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Development of an Indoor Positioning System for the Elderly in the Home

Using Thermopile Arrays

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Table of Contents

Table of Figures

Part I: Introduction

Project Background

The UK expects to be home to 19 million people over the age of 65 by the year 2050, which is nearly double the 2012 population [1]. A significant number of people in the +65 age group (1 in 100) suffer from some form of dementia and there are estimated to be 700K suffers as of 2012 in the UK [2].

The underlying proposition is that a suitable Indoor Positioning System could be used as part of a Telecare Package within the Social, Personal, and Community Care domains to assist the Elderly to remain in their homes.

Project Aim and Objectives

The aim of this project is to explore the criteria an Indoor Positioning System would need to meet in order to support a Telecare package, and then to develop a prototype Indoor Positioning System suitable for assisting the elderly to remain in their homes.
To achieve this aim a survey of available location techniques and technologies has been completed, along with a review of the requirements and constraints that are specific to tracking users within the home.
The information collected has been used to shape the development of a prototype which addresses all the challenges of this task. A small number of interviews have been completed with Health Care professionals to explore unique requirements and constraints applicable to this domain, and the insights gained during these interviews have been used to shape the design of the indoor application.

The project addresses the following ***Research Questions***

- What types of techniques and technologies are available to develop Indoor Positioning systems?
- How accurate and precise are the solutions built using different Indoor Positioning methods/technologies, both individually and in combination with each other?
- What are the key requirements and constraints for Indoor Positioning Systems to track users' movements around the home?
- What are the key requirements and constraints for Indoor Positioning Systems used to support *Social Care Uses cases*?
- What is the ideal Indoor Positioning System infrastructure for tracking a person's movement around the home?
- What is the ideal Home Indoor Positioning System infrastructure to support *Health Care*?
- How can the Indoor Positioning System be used to determine the location of a person within a building?
- How can existing infrastructure in the home be used and/or modified to develop a home Indoor Positioning System?

Report Structure

This report is structured as follows:

- **Part I Introduction**: This section provides a brief introduction to the project, the key research questions being addressed, and an overview of the project report.
- **Part II Context and Requirements**: This section begins by exploring the broad context for Elder care in the UK, then moves on to focus on Telecare, and finally onto the Indoor Positioning Systems which can provide support for later generation Telecare platforms. The section concludes with a summary of the key constraints/requirements for an Indoor Positioning System to support Elder Care as part of a wider Telecare package.
- **Part III Survey of Indoor Positioning Technologies:** This section provides a critical review of Indoor Positioning System solutions as documented in the current literature and a High Level design for a home Indoor Positioning System that attempts to address all the constraints/requirements identified.
- **Part IV High Level Design**: This section presents the design for the Indoor Positioning System Developed as part of this project.
- **Part V Conclusions**: Provides a summary of the conclusions found from the project and ideas for further work.

Part II: Context and Requirements

Related research questions: -

- *What are the key requirements and constraints for Indoor Positioning Systems to track user's movements around the home?*
- *What are the key requirements and constraints for Indoor Positioning Systems used to support Health Care Uses cases?*
- *What is the ideal Indoor Positioning System infrastructure for tracking a person's movement around the home?*
- *What is the ideal Home Indoor Positioning System infrastructure to support Health Care?*

This part of the paper provides the context and high level requirements analysis for the Indoor Location System developed as part of this project. The content is based on a small number of interviews held with Health Care Professionals as part of the project supplemented with supporting literature, both general and in the computer science domain. It is structured as follows:

- **Context:** Provides background information and motivation for general Telecare requirements including:
    - **Ethical Considerations:** Highlights some of the ethical considerations that must be accounted for when deploying a Telecare system.
    - **Current Use of Telecare for Elder Care:** Provides a brief summary of the types of Telecare solutions currently used in the public and private health care sectors and the process for introducing and selecting Telecare.
    - **Future Trends in Telecare:** Provides a summary of changes expected in the Telecare industry over the next 5-10 years.
    - **Well-Being Contextual Model:** Introduces the contextual model used to frame the scope and requirements of 3rd Generation Telecare systems.
    - **Role of Indoor Positioning Systems:** Sets the scope for this project with respect to the broader themes introduced earlier in this part of the paper.
- **Key Use Cases:** The key Telecare use cases supported by Indoor Positioning Systems are presented.
- **High Level Requirements:** Provides a summary of the functional and non-functional requirements to be fulfilled by an Indoor Positioning System used to support Telecare.

