A Smart Home Environment to Support Safety and Risk Monitoring for the Elderly Living Independently

By

Tongai Chiridza

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Supervisor: Prof J Wesson

Co-Supervisor: Dr D Vogts

Declaration

I, Tongai Chiridza s210153679, hereby declare that the dissertation for MSc Computer Science and Information Systems to be awarded is my own work and that it has not previously been submitted for assessment or completion of any postgraduate qualification to another University or for another qualification.

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Tongai Chiridza

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Abstract

The elderly prefer to live independently despite vulnerability to age-related challenges. Constant monitoring is required in cases where the elderly are living alone. The home environment can be a dangerous environment for the elderly living independently due to adverse events that can occur at any time. The potential risks for the elderly living independently can be categorised as injury in the home, home environmental risks and inactivity due to unconsciousness.

The main research objective was to develop a Smart Home Environment (SHE) that can support risk and safety monitoring for the elderly living independently. An unobtrusive and low cost SHE solution that uses a Raspberry Pi 3 model B, a Microsoft Kinect Sensor and an Aeotec 4-in-1 Multisensor was implemented. The Aeotec Multisensor was used to measure temperature, motion, lighting, and humidity in the home. Data from the multisensor was collected using OpenHAB as the Smart Home Operating System. The information was processed using the Raspberry Pi 3 and push notifications were sent when risk situations were detected.

An experimental evaluation was conducted to determine the accuracy with which the prototype SHE detected abnormal events. Evaluation scripts were each evaluated five times. The results show that the prototype has an average accuracy, sensitivity and specificity of 94%, 96.92% and 88.93% respectively. The sensitivity shows that the chance of the prototype missing a risk situation is 3.08%, and the specificity shows that the chance of incorrectly classifying a non-risk situation is 11.07%.

The prototype does not require any interaction on the part of the elderly. Relatives and caregivers can remotely monitor the elderly person living independently via the mobile application or a web portal. The total cost of the equipment used was below R3000.

Keywords: Ambient Assisted Living, Ambient Intelligence, Context-Awareness, Elderly, Remote monitoring, Smart Home Environment

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Glossary

Abbreviation	Definition
AI	Artificial Intelligence
AmI	Ambient Intelligence
DSR	Design Science Research
IoT	Internet of Things
JSON	JavaScript Object Notation
NMMU	Nelson Mandela Metropolitan University
openHAB	Open Home Automation Bus
OSGi	Open Services Gateway Initiative
SHE	Smart Home Environment
Smart Home OS	Smart Home Operating System

Chapter 1. Introduction

1.1 Background

There have been noticeable demographic changes worldwide whereby current generations are living longer. The general trend is that the birth rate is falling and people are living longer (Department of Economic and Social Affairs Population Division United Nations, 2015). The potential danger posed by the ageing trend can be described as an “elderly demographic time bomb” (Layzell, Manning, & Benton, 2009).

Anyone above the age of 60 years is considered to be old, and at least 12% of the current world population is 60 years or older. This is expected to rise to 22% by 2050 (Department of Economic and Social Affairs Population Division United Nations, 2015). An increase of more than a fifth of the global population is expected in Africa between now and 2050. A projection for the world is illustrated in Figure 1-1 below.

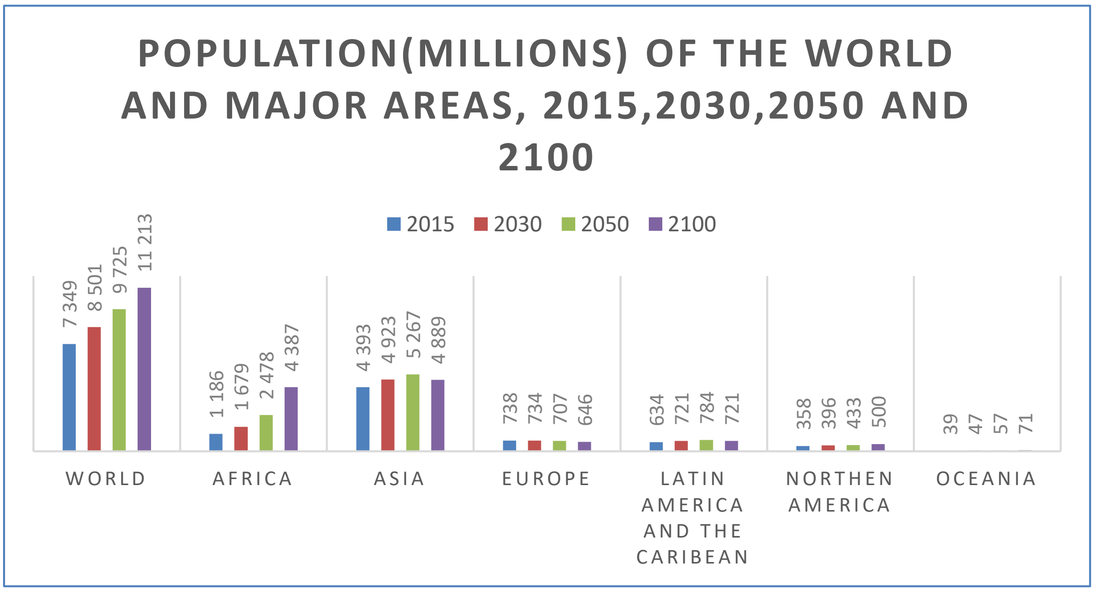


Figure 1-1 World population estimate for 2015, 2030, 2050 and 2100 (Department of Economic and Social Affairs Population Division United Nations, 2015)

South Africa has the highest percentage of the elderly in Africa, although slightly lower than developed countries (Department of Economic and Social Affairs Population Division United Nations, 2015). The percentage of the population aged 60 years and above rose from 7.1% in 1996 to 8.0% in 2011, and the population is expected to double by 2050 (Stats SA, 2014).Variations show that the proportion of elderly women living alone is higher compared to that of their male counterparts in the ratio of 64-66 elderly men per 100 elderly women (Stats SA, 2014). The rise in the ageing population can be attributed to advances in healthcare and the higher standards of living of the current generations.

Stats SA (2014) highlighted an upward trend in the prevalence of elderly single-member households from 16.3% in 1996 to 26.7% in 2011, predominantly in the white population group. In the last population census in South Africa about 38% of the elderly persons were using chronic medication by the age of 60-64 years (Stats SA, 2014).

The rapid ageing of our population, and the desire by the elderly to maintain their independence, are presenting new challenges in safety and risk monitoring for the elderly. Conditions affecting cardiovascular, nervous and musculoskeletal systems are the main contributors to the safety problems experienced by the elderly (Wold, 2012). Chronic ailments require that medical providers, family members or caregivers constantly monitor the elderly persons because their condition can deteriorate at any time. For example, people suffering from dementia tend to forget things easily and it is important that they are constantly monitored.

Gait and balance deteriorate as people age and they are more prone to falls. Hypertension and heart attack can result in fainting or unconsciousness at any moment. Neurological disorders result in gait and balance alterations, intensifying the risk of falling. Conditions such as arthritis reduce joint mobility and flexibility resulting in the increased likelihood of injuries and decreased ability to respond to hazards.

Fire is also a common hazard for the elderly living independently. Forgetting to turn off electrical appliances and smoking in the home can lead to fire breakouts. Temperature extremes in the home environment are also a risk with the elderly. Exposure to excessively cold or hot environments has a huge impact on the elderly, especially if they are frail or chronically ill. Home security can also present a risk to the elderly living independently. Older adults are more vulnerable to attack and injury as they are more defenceless (Wold, 2012).

It is very important to support active ageing for the elderly by facilitating self-care and promoting empowerment in the home (Olivier & Adrie, 2009). Active ageing takes place when an elderly person can live independently in their home. Safety and risk monitoring are some of the key attributes that contribute to active ageing. The term "risk" implies the possibility of an adverse outcome that impacts the elderly living independently.

Physical spaces can be enhanced with information, communication and sensing technology to make them sensitive and responsive to users' needs and provide assistive services in safety and risk monitoring. A SHE can be defined as a residence that uses various forms of ambient intelligence to enhance traditional home automation systems with smart functions that address higher level goals. Ambient intelligence refers to the ability of electronic environments to acquire the user's needs and respond to these needs.

1.2 Research Relevance

The elderly prefer to live independently in their homes, in many cases without anyone to watch over them. If an elderly person is living alone, it is important that they are monitored constantly as emergency situations can arise at any time. Independence and safety are critical issues in older adults as they face age-related challenges or risks such as falls, forgetfulness, sensory impairment, immobility and isolation (Demiris, Hensel, Skubic, & Rantz, 2008).

There are limited options for people who are responsible for taking care of the elderly. Families have become distant due to the pursuit of jobs by family members, therefore they cannot be present to physically monitor their elderly relative. The number of elderly people requiring healthcare and continuous monitoring is increasing every year and at the same time the number of people of working age is decreasing (Röcker, 2013).

Nursing homes provide an option for ageing adults who need constant surveillance, although these homes may not be a perfect solution (McKinley, 2014). This inevitably leads to a situation whereby there are more elderly people needing care than people who can actually provide care. Elderly people often resist the option of moving into a nursing home or assisted living facility (McKinley, 2014).

Bodily functional decline can be exhibited through falling, memory loss and collapsing. Falls and injuries are common in the elderly population (Morris et al., 2013). The inability to move leads to the inability to call emergency services. Emergency services, family and caregivers need to be notified when there are emergencies for elderly persons living alone. The probability of being unassisted when an emergency occurs increases as loneliness sets in for the elderly (Costa, Castillo, Novais, Fernández-Caballero, & Simoes, 2012).

During focus groups that were done with the elderly we found out that falling is common among the elderly. The elderly said they sometimes forget to carry their panic buttons with them and when they fall they are not be able to seek emergency help if they cannot get up. Some of the residents forget where they would have put their panic buttons. If they fall due to a life threatening condition they could die before emergency services arrive. About three-quarters of falls among the elderly result in serious injuries such as head traumas and hip fractures (RoSPA, 2015)

Solutions that use panic buttons, video systems, wearables and smart mobile devices have been implemented, but they have major drawbacks in their adoption. The adoption of technology by the elderly is dependent on the perceived privacy, ease of use, cost and obtrusiveness of the technology. Smart mobile devices are relatively costly and are not easy to use by the elderly. Panic buttons and wearables can be forgotten or misplaced and the elderly will not be able to use them to raise the alarm.

SHEs have been proposed as an emerging space for positive ageing, due to their potential to increase the ease and safety in performing domestic tasks and improving communication (Lê, Nguyen, & Barnett, 2012). SHEs can facilitate independent living for the elderly by providing them with emergency assistance, fall detection, reminder systems, medication administration and assistance for those with hearing, visual or cognitive impairments (Cheek, Nikpour, & Nowlin, 2005).

1.3 Problem Statement

There is a need for a low cost, unobtrusive solution that can support safety and risk monitoring for the elderly living independently.

The elderly population is increasing in South Africa. Longevity is associated with bodily functional decline, which can manifest itself as sensory impairment, chronic ailments and cognitive impairment. The elderly prefer to live independently despite the risks associated with longevity. Increased longevity and the desire by the elderly to live independently are presenting new challenges in supporting safety and risk monitoring for the elderly. Living independently and being alone can result in no one being able to intervene if emergency situations occur.

Existing solutions are proving inadequate due to issues surrounding their adoption. Privacy, cost, perceived ease of use and extensibility impact on the adoption of existing technologies that support safety and risk monitoring in the home. The elderly live on a fixed income and are not keen on learning new technologies. Societies have not developed solid and cost effective solutions for the well-being, safety, healthcare and social needs of the elderly to support active ageing (Deen, 2015).

1.4 Aim of Research

The aim of this research is to design a model of an affordable SHE to support safety and risk monitoring for the elderly living independently.

1.5 Research Objectives

i. To identify the risks facing the elderly living independently and how they can be monitored in the home.

ii. To review the existing solutions and/or technologies and tools that can be used to support affordable safety and risk monitoring for the elderly living independently.

iii. To design a prototype of a SHE using cost effective devices.

iv. To evaluate the accuracy and consistency of the proposed SHE in supporting safety and risk monitoring.

1.6 Research Questions

The research was conducted by answering specific research questions in relation to the research objectives.

1.6.1 Main Research Question

How can a SHE prototype be designed to support safety and risk monitoring for the elderly living independently?

The main research question can be answered through the following sub-questions:

1.6.2 Sub-Questions

i. What are the risks facing the elderly living independently?

ii. How can smart technologies be incorporated in the home environment to suit the safety needs of the elderly?

iii. Which cost effective and scalable technologies and/or equipment can be used to implement a SHE for the elderly living independently?

iv. How accurate and consistent is the SHE in supporting risk and safety monitoring?

1.7 Scope and Constraints

Not all the problems related to the safety and risk monitoring of the elderly were addressed by this research. For the purposes of this research, the SHE was designed for the living room or lounge only. The most common areas for adverse events are the living room, stairs, bedroom and bathroom (RoSPA, 2015).

This research addressed the following:

i. Fall detection;

ii. Home environment monitoring;

iii. Inactivity monitoring.

The elderly could not be used to simulate falling events in order to avoid injuries, and therefore active and suitable participants were used to model falling simulations.

1.8 Research Methodology

The research methodology that was used for this research was Design Science Research (DSR). The aim of DSR is to produce a viable artefact that is important and relevant to specified problems. The problem domain is thoroughly investigated in DSR and existing solutions are evaluated for their strengths and shortcomings. The identification of the strengths and weakness of existing solutions can provide a strong foundation for the better design of a SHE that can support safety and risk monitoring for the elderly.

The design is rigorously evaluated and demonstrated via well-executed evaluation methods. DSR provides clear and verifiable contributions to the design of a SHE for this research. Figure 1-2 illustrates the typical features of DSR.

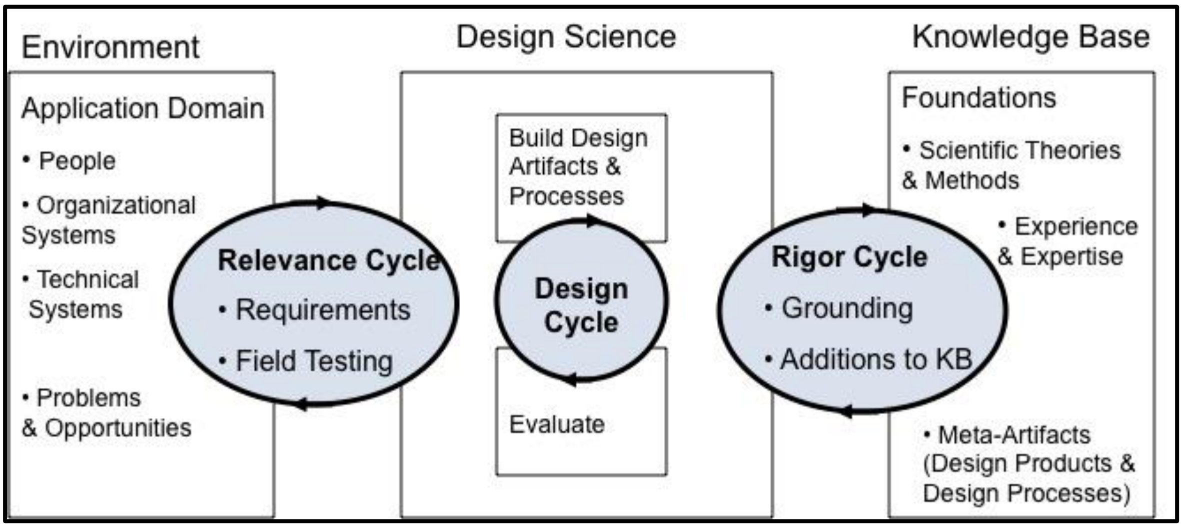


Figure 1-2 Typical Design Science Research paradigm. (Hevner & Florida, 2011)

The Relevance Cycle includes understanding the problem, exploring existing knowledge and tools, choosing methods and planning processes. The research is grounded in a philosophical research perspective (A. R. Hevner & Florida, 2011). The Relevance Cycle will be addressed in Chapter 2 and Chapter 3, the literature and existing systems review chapters. Existing systems will be analysed for strengths and weaknesses. Opportunities for better solutions will be derived from the synthesis of the existing literature and systems. User requirements will be identified in the Relevance Cycle. Data for requirements analysis can be obtained in the Relevance Cycle by using questionnaire, interviews or focus group meetings.

The Design Cycle includes the design of a prototype that can satisfy the requirements obtained in the Relevance Cycle. The prototype is built and evaluated in this cycle. Processes are also evaluated and updated in the Design Cycle. The Design Cycle will constitute Chapter 4 of the project. The proposed design will be a product of Chapters 2 and 3 that examine the strengths and weaknesses of existing systems. Continuous evaluation will be used to justify the various components of the design. Evaluation will consist of conducting laboratory usability studies among the target population. Field studies, surveys and simulation can also form part of the evaluation.

The Rigor Cycle shares functions similar to the Design Cycle. It consists of continuous evaluation and updates to the design of the SHE for the elderly. The Rigor Cycle is an iterative process throughout the life of a project and strives to align the design to established frameworks.

DSR is the research methodology of choice for this project because it involves analysing the advantages and shortcomings of existing systems and/or models for SHEs that support safety and risk monitoring for the elderly. The review of related systems and literature should ensure a stable design for the SHE. Another advantage derived from using DSR is that it ensures that a proper understanding of the problem is established. DSR also emphasises the evaluation of the final product and this will help determine if the SHE can support safety and risk monitoring for the elderly living independently.

1.9 Research Methods

The following research methods were used:

- *Literature study and existing systems review:*

  A literature study was conducted to review the models and technologies proposed and existing solutions that support safety and risk monitoring for the elderly. The strengths and shortcomings of existing models and solutions were identified.

- *Survey:*

  The aim of the survey was to identify the risks faced by the elderly and the safety requirements of the elderly. Data for requirements analysis was collected through questionnaires, focus group meetings and interviews.

- *Prototyping:*

  Prototyping produces a proof of concept that can be evaluated to determine if it can support safety and risk monitoring for the elderly. The SHE was implemented as a prototype. The Rational Unified Process was used as the software development methodology for this research. The Rational Unified Process allows for iterative design, which supports continuous refinement of the functionality of the prototype.

- *Experimental evaluation:*

  An experimental evaluation was conducted to determine the accuracy of the prototype to detect risks and send notifications to caregivers and family members.

1.10 Chapter Outline

Chapter 2 reviews the safety and risk issues facing the elderly. A focus group interview was conducted to collect information to supplement the requirements found in literature. Chapter 3 reviews existing solutions and technologies that can be used in SHEs. Requirements analysis, the design of prototype and the implementation are discussed in Chapter 4. Chapter 5 discusses the evaluation of the prototype. The conclusion of the dissertation is discussed in Chapter 6. The observations and shortcomings of the research are also highlighted.

Table 1-1 Summary of research questions, research methods and related chapters

Research Question	Research Method	Chapter
1. What are the risks facing the elderly living independently?	• Literature Study • Focus group interview	• Chapter 2
2. How can smart technologies be incorporated in the home environment to meet the safety needs of the elderly?	• Literature study • Focus group Interview • Prototyping	• Chapter 3 • Chapter 4
3. Which cost effective and scalable technologies and/or equipment can be used in implementing a SHE for the elderly living independently?	• Prototyping	• Chapter 4
4. How accurate and consistent is the SHE prototype in supporting risk and safety monitoring?	• Evaluation	• Chapter 5

1.11 Conclusion

The population of the elderly is increasing in our society. As people age, disease and physical impairment become significant and their demands for constant safety and risk monitoring also increase. The elderly prefer to live independently and if they are not monitored their condition could deteriorate unnoticed. The caregiver and/or emergency services need to be informed as soon as an emergency situation occurs. SHEs can be designed to maintain the balance between safety, healthcare and independence for the elderly in the home.

SHEs can be a cost effective way of improving home care for the elderly and the disabled in a non-obtrusive way. The technologies that make up smart homes need to be carefully selected for cost effectiveness. Successful implementation of a SHE that can support safety and risk monitoring can ensure that the elderly live independently for longer in their homes and any safety needs can be automatically communicated to caregivers and family.

The safety and risk monitoring requirements for the elderly are discussed in Chapter 2. Chapter 3 discusses the technologies that can be used to implement a SHE to support safety and risk monitoring for the elderly. Chapter 4 discusses the implementation of the prototype in accordance to the requirements identified in Chapter 3. The evaluation of the prototype is discussed in Chapter 5 and Chapter 6 is the conclusion chapter.

Chapter 2. Safety and Risk Monitoring for the Elderly

2.1 Introduction

Chapter 1 highlighted the ageing of the South African population and the implications thereof. Improvements in the healthcare sector, good nutrition and personal hygiene will continuously contribute to the ageing of our population. Longevity and living independently are associated with an increased risk of experiencing an adverse event (Vincent & Amalberti, 2016a).

This chapter discusses the safety and risk monitoring requirements for the elderly living independently. Figure 2-1 shows the position of this chapter in the DSR methodology.

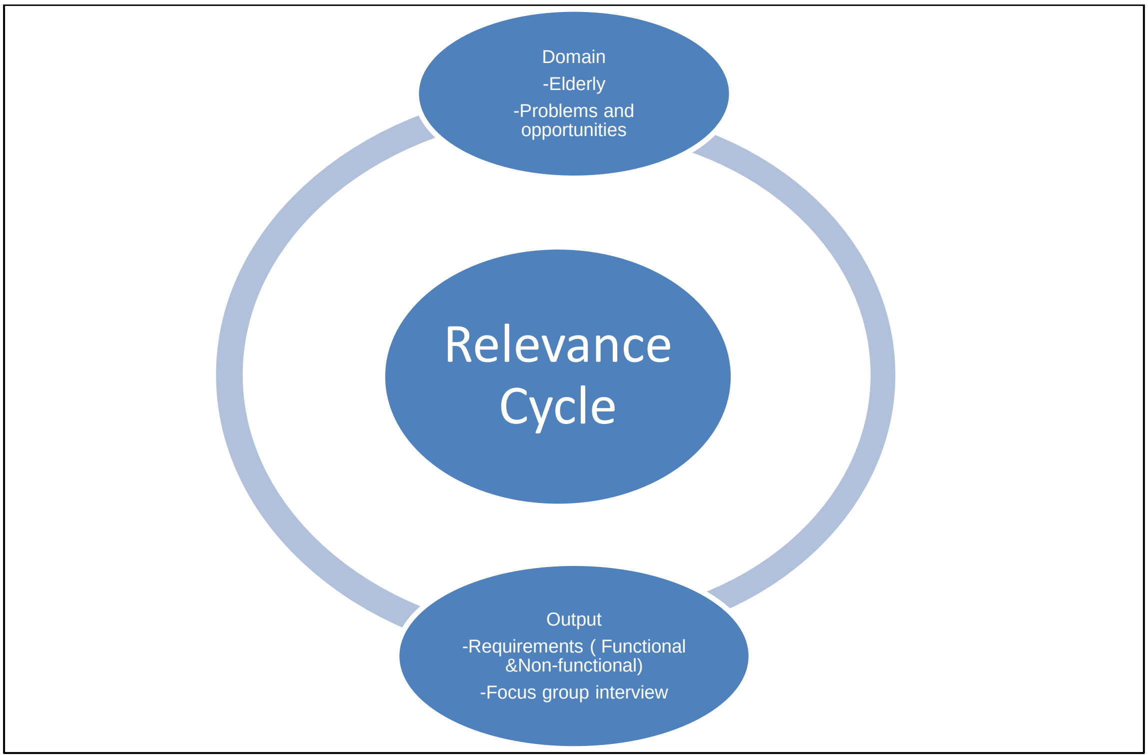


Figure 2-1 Chapter 2 as part of the DSR relevance cycle (adapted (R. Hevner, March, & Park, 2004)*)*

The goal of this chapter is to establish the safety and risk requirements for the elderly living independently. The requirements are elicited from existing literature and a focus group interview.

2.2 Risks facing the Elderly Living Independently

The home environment can be a dangerous environment for the elderly living independently. The risks considered for the purposes of this research are discussed in the following sections.

2.2.1 Injury in the home

There are multiple risk factors for injury in the home. Typical risk factors include sensory impairment, chronic diseases, environmental hazards, gender, and a history of previous falls (Vincent & Amalberti, 2016b). Poisoning, burns, and airway obstruction have been reported to be causes of injury in the home for the elderly.

Falling is a major consequence of the risk factors mentioned above among the elderly. A fall is defined as an event whereby a person comes to rest inadvertently on the ground as a consequence of sustaining a violent blow or unconsciousness (Todd & Skelton, 2004). The frequency of falls increases exponentially with age-related biological changes (Igual, Medrano, & Plaza, 2013). One out of every three elderly adults falls yearly (Dong, Yang, Hongjun, & Jian-hua, 2015). About three-quarters of falls among the elderly result in serious injuries such as head traumas and hip fractures (RoSPA, 2015). If an elderly person is living alone, there will be no one to alert emergency services and/or assist them.

The deterioration in health is the leading cause of falls among the elderly. The inability to get up due to a fall or a medical condition increases the risk of physical and physiological complications (Stone & Skubic, 2014). If a head trauma occurs as a result of a fall and if emergency help is not received, neurological complications may occur.

The common categories for factors that contribute to falling are shown in Figure 2-2. Figure 2-2 illustrates the two main categories of risk factors that contribute to falling among the elderly, namely personal and environmental risk factors. Personal risk factors can be considered intrinsic risk factors and environmental risk factors are extrinsic. The risk factors are either uncontrollable or controllable.

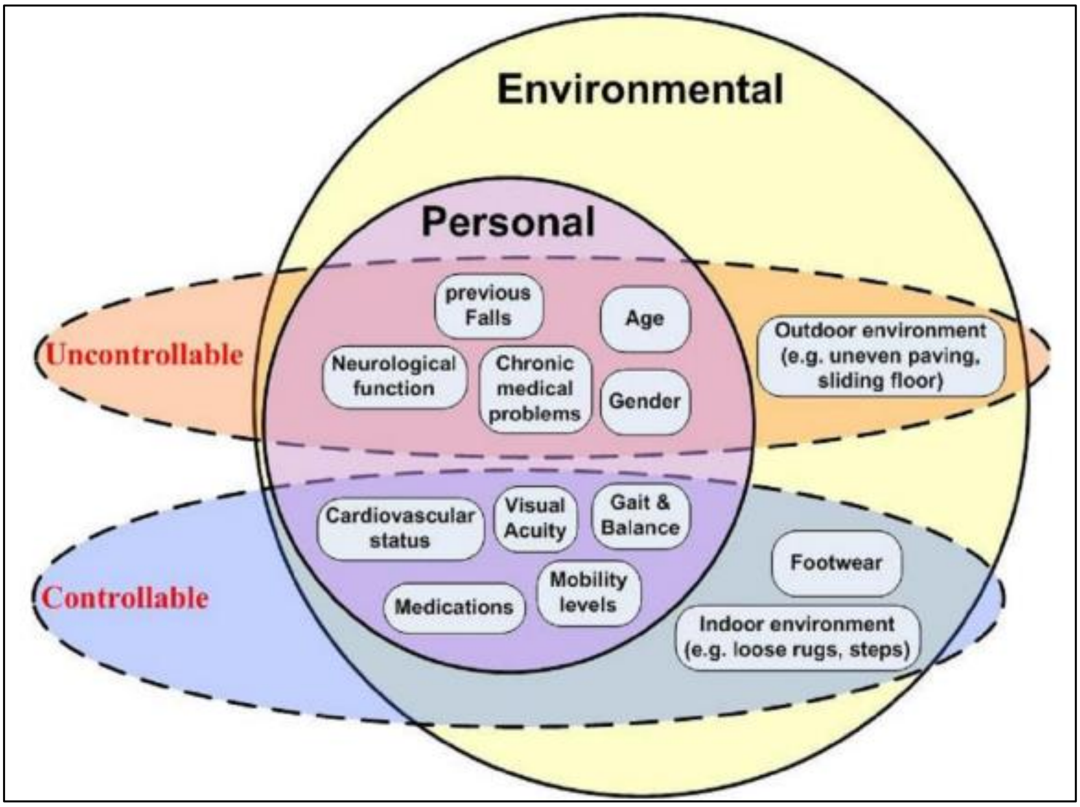


Figure 2-2 Common categories and reasons for falling (El-Bendary, Tan, Pivot, & Lam, 2013)

The category of concern is uncontrollable falls, which result from chronic medical conditions, neurological function, age, gender and the history of falls. Chronic cardiovascular conditions like hypertension can result in the elderly collapsing/fainting at any moment. Elderly females are prone to falling more than their male counterparts (Chiarini, Ray, Akter, Masella, & Ganz, 2013). The medication that the elderly person is taking also has an impact on the risk of falling. The risk of falling due to medication increases significantly if a person is on more than four medications (Todd & Skelton, 2004).

As people age, there is a decline in strength and endurance, which results in a drop in physical functioning. When muscle power is low, one is unable to prevent a slip or stumble, which becomes a fall (Todd & Skelton, 2004). There is a correlation between fear of falling and falling. An individual who falls may subsequently develop a fear of falling, which can increase the risk of falling (Igual et al., 2013). Vincent & Amalberti (2016) also discovered that a history of falls is associated with an increased risk of falling.

Technologies have been developed that seek to address some of these risk factors. Wearable devices and mobile phones have been adopted to assist the elderly in monitoring their cardiovascular status, medication adherence and other health parameters. Mechanical systems have been developed to support gait and balance for the elderly. The solutions developed do not scale very well to support unobtrusive risk monitoring in a home environment. Cost is also another critical factor in the adoption of the existing technologies.

2.2.2 The Home Environment

Home environment variables such as ambient temperature can be too high or too low and this can result in a negative impact on the resident. Exposing the elderly to extreme temperatures can contribute to injury or worsening of their health condition (Wold, 2012). For elderly persons, extreme temperature is any temperature less than 15 degree Celsius or greater than 32 degrees Celsius (Wold, 2012). The ability of the body to maintain body temperature is affected by humidity, ambient temperature and air movement.

Hypothermia and hyperthermia can easily result in death in the elderly. Hypothermia occurs when the body temperature is less than the 35 degree Celsius and hyperthermia occurs when the body temperature is greater than the normal body temperature of 37 degrees Celsius. Hyperthermia is due to high environmental temperatures, inability to dissipate heat and increased muscular activity. High humidity and high temperature affect the normal cooling mechanisms of the body in the elderly and this can result in heat exhaustion and heatstroke. Hyperthermia has deadly effects in persons with cardiovascular problems because of the strain it imposes on the heart and blood vessels during attempts to cool down (Wold, 2012).

Emergency notifications should be sent in circumstances of fire and electrical hazards that can result in a fire, such as unsafe smoking habits and leaving cooking equipment on for a long time. The acuteness of senses diminishes as people age and the risk of injury increases as well. Poor mobility, poor sense of smell, and forgetfulness contribute to most of the fatalities in fire-related deaths (RoSPA, 2015). The elderly suffering from dementia may forget that they were cooking and leave their cooker/stove on and this may result in a fire breakout. Relatives or caregivers can intervene when the temperature in the home increases rapidly over a short period of time.

Diminished vision can interfere with the ability to judge distance and the height of stairs or furniture items and this results falls and injuries in the home. Poor lighting and poor eyesight have been identified as contributing to falling in older adults ("Dangers of Seniors Living Alone," 2013).

The setup of the indoor environment, i.e. the arrangement of furniture, can pose injury risks to the elderly. Loose rugs, unorganized furniture and even footwear are some examples of hazards in the home environment as shown in Figure 2-2.

2.2.3 Adverse medical events

Medical emergencies are common for the elderly with chronic ailments. The emergency could require admission to a medical facility or it could require certain drugs to be purchased immediately ("Home Accident Prevention for Elderly," 2002). The elderly can forget their emergency numbers and where they placed their phones. Serious complications or death can result from lack of emergency medical assistance.

The association between ageing, disease and disability can be challenged by many elderly people claiming to be in good health. However health and cause-of-death statistics show that the prevalence of chronic diseases and disability increases with age (Jané Joubert, 2006). Figure 2-3 on the next page shows the 20 leading causes of death in men and women of at least 60 years of age.

Elderly persons suffering from chronic ailments and cognitive impairment need constant monitoring so that when an emergency occurs, they can be quickly attended to. Cardiovascular Diseases (CVD) are the leading causes of death in the elderly as shown in Figure 2-3. Heart failure is an example of a cardiovascular disease and it mainly affects people older than 65 years (Villalba et al., 2007).

A person suffering from a heart disease can collapse at any time and emergency services must be quickly notified. Providing aid directly after an elderly person falls is crucially important as falling can result in death (McKinley, 2014). The vital measures of physiological data such as blood pressure and activity or lifestyle patterns can be used to build personalized data that can warn family or caregivers of emergency situations (Chan, Campo, Esteve, & Fourniols, 2009).

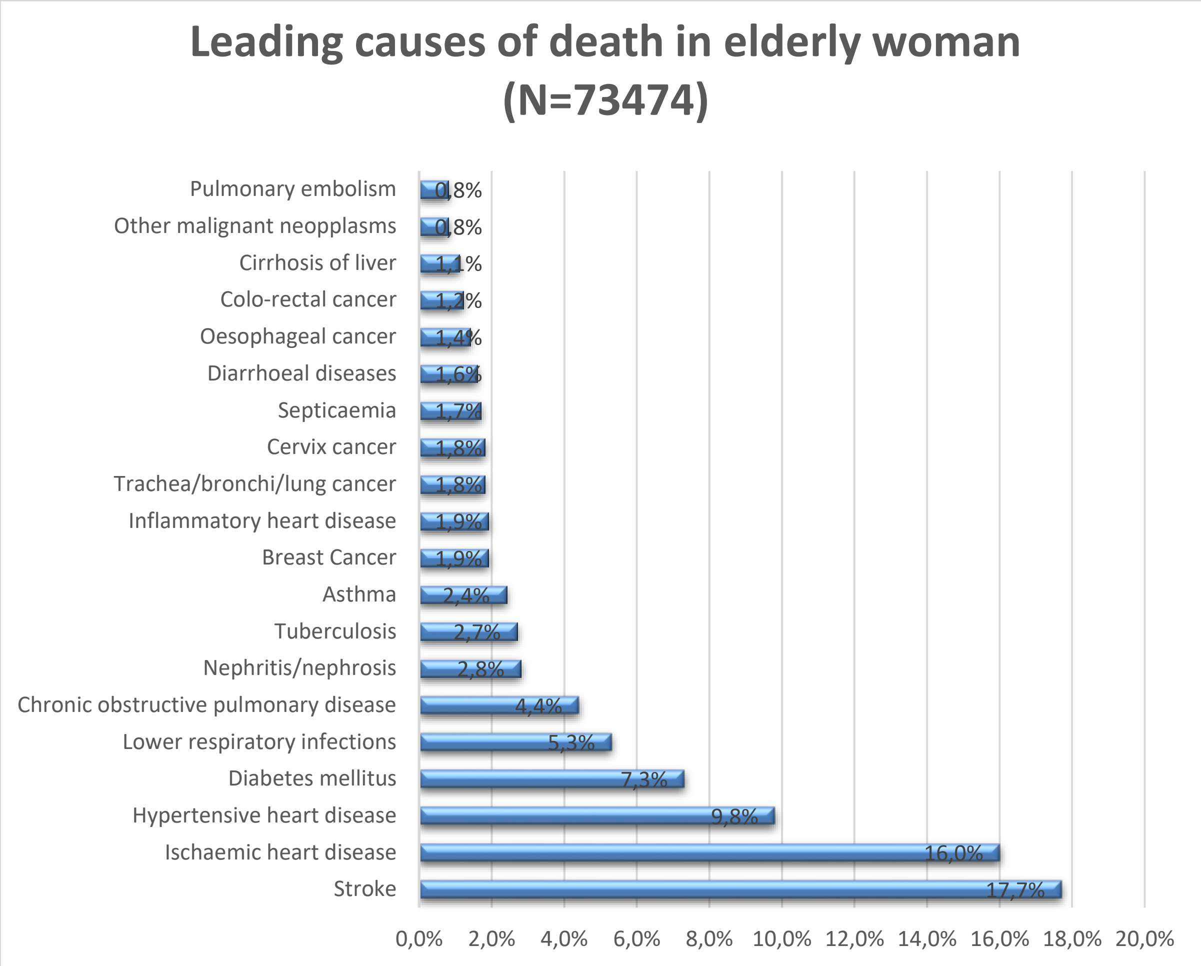


Figure 2-3 Twenty leading causes of death in women 60 years or older (Joubert & Bradshaw, 2006)

Figure 2-4 shows the twenty leading causes of death in men 60 years or older. Stroke in elderly persons is the second leading cause of death in men and the first cause of death in women, as shown in Figure 2-3. High blood pressure can cause a stroke. Symptoms of a stroke can include inability to move, cognitive impairment and loss of vision. If an elderly person living alone is known to be suffering from high blood pressure, his/her daily activities can be monitored remotely by the caregiver to determine whether he/she is active or inactive. It can be deduced from inactivity that a person suffering with high blood pressure has experienced a stroke or collapsed, or in severe cases, may have died.

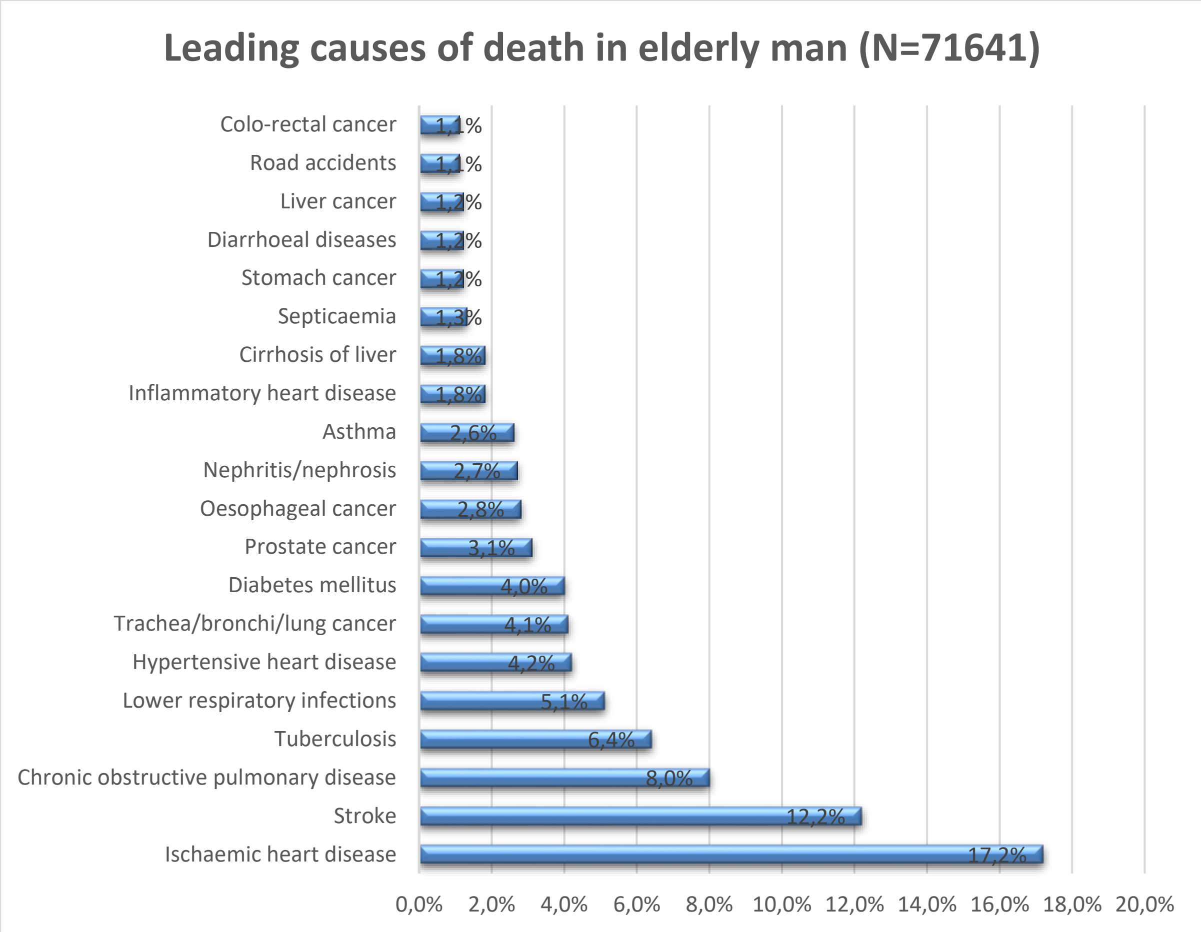


Figure 2-4 Twenty leading causes of death in men 60 years or older (Joubert & Bradshaw, 2006)

Cognitive impairment illnesses such as dementia are common among the elderly and diminish the cognitive ability of patients (Morris et al., 2013). Cognitive impairment severely diminishes the capability of executing common daily activities (Costa et al., 2012). Episodes of memory lapse can disorient the elderly, putting them in danger of hurting themselves in a panic attack.

There are possibilities for multitasking while performing daily domestic tasks and this can increase the likelihood of forgetting a previous activity (Fahim, Fatima, Lee, & Lee, 2012). For example, it is easy to forget that one has been cooking once engaged with watching television and this creates a high possibility of a fire. Unconsciousness is another potential risk for the elderly. They may suffer from a heart attack, stroke or high blood pressure and they may fall unconscious in their residence and no one will know what happened. Declining health is a sign that it is no longer safe for the elderly to stay alone without being monitored. Health is not merely the absence of disease, but rather a manifestation of the evolving pattern of person-environment interaction (Stec, 2016).

Margaret Newman formulated a conceptual model of nursing called "health as expanding consciousness". The health as expanding consciousness model offers a paradigm that illustrates health as the undivided wholeness of a person interacting with the environment in which they are living (Stec, 2016). The key concepts of the health as expanding consciousness are:

- Consciousness – this is the capacity of a person to interact with the environment they live in. Consider the case of John, who is 75 years of age and lives alone in a retirement village. John retired at the age of 60 and since then found a hobby in gardening. For the past six months, John has been waking up at about 6:00am and tending to his garden. One day he does not wake up at the usual time and he spends the whole day without being seen outside cleaning his yard. An immediate conclusion will be that something has happened to John, since it will seem as if he does not have conscious interaction with the immediate surroundings.
- Movement – this is the manifestation of consciousness. It is the transformation of energy in the space and time of a person's life. Lack of movement exhibits lack of consciousness hence poor health. Therefore an alarm could be raised if no movement is detected in an environment or space that a person is living in.

2.3 Safety and risk monitoring for the elderly

The needs of the elderly can be addressed by having an efficient home care system in place (Kleinberger, Becker, Ras, Holzinger, & Müller, 2007). The home care system domain is illustrated in the Figure 2-5.

There are three core features of the domain, and these are emergency assistance, autonomy enhancement and comfort. Emergency assistance is concerned with the detection and prediction of emergency situations. The assistance and preventive measures that can be implemented depend on the nature of the emergency situation detected or predicted. Autonomy enhancement includes higher level goals like medication, dressing, eating, cooking and cleaning. Comfort is the overarching goal in home care design and incorporates emergency assistance and autonomy enhancement.

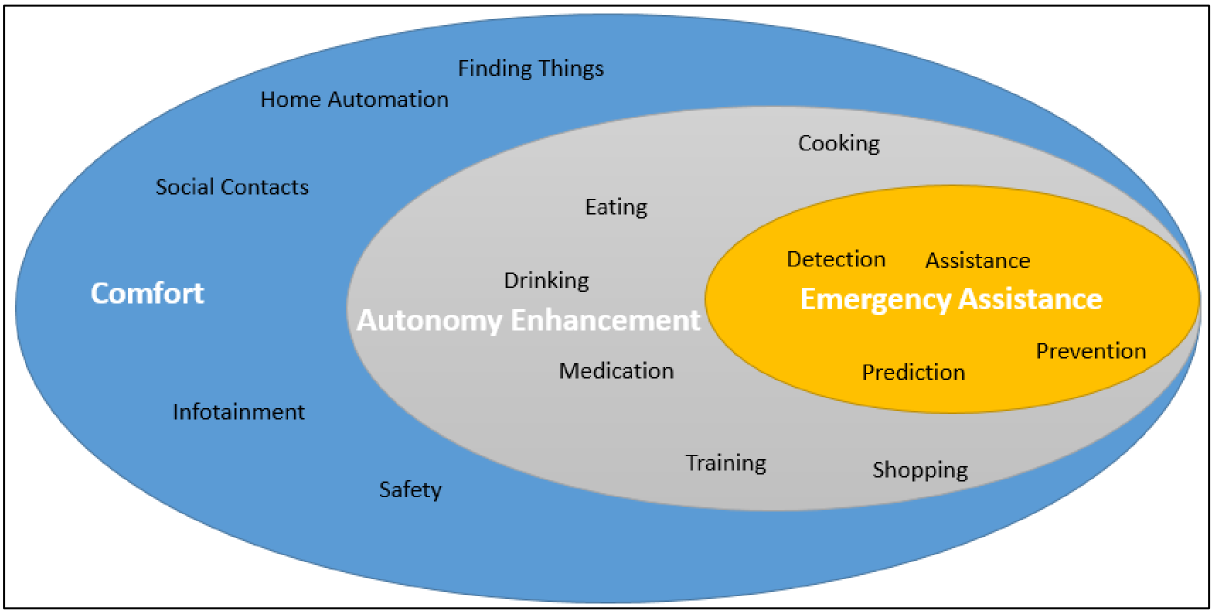


Figure 2-5 Home care system domain - Adapted (Kleinberger et al., 2007)

Christensen & Gronvall (2011) found that home care management for elderly people living independently is highly cooperative and requires substantial coordination between the various actors involved in providing the necessary safety and related services.

The roles of relatives as caregivers and the role of professional caregivers are complimentary. Christensen and Gronvall (2011) emphasized the need to understand the attitudes and values of the actors involved in taking care for the elderly. Care providers and family members harbour diverging values and attitudes towards their joint efforts in providing healthcare for the elderly. A risk factor that can be attached to these diverging values is abuse of the elderly person involved.

Family members are emotionally attached to the care they provide to their ageing relatives. Caregivers can be emotionally detached to the care and assistance they provide to the respective elderly person. It is therefore necessary to understand the attitudes and values of the relevant actors and incorporate them in the design of the technologies that can assist in providing the necessary safety and risk monitoring.

The roles that are played by family members and caregivers are illustrated in Figure 2-6.

