the three segments of the day, as simulated in the two user profiles of the synthetic datasets. The matrices show the average of the estimated stay probabilities at each room (diagonal of the matrix) during the three segments of the day. First, we present the matrices of the user profile A and then the matrices of the user profile B, respectively, to confirm the illustrated results in the previous figures. As shown, the estimated probabilities in the matrices clearly follow the simulated behaviours of the two persons as described in their profiles. The first user (profile A) spends most of the early hours of the day in the bedroom, probably sleeping during that time while going outside in the middle of the day and spending the evening in the living room. The second user (profile B) goes outside in the midnight and early hours of the day and stays in a bedroom in the middle of the day and the evening in the living room. These estimated behaviours conform correctly to their simulated behaviours. The values in the matrices illustrate the average of the estimated probabilities of each segment.

Profile A:

(0-8]

$$\begin{array}{cc} & \begin{array}{cccccc} \mathit{Bedroom} & \mathit{Bathroom} & \mathit{Livingroom} & \mathit{Kitchen} & \mathit{Store} & \mathit{Outside} \end{array} \\ \begin{array}{c} \mathit{Bedroom} \\ \mathit{Bathroom} \\ \mathit{Livingroom} \\ \mathit{Kitchen} \\ \mathit{Store} \\ \mathit{Outside} \end{array} & \begin{bmatrix} 0.99 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

(8-16]

$$\begin{array}{cc} & \begin{array}{cccccc} \mathit{Bedroom} & \mathit{Bathroom} & \mathit{Livingroom} & \mathit{Kitchen} & \mathit{Store} & \mathit{Outside} \end{array} \\ \begin{array}{c} \mathit{Bedroom} \\ \mathit{Bathroom} \\ \mathit{Livingroom} \\ \mathit{Kitchen} \\ \mathit{Store} \\ \mathit{Outside} \end{array} & \begin{bmatrix} 0.002 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.998 \end{bmatrix} \end{array}$$

(16-24]

$$\begin{array}{cc} & \begin{array}{cccccc} \mathit{Bedroom} & \mathit{Bathroom} & \mathit{Livingroom} & \mathit{Kitchen} & \mathit{Store} & \mathit{Outside} \end{array} \\ \begin{array}{c} \mathit{Bedroom} \\ \mathit{Bathroom} \\ \mathit{Livingroom} \\ \mathit{Kitchen} \\ \mathit{Store} \\ \mathit{Outside} \end{array} & \begin{bmatrix} 0.02 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.97 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.01 \end{bmatrix} \end{array}$$

Profile B:

(0-8]

$$\begin{array}{cc} & \begin{array}{cccccc} \mathit{Bedroom} & \mathit{Bathroom} & \mathit{Livingroom} & \mathit{Kitchen} & \mathit{Store} & \mathit{Outside} \end{array} \\ \begin{array}{c} \mathit{Bedroom} \\ \mathit{Bathroom} \\ \mathit{Livingroom} \\ \mathit{Kitchen} \\ \mathit{Store} \\ \mathit{Outside} \end{array} & \begin{bmatrix} 0.051 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.002 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.947 \end{bmatrix} \end{array}$$

(8-16]

$$\begin{array}{cc} & \begin{array}{cccccc} Bedroom & Bathroom & Livingroom & Kitchen & Store & Outside \end{array} \\ \begin{array}{c} Bedroom \\ Bathroom \\ Livingroom \\ Kitchen \\ Store \\ Outside \end{array} & \begin{bmatrix} 0.95 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.05 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

(16-24]

$$\begin{array}{cc} & \begin{array}{cccccc} Bedroom & Bathroom & Livingroom & Kitchen & Store & Outside \end{array} \\ \begin{array}{c} Bedroom \\ Bathroom \\ Livingrooom \\ Kitchen \\ Store \\ Outside \end{array} & \begin{bmatrix} 0.01 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.98 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.01 \end{bmatrix} \end{array}$$

6.2.2. Model Adaptation

The behaviour model of the monitored person is updated on a weekly basis to incorporate the latest observed behaviour of the person into the model. This allows the model to adapt to any behavioural changes that are not necessarily abnormal behaviours. To demonstrate this ability, we performed an experiment in which we merged the two user profiles (profile A and profile B) into a single user profile that simulates a person having a steady behaviour during an initial period (represented as profile A) and then changes his behaviour and follows different daily profile that extremely varies from the previous one (represented as profile B). To look at the changes during the experiment, we selected the first segment of the day (i.e. hours (0-8]) and focused on the person's behaviour in the bedroom only. Firstly, the person followed the daily routine of user profile A, which means spending most of the time sleeping in the bedroom during this segment of the day, and then the person changed his behaviour and followed the daily routine of the user profile B, which means no sleeping during this segment of the day, and therefore not being detected in the bedroom during this time segment (i.e. hours (0-8]). Figure 6-2 shows the obtained results of this experiment.

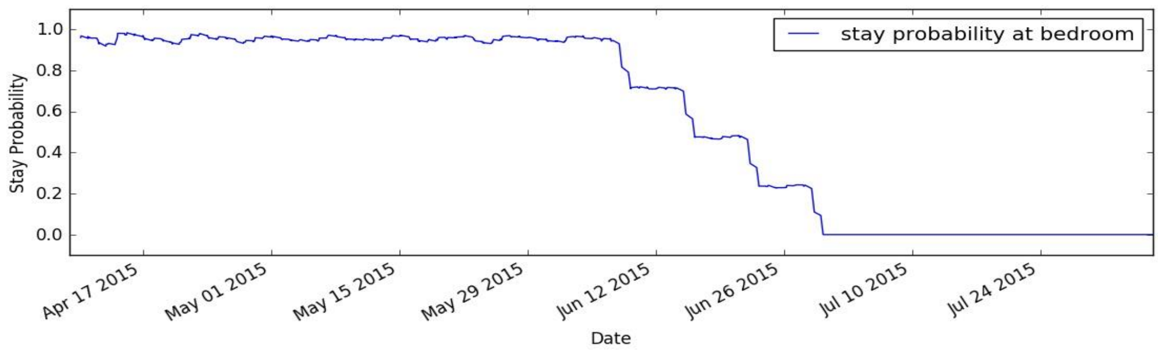


Figure 6-2: Learning Adaptation- merging different behaviour profiles

As shown in Figure 6-2, the learning module was able to estimate the behaviour of the monitored person during the first period of the experiment (profile A), giving high stay probability estimates for staying in the bedroom in this segment of the day. Then the behaviour of the person has changed gradually to new user behaviour (profile B). This happened in clear distinguished four steps that represent the length of the learning window (4-weeks window). As the learning window gets shifted weekly, the model is updated and adapted gradually to the new daily routine of the monitored person. This ability shows how the learning module can adapt its internal behaviour model automatically and perform online and continuous learning of the user's behaviour.

6.3. The Detection Module

The estimator and the automaton in the detection module have multiple parameters that need to be tuned properly in order to get the desired results. In the following, we present the experimental results that we performed to optimise these parameters. The parameters are:

- The window length of the low-pass filter used for smoothing the Location Likelihood l_n in the estimator and generating smoothed Location Likelihood g_n (Figure 4-3).
- The normal timeout (*N1*) used to control the transition between the states "Normal" and "Potential abnormal" in the automaton (Figure 4-6).
- The abnormal timeout (*N2*) used to indicate the transition to "Abnormal" state in the automaton (Figure 4-6).
- The threshold value used for abnormality detection.

6.3.1. Parameters Optimization

Figure 6-3 shows the results of the parameters optimisation experiment with respect to the performance metrics (Chapter 5, Section 5.4). The experiment was performed to select the optimal values for the parameters. As shown in the figure, the ADD results vary based on the setting of the parameters, while the results of the average weekly false alerts show a slight difference and the ACT results have no variations as the settings of the parameters change.

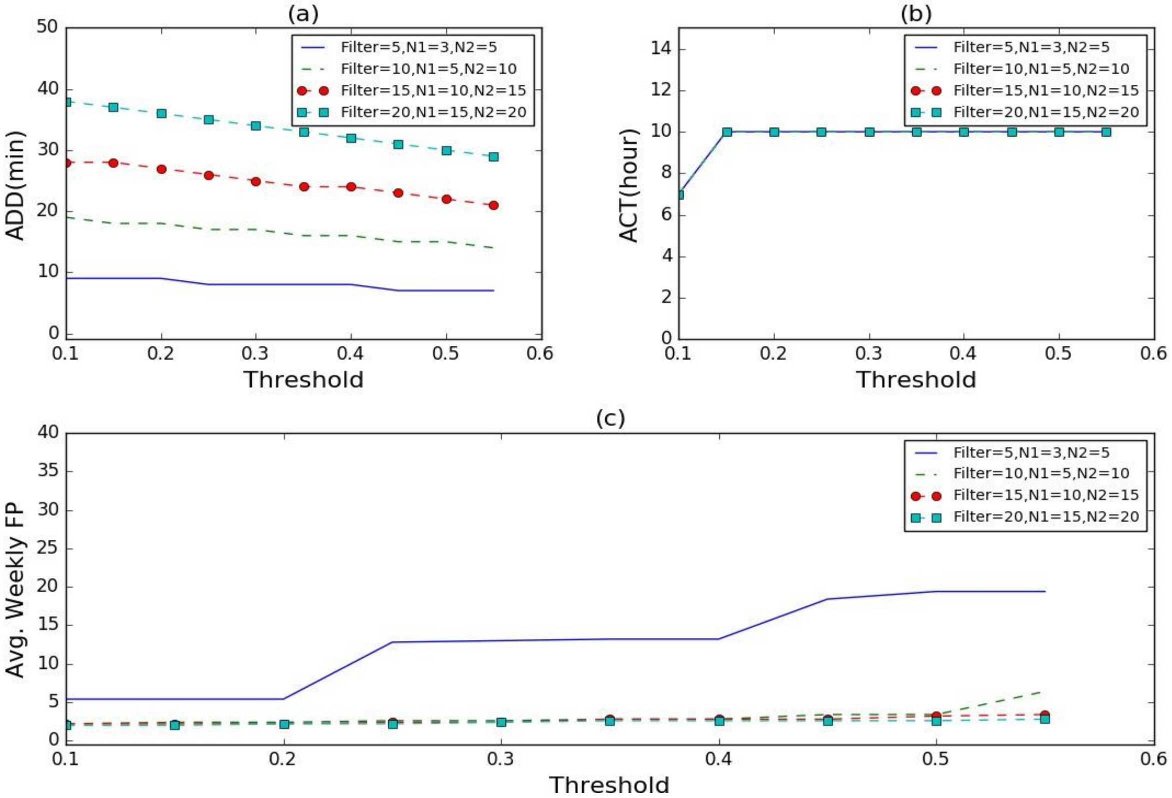


Figure 6-3: Detection Module - Parameters Optimisation - automaton

Based on the results of this experiment we chose the best values. We set the window length of the low-pass filter in the estimator to 10 minutes, the normal timeout in the automaton *N1* to 5 minutes, and the abnormal timeout in the automaton *N2* to 10 minutes. These values have been used to obtain the final results of the detection module throughout the experiments.

6.4. Anomaly Detection Delay (ADD)

This section presents the obtained results of the Anomaly Detection Delay (ADD) on the datasets used in the experiments. The aim of this performance metric, as described in

Chapter 5, is to evaluate the responsiveness of the detection module in terms of the minimum time required to detect an anomaly (abnormal behaviour). Figure 6-4 illustrates the ADD results on the datasets, showing the results of the estimator and the automaton, respectively. The figure shows the ADD results of detecting the "LessSleeping" abnormal behaviour in all the datasets. As the threshold increases, the ADD result slightly decreases in the three datasets.

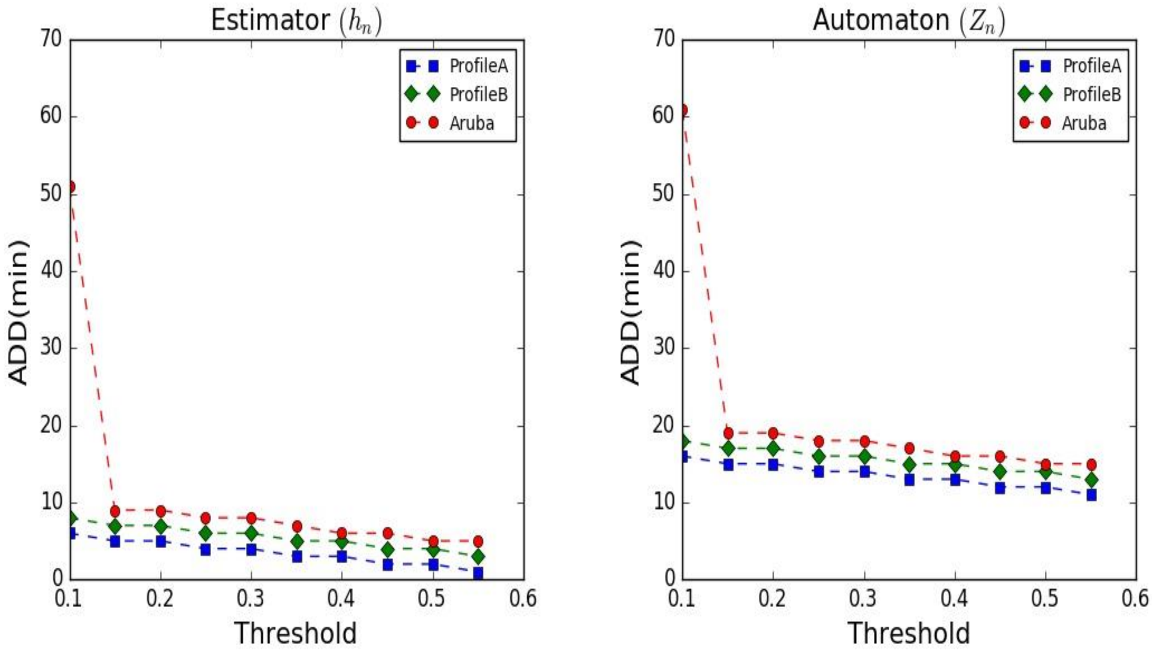


Figure 6-4: ADD results - Estimator and Automaton

Figure 6-5 illustrates the ADD results after applying the rule-based classifier into the detection module. A similar trend is also shown in the figure, however, there is no significant effect of the threshold value on the obtained results.

