WESTERN SYDNEY UNIVERSITY

Central Monitoring System for Ambient Assisted Living

© Manbir Kaur

A thesis submitted in fulfilment for the degree of

Master of Research

Supervisor:

Dr Upul Gunawardana

Western Sydney University

School of Computing, Engineering, and Mathematics

September 2018

Abstract

Smart homes for aged care enable the elderly to stay in their own homes longer. By means of various types of ambient and wearable sensors information is gathered on people living in smart homes for aged care. This information is then processed to determine the activities of daily living (ADL) and provide vital information to carers. Many examples of smart homes for aged care can be found in literature, however, little or no evidence can be found with respect to interoperability of various sensors and devices along with associated functions. One key element with respect to interoperability is the central monitoring system in a smart home. This thesis analyses and presents key functions and requirements of a central monitoring system. The outcomes of this thesis may benefit developers of smart homes for aged care.

ACKNOWLEDGEMENT

I would primarily like to acknowledge the support of my supervisor Dr Upul Gunawardana, who has displayed untiring interest in the research project and continued to encourage me throughout the various phases of the research project. I am sincerely grateful for his expert advice in regard to the subject, the time that he has contributed to the supervision of my project and the valued feedback that he has provided me throughout the process. I would like to extend my regards to the academic team of my school who have guided me throughout my research training. I am most grateful to Graduate Research School who have supported me to continue my research training when I gave birth to my child. It is all thanks to the genuineness of the school that I was able to manage the need of my baby and also continued to work on my research training. I am grateful to my husband Simaranjit Singh who has been very understanding and supportive of me during the process. I would also like to express my gratitude to my sister Kuljit Kahlon and Ravleen for supporting me to look after my baby so that I could complete the thesis.

Statement of Authentication

The work presented in this thesis is, to the best of my knowledge and belief, original except as acknowledged in the text. I hereby declare that I have not submitted this material, either in full or in part, for a degree at this or any other institution.

[redacted]

……………………………….

(Signature)

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AAL	Ambient Assisted Living
ABAC	Attribute-Based Access Control
ADL	Activities of Daily Living
ADP	Access Decision Point
AEP	Access Enforcement Point
ANN	Artificial Neural Network
CHMM	Coupled Hidden Markov Model
CMS	Central Monitoring System
CRL	Conditional Random Field
DTW	Dynamic Time Warping
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyography
FFT	Fast Fourier Transform
FTFT	Fast Time-Frequency Transform
GMM	Gaussian Mixer Model
HMM	Hidden Markov Model
ML	Machine Learning
MLP	Multi-Layer Perception
NBC	Naive Bayes Classifier
NFS	Neuro-fuzzy system
OWL	Ontology Web Language
RDF	Resource Description Framework
SH	Smart Home
SVM	Support Vector Machine
UML	Unified Modelling Language
UWB	Ultra Wideband Communication
VLC	Visual Light Communication

1 Introduction

The life expectancy of older people is increasing drastically over the last decades worldwide. The proportion of the world population of 65+ was nearly 7% in 2012 and this is projected to increase by almost 20% in 40 years (Meg Morris et al. 2012). The ageing population is growing faster in high-income countries. Japan has the highest number of older people, 33% Japanese were over 60 years followed by Germany (28%), Italy and Finland (28% each) in 2015 (World Population Ageing 2015). Along with the other parts of the world, Australia is also experiencing a great increase in the elderly population. The percentage of people over the age of 65 in Australia was 13% in 2010 and is estimated to be 20% by 2050. Especially, the ageing population of 65 to 84 years is projected to a more than double, with the highest number of 85+ age group by 2050 (Lê, Nguyen, and Barnett 2012). At the Beginning of the twentieth century, the life expectancy of the people in Australia was 47 years and it is expected to be 80+ by 2025. In the next 30 years, the number of people over 65 years of age will be one-quarter of the total population of Australia and 5% will be over 80 years (Meg Morris et al. 2012).

Elderly people are more vulnerable to physical and psychological illness, health risk factors and a higher rate of hospitalisation than other age groups. More than half the proportion of the elderly population has a physical or physiological illness such as diabetes, cancer, arthritis, heart failure and depression (Majumder et al. 2017). Another significant concern of elderlies is the risk of falling and injuries. Falling is one of the common concerns that affect elder people. The one-third population of the older citizens fall each year and nearly 10% falls leads to fractures or serious injury. Apart from the injuries falls lead to loss of independence, mobility, confidence, hospitalization or even death(Xiaodan Zhuang et al. 2009). These health issues in older citizens are mainly caused by age-related changes. A balance disorder is a major age-related condition that leads to the loss of mobility and independence. These age-related conditions and diseases prevent elderlies to stay in their own homes for a long time. As a result of that, the trend of increasing ageing population has put pressure on aged care and health services to maximise the wellbeing and to serve an increasing proportion of older people. Therefore, the prevention of old age-related physical and mental conditions and risk factors is the biggest concern currently.

It is necessary to monitor general health conditions and behavioural patterns of the elderly to prevent health risks. Given that healthcare services are expensive and there is a shortage of caregivers, the idea of Ambient Assisted Living (AAL) has risen. Ambient assisted living (AAL) can be defined as "the use of information and communication technologies (ICT) in a person's daily living and working environment to enable them to stay active longer, remain socially connected and live independently into old age" (AAL Programme - Active Assisted Living Programme - Ageing Well 2018). The living environment where AAL is implemented with context-aware health monitoring systems is called the Smart Homes (SH) for aged care. The current smart homes can be defined as an application of ubiquitous computing which is capable to provide user context-aware services (assistive or automotive services) related to remote home control, ambient intelligent or home automation (M. R. Alam, Reaz, and Ali 2012). Smart homes can provide a better quality of life by offering the Assistive services to elderlies and increase the comfort of them by utilising context awareness. Moreover, smart homes can increase independent living of elderlies, reduce the cost of health care and maintain safety through continuous monitoring.

While smart homes for aged care provide many benefits, there are some shortcomings. There is no immediate medical attention compared to traditional-aged care facilities. Medical and other interventions will be made when such events/emergencies are detected via the monitoring sensors. Another pressing issue is privacy. As a general rule, the use of video cameras is not a preferred option in monitoring occupants in SHs. The security of data and access methods is another important aspect.

There are many experimental SH systems currently under investigation (Helal et al. 2005)(Kautz et al. 2002). These systems use various sensors to detect activities of daily living (ADL) and provide context-aware monitoring. ASH utilises a central computer or central monitoring system (CMS) for processing. The capabilities and the performance of the SH are directly influenced by the capabilities and performance of the CMS. Also, there is a need for interoperability, open standards and common platforms for SH for aged care (Barnett et al.

2017). The CMS plays a vital role in interoperability and implementing standards which are still under development.

1.1 Objective and Research Questions

Almost all smart home system implementations found in the literature have used ad-hoc implementations of CMS. While security and privacy have been identified as key issues, how security will be implemented in SH for aged care have been rarely discussed in the literature. The issue of interoperability is also rarely addressed.

The main objective of this project is to define the requirements of the CMS and identify the capabilities it requires.

In order to define requirements, it is necessary to address the following research questions:

What are the main functions of the CMS?

What are the main requirements of the CMS?

How can devices be used across different SH implementations?

1.2 The organisation of the thesis

This thesis is organised as follows:

Chapter 2 presents a literature review on smart homes and Ambient Assisted Livings for aged care. Further, this chapter describes the main functions of Smart homes and the review the research works that apply ambient and wearable sensors to monitor the health status of elderlies and finally introduce the Central Monitoring System for aged care.

Chapter 3 presents the requirements of central monitoring systems for smart homes. The chapter is divided into three main sections to describe the function of CMS: Sensing layer, Data processing and management layer, Security and access control layer.

Chapter 4 presents the design considerations of CMS. Firstly, the communication requirements of the CMS is described. Secondly, various steps of data processing are highlighted. Thirdly, the implementation consideration of Security and Access control is presented. Finally, chapter 5 presents a discussion and future work related to this thesis.

2 Literature Review

The rapid growth of the ageing population and increasing demand for self-care for elderly people has led to increasing research work on smart elder care systems in the last few years. Smart care or smart home for the elderly is one of the pioneering technological advancement. Several research works and surveys are carried out in smart home Ambient Assistant Living for elderly care area.

Section 2.1 provides a description that is necessary to understand the concept of Ambient Assisted Living and Smart Homes for aged care. Section 2.2 elaborates the major functions of Ambient Assisted Livings for aged care. Section 2.3 gives an insight into the ambient and wearable sensors and technologies that are used in the previous work of the smart homes. Section 2.4 gives details of the previous smart home project. Section 2.5 briefly introduce Central Monitoring Systems for aged care.

2.1 Ambient Assisted Living and Smart Homes for Aged Care

The demographic shift will have major effects on many facets of human life such as homes, infrastructure, community. The demand for health services and aged care is expected to increase dramatically. Studies have indicated that from the year 2010 to 2050, the quantity of elderly (65-84 years old) requiring aged care will be more than twofold the measure of earlier years (Morris et al., 2012). Additionally, the elderly not only require intense physical therapy but support their mental and psychological health. Thus, the development of progressing treatments is necessary to enhance and sustain their wellbeing.

As previously stated, AAL aims to help seniors live longer in their own homes and SH for aged care is the environment that enables the AAL principles. Satpathy defines smart home as, “A home which is smart enough to assist the inhabitants to live independently and comfortably with the help of technology" (Satpathy 2006). Smart home technology can help elderly people to increase independence and the quality of life and reduce healthcare cost. The main features and functions of AAL can be illustrated using Figure 2.1.

As the following figure shows, AAl technology is used to monitor the vital signs and Activities of Daily Livings (ADL), emergency detection, assist with cognitive impairment, promote the healthy living and well being and therapy and rehabilitation application. The benefits of AAL are for three types of users: Primary users who the elderly being cared for, Secondary users – immediate family members and caregivers, and Tertiary users – public health services and insurance companies.

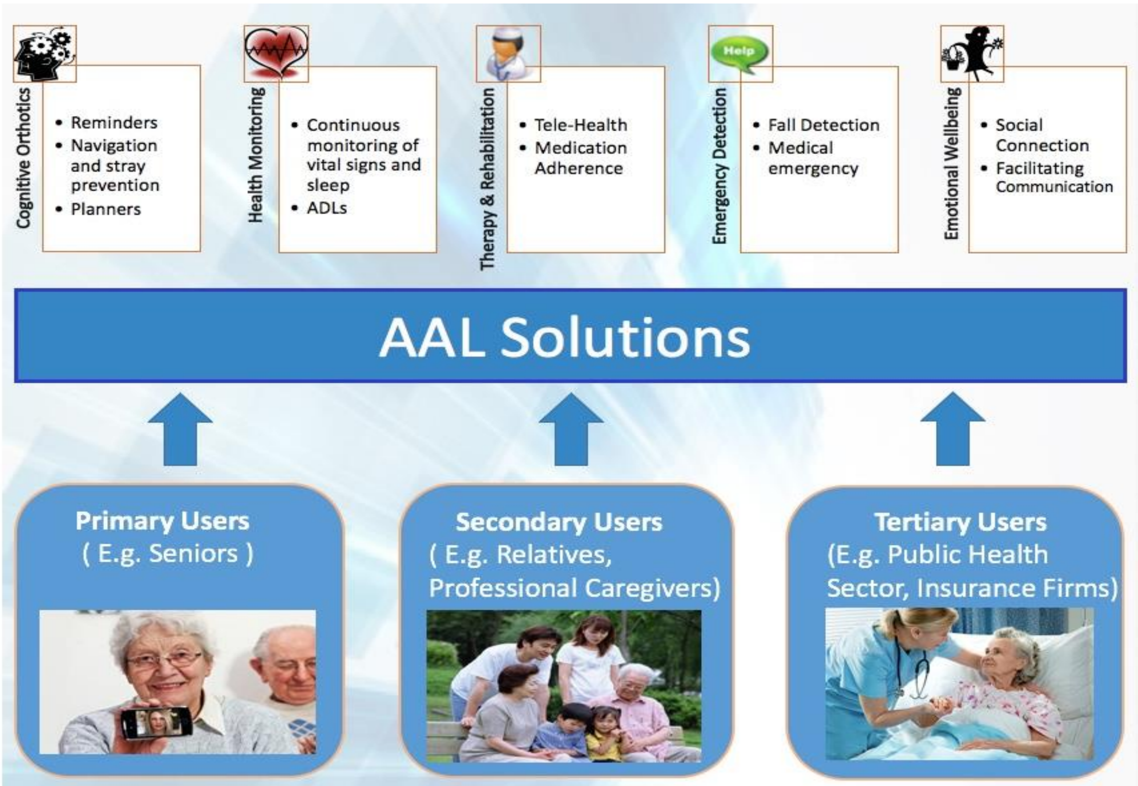

Figure 2.1. AAL Features and Types of Users (Maan 2017)

2.2 Major Functions of Smart Homes for Aged Care

The major functions of AAl can be categorised into these areas: health monitoring, emergency detection, rehabilitation and therapy, emotional wellbeing and cognitive orthotics.

2.2.1 Health Monitoring

AAL systems are basically designed to monitor the activities of daily living of a person and for providing healthcare services. The health monitoring is a system fixed within the smart home or in a smart environment that can be used to evaluate the health status of and to monitor the daily activities of the subject. Eventually, these systems provide confidence to elderlies to live independently in their own homes for longer and assist the health care professional for providing advanced communication. Some of the previous work on health monitoring are presented in this section.

2.2.1.1 Human Activity Recognition

Chen et al. (2012) carried out a comprehensive survey to investigate the current status and development in the field of sensor-based and video-based activity recognition system. (Liming Chen et al. 2012). The research work highlighted the strengths and weakness of the methods that are associated with smart home technology and presents the difference between data-driven and knowledge-driven approaches. They divide assisted living into two categories; direct and indirect based on sensing method

Celler et al. (1995) presented a telemonitoring system to determine a functional health status of older people by constantly monitoring remotely by identifying some parameters which observe the interaction between participants (Elderly people) and the environment (Celler, Earnshawa, et al. 1995). This research work proposed that the functional health status of elderly people can be identified by observing the changes in some measures such as sleep pattern, mobility, utilisation of toilet, washing and cooking facilities. The telemonitoring system used infrared sensors, sound sensors, magnetic switches to detect activities and record moments.

Zhu and Sheng proposed a method for recognising the indoor daily activities that link motion and location data of the subject (Zhu and Sheng 2011). They attached an inertial sensor on the right thigh of a person to collect motion data and an optical motion capture system is used to get the location data. The combination was less invasive and it has maintained the high accuracy rate of identification. To identify the basic activities, they use two neural networks. First, the Viterbi algorithm is used for daily activity recognition and Bayes theorem is used to get the location data. They conducted their experiment in a mock apartment and get the results proved the algorithm is accurate and effective for activity recognition.

Papamatthaiakis et al built a smart system for activity recognition of people in their home by using data mining methods (Papamatthaiakis, Polyzos, and Xylomenos 2010). They monitored and analyse the daily indoor activities of individuals in their homes. For the experiment, they used a set of events for each activity to produce temporal relations between events and try to find the prominent temporal relations based on association rules to recognise the actually executed activities. They recorded the activities of different people in two apartments they concluded that the technique is 100% accurate for some activity recognition than other techniques which are based on data mining classifier. They state that the proposed technique is adaptable and flexible for a dynamic environment.

Helmi and Almodaresi presented a fuzzy inference System for activity recognition of a person by utilizing a triaxial accelerometer (Helmi and AlModarresi 2009). The purpose of the accelerometer was to detect the motion of a person and collect the motion data to classify motion into four categories that were jumping, moving forward, going upstairs and going downstairs. The identification system included three different features standard deviation, peak amplitude and the correlation between different axes. The membership features and fuzzy rules were described from the experimental value. They claimed that the fuzzy inference system can perform better than another classifier.

Le et al proposed a technique to build smart homes equipped with a noninvasive sensor to enable activity recognition in order to improve the living condition of alone elderlies (Le et al. 2008). They undertook a case study of a person to detect the loss of his independence on the basis of activity performed. Firstly they processed the mobility states sequence in various allocation around the home then they took out the descriptive rules to identify the activities that influence the loss of independence of a person.

Eunju et al examined the activity recognition and demonstrated that it can be extended in order to get societal benefits in human-centric applications (E. Kim, Helal, and Cook 2010). They focused on simple human activities recognition. They claimed that the understanding of activity pattern is required to understand human activity. They described the two techniques to make an activity model. The First technique is based on an initial personalised model for activity recognition. The second one focuses to use an algorithm based on probability to build a model for activity recognition. For this purpose, they used the Hidden Markov Model (HMM) and Conditional Random Field (CRF) techniques.

2.2.1.2 Continuous of Monitoring of Vital Signs

The research work of this category provides the health facilities for elderly people in smart homes. Healthcare services can be implemented locally or remotely to create a health report.

Local monitoring in smart homes can be used to identifying health conditions and to generate local warnings alarms. The smart environment produces the long term health record that can be analysed by the medical service provider.

Mihaildis et al designed a system for pervasive healthcare to improve the quality of life and independence of older people (Mihailidis et al 2004). The aim of the research was to use pervasive computing to develop a smart environment which will monitor the activities of elder people with dementia and provide assistance with commands. The system includes three agents: sensing, planning and promoting. They traced the face and hands by using statistic based skin colour segmenting to extract the information of users' activities. When the sensing step is completed, the planning agent confirms which plan (sequence of steps) the user is attempting and if the plan is incorrect such as missing a step the system select and play a command automatically.

The ENABLE project analysed the impact of assistive technology for dementia patients in some Europe counties (Adlam et al. 2004). The patients were selected based on the mild or moderate state of dementia by their local social service department. Two devices were installed for this project: cooker monitor and night light. The cooker was a controlling system that detects the dangerous situation and intervenes by turns off cooker knobs automatically if the first intervenes fails the system sends a text message to primary carer. The night light detects and turns bedside light when a person gets out of bed. The light sensor measures the changes in weight on the bed such as getting into or getting off the bed. The researcher believed that good relationship and consistent communication between project staff, patients and carer are important for effective evaluation. They concluded that the researcher should have a better understanding of patients and patience as well to innovate the equipment for people with dementia.