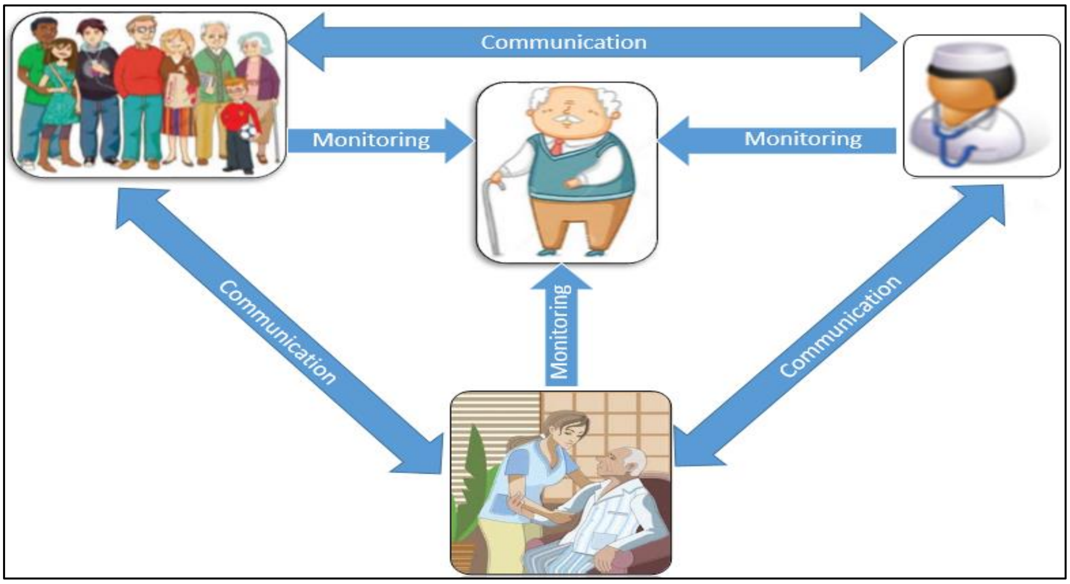


Figure 2-6 Typical roles for home based care support for the elderly

Professional caregivers handle “ordinary tasks” relating to personal care, for example food preparation, bathing and house cleaning. Family members are emotionally invested in taking care of the elderly. Emotions towards the relatives vary depending on various circumstances pertaining to the care of the elderly relatives (Christensen & Grönvall, 2011).

For the purposes of this research, the scope will be limited to safety and risk monitoring which falls under the emergency assistance domain. Section 2.3.1 will discuss the strengths and weaknesses of some of the existing systems.

2.3.1 Current solutions of safety and risk monitoring for the elderly

A variety of solutions has been implemented to try and address the safety requirements for the elderly living independently. These existing solutions will be reviewed to identify their strengths and weaknesses.

2.3.1.1 Activity Monitoring and Fall Detection

There are different kinds of falls ranging from falls from walking or standing, falls from sleeping on the bed and falls from sitting in a chair (Mubashir, Shao, & Seed, 2013).

Various techniques have been proposed for fall detection and reporting on the detected fall. These techniques can be broadly categorized as vision and non-vision based techniques. Mubashir et al (2013) reviewed some of the existing fall detection techniques and they categorized the techniques into three categories as illustrated in Figure 2.7.

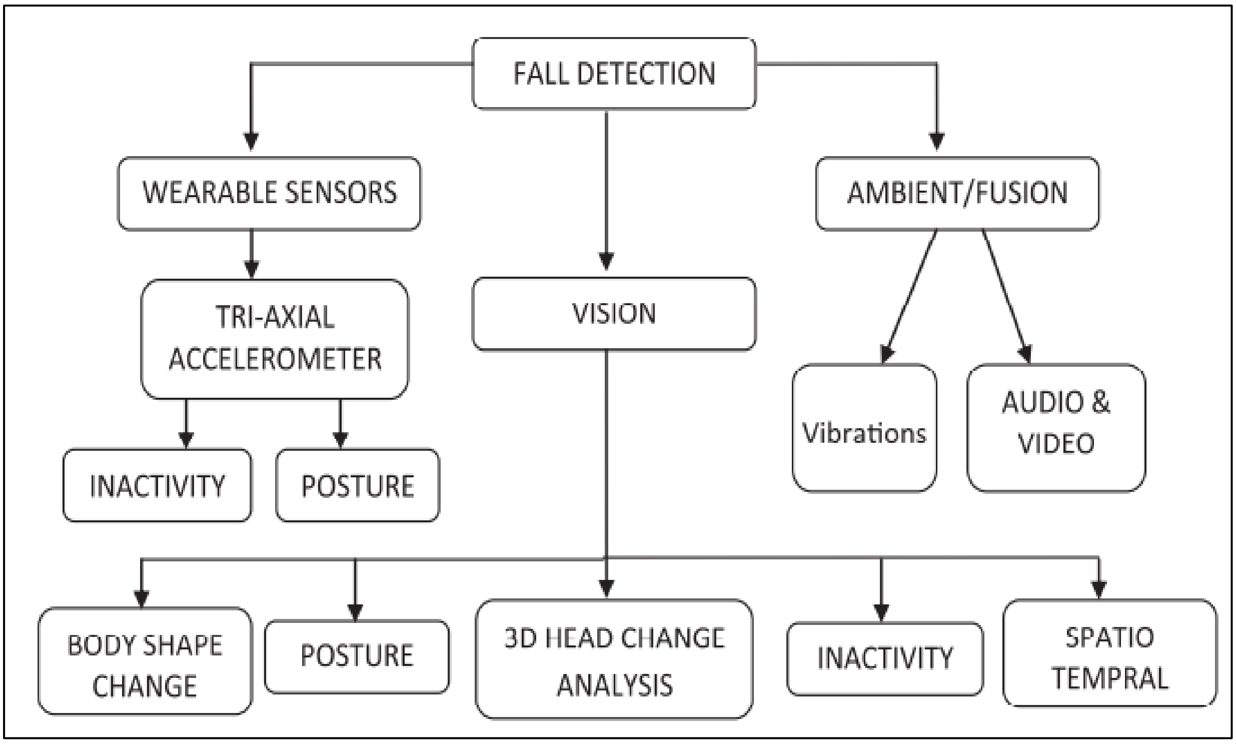


Figure 2-7 Classification of fall detection strategies (Mubashir et al., 2013)

The categories illustrated in Figure 2-7 are wearable device based detection, computer vision and ambient techniques. The wearable sensors, mobile devices and ambient based techniques comprise the non-computer vision category.

- **Non-Vision Techniques**

This category comprises technologies that can contain at least one sensor device, which can be worn or pressed in case of emergency, or can utilise environmental variables. Figure 2-8 illustrates a typical framework for non-computer vision techniques. Examples of technologies in this category include panic buttons, wearable devices, smart devices, and acoustic sensors.

Wearable technologies have developed rapidly and can be used as panic buttons or for motion sensing and detecting a fall (Patel, Pettitt, & Wilson, 2012). Wearable devices often use a Tri-axial accelerometer to measure posture and inactivity. An integrated approach was developed by Mathie et al. (2014) that uses a waist based accelerometer.

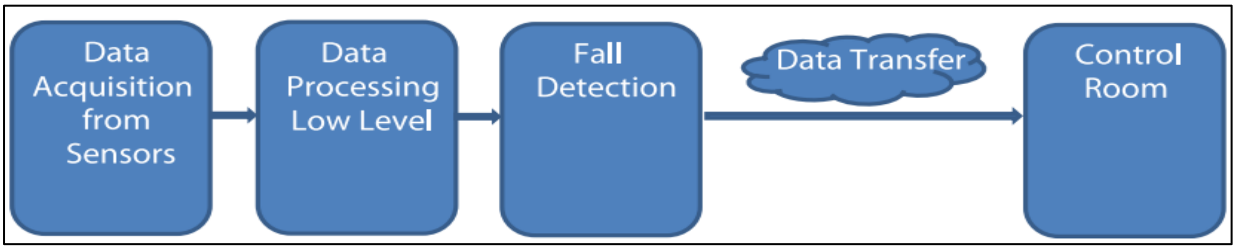


Figure 2-8 Typical framework for non-computer vision techniques (Mubashir et al., 2013)

A fall is detected when there is an increase in negative acceleration due to change in orientation from upright to lying down (Mubashir et al., 2013). A decision tree classifier is used to detect a fall depending on the values measured from the wearable device. Wearables need to be worn and charged and this presents a challenge for adoption.

Mobile applications have also been implemented to facilitate remote monitoring for the elderly living independently. An Android mobile application was developed that tracks everyday activities for the elderly to monitor risks (Fahim et al., 2012). The mobile application enables family members of the elderly person to keep track of their relative's activity. When no activity is detected in the home, a notification is sent to the relatives.

The main drawback of this technique is that it cannot distinguish whether the person is willingly not doing any activity or if the person is inactive due to falling. Furthermore, the elderly may have limited knowledge of using smartphones and they might misplace their mobile phone. Mobile devices have batteries, which have limited battery life.

Acoustic sensor systems have been developed to detect falls based on the level of noise detected. This is not very effective, because if any other object falls the system would classify the event as a person falling (Ni, Hernando, & de la Cruz, 2015). Floor vibration sensors have also been implemented, but they are costly if covering a large area. Furthermore, they cannot differentiate a person from any other object.

Other fall detection solutions use fuzzy logic to recognize a posture, and they can classify whether the person is standing lying down or sitting (Chiauzzi, Rodarte, & DasMahapatra, 2015). The main drawback is that any object lying down is recognized as having fallen.

- **Computer Vision Techniques**

Computer vision techniques do not require the elderly to wear any devices and hence are unobtrusive. The main component of computer vision techniques uses at least one camera to keep track of information about the elderly such as location, actions and motion. Figure 2-9 illustrates a typical computer vision framework.

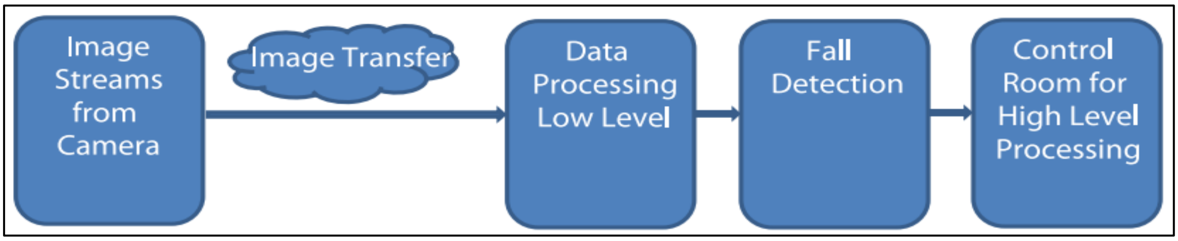


Figure 2-9 Typical computer vision framework (Mubashir et al., 2013)

The development of depth cameras has led to the adoption of computer vision techniques when privacy needs to be maintained. Typically a computer vision technique starts with feature extraction. Low level data processing can then be performed on the extracted features and a decision is made to detect whether the features indicate a fall. Computer vision techniques can unobtrusively monitor the home of the elderly for an adverse event. The main challenge is to convince the elderly to adopt them.

2.3.1.2 Adverse medical events monitoring

Patient engagement in the management of chronic illness can be enhanced by the expansion of activity tracking and personal data collection (Chiauzzi et al., 2015). Various solutions have been implemented to support health monitoring for the elderly.

- **mHealth**

Mobile phone use has become ubiquitous, changing the way we communicate, conduct business, and provide care and services. Mobile technologies have some compelling benefits in disease prevention, chronic disease management and improving healthcare (Center for Technology and Aging, 2011). There are many applications for mobile healthcare management for the elderly. Mobile health or mHealth broadly refers to health-related services offered to patients by caregivers and clinicians through mobile technology platforms on cellular or wireless networks (Center for Technology and Aging, 2011).

The commonality of mobile health applications is that they use a combination of embedded sensors, which collect information about a person's health, for example step count, blood pressure, heart rate, and electrocardiogram (ECG) (Nanhore & Bartere, 2013). The mHealth applications are used by clinicians, caregivers, patients and family members to improve self-management of care. mHealth also enhances communication and information transfer between the various parties involved in the healthcare and emergency notification provision to the elderly. The adoption of mHealth technologies can reduce healthcare costs significantly.

Chronic disease management, medication adherence, safety monitoring, access to health information and wellness information are the five key mHealth application areas (Centre for Tecnology and Aging, 2011). Mobile smart devices already have some mHealth applications preinstalled that are useful in monitoring health and activity monitoring. The applications are designed for personal use, and there is limited sharing of information with family members and caregivers.

Chiarini et al. (2012) proposed a taxonomy of mHealth solutions as illustrated in Figure 2-10 on the next page. Continuous monitoring is necessary for elderly patients suffering from chronic illnesses. Mobile technologies can aid in providing real-time sensor data that can be used for "around the clock" medical diagnosis that is integrated into the life of the elderly person (Chen et al., 2012). Remote automated analysis can be performed on the collected sensor data and the necessary medical feedback and/or emergency assistance given to the elderly patient.

Supervised healthcare is offered by caregivers periodically to their patients. Healthcare providers can give medical guidance in terms of medical adherence and ways to stay healthy. Current and historical data is usually exchanged between the caregiver and the elderly patient.

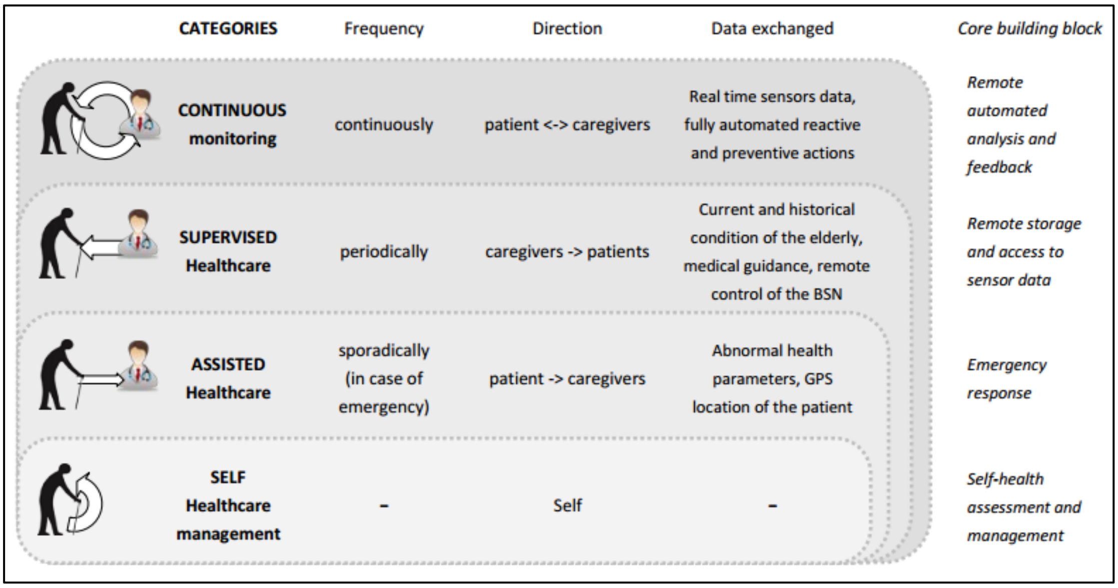


Figure 2-10 A taxonomy of mHealth solutions (Chiarini et al., 2013)

Safety and wellness monitoring is useful for assisted healthcare. Assisted healthcare can be necessary at any point in case of emergency. Abnormal health parameters and the GPS location of the patient are common data that is exchanged between patients and caregivers. The iWander Android application, popular for use with people suffering from Alzheimer's disease or dementia, uses smartphone GPS to locate them if they get lost. The use of mobile applications and/or social media to assist the elderly suffering from chronic ailments is gaining popularity (West, 2013).

Mobile health applications are rich sources of medical data that can be shared between caregivers and the elderly. The successful adoption of mHealth applications is limited by the lack of tools that make sense of the data collected (Chen et al., 2012). The major limitation for adoption of mobile technologies is their need to be carried by the user. Furthermore, elderly people have a tendency to forget, therefore they can easily misplace their phones and there will be no way to contact emergency services if the need arises. Mobile technologies are also fairly expensive considering the fact that the elderly live on a fixed income. The learning curve involved in learning how to use the system is a major cause of concern in the elderly. Cognitive impairments result in the elderly forgetting the instructions on how to use the system. The mobile devices use batteries and the elderly can easily forget to charge their devices as they may not be using them often.

There is no shared data architecture because mHealth applications are built independently, addressing only a subset of medical conditions with little sharing of data. The heterogeneous nature of mHealth applications makes it very difficult to process and make sense of the data. In addition, mHealth data tends to have bias, noise, variability and gaps that make it difficult to make sense out of the data (Chen et al., 2012). Furthermore, there is a lack of visualization and analysis tools to generate and display clinically relevant data that can enable elderly patients, caregivers and family members to understand the health status of a particular elderly patient.

- **Wearable technologies**

Wearable technologies have developed rapidly and have a number of clinical applications. Wearable technologies are an example of mobile-enabled health diagnostic and monitoring devices. The current capabilities include remote monitoring, motion sensing, and physiological and biochemical sensing. Remote monitoring can help in solving the elderly's home care issues by assisting in the diagnosis and on-going treatment of the elderly with neurological, cardiovascular and pulmonary diseases (Patel, Park, Bonato, Chan, & Rodgers, 2012). With remote monitoring, the elderly patient does not have physically go for routine medical check-ups.

Patel et al. (2012) found that the most important physiological measures for patient rehabilitation include blood pressure, heart rate, respiratory rate, blood oxygen saturation, muscle activity, and sleep patterns. The physiological measures provide useful indicators of health status and aid in illness diagnosis. Fig 2-11 illustrates a conceptual representation of a system for remote monitoring.

Motion sensors can be used to monitor the effectiveness of home-rehabilitation interventions in stroke survivors or in mobility assistive devices for the elderly (Patel et al., 2012). The first component of a wearable technology system is the sensing and data collection hardware component. In Figure 2-11, wearable sensors are used to monitor the status of the patient. The choice of the wearable sensors depends on the health condition of the patient. Sensors that monitor heart and respiratory rate can be used for patients with chronic heart-related illness or patients with chronic pulmonary illness.

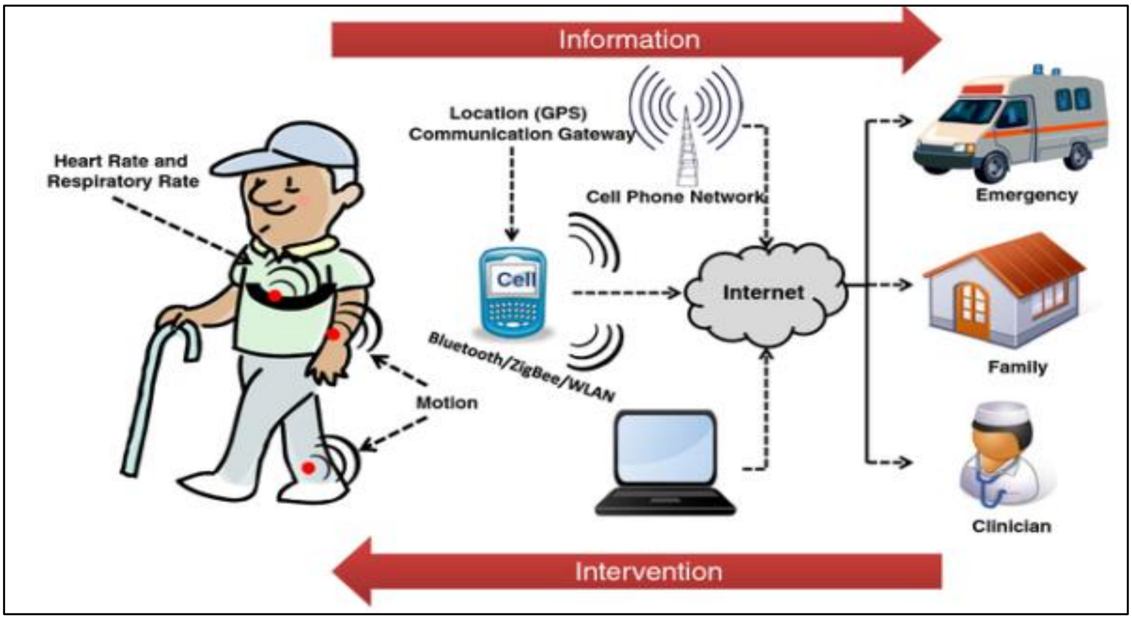


Figure 2-11 A remote health monitoring system based on wearable sensors (Patel et al., 2012)

The Fitbit wearable device is one of the market-dominant wearable devices for personal activity monitoring (Guo, Li, Kankanhalli, & Brown, 2013). An example of a Fitbit wearable device is shown in Figure 2-12.

Figure 2-42 Fitbit Charge HR wearable device (Zhu et al., 2015)

The Fitbit Charge HR offers continuous heart rate monitoring for better estimation of a person's daily activity, the number of steps, calories burnt and sleep patterns. Heart-related illnesses have been shown to be the leading causes of death amongst the elderly, as discussed in Section 2.2.3. Fitbit Charge HR uses Bluetooth to connect with mobile devices for uploading data to the Fitbit website. The Fitbit Charge HR also has a caller ID feature, which buzzes when someone calls the connected smartphone, and displays the caller ID.

The heart rate monitoring could be very useful for health monitoring of elderly adults with cardiovascular diseases. The sleep monitor can detect if the person has woken up or for how long he has been asleep. If the elderly person spends the whole day asleep, it could mean that something is not right and the necessary interventions can be made.

The communication hardware and software are used to relay data to a remote centre that performs data processing. Modern wireless communication technology is cheap, small in size and consumes less power. The IEEE 802.15.4/ZigBee standard consumes less power and is low cost, but has high data transmission rate. Mobile phone use has become ubiquitous, providing a “ready to use” platform to log and transmit data to a remote site (Patel et al., 2012).

Data processing is implemented in the system to detect emergency situations, and any abnormalities in the patterns of data collected can be relayed to emergency services, family members and caregivers. Artificial intelligence can be used to extract the clinically relevant data and process it accordingly.

The successful adoption of wearable devices by the elderly and care providers depends on good measurement and data validity properties, the user experience, behaviour change, privacy, safety, care delivery and integration (Chiauzzi et al., 2015). There is a lack of standardization of the measurements that are obtained from wearable devices. Wearable devices used for passive monitoring do not capture all the possible physical activity. Fitbit has been found to have erroneous characterization of true activity, due to infrequent use and compromised accuracy due to predominant hand motion activities, driving, and long or short stride length (Chiauzzi et al., 2015).

Technological and cultural barriers, such as the association of a stigma with the use of medical devices for home based clinical monitoring, are some of the significant challenges that need to be considered before implementing the system illustrated in Figure 2-11 (Patel et al., 2012). The size of some of the sensors and related front-end electronics have been the major technological hurdle in the adoption of wearable technologies in the past, making data collection too obtrusive.

The user experience of wearable devices consists of use and setup, battery life, synchronisation via wireless technologies, aesthetics of the device itself and corresponding companion applications. Sustained use of the wearable device is also dependent on the disease, patient behaviour, and measurement need (Chiauzzi et al., 2015).

Some of the user experience issues can be addressed by alterations to the design of the wearable device, for example attention to fashion, and good data visualization. Individual characteristics such as negative perceptions, and inconsistent use can be addressed by the integration of engagement and behaviour change principles.

2.3.1.3 Home Environment Monitoring

In order to counter the risk factors facing the elderly, sensors and other smart technology can be installed in the home of the elderly. A SHE can be defined as a residence equipped with smart technology that facilitates monitoring of residents to improve quality of life and promote physical independence, as well as to reduce burden on the caregiver (Frisardi & Imbimbo, 2011).

Temperature can be monitored in the home to determine the risk of a fire breakout and to avoid exposing the elderly to extreme temperatures, which can result in medical complications. Light and motion sensors can be installed in the home to determine if there is any activity in the home.

Fahim *et al.* (2012) developed an Android application that monitors user activity inside and outside the home. Figure 2-13 shows the architecture of the application. The Smartphone application enables family members of the elderly person to keep track of their relative's activity. When a critical situation is left unattended, a notification is sent to the relatives.

The notification activates a customized interface displaying the elderly person's picture and the current atmosphere, including humidity, temperature, location and gas usage. High temperature and gas usage indicates the possibility of a fire breakout and emergency services can be called immediately. The application allows the caregiver or relatives to query the last activity done by the older person, as long periods of inactivity might mean the person has collapsed or has been attacked by thieves.

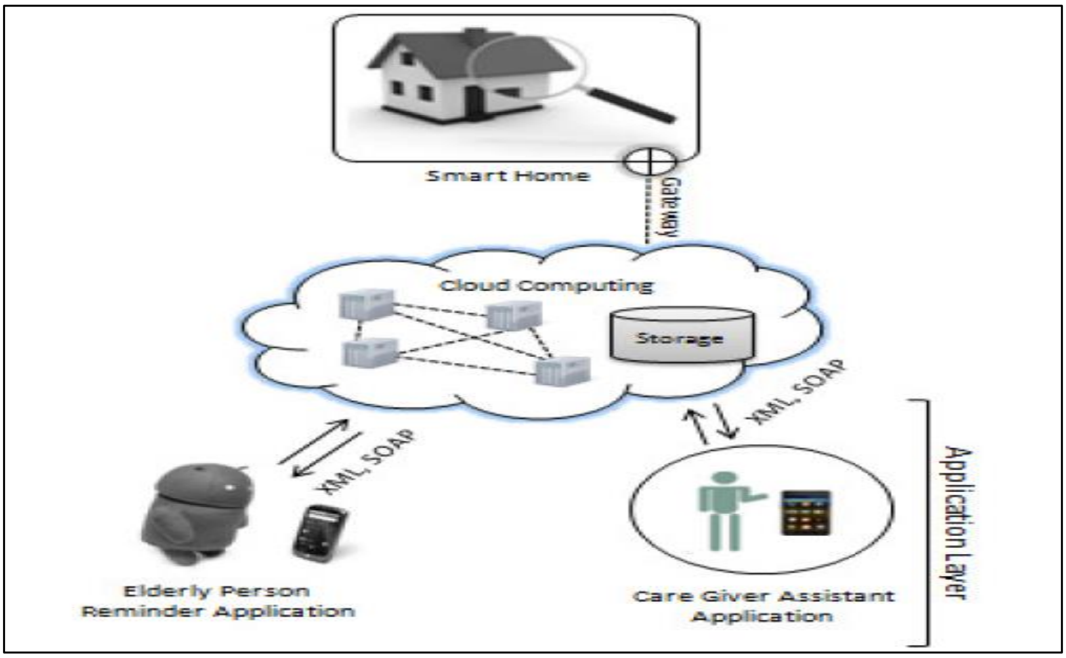


Figure 2-13 Architecture of an activity tracking application (Fahim, Fatima, Lee, & Lee, 2012)

The disadvantage of using mobile applications is that the elderly person can forget where he has put his phone and therefore it might seem as if he is inactive or has collapsed. The elderly person can also forget to charge his mobile devices and, when they turn off, there will be no way of determining the situation in the home. Learnability of the mobile application is also an issue for the elderly. The application should be easy to use because cognitive abilities diminish as people age. For example, someone suffering from dementia might not remember how to use the application. User experience is a critical issue in the design of applications that assist the elderly and disabled.

The costs associated with the technologies used in designing a smart home should be taken into consideration. Elderly people live on a fixed income therefore they might not be interested in acquiring these technologies. Care providers perceive lack of financial assistance, and the high costs associated with implementing automated home based healthcare, as the main inhibitor in the adoption of smart home technologies to support the elderly (Chan, Campo, Esteve, & Fourniols, 2009). The time and effort spent on learning how to use smart technologies is also a major barrier in the adoption of these technologies (Chan, Campo, Esteve, & Fourniols, 2009).

Sensors and actuators can be incorporated into a home environment forming a technological ecosystem for unobtrusive safety and risk monitoring for the elderly (Hansen, 2014). The prices of autonomous off-the-shelf sensors are dropping on a yearly basis and this makes it easy to build a low cost SHE. SHEs have the advantage that they are non-obtrusive and there is minimal interaction between the elderly and the smart system.

2.4 Smart Home Environments for the Elderly

Emergency systems for the elderly contain at least one sensor, which can be worn or pressed in case of emergency (Zambanini & Kampel, 2013). False alarms can be raised when there is no medical and/or safety emergency. The main drawback of these types of sensors is that no information is exchanged, hence it is difficult to determine the nature of the emergency situation. To ensure the detection of emergency situations where the elderly is not able to raise an alarm, sensors acting autonomously are needed (Mattheyses & Verhelst, 2015).

Smart sensors can be installed in the home to detect specific nuances of human interaction with the environment providing an awareness of the resident context, physical context and the time context (Cook & Krishnan, 2014). Figure 2-13 shows the components of a smart home and the three services that a SHE can support for the elderly. The SHE is made up of a combination of various devices as illustrated in Figure 2-14.

The smart home is centred on the needs of the resident. The needs of the resident determine which devices to install in the home to fulfil the resident’s needs. The hospital service layer consists of health-related care or services. Vital sign measurement devices are used to measure data such as blood pressure, respiration and body temperature. Mobility sensors can be used to assess the activity of the resident. Hospital-based professionals or any other remote caregivers can give tele-consultations and virtual visits. Tele-consultations and virtual visits ensure that the elderly receive care in the comfort of their homes and constant monitoring of the elderly resident's health status can be enhanced.

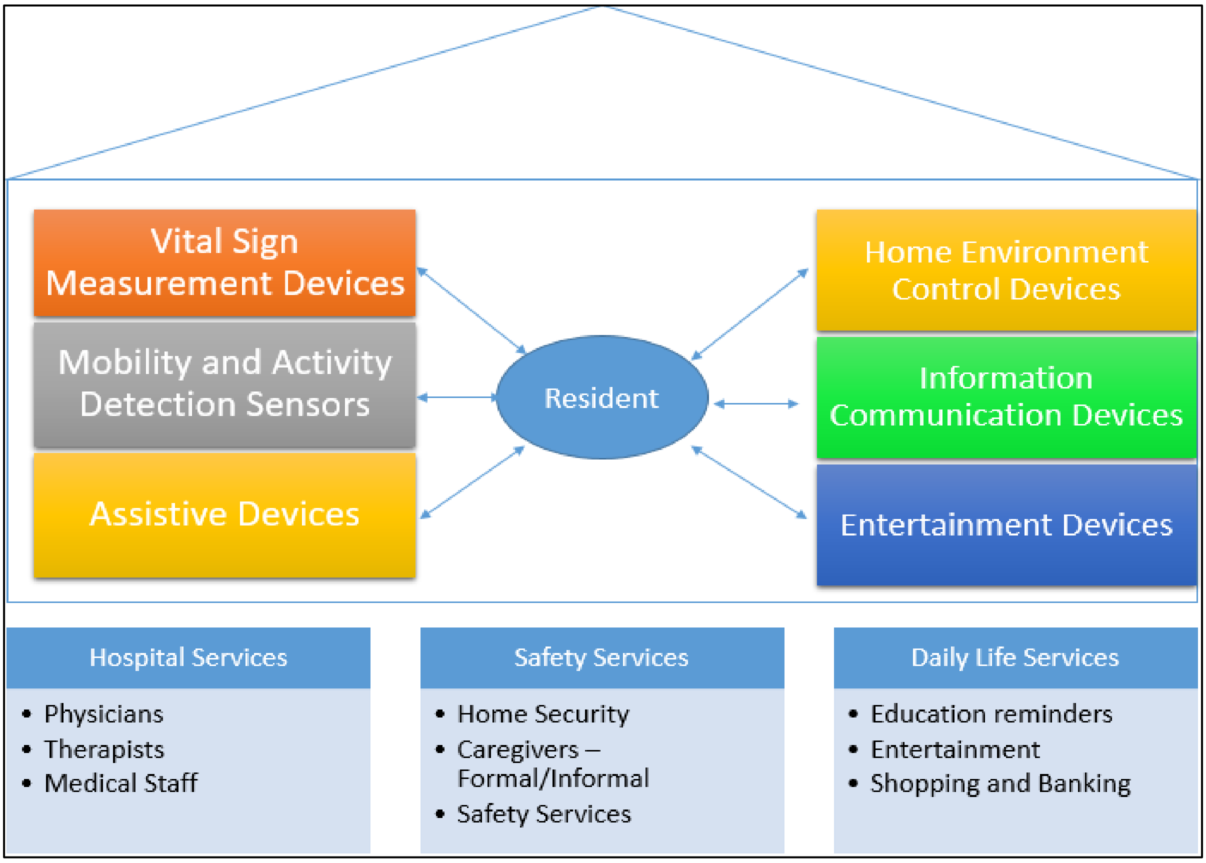


Figure 2-14 Key components of a SHE and services offered (Chan, Adapted - Campo, Esteve, & Fourniols, 2009)

The devices used for health monitoring are capable of performing integrated analysis of data collected to aid in health diagnoses and decision making. Healthcare access and resource optimisation for the elderly could be enhanced in the proposed SHE. Safety services and daily services can also be supported by a SHE. Assistive technologies such as robotic assistants and automatic wheel chairs can assist with daily physical tasks. Air conditioning, heating and bath water control can be achieved by devices for home control environments. The services supported by a SHE are all examples of Ambient Assisted Living. Chan et al. (2009) identified the following smart home residents who can benefit from a SHE:

i. *Elderly who are living independently but are unable to seek help in emergencies*.

For example, if a person living alone becomes unconscious, there is no way the emergency services can know of the situation. An elderly person could experience a stroke and there would be no way of alerting emergency services if he is living alone.

ii. *Elderly or disabled who suffer from cognitive diseases and/or physical impairments.*

Physical impairments can be hearing, visual, mobility, and speech impairments.

iii. *People who need help to accomplish daily activities*.

The homes of these people are equipped with assistive technologies, to assist the residents to accomplish daily living activities like eating, bathing and toileting.

iv. *Caregivers.*

Caregivers can be formal or informal. Examples of informal caregivers are family, friends and neighbours. Health professionals are the formal caregivers. Caregivers can remotely monitor their patient and, in case of emergency, they can quickly intervene.

2.4.1 User Acceptance of Smart Home Environments

It is important to plan for the perceptions, needs and expectations of the elderly (Demiris et al, 2004). Demiris *et al* (2004) conducted focus groups with 15 older adults aged 65 and over to determine their perceptions of smart technologies. They identified the following concerns related to the use of smart technologies.

(i) *Possible privacy violation.*

If cameras were used, users feel that this would be obtrusive and violate their privacy.

(ii) *Lack of human responders.*

The elders also expressed concern that smart technologies would replace someone who would be able to react to the information provided.

(iii) *User friendliness of the devices and need for training tailored to older learners.*

The user interfaces of the devices that can be used in a SHE should be easy to learn for the elderly.

Despite these concerns, Demiris *et al.* (2004) discovered that participants had a positive attitude towards devices and sensors that can be installed in their homes and towards the concept of smart homes.

The overall acceptance of smart home technology by the elderly is generally positive, and great leaps in technology and the prevalence of technology in everyday life are now a reality (McKinley, 2014). The advent of advanced technologies makes it possible for SHEs to become a more feasible solution for elderly care. McKinley (2014) advocates for a user centred design process (UCD) in the adoption and implementation of technology for senior citizens.

It is very important to understand the risks facing the elderly before implementing a suitable design. Interacting with the elderly can help in eliciting their safety and risk monitoring requirements. Focus group interviews with the elderly were conducted to elicit their requirements. Section 2.5 outlines the design of the focus group interviews and the analysis of the results obtained.

2.5 Focus Group Interview

A focus group is a group of people assembled by a principal investigator to discuss and comment on a topic from a personal perspective (Powell & Single, 1996). Focus group interviews generate qualitative data and their use as a data collection tool has gained popularity in health service research (Doody, Slevin, & Taggart, 2013).

Kitzinger highlights the usefulness of focus groups in exploring people's knowledge and experiences (Kitzinger, 1995). Focus group interviews enable researchers to examine not only what people think, but also how they think and why they think that way, through tapping into the different forms of communication that people use daily.

The number of participants can vary between 4-6 and there should be a good balance in the group's diversity (Breen, 2006).

Data becomes redundant with more focus group interviews (Mclafferty & Mclafferty, 2004). Mclafferty emphasizes the ease of managing smaller groups and avoiding data redundancy from too many focus groups. A focus group interview session was facilitated by a moderator. The principal researcher is not always the best person to act as a moderator, as they may not have necessary skills and may presuppose the solution required (Powell & Single, 1996).

The focus-group interview followed a procedure outlined below:

- The Welcome;
- An overview of the topic;
- A statement of the ground rules of the focus group, signing of consent forms and assurance of confidentiality;
- Interview questions. The questions began with general issues progressing to specific problems. The focus group moderator used a probing technique. The probing technique is used to obtain answers from participants and to encourage discussion (Breen, 2006);

  The principal investigator transcribed the notes and answered any questions from the participants.

The focus group was composed of participants, instruments and analysis of data collected as outlined below:

a) Participants

- The participants had an average age of 70 years.
- Session moderator.
- Principal Investigator.

b) Instruments

- Questions.

- Audio recorder.
- Round Table microphone.

c) Analysis methods

- Qualitative data analysis techniques were employed to analyse the data obtained from the focus groups. Atlas.ti was used as the data analysis tool.
- The nominal group technique was used to determine the extent to which the elderly agreed and prioritised the healthcare issues raised during the session.

The documentation used for the focus group interview is attached in Appendix C.

2.5.1 Focus group interview results

A focus group was conducted at Walton Park, Summerstrand, Port Elizabeth. The participants included 5 females and 1 male and the average age was 70 years. The session lasted for 1 hour.

One question was initially developed to probe for healthcare requirements from the elderly. We did not know what to expect, therefore the question was supposed to be as general as possible. The question that was asked was:

- What kinds of risks would you find useful to have monitored in your home – either for your own "heads-up" warning and/or for centralised/family monitoring and warning?

The issues raised were recorded on a flip chart and towards the end of the focus group interview the moderator used the nominal group technique to determine which issues were of high priority to the elderly. Figure 2.15 on the next page shows the pictures of the flip charts with the healthcare requirements raised during the focus group interview.

Although the elderly have panic buttons, they all agreed that they do not use them consistently. Some said they always keep them on their bedside in case something happens at night but they do not carry them during the day. Panic buttons are not water resistant hence they cannot be worn during bathing, laundry or doing dishes. Three out of six participants said that they do not bother to use the panic button because they feel that they are not going to get help from the resident nurse anyway. They would rather call their friend or relative for help.

Four out of six participants agreed to have sensors installed in their home to support fall detection, activity tracking and home environment monitoring. Fall detection was emphasized the most. The participants highlighted the fear of falling/collapsing with no-one knowing what happened since they live independently.

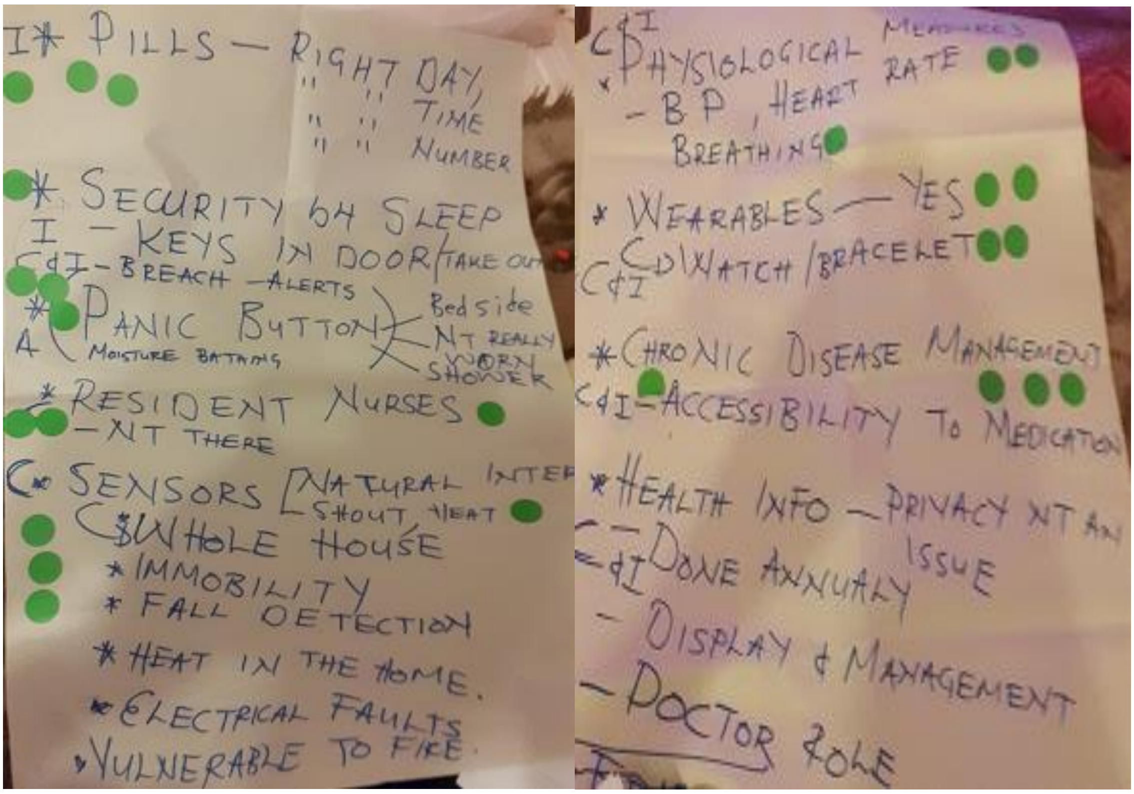


Figure 2-55 Flip charts and participants' priorities

The recording for the interview was transcribed and the notes were fed into a word map generator and the results are illustrated in Figure 2-16. Participants were worried about the possibility of a fire breaking out in the event that they forget to turn off their stove or there is an electrical fault. They stressed that the sensors should not be intrusive and they would prefer to use natural interaction, for example voice.

The use of wearables to measure physiological measures was identified as being important by the participants. Four participants said they would prefer wearing wearable devices than using panic buttons. One of the ladies remarked, "as long as it is a pretty bracelet”. They did not express any concern with the physiological measures being monitored remotely by their next of kin.

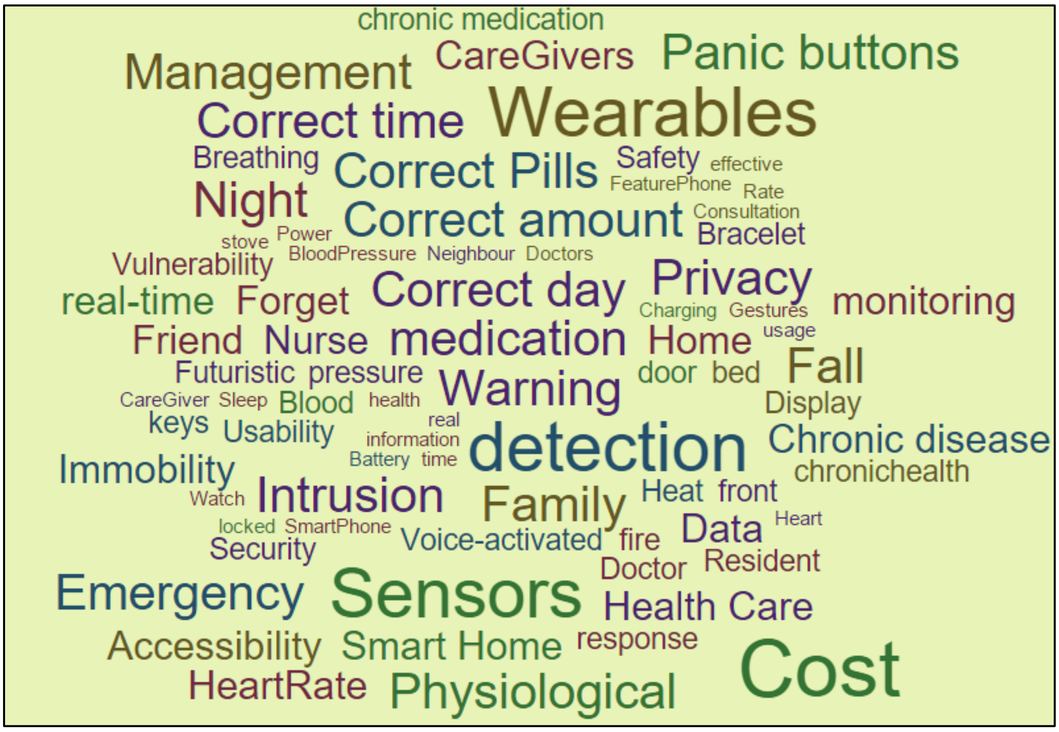


Figure 2-16 Word map for the focus group interview

Chronic disease management was also identified as a high priority by the elderly. They stressed that they need continuous access to wellness information and that their medicine is not accessible especially when they have to purchase another month’s supply. Three of the participants said that they struggle with remembering to take their medication at the right time and in the right amount. They were not worried with sharing their medical information with caregivers and family members.

The elderly expressed concern about the cost of the technology that would meet their requirements. Concerns were raised regarding battery powered technology. They were worried about the battery life and forgetting to charge their devices.

Usability of the technology was also noted as a cause of concern. One of the participants said, “Most of the technology I have used to assist me in the home is overwhelming, I can’t even use the remote control of the TV set my son bought me”. None of the participants had a smart phone. They said feature phones are easier to use than smart phones. The participants said that they do not use the phones often and they would prefer to have information displayed on a bigger screen such as a television set.

2.6 Safety and Risk monitoring requirements for the Elderly

The analysis of the data from the focus group interview and the literature review illustrate the commonality between risks identified in literature and the ones from the focus group interview. The analysis yielded the following requirements to support risk and safety monitoring for the elderly.

i. Fall detection;

ii. Home environment monitoring;

iii. Inactivity monitoring;

iv. Emergency notification;

v. Access to safety/risk information.

Cost is a key factor to consider when designing the SHE. Privacy must be preserved and there needs to be minimal interaction between the elderly and the smart technology.

2.7 Conclusion

There are multiple risk factors that contribute to the risks faced by the elderly living independently. Emergency assistance is key when adverse situations occur for the elderly. Chronic diseases, sensory and cognitive impairment become pronounced as people age. The elderly prefer to live independently with no one to respond when emergency situations occur. An adverse event can occur at any moment especially when they are alone. Caregivers and family members can take turns to monitor the elderly, but they are not always there.

The main risks identified were injury in the home, adverse medical events and home environmental hazards. Falling is a major cause of injury in the home. A fall often results in injuries like hip fractures and head traumas, resulting in the elderly person not being able to get up; hence they cannot seek emergency assistance. Inactivity in the home can be a sign of an adverse medical condition for the elderly suffering from chronic illnesses. It is possible for elderly people to fall unconscious due to their medical condition.

Fire and intruders in the home are also risks associated with the elderly living independently. Exposure to extreme temperatures in the home can worsen the condition of the elderly suffering from chronic illness.