Context

As noted in the introductory section, the UK will see a significant rise in the number of people aged 65+ over the next quarter of a century. Of this 65+ age band 76% [3, Ch. 1] of men and women will need some form of care within the rest of their lifetime, and this increasing demand will put additional pressures on the current Social & Health Care systems, which are already struggling to manage the demand placed upon them [3, Sec. Exec Summary]. The changes called for as part of the Reforming Care White Paper [3] involve the provision processes and technologies that will help prevent people from getting to crisis point, and therefore requiring intensive care and support. Access to Assistive Technology is being proposed as a key supplemental measure to support sustained independence and well-being, and with this in mind the UK Government has launched the 3 Million Lives program to accelerate the rollout of Telecare and Telehealth services in the UK over the next 5 years [4].

The following definitions for Telecare and Telehealth have been taken from the 3 Million Lives programme:

- *Telehealth – refers to services that use various point-of-care technologies to monitor a patient's physiological status and health conditions. Typically, it involves electronic sensors or equipment that monitors vital health signs remotely from home or while on the move. Readings are automatically transmitted to an appropriately trained person who can monitor the health vital signs and make decisions about potential interventions in real time, without the patient needing to attend a clinic* [4, p. What is Telehealth]
- *Telecare - is a service that enables people, especially older and more vulnerable individuals, to live independently and securely in their own home. It includes services that incorporate personal and environmental sensors in the home, and remotely, that enable people to remain safe and independent in their own home for longer.* [4, p. What is Telecare].
  Telecare systems are further categorised by their general evolution from telephony-based alarms to sophisticated monitoring solutions [5]:
  - **1st Generation**: Telephony-based social alarm; pendant and pull cord-based remote alarm system; covered by BS8521, which hopes to address interworking of Social Alarms [6].
  - **2nd Generation**: Adaptive and personalised event driven alarms based on multiple sensors.
  - **3rd Generation**: Moves focus of telecare away from responding to events into a pro-active monitoring tool which will enable Social Health workers, Care Users, and carers to measure general well being and help determine and optimise any intervention required.

The use of Telecare and Telehealth has been shown to make significant reductions in the number of A&E, Emergency, and Elective admissions as part of the Whole System Demonstrator programme [7], [8].
Age UK estimated as part of its Future of Who Uses Telecare report [8] that there could be as many as 2.5 Million potential users of telecare who live alone and could be considered a core target for Telecare services in the UK today.

Ethical Considerations

The use of telecare has potential to support the independence and dignity of the elderly, allowing them to remain at home for longer. In addition, benefits have been highlighted for carers (the majority of whom are informal) by reducing concerns about the whereabouts and well-being of the person they care for without them having to be constantly present, which has subsequent benefits of allowing the carer to re-join the labour market and thus contribute to the economy [8].

However, great care needs to be taken to place primacy on the needs and well-being of the care user - a significant body of completed research places special emphasis on managing the risk of injury or death, and thus can be compared to the systems used to manage prisoners or young children [9, p. 2]. Tagging in particular raises great concerns, especially as to be effective for dementia sufferers the tags either need to be emotionally connected, non-removable, or hidden, as the sufferers are prone to remove them and thus render them in-active - thus the motivation for tagging is brought into question and the balance of safety and autonomy needs to be considered [10]–[12].

It is beyond the scope of this paper to address these ethical questions, however the solution proposed is done so based on an awareness of the issues and attempts to balance privacy, autonomy, and safety in a pragmatic way.

Current Use of Telecare for Elder Care

A variety of 2nd Generation Telecare sensors are currently used in both the private and public social care domains to support the management of risks to posed by the elderly or vulnerable adults to self, others, and property. Sensors offered by Hertfordshire County Council include [13]:

- Fall Detectors
- Passive Infrared movement detectors
- Environmental sensors such as Smoke, Carbon Monoxide, and Flood detectors
- Social Alarm pendants
- Occupancy sensors and pressure mats
- Epilepsy and Enuresis Sensors
- Medication Reminder/Dispensers

Video cameras are occasionally used in the Private sector for personal/community care where the Care User and Family have agreed and the risk assessment carried out suggests it would be a useful intervention. However, the use of images is generally viewed as an intrusion of privacy and is not currently used by the public sector, although at the time of writing there is an on-going debate about their use by the regulatory body responsible for the quality of Social Care[14].