Arcelus et al proposed Sit to stand transfer (SiST), a measure of sit and stand the duration of a person to predict the physical mobility status of patients (Arcelus et al., 2009). The researchers embedded pressure sensors on the floor and bed to measure the SiST duration. The start time was set with an algorithm of motion of the centre of pressure (CoP) on the front edge of the bed and the end time was set by the third order transfer function by using the foot pressure on the floor. They reviewed the video recorded data to estimate the time error. The system did not implement complex equipment to estimate the SiST duration. They have not provided a detailed characterisation of the system such as the measure of stability while standing, a measure of usage of hands, a measure of leaning of the forward trunk.

Vainio et al designed a proactive and adaptive home control system to anticipate the user's requirements (VainIo et al., 2008). The aim of the research was to control the environment actuators in order to fulfil the need and desire of the user. The system can recognise normal living habits and provide notifications of daily activities such as sleeping pattern, medicine taking to caretakers. The system works autonomously, however, the residents still have control of the home.

Barnes et al developed a telecare system based on lifestyle monitoring that can detect the movement of the residents (Barnes et al., 1998). The aim of the project was to provide a low-cost technological solution to increase the provision of care, quality of life and independence to elderlies in their own home. The trial was performed with monitoring data of the elderly by British Telecom and Anchor trust. Researchers installed magnetic contacts and the IR sensors at the entrance door the house. It measures the temperature in the living area by using temperature sensors and an alarm activation system was implemented to detect behaviour and communicate with caregivers. They used a new telecom the feature No Ring Calling in order to make the system non-invasive. The No Ring Calling was a phone call without a ring. As the main objective of the life monitoring system was the low cost and non-invasive technology, so they used clients existing telephone line for the collection of data.

William et al proposed an architectural model of integrated telecare system named CareNet (Williams, Doughty, and Bradley 1998). The main components of the model are a sensor bus, a sensor set, a control unit and an intelligent monitoring system. In order to collect the psychological data, the authors used the spirometer, PPG, ECG, temperature, colourimeter and pulse measuring tools. The communication network is implemented with Body Area

Network and HomeLAN in order to collect real-time data, command and control data and event data which has allocated a smart system including body hub, clients healthcare record, smart sensors. The system provides health information, emergency alarms and monitoring services. The CareNet system used distributed intelligent to provide information processing features which enhances its capacity to perform online data.

2.2.2 Emergency Detection

Various AAL technologies have been developed for emergency detection in order to assist elderlies. These technologies include fall detection, detection of anomalous situations and event automation. The detection of anomalous activities is an important part of AAL that measures the functional ability of a subject and ensures safety by monitoring daily activities. The role of anomaly detection is to identify the unexpected and rare events that may lead to the situation of concern. Fall detection technology is used to rapidly detect falls and intervention for subjects who have experienced the falls. The following section will review the work related to fall detection and anomaly detection

2.2.2.1 Detection of anomalous situations and Event Automation

Phua et al developed erroneous plan recognition (EPR) to detect the faults in the performing daily activities of older people suffering from dementia (Phua et al. 2009). The system detects and sends audio and visual messages to older people in order to enhance their problem-solving abilities and to replace their diminished memory. To monitor the activity of daily living they used sensors deployed in SH. The biggest challenge of the research was the highly inaccurate behaviour of dementia patients. The sequential and independent layers were arranged in a prioritised way to detect a specific error first.

Ordonez et al proposed an automated behaviour analysis system to improve the efficiency of old aged people and disables (Ordóñez et al., 2014). Authors used behaviour patterns to record the measurement from different sensors and detect the anomalous behaviour that shows changes in health status by predicting the standard behaviours.

Ghasemzadeh et al designed a system with physiological monitoring for human body balance, the system collects muscle activities and acceleration signals for assessing standing balance (Ghasemzadeh et al 2010). To get the relevant information from the interaction between

Electrogram (EMG) and accelerometer measurement they used statistical techniques and machine learning algorithm.

Das et al introduced Mavhome by using artificial intelligence, mobile computing, multimedia technology and robotics (Das et.al., 2002). They divide the design into four layers; physical, communication, information and decision. They used the X10 protocol to monitor the devices installed into the electric wiring system of the home. They used an Active LeZi algorithm to make accurate prediction and decisions. The goal of the project was to increase the comfort of inhabitants and minimus the operational cost.

ACHE was a system designed with different sensors to monitors the device usage patterns of inhabitants (Mozer 1998). They used a neural network and build an adaptive inferential engine to control the heating, lighting and temperature of the home. ACHE was one of the oldest smart homes. The capabilities of this project were limited to only three components; to control light, heat and temperature.

Brdiczka et al described a framework for contextual learning in smart homes to address the problem of learning situation models (Brdiczka, Crowley, and Reignier 2009). The authors designed a 3D smart home with cameras and microphone for situation modelling. It depends on the video tracking and role detection of residents. It can detect the speed and distance of residents from the interacting object. The identification error rate of the proposed system was 82 %.

Yamazaki proposed a real-life testbed named Ubiquitous Home for context-aware services. The system linked the sensors, appliances and devices to create new house services (Yamazaki 2006). Active and passive RFID receiver was installed into the house to detect the residents. Pressure sensors were embedded to locate the residents, they installed plasma panels, microphone, liquid crystal display for user interaction. The project was aimed at creating an environment between system and human. However, the system was useful for a few house services for example recipe display, search for forgotten property.

Pirttikangas et al researched activity recognition with small wearable sensor devices attached to four different parts of the body (Pirttikangas, Fujinami, and Nakajima 2006). For the experiment, they collected data from 13 persons performing 17 daily activities. They used the forward-backwards sequence algorithm for feature selection.

Swaminathan et al presented an object recognition approach using image localisation and registration (Swaminathan, Nischt, and Kuhnel 2008). They used direct feature matching approach to register the appliances with an image processing system. The environmental map was used to select the different objects according to the voice command of the user. The project demonstrated the benefits of visual and verbal inputs combination for the smart home.

Shehata et al. designed a runtime policy interaction management module for detecting and resolving user-defined policies (Shehata and Eberlein, 2007). They used the identified requirements interactions by using the semi-formal method to differentiate the interaction pattern between home appliances. They proposed to extend traditional KNX networking system to use it as an engineering Tools Software for applying the policies. The contribution of this research was to detect and resolve unwanted policies interactions. It was the first module that can be implemented in the KNX network.

Ma *et al* gave prominence to context awareness for automated services in ambient assisted living (Ma et al 2005). They aimed to implement the context awareness into Case base reasoning to provide more appropriate services in a smart home. The case base reasoning relies on previous experience and interactions to resolve current issues. To test the methodology authors used cancer diagnose database contains geospatial context. In this research, they used a few scenarios for example tv interactions, lamp interactions and Ac interactions and plan to add more contexts and to enhance the features of the case table in the future research.

2.2.2.2 Fall Detection

Gjoreski et al proposed a system to detects fall in older people by joining the two subsystems; electronic cardiograph sensors (ECG) and accelerometer (ACC) (Gjoreski et al. 2014). To recognise the activities and falls they used ACC data and ECG data was used to detect physiological signal such as heart rate, respiration rate. The combination of accelerometer signal and ECG signals was used to detect the anomalies in older people. The researchers claimed that the proposed work can be very useful health care and for patient’s safety.

Wu and Xue proposed a pre-impact system with inertial sensors for fall and injury prevention in order to increase the confidence of independent living for elderly people (Wu and Xue

2008). Inertial profile of the body was used to recognise falls from non-fall activities and to detect the early falls they used the threshold detection algorithm.

Rimminen et al proposed a fall detection method using near floor sensor and pattern recognition (Rimminen et al. 2010). The purpose of the floor sensor based on near field imaging are to detect the location and pattern of people with a measure of impedances. For the classification, size, shape and magnitude of the pattern are used and the system showed a good performance with 91% of sensitivity and specificity.

Zhuang et al proposed a fall detection system that distinguishes falls noise from other noise. They differentiate other sounds by only using far field microphone. They used a Gaussian mixture model (GMM) to model audio segments and falls then make a pairwise difference between audio segments using Euclidean distance (Xiaodan Zhuang et al. 2009).

2.2.3 Cognitive Orthotics

Cognitive orthotics are personal reminder systems to assist people with cognitive decline. In other words, it is a software-based personal reminder system, which can be beneficial for people with cognitive impairment including elderlies (Koziol et al. 2017). It is also known as cognitive artificial devices. These systems may include the features of artificial intelligence to fulfil the needs of the person more appropriately. These system assists elderlies to perform ADL satisfactorily and enable them to stay in their own homes longer. The idea to enhance cognitive of disabled people with the help of technology was originated nearly 1960s, early devices were calendar system, talking clocks (Douglas 1963). The earlier cognitive orthotics was mainly focused on alarm systems to remind elderlies of specific tasks at a fixed time. Auto minder is a system that uses a plan management technology and AI planning to schedule the daily activities of a person (Pollack 2002). In recent time, these devices and tools are designed with the help of data mining and Artificial intelligence. A walker reminder device was designed to reduce the incident of walker non-use. It detects a person and provides reminding signals. When a person starts to use the walker signalling stops. Infrared and ultrasonic sensors were used for detection. It uses a switch to the handle of the walker that send feedback to the system to stop reminding when the person is engaged (Koziol et al. 2017). A model was proposed which focus on well-known places or point of interest to suggest the user-friendly routes to the destinations according to the context of the user rather than conventional street names. The system was based on a client-server approach. (Hervas, Bravo, and Fontecha 2014). A multifunction cognitive orthotics system names "Essential Steps" was developed for people with chronic brain damage to assist with ecologically relevant activities. It was a personal computer-based compensatory approach that uses the technology and neuroscience to full fill the needs of people with cognitive impairment (Bergman 2003).

2.2.4 Therapy and Rehabilitation

AAL can be used to assist in rehabilitation and therapy of the elder persons with physical and cognitive disability resulting from neurological conditions such as stroke or traumatic brain injury. The elder patients who suffer from these neurological conditions may require long term rehabilitation after discharge from an acute rehabilitation hospital. Telehealth has the potential to address the rehabilitation and follow up care of the elderlies with physical and neurological conditions.

Telehealth which involves the services of telerehabilitation, telemedicine and teleconsulting is a way of care delivery that improves the access to health services. Telehealth can be defined as the use of ICT devices for providing healthcare services for a specific patient including a healthcare provider at distance(AHRQ 2016). The mechanism of providing telehealth care involves the mode of communication between parties(patient and providers) to exchange the data or can be provided with real-time interaction (Pramuka and van Roosmalen 2009). The technology for the exchange of data to provide healthcare includes emails, video conferencing, texting, cameras, GPS, 3D motion sensors or robotics. The pairing of these technologies to deliver healthcare services can be affected by a specific clinical application. So, it is important to understand the need for a clinical application to select technology and data mode for healthcare delivery (Pramuka and van Roosmalen 2009).

Research by the Agency for Healthcare Research and Quality (AHRQ) have provided the evidence and benefits of providing telerehabilitation for cardiovascular conditions. The research claimed that the telehealth was used for counselling, remote monitoring, communication for chronic diseases including diabetes and cardiovascular. The outcome benefits of the telehealth were cost-effectiveness and less hospitalisation (AHRQ, 2016).

Telestroke is an established mode of care that is used to provide emergency stroke care remotely (Hess and Audebert 2013). Research has examined the management of the stroke patient with thrombolysis using tissue plasminogen activator by using the telestroke network. The study claimed that the result was similar between a patient who receives the thrombolysis (tPA) through telemedicine using video teleconferencing and patient receiving tPA at a stroke centre, the thrombolysis using tissue plasminogen is delivered to three hours' time window for three months. The study also considered that telestroke is cost-effective (Kepplinger et al. 2016).

Additionally, Telehealth research has explored the area of delivering the physical therapy services with a recent study of using the telehealth services for the rotator cuff injury (Macías-Hernández et al. 2016). Moreover, the review of the diagnosing imaging of the elderlies has been managed by using the telehealth. The software-based interface allows the medical provider to share the images with patients, teleradiology algorithm has been used for decades to deliver the service of diagnosis imaging review (Bashshur et al. 2016).

In regard to medication adherence, many research has been conducted to provide medication assistance to elderlies. Medication adherence is a medication-taking behaviour. It can be described as an extent to which patients take the medication prescribed by the providers (Osterberg and Blaschke 2005). A number of medication adherence for elderlies has been designed ranging from electronic pill boxes to mobile-based apps. MedTracker, an instrumented portable pillbox that monitors the medication adherence uninterruptedly. This device provides information about medication errors and non-adherence (Tamara. L. Hayes et al. 2006). Radio frequency identification tags (RFID) based medication monitoring was developed (Fishkin, & Wang, 2003). It was a flexible system that detects medication status. It also includes a user interface to provide medication information. Some studies also used the prompting services in order to remind the subject to follow the medication with the help of images, audio and videos. A study presented a medication adherence using ubiquitous multimedia services, Multimedia Healthcare System (MHS) automatically monitor medication (Tang et al. 2011). A recent study, PillSense has designed a pill bottle based on non-invasive medication monitoring system attaching the analogue and digital sensors on the pill bottle. These sensors work collaboratively to detect the cap removal, perform motion monitoring and measure sensing activities (Aldeer, Martin, and Howard 2018).

2.2.5 Emotional Wellbeing

The AAL technology has been aimed to provide social connectedness or emotion support to elder people. The social connectedness can be referred to as an attitude or relationship of a person to society (Rettie, 2003). It can be aroused with the presence of other persons. The social connectedness can be provided with the interaction between subject and smart devices. It can be divided into two categories: interaction or connection between user and devices in the smart home and the interaction or connection between the user and smart devices in another person's home (B. Lee et al. 2017). The AAl technology for social connectedness and emotional well-being includes the web-based intervention and communication program, access to asynchronous discussion forum online self-help program and remote family communication. Research has designed a digital family portrait for visualising the daily living of the elderlies parent remotely. CareNet Display is another system that provides interactive access of a member of the elderlies' care network to daily activities of the elderly person. Family Window System was a video-based communication tool was invented to promote the feeling of connectedness to the family. Some systems are developed to support a subtle form of social awareness, for example, a lamp glows when the system detects a movement in the remote living room. This research aimed the ambient awareness to show the emotions between the elderlies and family

2.3 Sensors and Technologies used in Smart Homes

The sensor technology can be divided into three categories on the basis of the ability to sense human activity in the smart home; wearable sensors which are attached to the human body, Ambient sensors which are embedded into the infrastructure and objects of smart homes and combination of wearable and ambient sensor.

2.3.1 Ambient sensors

Ambient sensors are smart devices embedded in different parts of the home or attached to various objects that are common in daily activities. The role of these sensors is to collect data unobtrusively. Some of the commonly used ambient Sensors are described as follows.

2.3.1.1 Contact Switches

Contact switches are embedded on the front doors, doors of appliances and cabinets doors of the home to get the information about the specific interaction between the occupants and objects. A smart home project classified the data into six activities such as sleeping, eating food, they logged the data from the contact switches and motion sensors. (Brown, Majeed, Clarke and Lee ., 2006).

Wilson and Atkeson used contact switches with break beam sensor, motion detector and pressure sensors, these sensors can be triggered by gross movement, point manipulation, point movement and point manipulation (D. H. Wilson and Atkeson 2005).

Ordonez et al employed datasets by using three kinds of binary sensors installed in five different part of the home to detect seven daily activities of using the toilet, leaving the house, having dinner, eating breakfast, drinking, sleeping, taking shower). They used the passive infrared sensors to detect the movement in a particular area. In order to measure toilet being flushed flush sensors were used and read switches were used to detect the open/close state of the doors (Ordóñez, de Toledo, and Sanchis 2013).

2.3.1.2 Video sensors

Video sensors are commonly used, high content sensors for aged care. These sensors are used for various application in ambient assisted living such as to recognise the activities of residents, locating residents in their homes and provide information for computer interpretation. The main drawbacks of the video camera are its technical issues regarding information extraction and storage requirements and social issues regarding privacy (Y.-S. Lee and Chung 2012).

Tabar et al used the three cameras in a room with a combination of a wearable accelerometer for fall detection (Tabar, Keshavarz, and Aghajan 2006). They used a real-time image processing to estimate the position of the residents and to analyse the data. This setup was very useful to reduce the false alarms which were caused by sensitive accelerometer signals. The key benefit of the setup was its ability to preserve the privacy of residents when transmitting visual data is not needed.

The PlaceLab, a living laboratory in the home for the research of ubiquitous computing installed nine colour camera, nine infrared cameras and eighteen microphones in different areas of the home such as in cabinets, on the kitchen counter, on the office desk. To capture the residents' behaviour, four video streams and one audio stream was used. The image processing algorithm was used to select from video stream which detects the behaviour of residents based on motion and camera layout in the home. The data of the streams were organised with other sensor data to save to a disk drive (Satpathy 2006).

2.3.1.3 Radio Frequency Identification

RFID refers to the technology that is used to track the subject and object in a smart home independently through radio waves. It has passive RFID tags which are attached on the objects to monitor the interaction between user objects and the active RFID tags which that can be carried by a person and provide greater range. When a reader interrogates the tag, its response to a unique identifier. The passive RFID tag does not come with a power source and mostly attached to the object to detect the interaction between user objects and the active RFID tag is worn by a person for personal identification.

The SmartWave system and SmartPlug system developed by GatorTech Smart Home is based on RFID technology. All the power outlets in the Smartplug system was designed with an RFID reader and all the electronic devices are attached with RFID tags. The RFID reader into power outlet read the tags when a device was plugged in and send data to the main system and system control the device and identify its location (Elzabadani et al. 2005). Observing the usage of electronic devices provide information about the specific daily routine of the residents. The SmartWave system is a microwave-based cooking system that has used RFID. RFID readers were attached under the counter of the kitchen to scan the food packets in order to get the cooking instruction from the database and automatically start microwave according to instructions (Russo et al. 2004).

Pirttikangas et al. used the RFID tags to detect the long term daily activities of dementia patients, they attached the RFID tags into the slippers of the residents in a smart home. (Pirttikangas, Fujinami, and Nakajima 2006) . Then they designed a system by attaching RFID tags into the objects in order to track the daily activities, the information of the activities are obtained with the sequence of used objects.

Kim et al developed RFID technology based ubiquitous healthcare system for real-time monitoring and to accurately locating elderlies. They analysis the location based on the length of time the residents stay in a specific location. The collected data is used to identify the movements and activity patterns and to predict the wellbeing of elderlies (E. Kim, Helal, and Cook 2010).