Existing systems have a major limitation in that they are obtrusive in monitoring the safety and risks facing the elderly. Cost is also a key factor in adoption of any of the solutions developed for the elderly as they live on a fixed income. The systems that adequately address risk and safety monitoring for the elderly are very expensive and do not suit the income levels of the elderly.

There is a lack of consideration for user interaction and information visualisation in the current safety and risk monitoring solutions. The elderly would prefer minimal interaction with the system set up to monitor them. The learnability and ease of use of the existing systems have a significant impact on their adoption.

SHEs can unobtrusively monitor the elderly living independently. Low cost sensors are available off the shelf and the elderly do not mind if sensors are installed in their homes to monitor the risks facing them in their home, as long as the solution is not costly and obtrusive.

Chapter 3 will discuss existing models and technologies that can be incorporated in the design of a SHE that can unobtrusively support healthcare for the elderly living independently.

Chapter 3. A Smart Home Environment to Support Safety and Risk Monitoring for the Elderly

Chapter 2 reviewed safety and risk monitoring requirements for the elderly. This chapter reviews existing models and existing technologies that can be incorporated in a SHE to support the safety and risk monitoring requirements identified in Chapter 2. A SHE is an environment enriched with sensing, actuation, communication and computation capabilities, which permits it to adapt to the preferences of the inhabitant (Cicirelli et al., 2016).

The selection of models and technologies was influenced by the requirements identified in Chapter 2. The diagram below shows the position of this chapter in the DSR methodology as an iteration of the relevance cycle.

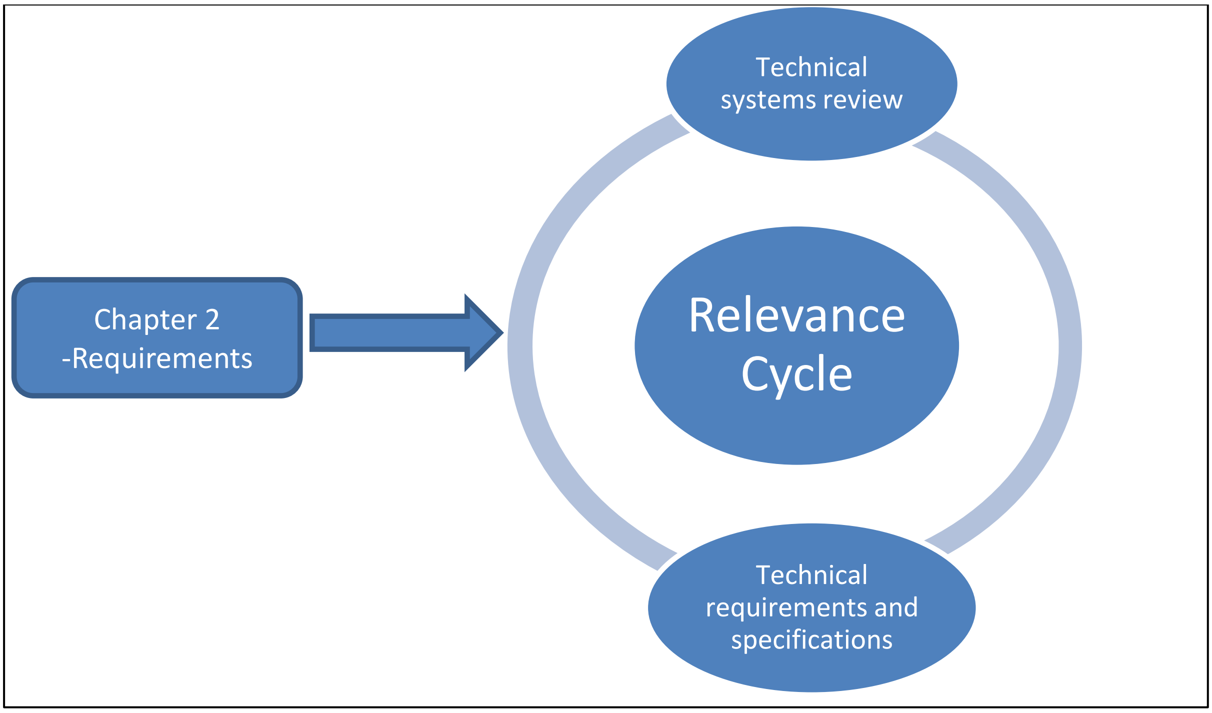


Figure 3-1 Position of Chapter 3 in the DSR methodology

This chapter is another iteration in the relevance cycle, focusing on the technical systems review. The existing technologies and models are reviewed according to their applicability to the requirements identified in Chapter 2. The output of this review is a set of technical requirements and specifications for a model of a SHE that can support the requirements identified.

3.1 Functional Requirements

The requirements obtained in Chapter 2 are illustrated in the use case diagram in Figure 3-2.

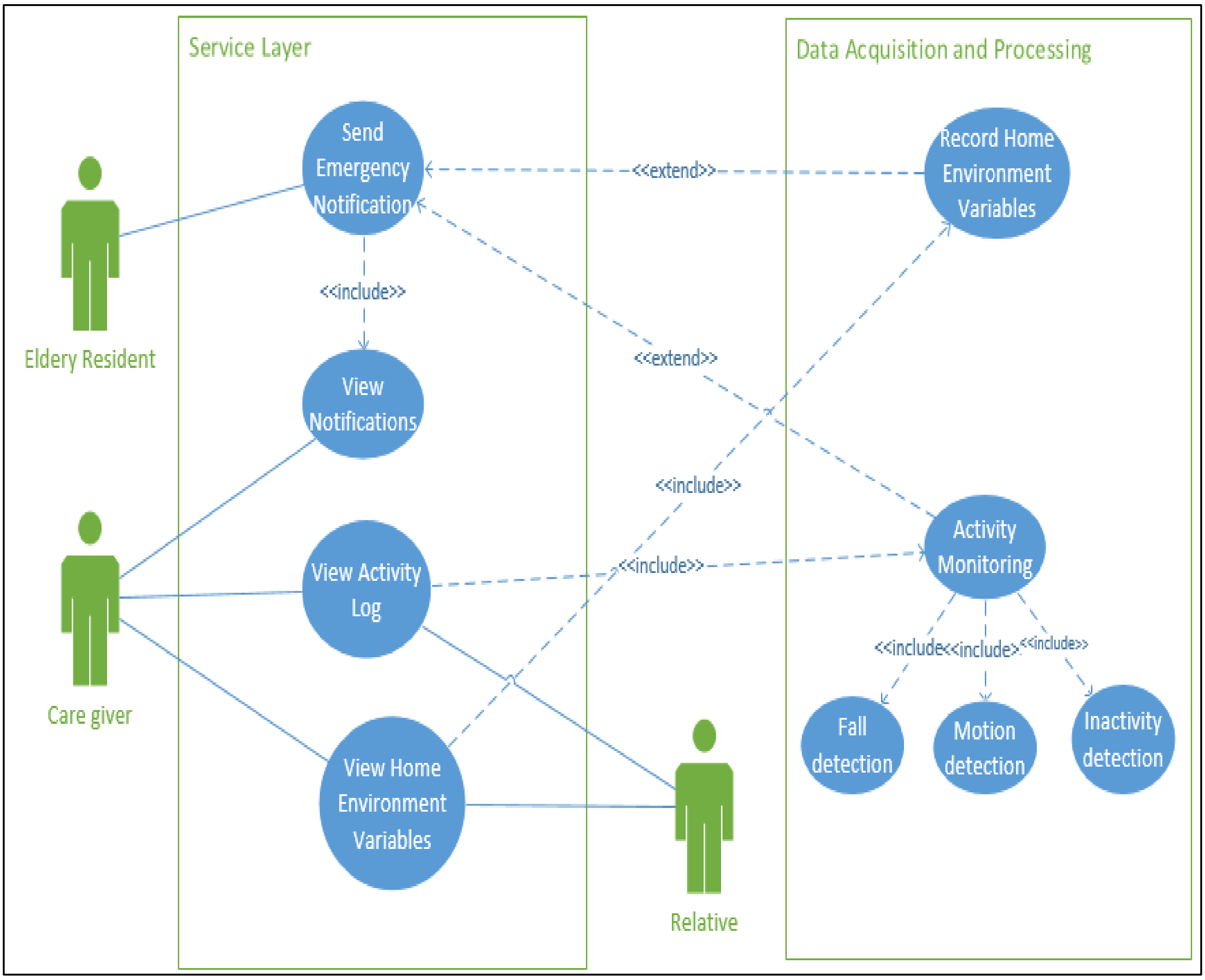


Figure 3-2 Functional requirements for supporting safety and risk monitoring for the elderly

The three actors considered for the purposes of this research are the elderly resident, a caregiver and a family member. Home environmental sensors collect environmental variables like temperature, lighting, motion in the home and humidity. If the environmental variables exceed the set threshold an emergency notification can be sent to the caregivers and family members. The family members/relatives should be able to view notifications, and the current state and history of the home environment variables.

User tracking in this context encompasses fall detection, inactivity detection and motion sensors. If a fall occurs, the system should automatically send an SMS to the relatives or caregivers. If there is inactivity in the home for a certain duration, an alarm should be sent to relatives or caregiver. Relatives and caregivers should be able to view the activity log of the elderly person at any point in time.

The non-functional requirements include the following:

- Security
- Cross platform, mobile and web interfaces
- Reliability
- Extensibility

Section 3-2 discusses the components that can be included in the home to make it a SHE that can address the identified functional requirements.

3.2 Components of a Smart Home Environment

Sensors have become ubiquitous in our everyday lives; they can be installed in the home, embedded in smart phones or worn on the body. A collection of ambient sensors can be installed in the home resulting in a SHE. Sensor data forms a time series dataset in which each reading has a timestamp. The time series data can be useful in detecting and analysing changes associated with health related events, such as falls (Sprint, Cook, Fritz, & Schmitter-Edgecombe, 2016).

There are two broad categories of Smart Home sensors, namely environmental sensors and wearable sensors, that can be used to monitor the elderly (Cook & Krishnan, 2014). Environmental sensors are installed in the home and wearable sensors are worn by the resident. The smart sensors installed in the home can monitor values obtained from human motion, location, lighting, doors, windows and temperature in the home.

SHEs are placed at the intersection of computer networks, embedded systems and applied computing. Badica et al. (2013) identified a SHE as a heterogeneous environment comprising the following components:

i. **Home automation system**.

The home automation system contains a set of smart objects. Smart objects consist of a hardware infrastructure and a software layer that provides the smart capabilities of the object (Cicirelli et al., 2016). Smart objects can be defined as autonomous digital objects that augment sensing, processing and network capabilities to satisfy the needs of the user (Foko, Dlodlo, & Montsi, 2013). Smart objects execute application logic that enables them to make sense of the immediate environment and exchange information with human users and/or with other devices.

ii. Control system.

The control system combines user's effort with software-based control to get information from sensors and send instructions to actuators in order to achieve one or more high-level goals.

iii. Home automation network.

The home automation network consists of physical technology and communication protocols combined to ensure the home automation system and control system can exchange status and control information.

The above mentioned components can be combined together to achieve a robust SHE architecture that can meet the needs of the elderly.

3.2.1 Smart Home Environment Architecture

Tazari et al. *(2012)* defined a consolidated OSGi-based Service Oriented Architecture reference model for ambient assisted living systems, called UniversAAL. Open Services Gateway initiative (OSGi) is a popular SHE standard that will be discussed in Section 3.2.1.1. The abbreviation UniversAAL stands for Universal open platform and reference specification for Ambient Assisted Living. Figure 3-3 on the next page illustrates the higher levels of any ambient assisted living system.

An Ambient Assisted Living (AAL) space can be any place or environment that can be occupied by one or more occupants. For example, the home environment or the supermarket can be transformed into an AAL space. The space is embedded with networked artefacts, which use a specific (AAL) platform that implements an OSGi based AAL reference architecture.

For the purposes of this research, a SHE is considered to be an AAL space with all the components required to support the requirements for the elderly that were identified earlier.

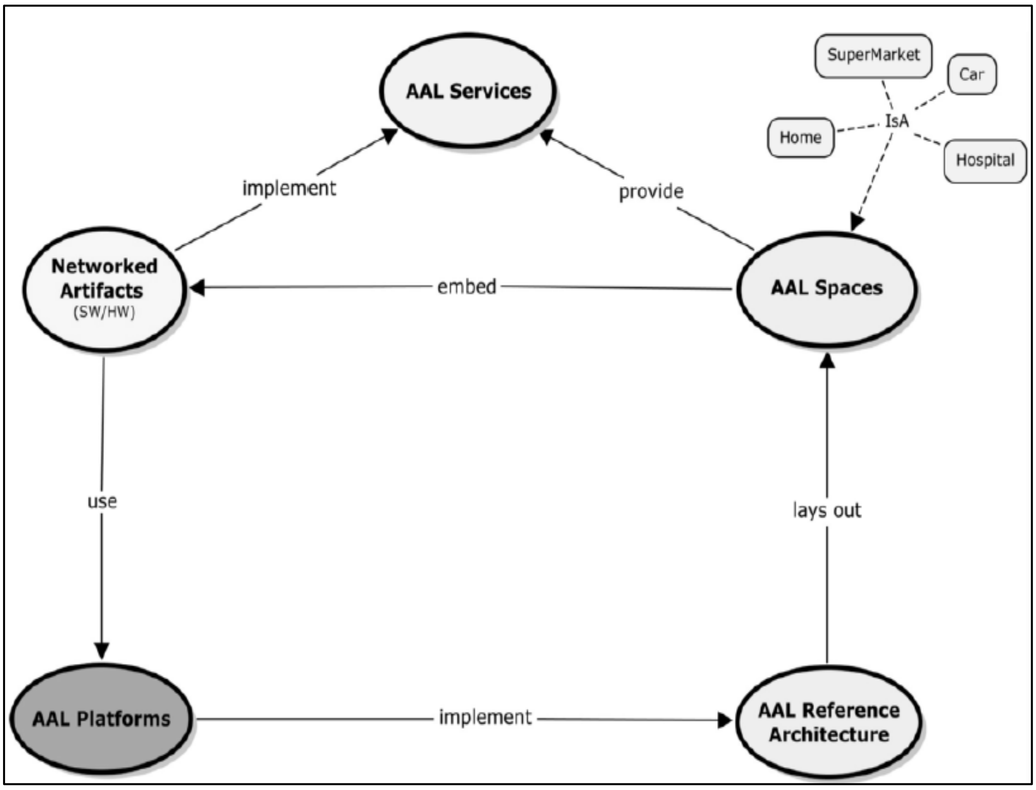


Figure 3-3 The universAAL reference model root concept map (Tazari, Furfari, & Fides, 2012)

The networked artefacts can implement a number of AAL services that suit the needs of the occupant. The AAL reference architecture abstracts the finer details, which make up the various platforms that implement it. Figure 3-4 on the next page illustrates a SHE as an AAL space.

A SHE is centred on a person living in the environment and provides for personalisation, context-awareness, reactivity and proactivity. These features are enhanced by the ability to gather data from networked artefacts and perform data processing and deduce the appropriate actions. To the occupant, it will look like the

AAL space is providing the desired AAL services and they are not aware of how the components are interlinked.

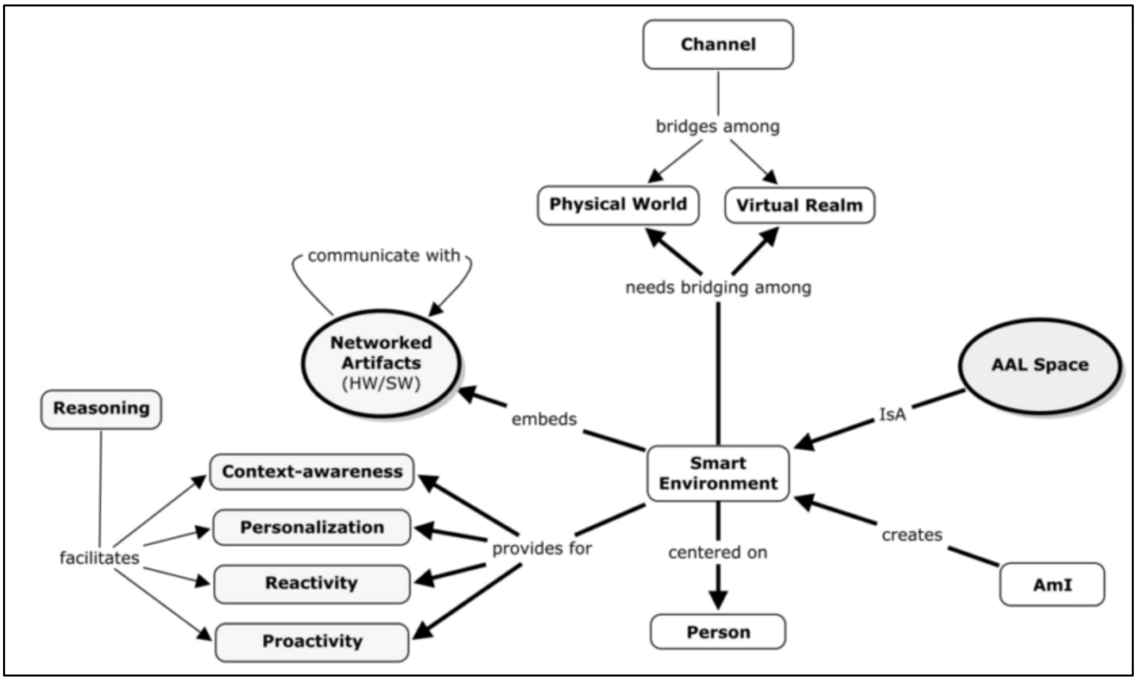


Figure 3-4 A Smart Environment as an AAL

Figure 3-5 shows assistance as the main AAL service. The assistance can be remote, delivered by accessing it via an interface, or local, relying only on resources from within the home environment. Caregivers also play a part in offering assistance to the occupant. The caregivers can be formal or informal and they can interact with the occupant either providing assistance or general social interactions. Social integration is also a key necessity especially if the elderly person is living alone. Family, friends, neighbours or colleagues comprise a vital component of social integration for the elderly living independently.

The advantage of such a reference model is that it prioritizes the separation of concerns, and hence the maintainability, extensibility or scalability will not pose serious problems. The modular nature allows for developers to work on each component independently without worrying about how it will interface with the next component, as this is already defined as part of the standard.

Figure 3-6 on the next page diagram illustrates the overall architecture of activity monitoring systems in a typical SHE. The architecture comprises components of the AAL space, AAL platform and the AAL services.

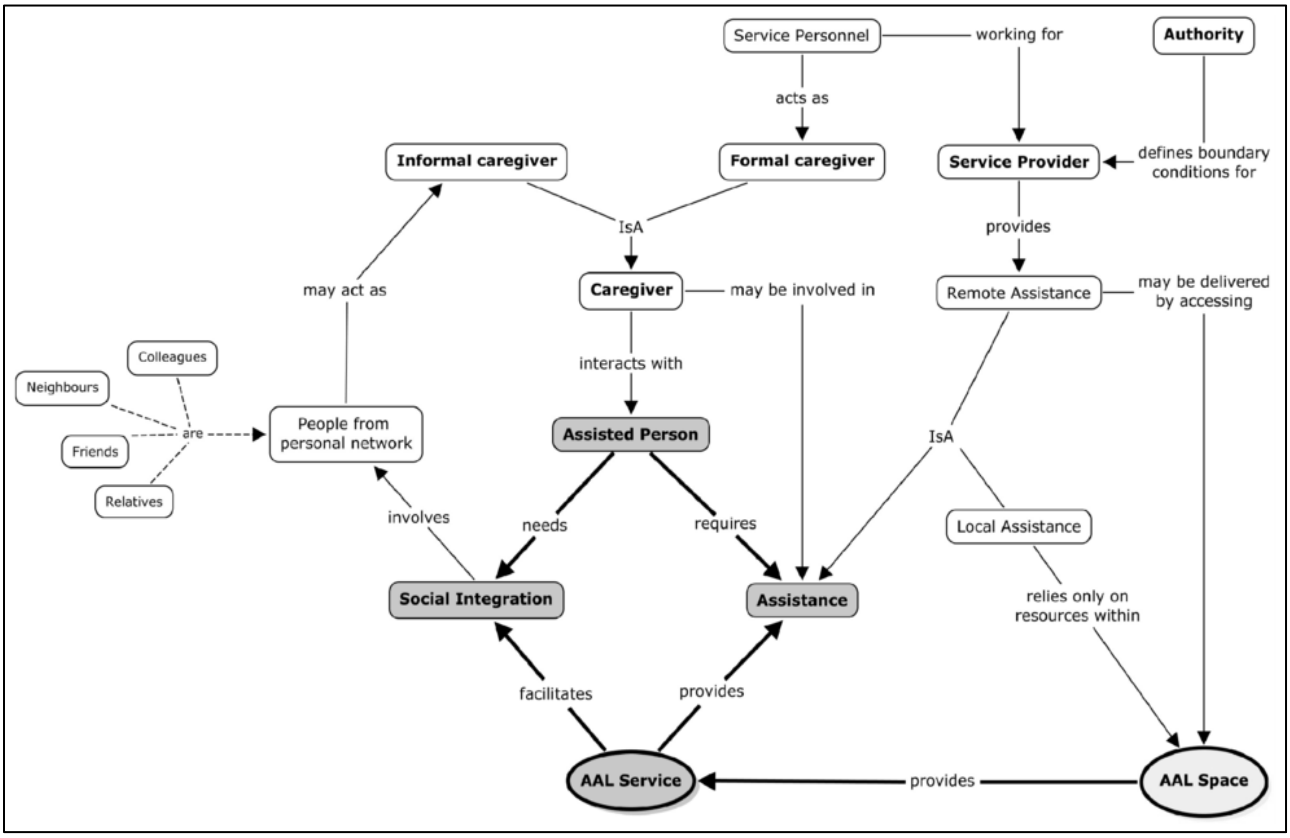


Figure 3-5 Elderly Care AAL services (Tazari et al., 2012)

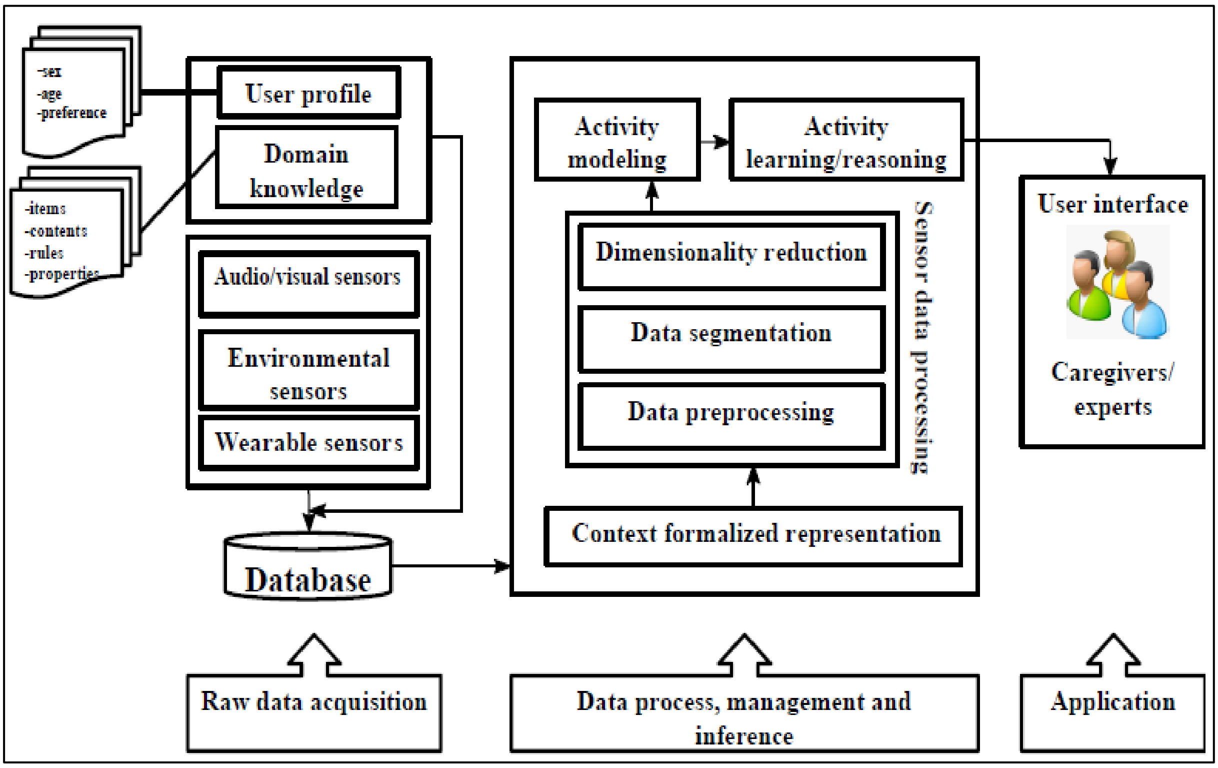


Figure 3-6 Overall architecture of activity monitoring systems (Ni et al., 2015)

The architecture in Figure 3-6 comprises three layers: the raw data acquisition, data processing and management, and an application layer, which allows caregivers and experts to intervene where necessary. Data acquisition is performed by sensors worn or placed in the home environment. The data is stored in a repository together with the profile of the occupant. The data processing consists of two primary components, activity modelling and activity learning/reasoning. The user profile is very important in establishing the boundaries of the reasoning of the system. A user interface displays the processed activity data to the caregivers who can then intervene when necessary.

The architecture of a SHE is strongly influenced by the computational capabilities of its components. Badica et al. (2013) identified the two main architectural styles of a SHE:

i. *Centralized*

   The centralized architecture is made up of a computer system that is responsible for data acquisition from sensors, as well as implementation of control algorithms and sending instructions to actuators. The centralized computer can be referred to as the Home Gateway (Dickerson, Usa, Emi, & Stankovic, 2015). In addition to the control function, the Home Gateway is responsible for interfacing the SHE with the outside world via the Internet.

ii. *Distributed*

   In a distributed architecture, the control system is implemented as a distributed computing system. The distributed architecture benefits from the computational resources of smart objects to embed software components into the nodes of the home automation network (Badica, Brezovan, & Badica, 2013).

SHEs are evolving into distributed and open systems incorporating heterogeneous and more powerful smart objects. Middleware is used to integrate and manage the interoperability of the heterogeneous smart devices. The middleware interfaces with device drivers, and uses standard interfaces and protocols to manage interoperability.

3.2.2 Smart Home Environment Middleware

The middleware of a SHE can be proprietary or based on open standards. The middleware is essentially an operating system that coordinates the various components of a SHE. The standards are useful to interface the SHE with the outside world. Badica, Brezovan and Badica (2013) identified the following open standards for SHE middleware:

i. *The Open Services Gateway initiative (OSGi)*

   The OSGi is a Java framework that facilitates developing and deploying modular software programs and libraries. It is an open standard for service-oriented dynamic software that offers enhanced support for the installation/removal, update/replacement and start/stop of software components. Platforms based on the OSGi specification require a Java Virtual Machine (JVM) and they also require the use of a database system (Morais, 2015). Java is installed in billions of embedded devices and this makes OSGi a firm favourite as a standard for home automation.

ii. *The Foundation for Intelligent Physical Agents (FIPA)*

   FIPA specifications represent a collection of standards that promote interoperability of heterogeneous agents and the services they represent. The middleware provides support for component management and interaction protocols.

iii. *Web Standards*

   Web standards are a set of standards that includes Web services standards such as Representational State Transfer (Rest). The standards allow for the transfer of data over the internet. HTML interfaces can be built to consume data collected from the smart environment.

Table 3-1 shows the Smart Home Operating systems that were considered for the purposes of this research. The operating systems were reviewed according to the technical specifications of the platform, data persistence, technical support and extensibility.

Table 3-1 Smart Home Operating Systems

OS	Language and Technical details	Data Persistence	Platform	Support	Extensibility
openHAB	Java Pluggable OSGi (dynamic component model) Native UIs for iOS and Android-Single unified interface Notion of an Item (data-centric functional atomic block) Vendor Neutral	RDBMS NoSQL IoT Cloud services Log files	Any machine capable of running a JVM (Linux, Mac, Windows) Java 1.7 Raspberry Pi BeagleBone Black	Open source-up to date downloads Community still growing	Easily Extensible (Uses “binding to integrate with other systems) Provides APIs for integrating with other systems
Lab of Things-HomeOS	HomeOS is the core client-side component Requires Windows 7, 8 and 10. Microsoft .NET Framework 4.5. Visual Studio	Windows Azure	Raspberry Pi 3 with Windows 10 Desktop PC	Open Source Microsoft research IP Cameras Z-Wave sensors Kinect Sensor	
Eclipse Smart home	Offers modularity for OSGi for Java Applications Parent to openHAB. Strong focus to heterogeneous environments REST APIs for communication Eclipse IDE	RDMS	Raspberry Pi BeagleBone Black Intel Edison	Large Developer community	Easily extensible
OpenMTC	A prototype implementation of an M2M middleware aiming to provide a standard compliant platform for M2M services. Supports local access technologies like ZigBee, FS20 and Bluetooth.	Cloud based Services	Android Arduino Raspberry Pi		

The platform supported is a key aspect because it also determines the cost involved in developing the solution. A solution that runs on a Raspberry Pi or Arduino is cheaper than a solution that runs on a desktop computer. Furthermore, small board computers are small in size and can be fitted in a hidden location in the home so that the occupant is not aware that he is being monitored. The platform selected also affects the programming language used and the various libraries needed. The technical support is also tightly coupled with the platform. It is advantageous to select an open source platform that has free and readily available support, as compared to vendor based paid services.

Data persistence was also considered as it has direct implications on the cost and scalability of the system. A solution that uses Windows Azure to store data is expensive in the long run compared to a solution that runs from a local server or other cheaper IoT cloud services. The support of relational databases is important for storing and querying the information collected from the home environment. Historical data can also be collected in these databases and can be used for data mining purposes.

The extensibility describes how easily the operating systems can integrate additional components and computational layers in future. It is a key component since SHEs continue to evolve.

OpenHAB is the best middleware of choice for a Smart Home Operating System. It is fully open source and uses a modular approach in setting up a network of Smart Objects. The middleware or operating system can coordinate all the heterogeneous smart sensors in the IoT solution. The IoT is an infrastructure that enables objects to see, hear, think and perform jobs by having them communicate with each other by sharing information and coordinating decisions (Al-Fuqaha, Guizani, Mohammadi, Aledhari, & Ayyash, 2015). Section 3.2.3 discusses the vital components of any IoT solution.

3.2.3 IoT Elements

The IoT is a manageable set of convergent technologies comprising sensing, identification, communication, networking and informatics devices and systems (Rahmani et al., 2015). The IoT elements are illustrated in Figure 3-7.

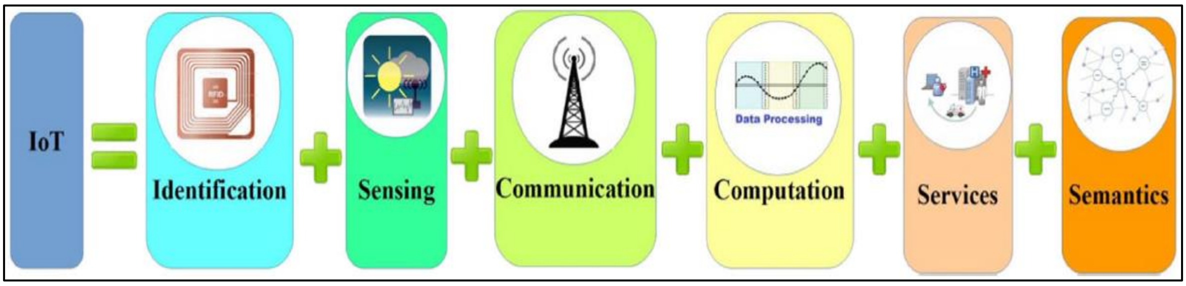


Figure 3-7 Components of an IoT solution (Al-Fuqaha et al., 2015).

The first element that is important in any IoT network is to identify and address each IoT object or service. Identification consists of an object's id and the object's network address, and hence it uniquely identifies each object in a network (Al-Fuqaha et al., 2015). Typical addressing methods for IoT include IPv4 and IPv6.

Sensing involves the gathering of data from various objects within an IoT network. The data can be stored in a data warehouse or in the cloud. Data analysis can be performed on the collected data and appropriate decisions made. Examples of IoT sensors include smart sensors, actuators and wearable devices. The sensors within IoT networks are usually connected to a hub or gateway that will be responsible for channelling the data to appropriate data processing components. The sensors are typically integrated with Single Board Computers (SBCs) like Raspberry Pi and Arduino, which often act as the gateway to a central management portal that provides data to users (Zhu et al., 2015).

The communication layer consists of connecting heterogeneous objects so that they are able to share their data or smart services. Communication protocols continuously evolve to address power consumption, speed, reliability and effective range. Common examples of communication protocols used for the IoT include Wi-Fi, Z-Wave, IEEE 802.15.4, Bluetooth, ZigBee, LTE-Advanced, Radio Frequency Identification (RFID) and Near Field Communication (NFC). Wi-Fi uses radio waves to transmit data within a range of 100m. Bluetooth uses short-wavelength radio to exchange data between devices over short distances. The IEEE 802.15.4 targets low-power wireless networks with the aim of achieving reliable and scalable communication (Al-Fuqaha et al., 2015). Long-Term Evolution (LTE) is a wireless communication protocol for high speed data transfers.

Computation is achieved by processing units and software applications that act as the "brain" of the IoT network. Real-Time Operating Systems (RTOS) exist that can aid in real-time computation and decision making. Cloud computing also forms the back bone of computation as a storage service and also offers more computational power to clients. The processed data can be used to support various services that address our day to day needs. IoT services in the home enable us to monitor and operate home appliances conveniently.

Semantics involves extracting knowledge from the data collected. Data mining techniques are often used to identify patterns in data. The knowledge extracted is used to inform decisions that can be taken by devices or users of the smart technology.

A possible arrangement of an IoT solution that can support risk and safety monitoring for the elderly is shown in Figure 3-8. The first layer involves automated technologies for data acquisition and processing.

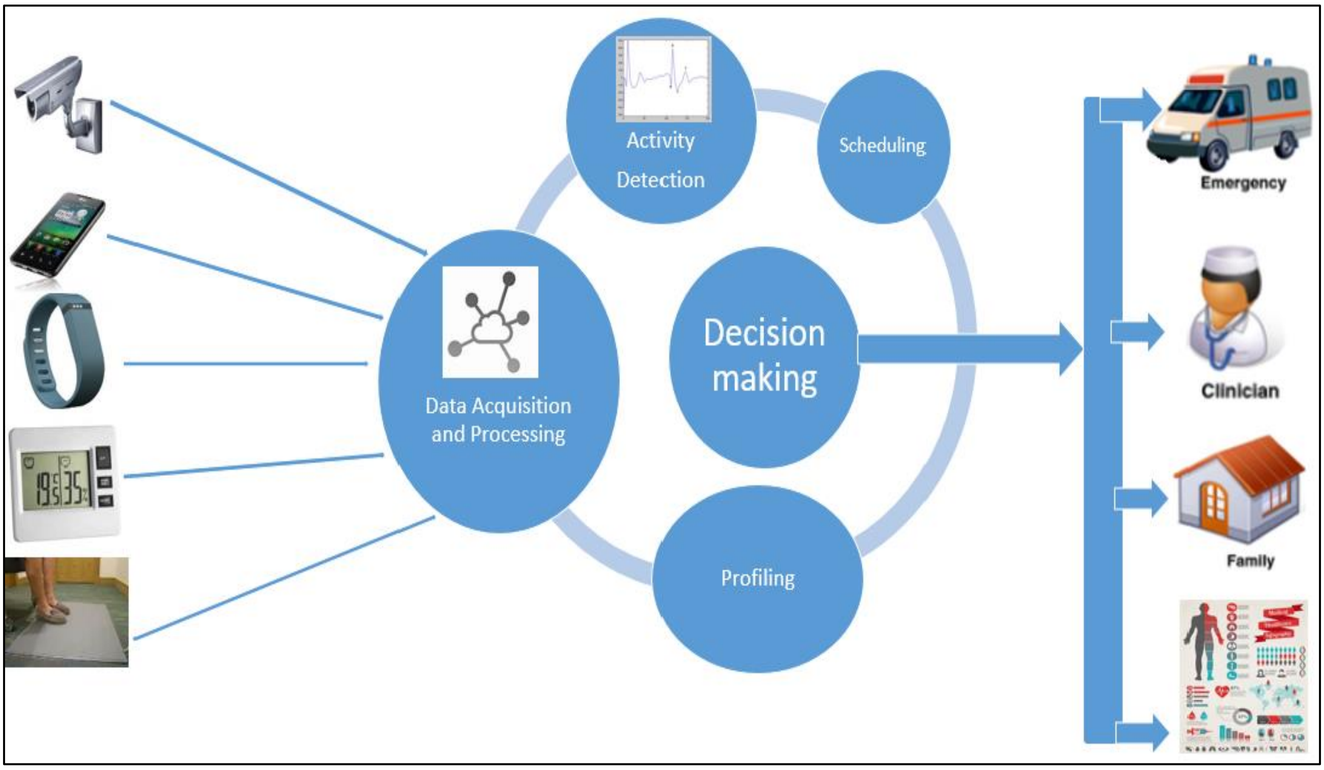


Figure 3-8 Example of components that can make up a SHE - Adapted (Costa, Castillo, Novais, Fernandez-Caballero, & Simoes, 2012)

The data acquisition layer comprises a variety of mobile sensors carried by the user and the static sensors installed in the home. Examples of home automation technologies shown in Figure 3-8 are cameras, pressure sensors, temperature sensor and wearable devices. Motion sensors are readily accepted for use in the home but cameras have faced resistance in their adoption due to privacy concerns (Cook & Krishnan, 2014).

The raw data acquired is processed by a control system, which is the second layer in Figure 3-8 Layer 2 includes data processing, activity monitoring algorithms and decision making algorithms. The detected activity can determine whether emergency services or caregivers can be contacted or whether to remind the resident of specific events.

A personal agenda can be used as a cognitive assistant to remind the elderly person of important events/activities. Caregivers and medical practitioners can remotely profile the health status of their elderly patients and can intervene if abnormal patterns are observed. A home automation network will connect the devices in the SHE and the caregivers or emergency services.

Dickerson *et al.* proposed the Empath2 architecture as a flexible architecture that can apply to a variety of healthcare issues and resolve the issues of actual deployment. Empath2 consists of the typical IoT elements highlighted in Figure 3-9.

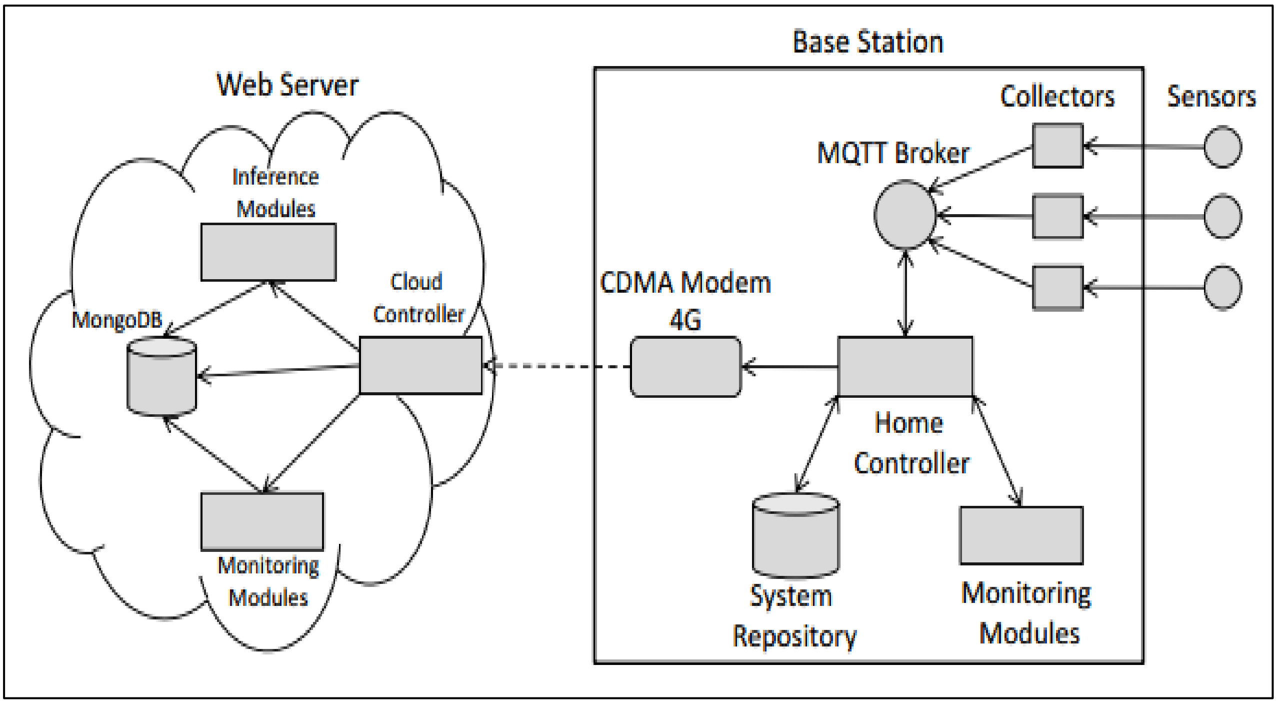


Figure 3-9 Home area network framework (Dickerson et al., 2015)

The basic architecture of Empath2 consists of the sensing layer, base controller and cloud based web and database server. The sensing layer consists of wireless sensors that generate continuous or event related data. The framework allows for various communication protocols. When a new sensor is added to the network, a new data collection class should be created to read the raw sensor data. The MQ Telemetry Transport (MQTT) broker is responsible for publishing the data collection class.

The base station consists of the home controller, monitoring modules, MQTT brokers and system repository. The home controller supports middleware that is responsible for simplifying the networking between components. The cloud layer consists of modules and controllers that enable the centralized management of data collected. The cloud layer facilitates remote monitoring and push notifications.

SHEs have several challenges, mainly arising from the architecture and standards used. Section 3.2.4 discusses some of the challenges that are associated with the components identified previously.

3.2.4 Smart Home Environment Challenges

A system architecture defines the distribution and relationship among the components, applications and gateways in the SHE (Hansen, 2014). If a system architecture is not carefully developed, problems will arise with integration, interoperability and scalability.

Interoperability refers to the ability of systems, applications and services to work together reliably in a predictable fashion (Perumal, Ramli, Leong, Mansor, & Samsudin, 2008). Figure 3-10 illustrates the interoperability tiers in a SHE.

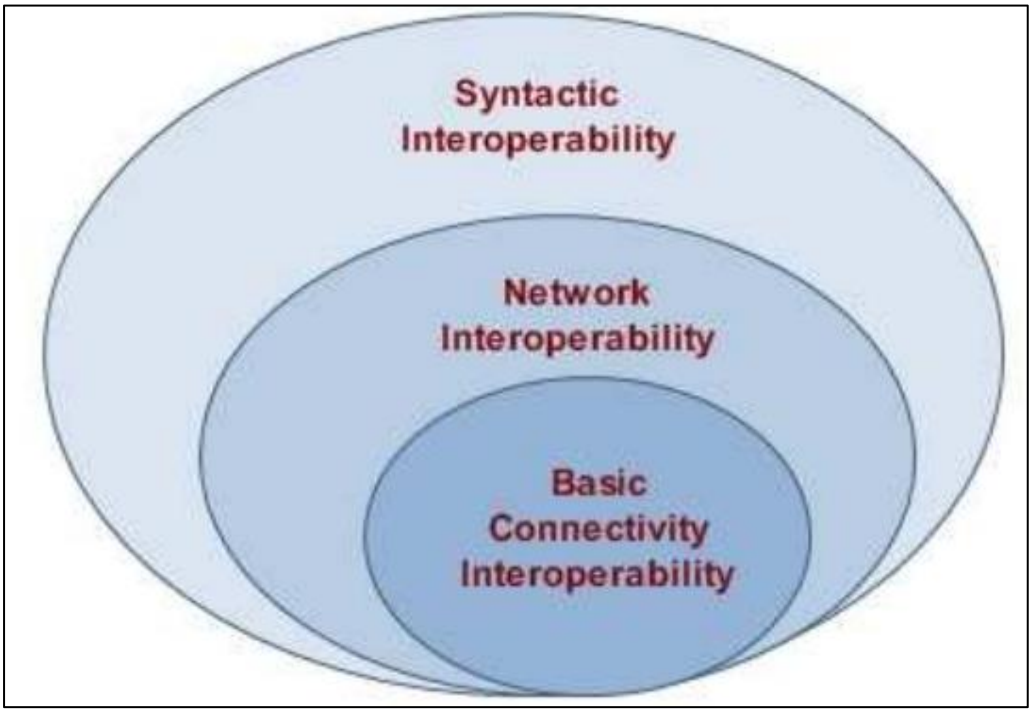


Figure 3-10 Interoperability tiers in SHEs (Perumal et al., 2008)

Basic connectivity is the first tier in Figure 3-10 that provides a means of data exchange between sensors, gateways and/or subsystems. There has to be an agreement regarding the data transmission medium, data encoding and rules of accessing the data. Common data transmission standards include Wi-Fi, ZigBee, and Z-Wave. Network interoperability enables message exchange across heterogeneous networks in the home environment. Examples of network interoperability standards include the Transport Control Protocol (TCP), File Transfer Protocol (FTP) and Internet Protocol (IPv6).

The final tier is the syntactic interoperability, which refers to the agreement of rules that governs the format and structure for encoding information between smart home components. Syntactic interoperability ensures smooth message transition between sub-systems in a SHE (Perumal et al., 2008).

Security and privacy are a cause of great concern when implementing a SHE that collects sensitive information about the home and the occupant. Normal video cameras do not protect the privacy of the occupant in a SHE. It will be more difficult to convince users to adopt a technology if their privacy is not preserved. Security is also a big challenge especially if the system is going to be online as it will be prone to a variety of cyber-attacks. Data should be securely transmitted to the cloud for access by family and caregivers of the occupant. The communication protocols used must be robust and secure from attack when the system is deployed online. Multiple 3DES and AES encryption algorithms can be applied to the transmitted data (Hansen, 2014).

Dependability is governed by the accuracy and availability of the designed SHE. Users should be able to rely on the system to give them accurate information pertaining to the status of the home environment. The SHE should always be available with no unannounced downtime.

Cost is a critical factor as people age, because they live on a fixed income. The SHE can only be adopted by the elderly if the costs are sustainable and not exorbitant. The chosen equipment has to be cheap and durable, and consume less power as that can result in an increase in costs.