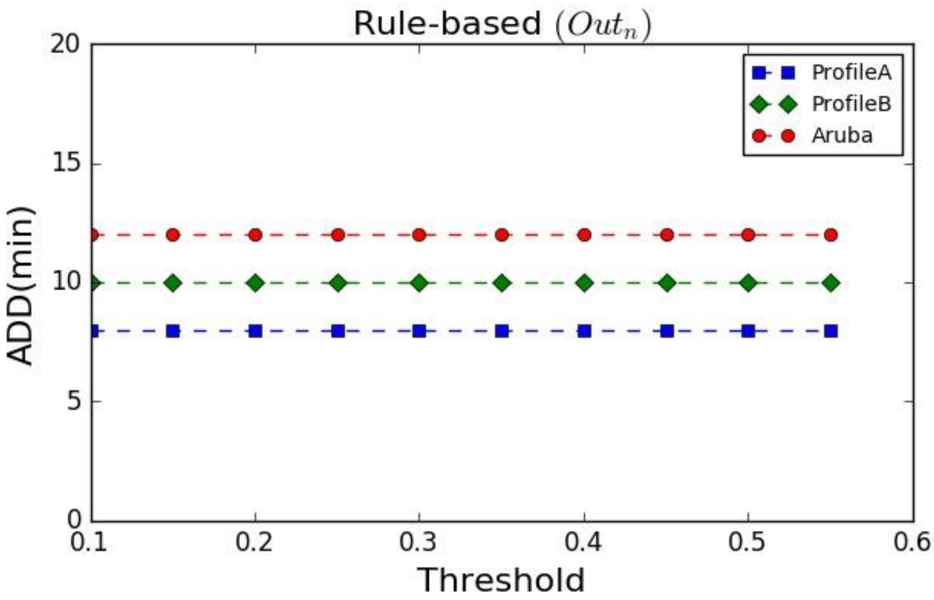


Figure 6-5: ADD results - Rule-based

The ADD results after applying the rule-based classifier are better because this classifier incorporates the other dimensions of the model besides the consideration of the “potential abnormal” state from the automaton, as shown in the flow chart diagram of the rule-based classifier (Figure 4-7). This allows the detection module to detect the abnormal behaviour much faster, considering the other dimensions to confirm the detection. The description of this classifier is presented in Chapter 4, section 4.5.3.

Table 6-3 presents a summary of the ADD results compared to some approaches from the state of the art. Our approach outperforms the other approaches and detects the abnormal behaviour much faster, producing the least detection delay.

Table 6-3: Summary of ADD (minutes) results compared to state of the art (threshold 0.25)

	h_n	Z_n	Out_n	[64]	[65]
Profile A	4	14	8	-	-
Profile B	6	16	10	-	-
Aruba	8	18	12	23	200

6.5. Anomaly Confirmation Time (ACT)

The following are the obtained results of the Anomaly Confirmation Time (ACT) on the datasets used in the experiments. The aim of this performance metric, as described in Chapter 5, is to evaluate the ability of the developed system in terms of the time taken to confirm the detection of the abnormal behaviours. Figure 6-6 illustrates the ACT results on the datasets, showing the results of the estimator and the automaton, respectively. The figure shows the ADD results of detecting the “LessSleeping” abnormal behaviour in all the datasets.

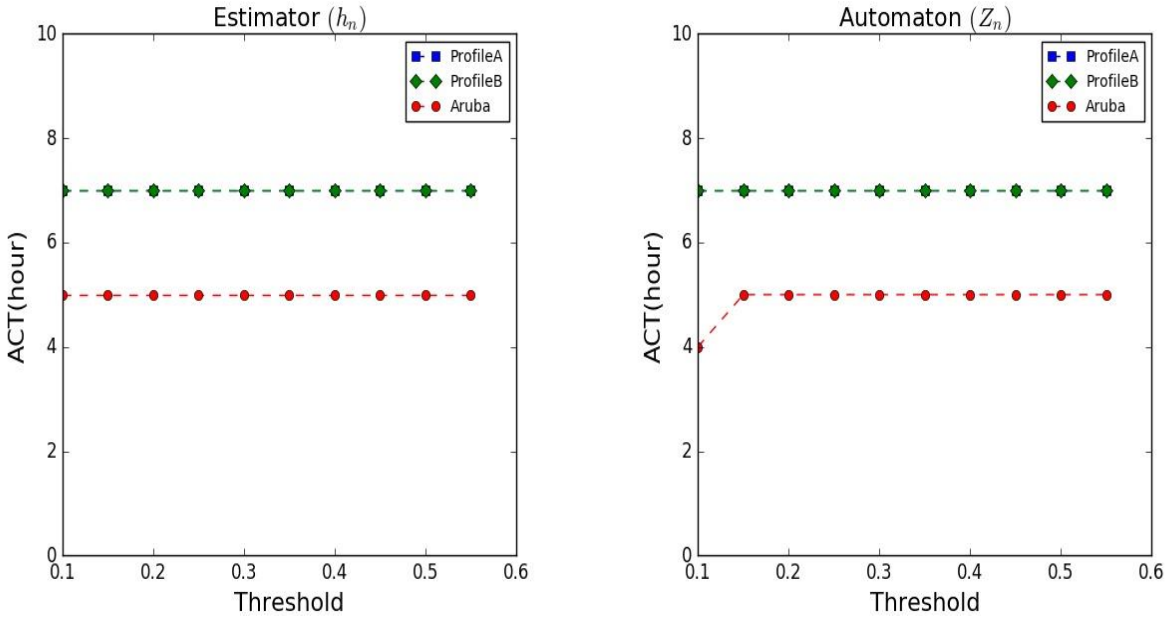


Figure 6-6: ACT results- Estimator and Automaton (no significant variations - Profile A & B)

Figure 6-7 illustrates the ACT results after applying the rule-based classifier. As shown in the ACT figures, the results did not change significantly as the threshold value changes. The results on the two user profiles of the synthetic data show similar results (more than 7 hours of confirmation time) while the results on the Aruba dataset show shorter confirmation time (5 hours on average). However, the obtained ACT results ,in general, show enough time to confirm the detection of the abnormal behaviour, the “LessSleeping” in this case.

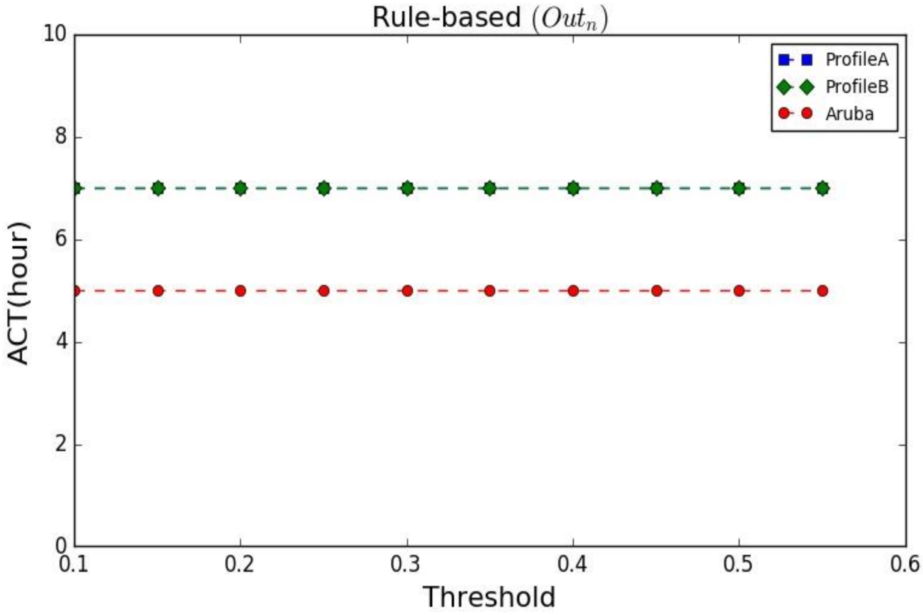


Figure 6-7: ACT results - Rule-based (no significant variations - Profile A & B)

6.6. Average number of False alerts (FP)

Figure 6-8 illustrates the obtained results of the average weekly false positive detection of the system on the datasets used in the experiments. The results on the synthetic data show similar behaviour for the two user profiles: as the threshold value changes, a low number of false alerts were generated (automaton results); on the other hand, the results on the Aruba dataset show high rates of false alerts. We believe that this high rate of false alerts is due the fact that the Aruba dataset includes days where the monitored person received multiple visits from her relatives during the experiment period. This may affect the accuracy of the learned behavioural model of the monitored person and lead to an increase in the number of false detections generated by the system.

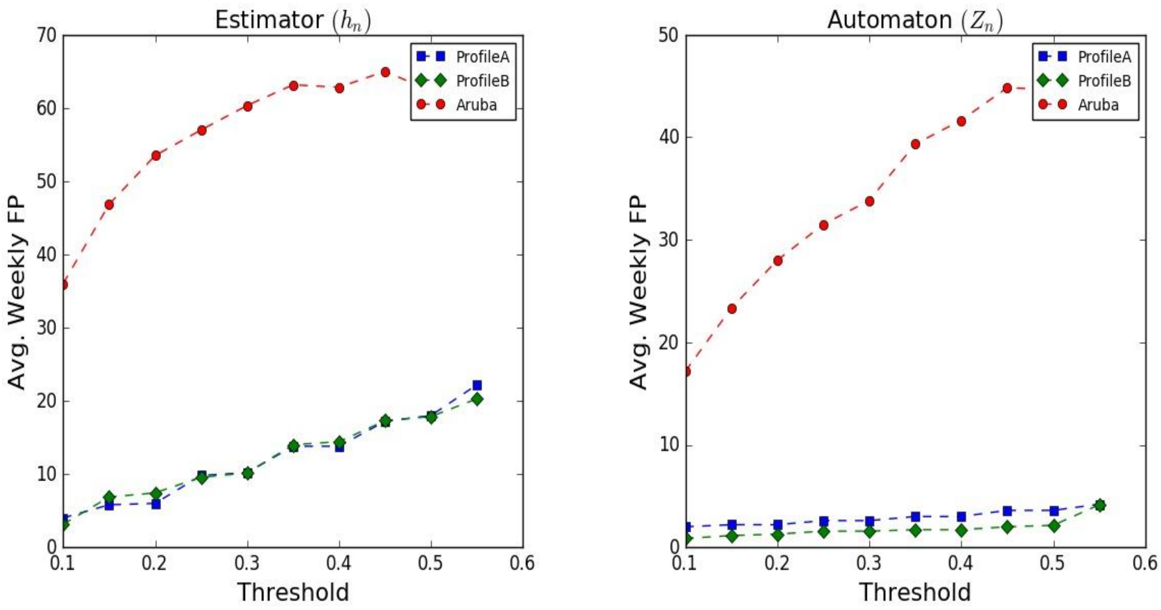


Figure 6-8: Avg. Weekly FP results - Estimator and Automaton

Figure 6-9 illustrates the results of the average weekly false alert detection of the system after applying the rule-based classifier. It shows a steady rate of false alerts as the threshold value changes. The results show a lower rate of false alert on the synthetic data and a significant reduction in the false alert results on the Aruba dataset. The rule-based classifier incorporates some of the other dimensions of the behaviour model to provide the final detection results. This enriches the ability of the detection module to differentiate the abnormal behaviour from the normal routine. The details of the rule-based classifier are provided in Chapter 4.

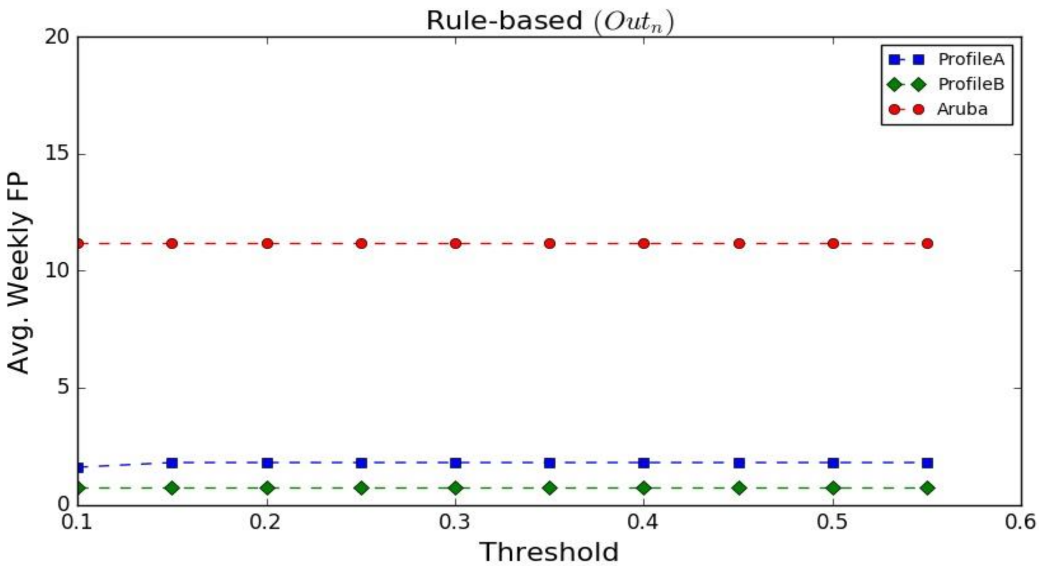


Figure 6-9: Avg. Weekly FP results - Rule-based

Table 6-4 presents a summary of the results of the average number of weekly false alerts compared to some approaches from the state-of-the-art which have similar objectives. The other approaches mainly focus on detecting falls and long inactivity periods. In the table, we present the results of the estimator (h_n), automaton (Z_n), and the rule-based classifier (Out_n), respectively.