The key advantages of RFID are its low cost and small size. Moreover, RFID is well suited for monitoring the activities of several people. Unique identification of RFID is very useful for tracking the multiple people location and interactions. However, the issues of tag collision and reader collision are the disadvantages of RFID technology. Tag collision issue arises when an RFID tag reader reads a large number of tags and not able to differentiate the tag signals. The reader collision occurs when the tag is not able to answer all the reader, as the tag is being read by multiple readers at the same time.

2.3.1.4 Passive Infrared Sensors

PIR motion sensors are mostly used to monitor the movement of a person. A lot of researchers have applied PIR sensors for motion detection in a smart home. These sensors are embedded on the ceiling and walls of the smart home for elderlies to obtain motion data related to redefined activities. Various sensors are installed into parts of the home to detect different activities such as room temperature, stove use, water usage, the opening of cabinets. The obtained motion data is transmitted to the caregiver of the elderlies by using a base station, data is further analyzed for the trend to detect the changes in activities and also to distinguish the changes of health status, PIR sensors can also generate alarms if the change occurs. These sensors are also very useful for fall detection and detection the degree of the activities, to analysis gait velocity, sleeping pattern, time out of the home, activities at night and user location.

Alwan et al analysis the validity of the rule-based inference method of specific Activity of daily living. They have installed fifteen different switches in various part such as on doors, microwave. The result proved that the rule-based algorithm combined with detectors can identify the activities of meal preparation and showering (Majd Alwan et al. 2005).

Barger et al presented the probabilistic mixture model, they used motion sensor data for activity detection. They used a set of motion data in order to evaluate the work and off days. The motion data was divided into 139 clusters (Barger, Brown, and Alwan 2005). Celler explained the technical features for monitoring the health status of elderlies. The changes in health status were recorded continuously for five months at the smart home (Celler, Earnshaw, et al. 1995).

Hayes et al described a Gaussian Kernel-based model based on probability density method for detecting the walking. Authors embedded different types of sensors in homes of 265 people It has produced 98% accuracy (T.L. Hayes, Pavel, and Kaye 2004). Lee et al developed a behaviour monitoring system based on PIR sensing system which can detect the motion of elders. Moreover, a remote monitoring system was developed for caregivers to monitor the elderlies (Lee S.-W., Kim Y.-J., Lee G.-S., Cho B.-Q. 2007). Noury and Hadidi et al designed a simulator that identifies activities of a person by using presence sensors in the smart home for elderly care. A mathematical model based on HMMs was designed by using real recorded data in order to generate simulated data series for different situations, then real data and simulated data was measured on the basis of similarity (Noury and Hadidi 2012). Virone et. al. conducted a simulated case study to test the pattern recognition model for the activity of daily life and they also look at activity deviation during daily activity monitoring. Wang considered the activity pattern deviation for early detection of health issues. The differences among various activities density map were measured to automatically detect changes in activity pattern. The result showed the dissimilarity of activity density map was from 0.3 to 0.5 (Virone 2009). The smart Condo project in Alberta, researchers used 13 passive infrared motion sensors to locate the residents at key areas (Bores et al2010).

2.3.1.5 Pressure sensor

One of the main function of pressure sensors is to detect the presence of inhabitants within the house and transition from sit to stand or stand to sit, these sensors are usually embeded into furniture. Arcelus et al used the pressure sensor array under the mattress and beside the bed in order to automatically measure the duration of sit to stand transition of a person. The pressure information extracted from the sensor data was analysed over time. The centre of pressure (CoP) motion was detected in the wavelet domain to detect the occurrence of the motion. The pressure sensing technique provides useful information for the monitoring of patients in a smart home. For further research Arcelus et al installed the pressure sensors in a toilet on the commode. In experiment elderly people were included as a subject. The clinical parameters showed that the older people took more time to sit to stand transition and stand to sit transition. Arcelus et al again conduct research that focuses on the analysis of state transition (sit to stand and stand to sit) performed by the inhabitants in bedroom and toilet to assess the behaviour. The information was obtained in various modalities and the clinical features were extracted from the bed exits and from the toilet to obtain a warning level. They have shown the functions of a pressure sensor array system for tracking the warning signs based pressure measurement sequences (Arcelus et.al., 2010).

2.3.1.6 Floor sensor

The floor sensors are commonly used sensors in a smart home environment. These sensors are used in different areas of smart environment for eldercare to predict the emergency situations, for example falls and for movement detection. Alwan et al.2006 described the design and functionality of a floor vibration based sensor to which was fully unobtrusive to the inhabitants. The performance of the detector was analysed by conducting an experiment using anthropomorphic dummies. The fall detection accuracy rate was 100% with the minimal potential for false alarms (Alwan et al. 2006).

Lombardi et al. proposed a data model to store and process the data of the sensing floor. The model used the biomechanical based on the ground reaction force (GRF) concept to estimate the centre of floor pressure. The experiment was conducted several times on the real sensing floor prototype. The approach outnumbered the old background subtraction schemas that accurately detect the presence of the people in the smart home (Lombardi et. al.,2015).

Serra et. al. proposed a smart flooring system based on the piezoelectric polymer floor sensors. The aim of the research was to recognise human footsteps. The sensors generate a signal used for the normalization calculation to compare a signal and reference signal. The Pearson product moment correlation coefficient (PPMCC) used between the two signal for similarity calculation. They obtained 99% accuracy (Serra et. al., 2014).

2.3.1.7 Sound sensors

The sound sensors are utilized to detect daily activities in a smart home. For example, a sound that is created when an object or a person falls. Li et al developed an acoustic fall detection system that automatically informs the caretaker about the falls. They used 8 microphones circular array to predict the sound location. The sound estimation experiment showed that sound array circulation system is robust and reliable to interference. Mel frequency cepstral coefficient was used for sound classification. The classification result on pilot dataset was excellent with 120 non-fall sound and 55 fall sound (Yun Li et al. 2010). They proposed a new approach to increase the accuracy of the acoustic fall detection system. Popescu et al presented an acoustic fall detection system. The experiment was performed on the five different falls (Popescu et.al., 2008). They applied the array of acoustic sensors to get information about the sound source height. If the sound comes from the source above 2 feet in height, it is considered a false alarm. They tested the system in 23 sets of falls, falls was performed by the stunt actors, who imitate to falls of an older person. The system reduced the fall rate from 32 to 5 per hours with 100% accuracy

Zhuang et al. proposed a system to using the audio signals generated from a single microphone (Xiaodan Zhuang et al. 2009). The system used the Gaussian Mixture model to measure the difference between audio segments. The system improves the fall classification from 59% to 67%. The system also detects the falls which are more difficult to detects

2.3.1.8 Radar sensors

Radar sensors are used to detect the moment, to detect the human cardiopulmonary motion. They are more powerful than the vision-based vision in as it can go through the strong obstacles such as walls and furniture. Moreover, it maintains privacy while monitoring in a smart home. Forouzanfar et al presented a methodology for the classification of various events. They have used a radar signal to derive the time and frequency domain features and used the Bayesian classifier in order to detect the target event (Forouzanfar et al. 2017).

Kim and Toomajan used a deep convolutional neural network and micro-Doppler signature for recognition of hand gesture. A Fourier transform feature of the radar sensor is used to recognise ten types of hand gesture (Kim & Toomajian 2016).

2.3.2 Wearable Sensors

The wearable sensors play an important role in the Ambient Assisted living in elderly care. The wearable sensors are worn by the residents, these sensors can be embedded into wristwatches, shoes, clothes or placed directly or indirectly on the body. These sensors monitor the features related to psychological or movement of a person, for this purpose they run continuously. They also get used to obtain information regarding body movement, body position, body temperature and so on.

Matthews et al developed a physiological Sensor Suite(PSS) that provide a completely integrated. it is developed at QUASAR in the form of the body-worn system, the purpose of the PSS was real-time monitoring of the physiological and cognitive monitoring of a person, more specifically the system was used to monitor the cardiac and neurological conditions. The system measure four bioelectric signals; EOG which was used to monitor the blinking of eyes these sensors were embedded into the glass, ECG was used to measure heart rate (embedded into a belt), EMG was placed on the bicep to measure the muscle activities, EEG is a bioelectrode of monitoring through hair (Matthews et. al, 2007).

Tartarisco et al 2012 proposed an automatic pervasive system to measure the stress status of an individual. They used the ECG sensors integrated into a wearable device to monitor the stress level of a person during daily activities. The system is capable to collect the data from the wearable sensors remotely and from that data the detection of the anomalous situations (Tartarisco et al. 2012). Zhu and Sheng monitored the daily activities; walking, standing, sitting, sit to stand, stand to sit, sit to lie in a home (Zhu and Sheng 2011). They placed an accelerometer on the right thigh of the resident to get the motion data. They also use the optical motion capture system to get the location data. researchers of the Activity recognition based project placed accelerometers on the chest, waist, thigh and left underarm to detect the activities of walking, lying, sitting, standing, transition. (Gao, Bourke, and Nelson 2014). Narayan et al used the triaxial accelerometer for the fall detection, it was placed on the waist to measure the time for sit to stand transition (Narayan et al., 2009). et al used the used the gyroscopes with the accelerometer to measure the sit to stand movement rising from a chair. Gao et al used multiple sensors on distributed body places to recognise the activities more accurately and more specifically. For the experiment, they fitted four accelerometer based sensors on the chest left thigh, waist and underarm of eight elderlies (Gao, Bourke, and Nelson 2014).

Kwapisz et al. described a phone based accelerometer for activity recognition. The accelerometer data of the daily activities performed by twenty-nine users was collected and then aggregated the data to summarise the user activities over 10 second interval and the resulting data was used to build a prediction model (Kwapisz et.al, 2011).

Hemalatha et al used the triaxial accelerometer for the bit pattern of the daily activities such as walking, sitting, laying in a time sensitive sliding window. The fall was detected by setting the most important bit of bit pattern and the lying activity used to distinguish falls (Hemalatha and Vaidehi 2013).

Mannini et al proposed an algorithm to process the data obtained from the wrist and ankle wearable sensors. They classify the activities on the basis of behaviour into four categories these are the cycling, sedentary, ambulation and other categories. The subjects had worn the accelerometer on the wrists and ankles while performing twenty-six different activities. Then the was collected and processed (Mannini et al. 2013)

Harrison et al developed a mobile sensing platform based on the machine learning to detect the activities. They used multi axial sensors such as barometer, accelerometer, gyroscope, placed on a single the body part such as hip, shoulder. The accelerometer was used to measure the motion and barometer was used to measure the air pressure in order to detect the walking activity of a person (Harrison et.al.,2010).

Arif and Kattan 2015 developed a time domain based system to recognise the physical activities such as cycling, walking, running, ascending stairs and descending stairs, vacuuming clothes, jumping rope and ironing. Various sensors including accelerometer, magnetometer, gyroscope, temperature sensors were worn by the person (Arif and Kattan 2015).

Dong et al 2011 detected the activity of eating by placing a magnetometer, gyroscope, accelerometer on the wrist of the user. The data was collected and then data was divided for the different activities. The accuracy of the activity of eating was 91%. Wildhorse and Baldauf 2015 attached the three sensors accelerometer, magnetometer and gyroscope on the wristwatch for the detection of drinking activities. The researchers developed a system based on the data mining technique to automatically detecting the activity of drinking. The accuracy rate was 91% to 97%

So the wearable sensors used for ambient assisted living for elderly care can provide the accurate detection of some activity of daily living.

All of the recent research has not tried to interconnect these smart and wearable devices to a system or infrastructure. However, there are few algorithms designed for wireless sensor network but none of these algorithms is suitable for a wearable sensor. The data rate, communication, transmission, number of sensors, energy consumption are major challenges in sensor area. There is a need to connect these sensors and smart devices altogether to extract the data automatically.

2.4 Smart home projects

Smart homes for aged care research have been carried out over a few decades. Some of the recent smart home projects are as follows.

Casattenta,(2010) a research project in Itlay demonstrated a system by using the ambient intelligence, sensor fusion and wireless network to monitor and recognise the critical conditions such as falls and immobility of older people. The system was designed with wearable sensors nodes and fixed sensor nodes to monitor the health and activities of inhabitants and to recognise the dangerous events (Farella, Falavigna, and Ricc 2010).

The aim of the Gator tech project was to design an assistive environment by using pervasive computing to promote the independence and quality of life of aged people. This project focused on the integration and interconnection of sensors, computers and devices. They used the generic design for the smart environment to maintain a service definition for sensors and actuator (Helal et al. 2005).

CASAS project (Cook et al. 2013) introduced a lightweight design of a smart home that was easy to install and can link multiple smart homes together. They used machine learning for activity recognition of elderlies. They proved that the implemented algorithm can detect the difference between the activities. Users can add new bridges without changing middleware. They used a compact middleware, all the components of CASAS was fitted in a box. All the sensors were embedded in physical components and users can add more sensors and controllers as needed. They used a computer with ITX form factor server for database, application component and middleware.

Assisted Cognition Environment (ACE) was an interdisciplinary project which used an artificial intelligence system to support and improve the quality of life of cognitive patients. The aim of the project was to provide active assistance to the patient by sensing the location with the help of GPS, motion detectors and badges, identify the daily behaviour patterns and then support patients by providing the physical and verbal intervention in case of danger. The Assisted Co gnition system used two models, the activity compass and adaptive prompter. The activity compass was basically an activity supervision model that helps to direct the disoriented patient to their destination. The adaptive prompter directs the patients to perform multistep everyday activities (Kautz et al. 2002).

2.5 Central Monitoring System for Smart Homes for Aged Care

The central monitoring system is responsible for all the functionality of a smart home. In other words, centralised monitoring system can be based on a device which can control all the functionality of the system including data collection from sensors, data processing with various algorithms and reasoning techniques and sharing the information with outside parties and providing services. However, the information about CMS in the literature is very limited. While several functions of the central unit have been identified by various authors, for example, the research identified three stages of activity based AAL; the raw data acquisition, sensor data processing and provide the useful information to caregivers (Ni, García Hernando, and de la Cruz 2015). However, a full description of the central unit cannot be found. Another example can be found.

2.6 Summary

Although there are numerous developments in Smat home and lots of research work on AAL especially on sensors and activity recognition. These researches have mainly focused on health prosprctives of smart homes. The information about the design of a centeral monitoring system (CMS) for smart home is limited. Moreover, there is no clear definition of the main functions of CMS. Also, there is no path for interoperability of different sensors by various developers. Hence, there is a need to identify the requirements of the CMS for the full functionality of SH.

3 Central Monitoring System for Smart Homes for Aged Care

In the previous chapter, the concept of AAL and the development of smart home technologies were discussed. As described earlier, a smart home is a regular home which has been augmented with various technologies in order to provide comfort and to monitor the wellbeing of the residents (Al-Shaqi et al 2016). This is achieved by extracting context information by combining various forms of sensor data where the central monitoring system (CMS) of the smart home plays a significant role. While the existence of the CMS is presented in almost all AAL related papers and its function has been described by some papers (Mshali et al 2018), a clear definition or the complete function of the CMS has not been articulated in literature. A lot of researchers have developed Smart home technologies such as wearable devices, intelligent control, indoor condition monitoring, smart appliances and various sensors that can be used in the smart home to provide comfort and safe environment to the elderlies. However, these devices and sensors are controlled separately, which can effect the efficency of the system. So, SH for aged care solutions are becoming available, so are the various sensors and devices that go. We need a unified platform for interoperability of devices. As a result, we need a unified architecture for CMS that can work across different vendors/devices.

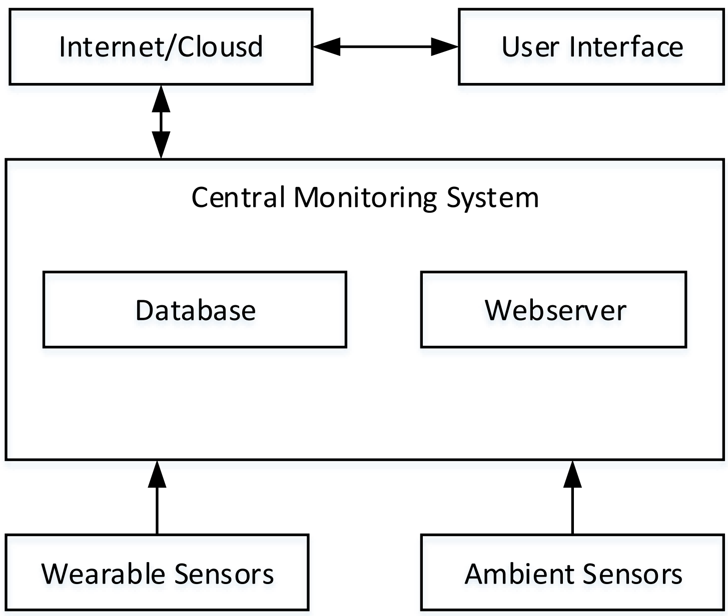

Figure 3.1 Overview of Central Monitoring System

3.1 Main requirements of CMS

In short, CMS should collect data from sensors and actuators, analyse data, extract contextual information, report alters and warnings as necessary and upload data to external servers or cloud for relevent parties to access.

In order to develop an efficient central monitoring system that can assist the elderlies proactively, a system needs to have full access to contextual information and should capable to collect and process the information. Moreover, the CMS should be aware of the surrounding of the elderlies in order to provide the services. So, there is a need to have a continuous process to automatically acquire the surrounding, behaviour and physiological information of the aged people and that can eventually provide the proactive services on the basis of available the information.

The CMS should able to collect the healthcare data from the sensors and medical sources, process and manage the data and make the health status information available on the cloud for the caretakers, healthcare professional of the elderlies or other parties. A three-layer architecture can be adopted; Sensing layer, Data Processing and Management layer, Security and access control layer. Similar approaches have been used in (Ni, García Hernando, and de la Cruz 2015),(Salama et al. 2018) in describing the CMS.

The sensing layer should manage the smart devices, wearable sensor signals and the medical data. Various ambient sensors and wearable sensors can be utilised to gather information about the elderlies.

The data processing and management layer should process the contextual data. In this layer, the activities can be aggregated from the sensor data feed and the various analytics methods can be performed to process the data. The key function of Data processing and Management layer should extract the activity recognition and localisation by using data collected from sensors. The other function of the data processing and management layer is to gather all the data and store it with the healthcare data in a secure cloud. Moreover, the data management layer should send the data to the main engine, so it can generate alerts or warning if the data indicate any health issue.

The third layer Security and Access control is an access control mechanism. The main function of this layer is to respond to the data access requests that can be made by caretakers or other parties. The user can make a request at the work station to access the healthcare data. Further, authentication and authorisation are performed. The authentication server sends the access request for authorisation and further, its evaluated with Access rules and Policies and the final result is sent back to the user.