Usability has to do with the effectiveness, efficiency and utility of the SHE. If the SHE does not satisfy the three aspects of usability, then the adoption of the technology will be poor. Poor usability often results into a poor user experience. The following sections discuss the aspects of the functional requirements identified in Chapter 2, which are illustrated in Figure 3-2.

3.3 Home Environment Monitoring

The elderly are likely to forget basic things like switching off lights or switching off cylinder gas causing LPG gas leakage, or they may forget to close doors at night resulting in financial loss (He, 2016). A simple solution would be to install a number of sensors to monitor the environment inside the home. Too many sensors can become obtrusive, negatively affecting the user acceptance.

A SHE needs various types of sensors to achieve remote monitoring of the living environment of the elderly, such as temperature, humidity, noise, lighting and motion sensors (He, 2016). The collected data can be analysed and displayed to the elderly or their family members wherever they are.

The diagram in Figure 3-11 shows a generic layout of a software system of sensor nodes for home environment monitoring.

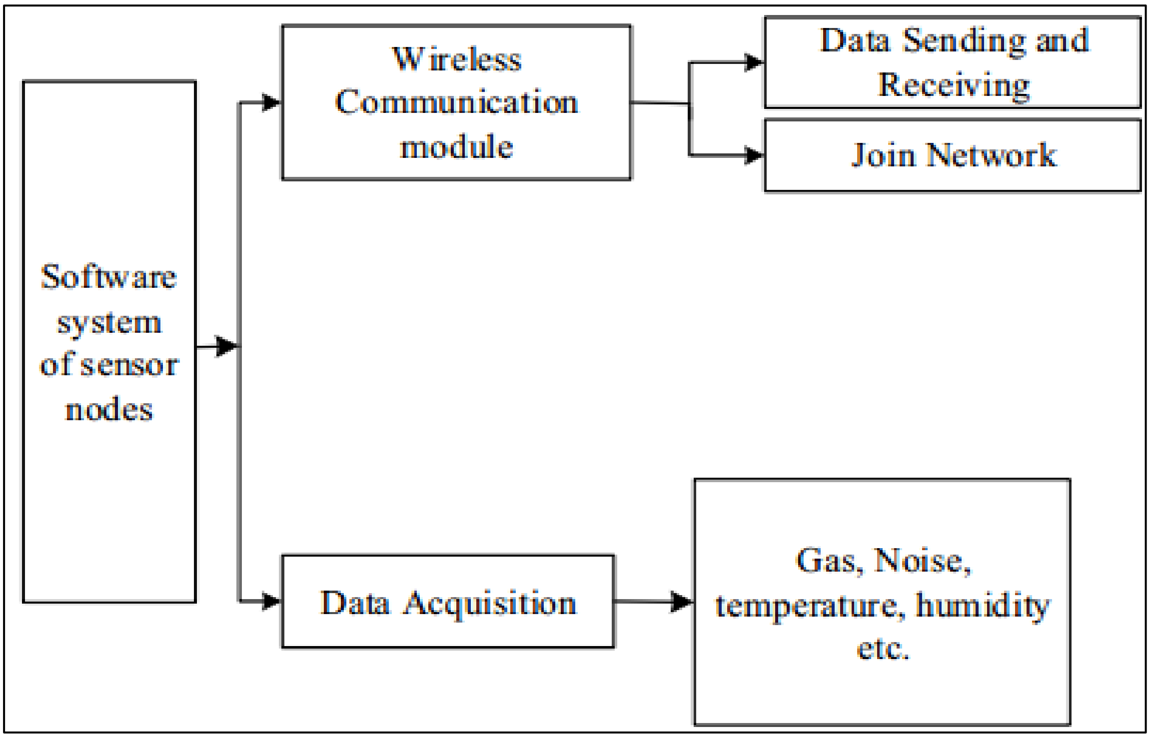


Figure 3-11 Software system of sensor nodes (He, 2016)

The wireless communication module is responsible for connecting all the sensors. Each sensor reads data and the data is transmitted to the data acquisition module via the wireless communication module. Data analytics can be performed on the collected data and any anomalies can be detected and emergency notifications can be sent.

The use of embedded and wireless sensors to construct an IoT in the home is gaining popularity in supporting remote sensing and control (Guo, Wang, & Yu, 2016). The transmission of data between the sensors and the computational module can be supported by Z-Wave or ZigBee technologies. Z-Wave and ZigBee are becoming popular for short range indoor communication. They work well for applications where lower data rate, low cost and longer battery life are key requirements.

Home environment variables can be useful in determining activity in the home. The analysis of home environment variables against time can yield useful information pertaining to risk monitoring in the home of the elderly. Section 3.4 discusses the components of activity monitoring.

3.4 Activity Monitoring

Activity monitoring is useful to implement and detects dangerous situations like unconsciousness, which may occur in home environments. Figure 3-12 illustrates a conceptual description of an activity.

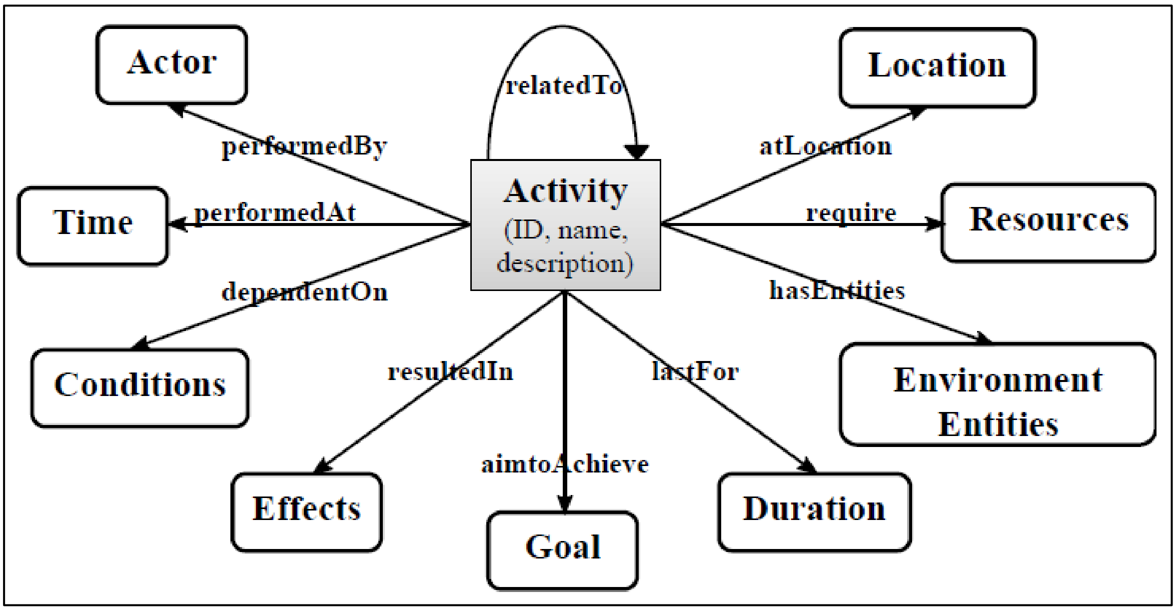


Figure 3-12 Conceptual description of an activity (Ni et al., 2015)

An activity can be defined by a number of properties, as shown in Figure 3-12. A unique identifier can be used to identify an activity. An activity occurs in a specific location under certain conditions for a certain duration starting at a specific time. An actor performs an activity and the activity will have specific environmental entities. In some cases, an activity requires resources depending on the nature of activity. This breakdown of an event makes data processing much easier. Querying of the activity information becomes easier and the activity can be easily categorised.

Cicirelli et al. (2016) developed a Smart Home architecture for activity monitoring, called Cloud-assisted Agent-based Smart Home Environment (CASE). Figure 3-13 illustrates the CASE architecture.

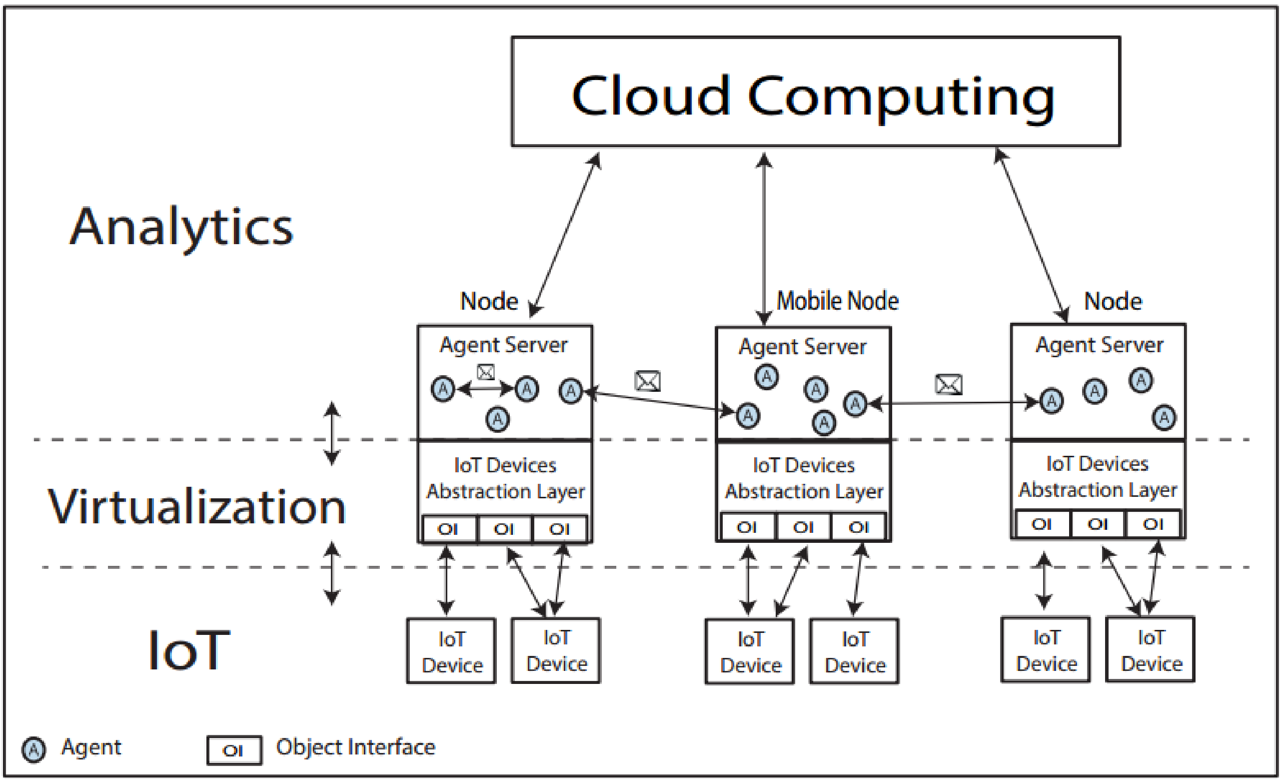


Figure 3-13 CASE architecture (Cicirelli et al., 2016)

The CASE architecture is suitable for the design and implementation of complex solutions where human activities need to be determined from raw sensor data. The CASE architecture combines both home environment data and mobile sensors to discover and analyse complex activities.

The IoT layer consists of the sensors, actuators or any other complex devices, which are installed in the home environment or carried by the elderly. The virtualization layer abstracts the sensors and actuators from the upper layers by supplying a uniform interface to heterogeneous IoT devices. The virtualization layer handles all the low level issues, such as connectivity, reliability and resilience (Cicirelli et al., 2016). The analytics layer employs complex algorithms to determine high-level activities in the home. The algorithms can use data mining and other artificial intelligence optimisation techniques.

The computing nodes that can be used in the CASE architecture are either fixed or mobile. Examples of single board computers that can be used are Raspberry Pi or Arduino. Single board computers have low power consumption; they are relatively cheap and have small dimensions. Smart phones can be used as mobile computational nodes.

The four main tasks of activity monitoring in the home are data acquisition, feature extraction, activity discovery and activity recognition, as illustrated in Figure 3-14.

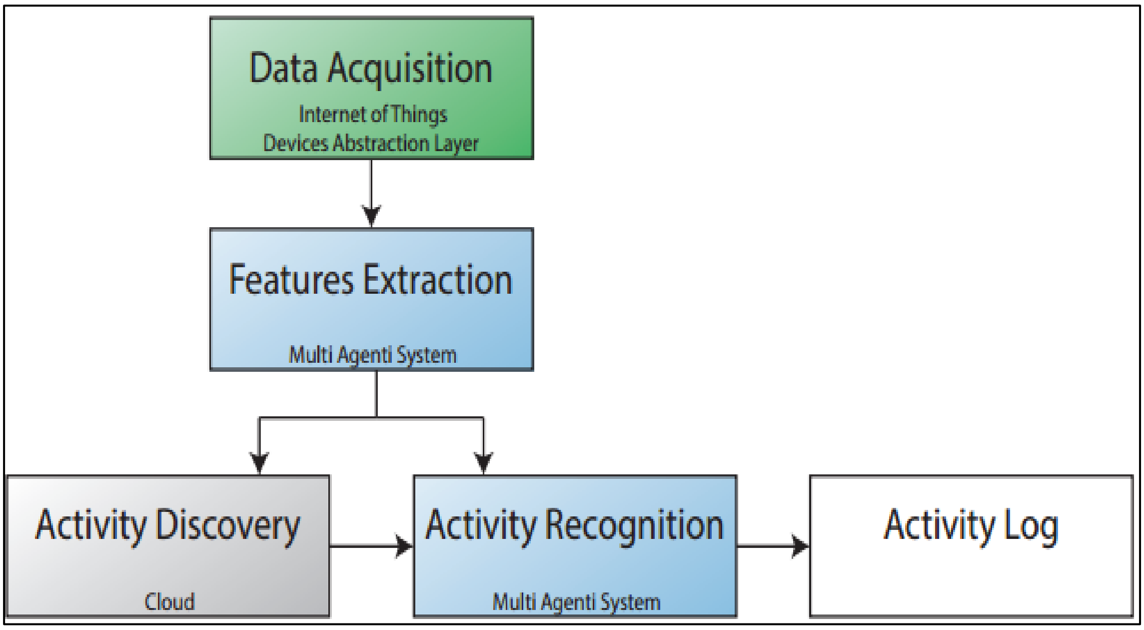


Figure 3-14 Activity monitoring tasks flow (Cicirelli et al., 2016)

The data acquisition consists of collecting the sensor data from the home environment, for example motion, lighting and temperature. Feature extraction is focused on filtering the acquired data in order to obtain relevant information, which can be rearranged before being passed to activity discovery or activity recognition (Cicirelli et al., 2016).

Activity discovery uses identified features to discover previously unknown activities. A typical activity discovery approach involves generating occupancy episodes from the environmental sensor data and detecting the frequent occupancy episodes, which can be clustered to represent a particular activity. The Apriori algorithm is used for identifying occupancy episodes for each room and each occupancy episode consists of the start time, duration and sensors used (Cicirelli et al., 2016).Table 3-2 shows the environmental sensor usage in the CASE SHE.

Table 3-2 Environmental Sensor usage in the CASE SHE - adapted (Cicirelli et al., 2016)

Detection Type	Sensors
Presence/Activity	Passive Infrared, Active Infrared, Ultrasonic, Pressure, Smart Tiles, Camera, Microphone, Microwave Occupancy Detector
Identification	Camera, RFID, Microphone, Active Infrared
Comfort/Environmental Measures	Luminosity, Temperature, Humidity, Microphone, Gases Detector, Airflow
Power / Electricity	Smart Plug, Electricity Monitor Clip
Usage (thins or devices)	Magnetic Switch, Smart Plug, Pressure, Accelerometer
Emergency	Smoke, Liquid Presence, Glass Break, Temperature, Gases Detector

A case study was performed by Cicirelli et al, to determine the accuracy of activity detection for the CASE architecture. The activities monitored are shown in Table 3-3.

Table 3-3 Activities monitored for the case study (Cicirelli et al., 2016)

Activity	Involved Room	Involved Sensors
Sleeping in bed	Bedroom	IRMotion, Switch Contact
Bathing	Bathroom	IRMotion, Switch Contact
Personal Hygiene	Bathroom	IRMotion, Switch Contact
Taking Medicine	Bathroom	IRMotion, Switch Contact
Meal Preparation	Kitchen	IRMotion, Switch Contact
Eating	Living Room	IRMotion, Switch Contact
Leave Enter Home	Living Room	IRMotion, Switch Contact
Relaxing	Living Room	IRMotion, Switch Contact
Storage Room Used	Storage Room	IRMotion
Bed To Toilet	Bedroom, Bathroom	IRMotion, Switch Contact
Body Posture Recognition	All rooms	3-axes Accelerometer

An alert agent uses inference rules to determine whether to send an alert or not. The inference module uses both environmental sensors and wearable sensors for posture detection. The knowledge base of an alert system consists of the inference rules shown in Table 3-4. A faint alert can be sent if a person was preparing a meal and all of sudden their body posture is deduced as lying down. Spending too much time standing at night can mean that the person has insomnia or is ill and therefore an alert is sent.

Table 3-4 Inference rules for the automated alert agent (Cicirelli et al., 2016)

Condition One	Condition Two	Alert
Meal Preparation	Body Posture Lying	Faint
Personal Hygiene	Body Posture Lying	Faint
Night(Time)	Too Long (Standing Still)	illness
Bathing	Too Long (Standing Still)	illness
Any Home Activity	Body Posture Falling Down	Accidental fall or faint

The CASE system can be implemented using low cost computing nodes and the wireless environmental sensors allow for unobtrusive data collection. Storing the elderly's information in the cloud can result in privacy concerns. The elderly can forget to wear wearable sensors used for posture detection, hence the system will not be able to achieve its purpose. The elderly might also consider the wearables to be obtrusive in their data collection. The battery life of wearables is also a cause of concern as the elderly might forget to charge their phones.

3.5 Fall detection

The ability to detect falls when they occur is a major goal of smart homes, since falls are a leading cause of injury and death among senior adults (McKinley, 2014). Receiving help quickly after a fall reduces the risk of death by over 80% and the risk of hospitalization by 26% (Noury et al., 2007).

Two categories of fall detection methods were introduced in Chapter 2, namely computer vision and non-computer vision techniques.

3.5.1 Non-Computer Vision

Non-computer vision techniques incorporate the usual features of fall detection such as pressure, vibration, sound and infrared. Pressure sensors can be used but they may be costly if the area to be covered increases and they have a detection accuracy of less than 90% (Yang, Ren, & Zhang, 2016). The probability of false alarms is also high, because any heavy object can fall and the system will then detect a fall. There is also a direct relationship between accuracy and the distance where the fall occurred; accuracy will decline if the fall occurs 5m away (Yang et al., 2016).

Proximity sensors have also been implemented as a solution to fall detection (Delahoz & Labrador, 2014). A proximity sensor is attached to a walking aid device and a fall is detected by measuring sudden changes in the person's movements and the distance from the proximity sensor. The main disadvantage of this solution is the short range of proximity sensors.

Wearable sensors are frequently employed in fall detection. They are generally cheaper and smaller than external sensors. Accelerometers are the most common type of wearables implemented in fall detection systems. They can be worn on any part of the body and will derive all the necessary movement characteristics that can be used in fall detection. The main drawback with wearables is that they still need to be worn. The elderly can easily forget to wear the device, as identified in Chapter 2.

Computer Vision techniques, particularly the ones that use depth cameras, have an inherent ability to preserve the privacy of the person being monitored. Section 3.5.2 discusses computer vision techniques related to fall detection and inactivity monitoring.

3.5.2 Computer Vision

Computer vision techniques can be used at a lower level to track the current status of the occupant of a home. A fall typically occurs within a fraction of a second (0.45s to 0.85s) during which there is a noticeable change in posture and shape (Delahoz & Labrador, 2014). Since cameras can be used for monitoring falls, privacy becomes a key concern, yet it is important to detect falls. To preserve privacy, depth sensors are now being incorporated in various computer vision solutions. The Microsoft Kinect is a depth sensor of choice as it has gained popularity over the years.

A project called *fearless (*Fear Elimination as Resolution of Elderly's Substantial Sorrows) was dedicated to fall detection in the homes of the elderly (McKinley, 2014). The *fearless* system can work with multiple persons, and uses fuzzy logic to accurately determine whether the person is upright or lying down. The Microsoft Kinect and X-Box camera can be used to gather depth images in order to detect falls. Depth data does not show the person or environment in the depth images, hence the privacy of the elderly is not violated. The *fearless* system was evaluated for consistency and it was found to be 78.6% accurate for the 72 examples it was given (McKinley, 2014).

Figure 3-14 illustrates the difference between a depth buffer image and the actual footage when there is no depth buffer.

Figure 3-14 Depth buffer image and the corresponding RGB picture

The major disadvantage of the *fearless* system is that the background subtraction algorithm does not completely isolate the person object from the background in the captured video, hence object detection can be inaccurate. There is too much noise in the background. Furthermore, the *fearless* system does not cater for varying lighting requirements and occlusions. The *fearless* system only caters for fall detection and does not incorporate the other risk monitoring requirements identified for the elderly.

There is no automated emergency alert when a fall is detected, and the *fearless* system cannot run on low cost embedded systems.

A fall detection technique was implemented by Yang et al. (2016) that detects falls based on shape analysis of 3D depth images captured by the Kinect sensor. The flow chart in Figure 3-15 on the next page illustrates the proposed fall detection method.

Background subtraction and median filter are implemented to obtain the silhouette of a person. Moment functions are used to analyse the shape information and a coefficient of ellipses is used to determine the direction of the person. A disparity map is used to determine the floor plane estimation. A disparity map shows the apparent pixel difference between a set of images.

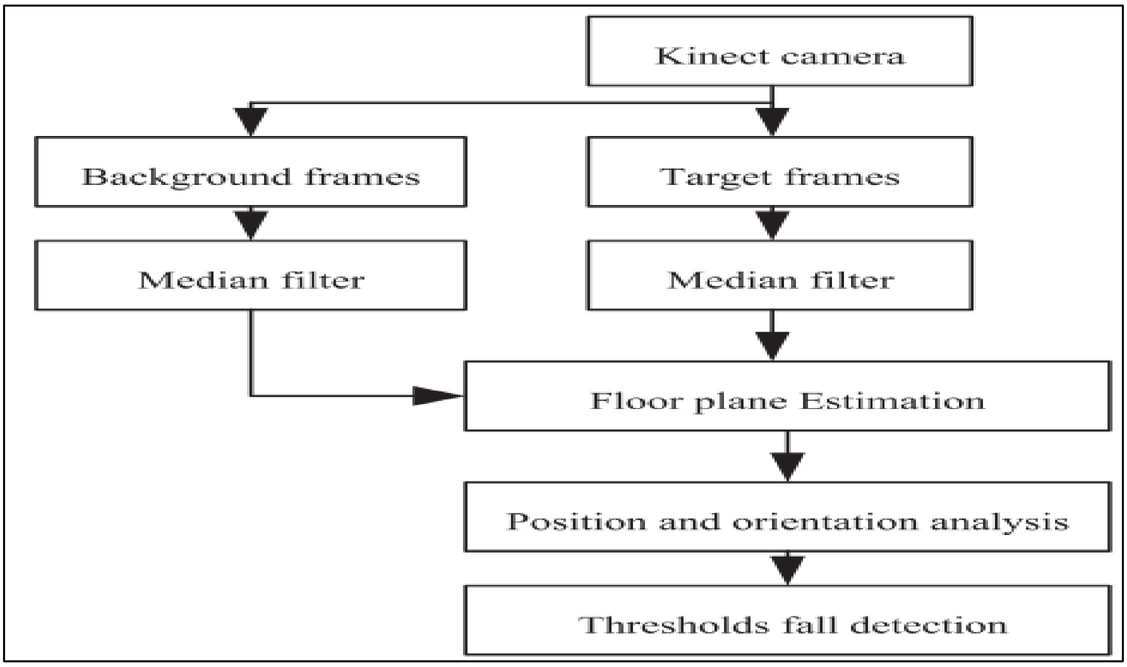


Figure 3-15 Flow chart for 3D depth analysis for fall detection (Yang et al., 2016)

The system calculates the centroids and also the angle between the human body and the floor. If the angle between the human body and the plane is lower than a set threshold, then a fall is detected. The system uses two Microsoft Kinect v1 sensors as shown in the diagram in Figure 3-16.

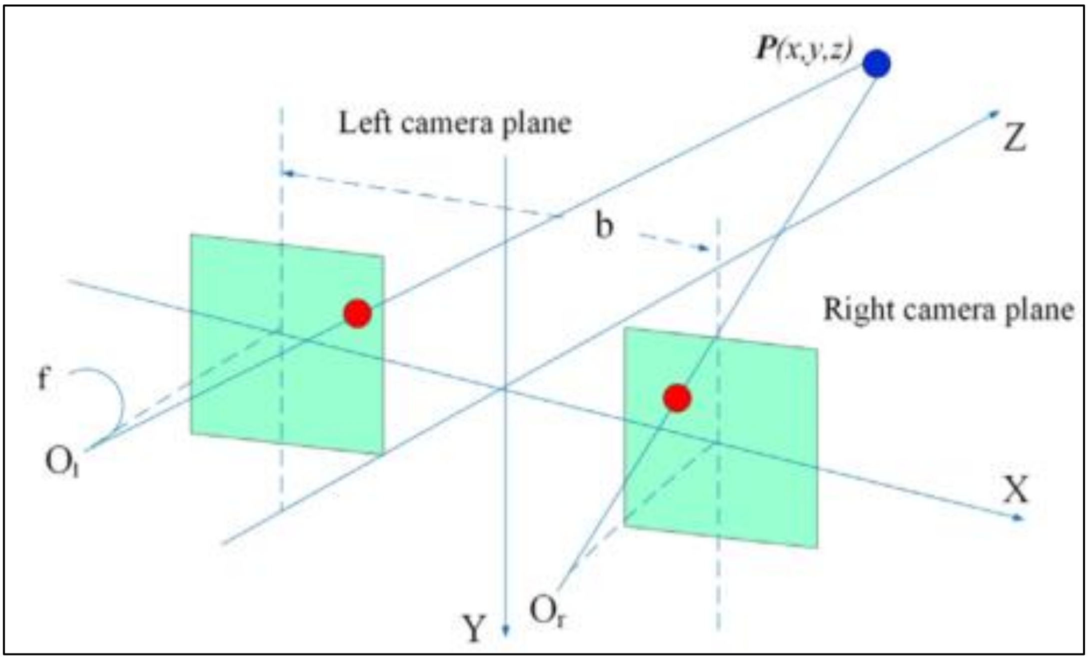


Figure 3-16 Imaging system model using Kinect (Yang et al., 2016)

The main disadvantage of the solution proposed by Yang et al. (2016) is that it is based on threshold detection rather than classification, which often results in false alarms. The system also does not contain an emergency notification module and using two Kinect sensors may prove costly as compared to using one. Having the Kinect mounted sideways can result in inaccuracies during floor plan estimation. The system does not cater for line of sight occlusions, and therefore no detailed analysis can be performed.

Yu et al. (2012) proposed a computer vision technique that uses a directed acyclic graph support vector machine (DAGSVM) to perform posture classification to determine fall detection. Support vector machines are based on statistical learning theory and have good generalisation performance compared to traditional classification methods (Rhuma, Yu, & Chambers, 2013). The proposed system is shown in Figure 3-17.

The incoming frames are obtained from a single USB camera mounted on the wall. A codebook background subtraction algorithm is applied to extract the human body foreground. The extracted silhouette is used to obtain information from the fitted ellipse and projection histogram, which are then used for classification purposes. The output from this operation is then fed into the DAGSVM, and classified as one of four postures: bend, lie, sit and stand.

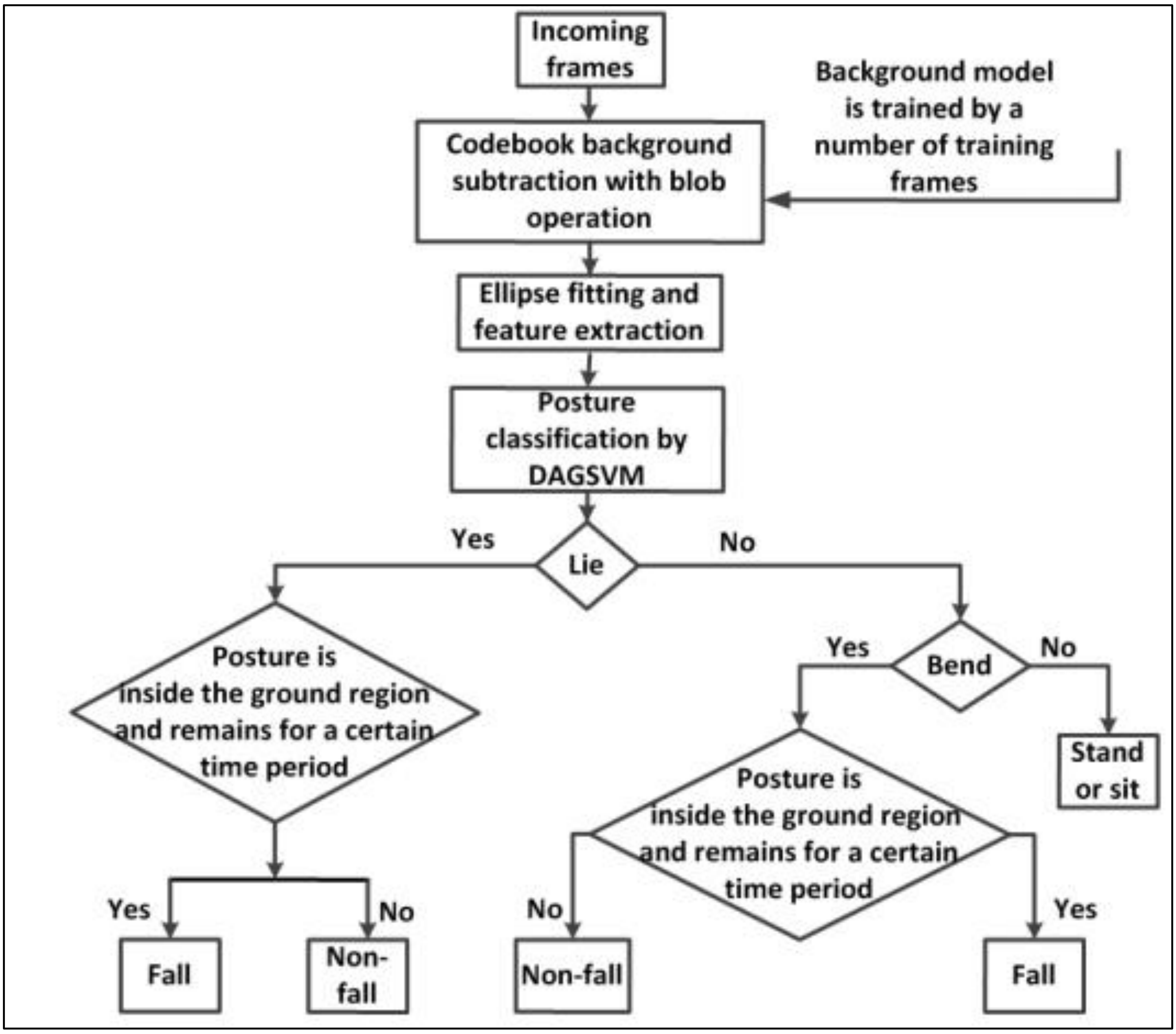


Figure 3-17 Fall detection posture classification using DAGSVM (Yu, Rhuma, Naqvi, Wang, & Chambers, 2012)

The posture classification information, together with the detected floor information, is then used to determine fall or non-fall activities. Fifteen trials were conducted and the system was found to have a fall detection accuracy of 97.08% in a simulated home environment (Yu et al., 2012).

The disadvantage of this system is that it uses an USB camera, which uses colour (RGB) information instead of depth, so further processing needs to be performed to obtain depth information, before processing can commence. The processing is done by a desktop computer, which is expensive compared to lower cost devices like the Raspberry Pi. Posture classification is inadequate when used alone, because at times someone will be lying down while watching television and the system can confuse that as a fall. The time factor can be implemented to aid in accurately determining a fall.

3.6 Conclusion

The elderly face risks which can be categorised as injury in the home, home environment hazards and inactivity. Current solutions are obtrusive, costly and fragmented and isolated in their data collection and purpose. A SHE can be designed to unobtrusively monitor the elderly living independently. A robust system architecture is a key component of a SHE. The system architecture should allow for the easy addition of smart items, be easy to maintain and the model should use less power and be small in size.

Environmental sensors can be installed in the home and automated alerts can be sent if certain thresholds are reached. Extreme temperatures can affect the health of an elderly person, hence it is important that temperature be continuously monitored. Motion detectors can be used to determine activity in the home, and if no activity is detected after a set period of time, automated alerts can be sent. Data collected from the home can be stored in the cloud or on a server accessible to people who can intervene when an emergency situation occurs.

Computer vision techniques for fall detection, using low cost depth cameras/sensors like the Kinect, can be implemented in a SHE to detect injury in the home resulting from falling. The advantage of using the depth cameras is that privacy can be preserved, whereas the normal video cameras show the person. Computer vision can also aid in unobtrusive activity detection in the home of the elderly. Adverse medical events can occur at any time in the home and emergency help is a key factor in ensuring that serious consequences are averted. The elderly can fall unconscious at any moment and an activity monitoring module can detect inactivity in the home and send notifications.

Chapter 4 outlines the design and implementation of the prototype SHE that supports the requirements identified in Chapters 2 and 3.

Chapter 4. Design and Implementation

Chapter 3 discussed the components and technologies that can be incorporated into a SHE to support safety and risk monitoring for the elderly. This chapter focuses on the design cycle of DSR, as shown in Figure 4-1.

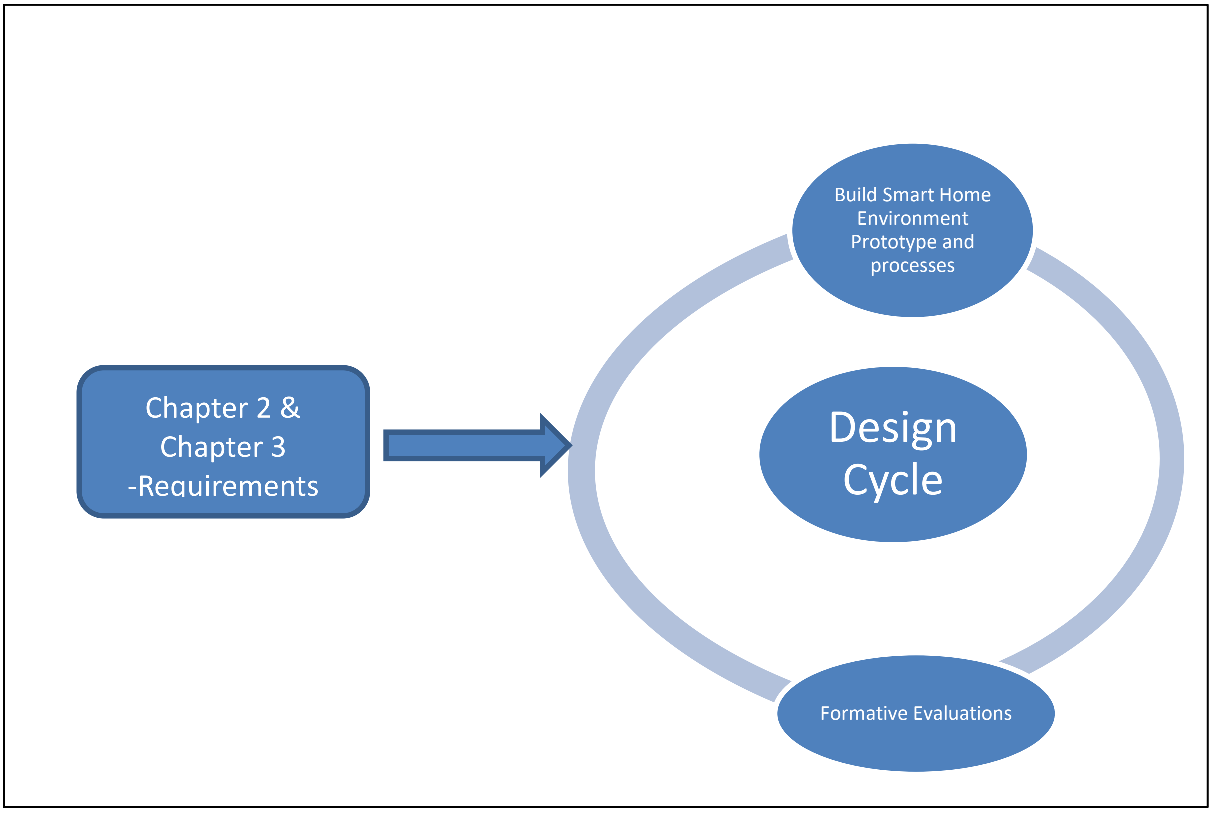


Figure 4-1 Adapted DSR design cycle

The SHE prototype was developed in iterations. Each iteration consisted of a use case and a subsequent formative evaluation. Formative evaluations provided continuous feedback during the development lifecycle of the prototype. The iterations were performed rigorously until the use case was completely addressed. The use cases for the prototype developed in this section were outlined in Figure 3-2 in Chapter 3.

The choice of the technologies for the purposes of this research was determined by the cost and unobtrusive nature of the equipment. Open source middleware and libraries were chosen over proprietary software to cut the costs of the solution. Open source communities have grown in the past few years and the multiple user input into the product development has led to robust libraries and middleware. Scalability and extensibility aspects were also considered in selecting the correct platform i.e. tools and libraries. This chapter will outline the technologies, algorithms and implementation of the SHE prototype to support the requirements identified in Chapter 2.

4.1 System Architecture

The system architecture defines the types of components and interaction patterns for the system to be developed (Badica, Brezovan, & Badica, 2013). The proposed system architecture of the SHE is illustrated in Figure 4-2.

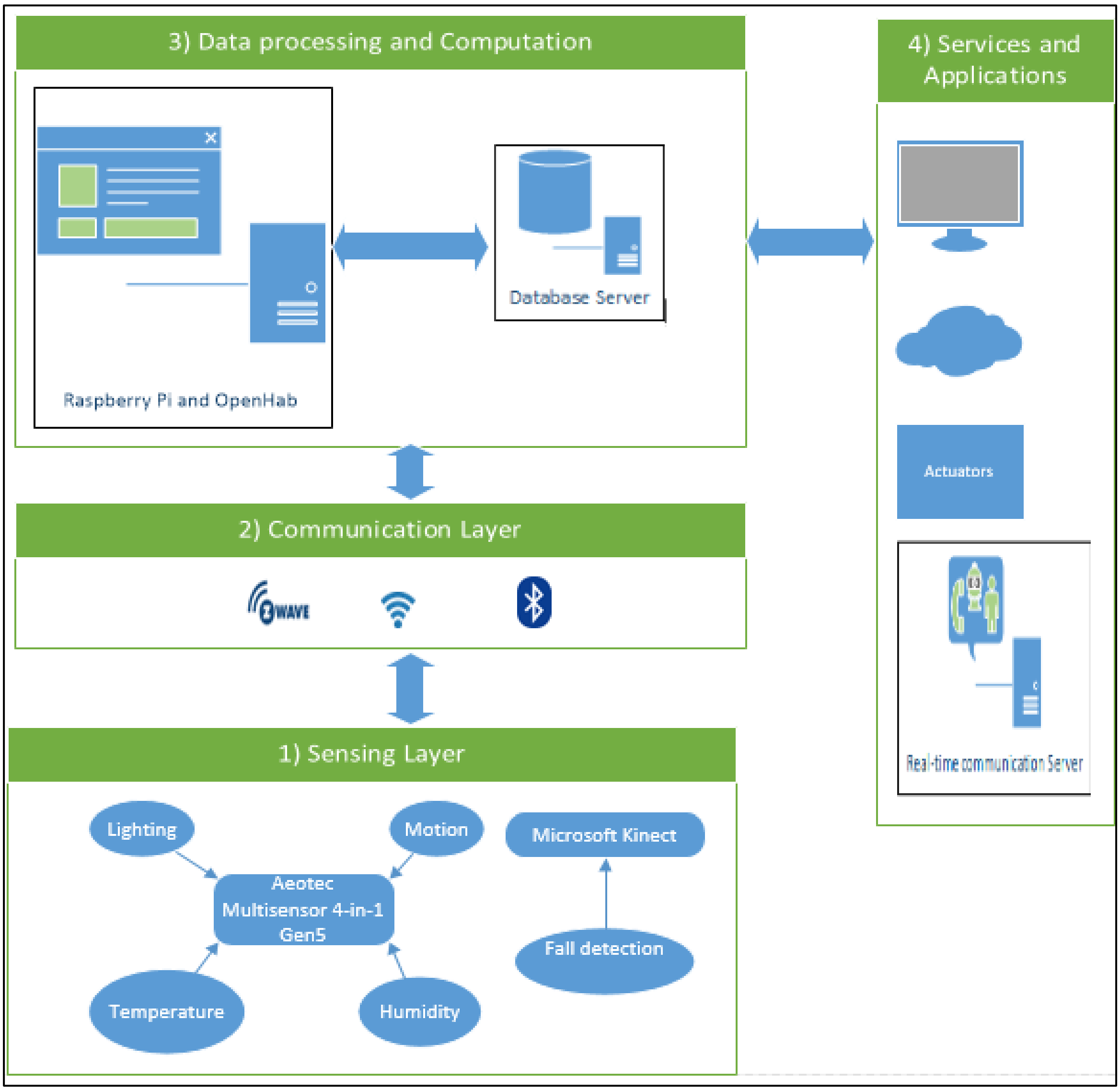


Figure 4-2 System architecture for the SHE to Support Safety and Risk Monitoring for the Elderly Living Independently.

The need for off-the-shelf devices, support for non-expert users, ease of installation and maintenance, handling large scale of data and extensible monitoring over time are some of the challenges that arise with SHE system deployments to real users

(Dickerson et al., 2015). The architecture proposed in this section seeks to limit the challenges associated with the deployment of SHEs to actual users.

The system architecture consists of low cost sensors and an open source Smart Home Operating System (OS) that supports multiple smart devices and has a large community of users. The communication protocols were selected depending on the number of devices they support and the level of security, since the system has to be online. The layers depicted in Figure 4-2 are discussed in detail in the following sections.

4.1.1 Sensing Layer

The sensing layer consists of a home monitoring sensor and a fall detection sensor. The Aeotec 4-in-1 multisensor is used as a home monitoring sensor and the Microsoft Kinect sensor is for the fall detection.

4.1.1.1 Home Environment Monitoring sensor

The Aeotec 4-in-1 sensor measures the ambient temperature, lighting, motion and humidity. The current cost of the Aeotec 4-in-1 sensor is between R1500 – R1900, depending on the local supplier. The sensor is cheaper if purchased directly from the supplier. Individual sensors for each of the home environment variables are costly compared to buying a multisensor. Configuring each one of them could also be difficult compared to configuring the multisensor. Figure 4-3 on the next page shows the Aeotec 4-in-1 sensor.

The measurement ranges of the variables measured are as follows:

- Temperature: -20 to +50°C (±1°C)
- Humidity: 20% to 90% (±5%)
- Light: 0 – 1000 Lux
- Motion: Binary 0 – 1. Zero means there is no motion detected and 1 means motion has been detected.

Figure 4-3 Aeotec 4-in-1 Multisensor (Aeon Labs, 2016)

The diagram in Figure 4-4 below shows a detailed view of the Aeotec 4-in-1 multisensor.

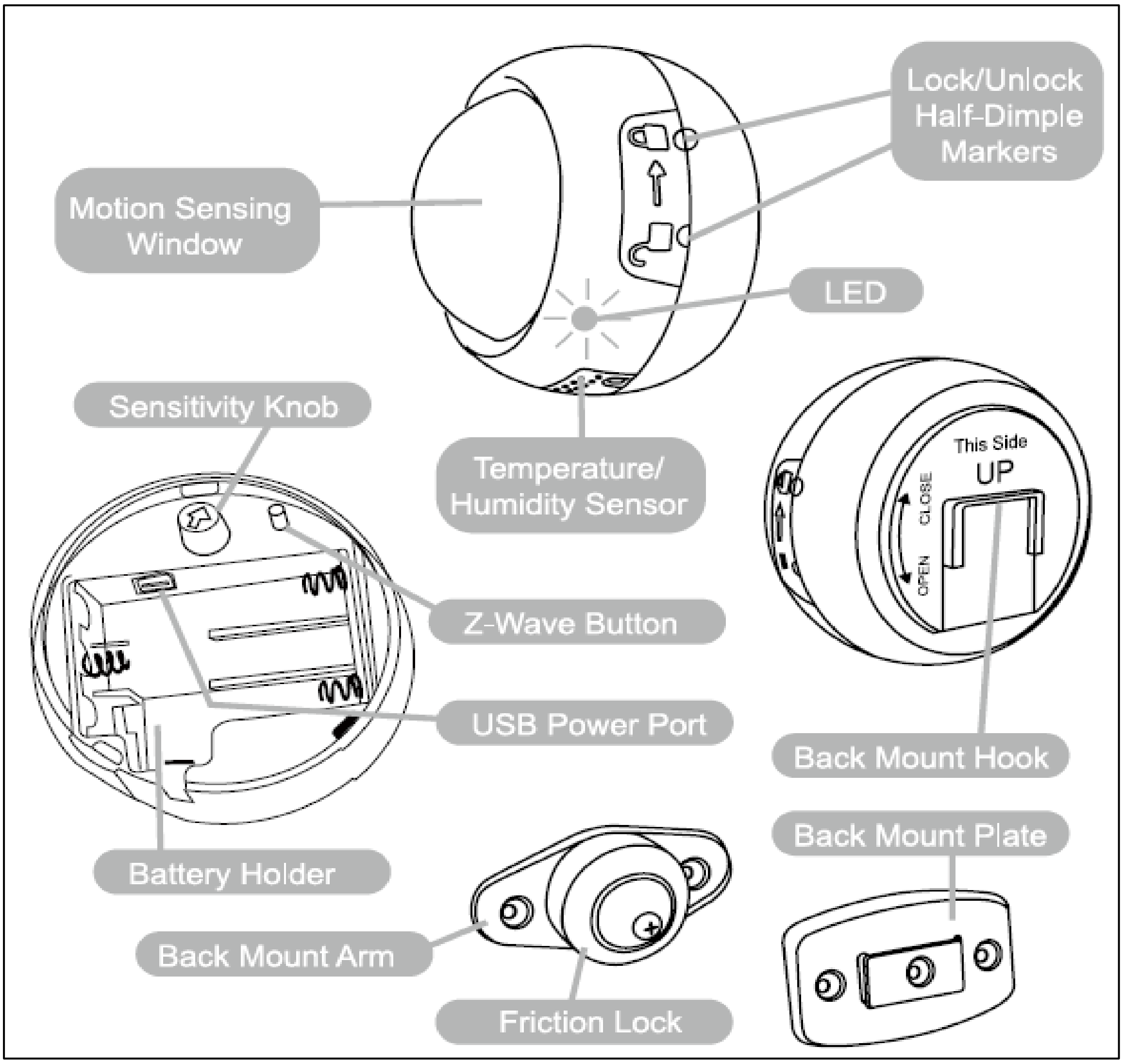


Figure 4-4 Detailed view of the Aeotec 4-in-1 multisensor (Aeon Labs, 2016)

The 4-in-1 sensor can be powered by four AAA batteries or USB at DC 5V 500mA. The battery life depends on how often the sensor is polled. Under optimal operating conditions, the battery life can be more than 10 months. Some features can be put into a dormant mode in order to conserve battery power. The sensor cannot be actively queried when in dormant mode, but it pro-actively sends its own report when changes are detected. USB power gives the greatest control over the multisensor. The sensor never sleeps when powered via USB, making it easy to configure.