Table 6-4: Summary of Avg. Weekly FP results compared to state of the art (threshold 0.25)

	h_n	Z_n	Out_n	[64]	[65]
Profile A	9.8	2.6	1.8	-	-
Profile B	9.5	1.5	0.7	-	-
Aruba	57	31	11.16	20.7	1.23

From the obtained results of the average number of false alerts, the results after applying the rule-based classifier are better than the estimator and the automaton results. We achieved a lower number of weekly false alerts on the synthetic data on the two profiles. However, on the Aruba dataset, we still suffer from higher rates compared to other approaches. The presented results in the table are selected using 0.25 threshold value on the datasets of the “LessSleeping” anomaly. This is relatively due to the multiple visits of the relatives that the monitored resident received during the data collection phase of the Aruba dataset. These visits caused the learned model to be a bit fuzzy, not reflecting exactly the daily routine of the monitored resident. We intend, as future work, to include a more reliable method to eliminate these visits as a pre-processing step before learning the daily behaviour of the monitored person.

6.7. Sensitivity of the learning window size

Figure 6-10 shows the obtained results of the Anomaly Detection Delay (ADD) and Anomaly Confirmation Time (ACT) as well as the average number of false alerts (FP) as a function of the learning window size. We performed this experiment on the synthetic dataset of the user Profile A with windows of size 2, 3, and 4 weeks. The size of learning window specifies the required initial and sufficient period to build valid behaviour model for the monitored person.

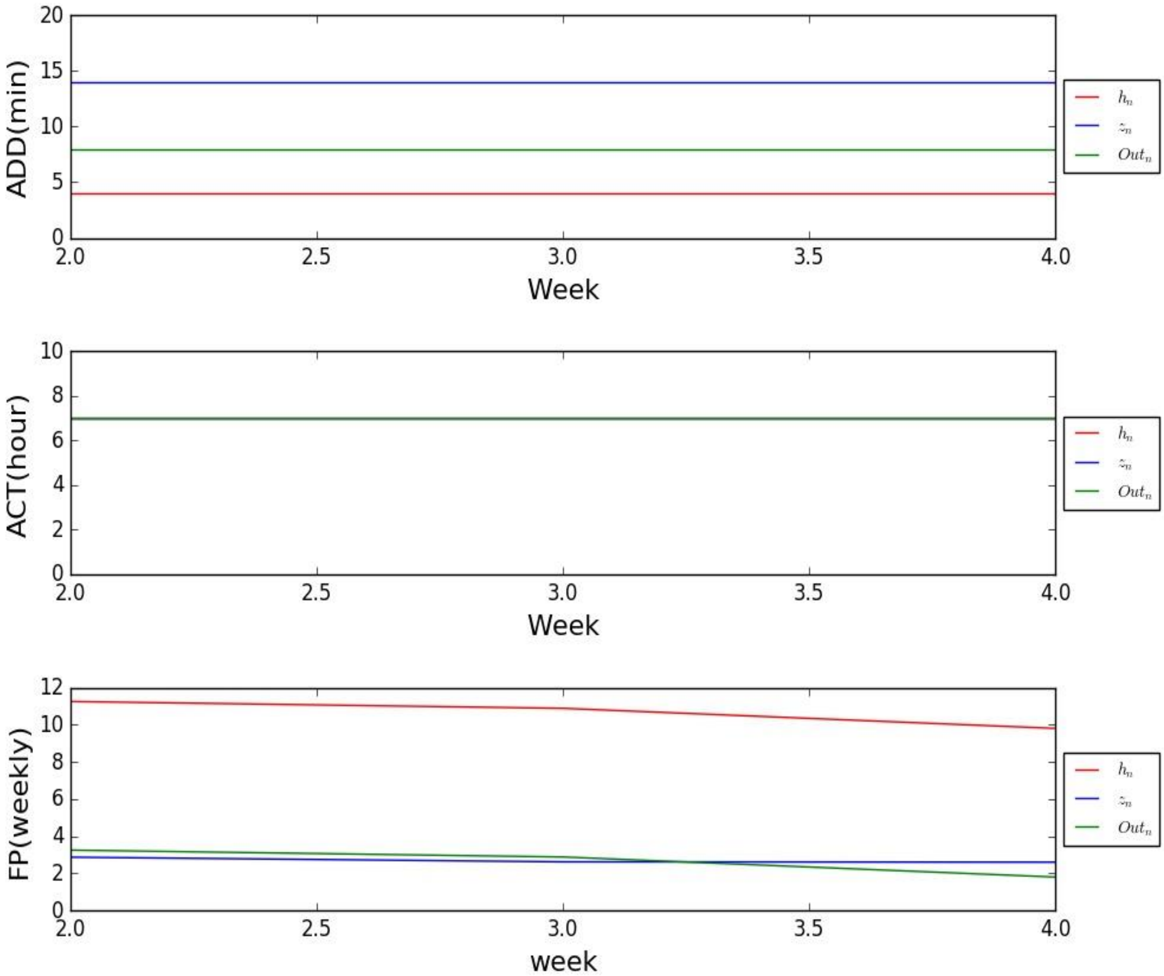


Figure 6-10: Sensitivity of learning window size

As illustrated in Figure 6-10, no significant change occurs in the obtained results as the size of the learning window increases, as illustrated in the ADD and ACT results. However, the results of the weekly number of false alert show slight reduction as the learning window size increases. In the figure, we present the effect of the learning window size on the results of the estimator (h_n), automaton (Z_n) and the rule-based classifier (Out_n). The presented results are selected using 0.25 threshold on the datasets of the "LessSleeping" anomaly.

6.8. Classification of Abnormal behaviour

The anomaly classification results are presented in Table 6-5. The values in the table illustrate the classification percentage results on the pre-defined abnormal behaviours (Table 6-2) to show how correctly the detection module was able to identify these abnormal behaviours using the rule-based classifier. The results were obtained using 0.25 threshold in the detection module.

Table 6-5: Classification of Abnormal behaviour results

Dataset	OverSleeping	LessSleeping	NotBackHome	Dead
Profile A	96.26%	97.86%	93.80%	70.69%
Profile B	69.72%	65.37%	74.72%	23.24
The Aruba	81.97%	91.94%	34.71.80%	83.12%

As shown in Table 6-5, the applied rule-based classifier in the detection module was able to correctly classify the abnormal behaviours with high classification accuracy in most of the cases on the two datasets (synthetic and the Aruba), expect for the “ Dead” behaviour on the user profile B of the synthetic data and the “NotBackHome” behaviour on the Aruba dataset. These abnormal behaviours were a bit tricky and difficult to differentiate. The user Profile B of the synthetic data was designed particularly for a “Nightly” person who usually sleeps during the day and goes outside in the midnights. The classification results of the “Dead” behaviour for this profile was mostly misclassified as “LessSleeping”. The presence of the monitored person at any rooms, other than bedroom, during the day would be misclassified and considered as “LessSleeping” behaviour. On the Aruba dataset, the “NotBackHome” behaviour was mostly misclassified as “normal” behaviour. It was difficult for the rule-based classifier to differentiate the time when the monitored person goes outside. These results introduce the need for additional features to be included in the detection module to correctly classify the abnormal behaviours. The classification experiments on the synthetic datasets were repeated three times for each abnormal behaviour and here we present the average of obtained results.

6.9. Discussion

The defined performance metrics in Chapter 5 describe the evaluation approach of the results from an implementation perspective. We used these metrics to evaluate the viability of the developed system on the synthetic datasets as well as on the real-life dataset (The Aruba). Our approach achieves the minimum Anomaly Detection Delay (ADD) and detects the anomaly much faster than other approaches which produce longer detection delay (Table 6-3). Our approach also achieves, on average, good Anomaly Confirmation Time (ACT) that is considered high enough to confirm the detection of any abnormal situations, with more than

5-hours confirmation time. Our approach also achieves a lower number of weekly false alerts on the synthetic data (Profile A & Profile B), however, on the Aruba dataset we still suffer from higher rates compared to other approaches. The resident individual of the Aruba dataset received some visits during her stay in the apartment which may make her daily routine a bit fuzzy with multiple irregular motions that were most probably caused by the visitors. Although we performed pre-processing step on the Aruba dataset to remove those visit days (Chapter 5, Section 5.1.2.1), the obtained results on the Aruba dataset still are not as good as the results on the synthetic datasets. In fact, the pre-processing step was done in an unsupervised way with no prior knowledge or ground truth to confirm this step. More advanced pre-processing method to detect the visit days is required to enhance the dataset before learning the behaviour of the monitored person.

Chapter 7. **Conclusion**

In this chapter, a brief summary of the main findings of this thesis is given, and its novel contributions are outlined as well as some limitations and topics for future work.

7.1. Summary

We have presented a system to automatically learn and build an individual model of the daily mobility behaviour of an older adult living alone at home environment. The system uses location observations collected from low-cost, non-intrusive PIR motion sensors to track the mobility of the monitored person and to detect unusual mobility habits. No prior assumptions have to be made about the typical daily behaviour of the monitored person before applying the system. The system can adapt its internal behaviour model to slight and slow shifts in behaviour such as seasonal changes and also to different people having different daily behaviours, such as someone usually sleeping all morning or staying outside the home during the nights. The system provides abnormal alarm notifications in quasi-real time, in contrast to most of the existing behavioural models and also reduces the rate of wrong detection and false alert notifications.

7.2. Limitations

The following are some of the identified limitations of this research work:

- The current version of the system does not properly support the detection of unusual mobility habits that happen due to falls or unconscious long stay during sleeping time. This kind of unusual behaviour would not be detected before 7-8 hours (the average sleeping time of a person).
- The detection of “Dead” state at bedroom might be considered oversleeping and therefore, will be detected only after usual sleeping time as well.
- The rate of false alarms in the system is a concern, and dealing with them requires manual intervention and support from the caregivers/relatives.
- The developed system is designed to be used mainly for monitoring the behaviour of a single user living alone at home, it does not take into account the presence of external people at home when leaning the behavioural model of the monitored person.

7.3. Future work

The current version of the detection module in the system uses fixed threshold classifier to detect the presence of abnormal behaviour. Whenever the estimated location likelihood drops to values lower than the threshold, an indicator of an abnormal behaviour is initiated. It would be much better to implement an adaptive method to select the threshold value based on the learned behaviour of the monitored person in each time of the weekdays. Moreover, the current version of the learning module assumes instantaneous transitions between rooms. This assumption can be further enhanced by considering the non-instantaneous room-to-room transitions when learning the underlying behaviour model. Moreover, the learning module can also be enhanced by developing a method to ignore the detected anomalous observations while learning the behaviour model. This step helps avoid poisoning the learned model with anomalous observations that are not part of the daily mobility habits of the monitored person. In addition, the detection of visit days as a pre-processing step in the learning module would be of much help to ignore those days during the model learning. A recent work on this topic can be found in [88]. Finally, the consideration of false location detection by the PIR sensors (false detection due to, for instance, heated air or other obstacles). A method to exclude the wrong location detection will increase the correctness of the learned model.

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Appendices

Appendix A. Synthetic Data Generator

We developed a synthetic data generator to simulate the daily room-to-room transitions and stays habits of an elderly person living alone at home environment. The generated data represent the events when the monitored person moves between rooms or causes movement while staying in a room. Each row in the data represents a time stamped observation to register the movement event of the person (sensor's activation). The software is a Java-based standalone application which has the ability to be configured for any kind of home layout that consists of multiple rooms and places.

I. Features

The main features of the data generator can be summarised as follows:

- It has an ability to be configured for any home layout and generate synthetic data for any period of time (variable size of datasets).
- It allows the data to be generated according to user profiles, giving the ability to evaluate different users with totally different behaviour.
- It allows the segmentation of the day into time intervals and then gives the possibility to describe the user's behaviour within each interval in a probabilistic way.
- The generated observations are produced in a random fashion; uniformly distributed in time.

- The observations are time stamped and the generation's frequency is based on the time interval of the day; each interval can have a different range of frequency (e.g. 1-10 minutes or 1-5 hours).
- It gives an ability to inject artificial anomalies that represent behavioural changes or deviations.

II. How it works

Firstly, the daily stay habits of the person that we would like to monitor should be described in a user's profile matrix. The matrix contains estimated stay probabilities that represent how probable the monitored person tends to stay in each room of the house within each time interval. An example of a user's profile matrix is shown below. As illustrated in this particular matrix, the day is divided into three intervals; each is an 8-hour segment. The length and number of the intervals are configurable and can be set to different values. The example here is based on the home layout that is shown in Figure 4-1.