3.2 Sensing and Data Access Layer

The sensing layer is the first stage in CMS, which is responsible for data acquisition. Various physical devices such as wearable sensors, ambient sensors and multimedia devices such as video camera and microphones are used to collect the information related to the health status of the subject, their ADL and their environment.

The functions of the commonly used ambient sensors and wearables can be summarised as in Table 1 and Table 2 respectively.

Table 1. Ambient sensors: Summary of main functions

Sensors	Functions	References
PIR sensors	detect motion and events to detect the pattern in ADL, detect the presence of subject by using temperature variation.	(Celler, Earnshawa, et al. 1995), (Barger, Brown, and Alwan 2005)
RFID Sensors	track the long-term ADL, track the location	(Pirttikangas, Fujinami, and Nakajima 2006),(Kim et al., 2013)
Pressure sensors	detect stand to sit or sit to stand transition, to detect the presence of subject on bed or chair.	(Arcelus et al., 2009),(Arcelus et al., 2010)
Video sensors	detect the ADL and location	(Willems, Debard, Vanrumste, & Goedemé, 2009),(Landau 2013),(Tabar, Keshavarz, and Aghajan 2006), (Abidine, Fergani, Abidine,&Fergani,2015), (Belshaw et al. 2011)
Floor sensors	detect the presence of the subject	(M. Alwan et al.,2006), (Lombardi et al., 2015),(Serra et al. 2014)

Microphones	sound recognition and detect various events.	(Fleury et al. 2008),(Li, Ho, & Popescu, 2012), (Popescu et al. 2008)
Temperature sensors	measure the temperature of the object.	(Celler et al., 1995),
Radar sensors	Detect cardiopulmonary of a subject, detect the movement of stationary clutter	(Forouzanfar et al. 2017), (Kim & Toomajian, 2016),(Lien et al. 2016),(Qian Wan et al. 2014)

Table 2. Wearable sensors: Summary of main functions

Sensors	Functions	References
Accelerometer	Measure the acceleration value based	(Gao, Bourke, and Nelson 2014),(Mannini et al. 2013)
Gyroscope	Movement detection	(Greene, Thapliyal, and Carpenter 2016), (Briere and Hurley 2011)
ECG	To measure cardiac activities	(Gjoreski et al. 2014),(Giri et al. 2013)
EEG	To monitor electrical brain activities.	(Dwivedi, Singh, and Shukla 2018),(Anwar et al. 2014)
EMG	To monitor muscle activities	(Khushaba et al. 2012)
Temperature	Measure body temperature	(Mansor et al. 2013),(M. W. Alam, Sultana, and Alam 2016)

Sensing layer should provide communication between sensors and the CMS. Sensors work on different data rates, different storage requirements, different monitoring requirements (frequency), issues. The use of remote monitoring for the vital signs can provide the early indication of the health conditions of residents, which can be useful for early and proactive care. It requires to develop a solution to record the vital signs electronically, to evaluate the warning score and to automatically generate the alarms for the caretakers. The system can also combine the recent medical data of a patient with the collected data from the sensors to detect the early indication of major risks such as heart attack, stroke or organ failure. So, some health risks can be detected by utilising health sensors data collections. In the Sensing and Data Access layer, various sensors can be used to collect information about the physical status of a person, to get the information about to the activities performed by them and their behaviour The main function of the sensing and data access unit is data collection from the ambient and wearable sensors.

At this stage, several sources such as smart devices or wearable devices and sensors can be used to collect information about the physical and psychological health status of the elderly or their environment. The data can be collected directly from the embedded sensors in the smart environment or data collection can be performed indirectly. In the indirect method, the sensor data is collected in a middleware-based system, where data can be collected from a database, storage server and additional software. The important feature of Sensing layer is the frequency of the data collection as the frequency of receiving data could affect the whole system. The data can be gathered continuously, instantly or on the few intervals. For the continuous events data is constantly extracted, the interval event requires the data after a few intervals, for example, sending information related to blood pressure measurement every two hours. The instant event applies that information is sent immediately when a different event is performed such as the opening of the cabinets.

Sensors are the most important part of the data collection and sensing layer that is utilised to create the raw data about the health of the elderlies and their surroundings. A wide range of sensors can be used for the central health monitoring for the elderlies. The commonly used sensors for collecting raw data in recent studies are a temperature sensor, light sensor, accelerometer, magnetic, motion sensor, pressure sensor, ECG etc. These sensors can be categorised into two main categories that are wearable and static or ambient sensors. Both types of sensors are required in the CMS. These sensors can be attached to the infrastructure, devices of the home and should be interconnected with each other to perform one or more task simultaneously. The static sensors are used for the purpose of recording the activities performed by the subject or events in the environment. The wearable sensors are used to detect the health conditions of the elderlies. Some electronic devices can be also used to get more contextual information such as cameras, TV, Speakers etc. These electronic devices can extract a rich amount of information. However, these devices can be suffered for privacy issues.

The static or environment sensors are used in order to generate the contextual data. These sensors can be embedded into the environment or attached to the objects for example on doors, sofa, beds, chairs, on cabinets doors to detect the elderlies' activities. The performance of an elderly in terms of daily activities can be measured on the basis of their interaction with the environment or objects in the environment. For example, if the sensor of a shower is on and the location of the person is detected in the bathroom with a motion sensor, it indicates that a person has performed the activity of taking showering. The most frequently used sensors for health monitoring are RFID. The radio frequency identification (RFID) has the tags attached to the object and a reader placed on the body part of a person. To track the location and movement of the elderly, pressure sensors can be used. The contact switches are used to measure the interaction of a person with appliances or another object in the environment. The power sensors can be used to measure the utilisation of the appliances, to manage the energy consumption and the usage of energy.

The wearable sensor can be worn by elderlies; the wearable sensors are a great source of information for real-time health monitoring. These sensors are usually embedded in clothes, belts or glasses. These sensors can be used to measure internal units such as heart rate, blood pressure. The wearable sensors that can be used inertial sensors are an accelerometer and ECG and gyroscope, these sensors are used to detect the movement or body gesture, for example, sitting, walking, standing. Triaxial is used to measure the acceleration rate by placing on the body of the (Jiang et al., 2011). The gyroscope can be used for the movement detection but gyroscope is mostly used with the accelerometer. These sensors can be placed on the arms, legs, the wrist of the person to recognise the activities of walking, sitting, standing etc. Another sensor that can be used as a wearable sensor is GPS to detect the location of a person. The main purpose to use the GPS can be to detect the means of transport of a person.

The wearable sensors can be used to measure the sign of the elderly for example the body temperature, heart rate, blood pressure, blood glucose etc. These sensors provide the real-time monitoring of the health conditions of the elderlies. Other wearable sensors could be electroencephalography (EEG) for brain activities monitoring, electrocardiography (ECG) for cardiac activities, electrooculography (EOG) for the eye movements, electromyography (EMG) to monitor muscle activity, photoplethysmography used to measure blood flow.

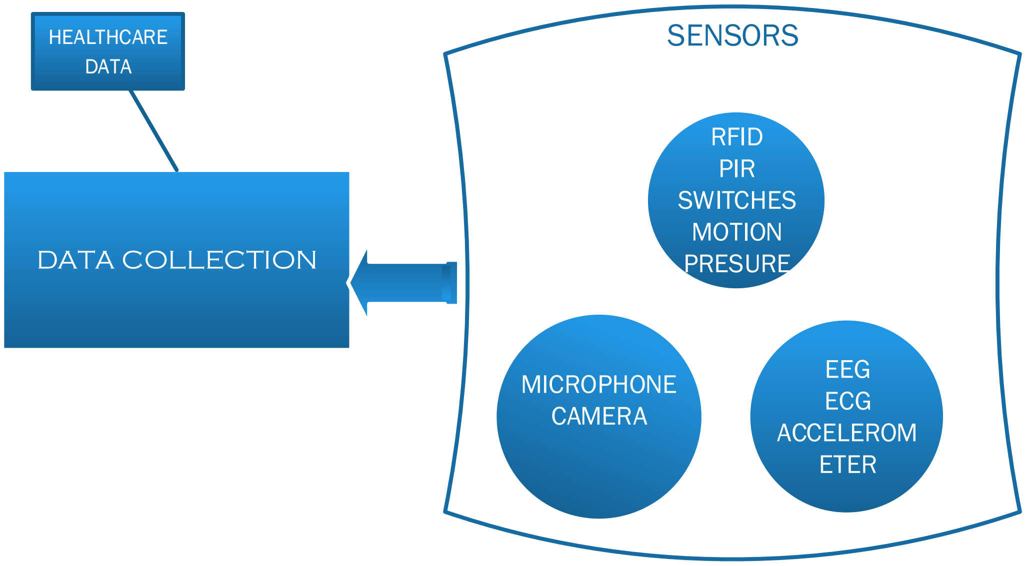

Figure 3.2 Sensing and Data Collection Layer

Three types of data can be aggregated for the system is

- Data collected from a number of sensors.
- Health care data of the patient related to the medical history, latest health status or health condition, early symptoms for an alarming disease obtained from the medical professionals
- Personal data such as background, authenticity or dietary information

However, data of sensors and data gathered from healthcare professional could be great in volume, so the graphs and table can be used to analyse data in order to utilise time properly.

3.3 Data processing and management

Data Processing and management is an important part of the centralised monitoring system. The key function of the data processing and management layer is to apply suitable methods and techniques to successfully recognise the activities and location of the elderlies. Various phases are responsible for data processing and management such as data representation, pre-processing, data fusion and context reasoning and machine learning.

Activities of daily living (ADL) are the tasks which are performed every day by a person such as drinking, eating, cooking or walking. The behaviour of elderlies can be detected by their activities and events. The events and activities performed by elderlies can be used to distinguish behaviour at a different complex level. The event is a task performed by a subject for a very short time such as close the door or turns off light. An activity is a sequence of the actions executed by one or more persons as they can interact with each other. The activities are the sequence of the actions, for example, the eating activity, the drinking activity includes the sequence of; pick a glass, turn on tap and turn off the tap. The subject can also perform two activities at the same time such as eating and watching TV. The location, time, posture and frequency are also very important in the monitoring activities. A location is an area where the activities are usually performed for example the meal preparation takes place in the kitchen. The duration, starting time and end time of an activity is also prominent for monitoring the activities. The posture of the subject is a key characteristic for activity monitoring some regular posture sitting, standing, lying are used to detect the activities of sleeping, walking or eating. The frequency is repeatability of activity, for example, the eating activity is mostly performed three times a day. The object can also indicate that an activity is being performed such as the usage of the plate can indicate the eating activity. Temperature and humidity can be also an important characteristic of activity monitoring.

Activity recognition is an important element in a health monitoring system for elderlies. Activity recognition can be performed with different methods and algorithms.

Moreover, to locate the elder people in their homes is a crucial task for a central monitoring system. The localisation refers to a place where most of the activities are performed on a daily basis by elderlies (Swaminathan, Nischt, and Kuhnel 2008). The location of the elderlies can be extracted automatically from the data gathered from the sensors. RFID tags can be used to locate people or objects. The received signal strength indicator (RSSI) could be uncertain in a complex environment. The passive tag array and some machine learning methods can be used to predict the location.

3.3.1 Context Data representation

The initial requirement of the Processing and management layer is Context data representation**.** The context data representation refers to a context representation of the collected data in a system (Schilit, Adams, and Want 1994). The aim of the context representation techniques is to represent the data into an integrated format to make it understandable and to share it. The data gathered from the sensors is raw data and it is useless unless it is evaluated and interpreted. When the data acquisition is started, the sensor data increase very fast so an effective technique for the data representation is necessary. It is important to present the data in a way that it can be read easily and with minimum efforts. The collected data should be categorised into different formats due to its nature of heterogeneity. A mechanism is required to organise the data into a readable format for further processing. Various context modelling techniques are available for the data representation such as key-value modelling, object-oriented logic based, graphics, mark-ups, ontology-based technique. One of the easiest methods that can be implemented for context representation is the Key value modelling. A list of key and value is used to represent the attributes and value. (Schilit, Adams, and Want 1994). The object-oriented modelling uses the reusability, inheritance, encapsulation to represent the context data. Zhang and Gu 2005 (Zhang, Gu, & Wang, 2005) used the context model in the smart environment project based on the context-aware system. The data is defined in the entities; these entities further describe the conceptual or physical objects for example as an activity or a person. The graphical representation of the data can also be used, the context information is presented in the form diagrams by using the Unified Modelling Language (UML) (Rialle, Lamy, Noury, & Bajolle, 2002.). Mark up modelling is the representation in the hierarchical structure by using XML. In mark-ups, the attribute and content of the attributes are used to define the information. This modelling can be very useful to store and share data in a flexible way. The ontologies based technique of data representation is based on semantic technologies. The relationship, concept and instances are used to define the context data. The Ontology Web Language (OWL) is used in ontology-based modelling for knowledge sharing, context representation. In the logically based technique, data is presented in the expressions, rules and facts. Logically based modelling uses the data and then used logical based rules to process the context data. (Ricquebourg et al. 2006)

3.3.2 Data pre-processing

The objectives of the pre-processing task are to perform further processing in order to retrieve the missing values, removing unnecessary data, cleaning the collected data. If the data is irrelevant, the process of the analysis becomes more difficult. The data pre-processing can be performed in various steps such as data cleaning, normalisation, data transformation and feature extraction. The data should be cleaned by removing and editing inappropriate records. The data normalisation could be used to uniform the various variables into 0,1. Data reduction can be used to transfer numerical data into a simple and systematic way. The feature extraction can be used to transfer input data into the set of features. When the input data become too large and difficult to process, then it can change into the feature vectors. The process of feature extraction starts with feature selection, only selected features are used to get the relevant information from the input data. So the Data Fusion process is used to make sensor data more consistent, useful and accurate.

3.3.3 Data Fusion

Data fusion is used to integrate data from multiple sensors to generate more useful and consistent information than single sensors. The aim of the data fusion task is to integrate data from various sensors in order to reduce errors. The data fusion can be divided into three categories data association, state estimation and decision fusion.

3.3.4 Context Reasoning and Machine learning

Context reasoning is the most challenging part of the data processing and management layer. The aim of the context reasoning is to obtain the real context of the subject by using various reasoning and learning algorithms. The implementation of these reasoning methods has an impact on the final results. Therefore, the success of the system is depended on these methods. These techniques are fundament to recognise activities and behaviour. The most common reasoning and learning methods are statistical technique, computational technique and knowledge-driven technique. A single technique could not be more effective for an efficient Central monitoring system, so, the best approach could be to combine the different techniques to provide a more accurate health status of the elderly in a smart home.

The statistical methods are an important part of the recognising the human activities for health care. These methods are used for the reasoning to deal with the task of behaviour recognition. The methods of the Hidden Markov Model (HMM) and Bayesian are probabilistic methods. These methods are capable of the modelling behaviours as these methods have the ability to show the dependence and random variables. In the HMM, the system uses the Markov process, it defines hidden states and observation for behaviour modelling (Atallah and Yang 2009).

Another statistical modelling could be conditional Random Field (CRF). The CRF can be used to encode the relationship between observation and interpretation and for the labelling of the sequential data. It does not make the assumptions between observation independently. classification for activity recognition (Vail, Veloso, and Lafferty 2007). Bayesian networks are used for the modelling of human behaviour. The Bayesian framework includes the Naive Bayes Classifier (NBC) based on the Bayes theorem to recognise the activities. The Bayesian model has produced satisfactory results for activity recognition in many projects. However, NBC require a large amount of data for activity recognition. The Gaussian Mixer Model (GMM) is another model used for activity recognition. GMM was combined with rule-based reasoning in Cardinaux et al (Cardinaux, Brownsell, Hawley, & Bradley, 2008).

The alternative to these statistical methods can be computational techniques such as Artificial Neural Networks (ANN), Suppport Vector Machines, data mining, fuzzy systems. These techniques play an important part to recognise the ADL and predict the health condition of a person. ANN presents mathematical tools, that can be useful for the data classification. The ANN has been employed in many healthcare monitoring systems. Xie et al. (Xie et al. 2013) authors have used the ANN with a wireless network for activity recognition. The ANN proved more accurate simulation results than other techniques. ANN is also used to provide decision support for the remote health system. The ANN can consist if different combination such as Multi-Layer perception (MLP) is used with a single hidden layer for activity recognition in (Ricquebourg et al. 2006).

The support vector machine (SVM) is also used for classification and pattern recognition. In SVM set of training, examples are connected with each other. SVM training algorithm creates a model which allocate a new example to one category. SVM can also be combined with HMM to detect the abnormality in the behaviour pattern of the elderlies and to train the ADL (Ordóñez, de Toledo, and Sanchis 2013).

The knowledge driven techniques such as Fuzzy logic, Rule-based, Case-based, Ontology-based can be also used for modelling activity recognition and human behaviours. The knowledge driven method is used to develop logical reasoning. The knowledge-based reasoning technique is used to observe the daily activities of people. The accuracy of the prior knowledge is fundamental in knowledge-based reasoning. The fuzzy system is mainly used to handle the uncertainty of the sensor data. The fuzzy logic can be applied to integrate activity recognition. The neuro-fuzzy system (NFS) can be used for the diagnosis of heart diseases. Fuzzy set theory is combined with rule-based to control the automated system in order to optimize contextual reasoning.

The ontology-based reasoning is well suited and commonly used method for the context reasoning. The benefits of the ontology-based reasoning are its interoperability of pervasive computer system, its efficient reasoning and knowledge sharing in a dynamic environment. The ontology-based reasoning is based on knowledge representation and logic description. The ontology reasoning is supported by the two semantic web languages these are Web Ontology Language (OWL) and Resource Description Framework (RDF). The ontology reasoning can be combined with the statistical reasoning to recognise the activities. The ontology-based reasoning can be used to discover the devices and location in the smart home. The reasoning is used to support to discover the activities (Ricquebourg et al. 2006).

The rule-based is one of the simplest reasoning techniques. The rule-based reasoning uses the low-level context to create a high-level abstraction. The weakness of Rule-based reasoning is that it is not able to detect activities directly. The rule-based reasoning could be more effective for activity recognition when it is combined with Bayesian networks (Nef et al. 2015).

In the case based reasoning, context knowledge is extracted on the basis of the previous similar cases. Case-based reasoning is usually used for activity recognition and behaviour recognition.