The effective range of the multisensor depends on where it is installed, as shown in Figure 4-5.

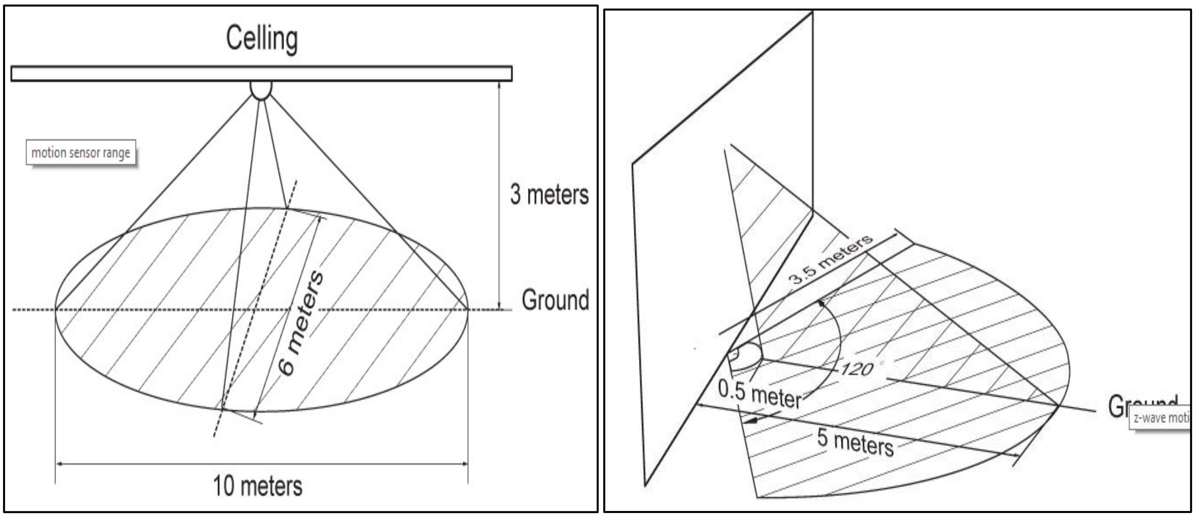


Figure 4-5 Multisensor range when mounted to the ceiling and when mounted to the wall (Aeon Labs, 2016)

The Aeotec sensor covers an effective range of 6 meters if installed 3 meters above the floor. When installed against the wall, the Aeotec sensor will cover a maximum radius of 5m in the direction straight ahead of it and 3.5 meters sideways at an angle of 120^{o}C.

The Fibaro multisensor was another alternative that was considered; however, it is more expensive than the Aeotec 4-in-1 multisensor and there are also technical challenges when setting up with the Z-Wave binding. The Samsung SmartThings hub and multisensor were also considered, but they are costly and require Samsung devices in the network.

4.1.1.2 Microsoft Kinect sensor

The Microsoft Kinect for Xbox 360 was used as a sensor for acquiring visual information from the home environment and tracking the activity of the occupant. Figure 4-6 illustrates the Microsoft Kinect and its components.

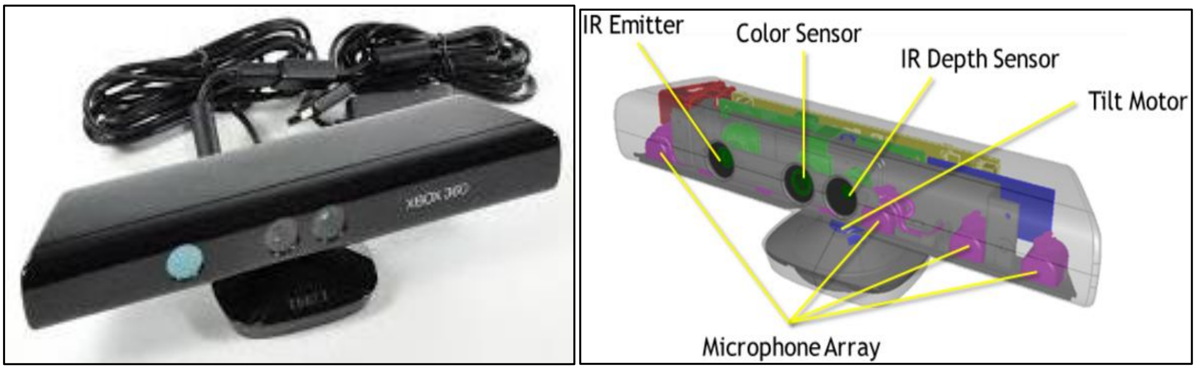


Figure 4-6 Microsoft Kinect and its components (Microsoft xbox 360, 2016)

The Microsoft Kinect costs between R1500.00 and R4000.00, depending on the extras included and other specifications, such as memory (Price Check SA, 2016). The Kinect sensor is cheaper compared to other depth sensors like Sony PlayStation Vr and Camera Ps Vr. Ordinary webcams do not produce depth information, which is necessary for privacy protection and night time user tracking, hence they were not considered for this research.

The Microsoft Kinect has the following properties and specifications.

- An RGB camera that stores three channel data in a 1280x960 resolution. This makes capturing a colour image possible. It detects three colour components, namely Red, Green and Blue.
- An infrared (IR) emitter and an IR depth sensor. The emitter emits infrared light beams and the depth sensor reads the IR beams reflected back to the sensor. The reflected beams are converted into depth information measuring the distance between an object and the sensor. This makes capturing a depth image possible regardless of lighting conditions.
- A multi-array microphone, which contains four microphones for capturing sound. Because there are four microphones, it is possible to record audio as well as find the location of the sound source and the direction of the audio wave.

- A 3-axis accelerometer configured for a 2G range, where G is the acceleration due to gravity. It is possible to use the accelerometer to determine the current orientation of the Kinect. The Kinect has 1° accuracy upper limit. The frame rate for both the colour and depth streams is 30 frames per second (FPS).

The sensors have to communicate with the data processing devices and careful consideration is required when selecting a communication protocol. Section 4.1.2 discusses the communication protocols adopted for this research.

4.1.2 Communication Layer

The communication layer consists of the communication protocols used by the devices that comprise the prototype. A range of communication protocols were discussed in Chapter 3. The communication protocols adopted for this research were Z-Wave and Wi-Fi. The choice of the protocols was governed by the compatibility with other devices included in the network and the scalability of the protocol. Aeotec is also a principal member of the Z-Wave alliance, hence it was an easy choice to use Z-Wave as the communication protocol of choice (Z-Wave, 2016).

4.1.2.1 Z-Wave

Z-Wave is a leading home automation wireless technology that is inside everyday products like lights, locks, thermostats, HVAC systems and speakers. Z-Wave is also an interoperable RF-based communications technology for controlling and monitoring of smart home devices (z-wavealliance, 2016).

The Z-Wave product portfolio consists of over 1700 devices that make up the Z-Wave alliance (z-wavealliance, 2016). Each of these devices is fitted with a ZW0201 Z-Wave single chip, which consists of an integrated RF transceiver, an 8051 micro controller, a Z-Wave SW Application Programming Interface and flash memory for user applications. The diagram in Figure 4.7 illustrates the placement of the ZW0201 chip on top of the Z-Wave protocol stack.

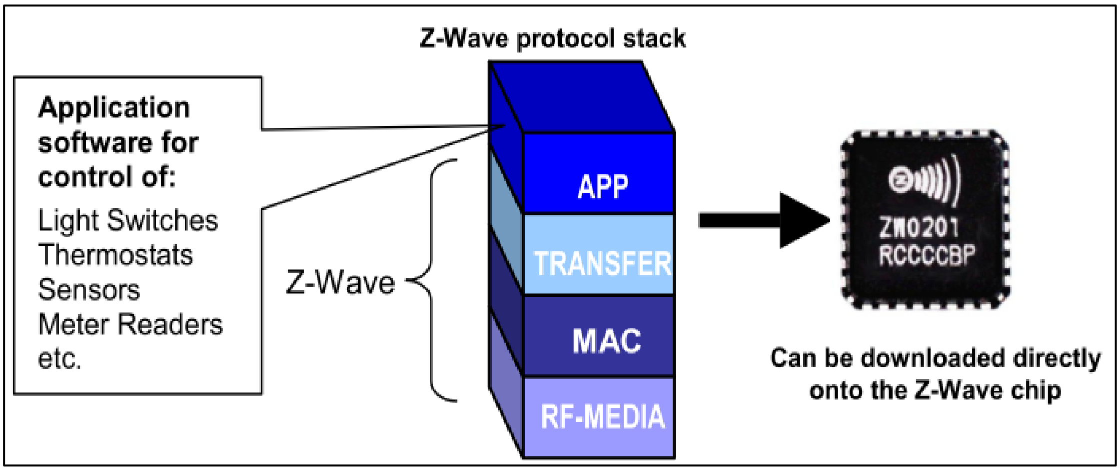


Figure 4-7 Z-Wave protocol stack and ZW0201 chip (Zensys, 2016)

The ZW0201 chip is the size of a matchstick head and is highly optimized for battery-powered applications and for products with demanding size considerations (Zensys, 2016). An Aeotec Z-Stick Series 2 can be used to acquire the measured variables from the Aeotec 4-in-1 sensor. The Z-Stick is a self-powered Z-Wave USB dongle with a push button for remote network creation. Attaching the Z-Stick to a host processor makes it a Z-Wave communication device exposing the Zensys API (SerialAPI) through integrated USB. Zensys is a leading provider of wireless networking technology for control and status reading applications. Zensys offers a family of low cost, low-power radio chip sets embedded with Z-Wave and a suite of development tools (Zensys, 2016). Figure 4-8 illustrates the Z-Stick.

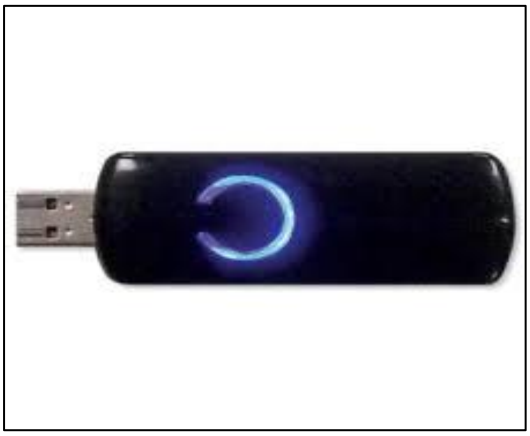


Figure 4-8 Z-Stick Series 2 also known as Z-Wave USB Stick (Aeon Labs, 2015)

The Z-Stick can support up to 243 Z-Wave supported devices. The Z-Stick can cover a range of up to 91 meters connecting all the devices in that range into a wireless mesh network (Aeon Labs, 2015). Z-Wave is resilient to wireless interference and is more secure as it provides multiple layers from device codes to signal encryption.

4.1.2.2 Wi-Fi

Wi-Fi provides a wireless local area networking solution for connecting the Raspberry Pi to the servers for real-time communication. It is fully compatible with the Raspberry Pi covering a range of 20 meters indoors, which is adequate for the purposes of this research. Unlike the Z-Wave protocol, Wi-Fi is prone to interference from other devices in the same area. However, for the purposes of this research, there was no significant impact on the interference of the Wi-Fi network.

4.1.3 Data Processing and Computation Layer

The Data processing layer consists of two Raspberry Pis, openHAB, MySQL database, SMTP Server and Twilio, a real-time communication server to send notifications via SMS.

4.1.3.1 Raspberry Pi

Raspberry Pi is a single board, low cost, high performance computer, which can be embedded seamlessly into applications or systems where size is a constraint (Raspberry Pi Foundation, 2016). The Raspberry Pi costs approximately R750. Two models of the Raspberry Pi were used, the Raspberry Pi 1 model B+ and the Raspberry Pi 3 model B, as illustrated in Figure 4-9. The reason for using two Raspberry Pi was to have a distributed architecture so as to distribute the computational load. The Raspberry Pi 3 is the third generation Raspberry Pi.

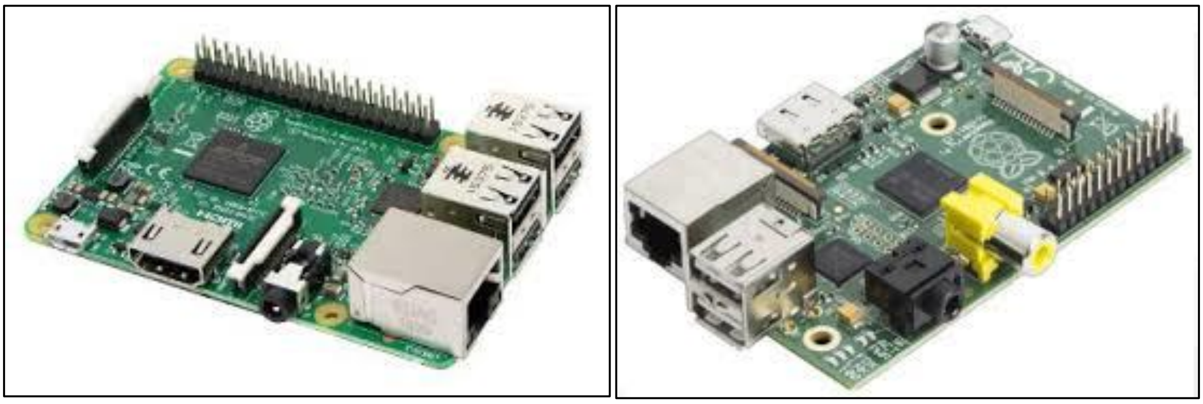


Figure 4-9 Raspberry Pi 3 (left) and Raspberry Pi 1 mode b+ (Raspberry Pi Foundation, 2016)

The specifications of the Raspberry Pi 3 are as below:

- 1.2 GHz 64-bit quad-core ARMv8 CPU
- 1GB RAM
- 4 USB Ports, 1 Full HDMI port and 1 Ethernet
- Micros SD slot
- 802.11n Wireless LAN
- Bluetooth 4.1
- Bluetooth Low Energy
- VideoCore IV 3D graphics

The Raspberry Pi 1 model B has 512 MB of RAM, two USB 2.0 port and a 100mb Ethernet port. It does not support wireless connectivity, hence a Wi-Fi adapter will be needed if Ethernet is not ideal. Initially the Raspberry Pi 1 model was used to connect and process data from the Kinect and the Aeotec sensor. However, due to the computational needs of the graphics generated from the Kinect, a distributed approach was used. The Raspberry Pi 3 was acquired and used to process data from the Kinect Sensor, and the Raspberry Pi 1 model B was used to process data from the Aeotec multisensor.

4.1.3.2 OpenHAB

The open Home Automation Bus (openHAB) is a vendor and technology agnostic open source home automation software (openHAB, 2016). The openHAB runtime is a set of OSGi bundles deployed on an OSGi framework (Equinox) (openHAB, 2016). The OSGi was discussed in Section 3.2 and it was decided that it was preferable to the other middleware technology standard. OSGi provides a highly modular architecture, which allows for adding and removing functionality during runtime without stopping the service. The openHAB system architecture is illustrated in Figure 4-10.

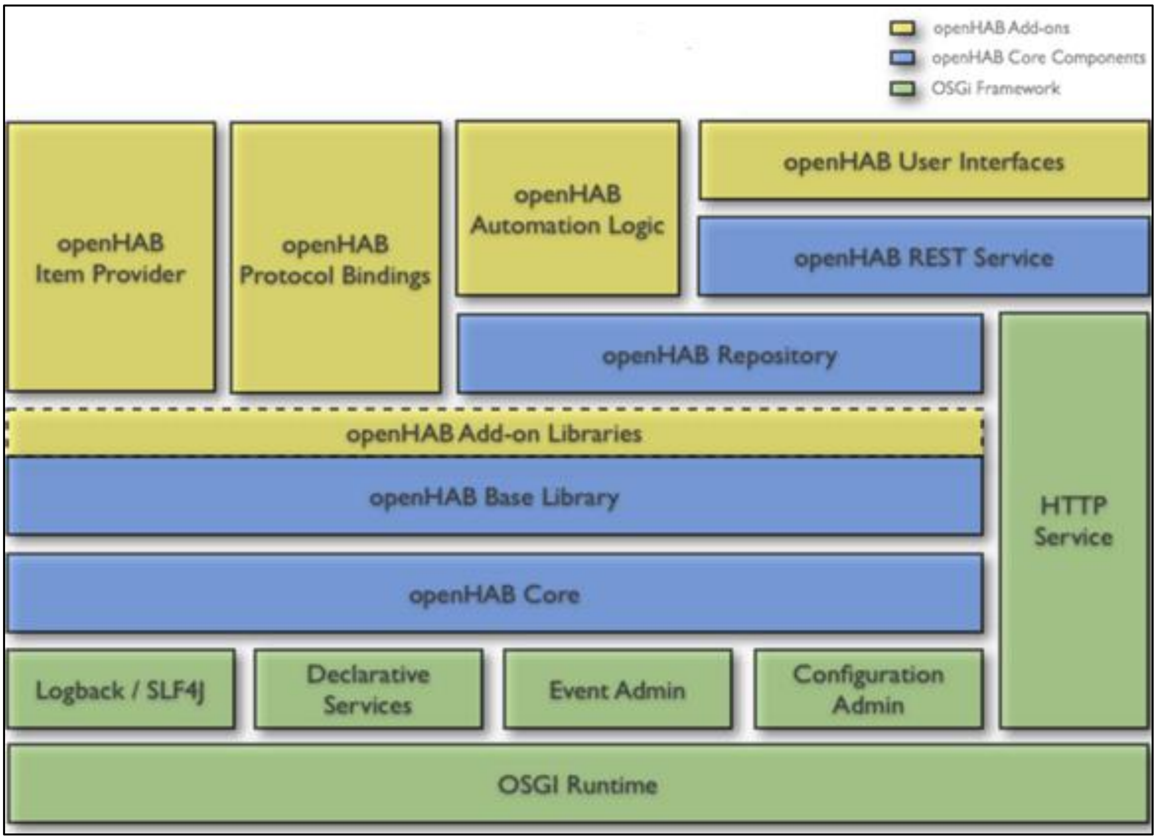


Figure 4-10 openHAB system architecture (openHAB, 2016)

OpenHAB can run on any device that is capable of running a Java Virtual machine (JVM) on Linux, Mac and Windows. Interoperability and extensibility are also key features supported by openHAB. The notion of a "thing" is a key concept for openHAB. A thing exposes items which offer various functionalities. Figure 4-11 illustrates a thing that can have multiple items.

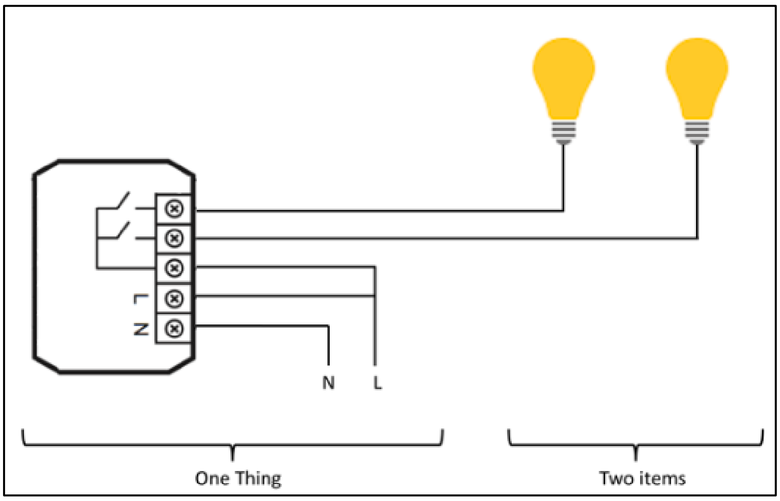


Figure 4-11 Example of a thing and an item (openHAB, 2016)

An item can be defined as a data-centric functional building block that can be physically added to a system providing many functionalities at once (openHAB, 2016). A thing can be an actuator as shown in Figure 4-11 or it could be an Aeotec multisensor as shown in Figure 4-12.

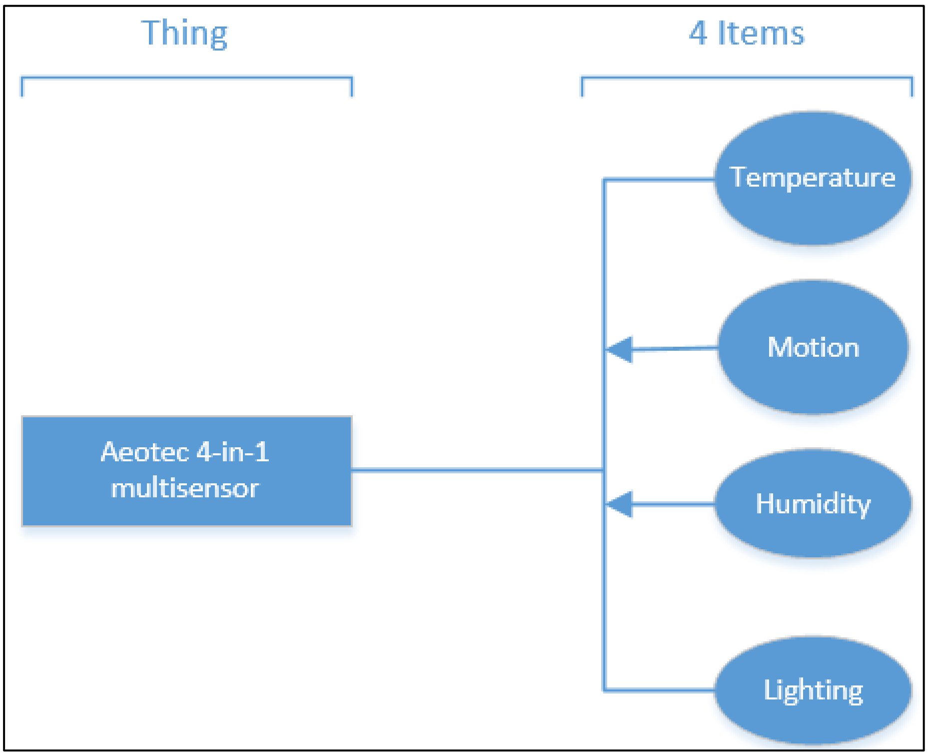


Figure 4-12 Aeotec 4-in-1 multisensor as a thing

Things provide functionality through channels and links which connect the thing and item objects in openHAB.

An item repository keeps track of all items and can be referenced whenever queries have to be sent to items. A home environment can then be defined as a collection of items, which can listen and respond to the changes in the home environment or to the needs of the occupant.

There are two internal communication channels in openHAB, an asynchronous event bus and a stateful repository, which can be queried at any time. The event bus is the base service for openHAB. An event can be either a command, which triggers an action or a state change of an item or a status update. OpenHAB also supports remote invocation therefore allowing for distributed computation. Bindings allow for different vendor specific technologies to communicate with the event bus sending status updates and/or commands. The communication channels are illustrated in Figure 4-13.

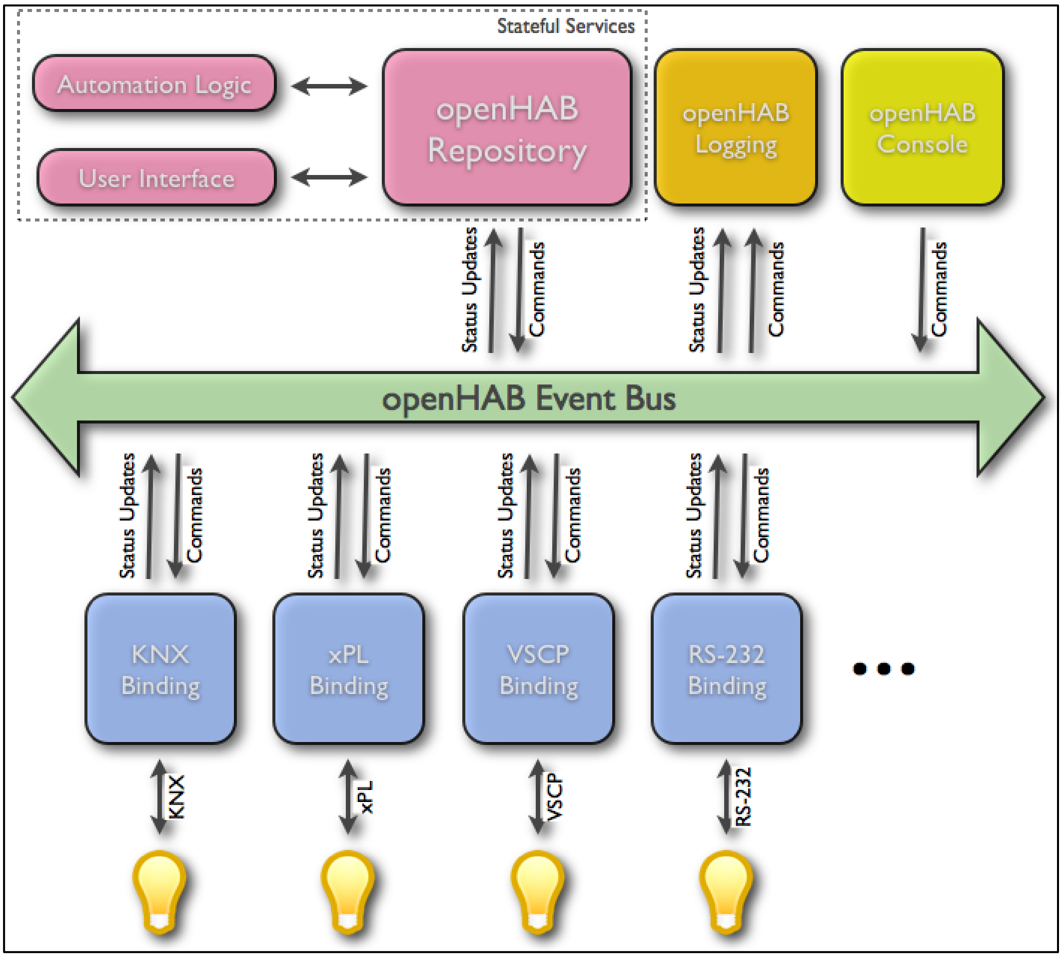


Figure 4-13 openHAB communication protocols (openHAB, 2016)

A user interface can be designed in openHAB to represent the items exposed by things in a SHE. The user interface is built on top of a sitemap, which is basically a collection of items in the home. Home automation rules can be implemented to provide the intelligence needed for a SHE. OpenHAB also has extensive support for logging and information can also be queried and displayed via a console.

The typical software and hardware requirements include:

- High availability – The system should be available 24/7 and always connected online. This feature is very useful since one of the requirements is that the system should be able to monitor the home continuously as emergency situations can occur at any moment.

- Energy and space efficiency – The device should perform without energy and space resources being over utilised. The energy costs due to the system must be sustainable and preferably the system should be able to be powered by batteries or uninterrupted supply system (UPS).

- Extensibility – The device and/or system should be capable of running additional add-ons i.e. software and peripherals.

4.1.3.3 Twilio

Twilio is a popular global SMS platform that allows for the sending and receiving of SMS with local numbers in any region (Twilio, 2016b). Twilio also supports voice and video messaging as some of its high end features. Twilio was chosen primarily for its popularity and the ease of integrating its API into any application.

4.1.4 Services and Applications Layer

The services and applications layer is made up of a user interface that allows the caregivers or family members to view the home environment variables and activity monitoring in the home. The user interface has to be a cross platform user interface to cater for as many users as possible. The data collected from the home should also be saved in the cloud to allow for remote real-time monitoring for the elderly. Emergency notifications can also be implemented as a service that is triggered when an emergency situation occurs.

4.1.5 Programming Languages

The programming languages used for the implementation of the functional requirements are Java and Python. The openHAB runtime was developed using Java, thus it is easy to develop custom requirements and rules depending on requirements. Python is a popular language in computer vision, as the majority of the popular and computationally powerful computer vision libraries support Python. OpenCV and Libfreenect were used in the implementation of the fall detection module.

The identified tools and technologies had to be linked together in order to address the safety and risk monitoring requirements identified in Chapter 2. Section 4.2 outlines the implementation of the requirements.

4.2 Functional Implementation

The functional requirements identified in Chapter 2 were home environment monitoring, fall detection, emergency alerts and activity monitoring. The prototype was set up in a laboratory mimicking the lounge area in a home. The lounge is one of the common areas in the home in which the elderly spend their time in, probably watching television, eating or reading.

The Raspberry Pi forms the backbone of the prototype and all the other equipment was connected to the Raspberry Pi.

4.2.1 Home Environment Monitoring

The Aeotec 4-in-1 sensor is the main data source for the home environment module. The data from the Aeotec 4-in-1 multisensor was collected by openHAB running on the Raspberry Pi.

4.2.1.1 Setting up the Raspberry Pi

The following components should be available before setting up the Raspberry Pi:

i. SD Card with a minimum size of 8GB.

ii. HDMI monitor. Other monitors/TVs can work, but they require adapters to convert the HDMI output to the input supported by the particular monitor/TV.

iii. Keyboard and mouse.

iv. Good quality USB Micro power supply.

v. Ethernet cable/wireless adapter for Raspberry Pi 1 model B.

The monitor and keyboard are needed for first time setup, after that remoting software, such as VNC, can be used to connect the Raspberry Pi to the laptop if there is a need. The following steps are then performed to set up the Raspberry Pi:

- Install the Raspbian Operating system onto the Raspberry Pi using New Out Of Box Software (NOOBS). Raspbian is a free operating system that is based on Debian optimized for the Raspberry Pi hardware. Debian itself is a Unix-like operating system composed entirely of free software. Debian has access to over 50 000 software packages in various repositories online.

- NOOBS is an easy software installation manager for Raspberry Pi, which includes other Linux based operating systems such as Pidora, Arch Linux and LibreELEC. NOOBS can be downloaded from the raspberrypi.org website. After downloading, NOOBS is extracted and the files are copied to the SD card so that they appear at the root directory of the SD card.

After setting up the Raspberry Pi, openHAB was installed and configured on the Raspberry Pi, as discussed in Section 4.2.2.

4.2.2 OpenHAB installation and configuration

The openHAB runtime needs the Java runtime 1.8 or higher installed before any installation is done. The version of openHAB used in this research was 2.0. The following steps are necessary to install and configure openHAB on the Raspberry Pi.

Installation of openHAB is achieved through a package repository which is added to the Linux package manager by the following commands:

When openHAB is started, it can be accessed via port 8080 on the localhost. For example entering the following IP address, 192.168.43.156:8080, in the browser returns a page containing all the user interfaces available in openHAB, as shown in Figure 4-14 on the next page.

The PaperUI interface was used for configuring the openHAB environment and is shown in Figure 4-15. The Paper UI can be used to configure openHAB for the first time, download add-ons and discover Things on a network, among other configuration options.

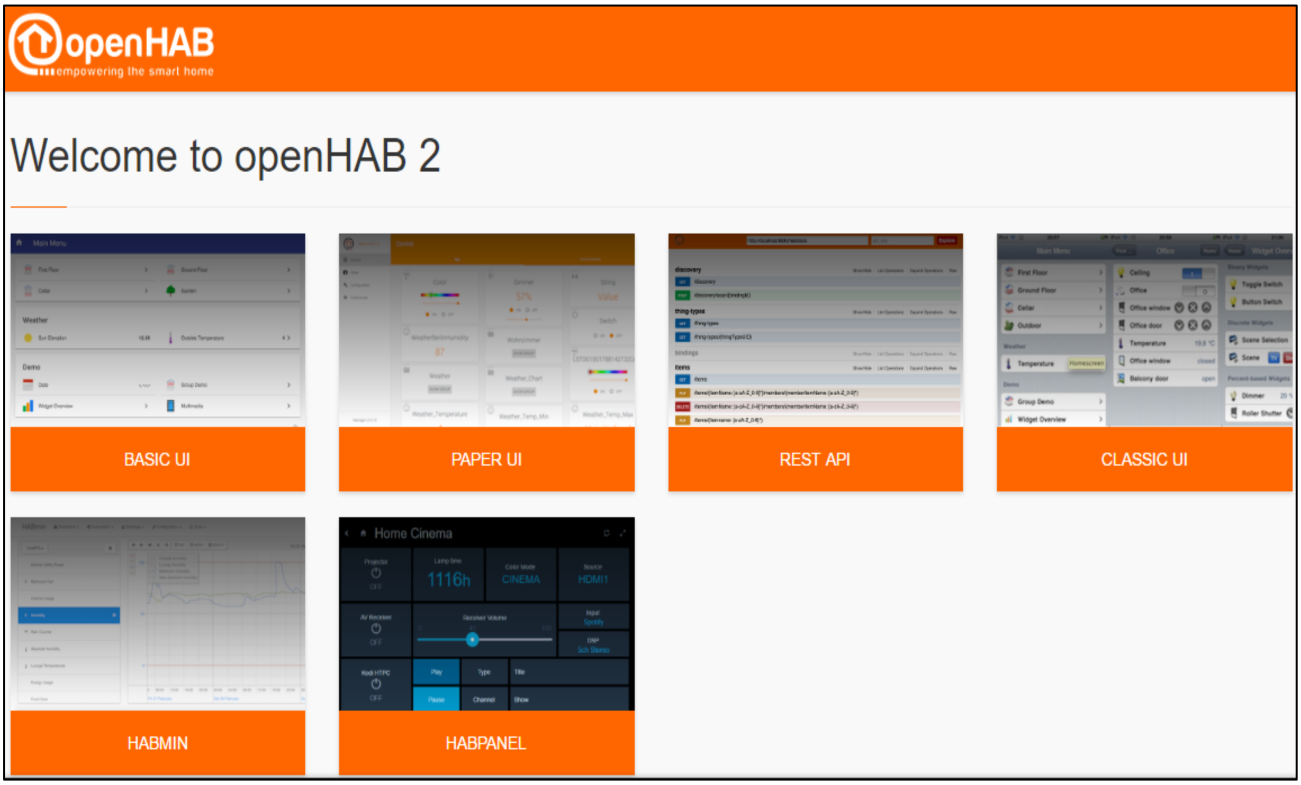


Figure 4-14 openHAB user interfaces

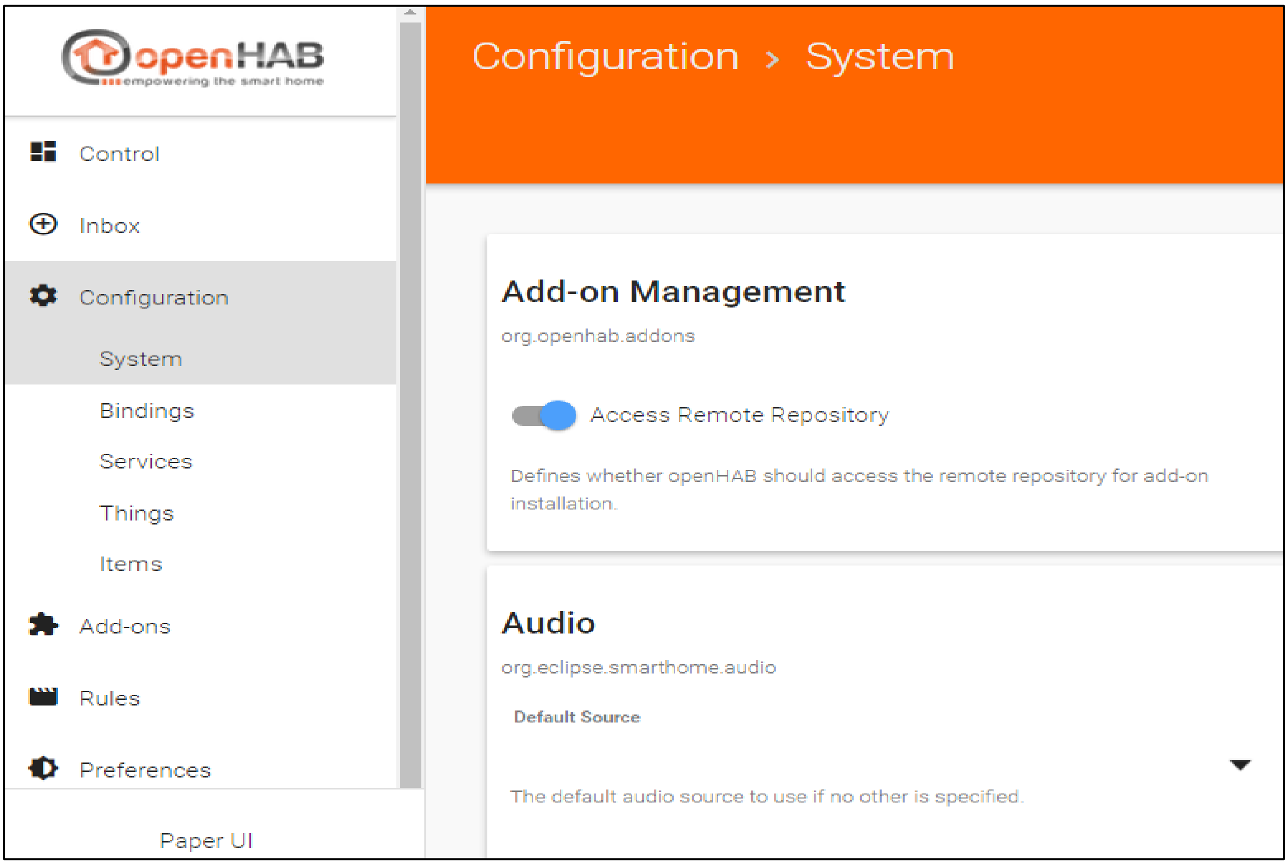


Figure 4-15 openHAB PaperUI interface

HABmin is also another important interface for configuring the openHAB system. The HABmin interface is shown in Figure 4-16. HABmin is a better interface to use especially for users coming from openHAB version 1.9 and below.

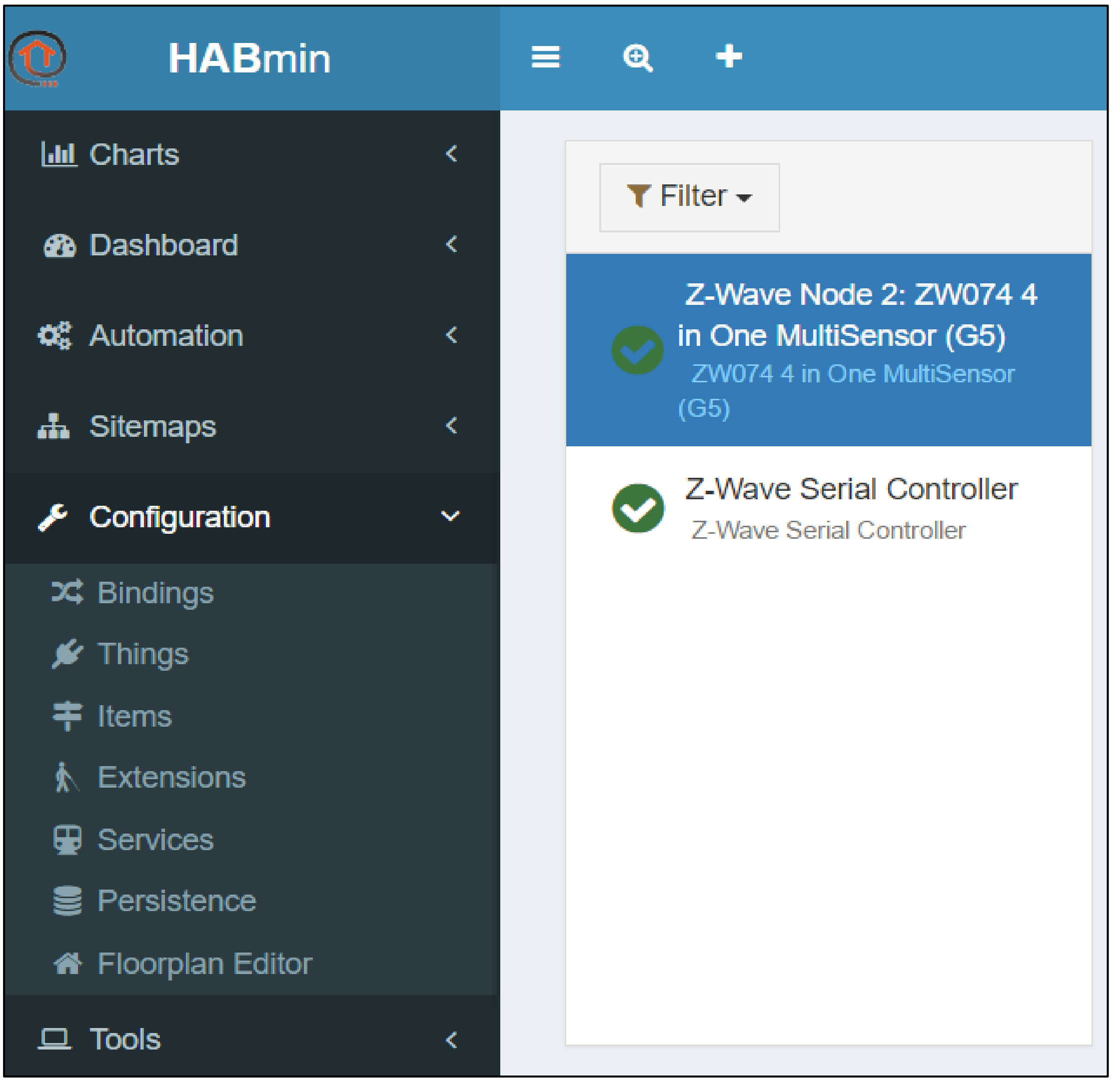


Figure 4-16 openHAB HABmin interface

The bindings, which correspond to the technologies or devices to be used, can be downloaded from the HABmin interface. As discussed earlier in Section 4.1.3.2, a binding is an optional package that extends the functionality of openHAB to interface with multiple vendor technologies. HABmin allows you to configure bindings, items, sitemaps, and Z-Wave network configuration, view OSGi binding status, view log file, write rules and view notifications.

By using HABmin, properties such as the configuration parameters, wakeup period and association groups can be set. The configuration parameters will be discussed in detail in the next section. Network healing can be manually initiated using HABmin as well. Network healing is an attempt to repair dead nodes in the network.

Six add-ons were selected from the add-ons distribution. The selected add-ons were:

- ***org.openhab.action.mail*** – This allows for the sending of email.

- ***org.openhab.binding.http*** – This add-on allows for openHAB to request a URL when a special event occurs or for periodic polling of a given URL. The http binding also allows for definition of optional headers, dynamic URL enhancement, JavaScript Object Notation (JSON) handling and caching. Caching is needed when multiple items are parsed from the same URL. JSON handling is useful for consuming information from web services, for example the weather service.

- ***org. openhab.binding.weather*** – Collects current and forecast weather from different providers with a free weather API. Providers supported include Yahoo, WorldWeatherOnline and Hamweather. The Yahoo weather provider was chosen because it is easier to configure than the other providers. Yahoo does not require you to provide your longitude and latitude, but rather requires a where on earth id (woeid), which can be found from the weather.yahoo.com URL. The limitation with all the free providers mentioned is that they have a daily request limit so an appropriate interval must be selected.

- ***org.openhab.binding.zwave*** – This binding allows you to connect to the Z-Wave devices network. The binding supports all controllers that implement the Z-Wave serial API. The network consists of one controller, the Z-Stick, and the Z-Wave enabled devices, i.e. Aeotec 4-in-1 multisensor. This binding has several configuration options including port configuration settings, network heal time, polling queue and soft reset. The port configuration option is necessary to indicate the serial port of a host system to which a controller is connected. The serial port on Raspbian is /dev/ttyUSB0. Initialisation can take several seconds to minutes depending on the number of devices and is typically slower for battery operated devices.

- ***org.openhab.persistence.mysql*** – This allows for openHAB to persist state updates using MySQL database. The service provided by this binding can be specified in the openHAB configuration file as shown in Appendix C.

  The tables created in the openHAB database are as below:

  - Item1 – Lounge_Motion
  - Item2 – Lounge_Sensor_Battery
  - Item3 - Lounge_Luminance
  - Item4 – Lounge_Humidity
  - Item6 – Lounge_Temperature

    Item7 – Posture

- ***org.openhab.io.openhabcloud*** **–** It is also known as the openHAB cloud connector which allows for connecting the local openHAB runtime to a remote openHAB cloud instance. The openHAB cloud instance used in this research is myopenHAB.org which is hosted by the openHAB foundation. The openHAB cloud configuration panel is shown in Figure 4-17.

The openHAB cloud connector allows for remote access without exposing ports to the internet or requiring complex virtual private network (VPN) configuration. The openHAB cloud connector also serves as a connector to Google Cloud Messaging (GCM) and Apple push notifications (APN) for pushing notification to mobile phone apps.