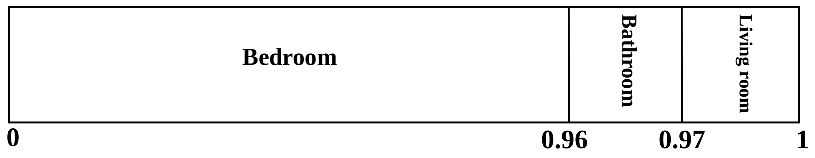
$$\begin{bmatrix} \boldsymbol{interval/room} & \boldsymbol{Bedroom} & \boldsymbol{Bathroom} & \boldsymbol{Livingroom} & \boldsymbol{Kitchen} & \boldsymbol{Store} & \boldsymbol{Outside} \\ \mathbf{0-8} & 0.96 & 0.01 & 0.03 & 0 & 0 & 0 \\ \mathbf{8-16} & 0.1 & 0 & 0 & 0 & 0 & 0.9 \\ \mathbf{16-24} & 0.02 & 0 & 0.95 & 0 & 0 & 0.03 \end{bmatrix}$$

The values in the matrix are based on the user's behaviour that we want to simulate. In this example, we are simulating a user's profile for an elderly person, and particularly we are simulating three different behaviours of the person: sleeping in the bedroom, being out of the home, and staying in the living room. This person usually sleeps during the first segment of the day (i.e. 0-8 interval) and accordingly, high stay probability is given to the stay at the bedroom. The person goes outside of the house during the second segment of the day (i.e. 8-16 interval) and according, outside having the highest stay probability within that segment. In the last segment of the day (i.e. 16-24 interval), the person usually spends most of the time in the living room, and therefore the highest stay probability is assigned to the stay in the living room.

Secondly, the data generator runs repeatedly for a predefined period (e.g. 4 months) and generates observations randomly every 1 to 10 minutes; uniformly distributed in time. However, for the day's segments in which the person is sleeping or being outside of the house the data generator is designed to generate fewer observations with longer time between each pair of observations (e.g. 1 to 8 hours), in order to simulate those behaviours in a more realistic way.

Starting from the current time instance, in every running cycle, the data generator produces a random stay probability, uniformly distributed. This probability is compared against the stay probabilities of the day's segment that corresponds to the current time instance of the cycle. The comparison is done as follows:

- The data generator distributes the stay probabilities of the selected day's segment into ranges according to their probability values, as illustrated in Figure_Apx 1.
- The produced stay probability gets compared against the distributed ranges and the room that corresponds to the range in which the produced stay probability fits in is selected to be the room of the generated observation.
- Finally, the timer of the cycle is updated to take new time instance for the next running cycle.



Figure_Apx 1: User's Profile - First day's segment (0-8)

III. Injecting Artificial Anomalies

The data generator also is designed to inject artificial anomalies that simulate the deviations in human behaviours. This works by stopping the normal flow of the generator at a pre-defined date and time and then set the room of the generated observation to unusual room/place different from the normal behaviour. For the experiments, we designed the generator to inject a set of anomalies (see section 5.2). Here we define them from a data generator point of view. Each of these anomalies may have negative implications on the health status of monitored person and might be an early indication for some health-declines.

- OverSleeping: being found in the bedroom for an extended period of time longer than the usual sleeping time of the monitored person.
- LessSleeping: being found not at bedroom during the sleeping time for relatively long time.
- NotbackHome: being outside the home for extended period of time and not back on time, according to the person's profile.

- Dead: being detected in a single room/place in the home for a long time; longer than usual.

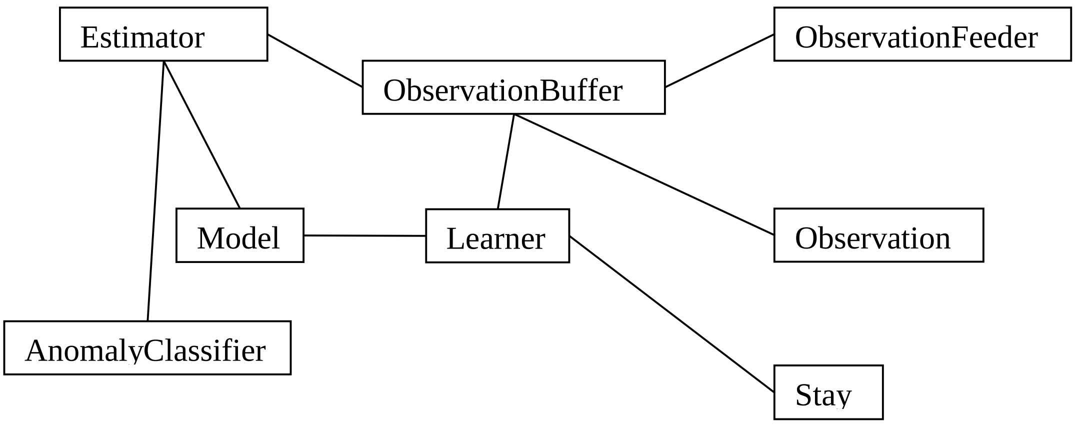
Appendix B. System Implementation

Figure 4-1 illustrates the overall architecture of the developed system which consists of multiple modules; each module is a separate Java thread that runs continuously to perform a single task.

- Observation Buffer: This module is responsible for receiving the observations from the sensor devices. It arranges the observations in the queue buffer according to their arrival timestamps.
- Learning Module: This module uses a time-based sliding window to process the observations from the queue buffer and then learns and builds the underlying behavioural model weekly.
- Detection Module: This module runs asynchronously from the learning module and in regular time instances (e.g. every one-minute) to generate detection results.

I. Class diagram

The following is the class diagram of the developed System. We show only the main classes of the system. The links in the diagram illustrate the interaction between the classes.



Figure_Apx 2: Developed System's Class Diagram

II. Main Classes

- Observation Feeder: It is used to simulate the sending of the observations from the sensor devices. The observations are read from a file previously generated by the Synthetic Data Generator. However, in a real system, this module is replaced by the set of PIR sensors installed in the house.

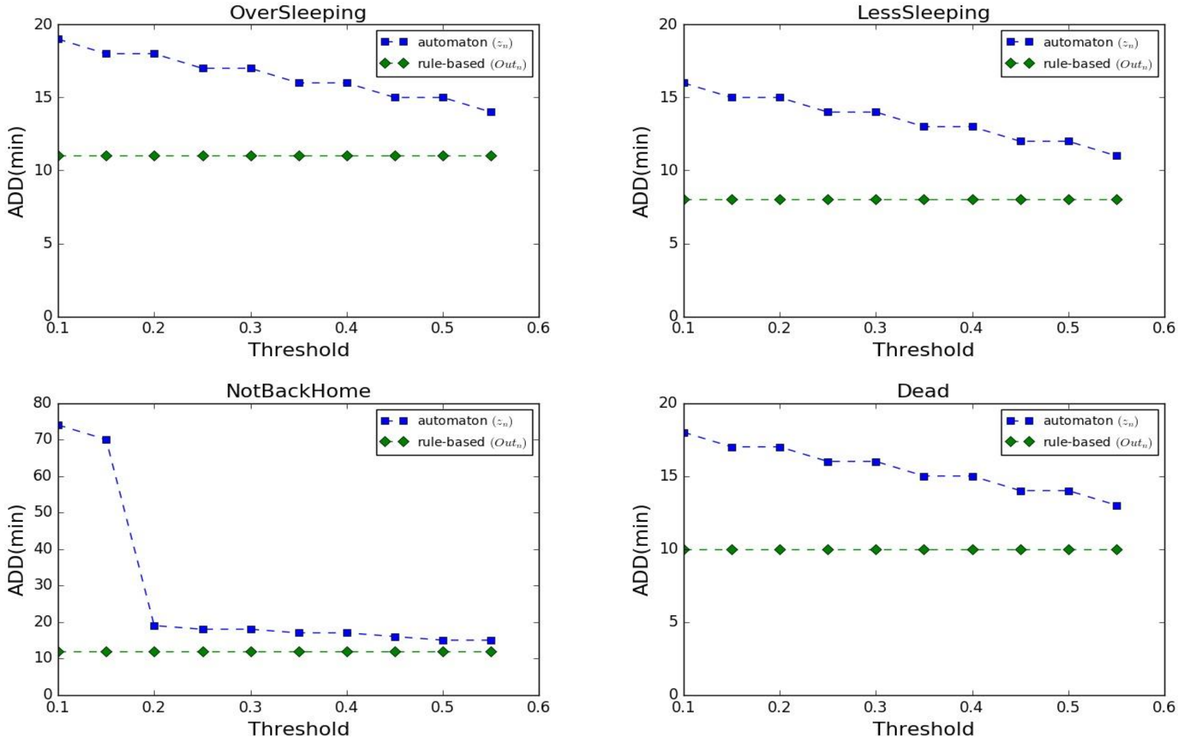
- Observation Buffer: The main storage for the sensors' observations in the system. It keeps storing observations and provides means to access them from other modules.
- Observation: It holds the definition of the observation in the system. An observation is a combination of a timestamp and associated room where the location of the person was detected.
- Stay: It holds the definition of the stay concept in the system; a stay is a time elapsed between any pair of consecutive observations.
- Model: it holds the structure of the underlying behavioural model. The structure of the model is divided into seven parts (one for each day of the week). Each part is further divided into equal intervals (e.g. one-hour intervals).
- Learner: This is the main class in the learning module. It builds and updates the model on a weekly basis. It also computes the stay between any pair of observations and handles cross interval stays.
- Estimator: This is the main class in the detection module. It runs periodically (e.g. every one-minute) and generates location likelihood estimate for the latest detected location of the monitored person. Then it uses time-based sliding window (low-pass filter) to smooth out the generated location likelihood. The smoothed location likelihood afterwards is passed through an automaton to figure out the state of the detection.
- Anomaly Classifier: classifies the detected anomaly state and produces the final detection results.

Appendix C. Extended Results

In this appendix, we present extended details of the obtained results from the experiments. These results complement the presented results in Chapter 6, with more elaboration on the obtained results of all of the targeted abnormal behaviour. The results are presented with respect to the performance metrics and the defined abnormal behaviours. We first show the results of the synthetic datasets of the two user profiles (profile A and profile B) and then we proceed to the results of the Aruba dataset. Finally, we present all the datasets together for comparison. We present the results of the automaton as well as the results after applying the rule-based classifier.

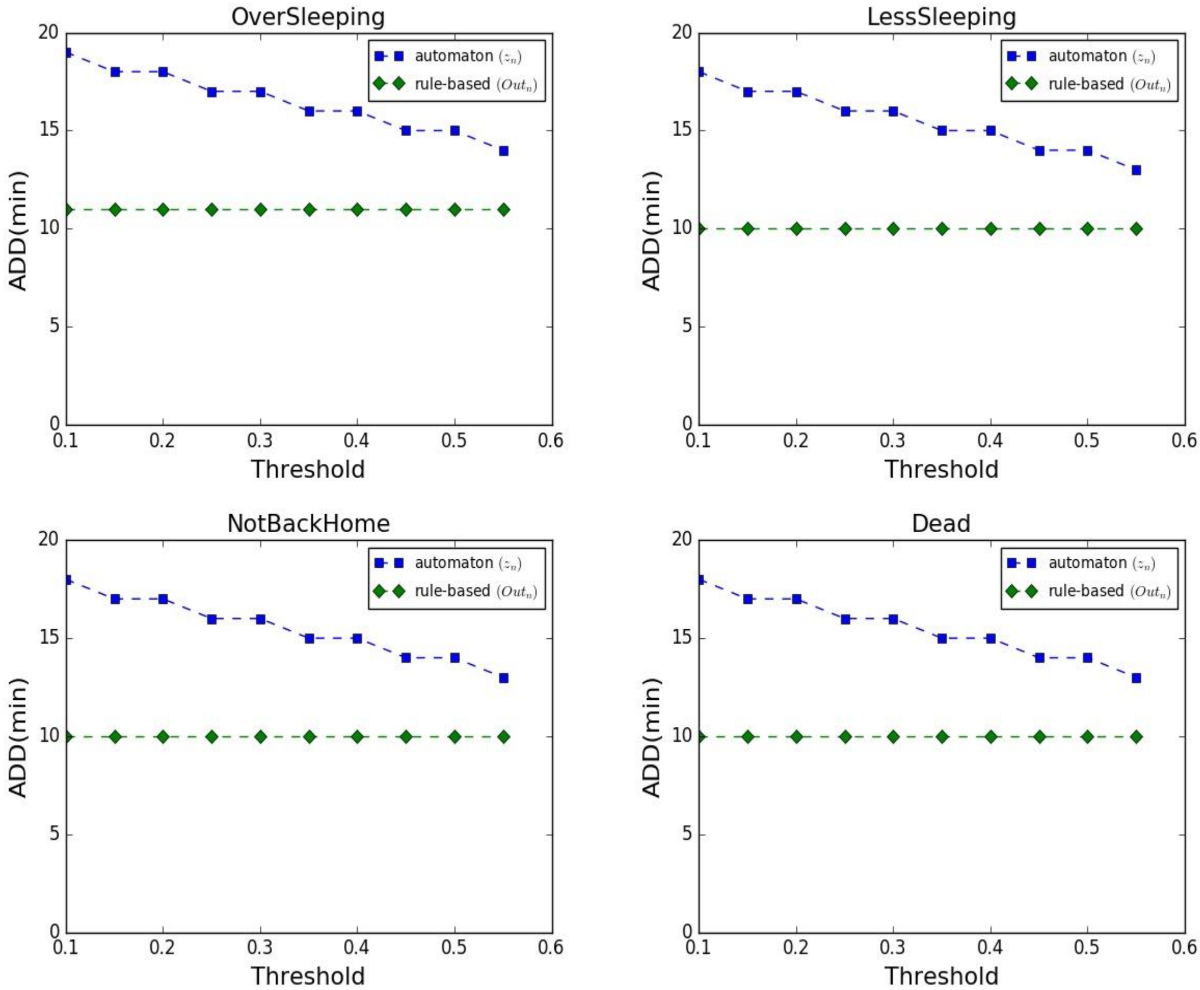
I. ADD

Figure_Apx 3 illustrates the obtained ADD results on the synthetic data of the user profile A. The results show the ADD with respect to each of the defined abnormal behaviours. The results after applying the rule-based classifier show no significant variations as the threshold changes while the automaton results show slight decrease as the threshold changes. The results of the "LessSleeping" abnormal behaviour showed the lowest ADD results among the other abnormal behaviours.