The reasoning techniques and methods that are described above are the commonly used for extracting the context. Each method has its own benefits and weaknesses. A single technique is not useful to handle the complexity of context reasoning. A single method could not able to perform well for the Central Monitoring System. So, there is a need to combine various method that complements each other in order to present a piece of comprehensive information related to the context of elderlies in the smart home

So the data management and inference layer need to process the perceived information with the data pre-processing and data fusion to observe the high-level contextual information, to use the reasoning methods and learning algorithm to infer activities.

The data processing and management layer can be used to extract the location and activities of daily living based on sensor data. The raw data collected through sensors should be managed and processed in order to recognise activities. Various machine learning algorithm and reasoning methods can be used to recognise the activities and location of the subject in order to evaluate the health status of the elderlies so required healthcare services can be provided.

3.3.5 Location Identification

Indoor-positioning or location identification systems provide information on the location of residents and movable objects in smart homes. There are many location identification methods which are based on WiFi, Bluetooth, Zig-Bee (Muñoz 2009), RFID (Alsinglawi et al. 2017) and visible light communications(Keskin, Sezer, and Gezici 2018). The location data provides important information for context reasoning. The location data help to track elderly with dementia and in general to identify where the subjects (Lin et al. 2006).

3.4 Security and Access Control

Security and Access control is a critical part of a health monitoring system. As the Central monitoring system will use sensitive subject data. So there is a need to have an access control system maximum security and privacy is required as the monitoring of the elderlies involves large data collection and processing.

In CMS the key function of security and access control is to manage the access requests made by the healthcare professionals or another user. The security and access control unit includes the user attributes, different types of the health records of the user such as mental, physical health data or personal information. The policies of access control which manage the viewing of data and update the health care data. The user should have a certificate to access the data. When the user requests the access for the health care data at the workstation, it forwards the request to the authentication server. The key function of the authentication server is to verify the digital certificate of a health care professional and patient ID and then send the access request to the authorisation server. The main function of the authorisation server is to check the access policies and grant access to the user.

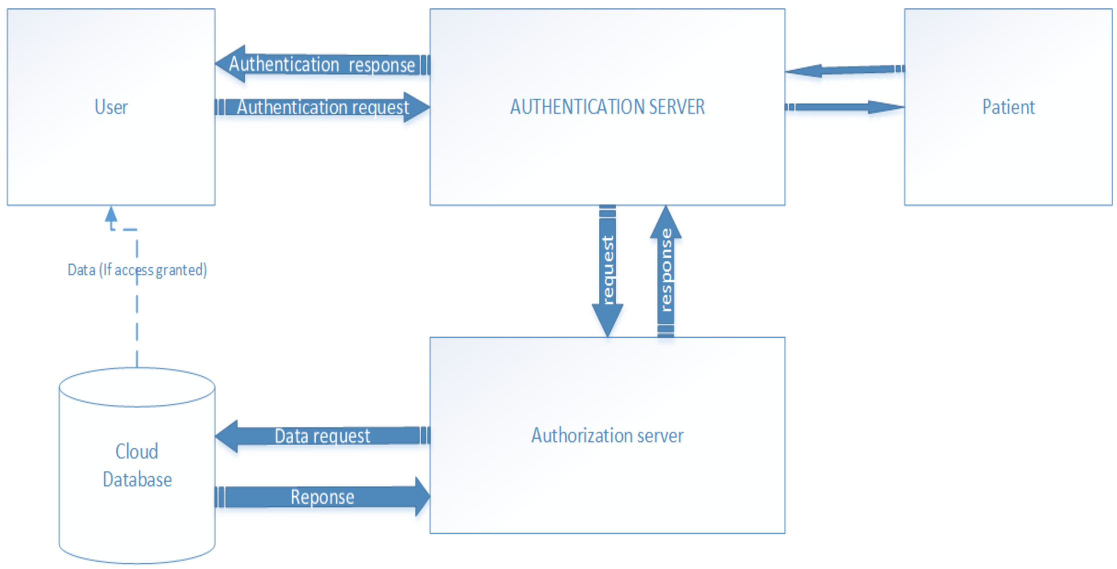

Figure 3.3 Security and Access Control Layer

3.4.1 Privacy requirements

In a health care system, there are many people who want to access the healthcare data of the elderlies such as doctors, organisations like imaging centre or laboratories, family member or friends. The patient or elderly person can manage his own medical data. The elderly should capable to response the request to access the sensitive healthcare data to a specific person or healthcare organisation. The elderly should give permission to a family doctor to access all types of healthcare data and the family doctor should have the ability to check the data classification. The practitioner should be able to provide immediate assistance in an emergency so an emergency attribute should be accessible for the available practitioner. Only healthcare units or doctors should have the ability to update medical records. Elderly should able to provide the access of data to any person if it is required. The access permission should be given to a particular period of time and location. Moreover, the healthcare data should be available to authorised users without interruption and the infrastructure should be easy to manage and modified if required.

3.4.2 Identity Requirements

The identity requirement for a robust Access control of CMS should as following.

Every component of the system should be able to classify the data it produces. The patient or elderly should able to grant or deny access to private information or healthcare data anytime. The patient should able to classify his Doctor, whom he wants to be capable to access all the healthcare data anytime. There should an emergency attribute that can be used by any available practitioner to access healthcare data in an emergency case to give immediate help. Moreover, there should be no obstruction for the eligible user to access the healthcare data. The policies should be easy to use and easy to change whenever required. The access should also be granted to a group of people such as to healthcare professionals. The patient should capable to give permission to anyone when required. The access of data could be conditional for a specific period. For example, the practitioner can access the data when a patient is hospitalised.

3.4.3 Authentication

The authentication is a process to identify a user before granting access to healthcare data. The healthcare professional requires to have a certificate in order to access healthcare data. The request for access to healthcare data can be made via a Workstation, which is connected to the authentication server. The main function of the authentication server is to verify the digital certificate of the healthcare professional and ID of the patient and authenticate the healthcare professional and forward the request to the authorization server. Various type of authentication approaches can be implemented for a health monitoring system to grant access to data by using the electronic documents such as V5 protocol, Semantic Access certificate (SAC), national authentication service for health (NASH), Microsoft Vault, PKB. The SAC can be used to authenticate a user. Nash grants access to the healthcare data by using a public key Infrastructure (PKI) certificate. The users can utilise the smart cards and PIN to access from any workstation. PKI certificate contains the information related to the public key of the user, identity of the user, digital signature certificated authority and list of certificate extensions. NASH sets a Record Access Code (RAC) in order to prevent or approve access to the record of the patient. It prevents the document from view and marks a specific document as limited access in patients record. NASH is also capable to control login issues such as multiple logins fail and control after-hours access

3.4.4 Authorization

The function of authorisation in a health monitoring system is to manage which user can access a specific resource, to give an access right to healthcare professionals, to define access policy, to decide if the request should be granted or denied.

So, the privacy and security layer handle the access control system. The system starts to work when a user sends a request to the user interface to access the data of the elderly. The user interfaces forwards the request to the authentication server, the authorisation server and then to the cloud database.

4 Design details of the Central Monitoring System

The requirements for CMS were identified in the previous chapter. The functions of the CMS were described using three main layers 1) Sensing layer, 2) Data processing and management layer; and 3) Security and access control layer. This is illustrated in Figure 4.1. Implementational considerations of the 3 main layers of the CMS are presented in this chapter.

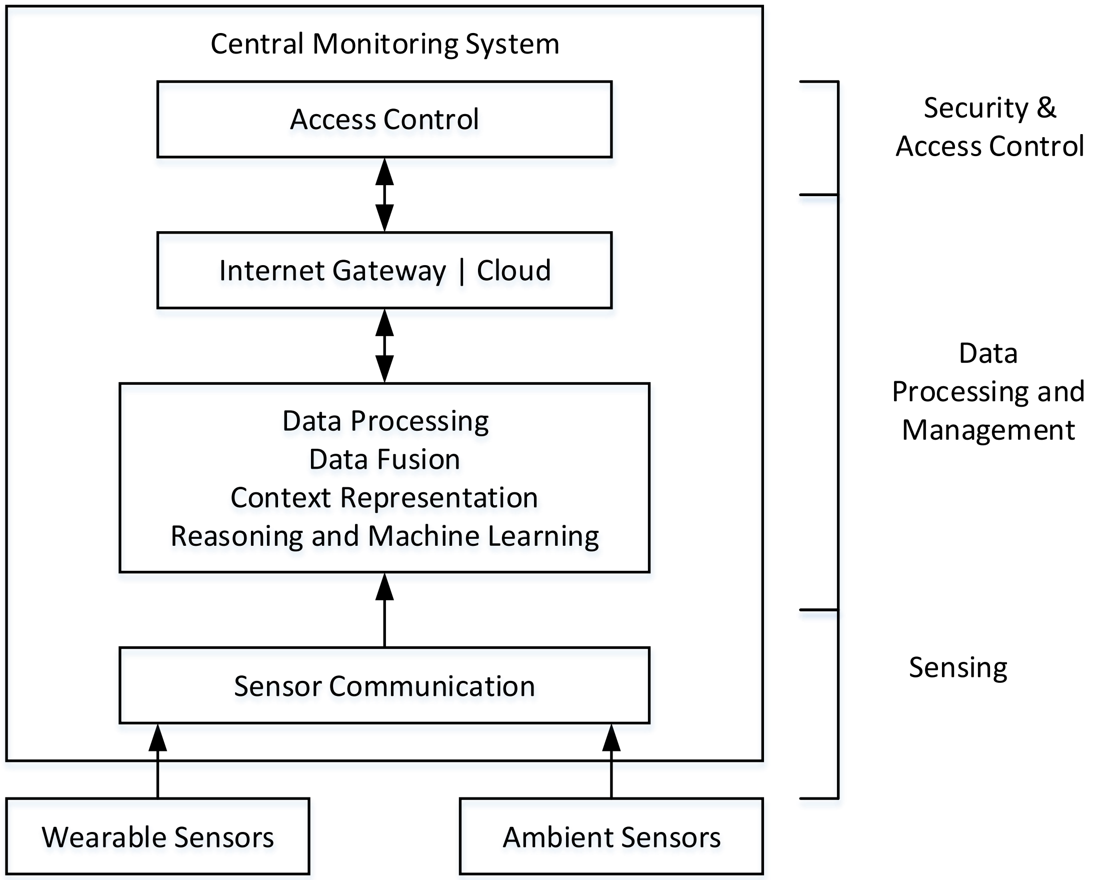

Figure 4.1 Three main layers of CMS

4.1 Sensing Layer

The main function of the sensing layer as described in Chapter 3 is to gather data from multiple sensors which can be both wearable and ambient. In general, the wearable sensors should have wireless connectivity such as Bluetooth. In cases where wearable sensors require high data rates, it may be necessary to consider wired connections. The ambient sensors may be able to connect to the CMS using either wired or wireless connections. The wired sensors may require the support of serial communication methods such as inter-integrated circuit (IIC, I^2C, or I2C), serial peripheral interface (SPI), universal serial bus (USB) or high-definition multimedia interface (HDMI).

4.1.1 Communication with Ambient Sensors

The communication requirements of commonly used ambient sensors can be summarised as shown in Table 3.

Table 3. Communication Requirements for Ambient Sensors

Sensor	Measurement	Date Rate	Communication Method
Pressure	Pressure on mats, chairs, etc.	Very low	I2C/SPI
Passive Infrared (PIR)	Motion	Low	I2C/SPI
Active Infrared	Motion, identification	Low	I2C, USB
RFID	Location, Object information	High	USB, Ethernet
Smart Tiles	Pressure on the floor, location	Very low	I2C/SPI
Magnetic switches	Door/Window/Cabinet opening closing	Very low	I2C/SPI
Temperature	Room temperature	Very low	Single wire or I2C
Ultrasonic	Motion	Low	I2C
Microphone	Sound, Activity	High	USB
Camera	Video, Activity	Very high	HDMI

4.1.2 Communication with Wearable Sensors

The communication requirements of commonly used wearable sensors can be summarised as shown in Table 4.

Table 4. Communication Requirements for Ambient Sensors

Sensor	Measurement	Data Rate	Communication Method
Accelerometer	Acceleration	High	Bluetooth
Gyroscope	Orientation	High	Bluetooth
Glucometer	Blood Glucose	High	Bluetooth
Temperature	Body temperature	Very low	Bluetooth
Pressure	Blood pressure	Low	Bluetooth
Pulse Oximeter	Blood oxygen saturation	Low	Bluetooth
ECG	Cardiac activity	High	Bluetooth
EEG	Brain activity	High	Bluetooth
EMG	Muscle activity	Very High	Wired or Wi-Fi

In addition to communication requirements, CMS should provide easy access to interfacing with external sensors, i.e. digital and analog inputs should be readily available for connection of sensors. Some sensors may also require additional signal conditioning units. The serial communication interface of CMU can be summarised as in Figure 4.2.

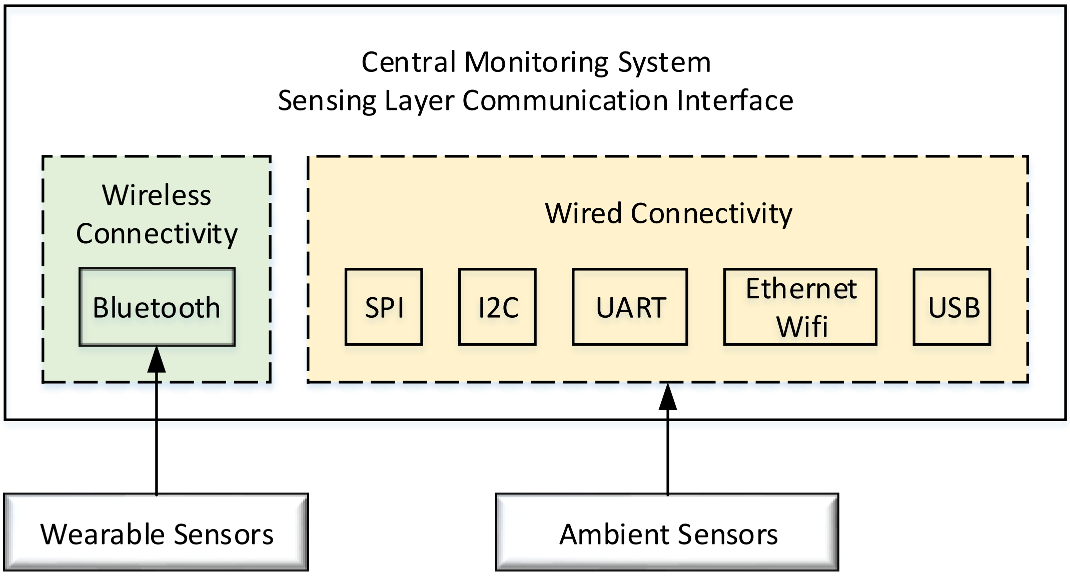

Figure 4.2 Sensing Layer Communication Interface

4.2 Data Management and Analysis

Data processing and management is a key phase of CMS. The appropriate reasoning and machine learning may increase the effectiveness of CMS. In the following section data preprocessing, feature extraction and machine learning methods are described, that can be implemented for the processing of sensor data for CMS.

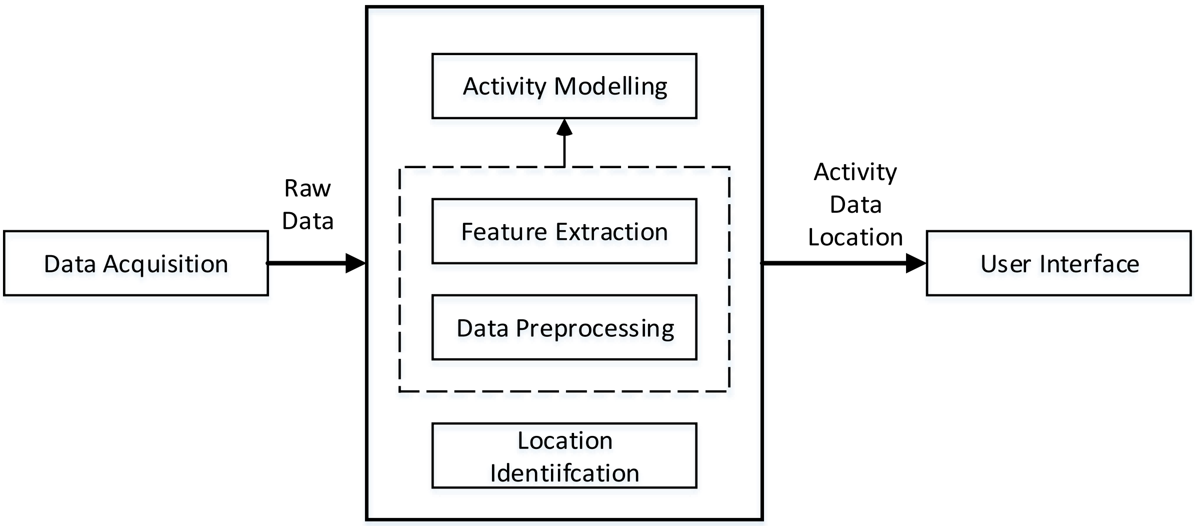

Figure 4.3 Data Processing and Management Layer

4.2.1 Step 1: Data Preprocessing

The data preprocessing operation is used to clean the noisy and unwanted data, to handle the missing values and to put data into a proper format. The first step of preprocessing is data cleaning. There are various cleaning techniques that can be used to filters artificial and unimportant data in order to get relevant information. The main data cleaning methods are as following;

The Bayes filter can be used to track a single user and to clean the RFID sensor data (Wilson & Atkeson, 2005). The particle filter is used to filter the Binary and RFID sensor data, it works well for the tracking of multiple users in a noisy environment (D. H. Wilson and Atkeson 2005). The median filter can be used to filter the non-linear data and to detect the abnormal measurements of passive presence sensor data (Noury and Hadidi 2012). The low pass filter can be applied to remove the constant gravity acceleration from the data set gather through the accelerometer (Khan, Siddiqi, and Lee 2013). Kalman filter can be used to remove the noise from ECG data. Clustering based undersampling (ClusBus) is another approach that can be used to overcome the issues of class overlapping and class imbalance. This approach was applied for the CASAS smart home data set by Barnan et al (B. Das, Krishnan, and Cook 2014).

After data cleaning the next step of data preprocessing is handling the missing values. Linear Interpolation is the widely used method for handling the missing values. Linear interpolation is usually applied to fill the missing reading of RFID datasets (Parlak and Marsic 2013). Other techniques that can be used to fill the missing values are a cubic interpolation and nearest neighbour interpolation. The cubic interpolation decreases the computational complexity and maintains the performance level (Ferrer-Arnau et al. 2012).