The use of Telecare in both the Private and Social care sector is based on the *Assessment* of the Care user's needs, a *Plan* which identifies key goals for the user - including, for example, the need to increase independence, the *Implementation* of which is agreed with the care user - and a continuing *Evaluation* of the success of the implementation. Thus the Plan to deploy a Telecare package is part of a wider care package, tailored to the specific care user's needs and goals [15].

Future Trends in Telecare

Spurred on by the recent government initiatives such as 3 Million Lives, Sethi et al. [16] predict that we should look to the emergence of open standards for the interoperability of IP telecare services and the convergence of technologies in the Telehealth and Telecare field employing household and wearable sensors, resulting in increased service integration and data sharing. These technology trends, spurred on by the emerging Government policies, will allow Telecare services to evolve from the reactive 1st and 2nd Generation services into 3rd Generation pro-active well-being monitoring services.

These 3rd Generation solutions will aim to provide the tools for carers to identify significant changes in the well-being of the care user, with the objective of preventing incidents from occurring rather than responding to them as per existing 1st and 2nd Generation solutions [5].

Well-Being Contextual Model

In order to deliver 3rd Generation Telecare solutions, a framework for Well-Being needs to be formulated so that key elements can be measured and analysed to provide a representation of the Elder care users' well-being, which can then be validated against expected results.

The model used in this project is based on the work of Hine et al. for the BT Care in the Community project [5], [17], [18] which includes Person Factors (made up from physical abilities, needs, preferences, goals and motivation), Context Factors (comprised of the home environment, social network and care provision), and Activities (including bathing, eating, hygiene, sleeping, hobbies commonly known in the social care domain as Activities of Daily Living, and leisure). These drivers act together to create an experience that determines well-being outcomes.

The focus of the proposed model is on the behavioural elements, which can be monitored and attributed, and it proposes these are important leading indicators for Well-Being.

An example from Hine et al. [17] examines the duration of time spent preparing and eating food and uses it to determine if the Elders' eating habits were changing over time. A reduction in the time spent preparing food, for example, might indicate a reduction of fresh ingredients and an increased preference for ready-cooked meals – a development that might indicate a change in physical capability or personal goals, and which ultimately reflects upon the care users' experience of life and their general well-being.

Role of Indoor Positioning Systems In Telecare Applications

A generic Telecare system is composed of *Activity Monitors* and *Activity Interpreters* [18]. The Indoor Positioning System, as part of the Activity Monitor domain, provides location information to the Activity Interpreter, and this information may be supplemented with other environmental sensors and actuators. The data generated can be combined in the Activity Interpreter, along with rules and other context information, to trigger events or determine the activities being completed.

Note: The purpose of this project is not to develop a complete Telecare system, but rather to explore the various technologies and constraints associated with an Indoor Positioning System suitable for use as part of an elder care Telecare package in order to answer the research questions posed in Part I Introduction of this paper.

Key Use Cases

Indoor Positioning Systems can be used within a Telecare system by providing location information to enable the following use cases to be implemented:

2nd Generation Telecare Use Cases

- UC-1: Triggering reminder messages based on particular contexts, e.g. remembering keys, reminders for appointments when leaving the house, encouragement to stay in the house if the care user is leaving at an in-appropriate time [19], [20].
- UC-2: Generating alerts when a care user has fallen, or has remained stationary for longer than expected [21]
- UC-3: Triggering the activation of lights when a care user starts to moving around at night to help reduce the risk of falls [22]

3rd Generation Telecare Use Cases

- UC-4: Helping clinicians monitor the progress of diseases such as dementia, for example by monitoring wandering patterns in care users [23], [24].
- UC-5: Monitoring Activities of Daily Living, e.g. Preparing Food, Sleeping, Hygiene [5]
- UC-6: Monitoring Social Interaction, e.g. Number of Visitors arriving, Time spent away from home [5]

High Level Requirements

Functional Requirements

ID	F.01	Reference/Use Case	UC-4, UC-5
Requirement	The Indoor Positioning System must be able to report position with sub-room accuracy, so that it can support identification of wandering patterns and Activities of Daily Living.		
Acceptance Criteria	Movement within a room can be identified and tracked for one or more users.		