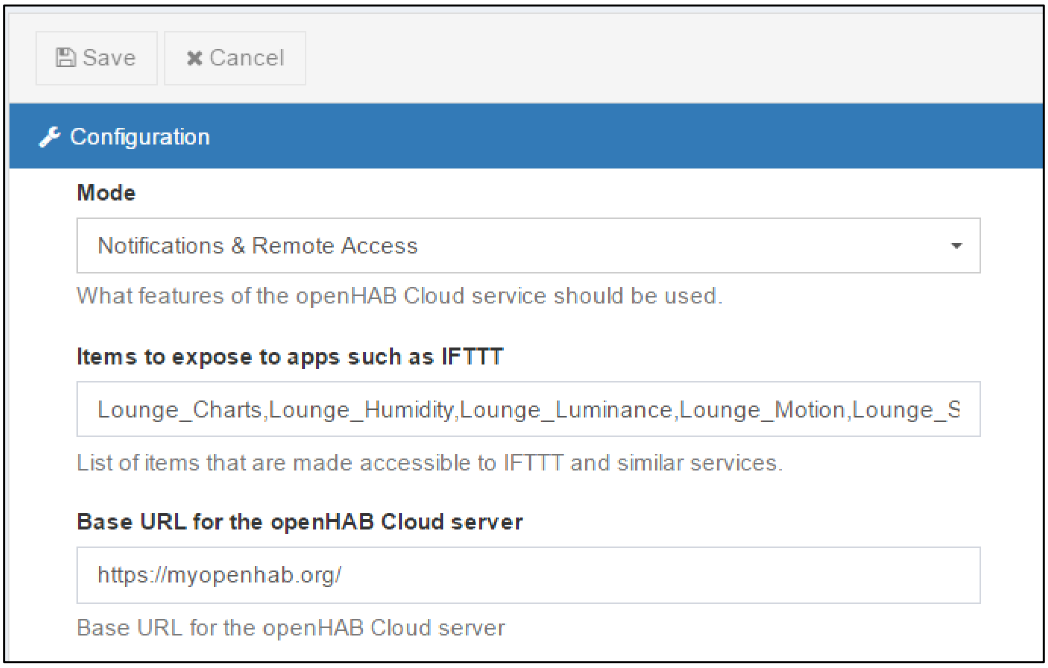


Figure 4-17 openHAB cloud connector configuration panel

4.2.3 Z-Wave Network setup

The next step was to set up the Z-Wave network and connect the network to the Raspberry Pi. The diagram in Figure 4-18 shows how the Raspberry Pi, the Z-stick and the Aeotec 4-in-1 multisensor were connected together.

Figure 4-18 Setting up the Z-Wave network and the Raspberry Pi

To include the Aeotec 4-in-1 multisensor into the Z-Wave network, the following steps were followed:

- Take the Z-Stick to the location of the multisensor.
- Press the action button on the Z-Stick followed by the Z-Wave button on the multisensor as shown in the diagram in Figure 4-19 below:

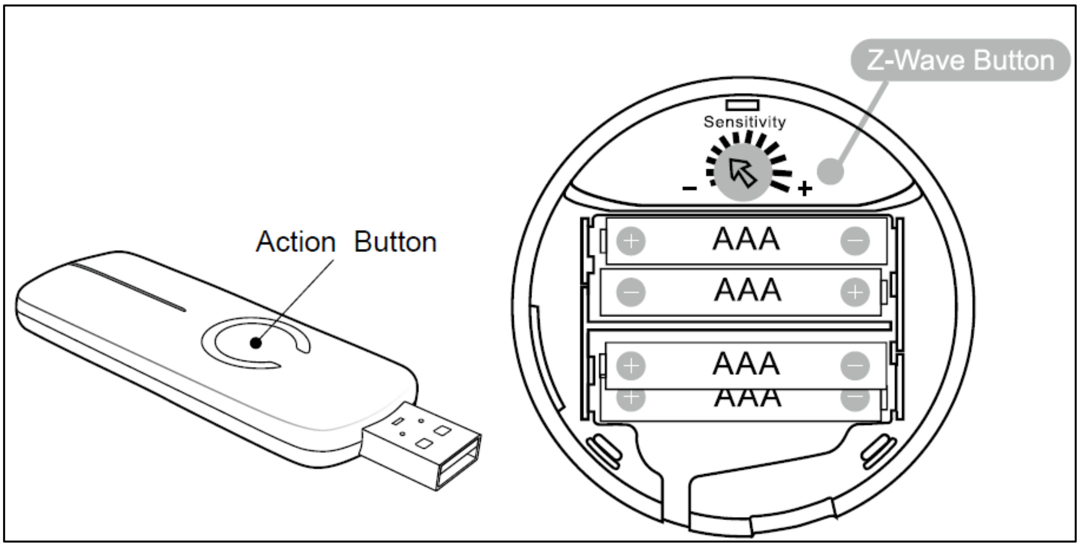


Figure 4-19 The action button and Z-Wave button (Aeon Labs, 2016)

- The multisensor LED should illuminate for a few seconds if syncing with the Z-Wave network was successful.

The multisensor can be removed from the Z-Wave network by pressing on the action button of the Z-Stick for 3 seconds and then pressing the Z-Wave button on the multisensor. If removal is successful, the multisensor LED should blink when the Z-Wave button is pressed.

4.2.4 Configuring Items and the Sitemap

An item is basically considered as an object, an abstraction of the device that you want to read from or write values to. The items can be easily configured using HABmin, the openHAB administration console. Each item is bound to a binding that allows openHAB to interact with the device. The items are defined in a file with the .items extension and should be placed in the openHAB/configurations folder. The syntax for adding an item is as follows:

```
itemtype itemname ["labeltext"] [<iconname>] [(group1, group2, ...)]
{bindingconfig}]
```

The items can also be placed into groups in such a way that each room can have its sensors grouped together and this makes it easier to display related values together.

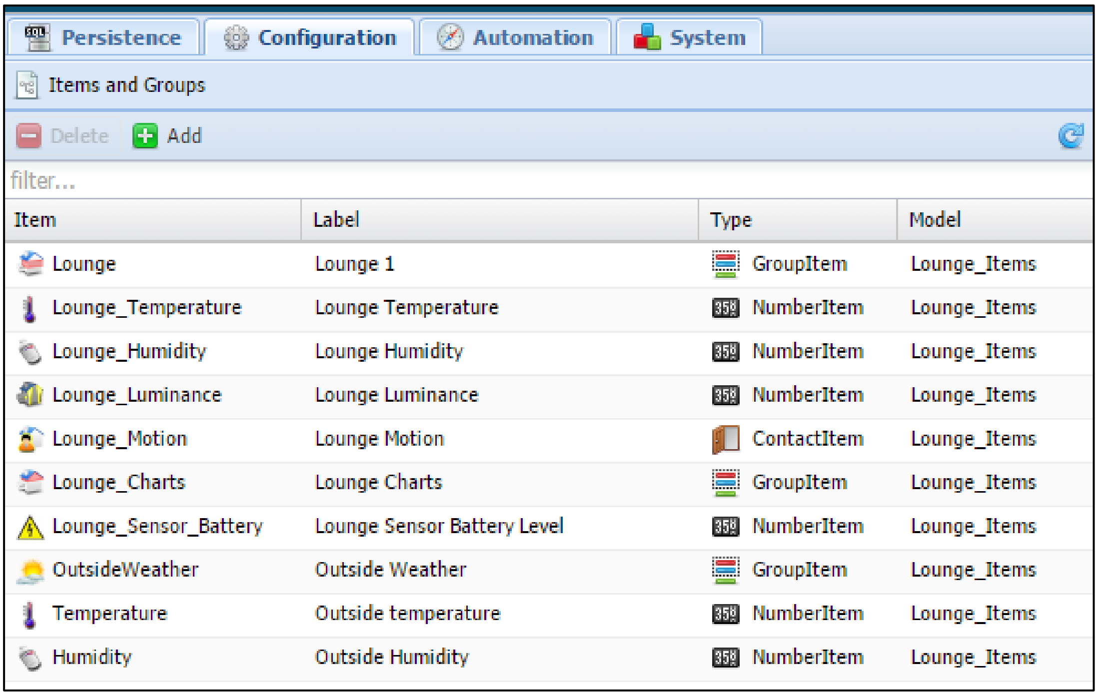
The binding configuration for interacting with the Aeotec multisensor is the *org. openhab.binding.z-wave*.

A file called Lounge_Item.items was created as follows to depict each type of sensor reading.

```
Group   Lounge   "Lounge 1 "      <firstfloor>
Number  Lounge_Temperature       "Lounge Temperature [%.2f
°C]"    <temperature>   (Lounge)        {
zwave="2:command=SENSOR_MULTILEVEL,sensor_type=1,sensor_scale=0,refresh_interval=2
40" }
Number  Lounge_Humidity  "Lounge Humidity [%.2f %%]"      <heating>
        (Lounge)        {
zwave="2:command=SENSOR_MULTILEVEL,sensor_type=5,refresh_interval=240" }
Number  Lounge_Luminance "Lounge Luminance [%.2f Lux]"    <outdoorlight>
        (Lounge)        {
zwave="2:command=SENSOR_MULTILEVEL,sensor_type=3,refresh_interval=180" }
Contact Lounge_Motion    "Lounge Motion
[MAP(motion.map):%s]"    <present>       (Lounge)        {
zwave="2:command=SENSOR_BINARY,respond_to_basic=true,refresh_interval=240" }
Group   Lounge_Charts    "Lounge Charts"  <attic>
Number  Lounge_Sensor_Battery    "Lounge Sensor Battery Level [%d %%]"
        <energy>(Lounge)         { zwave="2:command=BATTERY" }
```

In this case the multisensor is not seen by openHAB as one object but rather four different objects. The temperature is of item type “Number” and is assigned a variable Lounge_Temperature. The display label for the temperature is “Lounge Temperature” and is measured to 2 decimal places. The Z-Wave binding is configured for node 2 and the command is “Sensor_Multilevel”. Each node in the network provides functionality via Command classes. The command class “Sensor_Multilevel” is used to bind to the temperature sensor, relative humidity and luminance. The configuration for the luminance, battery power and humidity are similar to the temperature configuration. The motion sensor is of item type “Contact” and differs from the other sensors in terms of the command class used. The motion sensor binds to the “SENSOR_BINARY” command class. The collection of items in the home is a sitemap.

The items can also be configured easily by using HABmin. HABmin allows for the adding, removal and configuring of items easily. Figure 4-20 displays the items list in HABmin.



Item	Label	Type	Model
Lounge	Lounge 1	GroupItem	Lounge_Items
Lounge_Temperature	Lounge Temperature	NumberItem	Lounge_Items
Lounge_Humidity	Lounge Humidity	NumberItem	Lounge_Items
Lounge_Luminance	Lounge Luminance	NumberItem	Lounge_Items
Lounge_Motion	Lounge Motion	ContactItem	Lounge_Items
Lounge_Charts	Lounge Charts	GroupItem	Lounge_Items
Lounge_Sensor_Battery	Lounge Sensor Battery Level	NumberItem	Lounge_Items
OutsideWeather	Outside Weather	GroupItem	Lounge_Items
Temperature	Outside temperature	NumberItem	Lounge_Items
Humidity	Outside Humidity	NumberItem	Lounge_Items

Figure 4-20 List of items as displayed in HABmin

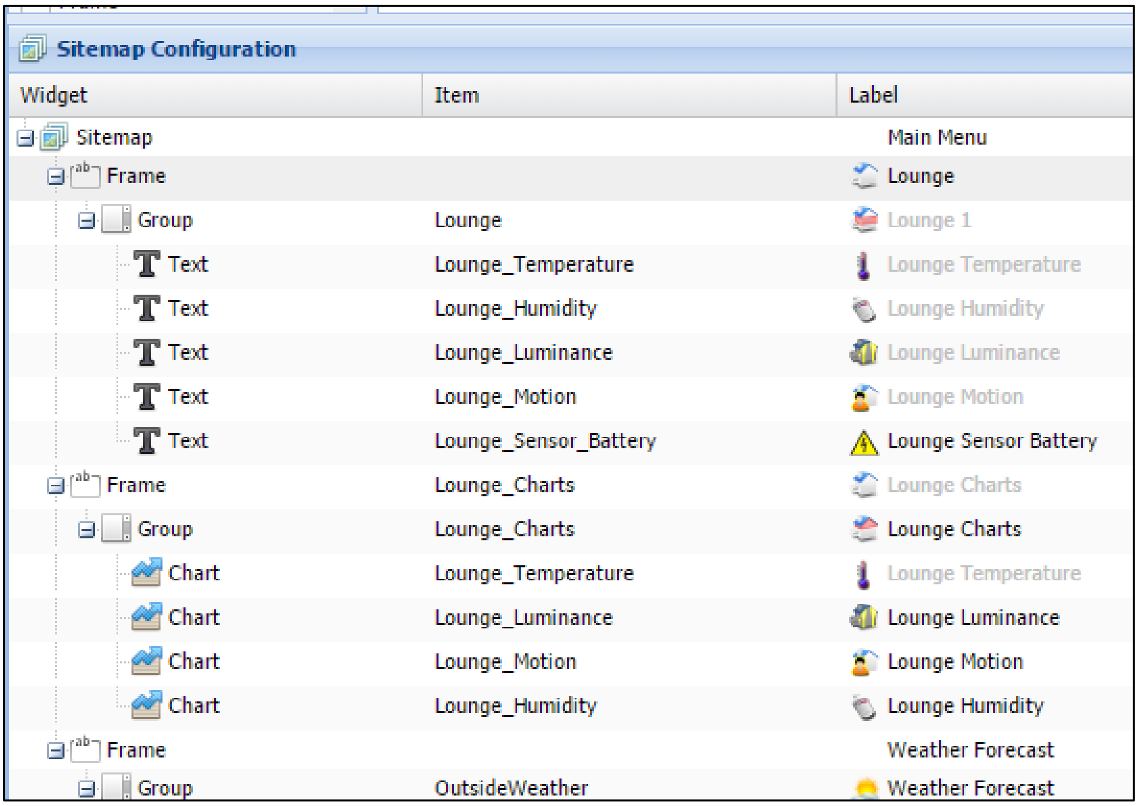
The items displayed in 4-20 are the graphical equivalent of the items created via the Lounge_Item.items script on the previous page. It is easy to change the label, item type and the model to which the item belongs by using openHAB.

To display the values measured from the items/sensors in our Smart Home, a sitemap was implemented. In openHAB, a sitemap is basically a document that lists the contents of our home environment that will display on the screen. Sitemaps provide a declarative way of defining the user interface (UI). The script below shows the sitemap for the corresponding Lounge_Item.items file defined on the previous page.

```
sitemap Lounge_Items label="Main Menu"
{
        Frame label="Lounge" icon="house" {
                Group item=Lounge {
                        Text item=Lounge_Temperature
                        Text item=Lounge_Humidity
                        Text item=Lounge_Luminance
                        Text item=Lounge_Motion
                        Text item=Lounge_Sensor_Battery label="Lounge Sensor
Battery [ %%]" icon="energy"
                }
        }
        Frame item=Lounge_Charts icon="house" {
                Group item=Lounge_Charts label="Lounge Charts" {
                        Chart item=Lounge_Temperature period=D
refresh=120000
                        Chart item=Lounge_Luminance label="Lounge Luminance"
period=D
```

```
                        Chart item=Lounge_Motion label="Lounge Motion"
period=D
                        Chart item=Lounge_Humidity label="Lounge Humidity"
period=D
                }
        }
        Frame label="Weather Forecast" {
                Group item=OutsideWeather label="Weather Forecast" {
                        Text item=Temperature
                        Text item=Humidity
                }
}
```

The above sitemap can be configured from HABmin as well. Figure 4-21 shows how the Lounge_Items.sitemap script displays in HABmin.



Sitemap Configuration

Widget	Item	Label
Sitemap		Main Menu
Frame		Lounge
Group	Lounge	Lounge 1
Text	Lounge_Temperature	Lounge Temperature
Text	Lounge_Humidity	Lounge Humidity
Text	Lounge_Luminance	Lounge Luminance
Text	Lounge_Motion	Lounge Motion
Text	Lounge_Sensor_Battery	Lounge Sensor Battery
Frame	Lounge_Charts	Lounge Charts
Group	Lounge_Charts	Lounge Charts
Chart	Lounge_Temperature	Lounge Temperature
Chart	Lounge_Luminance	Lounge Luminance
Chart	Lounge_Motion	Lounge Motion
Chart	Lounge_Humidity	Lounge Humidity
Frame		Weather Forecast
Group	OutsideWeather	Weather Forecast

Figure 4-21 Lounge Items sitemap in HABmin

The sitemap is much easier to configure and accuracy is guaranteed if configured in HABmin as well. The item to be added is picked from the corresponding dropdown menu, hence there is no need to remember the exact names of each and every item in the Lounge_Item.items file.

The above sitemap will display the items in our home environment on a mobile device, as shown in the Figures 4-22 to 4-24 on the next page.

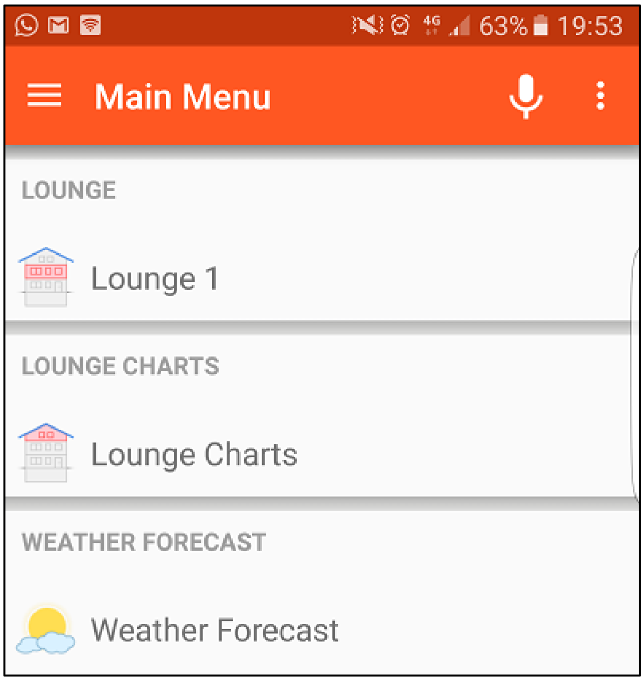


Figure 4-22 The main dashboard for viewing home environment variables

The items are grouped as defined in the sitemap. Lounge 1 is for viewing environment variables, Lounge Charts displays the graphical trend of the environment variables and the weather forecast displays the weather outside of the home. When Lounge 1 is clicked, Figure 4-23 is displayed on the UI.

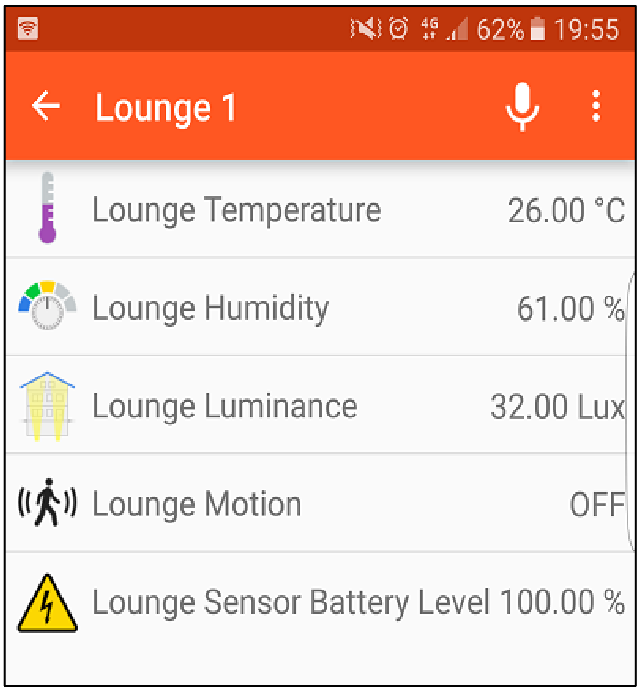


Figure 4-23 Home environment variables snapshot for the Lounge 1 group

The displaying of the sensor values is exactly as defined in the Lounge_Item.items file. The Lounge sensor battery does not display any value because the sensor was being powered by USB during configuration. The Lounge Charts group contains graphs for the four variables shown in Figure 4-24. The charts are configured in the sitemap by specifying the item the chart is bound to. The time series can be configured as periods with the following values: 1H(hour), 4H, 8H, 12H, D(Day), 3D, W(Week), 2W, M, 2M, 4M and Y. The period of refresh can also be set in milliseconds. Example charts are shown in Figures 4-27 to 4-30.

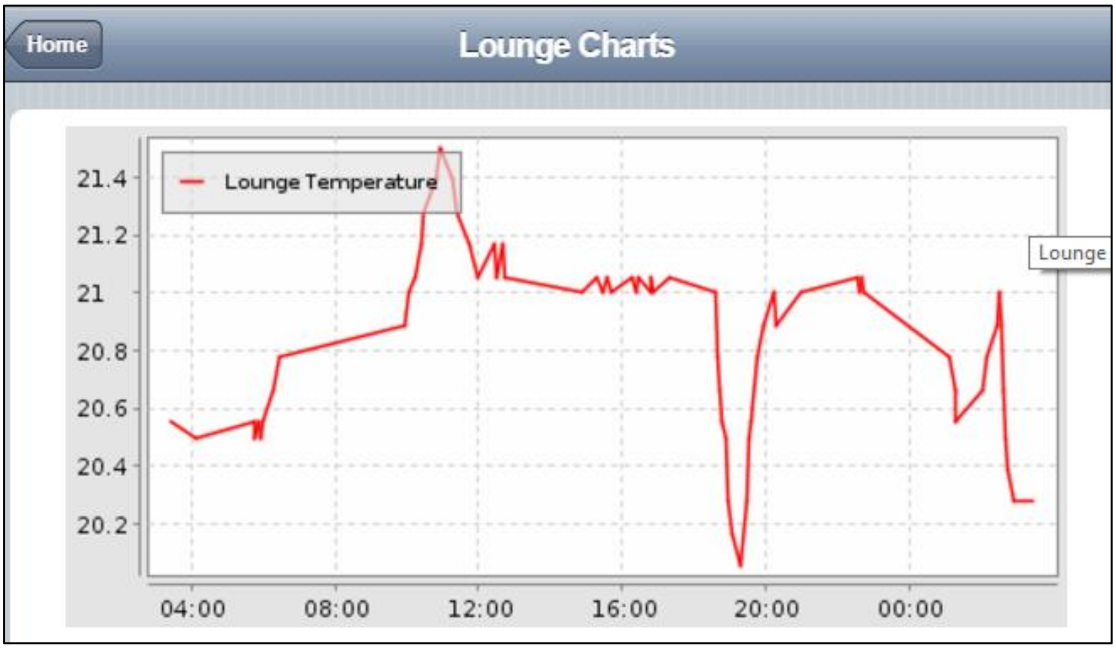


Figure 4-24 Example graph of lounge temperature vs time

The graph above displays the lounge temperature against time. The relative or caregiver is able to instantly notice abnormalities in the temperature recorded. A temperature higher than the normal temperature could mean that something is not alright in the home; it could be that a stove or heater was left on and this could result in a fire. Temperatures lower than the average temperature need intervention by the caregiver to ensure that the elderly person stays warm in the home.

The graph in figure 4-25 on the next page is an example of the lounge humidity recordings. High values of humidity indicate that there is too much moisture in the home and therefore intervention is necessary to ensure that adequate levels of humidity are maintained. If the sensor is in the bathroom, higher humidity indicates that the elderly person has taken a shower and hence they are active in the home.

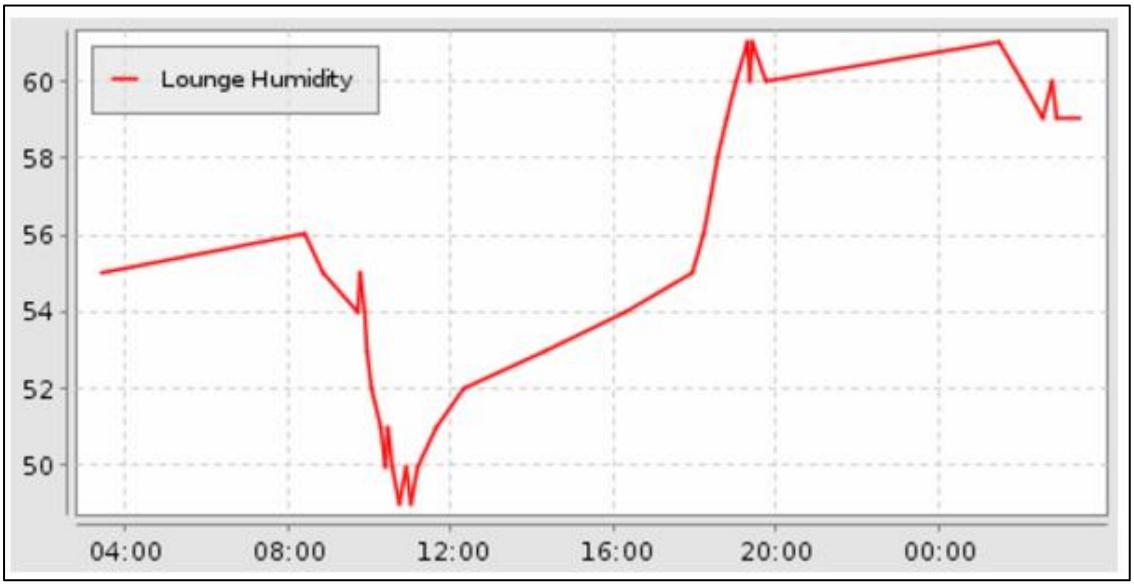


Figure 4-25 Example graph of humidity vs time

Figure 4-26 shows an example of the variation of lighting in the home with time. A sudden spike depicts an increase of lighting in the home and this can mean lights have been turned on or the curtains have been opened depending on the time of the day. If the lighting stays constant at night it could be because the elderly person is still awake or forgot to turn off the lights.

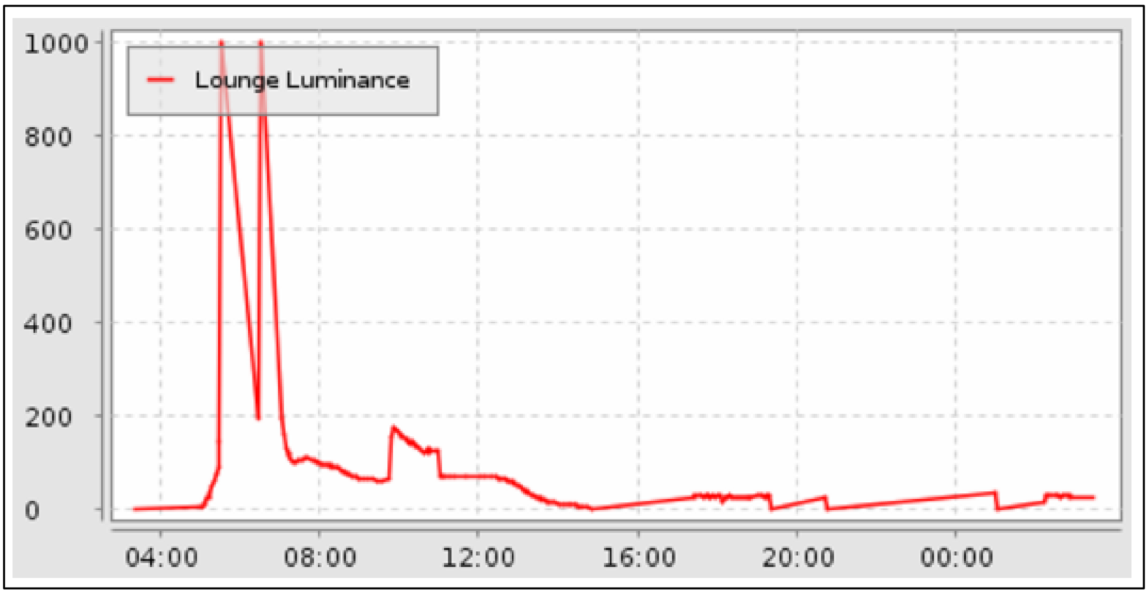


Figure 4-26 Example graph of lighting (Luminance) vs time

Figure 4-27 on the next page shows an example of the variation of motion against time in the home.

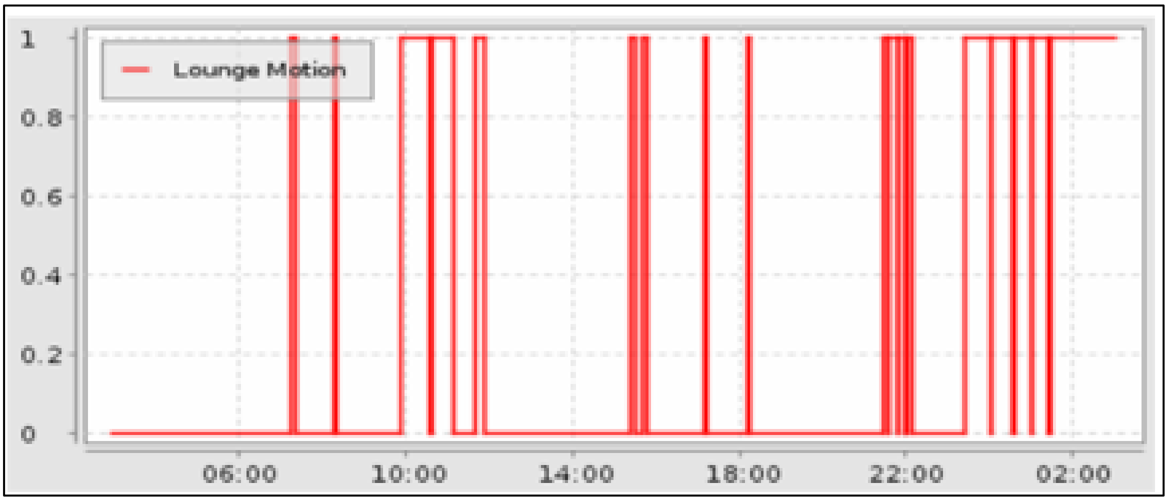


Figure 4-27 Motion vs time

The motion sensor records motion as a 1 if motion is detected in the home, or 0 if no motion is detected. If no motion is detected between 6am – 10:00am and we know that the elderly person wakes up at about 6:30 every day, it could mean that the elderly person has not woken up and this might mean he has collapsed in the home. The various scenarios which need monitoring and reporting were combined into rules, which are executed by openHAB. The following section discusses the risk detection and how the automation rules were implemented.

4.2.5 Risk detection

Risk determination and the sending of the corresponding notifications were achieved by developing a set of rules. All rules share a common execution context and therefore they can exchange values with each other. Each rule typically follows the following structure:

[Imports]

[Variable Declarations]

[Rules]

The Imports Section is for referencing any libraries that are used and the Variable Declarations Section can be used to declare variables that are used in the logic of the rule implementation. The Rules Section contains the trigger conditions and the execution block that should be executed when a trigger condition is met. The rule triggers can be Item based triggers, time based or system based triggers. Item based triggers react to events on the openHAB event bus and the time based triggers react at special times. The system based triggers react depending on certain system statuses.

Time is an important component of the rules that were implemented. The change in value of the home environment variables at certain times can be used to determine if a risk is possible. For example, if the temperature increases during 5pm to 7pm it could be due to cooking in the home and hence no notification will be sent. However, if the temperature continues to increase beyond an acceptable maximum, then a notification can be sent. Another example is if the luminance in the home does not change between 6am to 8am then it could be that the elderly resident has not woken up and a notification is sent.

The development of the rules and the decision making component varies from one elderly person to the other. In future the system has to learn the daily trends of the elderly person residing in the specific home. The threshold ranges and the specific times used in this research were derived from data that was collected from the sensor that was mounted in an actual home over a period of a month (Appendix C).

For the purposes of this research, the time series for each day was segmented into 7 segments during which there is anticipated activity in the home, typical of the elderly person living independently. The time segments and the anticipated activity are shown in Table 4-1.

Table 4-1 Activities and corresponding time segments

Time Period	Activity
06:00 - 10:00	Waking Up, Chores, Cooking
10:00 - 12:00	TV, Reading, Rest, Leave Home
12:00 - 14:00	Cooking, Eating
14:00 - 17:00	Rest, Reading, TV, Leave Home
17:00 - 20:00	Cooking, Eating
20:00 - 22:00	Rest, Reading, TV
22:00 - 06:00	Sleeping, Periodic Wake Up, e.g. for toilets or medication

Seven segments were selected based on times mentioned during the focus group interview. The elderly mentioned rough estimates of the time they would wake up, cook and other typical activities they do during the day.

Table 4-2 shows the risks dependent on changes in the home environment variables considered in this research.

Table 4-2 Risks and associated home environment variables

Risk	Temperature	Lighting	Motion	Humidity	Action
Falling			No motion detected		Emergency Notification – dependent on computer vision component as well
Extreme Temperature	Temperature values outside this range: 18<=T<=25.*		No motion detected	Humidity greater than 90%	Emergency Notification
Unconsciousness Inactivity	Rapid increase in temperature	No Change in lighting	No Motion detected		Emergency Notification
Adverse Medical Events – Hyperthermia, Hypothermia, Sudden illness	Temperature values outside this range: 15<=T<=25.*	Change in lighting at Night	Motion detected at Night		Emergency Notification

*The values are derived from literature and experimental results – they could change depending on location and season.

Cooking causes an increase in the temperature and humidity in the home environment. A continuous increase in temperature during the period in which cooking is taking place could indicate a fire risk, as the elderly person might have forgotten to turn off the stove. Waking up involves opening curtains and turning on lights and this causes an increase in luminance values in the home. Failure to wake up will result in no change in luminance, motion and temperature in the home, therefore there could be the risk of unconsciousness. Performing daily chores results in frequent motion being recorded in the home, and if no motion is detected, then a notification has to be sent.

For decision making purposes, the changes in the home environment variables have to be categorised depending on the time of the day. Each combination of variables is assigned a severity level depending on the duration of the variable combination. Table 4-3 shows the decision table for home environmental variable combinations for the time period 06:00am to 20:00pm.

Table 4-3 Decision-making table for time period 06:00am - 10:00pm, 12:00pm – 14:00pm and 17:00 – 20:00

Lighting *(Lux)*	**Temperature *(T°C)***	**Motion**	**Humidity *(H)***	**Duration (*t mins*)**	**Severity**	**Action**
dLux > 0	*0 ≤ dT ≤ 5*	*Open*	*0 ≤ dH ≤ 20%*	*dt ≤ 30*	*Low*	*None*
Lux = 0	*dT ≥ 5*	*Closed*	*0 ≤ dH ≤ 20%*	*dt > 30*	*High*	*Send Notification*
dLux > 0	*dT ≥ 5*	*Closed*	*dh>20%*	*dt ≤ 30*	*High*	*Send Notification*
dLux > 0	*dT ≥ 5*	*Open*	*dh>20%*	*dt ≤ 30*	*High*	*Send Notification*
dLux > 0	*0 ≤ dT ≤ 5*	*Closed*	*0 ≤ dT ≤ 20%*	*dt ≤ 30*	*Medium*	*Verify other activities*
Lux = 0	*0 ≤ dT ≤ 5*	*Closed*	*0 ≤ dH ≤ 20%*	*dt > 30*	*Medium*	*Verify other activities*
Lux = 0	*0 ≤ dT ≤ 5*	*Open*	*0 ≤ dH ≤ 20%*	*dt ≤ 30*	*Low*	*None*

The keys for the variables are shown in Table 4-4. The allowed changes in temperature ***(dT)*** and Lighting ***(dLux)*** in Table 4-3 were determined from the data collected in a typical home environment of a person living independently and also from values obtained from theory, as discussed in Chapters 2 and 3. The data used to derive these ranges was collected for a month. In future, the system is supposed to learn the daily patterns of the elderly person living in the home.

The time duration of 30 minutes was used so as to avoid false positives from using values recorded every 4 minutes. The sensor, however, can proactively send its own report if a change exceeds the set threshold before the 30 minutes elapse.

Table 4-4 Decision Table keys

Variable	*Definition*
dT	*Change in Temperature*
dLux	*Change in Lux(Lighting)*
dH	*Change in Humidity*
dt	*Change in time*
Closed	*No Motion Detected*
Open	*Motion Detected*

The time period between 06:00am – 10:00am typically comprises waking up, preparing breakfast and performing some household chores. There is an anticipated significant change in the lighting in the home from 0 Lux when a person wakes up. This could be due to opening of curtains or switching on the lights. Motion is also supposed to be detected frequently within this time as there will be movement when daily chores are being done. If there is no change in the lighting and no motion is detected after 30 minutes of the typical wake up time, a notification is sent. The wake up time varies from person to person but is more or less constant for a particular individual.

A reasonable increase in temperature is also expected, i.e. $\boldsymbol{0 \leq dT \leq 5}$ due to cooking of breakfast during this period. The acceptable temperature range for a normal room temperature is 18ºC – 25ºC, but this may vary depending on location. A rapid temperature increase of $\boldsymbol{dT > 5}$ triggers an emergency notification regardless of the other variables.

Sometimes no motion will be detected and there will be no change in lighting within the 30 minute period, but this may not mean that there is an emergency. It might be due to the resident partaking in other activities. Under such circumstances the computer vision module will be triggered to check if there is any activity on the human blob captured from the video stream. The computer vision component will be discussed in Section 4.2.2.

There is also an anticipated change in the humidity in the home if the resident is cooking or bathing. Sometimes the humidity can decrease if the windows or doors are opened. Therefore if the humidity stays constant for a long time it may be due to inactivity in the home.

The risks associated with the 06:00am – 10:00am time period include unconsciousness i.e. the elderly person has failed to wake up. Fire breakout is also a possibility if the elderly person forgets to turn off their cooking appliances after cooking. Adverse medical conditions like hyperthermia can arise if the temperature becomes too high compared to the acceptable range. Hypothermia will result if the temperature is too low compared to the acceptable range.

The decision table for the combined time periods 22:00pm to 06:00am is shown in Table 4-5.

Table 4-5 Decision Table for 22:00pm - 06:00am

22:00 - 06:00	**Lighting *(Lux)***	**Temperature *(T°C)***	**Motion**	**Humidity *(H)***	**Duration (*t mins*)**	**Severity**	**Action**
	dLux > 0	*0 ≤ dT ≤ 5*	*Open*	*0 ≤ dH ≤ 20*	*dt ≤ 30*	*Low*	*None*
	Lux = 0	*dT ≥ 5*	*Closed*	*0 ≤ dH ≤ 20*	*dt > 30*	*High*	*Send Notification*
	dLux > 0	*dT ≥ 5*	*Closed*	*dh>20*	*dt ≤ 30*	*High*	*Send Notification*
	dLux > 0	*0 ≤ dT ≤ 5*	*Closed*	*0 ≤ dT ≤ 20*	*dt ≥ 30*	*Medium*	*Verify other activities*
	Lux = 0	*0 ≤ dT ≤ 5*	*Open*	*0 ≤ dH ≤ 20*	*dt ≤ 30*	*High*	*Send Notification*

The time periods between 10:00am – 12:00pm and 20:00pm - 22:00pm are considered idle periods in this research. During these periods, the elderly person is most likely watching TV or reading or partaking in any other hobbies as shown in Table 4-5. The home environment variables are not expected to change much and most of the risk determination is done by the computer vision component as discussed in the next section. However, if there are any sudden increments in the temperature in the home, then a notification can be sent to the caregivers or family members.

The outside weather values are used to obtain a reference of how severe the changes in the home are. If it is very hot outside, one would expect the home to be cooler and the opposite is true; if the outside is cold then the home environment should be warmer.

4.2.6 Remote Monitoring

To enable relatives and caregivers to remotely monitor the home environment variables, the myopenHAB cloud service was configured. The myopenHAB cloud service allows for push notification to be delivered to all devices registered for the service. The cloud service can be accessed via a mobile device or via a web portal. Figure 4-28 below shows the configuration of the connection settings on a mobile device.

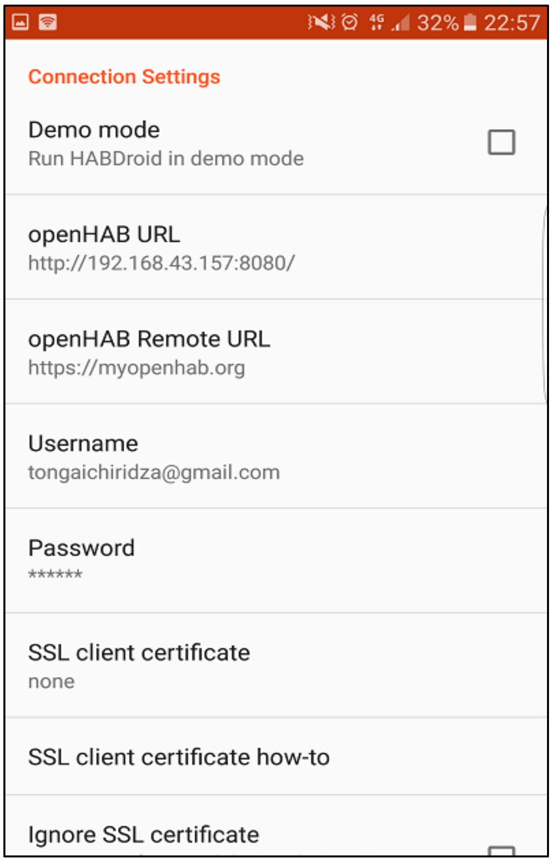


Figure 4-28 Configuring settings for myopenHAB cloud service

Once configured the mobile application dashboard will look as shown in Figure 4-29.

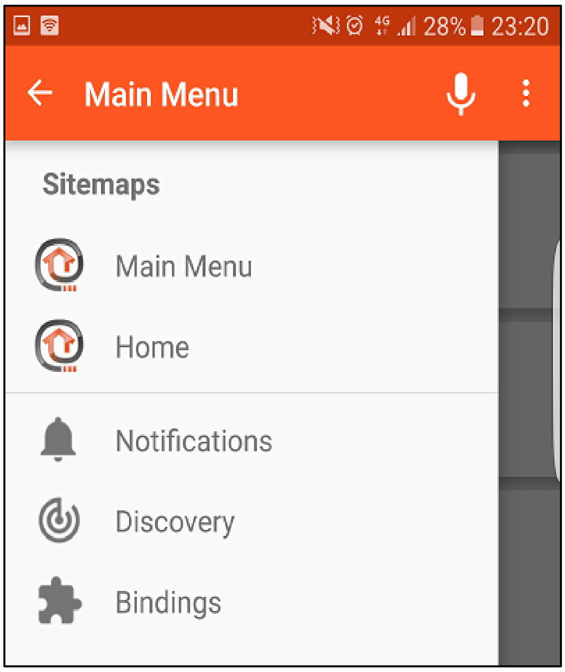


Figure 4-29 Main Menu for the myopenHAB cloud service on a mobile device

When a risk situation is detected, notifications are instantaneously sent to all configured mobile devices. Example notifications are shown in Figure 4-30 below:

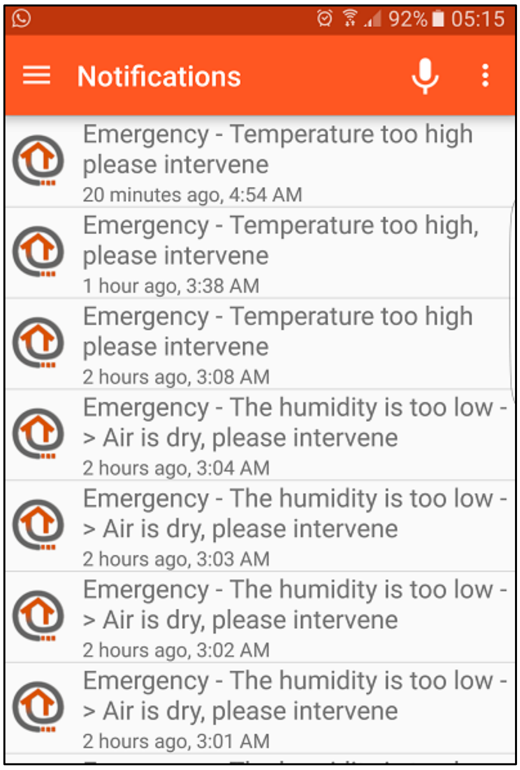


Figure 4-30 Push Notifications delivered to a mobile device

4.2.7 Fall Detection

Falling is common among the elderly and early intervention is vital when a fall occurs in order to prevent fatal consequences in some instances (Chapter 2). Chapter 3 discussed the use of wearable devices and mobile phones to detect falls by utilising values from the embedded accelerometer. The major drawback of using wearables is the fact that the user has to always have the device on him and this does not always work well as the elderly can forget to wear them. Furthermore wearables are viewed as an obtrusive form of data collection.

The solution that was developed uses computer vision techniques to detect if a fall has occurred. The key consideration was that the privacy of the user must be preserved whenever video is being used. This was achieved by using depth buffer video stream instead of the normal RGB video stream. An assumption made in the development of the algorithm is that only one person will be in the field of view of the camera. The diagram in Figure 4-31 illustrates the components of the fall detection algorithm.

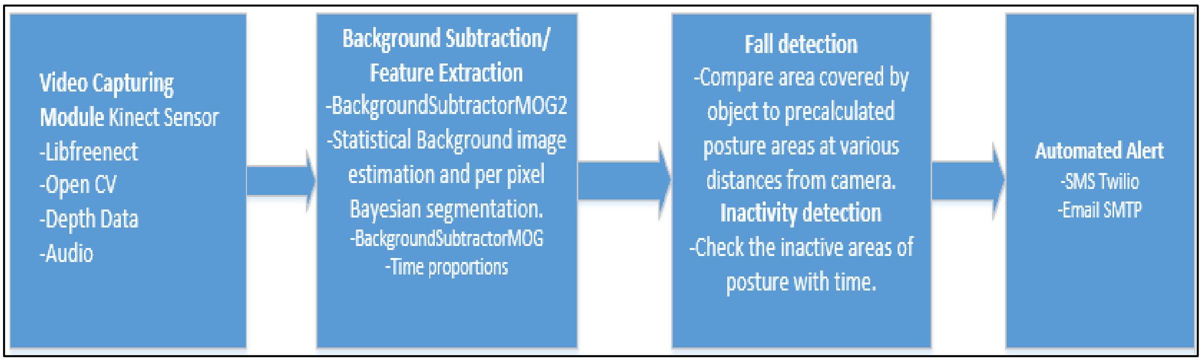


Figure 4-31 Fall detection components

The algorithm is part of the data processing and computation layer, which is implemented to run on the Raspberry Pi. The complexity of some of the steps requires heavy computational processes and thus the Raspberry Pi 3 was used instead of the Raspberry Pi model B used in the previous Section. The steps illustrated in Figure 4-31 are described in detail in the following sections.

4.2.7.1 Video capturing module

The video capturing module comprises the Kinect sensor, which was mounted on the ceiling covering an area 3.10m long and 2.30m wide. Mounting the Kinect on the ceiling yields a 2 dimensional view of the home environment. The Kinect sensor can record depth data hence protecting the privacy of the elderly person being monitored. Figure 4-32 below illustrates how the Kinect was set up.

Figure 4-32 Microsoft Kinect mounted on the ceiling

The area picked up by the Kinect was marked as shown in Figure 4-33.