For further data processing, the data transformation methods are used to put the data into a proper format. The main function of these methods is to change the raw data into attributes according to the requirements of a specific system. Normalization is a commonly used data transformation approach, in order to get a representation format of sensor outputs (Durrant-Whyte and Henderson 2008). There is a range of possible scales, so the normalisation can be performed on the basis of homogeneity, nature of scale, semantics. The homogeneity means wheater sensors are providing a measurement of the same physical phenomenon. Nature of scale is the mathematical properties of a scale. Semantics is a way in which the scale is interpreted such as the degree of similarity, probabilistic or utility (Durrant-Whyte and Henderson 2008).

4.2.2 Step 2: Feature extraction and Selection

Feature extraction refers to the extraction of the features that represent significant characteristics of data. The raw sensor data is converted into a feature vector, which should have useful information for advanced processing and machine learning algorithm. Various feature extraction methods are categorised on the basis of time domain, frequency domain and discrete representation domain (Figo et al. 2010). The main feature extraction techniques in these three domains are as follows:

Time domain features: the main features that can be extracted in the time domain are Mean, Standard deviation, Average, Median, Variance, Min, Max, Range, Correlation, Cross relation and integration. The mean can be used for almost every kind of sensors. It requires minimum computational memory and cost. In previous researches mean have been used to identifies the posture of the subject, to detect the activities, as an input for classifiers. The Standard deviation is also used as a basic metrics for classifiers like Dynamic Bayesian Networks and the Neural networks. The correlation can be used to measure the direction of the linear relationship between two signals. It is also used in activity recognition to distinguish the activities that involve translation in a single dimension (He and Jin 2009). Another metrics is Cross-correlation which is used to measure the similarity between waveforms. The median is used to separate the one half of the data sample from the others half

Frequency Domain methods are used to capture the repetitive sensor data. Fourier transform and Wavelet transform is commonly used methods. Fourier transform can be used to compute a time based discrete signal using Fast Time-Frequency Transform (FTFT) and Fast Fourier Transform (FFT) algorithms. The Wavelet transform is used to capture the transition between activities because it has the ability to detect sudden changes in sensor signals. Other frequency domain feature extraction for activity recognition are DC component, spectral energy, information entropy, key coefficients, coefficient sum and dominant frequency.

Discrete Domain: These features are used to transform the sensor signals into the string of discrete symbols. When the signals mapped to strings, then the key techniques Euclidean-based relation, Dynamic time warping and Levenshtein edit distance are used to examine the string similarity and to classify the activities. Euclidean-based relation allows quick discrimination between signals. The Dynamic time wrapping (DTW) is a feature for measuring the similarity of sequences. It has been used to find similarity between signals in automatic speech recognition and gesture recognition. Levenshtein edit distance is used to measure the similarity between two signals. It determines the number of symbols insertion, deletion and substitution for transferring the strings.

However, the extracted features from raw sensor data could have irrelevant information which may affect the performance of the system. The feature selection approach can be used to find more discriminative features. The role of the feature selection process is to select more relevant features within a dimensional feature vector to decrease the noise. The commonly used feature selection methods are Correlation-based Feature Selection (CFS), Minimum Redundancy and Maximum Redundancy (MRMR). MRMR method selects the features from the fixation, blink, saccade and wordbook feature group (Bulling et al. 2011). CFS has been used for accelerometer data (Maurer et al. 2006). Other feature selection methods thas has been used to select relevant features from high dimensional feature vector are SVM based feature selection (Bron et al. 2014), correlation-based feature (M. Zhang and Sawchuk 2011), Sequential Forward Floating Search (Gupta and Dallas 2014), Forward-backward Sequential search (Muhammad et al. 2012). The feature selection methods that used to transform the high dimensional feature vector into low dimensional feature vector are Linear Discriminant Analysis, Principal Component Analysis and Independent Component Analysis (Giri et al. 2013).

4.2.3 Step 3: Machine Learning

After the feature extraction and selection, the next step is Machine learning(ML). ML is used to generate the real context of the subject by using various methods. The commonly used methods for activity recognition and location identification is as follows:

Hidden Markov Models (HMM) and Bayesian networks are commonly used for recognition of daily activities. In HMM, the system uses a Markov process with unknown parameters. The HMM is composed of hidden states which represent the activities and sensor data represent observed output (Atallah and Yang 2009). The extensions of HMM such as Hidden Semi Markov model (HSMM) (Duong et al. 2005), Coupled hidden Markov Model (CHMM) (Wang et al. 2011) has been used for activity recognition. Another Statistical method for activity recognition is Conditional Random Field (CRF), it represents the conditional probability of a label sequence. CRF uses more computation of training data than HMM (Vail, Veloso, and Lafferty 2007). Bayesian Networks has been used for activity recognition. Support vector machines, Artifical Neural Networks and fuzzy systems and Decision trees are computational intelligence techniques used for activity recognition. SVM has been used to learn the habits related to ADL of the subject. ANN has been combined with another method for activity recognition.

Table 5. Data Processing methods

Functions	Processing Methods	Computing Power Requirement
Context data representation	UML, OWL, Object-oriented modelling	Medium
Data pre-processing	Filtering techniques (high-pass, band-pass, notch), applications of wavelets	Medium
Data Fusion	HMM, Bayesian techniques	High
Context Reasoning and Machine learning	Artificial neural networks, fuzzy systems, neuro-fuzzy systems, support vector machines, Bayesian techniques, HMM	High
Location Identification	Triangulation, multilateration	Medium

4.3 Access and Security Control

The main concern of healthcare data is privacy or confidentiality. As discussed in the last chapter an Access control system is required for CMS that should able to ensure the privacy, confidentially and integrity of the information. In addition to that, the Access control system should apply privacy policies in order to permit data Access to only authorised users. An Access control model based on Attribute-Based Access Control (ABAC) policies can be implemented for the CMS as described in (Salama et al. 2018). The proposed access and security control mechanism is illustrated in Figure 4.4.

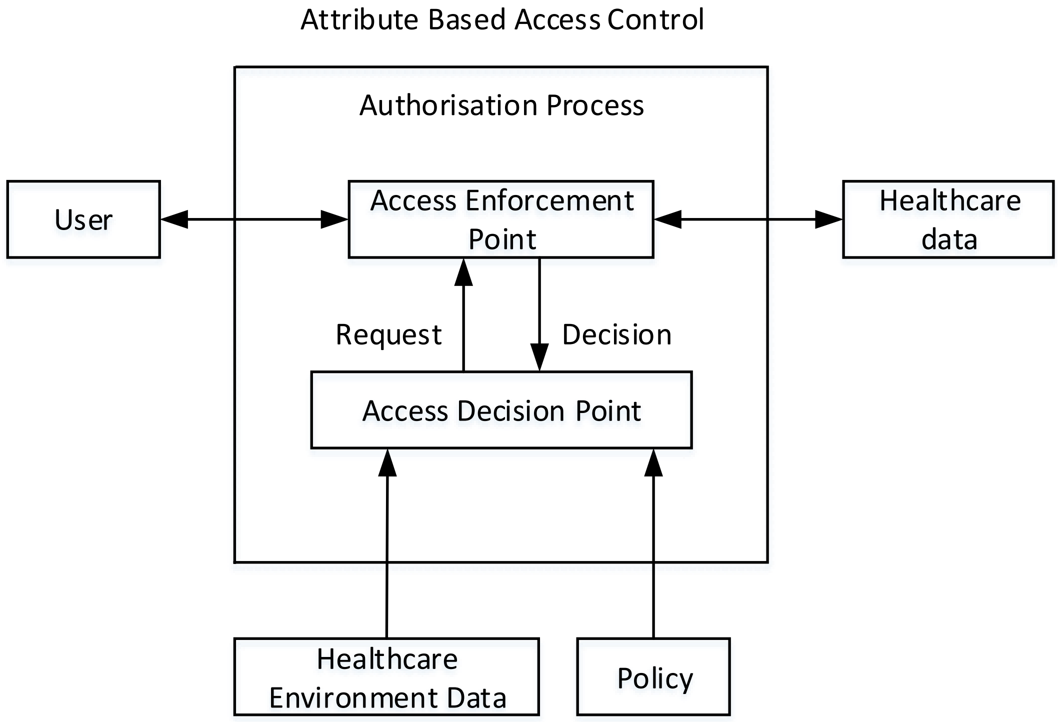

Figure 4.4 Access Control and Security

4.3.1 Attributes

Attributes are used to present the particular feature of the user, environment or resources. The user attributes could be any user who tries to access the healthcare data such as a doctor, nurse, family friend or researchers. Every user should have unified attributes such as his name or ID. The users can be divided into different groups such as 'patients', 'Doctors', 'friends', 'researchers', 'medical centre'.

Environment attribute could be time or date when the healthcare professional can access the medical record of the patients. Location and emergency could also be added as environmental attributes for example, the hospital staff can access the healthcare data when the patient is hospitalised.

Resource attribute could be medications, health record or immunisation or any entity acted upon by the user. The resources attribute can be defined into different categories such as 'physical health' that contains any ailments, details of radiology or pathology or any medical treatments or procedure performed on the patient. It could be 'mental' that contain medical history related to psychological ailments such as depression, bipolar or other mental disorders. Another category could be 'general' which could include the blood pressure, oxygen level or sugar level or other health data collected through sensors. the ‘general’ class could also include a warning, for example, the patient has allergies or taking a specific medication or smoking.

So the system starts to work when an authenticated user sends the healthcare data access request to the Access enforcement point (AEP), it extracts the user and healthcare attribute and forwards the request to the Access Decision Point (ADP). ADP will evaluate all the attributes with Access rules and policies and then return the decision. The request could be denied or granted.

4.3.2 Policy repository (PR)

It is used to store and retrieve the policies and access rules.

4.3.3 Attribute-Based Access Control

The attribute-based access control system grant access on the basis of the attributes of the user, environment and data. The two parts of the ABAC system are policy model and Attribute-based Access control architecture that can be used to implement policies.

The main components of the Access control architecture are authentication, AEP, ADP, Policy Repository (PR) and Healthcare data Server.

4.3.4 Authentication

The user authentication can be the initial process of the access control system. The authentication will start at the work station when a user request for the healthcare data. if a user is requesting to access healthcare data, he should have a certificate. The authentication server verifies the identity and certificate of the user and may forward his request for authorisation. Fast Identity Online (FIDO) can be also used to provide authentication for a health monitoring system (FIDO Alliance 2019).

4.3.5 Access Enforcement Point

AEP is an important part of the authorisation process. The authenticated users can send a request to AEP and it will further send the request to the ADP for authorisation. When AEP get data access request from a user, it will gather the data and user attribute and forward to ADP for evaluation. The output request must be enforced by AEP. The output could be a grant or deny access to the requested data.

4.3.6 Access Decision Point

ADP is the main component of the Access control system. ADP is responsible for attribute and policy assessment and makes access control decisions. The ADP receive the user and healthcare data attributes from the AEP, and it will extract the environment attribute and then evaluate the policy for a specific policy rule and return the decision to AEP.

4.4 Discussion

In this chapter, hardware, software and security requirements for the CMS were presented by detailing the requirements in each of the three main layers. While there are many implementations of SH for aged care are available, mostly in the form of experimental designs, almost all implementations have considered CMS implementations that work only for the underlined SH design. From the finding of this study, the following can be clearly identified:

- CMS requires processing power that is capable of implement high-level algorithms
- CMS should be able to acquire and process data from multiple sensors
- CMS requires to run a database
- CMS requires storage in order to process data as well as to publish in the cloud and other servers
- CMS requires Internet access
- CMS should be able to implement security mechanisms
- CMS software should be configurable and update mechanisms should be present
- CMS should be able to run continuously for longer periods (years) and should be robust
- CMS should be compact in size and should be tamper resistant
- CMS should provide debugging/diagnostic mechanisms
- CMS in developer mode also should be able to implement software development environments.

Given the above requirements, it is possible to conclude that a simple microcontroller platform such as Arduino or Raspberry Pi will not satisfy all requirements of a CMS. However, platforms such as Arduino and Raspberry Pi have been popular in this domain given that those provide easy communication with many sensors. A PC based platform (Windows or Linux) alone without any modifications will not satisfy requirements of sensor connectivity though provide processing power requirements.

Table 6. System Recommendation

Hardware platform	Intel-based NUC with a Celeron processor or higher
Operating System	A secure operating system using Windows or Linux
Storage requirements	128 Gigabytes or higher storage and 4 Gigabytes or higher of RAM
Acquisition device	Dedicated acquisition devices which enable both digital and analog IO which can be connected via USB (an example would be NI myDAQ). It is necessary for the device to have high precision ADC (e.g. 24-bit) if EEG signals are to be captured.
Software	SQL server, web server, access to high-level languages such as Python, being able to host run machine learning applications.

5 Conclusion

5.1 Discussion

Smart homes aged care is emerging as a solution for addressing issues with the increase in the higher portion of the elderly in society. Smart homes enable the elderly to stay longer in their own homes longer with the aid of technology. This thesis examined one key element of the smart homes for aged care which enables its functionality – the central monitoring system or the CMS. While there have been numerous research work performed on smart homes for aged care, several high profile examples on SH and devices, virtually no significant work has been performed exclusively for the CMS. That leaves these questions on interoperability of devices, scaling operations of SH and future developments in SH. As such the main objective of this thesis was to identify the requirements and capabilities of the CMS.

A comprehensive literature review was carried out in order to address the research questions. The main functions of the CMS were identified by collating functions presented in various implementations of SH for aged care. Similarly how different functions are implemented in SH were studied in order to identify the requirements of the CMS. Sensor interoperability was addressed by identifying the communication requirements.

The main objective of this research was achieved by proposing a three-layer model for the CMS. The sensing layer performs the functions of acquiring data from various sensors. The data processing and management layer extract the contextual information from the sensor data. The security and access control layer deals with the implementation of the security mechanism and the access control methods for the SH.

5.2 Future Work

In this thesis, we have identified requirements for designing a CMS for a smart home for aged care. While the details presented in the thesis may help the development of a unified CMS architecture and inter-operable devices, there are many questions still remain open.

This study was conducted without physical building a CMS and mainly based on reported material on laboratory settings on short time frames. It is necessary to continue this study considering long term human trials and real-world data collection as opposed to laboratory environments. It is also necessary to consider users' acceptance of devices and data collection methods.

Most published systems directly or indirectly assumed a single person's presence in a smart home. It is necessary to consider the impact of multi-user or at least 2-person SH for aged care on a CMS.

Generally, it is assumed that almost all wearable devices are based on Bluetooth. It is necessary to consider limits of Bluetooth, bandwidth and device requirements along with measurement requirements in the design process.

While it is important to identify the requirements of the CMS for interoperability, it is also important to standardise the communication interfaces and methods for sensors and other devices used in SH for aged care.

References

"AAL Programme - Active Assisted Living Programme - Ageing Well." 2018. http://www.aal-europe.eu/ (January 31, 2019).

Abidine, M'hamed, Belkacem Fergani, M'hamed Bilal Abidine, and Belkacem Fergani. 2015. "News Schemes for Activity Recognition Systems Using PCA-WSVM, ICA-WSVM, and LDA-WSVM." *Information* 6(3): 505–21. http://www.mdpi.com/2078-2489/6/3/505 (February 4, 2019).

Adlam, T. et al. 2004. "The Installation and Support of Internationally Distributed Equipment for People With Dementia." *IEEE Transactions on Information Technology in Biomedicine* 8(3): 253–57. http://ieeexplore.ieee.org/document/1331402/ (October 24, 2018).

Ahrq. *Telehealth: Mapping the Evidence for Patient Outcomes From Systematic Reviews E*. www.effectivehealthcare.ahrq.gov/reports/final.cfm. (February 9, 2019).

Al-Shaqi, Riyad, Monjur Mourshed, and Yacine Rezgui. 2016. "Progress in Ambient Assisted Systems for Independent Living by the Elderly." *SpringerPlus* 5(1): 624. http://www.ncbi.nlm.nih.gov/pubmed/27330890 (August 21, 2018).

Alam, Mohammad Wajih, Tanin Sultana, and Mohammad Sami Alam. 2016. "A Heartbeat and Temperature Measuring System for Remote Health Monitoring Using Wireless Body Area Network." *International Journal of Bio-Science and Bio-Technology* 8(1): 171–90. http://www.sersc.org/journals/IJBSBT/vol8_no1/16.pdf (February 25, 2019).

Alam, Muhammad Raisul, Mamun Bin Ibne Reaz, and Mohd Alauddin Mohd Ali. 2012. "A Review of Smart Homes—Past, Present, and Future." *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 42(6): 1190–1203. http://ieeexplore.ieee.org/document/6177682/ (January 23, 2019).

Aldeer, Murtadha, Richard P. Martin, and Richard E. Howard. 2018. "PillSense: Designing a Medication Adherence Monitoring System Using Pill Bottle-Mounted Wireless Sensors." In *2018 IEEE International Conference on Communications Workshops (ICC Workshops)*, IEEE, 1–6. https://ieeexplore.ieee.org/document/8403547/ (February 10, 2019).

Alsinglawi, Belal et al. 2017. "RFID Systems in Healthcare Settings and Activity of Daily Living in Smart Homes: A Review.” *E-Health Telecommunication Systems and Networks* 06(01): 1–17. http://www.scirp.org/journal/doi.aspx?DOI=10.4236/etsn.2017.61001 (February 25, 2019).

Alwan, M. et al. “A Smart and Passive Floor-Vibration Based Fall Detector for Elderly.” In *2006 2nd International Conference on Information & Communication Technologies*, IEEE, 1003–7. http://ieeexplore.ieee.org/document/1684511/ (December 8, 2018).

Alwan, Majd et al. 2005. “Validation of Rule-Based Inference of Selected Independent Activities of Daily Living.” *Telemedicine and e-Health* 11(5): 594–99. http://www.ncbi.nlm.nih.gov/pubmed/16250824 (February 27, 2019).

Anwar, Syed Muhammad, Muhammad Majid, Muhammad Ehatisham-Ul-Haq, and Bilal Khan. *Mapping Brain Activity Using Wearable EEG Sensors for Mobile Applications*. https://pdfs.semanticscholar.org/b5c3/dfa7ff65a6fd537428b5fd8ef6c7afca9f42.pdf (February 25, 2019).