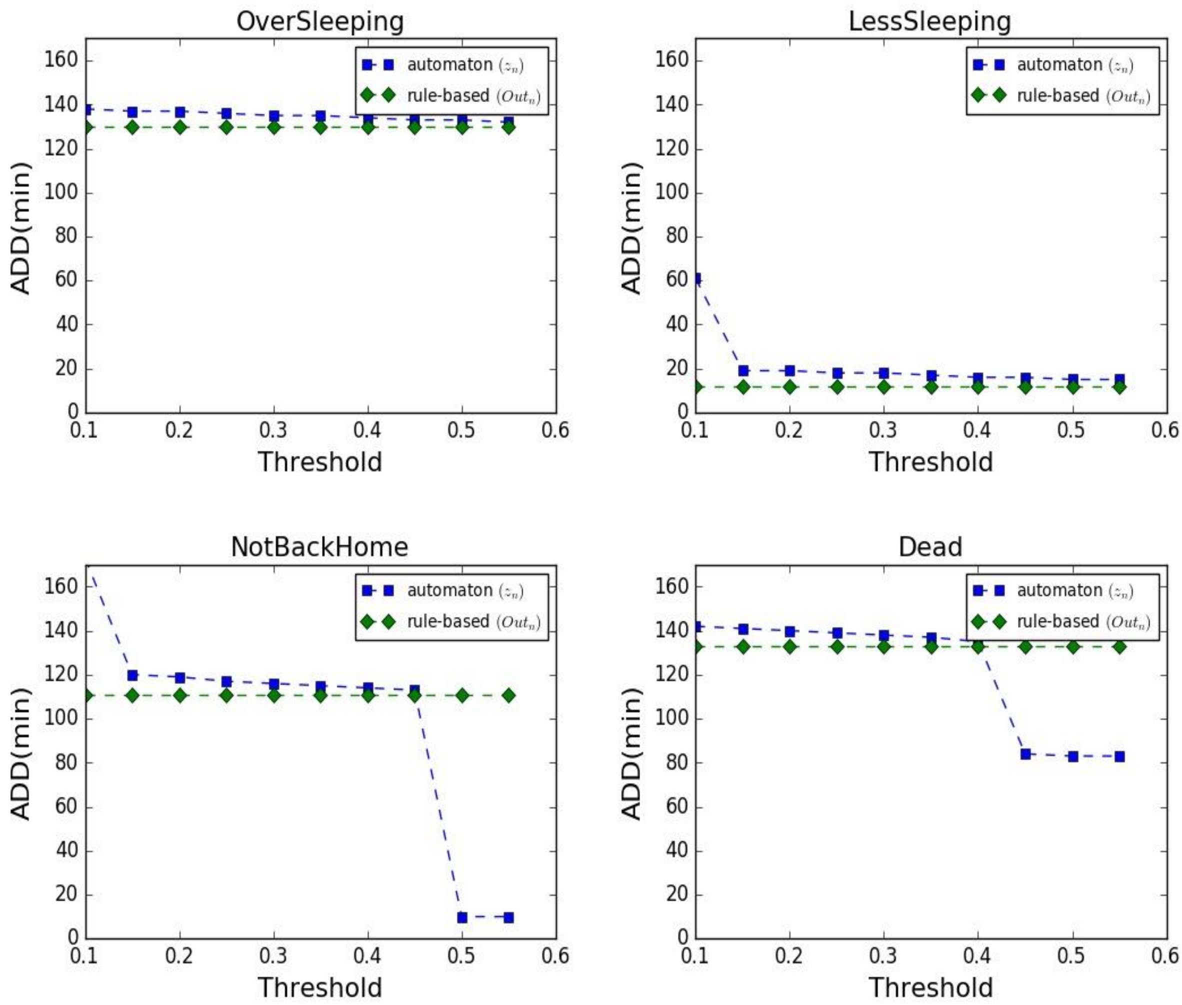
Figure_Apx 3: ADD results - Synthetic dataset - Profile A

Figure_Apx 4 illustrates the obtained ADD results on the synthetic data of the user profile B. The results show similar trend as for the user profile A on the synthetic data.



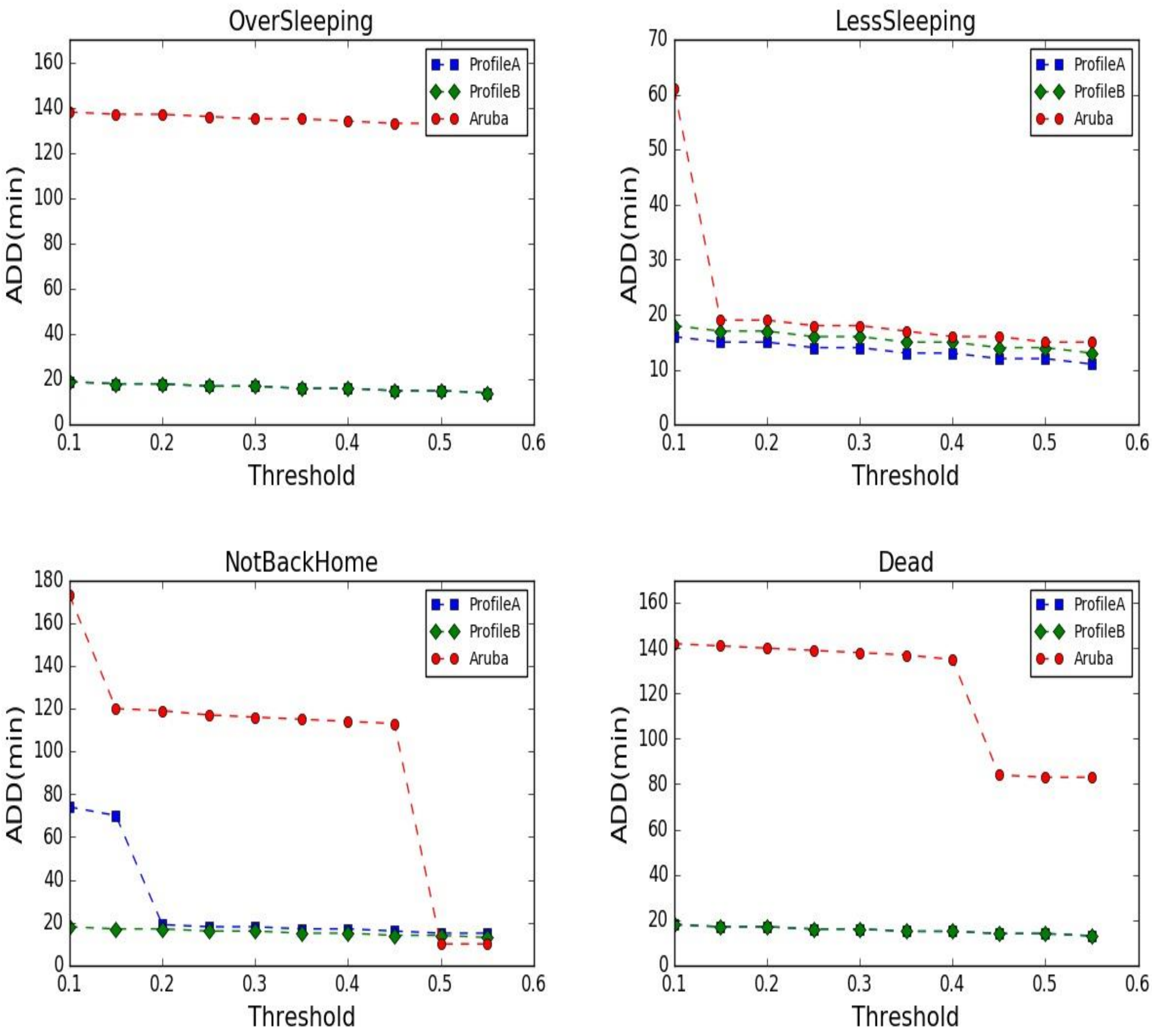
Figure_Apx 4: ADD results - Synthetic dataset - Profile B

Figure_Apx 5 illustrates the obtained ADD results on the Aruba dataset. The results were higher than the results on the synthetic datasets on both the automaton and the rule-based classifier. However, similar to synthetic data, no significant variations were detected, as the threshold changes, on the results after applying the rule-based classifier.



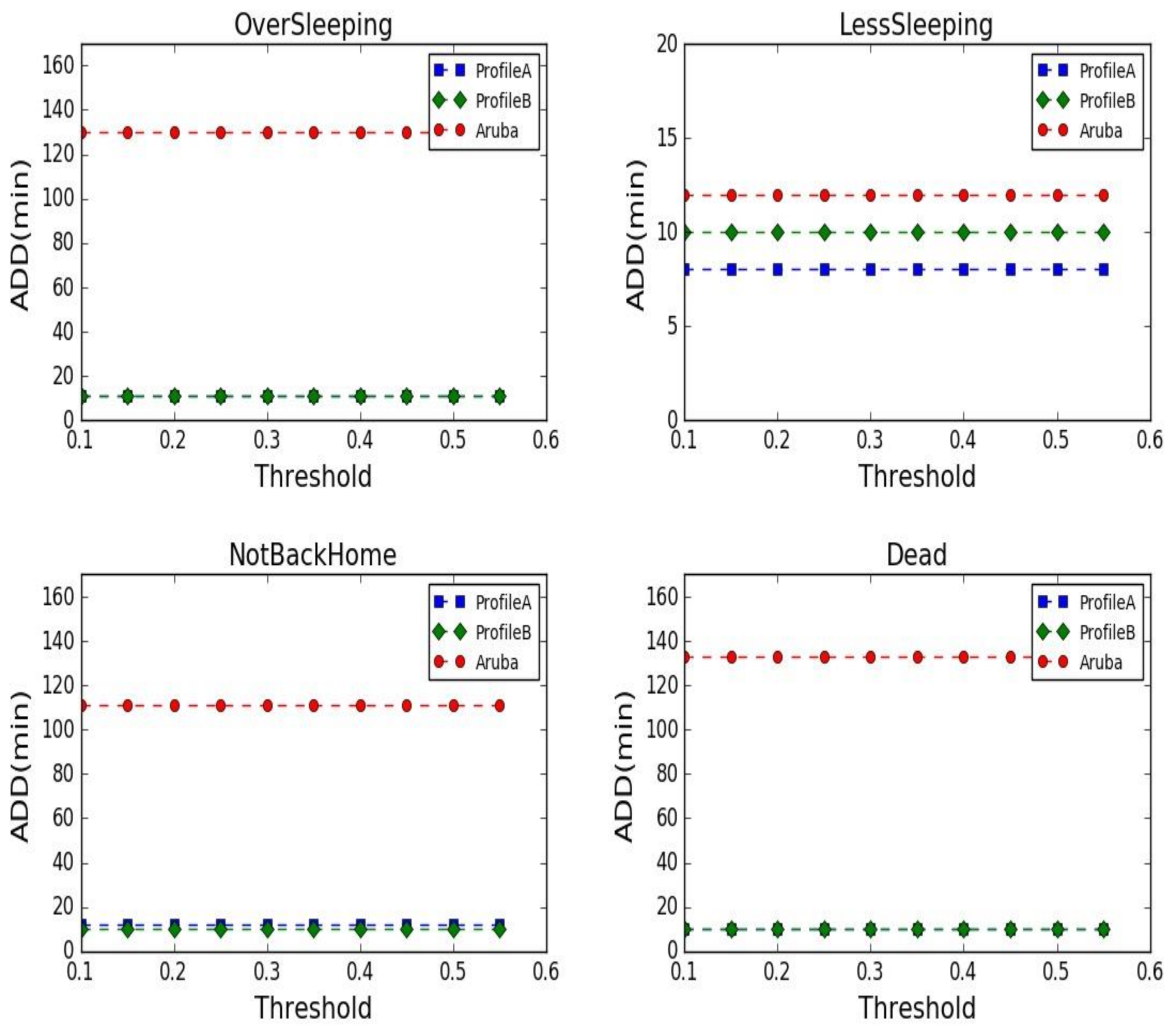
Figure_Apx 5: ADD results - The Aruba dataset

Figure_Apx 6 shows a comparison of the obtained ADD results on the synthetic data (profile A and profile B) against the Aruba dataset. The presented results in the figure shows the automaton results of each of the define abnormal behaviours before applying the rule-based classifier. As shown, the ADD results were lower on the synthetic data than the Aruba dataset, with slight variations as the threshold value changes.