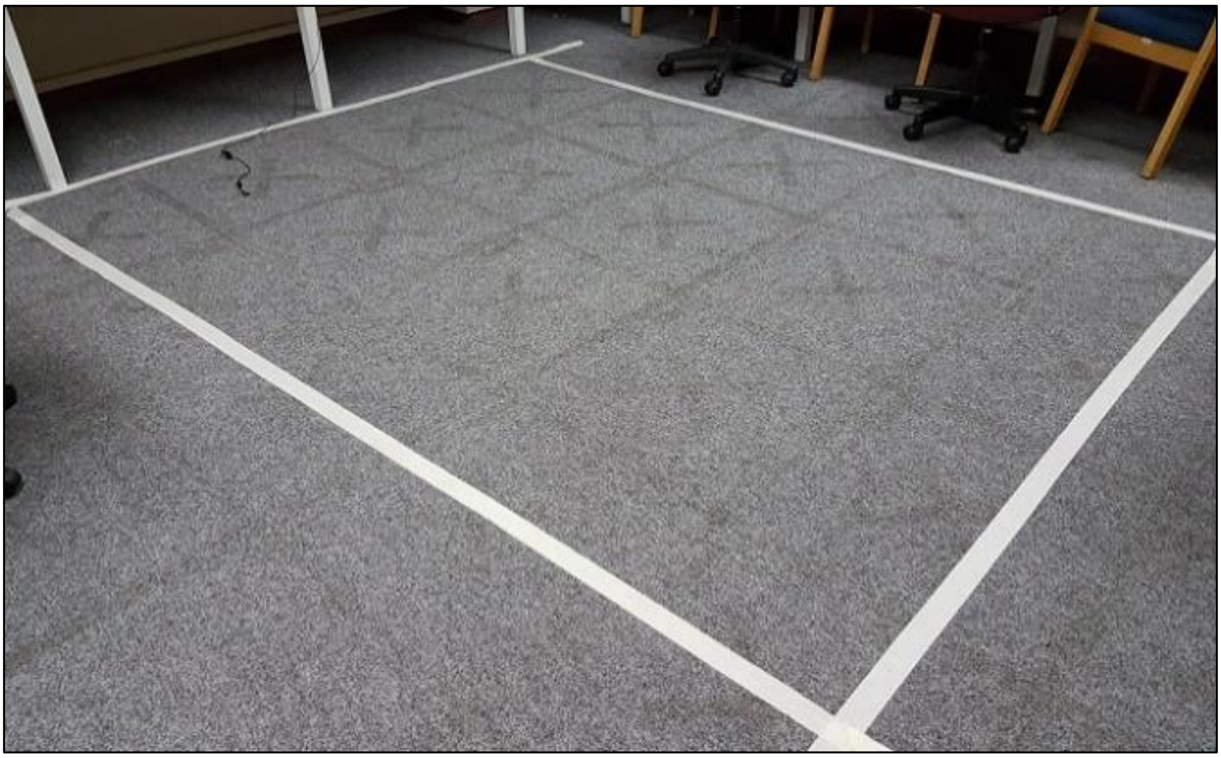


Figure 4-33 Area picked up by the mounted Kinect.

The image to the left in Figure 4-33 is a normal picture taken to show the area covered by the Kinect i.e. 3.10m X 2.30m. The image to the right is the picture of the same area obtained from the Kinect mounted on the ceiling.

Libfreenect is an open source cross platform driver that was used to get the depth buffer video stream from the Kinect. Libfreenect supports RGB image transfer, IR and depth image transfer, audio, the registration of RGB and depth images (Järemo Lawin, Forssén, & Ovrén, 2016). Libfreenect also has multiple GPU and hardware acceleration implementations for image processing, which are very useful for devices with limited computational resources (Xiang et al., 2016). Libfreenect has wrappers that support multiple languages including C++, Python, C# and Ruby.

The prerequisites for Libfreenect for the purposes of this research are Python and Open Computer Vision (OpenCV). OpenCV is an open source library primarily for real-time computer vision. OpenCV can support multiple languages like Java, Python, C++ and C and it can run on any platform. OpenCV has an extensive user community who continuously contribute to its expansion. OpenCV's application areas include facial recognition, motion tracking, object recognition, mobile robotics and augmented reality. OpenCV also has a statistical machine learning library that can support decision tree learning, artificial neural networks and support vector machines (SVM).

The installation of Libfreenect and its prerequisites is shown in Appendix C. Once the video stream has been acquired, the next phase is to remove the background so that the true object can be identified. The next section discusses the background subtraction and feature extraction.

4.2.7.2 Background Subtraction and Feature Extraction

Background subtraction offers real-time segmentation of moving regions in a video stream. It involves calculating a reference image and subtracting each new frame from this image and thresholding the result (Kaewtrakulpong & Bowden, 2001). Objects in a static scene have a regular behaviour that can be modelled by a statistical model. Moving objects are detected by considering the parts that do not fit the model (Zivkovic & Van Der Heijden, 2006). The result is a binary segmentation showing the moving objects.

A time-averaged background is the simplest form for a reference image (Kaewtrakulpong & Bowden, 2001). This method requires training in the absence of any foreground objects and cannot keep up with varying illumination conditions. Therefore a better model would consist of adaptive remodelling of the background.

The reference frame in this case is shown in Figure 4-34:

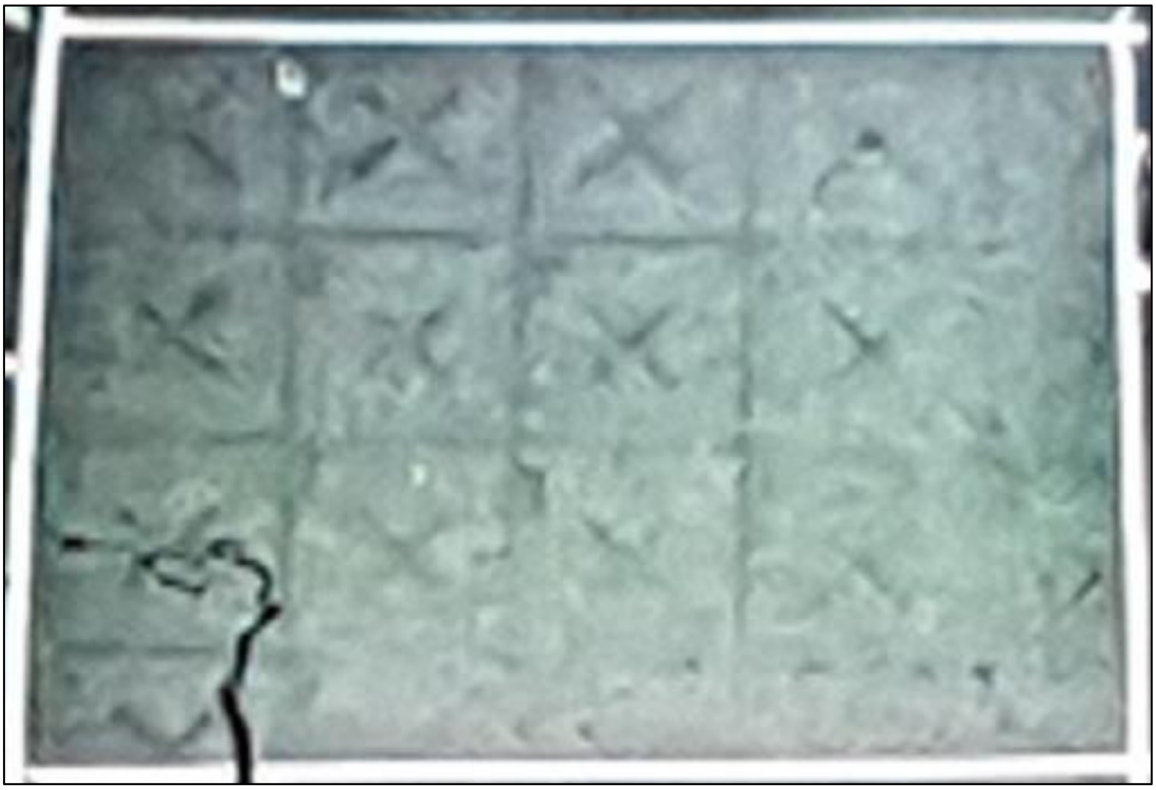


Figure 4-34 Reference frame for background subtraction with Kinect mounted on the ceiling

Three algorithms were considered for the background subtraction:

a. **BackgroundSubtractorMOG**

This algorithm models each background pixel by using a mixture of K Gaussian distributions, where $K = 3\ to\ K = 5$. The K-distribution is a family of continuous probability distributions composed of three parameters. Each Gaussian distribution represents a different colour and the weight parameters of each mixture represent the time proportions in which each colour remains the same in a scene (Kaewtrakulpong & Bowden, 2001).

The moving parts of a scene are shown as white and the static scene is depicted as black. In Figure 4-38 the person lying on the floor was moving her legs and the upper body was stationary.

In some instances the BackgroundSubtractorMOG method is inadequate because it cannot adapt to complex illumination changes and noise in the scene.

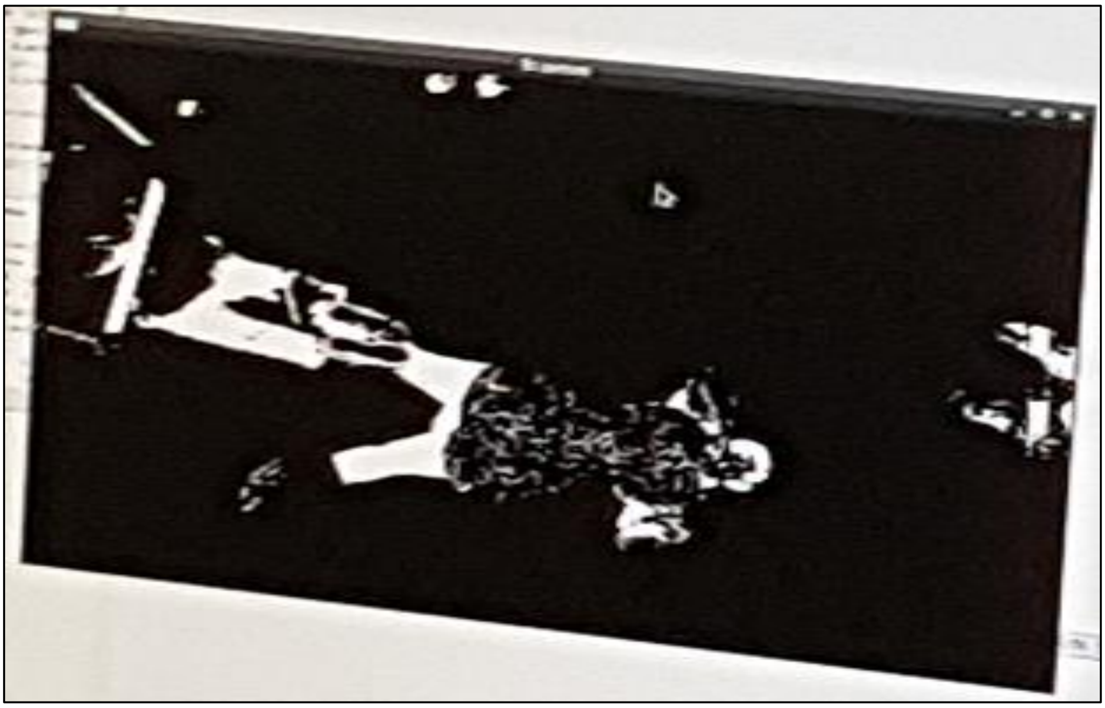


Figure 4-35 Foreground image from a scene with person lying on the floor using BackgroundSubtractorMOG

b. BackgroundSubtractorMOG2

This algorithm is an improvement on the BackgroundSubtractorMOG. The BackgroundSubtractorMOG2 selects the appropriate number of Gaussian distributions for each pixel whereas the BackgroundSubtractorMOG that uses a specific K distribution (Zivkovic & Van Der Heijden, 2006). This algorithm provides improved adaptability to varying scenes due to changes in illumination and other common noise.

The changes in illumination in a scene could be the turning on/off of lights and the gradual change in daytime or weather conditions. New objects can be brought into the scene and the present ones could be removed. These changes are not adequately supported by the BackgroundSubtractorMOG. Adapting to these changes requires continuously updating the training set and discarding old values over a time period. The BackgroundSubtractorMOG2 method removes more noise from the foreground image and does not rely on the time proportions of the pixels remaining static.

The algorithm is implemented in OpenCV and can be called in Python as cv2.createBackgroundSubtractorMOG2. Figure 4-36 shows the foreground image of the same person lying in the same position as shown in Figure 4-35.

Figure 4-36 Foreground image of a scene with person lying on the floor using BackgroundSubtractorMOG2

The area covered by the person depicted in a scene can be easily calculated if the BackgroundSubtractorMOG2 algorithm is used instead of BackgroundSubtractorMOG.

c. BackgroundSubtractorGMG

This algorithm is a hybrid of statistical background image estimation and per-pixel Bayesian segmentation. The BackgroundSubtractorGMG uses the first 120 frames to model the background and then uses a probabilistic foreground segmentation algorithm. Possible foreground objects are obtained using Bayesian inference with an estimated time-varying background model and an inferred foreground model (Godbehere & Goldberg, 2014). This algorithm is still in its beta version of OpenCV 3, hence it was not used in this research, to avoid incompatibility issues with some of the components. The other components used in this research were implemented using OpenCV 2.

The BackgroundSubtractorMOG2 was used as the background subtraction algorithm since it performs better than the BackgroundSubtractorMOG. Its ability to adapt to varying illumination changes makes it a perfect candidate for use in home environments. The area covered by the person in the scene can also be calculated easily if BackgroundSubtractorMOG2 is used.

4.2.7.3 Fall detection method

In Chapter 3 it was mentioned that a fall occurs within a fraction of a second (0.45s - 0.85s) during which there is a noticeable change in posture (Delahoz & Labrador, 2014). Posture can be defined as the position in which someone holds their body when standing, sitting or lying down (Oxford Dictionary, 2016).

Area is an intrinsic property of any posture. The width and the length of the foreground image can be used to classify a particular posture as sitting, standing or lying down. Lying down covers more width than sitting and sitting occupies more width than standing, as shown in Figure 4-37.

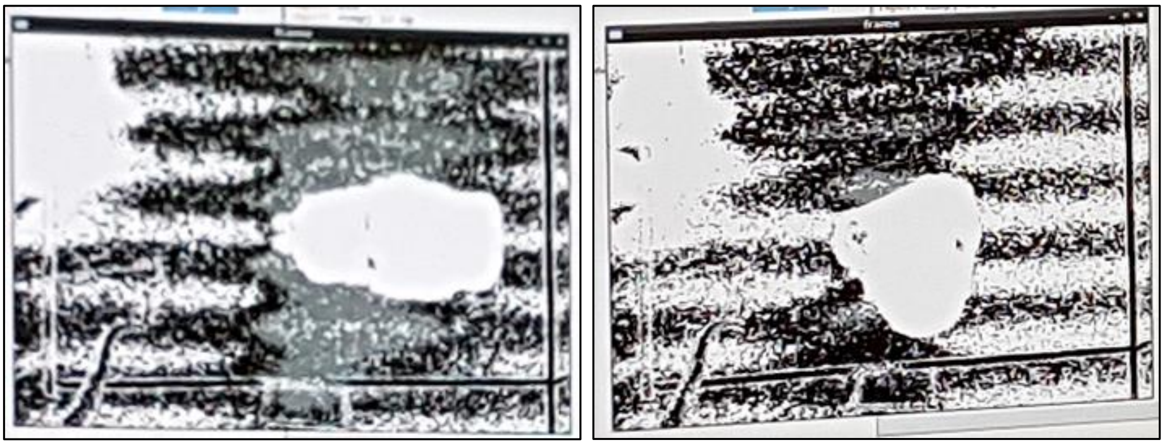


Figure 4-37 Foreground image of person sitting (left) vs standing (right)

The image of the same person lying down is shown in Figure 4-37.

Finding the object size and matching it with the known posture sizes acquired during calibration requires decoding the video stream into corresponding frames. The

Microsoft Kinect has a frame rate of 30 frames per second, which translates to 1 frame every $33\frac{1}{3}\ ms$. Earlier it was mentioned a fall occurs for a duration of at most 800ms, therefore it will take approximately 24 frames to detect a fall. To detect a fall, the change in the distance from the camera to the object is also considered. If the first posture was standing and the final posture is lying down and the change in distance is equal to the object's known height, a fall should be detected provided the change occurs within the 800ms.

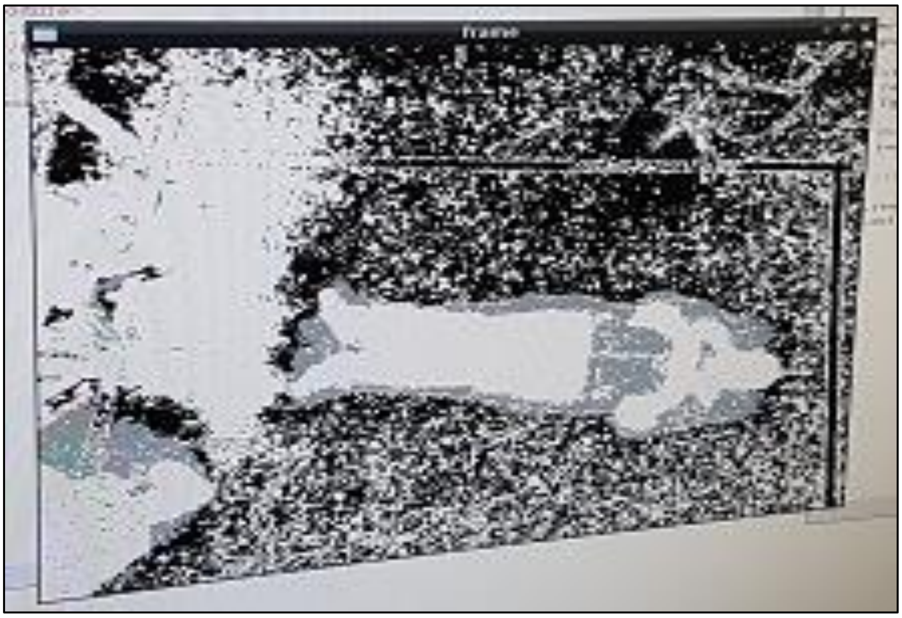


Figure 4-38 Foreground image of a person lying down.

The pseudo code for the fall detection method is shown in Figure 4-39 on the next page.

The first step of the algorithm is to initialise the sizes of the three known postures. The sizes are acquired during calibration. Because the camera is installed on the ceiling, the images displayed in the foreground image are two dimensional. Therefore the values that should be measured for the person are their shoulder to shoulder length and the breadth when standing, sitting and lying down. In this research, these values were measured physically; ideally these values should come from a personalisation module.

The second step involves background subtraction and edge detection. The code snippet in Appendix C shows the packages needed for the algorithm with the background subtraction and edge detection methods. The time durations used in the pseudo code are not absolute; they can be adjusted depending on the profile of the person being monitored.

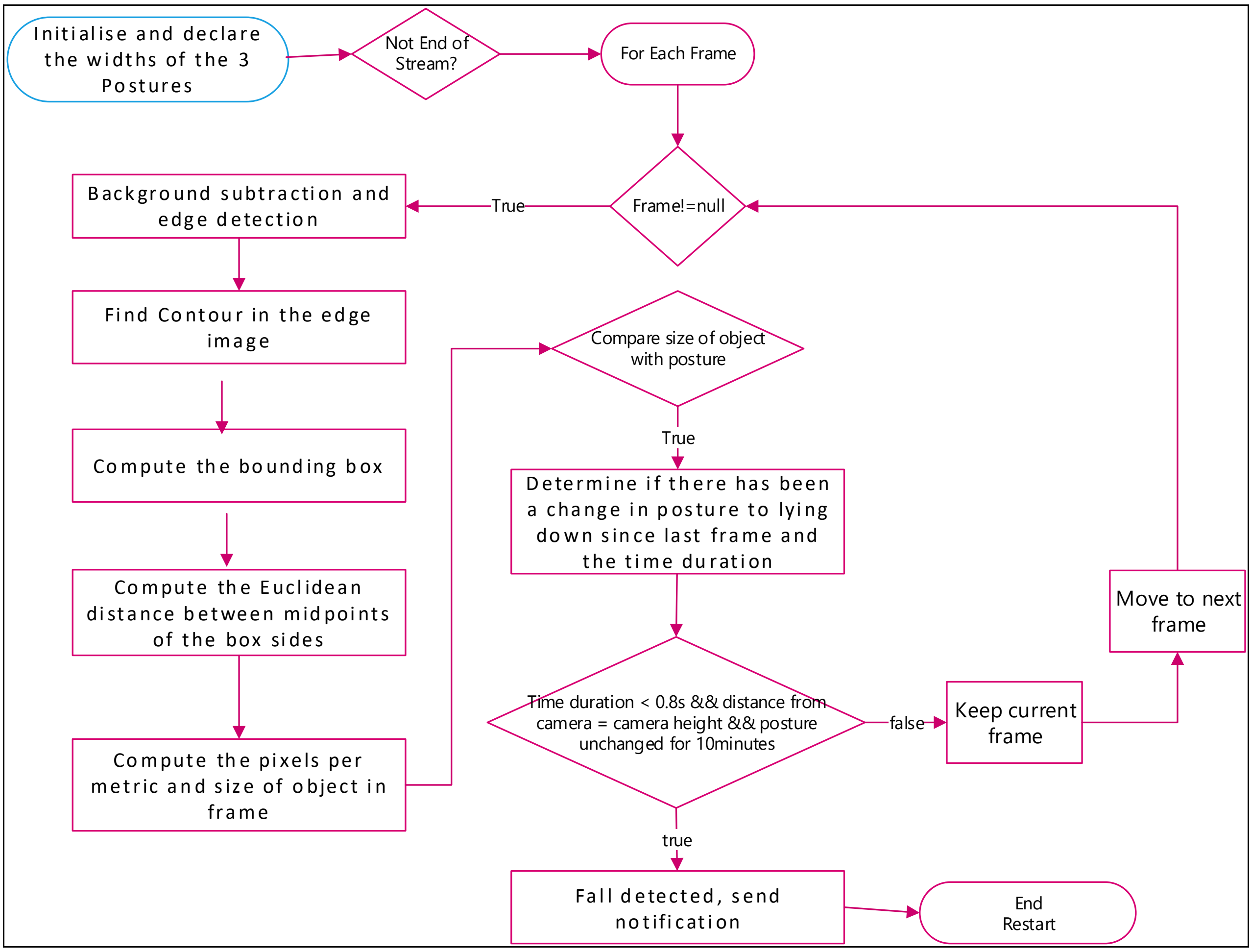


Figure 4-39 Fall detection pseudo code

The first setup section of the fall detection algorithm code is shown in Appendix C.

The first section in code snippet is the Imports Section, which references all the helper libraries that are needed. Numpy is a package for numerical computation on the images acquired as frames. It is the Matlab equivalent in Python because it defines a numerical array and matrix types, and performs basic operations on them. The Scipy library contains a large set of numerical algorithms and domain specific toolboxes, for example statistics and optimization. The imutils is a library of functions for basic image processing such as detecting edges, sorting contours and translation.

The second section involves looping through each frame and applying background subtraction. Edge detection is then performed on the foreground followed by dilation and erosion to cover up any gaps in the foreground image. The image resulting from the edge detection is then used in the third step to find the contours in the edged image. A contour is a line joining all continuous points along a boundary having the same colour. Contours therefore allow us to perform shape analysis and object detection in a scene.

To determine the size of an object in a scene, we need to perform a calibration by using a reference object. This calibration allows us to define a ratio that measures the number of pixels per given metric of measurement. The ratio is called the pixels per metric ratio. The pixels per metric ratio can be calculated as shown in Equation 4.1 below:

$$pixels\_per\_metric = {}^{object\_width}/_{known\_width} \tag{1}$$

The midpoint values obtained from the bounding box are used in finding the true width or breadth of the object in a scene. The Euclidean distance between the mid-points of the sides of the bounding box gives the width and the breadth and this is achieved by the code shown in Appendix C under the fall detection algorithm.

Figure 4-40 shows a bounding box for a person in a seating position. A comparison between the obtained dimensions and size of the object in the scene and the three postures defined from calibration, will determine which posture is depicted in the scene. A change in posture will only be categorised as a fall if the change in the distance from standing to lying down or sitting to lying down occurs in less than 800ms. The change in distance has to be included as well to verify if the change in posture is indeed a fall.

The last component of the fall detection algorithm involves determining if the change in distance from the camera from when the person is in an initial posture (i.e standing or sitting) to when the person is lying down is equal to the height of the person. The following section discusses the algorithm that was implemented to find the distance from object to camera.

Figure 4-40 Bounding box (green) on surrounding the person object in a frame

4.2.7.4 Finding Distance from Camera to Object

The distance from the camera to the person in a particular posture is important in order to verify that a fall has occurred. Whenever there is a change in posture, there is a change in the distance between the camera and the person object in a scene. The program flow for calculating the distance follows the program flow illustrated in Figure 4-41 below. The first step is getting an image or frame from the background subtractor, which was discussed in the previous section.

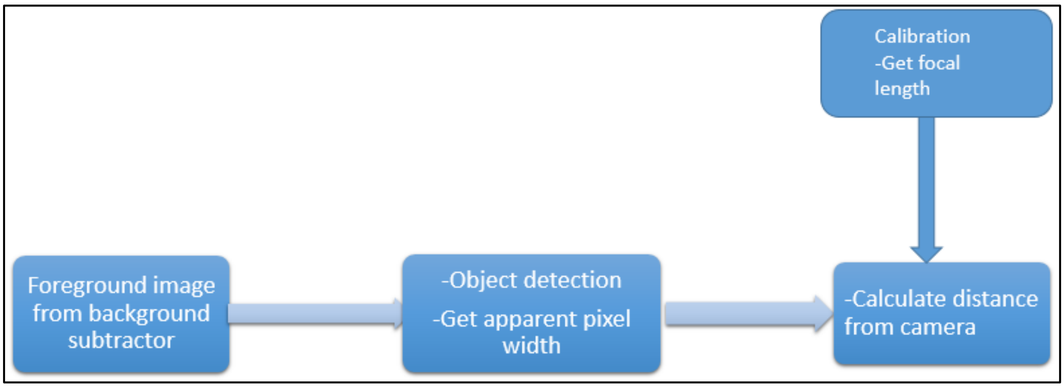


Figure 4-41 Prom flow for calculating the distance from camera to object

The distance from the camera mounted on the ceiling to the topmost part of a person in any posture was calculated by utilising the triangle similarity. Figure 4-42 shows the triangle achieved when the Kinect is mounted on the ceiling.

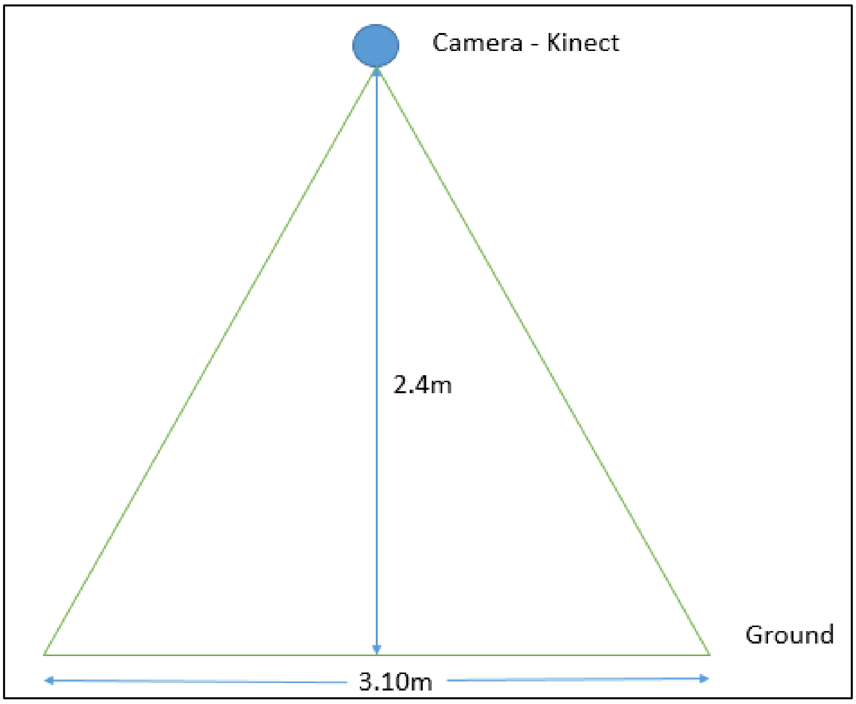


Figure 4-42 Triangular field of view for Kinect mounted on ceiling

The foreground image obtained from the background subtractor is used to identify the contour around the person object in a scene. The contours allow for the determination of the apparent pixel width. The focal length of the camera has to be determined first. To calculate the focal length (F), the following Equation 4.2 is used:

$$F = \frac{(A_p * D)}{W} \qquad (2)$$

A_p is the apparent width in pixels and D is the distance from the camera. In order to get the A_p an image of the scene without the object was taken and the width of the scene in pixels was noted. The known width (W) is depicted in Figure 4-45. After the focal length is established using the formula in Equation 4.2, the distance from object to camera was found by using the following Equation 4.3:

$$D' = \frac{(W * F)}{A_p} \qquad (3)$$

If the distance between the person object in a scene and camera is equal to the distance between the Kinect and the ground, then a fall is confirmed.

4.2.7.5 Inactivity Detection

Whenever there is an activity being conducted, there is some degree of movement. The motion sensor in the Aeotec 4-in-1 multisensor detects motion if there is physical movement from point *a* to point *b*. If motion is detected, the sensor registers open, and if no motion is detected, it registers a close. A lack of motion over a sufficient period of time can mean there is no occupant activity in the home. This type of detection is inadequate when a person is at rest.

If a person is at rest watching television they will at some point change the way they are seated or lying down. While the Aeotec multisensor does not pick up this kind of motion, the analysis of the video stream can detect motion at a lower level. The background in a video stream is often static over consecutive video frames. A substantial change over a period of time within the frames can be used to detect minute changes in motion.

Background subtraction forms the backbone of the inactivity detection algorithm. As discussed earlier, background subtraction involves calculating a reference image and subtracting subsequent frames. Thresholding the result yields a binary segmentation, which highlights non-stationary objects. To achieve the desired result, the Gaussian mixture model based BackgroundSubtractorMOG algorithm was used, because it uses a time average where pixels that did not change become darker. This algorithm relies on the time proportions that pixels in the same area remain static; therefore it can be used for motion detection.

Figure 4-43 shows in the foreground the difference between the moving parts and stationary parts of a person lying down. In Figure 4-43 the person lying down is only moving his legs and the upper body is stationary. The legs are shown as white pixels and the upper body is, to a greater extent, depicted as the dark areas. If no movement is detected for sufficiently long periods of time, the entire frame will be depicted as dark. At this point the absolute change in the pixel difference will be approaching zero.

Figure 4-43 Foreground image of person lying down moving the legs only

4.2.7.6 Automated Alerts

Automated alerts were achieved using openHAB push notification service and the Twilio API. The openHAB push notifications were discussed earlier and are suitable for people with smartphones.

The Twilio REST API was used to send out an SMS as an alert notification. The Twilio REST API allows for the querying of meta-data about phone numbers, text messages and calls. To use Twilio, an account was registered on www.twilio.com. A Twilio account comprises an account SID and Auth Token that need to be provided each time a call is made to Twilio REST services. All HTTP requests to the Twilio REST API are protected by HTTP Basic authentication (Twilio, 2016a).

In order to use the Twilio API in Python, the Twilio Python helper library was installed on the Raspberry Pi. The Twilio library was set up as shown in Appendix C under setting up Twilio. The TwilioRestClient accepts the account SID and the auth_token as credentials to authorize access to the Twilio REST resources. The TwilioRestClient creates a message by calling the create method, which accepts the cell number you are sending from and the one you are sending to. The create method also accepts the body of the SMS. The body contains the message of the SMS.

MMS will be considered in future additions to this research.

4.3 Conclusion

The aim of this chapter was to describe the development of a SHE using low cost and unobtrusive devices. A SHE was developed using the Raspberry Pi as a computational platform. The architecture of the SHE was derived from the key components of an IoT solution. Formative evaluations were done throughout the development lifecycle of the prototype in order to provide continuous feedback and adapt to changing requirements.

The cost of equipment and technologies used in the development of the prototype was less than R3000, and this can be substantially reduced if the equipment is acquired directly from the manufacturer. The Raspberry Pi 3 used was able to handle the computational needs of the components of the SHE.

The Aeotec 4-in-1 multisensor was used to collect data on four home environment variables. The four variables were temperature, lighting, motion and humidity. Rules were developed to determine the combination of variables that result in risk situations. The values used as the acceptable ranges differ depending on the geographical location and the personal traits of the occupant of the house. OpenHAB proved to be a robust open source Smart Home Operating System and can be easily configured to suit the required functionality. The Z-Wave protocol was a good choice for a communication protocol between openHAB and the multisensor.

The Microsoft Kinect sensor was used for fall detection and inactivity detection. The Microsoft Kinect used a camera, because of its ability to return depth buffer data, which ensures that the privacy of the elderly person is maintained. The Kinect was mounted on the ceiling providing a 2-D field of view. An algorithm was developed to determine if a fall occurred by comparing the dimensions of the current posture with those of postures obtained during calibration. The algorithm was further enhanced by utilising the distance from the camera to the person object in the scene, and the change in time when a change in posture occurs.

OpenCV is a very efficient library to use for computer vision techniques like the ones described in this section. The Python programming language was used to develop the fall detection algorithm and it integrated well with the OpenCV library. The Twilio REST API was used to send notifications and it can be integrated easily into Python. In future the system should be able to learn daily activity living patterns from the data collected and use artificial intelligence techniques to detect if any abnormal situations occur in a specified time period.

The next chapter will discuss how the evaluation of the prototype was conducted.

Chapter 5. Evaluation

Chapter 1 introduced the problem that this research is trying to solve, and outlined the research objectives and the research questions. Chapter 2 identified the risks and safety issues facing the elderly living independently. The existing technologies and frameworks that can be incorporated into a SHE were discussed in Chapter 3. A prototype of a SHE was developed in Chapter 4, to address the requirements identified, by incorporating the components and frameworks identified in Chapter 3.

This chapter addresses the last research objective, which was *"To evaluate the risk detection accuracy and consistency of the SHE prototype".* Without an evaluation, the results of DSR are unsubstantiated assertions that the designed artefact will achieve its purpose when deployed in practice (Hjalmarsson & Rudmark, 2012). Figure 5-1 illustrates the position of this chapter in the DSR methodology.

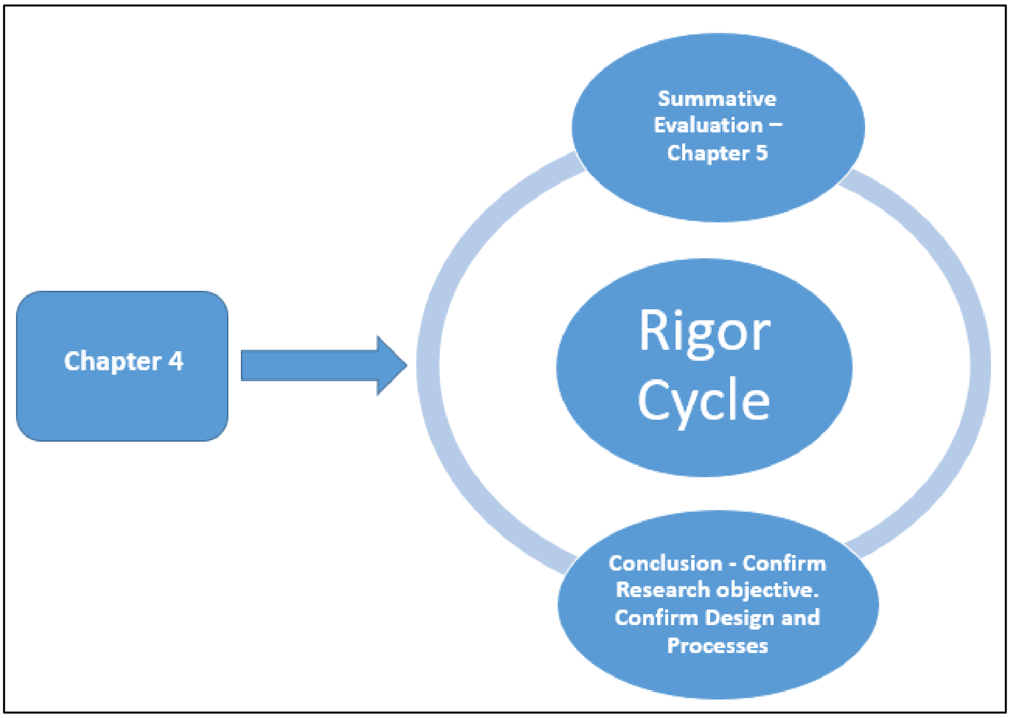


Figure 5-1 DSR Rigor cycle adapted (a. R. Hevner et al., 2004)

Two types of evaluation can be performed during the development lifecycle of a prototype. Formative evaluations were done in Chapter 4 during the development of the prototype. Summative evaluation is done at the end to verify if the prototype satisfies the goals of the research. The feedback from the evaluation of the prototype can be incorporated into the future iterations of the design cycle.

Evaluating a DSR artefact or prototype requires a robust approach in order to conclude that the prototype satisfies the requirements identified. Section 5.1 discusses the evaluation plan for the prototype developed in Chapter 4.

5.1 Evaluation Plan

The five most important dimensions to consider in evaluating a DSR artefact include the goal, the environment, structure, activity and evolution (Prat, Comyn-Wattiau, & Akoka, 2014). Figure 5-2 illustrates the various system dimensions, evaluation criteria and sub-evaluation criteria for a DSR artefact.

The system dimension consists of the efficacy, effectiveness and generality of the system. Efficacy is the degree to which the artefact achieves its goal (Prat et al., 2014). Generality refers to the broadness of the extent to which the goal is achieved by the artefact. The objective of the prototype developed in Chapter 4 is to support risk and safety monitoring requirements identified during requirements elicitation in Chapter 2. Therefore the effectiveness or distinguished efficacy of the system is concerned with to what extent the prototype can identify risks and respond accordingly. The generality refers to the completeness of the system in addressing all the specified requirements.

The environment consists of the people or organizations who are supposed to use the artefact. This dimension verifies the consistency of the artefact with the needs of the user and the technology used. Consistency is defined as the complete harmony of the parts or features of a system (Prat et al., 2014). In our case, the prototype has to be consistent with the needs of the elderly and consistent with low cost technology. The goals for this consistency with the users are utility, understandability, ease of use, ethicality and side effects. This means that our system should be able to accomplish all the functional requirements it is meant to address with ease of use on the part of the user. The user should be able to learn the system with ease and understand what it must do under given circumstances. Ethics requirements should not be contravened in any way by the system and any potential side effects should be identified and addressed. The system should exhibit the harnessing of recent technologies in solving the problems identified.

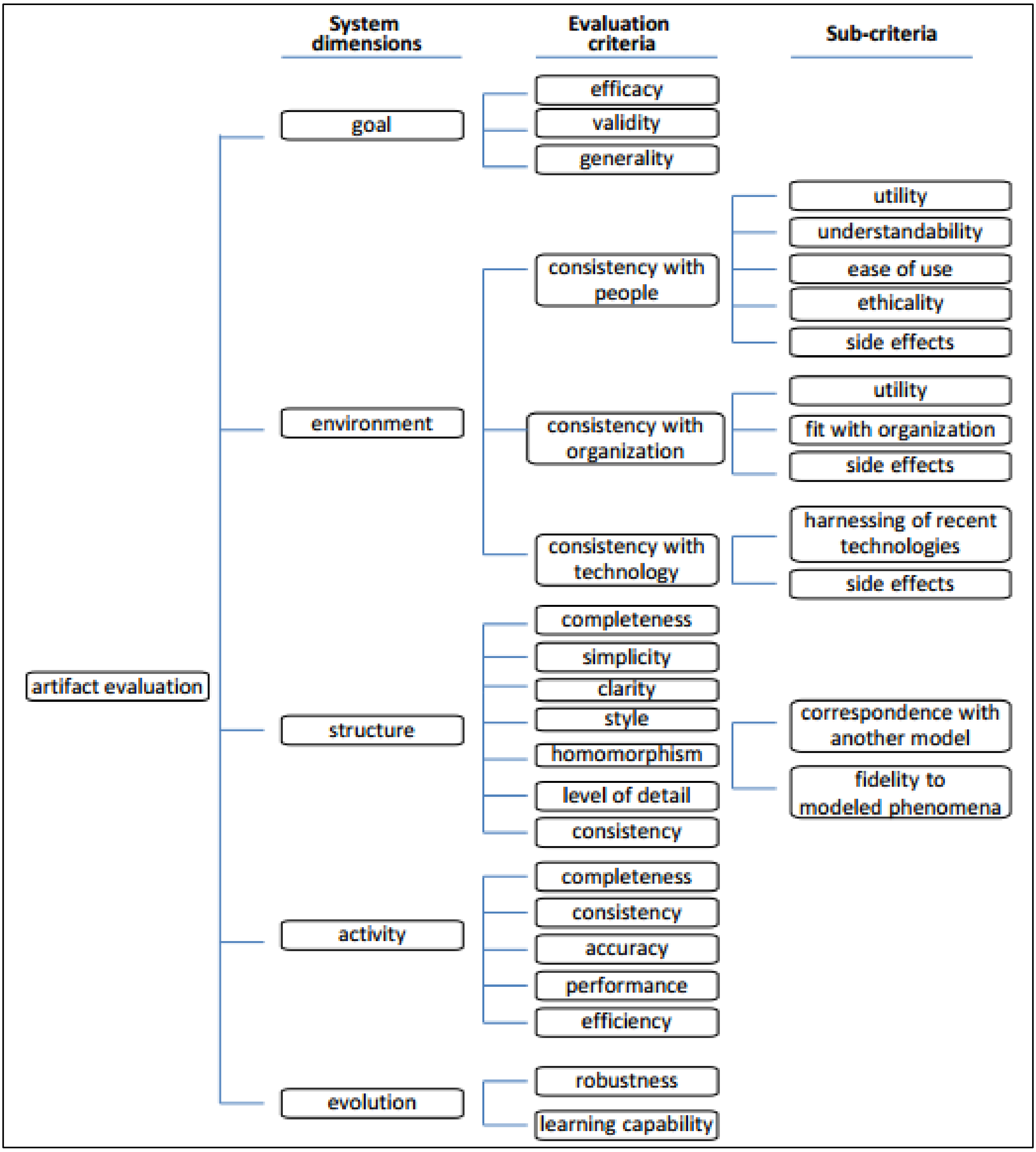


Figure 5-2 Hierarchy for evaluation criteria of a DSR artefact (Prat et al., 2014)

The structure of the prototype is assessed by the simplicity, clarity, completeness, level of detail and consistency. The prototype should be simple, minimalistic and elegant in design with a high degree of generality to achieve completeness. The structure is a static aspect of a system and it should not change.

The activity dimension is characterised by accuracy, performance, efficiency, consistency and completeness. In this dimension, consistency and completeness refer to the dynamic aspect of the artefact, i.e. activity. An activity is dynamic in the sense that at any moment multiple variables could be influencing the specified activity. Accuracy is a demonstrated agreement between the desired results and the experimental results. Efficiency is concerned with the ratio of input and output of the activity and is a dynamic aspect. Performance is determined by the time taken to complete a particular task.

The environment dimension consists of the user experience of the perceived users and the use of the latest technology and design principles in the system. In the prototype developed, the elderly do not need to interact with the system therefore the user experience will not be evaluated. The activity dimension experimentally derives the accuracy, consistency, efficiency and the performance of the prototype. The performance of the system can be determined from the system response time.

The last dimension is the evolution dimension, which is characterised by robustness and learning capability. Robustness refers to the ability of an artefact to respond to fluctuations in the environment. In our case, the prototype has to respond sufficiently to various changes in risk parameters or variables supplied to it.

5.2 Evaluation Method

Selecting the right evaluation method is key in accurately verifying if the goals of the research have been addressed. Evaluation is generally conducted from one of two perspectives, ex ante evaluation and ex post. Ex ante evaluation is for the purposes of deciding whether or not to acquire or develop a technology, similar to a cost-benefit analysis (Pries-Heje, Baskerville, & Venable, 2008). The artefact is evaluated on the basis of design specifications. Ex post evaluation is when the system has been developed and implemented. Table 5-1 illustrates a DSR evaluation method selection framework.

In our case the selected method is an ex post evaluation consisting of a Laboratory Experiment. The experimental evaluation consists of simulation of risk situations that can be experienced in the home. The Laboratory Experiment is in the artificial dimension in Table 5-1 and the results obtained can be used to determine the accuracy, efficiency, and performance of the system (Hjalmarsson & Rudmark, 2012). The Laboratory Experiment was conducted in the CoE Laboratory at NMMU with the participants being the researcher and the research supervisors.

Table 5-1 DSR evaluation method selection framework (Hjalmarsson & Rudmark, 2012)

DSR Evaluation Method Selection Framework	Ex Ante	Ex Post
Naturalistic	Action Research Focus Group	Action Research Case Study Focus Group Participant Observation Ethnography Phenomenology Survey
Artificial	Mathematical or Logical Proof Criteria based Evaluation Lab Experiment Computer Simulation	Mathematical or logical Lab Experiment Role Playing Simulation Computer Simulation Field Experiment

5.2.1 Evaluation objective

The overall goal of the evaluation was to determine if the prototype can accurately and consistently support risk and safety monitoring for the elderly living independently. The prototype should be able to achieve all the identified requirements as discussed in Chapter 2 accurately, consistently.

The dimensions considered for the evaluation of the prototype developed in this research are illustrated in Figure 5-3. The dimensions for the evaluation prototype were derived from Figure 5-2.

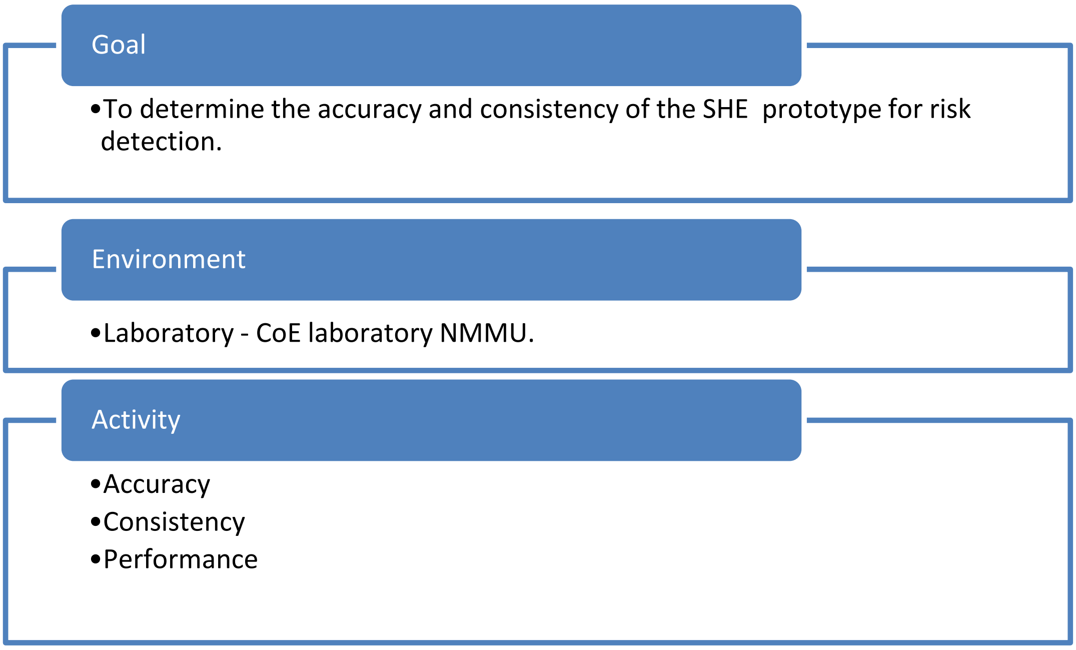


Figure 5-3 Adapted Prototype evaluation dimensions

5.2.2 Metrics

The expectation is that the SHE prototype should correctly identify all the risk situations from a sequence of events presented. Each result can have one of the following outcomes: true positive, true negative, false positive or false negative.