Arcelus, A., M. Holtzman, et al. 2009. “Analysis of Commode Grab Bar Usage for the Monitoring of Older Adults in the Smart Home Environment.” In *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 6155–58. http://www.ncbi.nlm.nih.gov/pubmed/19965075 (January 26, 2019).

Arcelus, A., C.L. Herry, et al. 2009. “Determination of Sit-to-Stand Transfer Duration Using Bed and Floor Pressure Sequences.” *IEEE Transactions on Biomedical Engineering* 56(10): 2485–92. http://www.ncbi.nlm.nih.gov/pubmed/19622434 (December 7, 2018).

Arcelus, Amaya et al. 2010. “Context-Aware Smart Home Monitoring through Pressure Measurement Sequences.” In *2010 IEEE International Workshop on Medical Measurements and Applications*, IEEE, 32–37. http://ieeexplore.ieee.org/document/5480223/ (December 7, 2018).

Arif, Muhammad, and Ahmed Kattan. 2015. “Physical Activities Monitoring Using Wearable Acceleration Sensors Attached to the Body” ed. Alejandro Lucia. *PLOS ONE* 10(7): e0130851. https://dx.plos.org/10.1371/journal.pone.0130851 (January 26, 2019).

Atallah, Louis, and Guang-Zhong Yang. 2009. “The Use of Pervasive Sensing for Behaviour Profiling — a Survey.” *Pervasive and Mobile Computing* 5(5): 447–64.

https://linkinghub.elsevier.com/retrieve/pii/S1574119209000583 (January 30, 2019).

Barger, T.S., D.E. Brown, and M. Alwan. 2005. "Health-Status Monitoring Through Analysis of Behavioral Patterns." *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans* 35(1): 22–27. http://ieeexplore.ieee.org/document/1369342/ (January 26, 2019).

Barnes, N.M., D.A.D. Rose, P. Garner, and N.H. Edwards. 1998. "Lifestyle Monitoring - Technology for Supported Independence." *Computing & Control Engineering Journal* 9(4): 169–74. http://digital-library.theiet.org/content/journals/10.1049/cce_19980404 (October 31, 2018).

Barnett, Kate et al. 2017. *A Technology Roadmap For The Australian Aged Care Sector*. http://aciitc.com.au/wp-content/uploads/2017/06/ACIITC_TechnologyRoadmap_2017.pdf (February 13, 2019).

Bashshur, Rashid L., Elizabeth A. Krupinski, James H. Thrall, and Noura Bashshur. 2016. "The Empirical Foundations of Teleradiology and Related Applications: A Review of the Evidence." *Telemedicine and e-Health* 22(11): 868–98. http://www.ncbi.nlm.nih.gov/pubmed/27585301 (February 9, 2019).

Belshaw, M., B. Taati, J. Snoek, and A. Mihailidis. 2011. "Towards a Single Sensor Passive Solution for Automated Fall Detection." In *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 1773–76. http://www.ncbi.nlm.nih.gov/pubmed/22254671 (February 4, 2019).

Bergman, Marilyn M. 2003. "The Essential Steps Cognitive Orthotic." *NeuroRehabilitation* 18(1): 31–46. http://www.ncbi.nlm.nih.gov/pubmed/12719619 (February 8, 2019).

Bianchi, F. et al. 2009. "Falls Event Detection Using Triaxial Accelerometry and Barometric Pressure Measurement." In *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 6111–14. http://www.ncbi.nlm.nih.gov/pubmed/19965262 (January 26, 2019).

Brdiczka, O., J.L. Crowley, and P. Reignier. 2009. "Learning Situation Models in a Smart Home." *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* 39(1): 56–63. http://ieeexplore.ieee.org/document/4625983/ (September 18, 2018).

Briere, Danny., and Pat. Hurley. 2011. *Smart Homes For Dummies*. John Wiley & Sons. https://books.google.com.au/books?hl=en&lr=&id=zWASd07YkVsC&oi=fnd&pg=PT18&dq=+Smart+Homes+for+Dummies&ots=ccQQHzNN5l&sig=ammV1ikN3UWzTI8Hi0_RaavnTzs&redir_esc=y#v=onepage&q=Smart Homes for Dummies&f=false (January 25, 2019).

Bron, Esther et al. 2014. "Feature Selection Based on SVM Significance Maps for Classification of Dementia." In , 272–79. http://link.springer.com/10.1007/978-3-319-10581-9_34 (February 22, 2019).

Brown S., Majeed B., Clarke N., and Lee B.-S., ". 2006. "'Developing a Well-Being Monitoring System—Modeling and Data Analysis Techniques,.'" *Promoting Independence for Older Persons With Disabilities, Mann W. C. and Helal A., Eds. Washington, DC, USA: IOS*.

Bulling, Andreas, Jamie A Ward, Hans Gellersen, and Gerhard Tröster. 2011. "Eye Movement Analysis for Activity Recognition Using Electrooculography." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 33(4): 741–53. http://www.ncbi.nlm.nih.gov/pubmed/20421675 (February 14, 2019).

Cardinaux, Fabien, Simon Brownsell, Mark Hawley, and David Bradley. *Modelling of Behavioural Patterns for Abnormality Detection in the Context of Lifestyle Reassurance*. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.583.9048&rep=rep1&type=pdf (January 29, 2019).

Celler, B.G., W. Earnshaw, et al. 1995. "Remote Monitoring of Health Status of the Elderly at Home. A Multidisciplinary Project on Aging at the University of New South Wales." *International Journal of Bio-Medical Computing* 40(2): 147–55. https://www.sciencedirect.com/science/article/pii/0020710195011396?via%3Dihub (January 26, 2019).

Celler, B G, W Earnshawa, et al. 1995. 40 International Journal of Bio-Medical Computing *Bin-Medical COmpltils*. https://ac.els-cdn.com/0020710195011396/1-s2.0-0020710195011396-main.pdf?_tid=def20013-c9b1-453f-ae83-487dd403c7ca&acdnat=1534816628_9844275c63fdb7b01c3dbe34d555ca36 (August 21, 2018).

Cook, Diane J, Aaron S Crandall, Brian L Thomas, and Narayanan C Krishnan. 2013. “CASAS: A Smart Home in a Box.” *Computer* 46(7). http://www.ncbi.nlm.nih.gov/pubmed/24415794 (September 11, 2018).

Das, Barnan, Narayanan C. Krishnan, and Diane J. Cook. 2014. “Handling Imbalanced and Overlapping Classes in Smart Environments Prompting Dataset.” In Springer, Berlin, Heidelberg, 199–219. http://link.springer.com/10.1007/978-3-642-45252-9_12 (February 14, 2019).

Das, S.K. et al. 2002. “The Role of Prediction Algorithms in the MavHome Smart Home Architecture.” *IEEE Wireless Communications* 9(6): 77–84. http://ieeexplore.ieee.org/document/1160085/ (September 17, 2018).

Douglas C. Englelbart. 1963. “A Conceptual Framework for the Augmentation of Man’s Intellect - 1963 (AUGMENT,133183,) - Doug Engelbart Institute.” In *Vistas in Information Handling*, http://dougengelbart.org/content/view/382/000/ (February 7, 2019).

Duong, Thi V, Hung H Bui, Dinh Q Phung, and Svetha Venkatesh. 2005. *Activity Recognition and Abnormality Detection with the Switching Hidden Semi-Markov Model*. https://espace.curtin.edu.au/bitstream/handle/20.500.11937/10349/116823_Activity%2520recognition%2520PID%2520116823.pdf?sequence=2&isAllowed=y (February 25, 2019).

Durrant-Whyte, Hugh, and Thomas C. Henderson. 2008. “Multisensor Data Fusion.” In *Springer Handbook of Robotics*, Berlin, Heidelberg: Springer Berlin Heidelberg, 585–610. http://link.springer.com/10.1007/978-3-540-30301-5_26 (February 20, 2019).

Dwivedi, Mukul, Robin Singh, and Shikhar Shukla. *Detection of Brain Abnormalities Using Internet of Things*. http://www.ijpam.eu (February 25, 2019).

Elzabadani, Hicham et al. 2005. “Self-Sensing Spaces: Smart Plugs for Smart Environments.” *3RD INTL. CONF. ON SMART HOMES AND HEALTH TELEMETRICS*. http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.89.4675 (December 4, 2018).

Farella, Elisabetta, Mirko Falavigna, and Bruno Ricc. 2010. “Aware and Smart Environments: The Casattenta Project.” In *Microelectronics Journal*,.

Ferrer-Arnau, Lluís et al. 2012. 5 International Journal of Computer Information Systems and Industrial Management Applications *Efficient Cubic Spline Interpolation Implemented with FIR Filters*. www.mirlabs.net/ijcisim/index.html (February 20, 2019).

FIDO Alliance. 2019. "FIDO Alliance - Open Authentication Standards More Secure than Passwords." https://fidoalliance.org/ (February 26, 2019).

Figo, Davide, Pedro C. Diniz, Diogo R. Ferreira, and João M.P. Cardoso. 2010. "Preprocessing Techniques for Context Recognition from Accelerometer Data." *Personal and Ubiquitous Computing* 14(7): 645–62. http://link.springer.com/10.1007/s00779-010-0293-9 (February 27, 2019).

Fishkin, Ken et al. 2003. *A Flexible, Low-Overhead Ubiquitous System for Medication Monitoring*. http://ecm.cachefly.net/pdf/IntelSystemForMedicationMonitoring.pdf (February 10, 2019).

Fleury, A. et al. 2008. "Sound and Speech Detection and Classification in a Health Smart Home." In *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 4644–47. http://www.ncbi.nlm.nih.gov/pubmed/19163751 (February 4, 2019).

Forouzanfar, Mohamad et al. 2017. "Event Recognition for Contactless Activity Monitoring Using Phase-Modulated Continuous Wave Radar." *IEEE Transactions on Biomedical Engineering* 64(2): 479–91. http://www.ncbi.nlm.nih.gov/pubmed/27187940 (January 26, 2019).

Gao, Lei, A.K. Bourke, and John Nelson. 2014. "Evaluation of Accelerometer Based Multi-Sensor versus Single-Sensor Activity Recognition Systems." *Medical Engineering & Physics* 36(6): 779–85. https://www.sciencedirect.com/science/article/pii/S1350453314000344?via%3Dihub (December 12, 2018).

Ge Wu, and Shuwan Xue. 2008. "Portable Preimpact Fall Detector With Inertial Sensors." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 16(2): 178–83. http://ieeexplore.ieee.org/document/4435088/ (October 18, 2018).

Ghasemzadeh, H., R. Jafari, and B. Prabhakaran. 2010. "A Body Sensor Network With

Electromyogram and Inertial Sensors: Multimodal Interpretation of Muscular Activities." *IEEE Transactions on Information Technology in Biomedicine* 14(2): 198–206. http://ieeexplore.ieee.org/document/5308441/ (October 18, 2018).

Giri, Donna et al. 2013. "Automated Diagnosis of Coronary Artery Disease Affected Patients Using LDA, PCA, ICA and Discrete Wavelet Transform." *Knowledge-Based Systems* 37: 274–82. https://www.sciencedirect.com/science/article/pii/S0950705112002249?via%3Dihub (February 22, 2019).

Gjoreski, Hristijan et al. 2014. "Telehealth Using ECG Sensor and Accelerometer." In *2014 37th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, IEEE, 270–74. http://ieeexplore.ieee.org/document/6859575/ (October 18, 2018).

Greene, Shalom, Himanshu Thapliyal, and David Carpenter. 2016. "IoT-Based Fall Detection for Smart Home Environments." In *2016 IEEE International Symposium on Nanoelectronic and Information Systems (INIS)*, IEEE, 23–28. http://ieeexplore.ieee.org/document/7829515/ (November 17, 2018).

Gupta, Piyush, and Tim Dallas. 2014. "Feature Selection and Activity Recognition System Using a Single Triaxial Accelerometer." *IEEE Transactions on Biomedical Engineering* 61(6): 1780–86. http://ieeexplore.ieee.org/document/6780615/ (February 22, 2019).

Hayes, T.L., M. Pavel, and J.A. Kaye. 2004. "An Unobtrusive In-Home Monitoring System for Detection of Key Motor Changes Preceding Cognitive Decline." In *The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 2480–83. http://www.ncbi.nlm.nih.gov/pubmed/17270775 (January 26, 2019).

Hayes, Tamara. L., John M. Hunt, Andre Adami, and Jeffrey A. Kaye. 2006. "An Electronic Pillbox for Continuous Monitoring of Medication Adherence." In *2006 International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 6400–6403. http://ieeexplore.ieee.org/document/4463275/ (February 10, 2019).

He, Zhenyu, and Lianwen Jin. 2009. "Activity Recognition from Acceleration Data Based on Discrete Consine Transform and SVM." In *2009 IEEE International Conference on*

Systems, Man and Cybernetics, IEEE, 5041–44. http://ieeexplore.ieee.org/document/5346042/ (February 14, 2019).

Helal, Sumi et al. 2005. “The Gator Tech Smart House: A Programmable Pervasive Space.” *Computer*.

Helmi, Mohammad, and S. M. T. AlModarresi. 2009. “Human Activity Recognition Using a Fuzzy Inference System.” In *2009 IEEE International Conference on Fuzzy Systems*, IEEE, 1897–1902. http://ieeexplore.ieee.org/document/5277329/ (November 15, 2018).

Hemalatha, C.Sweetlin, and V. Vaidehi. 2013. “Frequent Bit Pattern Mining Over Tri-Axial Accelerometer Data Streams for Recognizing Human Activities and Detecting Fall.” *Procedia Computer Science* 19: 56–63. https://www.sciencedirect.com/science/article/pii/S1877050913006212?via%3Dihub (December 12, 2018).

Hervas, Ramon, Jose Bravo, and Jesus Fontecha. 2014. “An Assistive Navigation System Based on Augmented Reality and Context Awareness for People With Mild Cognitive Impairments.” *IEEE Journal of Biomedical and Health Informatics* 18(1): 368–74. http://ieeexplore.ieee.org/document/6525386/ (February 8, 2019).

Hess, David C., and Heinrich J. Audebert. 2013. “The History and Future of Telestroke.” *Nature Reviews Neurology* 9(6): 340–50. http://www.nature.com/articles/nrneurol.2013.86 (February 10, 2019).

Javier Ordóñez, Fco, Paula De Toledo, and Araceli Sanchis. “Sensor-Based Bayesian Detection of Anomalous Living Patterns in a Home Setting.” https://search-proquest-com.ezproxy.uws.edu.au/docview/1647799324?accountid=36155&rfr_id=info%3Axri%2Fsid%3Aprimo (October 18, 2018).

Jiang, Ming et al. 2011. “A Method to Deal with Installation Errors of Wearable Accelerometers for Human Activity Recognition.” *Physiological Measurement* 32(3): 347–58. http://www.ncbi.nlm.nih.gov/pubmed/21330698 (December 12, 2018).

Kautz, Henry et al. 2002. *An Overview of the Assisted Cognition Project*. www.aaai.org (September 12, 2018).

Kepplinger, Jessica et al. 2016. “Safety and Efficacy of Thrombolysis in Telestroke.” *Neurology* 87(13): 1344–51. http://www.ncbi.nlm.nih.gov/pubmed/27566746 (February 10, 2019).

Keskin, Musa Furkan, Ahmet Dundar Sezer, and Sinan Gezici. 2018. “Localization via Visible Light Systems.” *Proceedings of the IEEE* 106(6): 1063–88. https://ieeexplore.ieee.org/document/8358018/ (February 25, 2019).

Khan, Adil, Muhammad Siddiqi, and Seok-Won Lee. 2013. “Exploratory Data Analysis of Acceleration Signals to Select Light-Weight and Accurate Features for Real-Time Activity Recognition on Smartphones.” *Sensors* 13(10): 13099–122. http://www.ncbi.nlm.nih.gov/pubmed/24084108 (February 14, 2019).

Khushaba, Rami N., Sarath Kodagoda, Maen Takruri, and Gamini Dissanayake. 2012. “Toward Improved Control of Prosthetic Fingers Using Surface Electromyogram (EMG) Signals.” *Expert Systems with Applications* 39(12): 10731–38. https://www.sciencedirect.com/science/article/pii/S0957417412004654?via%3Dihub (February 14, 2019).

Kim, Eunju, Sumi Helal, and Diane Cook. 2010. “Human Activity Recognition and Pattern Discovery.” *IEEE pervasive computing* 9(1): 48. http://www.ncbi.nlm.nih.gov/pubmed/21258659 (November 15, 2018).

Kim, Youngwook, and Brian Toomajian. 2016. “Hand Gesture Recognition Using Micro-Doppler Signatures With Convolutional Neural Network.” *IEEE Access* 4: 7125–30. http://ieeexplore.ieee.org/document/7590035/ (January 26, 2019).

Kimberly Miller, Arooke Adair et al. 2013. “Smart-Home Technologies to Assist Older People to Live Well at Home.” *Journal of Aging Science* 01(01): 1–9. http://www.esciencecentral.org/journals/smart-home-technologies-to-assist-older-people-to-live-well-at-home-2329-8847.1000101.php?aid=12044 (March 11, 2018).

Koziol, Scott, Paul A. Friedman, Blake Schultze, and Keith Schubert. 2017. “The Reminding Walker Cognitive Orthotic Device.” In *2017 International Symposium on Wearable Robotics and Rehabilitation (WeRob)*, IEEE, 1–2. https://ieeexplore.ieee.org/document/8383846/ (February 8, 2019).

Kwapisz, Jennifer R., Gary M. Weiss, and Samuel A. Moore. 2011. “Activity Recognition Using

Cell Phone Accelerometers.” *ACM SIGKDD Explorations Newsletter* 12(2): 74. http://portal.acm.org/citation.cfm?doid=1964897.1964918 (January 26, 2019).

Landau, Ruth. 2013. “Ambient Intelligence for the Elderly: Hope to Age Respectfully?” *Aging Health* 9(6): 593–600.

Lê, Quynh, Hoang Boi Nguyen, and Tony Barnett. 2012. “Smart Homes for Older People: Positive Aging in a Digital World.” *Future Internet* 4(2): 607–17. http://www.mdpi.com/1999-5903/4/2/607 (April 25, 2018).

Le, Xuan Hoa Binh, Maria Di Mascolo, Alexia Gouin, and Norbert Noury. 2008. “Health Smart Home for Elders - a Tool for Automatic Recognition of Activities of Daily Living.” In *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 3316–19. http://ieeexplore.ieee.org/document/4649914/ (November 15, 2018).