Figure_Apx 6: ADD results - Synthetic and Aruba - Automaton

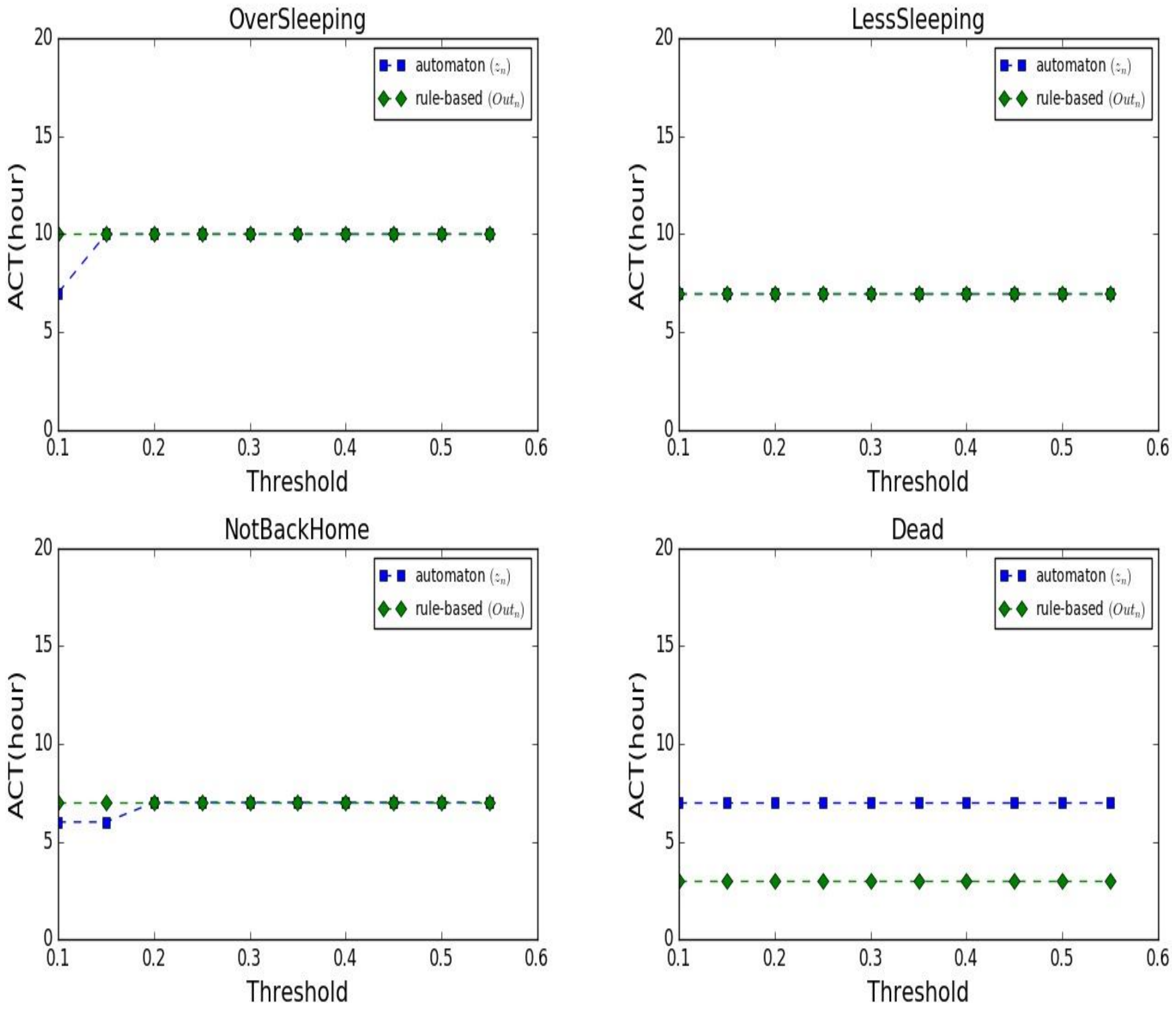
Figure_Apx 7 shows the ADD results after applying the rule-based classifier. The graphs in the figure present a comparison between the ADD on the synthetic data against the Aruba dataset. The results show no significant variations as the threshold value changes and the results of the “LessSleeping” abnormal behaviour showed the lowest obtained ADD among the other abnormal behaviours.



Figure_Apx 7: ADD results - Synthetic and Aruba - Rule-based

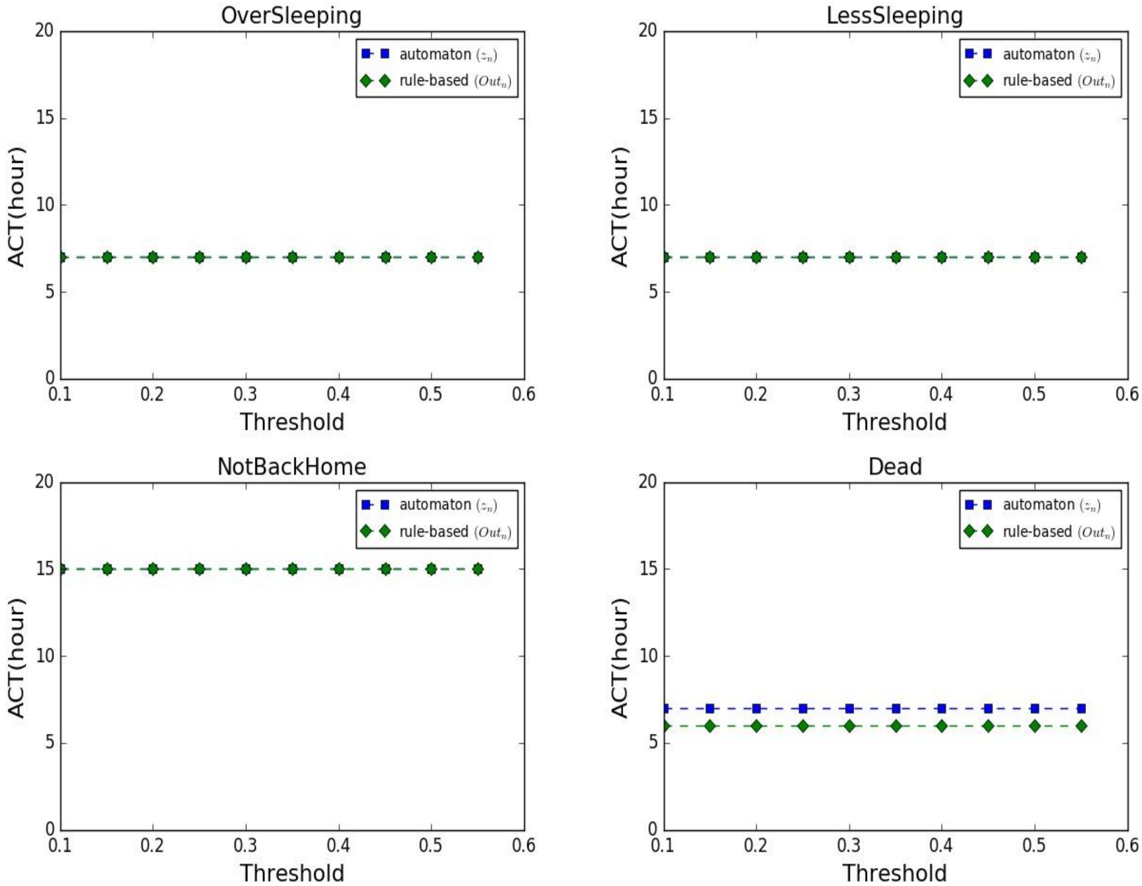
II. ACT

Figure_Apx 8 shows the obtained ACT results of the performed experiments on all the defined abnormal behaviours on the synthetic data of the user profile A. As shown in the graphs, there were no significant differences between the ACT results of the automaton and the results after applying the rule-based classifier, except the results of the "Dead" abnormal behaviour. The ACT results of the automaton were higher than the rule-based classifier. However, the obtained results show enough time to confirm the detection of the abnormal behaviour.



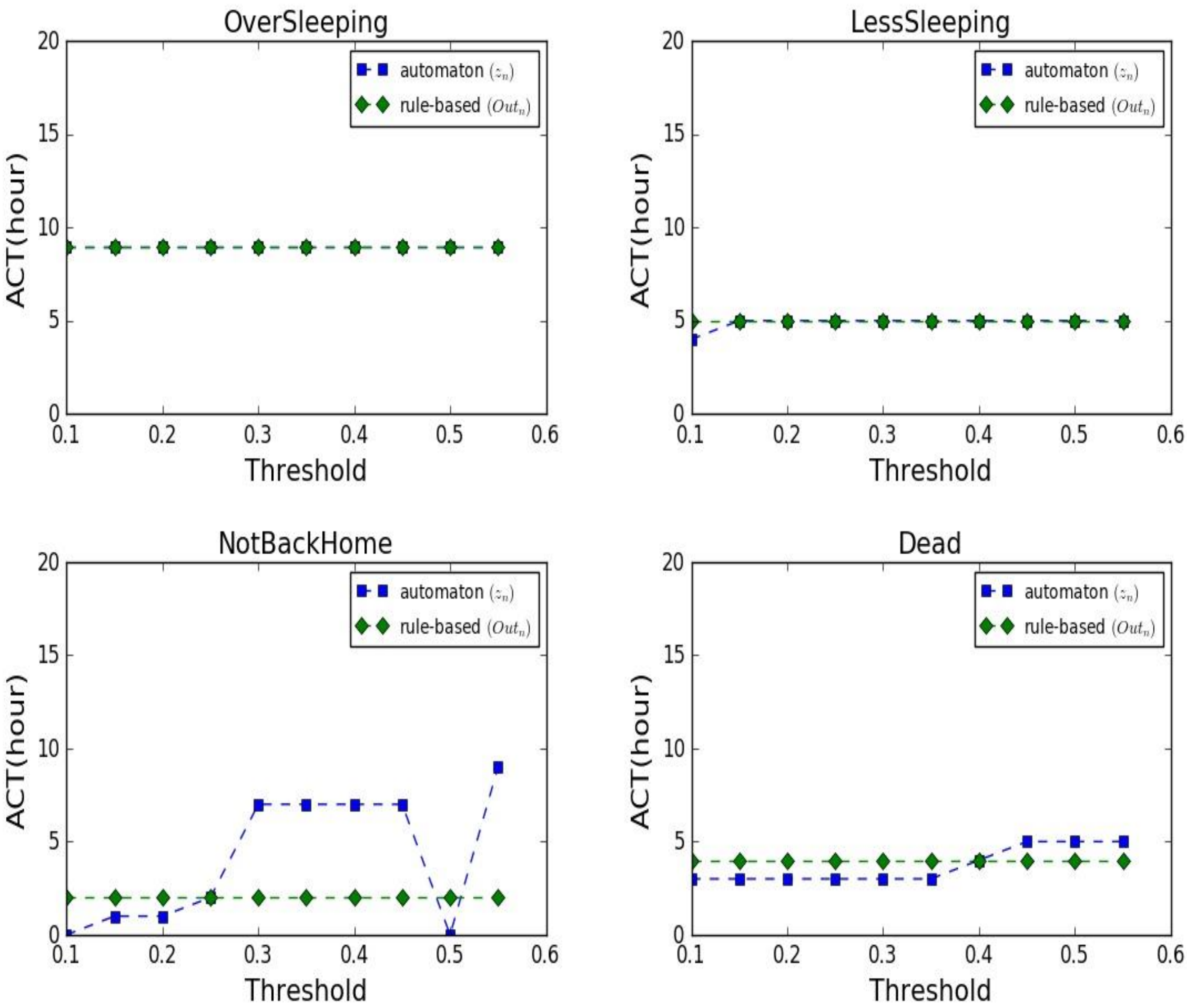
Figure_Apx 8: ACT results - Synthetic dataset - Profile A

Figure_Apx 9 illustrates the obtained ACT results on the synthetic data of the user profile B. The results show similar trend as the ACT results of the user profile A. No significant variations between the results of the automaton and the results after applying the rule-based classifier.