A true positive (TP) is when the system accurately detects an expected positive outcome, and a false positive (FP) is when an event is falsely classified as having occurred when it did not occur. A true negative (TN) is when the system accurately detects that there was no risk situation while a false negative (FN) is an incorrect negative prediction (Saito & Rehmsmeier, 2017). The classification of the results from a set of events yield a confusion matrix as shown in Table 5-2.

Table 5-2 Confusion matrix for binary outputs - adapted (Saito & Rehmsmeier, 2017)

		Predicted	
		Positive	**Negative**
Observed/Result	**Positive**	TP Count	FN Count
	Negative	FP Count	TN Count

Basic measures can be derived from the confusion matrix and these measures can be used as metrics for the evaluation. Each activity presented to the system has a predicted value which can result into a positive or negative outcome. Each activity also has an observed result which could be the same as the predicted outcome or it could be a different result. The key metrics of the evaluation were accuracy and consistency.

i. Accuracy

Accuracy can be defined as the degree to which the result of a measurement, calculation or specification conforms to the correct value or standard (Prat et al., 2014). The accuracy (ACC) can be calculated as the number of all correct predictions (TPs) divided by the total number of events i.e. positive (P) and negative (N) events as shown in Equation 5-1:

$$Acc = \frac{TP+TN}{P+N} \quad \textit{5-1}$$

An accuracy of 1.0 is the best result that can be obtained and an accuracy of 0.0 is the worst (Saito & Rehmsmeier, 2017). The error rate (ERR) can also be used to deduce the accuracy of the system and can be calculated as shown in Equation 5-2:

$$ERR = 1 - ACC \quad 5\text{-}2$$

The error rate should ideally be equal to zero but in some systems a small value close to zero is acceptable.

There is a direct relationship between accuracy, sensitivity (SN) and specificity (SP). Sensitivity can be defined as the degree to which a system can quickly detect or respond to slight changes. The sensitivity of system in detecting risk situations measures the probability of detection. Equation 5.3 shows how to calculate SN.

$$SN = \frac{TP}{TP+FN} \quad 5\text{-}3$$

The best sensitivity is 1.0, which shows that no TPs were missed and the worst is 0.0.

The specificity can be defined as the quality of belonging to a particular standard. It is also known as the true negative rate, because it measures the number of TNs that have not been missed. Specificity is calculated using Equation 5.4:

$$SP = \frac{TN}{TN+FP} \quad (5\text{-}4)$$

A SP result of 1.0 is the best whereas the worst result is a specificity of 0.0.

ii. Consistency

The consistency of the SHE can be derived from the variation of the results by repeating the events a number of times. A large variation in the measures calculated for each event's test set shows that the system is not consistent in detecting risk events. The ideal result is that the scores obtained from calculating the measures such as accuracy, should not vary for each event test set.

5.2.3 Evaluation Scenarios

Scenarios were developed to measure the metrics identified in Section 5.2.2. SHE prototypes can be evaluated in a realistic environmental setting with an evaluation participant performing actual tasks (Rashidi, Cook, Holder, & Schmitter-Edgecombe, 2011). Each scenario comprises tasks that can be carefully modelled to depict an envisioned real life situation, i.e. risk situation (Moeller et al., 2004). Each scenario comprises at least the following:

- Time duration
- Default Condition
- Test Condition
- Expected results

The variables that make up the conditions were selected from the variables in Table 5-3:

Table 5-3 Evaluation variables for simulations

Home Environment Variables	Computer Vision
Temperature	Posture
Humidity	
Lighting	
Motion	

The list of test scenarios developed is shown in Table 5-5 and Table 5-6. The key for the abbreviations used in the tables is shown in Table 5-4. Rashidi and Cook (2008) recruited a participant to evaluate their SHE implementation of activity tracking. They compressed the day's events into 1 hour performing different tasks for a specified duration. The same approach was used in this evaluation where each evaluation comprising all the identified scenarios was compressed into 1.5 hours.

The average duration of each task for this evaluation was experimentally derived during the formative evaluations discussed in Chapter 4 and a pilot summative evaluation. There are three possible notifications as discussed in Chapter 4, namely warning, emergency and informational notifications.

Table 5-4 Key for variables and labels shown in Table 5-5

Key	Definition
Lux	Lighting
dT	Change in temperature
dt	Change in time
dH	Change in Humidity
SC1	Scenario 1
ON	Motion detected
OFF	No Motion detected

Table 5-5 Evaluation scenarios which should result in a true positive

ID	Duration	Description	Default condition	Test condition					Outcome
	dt(mins)			Temp	Motion	Lighting	Humidity	Posture	
SC1	-	High Temperature	*0<=dT<=5*	*dT>5*	-	-	-	-	Emergency Notification
SC2	-	Low Temperature	*0<=dT<=5*	*dT<-5*	-	-	-	-	Emergency Notification
SC3	-	High Humidity	*0<dH<20*	-	-	-	*dH>=20*	-	Warning Notification
SC4	-	Low Humidity	*0<dH<20*	-	-	-	*dH<=-20*	-	Warning Notification
SC5	5	Inactivity	Random movement in the home	-	*OFF*	-	-	Lying down	Information Notification
SC6	5	Inactivity and possible unconsciousness	Random movement in the home	*dT>=5*	*OFF*	*dLux=0*	*dH>=20*	Lying down	Emergency Notification
SC7	5	Sleeping past normal wake up time	Change in lighting and motion is detected	-	*OFF*	*Lux=0*	-	Lying down	Warning Notification
SC8	5	Insomnia/Restlessness	Resident should be asleep	-	*ON*	*dLux>0*	-	Seated/standing/Walking	Warning Notification
SC9	5	Emergency at night	Temperature should not increase while the resident is asleep	*dT>=5*	*OFF*	*Lux>0*	-	Lying down	Emergency Notification
SC10	2	Intruder presence	Motion should not be registered in the dark and occupant lying down	-	*ON*	*Lux=0*	-	Lying down	Emergency Notification
SC11	dt<1	Fall from standing position	Slow transition from standing to lying down ***dt>1.0s***	-	-	-	-	Standing - Lying down ***dt<1.0s***	Emergency Notification
SC12	dt<1	Fall from seating	Slow transition from sitting to lying down ***dt>1.0s***	-	-	-	-	Seated - Lying down ***dt<1.0s***	Emergency Notification
SC13	dt<1	Walk a few steps and fall	Slow transition from standing to lying down ***dt>1.0s***	-	ON	-	-	Standing –lying down ***dt<1.0s***	Emergency Notification

Table 5-6 Test scenarios for expected true negative outcome

ID	Duration	Description	Default condition	Test condition					Outcome
	dt(mins)			Temp	Motion	Lighting	Humidity	Posture	
SC14	-	Normal room temperature	*0<dT<5*	*0<dT<5*	-	-	-	-	Normal
SC15	-	Waking up	Change in lighting and motion is detected	-	*ON*	*Lux>0*	-	Standing	Information
SC16	-	Normal Humidity	*0<dH<20*	-	-	-	*0<dH<20*	-	Normal
SC17	-	Frequent activity	Random movement in the home	-	*ON*	*Lux>0*	-	-	Normal
SC18	-	Sleeping	Resident should be asleep	-	*OFF*	*Lux=0*	-	Lying down	Normal
SC19	dt>1	Lying down	Slow transition from standing to lying down	-	-	-	-	Standing - Lying down	Normal
SC20	-	Sitting down	Slow transition from standing to sitting down	-	-	-	-	Standing-sitting	Normal

The scenarios in Table 5-5 should result in TPs being registered for the correct detection of the risk scenarios that can occur in the home. A FN will be obtained if an emergency notification is not sent. The opposites of the events, the scenarios in Table 5-6, were also tested to obtain TN. The TP and TN are used to calculate the accuracy of the risk detection as shown in Equation 5-1. The TP and FN are used to calculate the sensitivity of the system, while the TN and FP are used to calculate the specificity of the system.

The scenarios were tested using scripts which were performed 5 times each. A script is a list of events that a participant has to perform in order to evaluate a system (Cook, Crandall, Thomas, & Krishnan, 2013). Repeating a script more than 5 times is redundant as results tend to become uniform after 5 repetitions (Doody et al., 2013).

5.2.4 Evaluation Scripts

A script is a sequence of instructions that must be followed in performing a simulation of a risk situation. Each script has a goal, start time, end time and the list of events to be performed. Table 5-7 on the next page shows the scripts were used for evaluation of the SHE.

Table 5-7 Evaluation scripts for scenarios in Table 5-5 and Table 5-6

ID	Description	Goal	Duration (mins)	Procedure
T01	Temperature Increase	To increase the temperature in the home by at least 5 degrees Celsius	-	1) Turn on the heater. 2) Leave it on until the temperature has increased by at least 5 degrees Celsius
T02	Low Temperature	To decrease the temperature by at least 5 degrees Celsius	-	1) Turn on the AirCon. 2) Decrease the temperature by at least 5 degrees Celsius
T03	High Humidity	Increase the humidity by at least 20%	-	1) Position a kettle underneath the sensor. 2)Turn on the kettle 3) Leave the kettle to boil
T04	Low Humidity	Decrease the humidity by at least 20%	-	1) This script should follow directly after the high humidity.
T05	Inactivity in the home	To detect absence of motion and lying down for a long period.	5	1) Lie down for 5 minutes
T06	Sleeping	To detect there has not been activity at the expected time of waking up	5	1)Turn off the lights 2) Do not move/leave the room for 30 minutes
T07	Inactivity in the home and high temperature	To detect inactivity and high temperature	5	1) Turn on the heater. 2) Lie on the mattress, do not move/leave the room
T08	Falling from standing	To detect a fall from a standing position	5	1) Put the mattress in the area under the Kinect. 2) Fall onto the mattress. 3) Keep lying down for 5 minutes.
T09	Falling from seated	To detect possible unconsciousness after a fall	5	1) Put a chair at the end of the mattress. 2) Fall from chair onto the mattress. 3) Keep lying down for more than 5 minutes without moving.
T10	Fall when walking	To detect a fall when walking	1s	1) Make sure the mattress is in the path. 2) Walk a few steps and fall onto the mattress
T11	Emergency at night	To detect unusual activity at night	5	1) Turn on the lights. 2) Move around, sitting down in between movements. 3) Turn on heater or AirCon.
T12	Additional Presence	To detect the presence of an intruder	2	1) Turn off the lights. 2) Sleeping. 3) Movement in the room – research.

5.2.5 Materials and equipment

The list of materials required for the evaluation is listed below:

- Raspberry Pi 3.
- Microsoft Kinect
- Aeotec 4-in-1 multisensory and Z-Stick
- 3 X USB chargers
- Heater
- Electrical extension
- Rubber mat or thin mattress

5.2.6 Equipment Setup

The sensor was mounted onto the ceiling in the laboratory as shown in Figure 5-4.

Figure 5-4 Aeotec 4-in-1 sensor mounted onto the ceiling of the laboratory

The range covered by the multisensor when the multisensor is installed as shown in Figure 5-5 was discussed in Chapter 4. The Aeotec 4-in-1 sensor was powered by electric current instead of batteries. This was mainly due to polling restrictions when the sensor is battery powered. The Aeotec 4-in-1 sensor was polled at 1 minute intervals and it proactively sends reports when changes occur regardless of the polling interval. If powered DC is used, the Aeotec multisensor can actively send requests and the sensor is always alive and will proactively send results in real-time.

The Kinect was mounted on the ceiling covering and covered an area of $3.10m\ X\ 2.30m$. A mattress was laid directly underneath the Kinect.

5.2.7 Results

The results of the evaluation of the 20 scenarios are shown in Table 5-5. The first 13 Scenarios of each test were expected to yield TPs and the last 7 scenarios were expected to yield TNs.

Table 5-5 Evaluation results

Scenario	Test 1	Test 2	Test 3	Test 4	Test 5
SC1	TP	TP	TP	TP	TP
SC2	TP	TP	TP	TP	TP
SC3	TP	TP	TP	TP	TP
SC4	TP	TP	TP	TP	TP
SC5	TP	TP	TP	TP	TP
SC6	TP	TP	TP	TP	TP
SC7	TP	TP	TP	TP	TP
SC8	TP	TP	TP	TP	TP
SC9	FN	TP	TP	TP	FN
SC10	TP	TP	TP	TP	TP
SC11	TP	TP	TP	TP	TP
SC12	FN	TP	TP	TP	FN
SC13	TP	TP	TP	TP	TP
SC14	TN	TN	TN	TN	TN
SC15	TN	TN	TN	TN	TN
SC16	TN	TN	TN	TN	TN
SC17	TN	TN	TN	TN	TN
SC18	TN	TN	TN	TN	TN
SC19	FP	FP	TN	TN	FP
SC20	TN	TN	FP	TN	TN

Table 5-6 shows the total count for each of the four possible results for each evaluation test run.

Table 5-6 Total count of scenario outcomes per evaluation test run

TEST	TP COUNT	FP COUNT	TN COUNT	FN COUNT
TEST 1	11	1	6	2
TEST 2	13	1	6	0
TEST 3	13	1	6	0
TEST 4	13	0	7	0
TEST 5	12	2	6	0

The accuracy, specificity, sensitivity and error rate were calculated as shown in Table 5-7 using the values shown in Table 5-6. The overall accuracy of the system was 94% with a standard deviation of 4.47%. The accuracy is a ratio of the total number of correct predictions and the total number of events.

The average sensitivity of the system was 96.92% with a standard deviation of 5.62%. Sensitivity is a measure of the responsiveness to slight changes hence it indicates the probability of detection of a risk situation. The average value for the sensitivity shows that there is a chance of 96.92% of correctly classifying a TP and 3.08% of having a FN. The average specificity was 88.93% with a standard deviation of 5.22% and it measures the proportion of negatives that are correctly identified.

Table 5-7 Average measures per test

Measure	Test 1	Test 2	Test 3	Test 4	Test 5	Average	Stand Deviation
Accuracy %	85,00	95,00	95,00	100,00	95,00	94,00	4,47
Sensitivity %	84,62	100,00	100,00	100,00	100,00	96,92	5,62
Specificity %	85,71	85,71	85,71	100,00	87,50	88,93	5,09
Error rate %	15,00	5,00	5,00	0,00	5,00	6,00	4,47

The results from Table 5-7 were used to plot a bar graph in Figure 5-5 summarising the results and illustrating the consistency of the results.

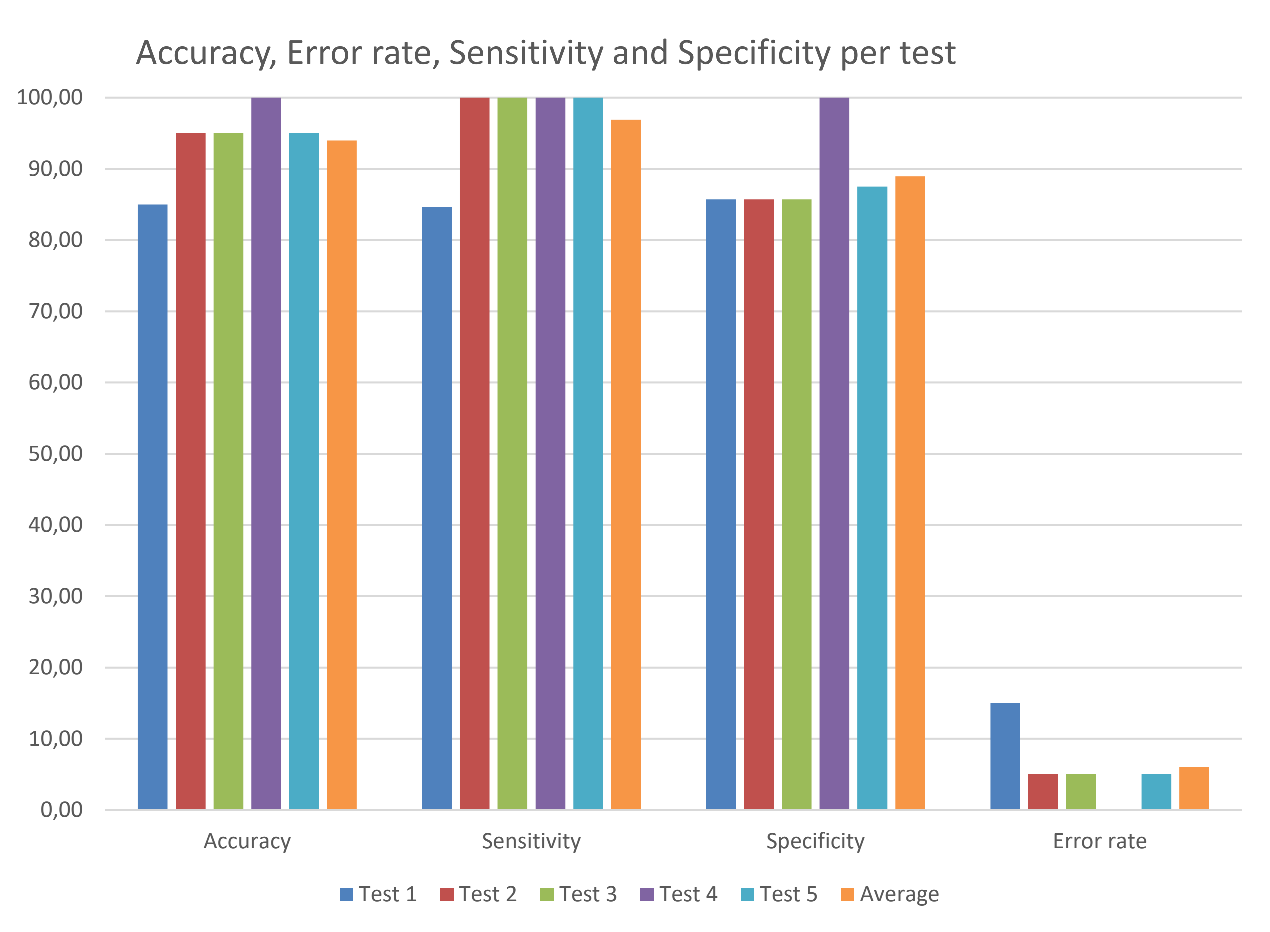


Figure 5-5 summative graph for accuracy, sensitivity, specificity and error rate measures

Test 1 had an accuracy of 85% mainly due to scenario 9 and scenario 12. Scenario 9 involved increasing the temperature while the participant was lying down. The scenario led to a FN when the anticipated result was a true positive. This discrepancy can be attributed to the fact that the system had warned of the high temperature and failed to proceed to the rule that checks the posture.

Scenario 12 involved falling from a sitting position and the outcome was classified as FN. The discrepancy could be because of the time taken for the fall and the participant did not remain still after the fall. Test 2, Test 3 and Test 5 had constant values of 95% because they had the same number of TPs and TNs. Test 4 had an accuracy of 100%, which means that no false notifications were sent, i.e there were no FPs and FNs.

In Test 2 and Test 5 the accuracy was reduced by the outcome of Scenario 19, which was expected to yield a TN instead of a FP. Scenario 19 comprised of a slow transition from standing to a lying position. The outcome of the scenario was detected as a fall instead of just someone lying down. The outcome can be attributed to the fact that the time duration for the event was faster than predefined value and also the participant was not lying still for the specified duration.

The sensitivity of Test 1 is lower than for the other tests because there were two TPs that were missed hence this affected the ratio. Test 2, Test 3, Test 5 and Test 5 had a sensitivity of 100% because no TPs were missed. Generally the specificity was lower than the sensitivity because there were TNs that were not correctly identified by the system. Test 1, Test 2 and Test 3 had a constant specificity of 85.71% because they had the same number of TNs and FPs, hence the ratio would always yield the same value.

The average error rate was 6%, and this might have been skewed by the error rate in Test 1. Test 1 had an accuracy of 85% hence the error rate of 15% and this was higher than the error rate of the other tests, which yielded error rates of at most 5%.

5.3 Conclusion

An experimental evaluation was conducted in order to measure the accuracy and consistency with which the prototype supports safety and risk monitoring in the home. The experiment was conducted in the CoE laboratory at NMMU and the researcher and the research supervisors acted as participants. The elderly could not be used because of the possibility of injury during activities like falling. The main variables considered in the evaluation were lighting, temperature, humidity, motion, posture and time.

A total of 20 scenarios were designed in order to simulate possible risk situations in accordance to the requirements identified in Chapters 2 and 3. Each scenario could either result in a notification sent or no notification sent. Scripts were used to simulate a particular scenario and a total of 20 scripts were used.

An average accuracy of 94% was obtained from the results of the evaluation with an error rate of 6%. The average sensitivity obtained was 96.92% and the average specificity was 88.93%. These results show that the rate of not missing a TP is 96.2% and the rate of not missing a TN was 88.93%. To a greater extent the prototype was able to accurately and consistently support safety and risk monitoring in the home in accordance with the requirements of the elderly living independently. The prototype will be improved in future by incorporating the feedback regarding the discrepancies observed during the evaluations.

Chapter 6 will conclude the dissertation and discuss future work.

Chapter 6. Conclusion and Future Work

The requirements for safety and risk monitoring for the elderly were established in Chapter 2 and they encompass home environment monitoring, fall detection and inactivity monitoring. Chapter 3 discussed the technologies that can be incorporated in a SHE that match the requirements identified in Chapter 2. The prototype that addresses the requirements was implemented in Chapter 4. Chapter 5 discussed how the evaluation was conducted and the results obtained.

This chapter summarises the project and concludes whether the initial aims and objectives of the research were met. The achievements of the research are discussed as well as the challenges faced during the project implementation and how they impacted on the project as a whole. Possible future enhancements to the SHE that can support risk and safety monitoring for the elderly will also be outlined in this chapter.

6.1 Research Objective

The main objective of the research was to design a model of a low cost SHE that can support safety and risk monitoring for the elderly living independently. This main objective was addressed in the following manner.

The risks facing the elderly living were investigated from literature and a focus group interview with the elderly as discussed in Chapter 2. The need of an unobtrusive low cost solution was identified from the focus group in Chapter 2. Existing solutions that address some of the requirements were identified and discussed in Chapter 3. The cost of hardware and software was considered as the main criteria for inclusion in the technology set for the SHE prototype.

The requirements and the technologies identified in Chapter 2 and 3 were used to derive use cases upon which the SHE prototype was designed as discussed in Chapter 4. The hardware and software used was of low cost and allowed for unobtrusive monitoring. The SHE prototype was then evaluated to determine the accuracy of the prototype.

The results from the evaluation produced an accuracy of 94%, which shows that to a greater extent the prototype can detect risks and alert responsible persons accurately.

Immediate interventions can be made depending on the severity of the detected risk. Therefore the prototype ensures the safety of elderly living independently. The total cost of the equipment used in the project was less than R3000.00, which is inexpensive compared to the costs of commercial home automation equipment.

6.2 Achievements and Contribution

The use of panic buttons is common but the elderly highlighted that they are unreliable as they might lose them or forget where they will have placed them. The elderly also emphasized that technology should be low cost and unobtrusive in the way it monitors them. While many of them do not mind wearing wearables devices to monitor them, concerns were raised about battery life and forgetting to wear the device. Falling was also identified as a common occurrence in the home and most of the times when the elderly fall there will be no one to assist.

The main contribution of this research was the design of a SHE model, and the implementation of a low cost prototype that could accurately, unobtrusively and consistently monitor safety and risk situations in a home environment. There are similar existing systems but their limitations includes high cost and the obtrusive nature of their data collection. A modular and extensible architecture was proposed from the requirements identified in chapter 2. The elderly live on a fixed income and the learnability of the system also inhibit them from adopting newer technologies.

The ability of the prototype to accurately and consistently support the functional requirements identified in Chapter 2 was confirmed in Chapter 5 during the evaluation. Emergency notifications were sent when a risk situation was detected in the home. The prototype had an average accuracy of 94%, an average sensitivity of 96.92% and an average specificity of 88.93%. Generally fall detection systems and risk monitoring systems notification systems are not 100% accurate, due to various limitations which result in false positives (El-Bendary et al., 2013).

In an experimental evaluation of an acoustic based fall detection system consisting of 120 falls and non-falls a 97.5% fall detection rate was recorded with a 3% false detection (L. Guo et al., 2016). A computer vision based algorithm was evaluated and had a correct detection rate of 84.44% (El-Bendary et al., 2013) . In another similar fall detection experiment a neural network based system consisting of 33 fall sequences achieved a fall detection rate of 92% and a false rate of 5% (Belshaw, Taati, Jasper, & Mihailidis, 2012). Another experiment performed for fall detection which used Support Vector Machines had a detection rate of 97.08% and a very low rate of false detection of 0.8% on a 15 fall scenarios (El-Bendary et al., 2013). In their experimental evaluation for a computer vision based fall detection system Solbach., et al recorded a fall detection rate of 91% from 20 scenarios (Solbach & Tsotsos, 2017).

The systems mentioned in the previous paragraph have comparative results to the evaluation results of the prototype developed in this research. They mainly focused on fall detection and analysis of activities of daily living to detect falls. The 94% average accuracy obtained from this research is significant as it lies within the range of the accuracy of similar evaluations. The prototype developed in this feature has added advantages as discussed in the next paragraph.

The prototype does not require any interaction on the part of the resident and therefore it is unobtrusive. Some of the existing systems as discussed in chapter 2 require the user to wear them and are generally obtrusive in their data collection. The mobile app and web portal developed allow for relatives and caregivers to remotely monitor the elderly and intervene as soon as an emergency occurs. This solution is better than the use of panic buttons which the elderly can easily forget to use or might not be having access to it at the time of the emergency occurring.

An extensible and scalable Smart Home Operating system, openHAB was identified and incorporated into the design of the prototype. This allows for future customisation and scaling of the prototype. At the core of the prototype developed are the IoT layers and hence the prototype can be easily integrated into other systems that are focused on elderly daily living. The modular nature of the architecture it can be expanded for future work for the provision of IoT services in the home.

6.3 Issues Encountered

The first issue that was encountered was the availability of elderly people to conduct a focus group meeting. Most of the elderly people we approached were either unwilling or there was no available time. The elderly who were unwilling to participate, had existing solutions such as panic buttons and continuous roll calls during the day, which they thought were enough.

Secondly the #FeesMustFall campaign had a huge impact on the completion of the implementation and evaluation of the prototype. There was limited access and sometimes no access to the CoE laboratory, hence submission of this dissertation was delayed.

The computer vision calculations proved computationally expensive for the Raspberry Pi 1 model B, resulting in the system responding slowly. The problem was solved by acquiring the Raspberry Pi 3.

6.4 Future Development

The prototype will be improved in future by incorporating the feedback regarding the discrepancies observed during the evaluations. Personalisation and daily activity pattern mining will be added to the prototype. Personalisation is a key factor because it allows for the construction of a profile which influences a behavioural model which can allow for better prediction of risk events (El-Bendary et al., 2013).

The developed prototype will serve as the data collection base. The prototype serves as a sensor and risk assessment model sending out emergency alerts. A personalisation model will be incorporated, which will be dependent on a user profile and a behavioural model. The behavioural model will rely on artificial intelligence to mine the data collected from the Activities of Daily Living. The personalisation model will then be evaluated for its effectiveness in supporting risk and safety in the home environment.

The fall detection component can also be enhanced to cater for the limitations that led to the false positives and false negatives that were identified during evaluation. The SHE prototype will also be deployed in the real home environments and an evaluation will be conducted with the users to determine the level of support of the prototype.

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Appendix A – Final Sensor List

- Z-Wave Aeon Labs Multisensor – Gen5.
  - Technology: Z-Wave Transmitter (868.42MHz)
  - Z-Wave Groups: One group with five devices (nodes)
  - 4-in-1 Sensor: Motion, temperature, humidity and lighting level
  - Temperature: -20 to +50°C (±1°C)
  - Humidity: 20 to 90% (±5%)
  - Light: 0 – 1000Lux
  - R805.00 (www.zasmarthomes.co.za)./ R 1834.00 (www.wantitall.co.za)
- Aeotec By Aeon Labs Gen5 Z-wave Plus 6-in-1 Multisensor 6 ZW100-A
  - R2160.00 (www.wantitall.co.za).
  - 6-in-1 sensor: motion, humidity, temperature, light, UV, vibration sensor. Designed to work INDOOR.
  - Motion Sensor : 16 feet, and 120° field of view; Humidity Sensor : 20% to 95%, accuracy:+/- 5% at 77°F; Temperature Sensor : 14°F (-10°C) ~ 140°F (60°C), accuracy: +/- 32.9°F (0.5°C); Light Sensor : 0 lux to 1000 lux; Vibration Sensor : acts as tamper switch, ON or OFF;
  - Z-Wave 500 series chip Security: AES-128 bit data encryption and tamper protection.
- Z-Wave Aeon Labs Z-Stick USB Controller – Gen5
  - Allows you to control and monitor any Z-Wave device from your gateway.
  - It enables you to add/exclude devices, conFigure, and control all aspects of your Z-Wave home automation system
  - R945 (www.zasmarthomes.co.za)/ R1314.00 (www.wantitall.co.za).
  - Controls up to 232 Z-Wave devices
  - USB specification 2.0 compliant, full speed (12 Mbps)

- Raspberry Pi B+ / Pi 2 Case – Smoke Base w/ Clear Top
    - R145.75 (www.pifactory.co.za).
- Miniature Wi-Fi (802.11b/g/n) Module
    - R219.77 (www.pifactory.co.za).

Appendix B – Focus Group

1. Ethics Clearance

Nelson Mandela Metropolitan University

for tomorrow

• PO Box 77000 • Nelson Mandela Metropolitan University
• Port Elizabeth • 6031 • South Africa • www.nmmu.ac.za

Chairperson: Research Ethics Committee (Human)
Tel: +27 (0)41 504-2235

Ref: [H15-SCI-CSS-010/Approval]

Contact person: Mrs U Spies

16 November 2015

Prof J Wesson
NMMU
Faculty: Science
South Campus

Dear Prof Wesson

A SMART HOME ENVIRONMENT TO SUPPORT HEALTH CARE FOR THE ELDERLY

PRP: Prof J Wesson
PI: Mr T Chiridza

Your above-entitled application served at Research Ethics Committee (Human) for approval.

The ethics clearance reference number is **H15-SCI-CSS-010** and is valid for three years. Please inform the REC-H, via your faculty representative, if any changes (particularly in the methodology) occur during this time. An annual affirmation to the effect that the protocols in use are still those for which approval was granted, will be required from you. You will be reminded timeously of this responsibility, and will receive the necessary documentation well in advance of any deadline.

We wish you well with the project. Please inform your co-investigators of the outcome, and convey our best wishes.

Yours sincerely

CB Cilliers

Prof C Cilliers
Chairperson: Research Ethics Committee (Human)

2. Consent Form

RESEARCHER'S DETAILS		
Title of the research project		**A SHE to support healthcare for the elderly.**
Reference number		
Principal investigator		**Tongai Chiridza**
Address		**Department of Computing Sciences, University Way, Summerstrand**
Postal Code		**6031**
Contact email address		**Tongai.Chiridza@nmmu.ac.za**
THE FOLLOWING ASPECTS HAVE BEEN EXPLAINED TO ME, THE PARTICIPANT:		
2.1	**Aim:**	To design an affordable SHE that can support safety and risk monitoring for the elderly living independently
2.2	**Procedures:**	I understand that I am required to participate in a focus group session to answer the questions discussed in the session.
2.3	**Risks:**	There are no risks attached to this research project.
2.4	**Possible benefits:**	A prototype of a SHE that will support healthcare for the elderly living independently.
2.5	**Confidentiality:**	My identity will not be revealed in any discussion, description or scientific publications by the investigators.
2.6	**Access to findings:**	Any new information or benefit that develops during the course of the study will be shared on request.
2.7	**Observation:**	Observations may be obtained and analysed.
2.8	**Voluntary participation / refusal / discontinuation:**	My participation is entirely voluntary. My decision whether or not to participate will not affect me in any way.
3.	The information above was explained to me/the participant by, Mr Tongai Chiridza, in English and I am in command of this language. I was given the opportunity to ask questions and all these questions were answered satisfactorily. No pressure was exerted on me to consent to participation and I understand	

	that I may withdraw at any stage without penalisation. Participation in this study will not result in any additional cost to me.

I HEREBY VOLUNTARILY CONSENT TO PARTICIPATE IN THE ABOVE-MENTIONED PROJECT:	
Signed/confirmed at PORT ELIZABETH on ___ October 2015	
Name of participant: Signature of participant	Signature of witness:
	Full name of witness:

3. Written information given to participants prior to participation

Faculty of Science
NMMU
Tel: +27 41 5042219 Fax: 041-504 2574 / 2731

Date 05/10/2015

Ref:

Contact person: Prof Janet Wesson

Dear participant

You are being asked to participate in a research study. We will provide you with the necessary information to assist you to understand the study and explain what would be expected of you (participant). These guidelines would include the risks, benefits, and your rights as a study subject. Please feel free to ask the researcher to clarify anything that is not clear to you.

To participate, it will be required of you to provide a written consent that will include your signature, date and initials to verify that you understand and agree to the conditions.

You have the right to query concerns regarding the study at any time. Telephone numbers of the researcher are provided. Please feel free to call these numbers.

It is important that you are aware of the fact that the ethical integrity of the study has been approved by the Research Ethics Committee (Human) of the university.

If you participate, you have the right to withdraw at any given time during the study without penalty or loss of benefits.

Your identity will at all times remain confidential. The results of the research study may be presented at scientific conferences or in specialist publications.

This informed consent statement has been prepared in compliance with current statutory guidelines.

Yours sincerely

Tongai Chiridza
Researcher

4. Oral Information

Thank you for participating in this research study. The goal of the study is to find the safety and risk monitoring requirements of the elderly living independently. I am going to ask you some questions about your experiences in adult healthcare especially chronic disease management, medication adherence, safety monitoring and real-time access to your health information.

I will not be contributing to the discussion but I will be moderating the session by keep track of time and making sure all issues are discussed. Please feel free to ask me to repeat a question if you need to.I am going to record the discussion, so please speak clearly and remember an audio recorder does not pick up actions. Do not interrupt each other during the discussion, you will all be given a chance to participate in the discussion.

5. Letter of request to conduct research

Faculty of Science
NMMU
Tel: +27 41 5042219 Fax: 041-504 2574 / 2731

Date 05/10/2015

REQUEST FOR PERMISSION TO CONDUCT RESEARCH AT RETIREMENT-VILLAGE

Dear sir/madam

My name is Tongai Chiridza and I am a MSc Computer Science and Information systems student at the Nelson Mandela Metropolitan University in Port Elizabeth. The research I wish to conduct for my Master's dissertation involving the designing of a SHE to support safety and risk monitoring for the elderly living independently. This project will be conducted under the guidance of Professor Janet Wesson (NMMU) and Dr Dieter Vogts (NMMU).

I am hereby seeking your consent to conduct focus group interviews at Summerdunes retirement village. The aim of the focus group interviews is to determine the healthcare requirements of the elderly.

Upon completion of study, I undertake to give you feedback on the design of a SHE that can support healthcare for the elderly. If you require any further information, please do not hesitate to contact me on 076 688 9817/ Tongai.Chiridza@nmmu.ac.za. Thank you for your time and consideration in this matter.

Yours Sincerely,

Tongai Chiridza

MSc Computer Science and Information Systems (Student)

Nelson Mandela Metropolitan University

Focus group discussion transcript – Pilot Study at Walton Park – 20 January 2016

- Six residents of Walton Park participated and signed informed consent forms.
- Dixie introduced the PI and the PRP and thanked all for coming.
- Dixie discussed the aims of the project, i.e. determine the requirements of a SHE to monitor the health of the elderly living independently.
- Existing problems:
    - Panic buttons are not necessarily effective due to lack of real-time response – need a resident nurse.
    - Panic buttons are not worn consistently.
- Activities that need to be monitored:
    - Taking of pills on correct day, at correct time, and in the correct amount.
    - Ensuring that property is locked up before going to bed at night.
    - No keys in front door.
    - Detection of a security breach.
    - Monitoring and reordering of chronic medication.
    - Excessive heat, e.g. stove left on.
    - Fire detection.
    - Management of chronic health conditions.
- Possible solutions:
    - Voice-activated sensors that trigger panic buttons/alarms using keywords.
    - Motion sensors that detect lack of movement/fall detection.
    - Monitoring of heart rate, e.g. using wearable devices.
    - Heat sensors that detect excessive heat or fire.
- Constraints:
    - No privacy issues – health conditions already public information and updated on an annual basis.
    - Participants agreed that they would be prepared to wear a wearable device.
    - Wearable devices need to be waterproof and reliable.
    - All participants had mobile phones, but not all had smart phones.

- Resistance to using mobile technology for several reasons, including cost and screen size.
- Technology needs to be non-intrusive.

- Most popular issues highlighted by participants:
  - Use of wearables to monitor physiological aspects, e.g. blood pressure, heart rate, breathing
  - Chronic disease management
  - Security, e.g. doors locked at night and security breaches
  - Internal sensors, e.g. for fall detection, extreme heat, electrical faults, etc.
  - Contacts should be informed in certain emergency cases, e.g. central control and next-of-kin

Appendix C

Installing and configuring OpenHAB

```
wget -qO -
'https://bintray.com/user/downloadSubjectPublicKey?username=openhab' | sudo
apt-key add -
echo 'deb http://dl.bintray.com/openhab/apt-repo2 sTable  main' | sudo tee
/etc/apt/sources.list.d/openhab2.list
sudo apt-get update
sudo apt-get install openhab2
sudo apt-get install openhab2-addons
sudo systemctl start openhab2.service
sudo systemctl status openhab2.service
sudo systemctl daemon-reload
sudo systemctl enable openhab2.service
```

Once openHAB is installed the folder structure looks as shown in Figure 7-1 below.

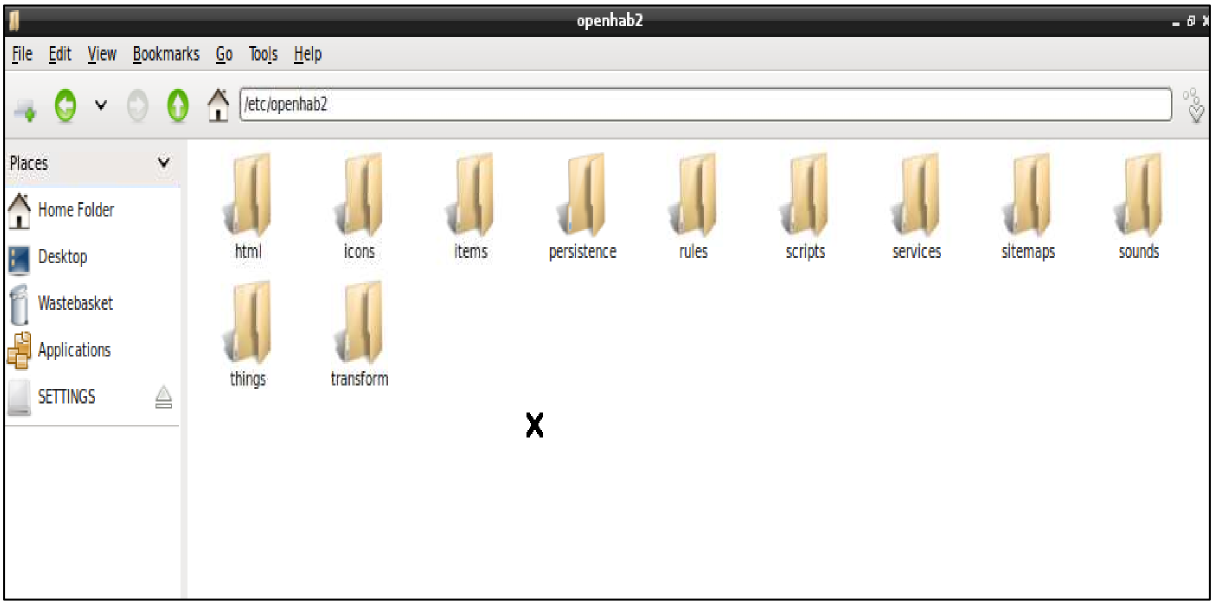

Figure 7-1 openHAB folder structure

Configuring MySQL Server

```
sudo apt-get update &&sudo apt-get upgrade
sudo apt-get install mysql-client mysql-server
mysql –u root –p password
create database OpenHAB

# the database url like 'jdbc:mysql://<host>:<port>/<database>'
mysql:url=jdbc:mysql://127.0.0.1/OpenHAB

# the database user
mysql:user=<your user here>

# the database password
mysql:password=<your password here>
```

```
# the reconnection counter
#mysql:reconnectCnt=

# the connection timeout (in seconds)
#mysql:waitTimeout=
```

The next step was to create a user and give the user full access to the openHAB database by issuing the following commands:

```
CREATE user 'OpenHAB'@localhost IDENTIFIED BY 'OpenHAB';
GRANT ALL PRIVILEGES ON OpenHAB.* TO 'OpenHAB'@'localhost';
```

To enable the MySQL add-on in the main configuration file the following command was issued:

```
sudo nano /opt/OpenHAB/configurations/openhab.cfg –opening the text editor
mysql:url=jdbc//localhost:3306/OpenHAB
mysql:user=OpenHAB
mysql:password=OpenHAB
mysql:reconnect=1
```

A configuration file called mysql.persit was created to log all the values read from the sensors when changes were detected. The contents of this file are shown in the following script:

```
Strategies {
    default = everyChange
}
Items {
    * : strategy = default, restoreOnStartup
}
```

The data stored in the MySQL database can be viewed from the Raspberry Pi terminal, displayed in an old-fashioned DOS way as shown in Figure 7-2:

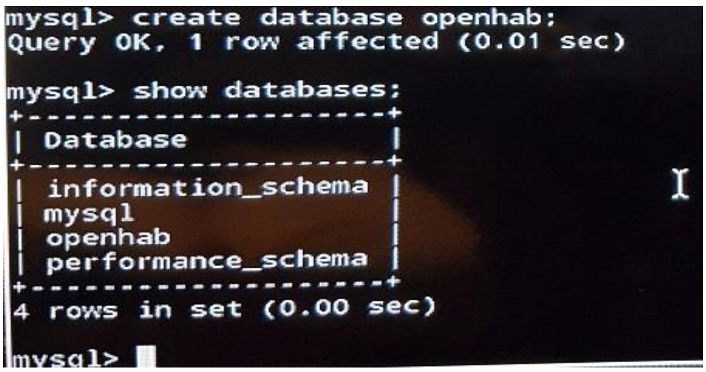

Figure 7-2 MySQL database displayed from the terminal

To be able to view the data stored in the database from MySQL, the MySQL workbench was used. The following steps were followed to set up remote connection to the MySQL database.

```
sudo nano /etc/mysql/my.cnf ----opening the mysql config file.comment out
the bind-address =localhost line.
mysql –u root –p ---login to mysql and issue the following command
GRANT ALL PRIVILEGES ON *.* TO ‘root’@’192.168.1.%’ IDENTIFIED BY
‘password’ WITH GRANT OPTION; ---use appropriate IP address for the PI.
FLUSH PRIVILEGES;
Quit;
sudo /etc/init.d/mysql restart
```

Fall detection Algorithm

```
########## Import Section############

from scipy.spatial import distance as dist
from imutils import perspective
from imutils import contours
import numpy as np
import argparse
import imutils
import cv2

########## Get Video Stream ############
cap = cv2.VideoCapture(0)
fgbg = cv2.createBackgroundSubtractorMOG2()

########## Loop over the streams ############
while(1):
    ret, frame = cap.read()
     fgmask = fgbg.apply(frame)

     edge_1 = cv2.Canny(fgmask, 50, 100)
     edge_2 = cv2.dilate(edged_1, None, iterations=1)
     edged_imaged = cv2.erode(edged, None, iterations=1)
cap.release()
cv2.destroyAllWindows()



        ############ Find contours on edged image#######
contours = cv2.findContours(edged_image.copy(), cv2.RETR_EXTERNAL,
        cv2.CHAIN_APPROX_SIMPLE)
contours = contours 0] if imutils.is_cv2() else contours [1]

########### Computing the bounding box###########
box = cv2.minAreaRect(contours)
box = cv2.cv.BoxPoints(box) if imutils.is_cv2() else cv2.boxPoints(box)
box = np.array(box, dtype="int")
box = perspective.order_points(box)
cv2.drawContours(orig, [box.astype("int")], -1, (0, 255, 0), 2)

#########Calculating Midpoint of the sides of the Box###########
```

```
(tl, tr, br, bl) = box
(tltrX, tltrY) = midpoint(tl, tr)
(blbrX, blbrY) = midpoint(bl, br)

        (tlblX, tlblY) = midpoint(tl, bl)
        (trbrX, trbrY) = midpoint(tr, br)


dL = dist.euclidean((tltrX, tltrY), (blbrX, blbrY))
dW = dist.euclidean((tlblX, tlblY), (trbrX, trbrY)
pixelsPerMetric = dW / know_width
#######compute size of object#####
dimL = dL / pixelsPerMetric
dimW = dW / pixelsPerMetric
```

Setting up Twilio

```
pip install twilio
```

To send an SMS the following code was used:

```
from twilio.rest import TwilioRestClient

ACCOUNT_SID = "******************"
AUTH_TOKEN = "$$$$$$$$$$$$$$"

client = TwilioRestClient(ACCOUNT_SID, AUTH_TOKEN)
message = client.sms.messages.create(to="+277*******7",
                                     from_="+278*******4",
                                     body="Fall detected!! Intervene immediately")
```

Twilio also allows for the sending of MMS. The code snippet below can be used to send MMS.

```
message = client.messages.create(
    body="Fall detected!! Intervene immediately",
    to="+277*******7",
    from_="+278*******4",
    media_url=[
        "http://server_domain/fall_1.jpg",
        "http://server_domain/fall_1.jpg",
    ],
)
```