Lee, Byounggwan, Ohkyun Kwon, Inseong Lee, and Jinwoo Kim. 2017. “Companionship with Smart Home Devices: The Impact of Social Connectedness and Interaction Types on Perceived Social Support and Companionship in Smart Homes.” *Computers in Human Behavior* 75: 922–34. https://www.sciencedirect.com/science/article/pii/S0747563217304016#bib63 (February 11, 2019).

Lee S.-W., Kim Y.-J., Lee G.-S., Cho B.-Q., Lee N.-H. 2007. “A Remote Behavioral Monitoring System for Elders Living Alone.” In *Proceedings of the International Conference on Control, Automation and Systems; Seoul, South Korea.*, , 2725–30.

Lee, Young-Sook, and Wan-Young Chung. 2012. “Visual Sensor Based Abnormal Event Detection with Moving Shadow Removal in Home Healthcare Applications.” *Sensors* 12(1): 573–84. http://www.ncbi.nlm.nih.gov/pubmed/22368486 (February 4, 2019).

Lien, Jaime et al. 2016. “Soli.” *ACM Transactions on Graphics* 35(4): 1–19. http://dl.acm.org/citation.cfm?doid=2897824.2925953 (February 4, 2019).

Liming Chen et al. 2012. “Sensor-Based Activity Recognition.” *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 42(6): 790–808. http://ieeexplore.ieee.org/document/6208895/ (November 15, 2018).

Lin, C.-C. et al. 2006. “Wireless Health Care Service System for Elderly With Dementia.” *IEEE Transactions on Information Technology in Biomedicine* 10(4): 696–704. http://ieeexplore.ieee.org/document/1707682/ (February 25, 2019).

Lombardi, Martino, Roberto Vezzani, and Rita Cucchiara. *Detection of Human Movements with Pressure Floor Sensors*. http://imagelab.ing.unimore.it (December 9, 2018).

M. Shehata, A. Eberlein, A. O. Fapojuwo. 2007. “Managing Policy Interactions in KNX-Based Smart Homes",.” In *Proc. 31st Annu. Int. Comput. Software Appl. Conf*, , 367–78.

Maan, Chetna. 2017. “ACCEPTANCE OF AMBIENT ASSISTED LIVING (AAL) TECHNOLOGIES AMONG OLDER AUSTRALIANS: A REVIEW OF BARRIERS IN USER EXPERIENCE © CHETNA MAAN A THESIS SUBMITTED IN FULFILMENT FOR THE DEGREE OF MASTER OF RESEARCH.” https://search.proquest.com/docview/2112266931/?pq-origsite=primo (February 13, 2019).

Macías-Hernández, Salvador Israel et al. 2016. “Proposal and Evaluation of a Telerehabilitation Platform Designed for Patients With Partial Rotator Cuff Tears: A Preliminary Study.” *Annals of rehabilitation medicine* 40(4): 710–17. http://www.ncbi.nlm.nih.gov/pubmed/27606278 (February 9, 2019).

Majumder, Sumit et al. 2017. “Smart Homes for Elderly Healthcare-Recent Advances and Research Challenges.” *Sensors (Basel, Switzerland)* 17(11). http://www.ncbi.nlm.nih.gov/pubmed/29088123 (February 13, 2019).

Mannini, Andrea et al. 2013. “Activity Recognition Using a Single Accelerometer Placed at the Wrist or Ankle.” *Medicine and Science in Sports and Exercise* 45(11): 2193–2203. http://www.ncbi.nlm.nih.gov/pubmed/23604069 (January 26, 2019).

Mansor, Hasmah et al. 2013. “Body Temperature Measurement for Remote Health Monitoring System.” In *2013 IEEE International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA)*, IEEE, 1–5. http://ieeexplore.ieee.org/document/6717956/ (February 25, 2019).

Matthews, Robert et al. 2007. “A Wearable Physiological Sensor Suite for Unobtrusive Monitoring of Physiological and Cognitive State.” In *2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 5276–81.

http://ieeexplore.ieee.org/document/4353532/ (December 12, 2018).

Maurer, U., A. Smailagic, D.P. Siewiorek, and M. Deisher. “Activity Recognition and Monitoring Using Multiple Sensors on Different Body Positions.” In *International Workshop on Wearable and Implantable Body Sensor Networks (BSN’06)*, IEEE, 113–16. http://ieeexplore.ieee.org/document/1612909/ (February 22, 2019).

Mihailidis, A., B. Carmichael, and J. Boger. 2004. “The Use of Computer Vision in an Intelligent Environment to Support Aging-in-Place, Safety, and Independence in the Home.” *IEEE Transactions on Information Technology in Biomedicine* 8(3): 238–47. http://ieeexplore.ieee.org/document/1331400/ (October 22, 2018).

Morris, M et al. 2012. “Smart Technologies for Older People.”

Morris, Meg et al. 2012. “Smart Technologies for Older People a Systematic Literature Review of Smart Technologies That Promote Health and Wellbeing of Older People Living at Home.” https://networkedsociety.unimelb.edu.au/__data/assets/pdf_file/0008/1661327/Smart-technologies-for-older-people.pdf (April 24, 2018).

Mozer, Michael C. 1998. *The Neural Network House: An Environment That Adapts to Its Inhabitants*. www.aaai.org (September 18, 2018).

Mshali, Haider, Tayeb Lemlouma, Maria Moloney, and Damien Magoni. 2018. “A Survey on Health Monitoring Systems for Health Smart Homes.” *International Journal of Industrial Ergonomics* 66: 26–56. https://www.sciencedirect.com/science/article/pii/S0169814117300082 (January 25, 2019).

Muhammad, Syed Agha, Bernd Niklas Klein, Kristof Van Laerhoven, and Klaus David. 2012. “A Feature Set Evaluation for Activity Recognition with Body-Worn Inertial Sensors.” In , 101–9. http://link.springer.com/10.1007/978-3-642-31479-7_17 (February 22, 2019).

Muñoz, David. 2009. *Position Location Techniques and Applications*. Academic Press.

Nef, Tobias et al. 2015. “Evaluation of Three State-of-the-Art Classifiers for Recognition of Activities of Daily Living from Smart Home Ambient Data.” *Sensors (Basel, Switzerland)*

15(5): 11725–40. http://www.ncbi.nlm.nih.gov/pubmed/26007727 (December 4, 2018).

Ni, Qin, Ana García Hernando, and Iván de la Cruz. 2015. "The Elderly's Independent Living in Smart Homes: A Characterization of Activities and Sensing Infrastructure Survey to Facilitate Services Development." *Sensors* 15(5): 11312–62. http://www.mdpi.com/1424-8220/15/5/11312 (October 11, 2018).

Noury, N., and T. Hadidi. 2012. "Computer Simulation of the Activity of the Elderly Person Living Independently in a Health Smart Home." *Computer Methods and Programs in Biomedicine* 108(3): 1216–28. https://www.sciencedirect.com/science/article/pii/S0169260712001782?via%3Dihub (January 26, 2019).

Ordóñez, Fco Javier, Paula de Toledo, and Araceli Sanchis. 2013. "Activity Recognition Using Hybrid Generative/Discriminative Models on Home Environments Using Binary Sensors." *Sensors (Basel, Switzerland)* 13(5): 5460–77. http://www.ncbi.nlm.nih.gov/pubmed/23615583 (December 4, 2018).

Osterberg, Lars, and Terrence Blaschke. 2005. "Adherence to Medication." *New England Journal of Medicine* 353(5): 487–97. http://www.nejm.org/doi/abs/10.1056/NEJMra050100 (February 10, 2019).

Papamatthaiakis, George, George C. Polyzos, and George Xylomenos. 2010. "Monitoring and Modeling Simple Everyday Activities of the Elderly at Home." In *2010 7th IEEE Consumer Communications and Networking Conference*, IEEE, 1–5. http://ieeexplore.ieee.org/document/5421717/ (August 22, 2018).

Parlak, Siddika, and Ivan Marsic. 2013. "Detecting Object Motion Using Passive RFID: A Trauma Resuscitation Case Study." *IEEE Transactions on Instrumentation and Measurement* 62(9): 2430–37. http://ieeexplore.ieee.org/document/6545303/ (February 20, 2019).

Phua, Clifton et al. 2009. "2-Layer Erroneous-Plan Recognition for Dementia Patients in Smart Homes." In *2009 11th International Conference on E-Health Networking, Applications and Services (Healthcom)*, IEEE, 21–28. http://ieeexplore.ieee.org/document/5406183/ (October 17, 2018).

Pirttikangas, Susanna, Kaori Fujinami, and Tatsuo Nakajima. 2006. “Feature Selection and Activity Recognition from Wearable Sensors.” In Springer, Berlin, Heidelberg, 516–27. http://link.springer.com/10.1007/11890348_39 (October 8, 2018).

Pollack, Martha E. *Planning Technology for Intelligent Cognitive Orthotics*. www.aaai.org (February 6, 2019).

Popescu, Mihail, Yun Li, Marjorie Skubic, and Marilyn Rantz. 2008. “An Acoustic Fall Detector System That Uses Sound Height Information to Reduce the False Alarm Rate.” In *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 4628–31. http://www.ncbi.nlm.nih.gov/pubmed/19163747 (January 26, 2019).

Pramuka, Michael, and Linda van Roosmalen. 2009. “Telerehabilitation Technologies: Accessibility and Usability.” *International journal of telerehabilitation* 1(1): 85–98. http://www.ncbi.nlm.nih.gov/pubmed/25945165 (February 10, 2019).

Qian Wan, Qian, Yiran Yiran Li, Changzhi Changzhi Li, and Ranadip Pal. 2014. “Gesture Recognition for Smart Home Applications Using Portable Radar Sensors.” In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 6414–17. http://www.ncbi.nlm.nih.gov/pubmed/25571464 (February 4, 2019).

Rettie, Ruth. *Connectedness, Awareness and Social Presence*. https://eprints.kingston.ac.uk/2106/1/Rettie.pdf (February 11, 2019).

Rialle, Vincent, Jean-Baptiste Lamy, Norbert Noury, and Lionel Bajolle. “Telemonitoring of Patients at Home: A Software Agent Approach.” www.biomed.ntua.gr/vital_home/ (January 29, 2019).

Ricquebourg, Vincent et al. 2006. “The Smart Home Concept: Our Immediate Future.” In *2006 1st IEEE International Conference on E-Learning in Industrial Electronics, ICELIE*,.

Rimminen, Henry, Juha Lindstrom, Matti Linnavuo, and Raimo Sepponen. 2010. “Detection of Falls among the Elderly by a Floor Sensor Using the Electric near Field.” *IEEE Transactions on Information Technology in Biomedicine* 14(6): 1475–76. http://ieeexplore.ieee.org/document/5477180/ (October 18, 2018).

Russo, James T. et al. 2004. "SmartWave – Intelligent Meal Preparation System to Help Older People Live Independently." https://www.semanticscholar.org/paper/SmartWave-—-Intelligent-Meal-Preparation-System-to-Russo-Sukojo/31e951f81685fbce2475b5d44757886d85678861 (February 27, 2019).

Salama, Usama et al. 2018. "An Internet of Things Based Multi-Level Privacy-Preserving Access Control for Smart Living." *Informatics* 5(2): 23. http://www.mdpi.com/2227-9709/5/2/23 (February 26, 2019).

Satpathy, Lalatendu. 2006. *SMART HOUSING: TECHNOLOGY TO AID AGING IN PLACE-NEW OPPORTUNITIES AND CHALLENGES*. https://search-proquest-com.ezproxy.uws.edu.au/docview/305315332?pq-origsite=primo (January 23, 2019).

Schilit, B., N. Adams, and R. Want. 1994. "Context-Aware Computing Applications." In *1994 First Workshop on Mobile Computing Systems and Applications*, IEEE, 85–90. http://ieeexplore.ieee.org/document/4624429/ (January 29, 2019).

Serra, Renan, Pascal Di Croce, Richard Peres, and Dominique Knittel. 2014. "Human Step Detection from a Piezoelectric Polymer Floor Sensor Using Normalization Algorithms." In *IEEE SENSORS 2014 Proceedings*, IEEE, 1169–72. http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6985216 (December 9, 2018).

Swaminathan, Rahul, Michael Nischt, and Christine Kuhnel. 2008. "Localization Based Object Recognition for Smart Home Environments." In *2008 IEEE International Conference on Multimedia and Expo*, IEEE, 921–24. http://ieeexplore.ieee.org/document/4607586/ (October 9, 2018).

Tabar, Ali Maleki, Arezou Keshavarz, and Hamid Aghajan. 2006. "Smart Home Care Network Using Sensor Fusion and Distributed Vision-Based Reasoning." In *Proceedings of the 4th ACM International Workshop on Video Surveillance and Sensor Networks - VSSN '06*, New York, New York, USA: ACM Press, 145. http://portal.acm.org/citation.cfm?doid=1178782.1178804 (December 4, 2018).

Tafeta. 2011. "Tafeta Smart Home for Health." www.tafeta.ca/home2.html.

Tang, Lei et al. 2011. "MHS: A Multimedia System for Improving Medication Adherence in

Elderly Care." *IEEE Systems Journal* 5(4): 506–17. http://ieeexplore.ieee.org/document/6026896/ (February 10, 2019).

Tartarisco, Gennaro et al. 2012. "Personal Health System Architecture for Stress Monitoring and Support to Clinical Decisions." *Computer Communications* 35(11): 1296–1305. https://www.sciencedirect.com/science/article/pii/S0140366411003720?via%3Dihub (December 12, 2018).

Tinghuai Ma et al. "Context-Aware Implementation Based on CBR for Smart Home." In *WiMob'2005), IEEE International Conference on Wireless And Mobile Computing, Networking And Communications, 2005.*, IEEE, 112–15. http://ieeexplore.ieee.org/document/1512957/ (October 16, 2018).

Vail, Douglas L, Manuela M Veloso, and John D Lafferty. 2007. *Conditional Random Fields for Activity Recognition*. http://www.eecs.ucf.edu/~gitars/cap6938/vail07conditional.pdf (January 30, 2019).

Vainio, A.-M., M. Valtonen, and J. Vanhala. 2008. "Proactive Fuzzy Control and Adaptation Methods for Smart Homes." *IEEE Intelligent Systems* 23(2): 42–49. http://ieeexplore.ieee.org/document/4475858/ (October 30, 2018).

Virone, Gilles. 2009. "Assessing Everyday Life Behavioral Rhythms for the Older Generation." *Pervasive and Mobile Computing* 5(5): 606–22. https://www.sciencedirect.com/science/article/pii/S1574119209000571?via%3Dihub (January 26, 2019).

Wang, Liang et al. 2011. "Recognizing Multi-User Activities Using Wearable Sensors in a Smart Home." *Pervasive and Mobile Computing* 7(3): 287–98. https://www.sciencedirect.com/science/article/pii/S1574119210001252 (February 14, 2019).

Willems, Jared, Glen Debard, Bart Vanrumste, and Toon Goedemé. 2009. "A Video-Based Algorithm for Elderly Fall Detection." In Springer, Berlin, Heidelberg, 312–15. http://link.springer.com/10.1007/978-3-642-03904-1_87 (January 26, 2019).

Williams, G., K. Doughty, and D.A. Bradley. 1998. "A Systems Approach to Achieving CarerNet-an Integrated and Intelligent Telecare System." *IEEE Transactions on Information*

Technology in Biomedicine 2(1): 1–9. http://ieeexplore.ieee.org/document/678527/ (October 31, 2018).

Wilson, D. H., and C. Atkeson. 2005. “Simultaneous Tracking and Activity Recognition (STAR) Using Many Anonymous, Binary Sensors.” In Springer, Berlin, Heidelberg, 62–79. http://link.springer.com/10.1007/11428572_5 (February 14, 2019).

Wilson, Daniel, and Chris Atkeson. *Simultaneous Tracking & Activity Recognition (STAR) Using Many Anonymous, Binary Sensors*. http://www.cs.cmu.edu/~dwilson/papers/wilsonPERVASIVE2005.pdf (December 3, 2018).

“World Population Ageing 2015.” http://www.un.org/en/development/desa/population/publications/pdf/ageing/WPA2015_Report.pdf (May 24, 2018).

Xiaodan Zhuang, Jing Huang, Gerasimos Potamianos, and Mark Hasegawa-Johnson. 2009. “Acoustic Fall Detection Using Gaussian Mixture Models and GMM Supervectors.” In *2009 IEEE International Conference on Acoustics, Speech and Signal Processing*, IEEE, 69–72. http://ieeexplore.ieee.org/document/4959522/ (October 18, 2018).

Xie, Xiaobo et al. 2013. “Neural-Network Based Structural Health Monitoring with Wireless Sensor Networks.” In *2013 Ninth International Conference on Natural Computation (ICNC)*, IEEE, 163–67. http://ieeexplore.ieee.org/document/6817963/ (January 29, 2019).

Yamazaki, Tatsuya. 2006. “Beyond the Smart Home.” In *2006 International Conference on Hybrid Information Technology*, IEEE, 350–55. http://ieeexplore.ieee.org/document/4021238/ (September 18, 2018).

Yun Li, Yun, K. C. Ho, and M. Popescu. 2012. “A Microphone Array System for Automatic Fall Detection.” *IEEE Transactions on Biomedical Engineering* 59(5): 1291–1301. http://www.ncbi.nlm.nih.gov/pubmed/22532430 (February 4, 2019).

Yun Li, Zhiling Zeng, M Popescu, and K C Ho. 2010. “Acoustic Fall Detection Using a Circular Microphone Array.” In *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, IEEE, 2242–45. http://ieeexplore.ieee.org/document/5627368/

(February 27, 2019).

Zhang, Daqing, Tao Gu, and Xiaohang Wang. *Enabling Context-Aware Smart Home with Semantic Web Technologies*. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.469.964&rep=rep1&type=pdf (January 29, 2019).

Zhang, Mi, and Alexander Sawchuk. 2011. "A Feature Selection-Based Framework for Human Activity Recognition Using Wearable Multimodal Sensors." In *Proceedings of the 6th International ICST Conference on Body Area Networks*, ACM. http://eudl.eu/doi/10.4108/icst.bodynets.2011.247018 (February 22, 2019).

Zhu, Chun, and Weihua Sheng. 2011. "Motion- and Location-Based Online Human Daily Activity Recognition." *Pervasive and Mobile Computing* 7: 256–69. www.elsevier.com/locate/pmc (August 22, 2018).