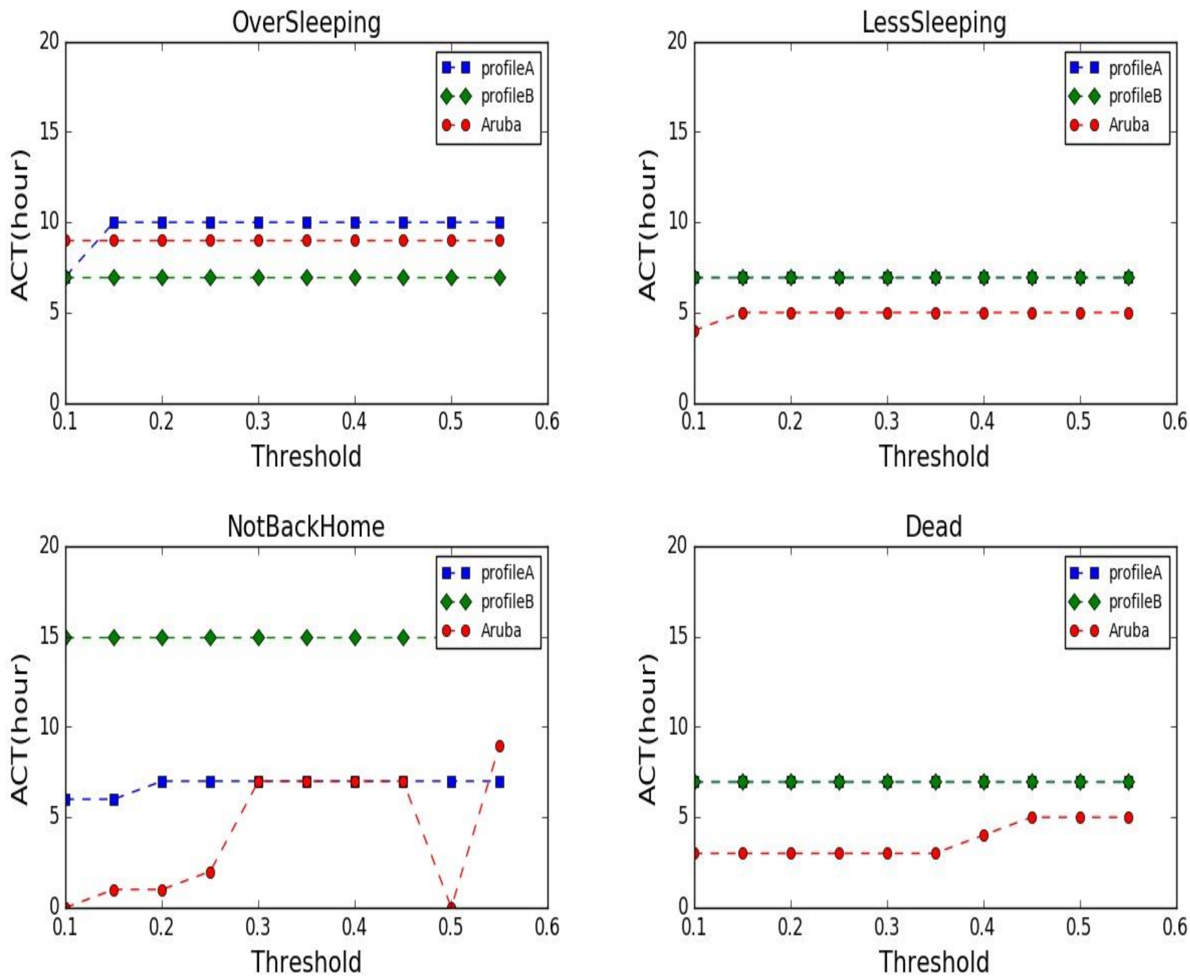
Figure_Apx 9: ACT results - Synthetic dataset - Profile B

Figure_Apx 10 shows the obtained ACT results on the Aruba dataset. The results show similar trends as the synthetic data, with no significant variations between the results of the automaton and after applying the rule-based classifier. However, the results of the "NotBackHome" abnormal behaviour show some fluctuation, mainly due to the fuzziness of the Aruba dataset, as described before. Nevertheless, the obtained ACT results also show enough time to confirmed the detection of the abnormal behaviours.



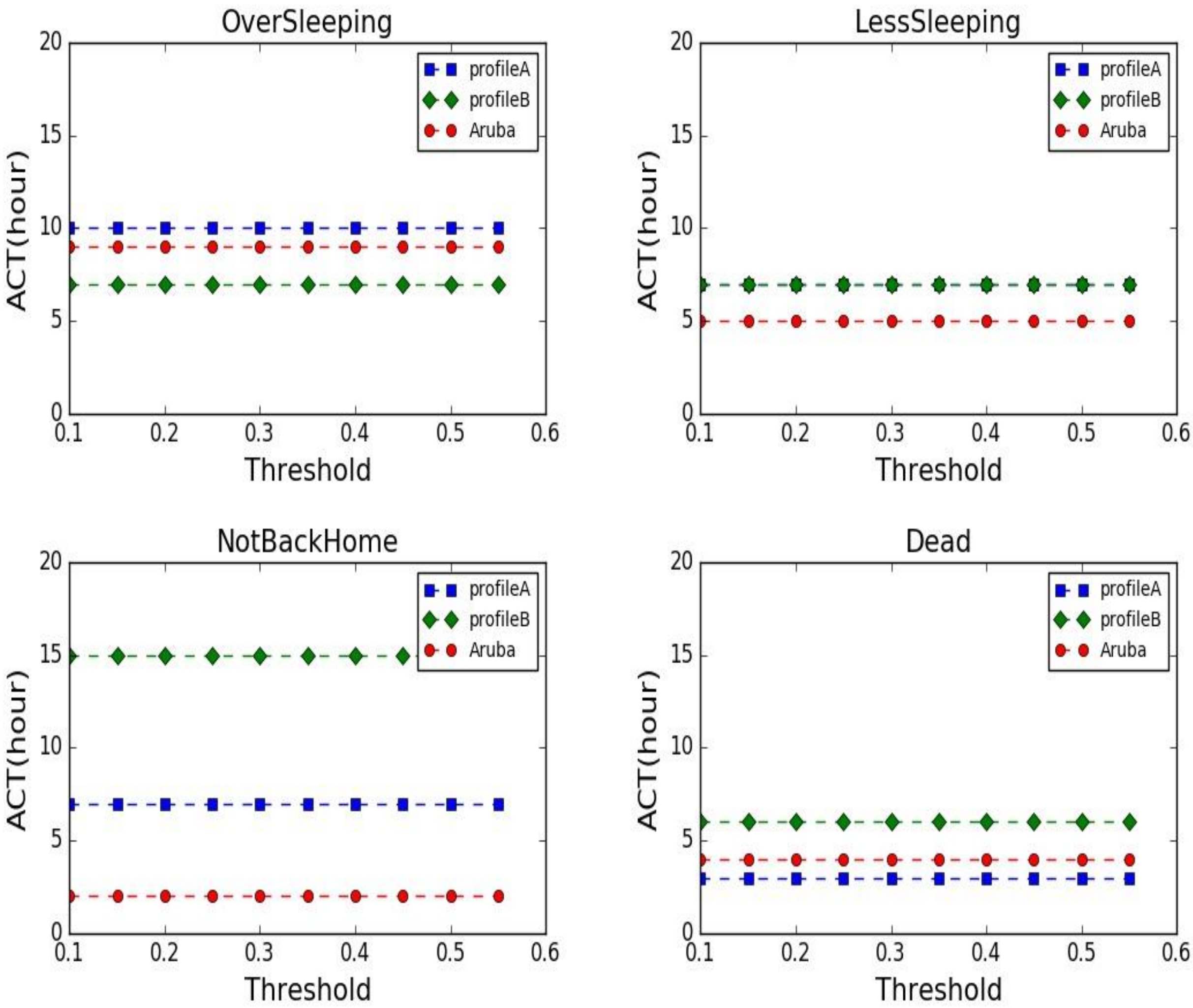
Figure_Apx 10: ACT results - Aruba dataset

Figure_Apx 11 shows the obtained ACT results of the automaton on the synthetic data compared to the Aruba dataset. The results on the synthetic data show higher confirmation time than the results on the Aruba dataset.



Figure_Apx 11: ACT results - Synthetic and Aruba - Automaton

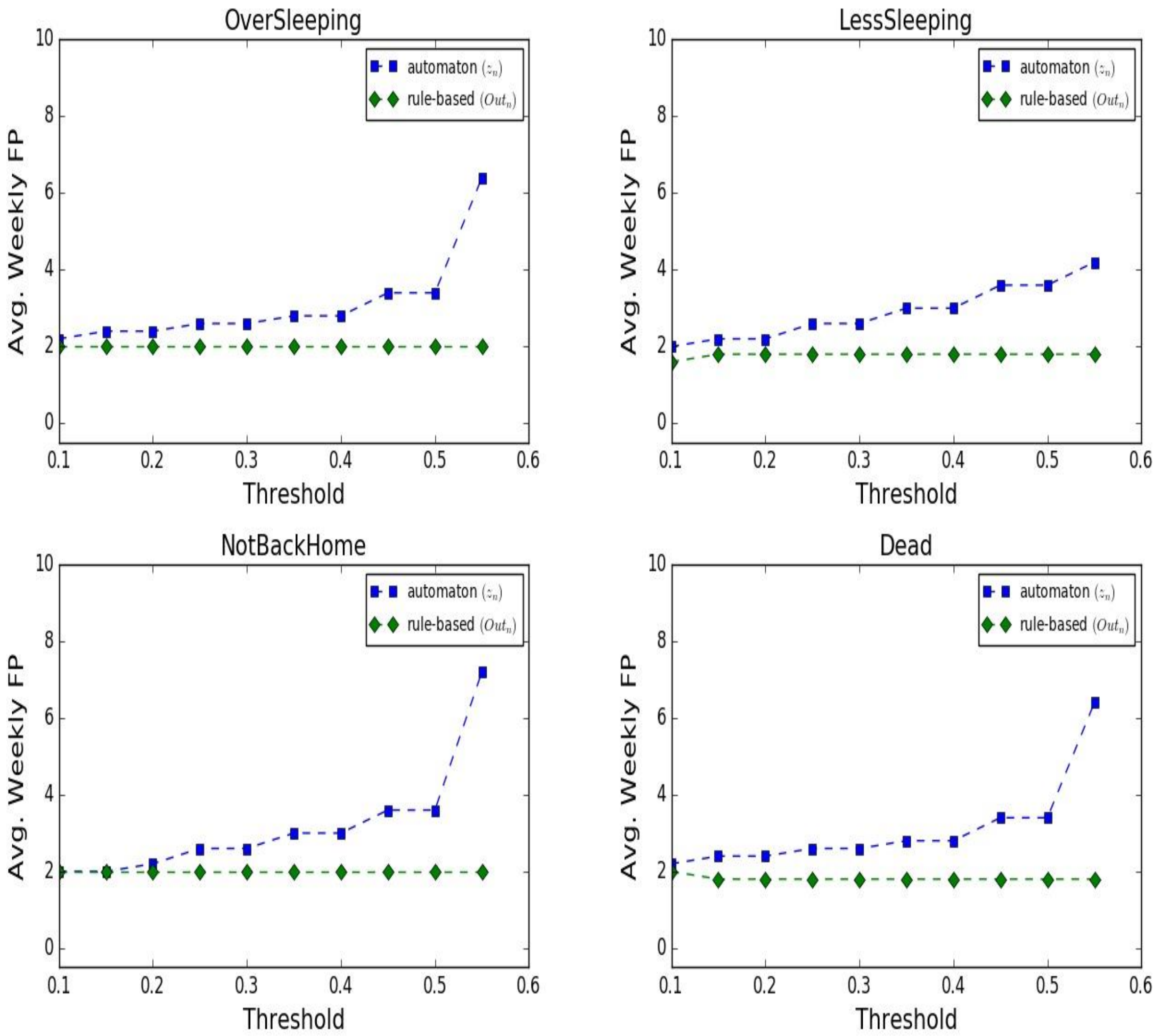
Figure_Apx 12 shows the obtained ACT results after applying the rule-based classifier. It shows a comparison between the results on the synthetics dataset and the Aruba dataset. The results show no significant variations as the threshold changes. However, the obtained ACT results were enough to confirm the detection of the abnormal behaviours.



Figure_Apx 12: ACT results - Synthetic and Aruba - Rule-based

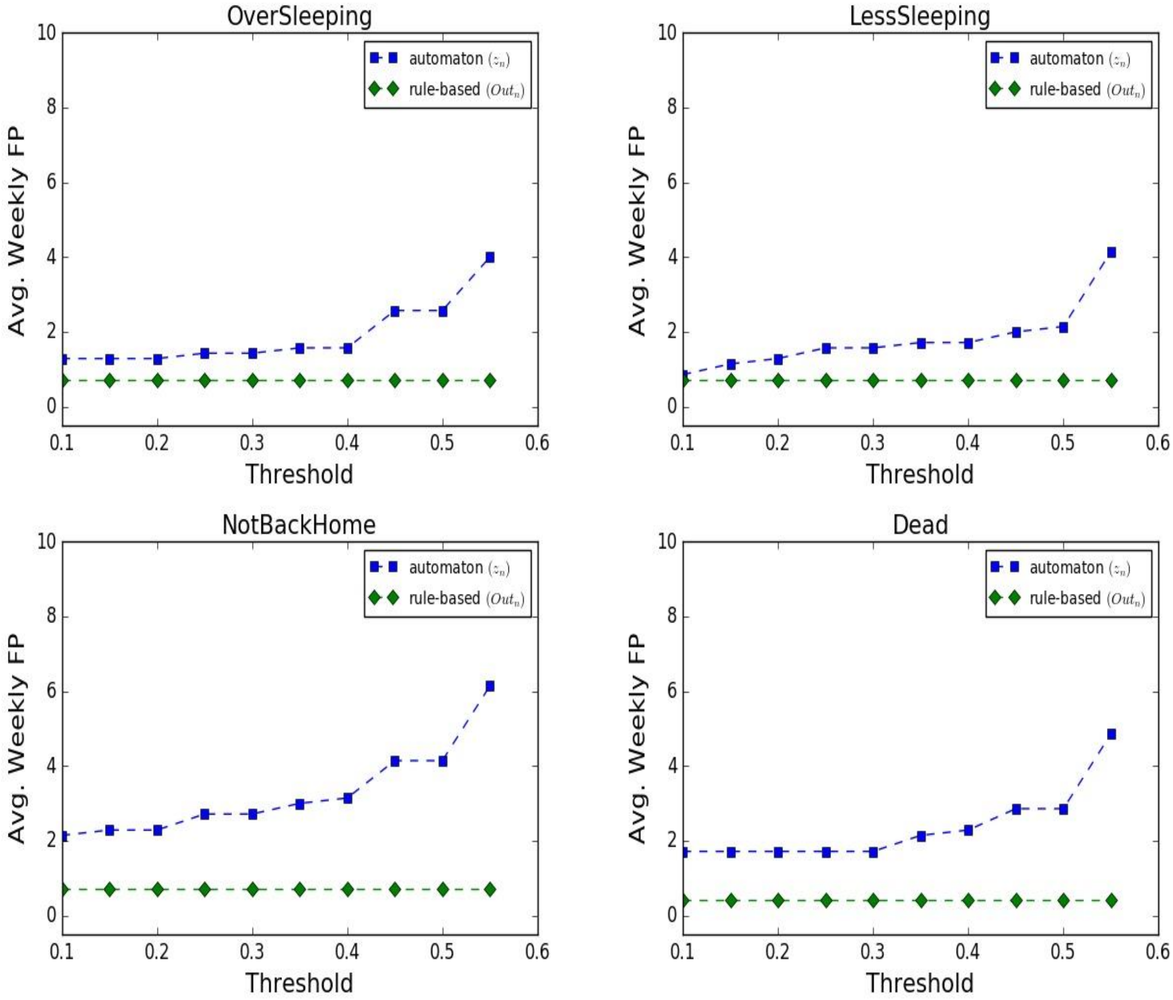
III. FP

Figure_Apx 13 illustrates the obtained results of the average number of false alerts on the synthetic data of the user profile A. The automaton results show some variations while the results after applying the rule-based classifier show steady trend as the threshold value changes.



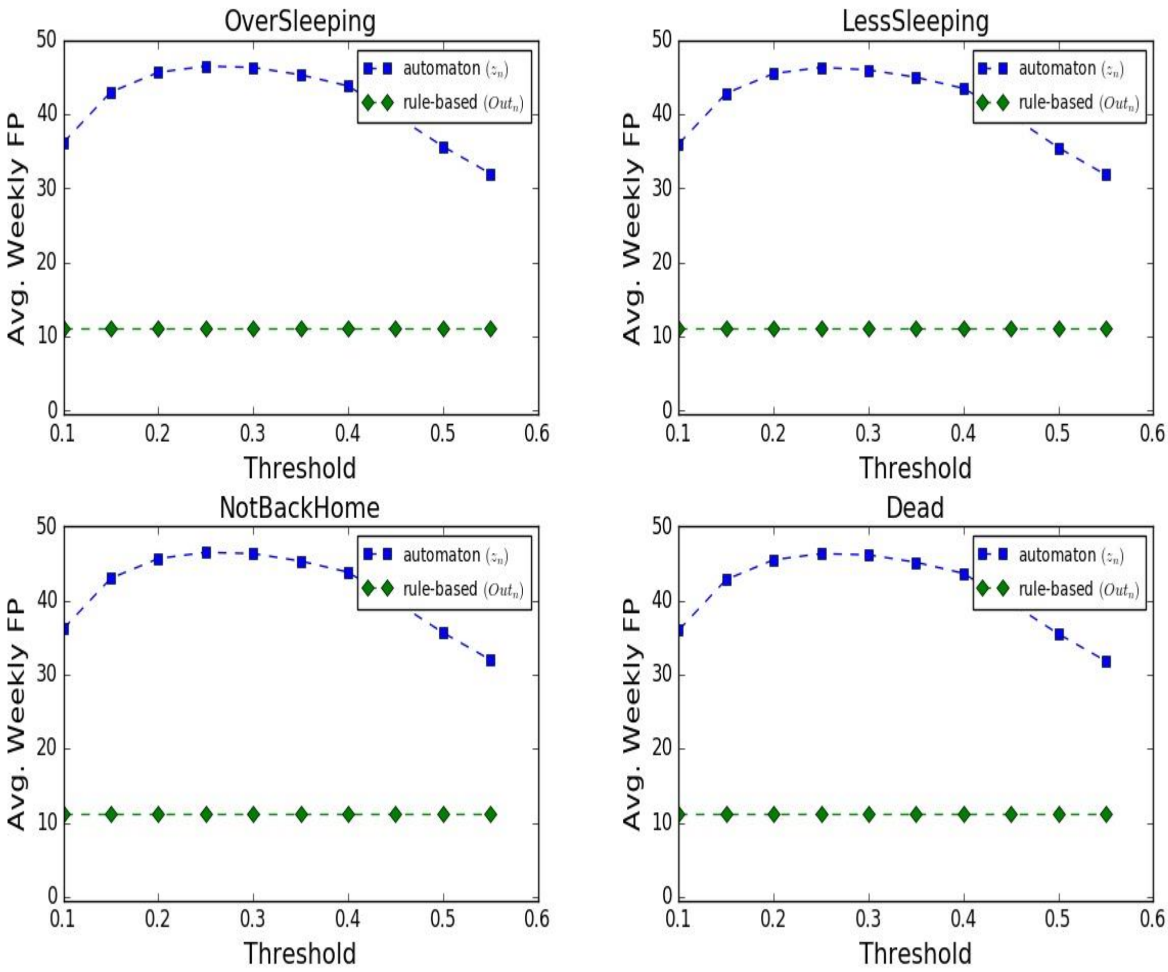
Figure_Apx 13: Avg. Weekly FP - Synthetic dataset - Profile A

Figure_Apx 14 illustrate the obtained results of the average number of false alert on the synthetic data of the user profile B. Similar to the results of the user profile A. The automaton results vary while the results after applying the rule-based classifier show no significant variations as the threshold value changes.



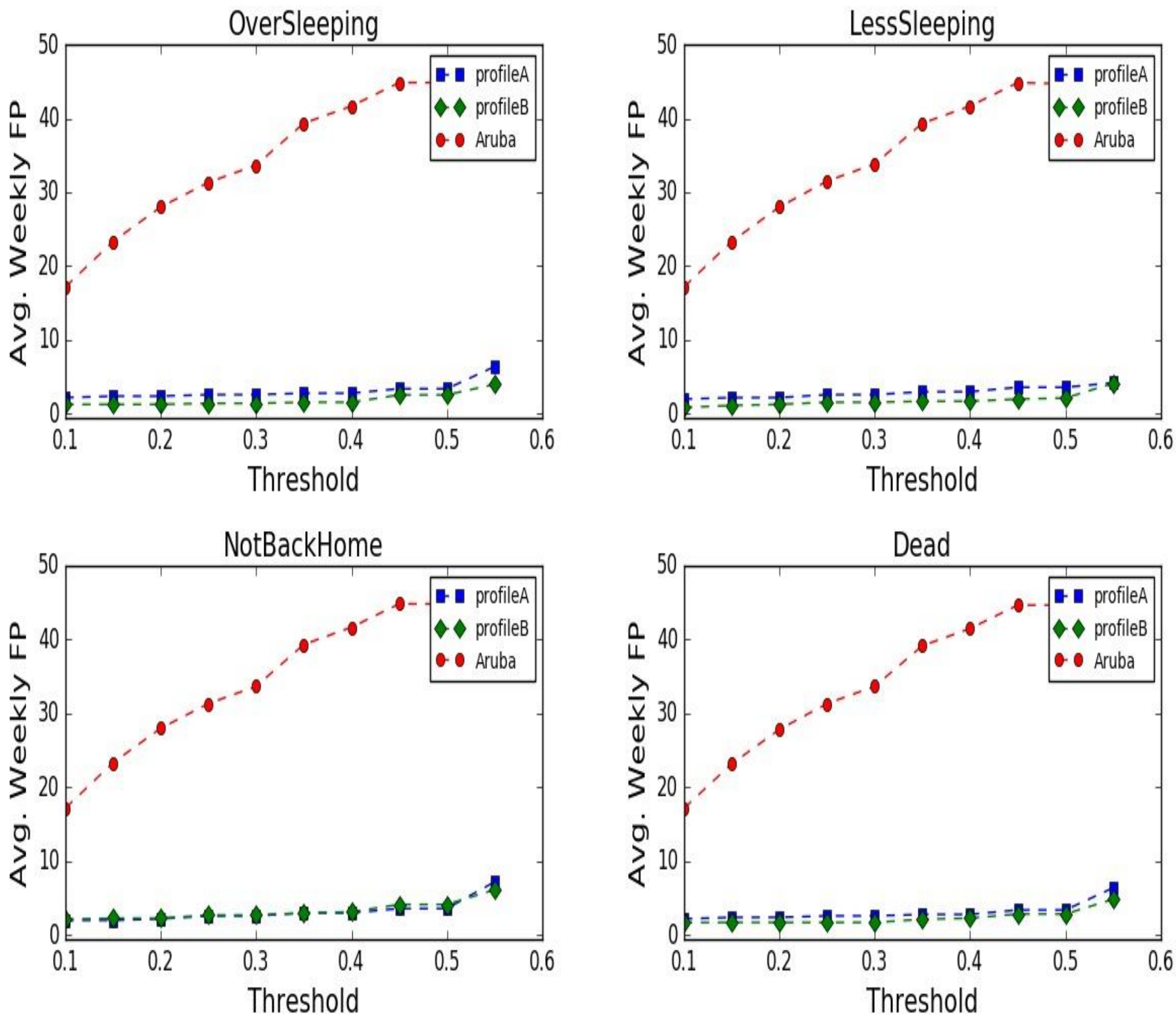
Figure_Apx 14: Avg. Weekly FP - Synthetic dataset - Profile B

Figure_Apx 15 shows the obtained results of the average number of false alert on the Aruba dataset. The results are higher than the results on the synthetics datasets. The automaton results change as the threshold changes while the results after applying the rule-based classifier show no variations.



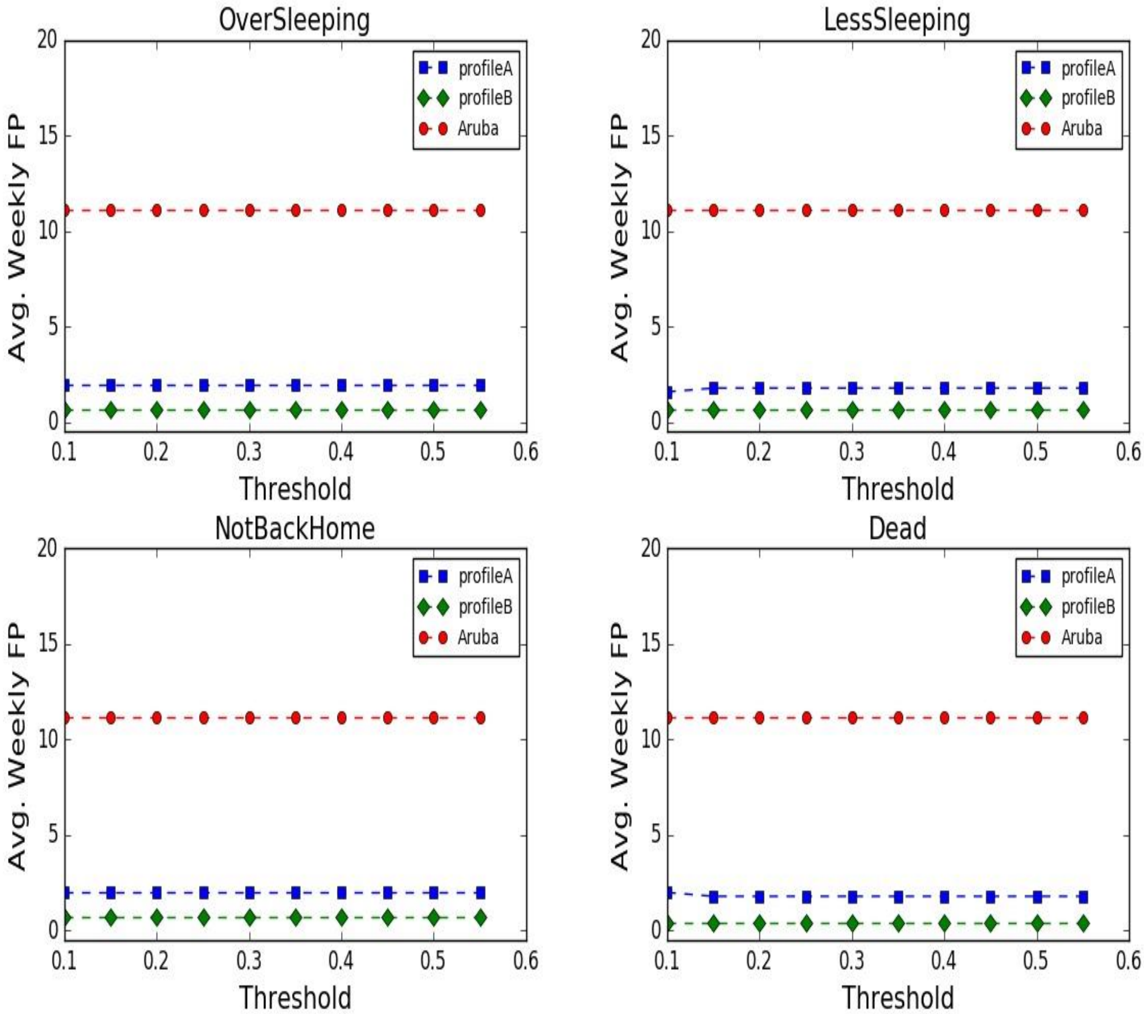
Figure_Apx 15: Avg. Weekly FP results - Aruba dataset

Figure_Apx 16 illustrates a comparison of the obtained results of the average number of false alerts on the synthetic data compared to the Aruba dataset. The presented results in the figure show the automaton results before applying the rule-based classifier. The results show low and steady number of false alerts on the synthetic data and higher and fluctuated number of false alerts on the Aruba dataset.



Figure_Apx 16: Avg. Weekly FP results - Synthetic and Aruba - Automaton

Figure_Apx 17 illustrates the obtained results of the average number of false alert generated by the system after applying the rule-based classifier. The results compare between the synthetic data and the Aruba dataset. The results on the synthetic data show lower number of false alert than the results on the Aruba dataset. However, in both datasets, there were no significant variations on the obtained results as the threshold values changes.



Figure_Apx 17: Avg. Weekly FP results - Synthetic and Aruba - Rule-based