ID	F.02	Reference/Use Case	Ethical Considerations
Requirement	The Indoor Positioning System must be able to report on the position of one or more targets without the need for active participation from the target, so that positioning is constantly available and the system does not make the Care User's life more complicated.		
Acceptance Criteria	The Indoor Positioning System can identify targets without the need for the targets to actively participant in the process by carrying a phone or wearing a tag, etc.		

ID	F.03	Reference/Use Case	UC-2
Requirement	The Indoor Positioning System must be able to identify the position of stationary targets, so that information about targets which are immobile for a defined period of time can be used by the Telecare system to trigger appropriate responses.		
Acceptance Criteria	The Indoor Positioning System can identify target position even if the target has been stationary for a prolonged period of time.		

ID	F.04	Reference/Use Case	UC-4, UC-5, UC-6
Requirement	The Indoor Positioning System must be able to track the historical position of a target, so that trends in the movement of targets can be established.		
Acceptance Criteria	The historical position of a target must be available to the Telecare platform for further analysis.		

ID	F.05	Reference/Use Case	UC-6
Requirement	The Indoor Positioning System must be able to track multiple targets, so that social interaction of Care Users can be monitored.		
Acceptance Criteria	The Indoor Positioning System has the ability to track and provide locations for multiple targets simultaneously. Unique IDs are available for tracked objects.		

ID	F.06	Reference/Use Case	[25]
Requirement	The Indoor Positioning System must provide the confidence of any location measurement for a target in its interface, so that the information can be used by the context aware applications in the Telecare stack.		
Acceptance Criteria	A measure of the confidence in the position is presented in the Indoor Positioning System interface.		

Non Functional Requirements

ID	NF.01 (Performance)	Reference/Use Case	UC-1, UC-3
Requirement	The Indoor Positioning System must be able to report on the position of one or more targets in real time, so that interaction between targets can be reported.		
Acceptance Criteria	The Indoor Positioning System can identify targets' positions in real time, to enable alerts or actions to be taken by the Telecare System.		

ID	NF.02 (Cost)	Reference/Use Case	[26] - Derived
User Story	The cost of the Indoor Positioning sensors must be low, to allow wide scale adoption by the Public and Private care domains.		
Acceptance Criteria	High cost sensors will act as a barrier to the adoption of the Indoor Positioning System's capabilities in the public and private care domains. The cost of sensors must be minimised.		

ID	NF.03 (Operability)	Reference/Use Case	[25]
User Story	The Indoor Position System should provide location information via standard IP protocols, so that it is possible to connect the Indoor Positioning System to existing or new Telecare platforms with minimal integration costs.		
Acceptance Criteria	Information can be collected from the Indoor Positioning System via HTTP.		

ID	NF.04 (Operability)	Reference/Use Case	[16], [25]
User Story	The location of targets should be provided in multiple frames of reference, so that the information can be aligned with other location information and geographic information data sets.		
Acceptance Criteria	Information can be collected from the Indoor Positioning System in an open standard for location.		

ID	NF.05 (Security)	Reference/Use Case	Derived
User Story	It should not be possible for unauthorised parties to collect information from the Indoor Positioning System, so that the privacy of the Care User is maintained		
Acceptance Criteria	Current and Historic location information is protected from unauthorised access.		

ID	NF.06 (Operability)	Reference/Use Case	[25]
Requirement	The Indoor Positioning System should be capable of fusing location data from multiple sensors, so that location accuracy and precision can be improved.		
Acceptance Criteria	The Indoor Positioning System is can be configured to incorporate new sensor data without new code changes.		

ID	NF.07 (Operability)	Reference/Use Case	Derived
Requirement	It should be possible to retrofit the Indoor Positioning System with minimal disruption, so that the solution can be deployed in existing homes.		
Acceptance Criteria	The Indoor Positioning System can be mounted in existing buildings without significant alteration, i.e. rewiring, redecoration.		

ID	NF.08 (Security)	Reference/Use Case	Derived
Requirement	The technology should not be intrusive and should be acceptable to the Care User, Family, and Provider to be used within the home, so that wide scale adoption of the Indoor Positioning System is possible.		
Acceptance Criteria	The Indoor Positioning Systems’ sensors should be of a form that does not cause distress or concern to the care user.		

Part III: Survey of Indoor Positioning Technologies

Related Research Questions:

- *What types of techniques and technologies are available to develop Indoor Positioning systems?*
- *How accurate and precise are the solutions built using different Indoor Positioning methods/technologies, both individually and in combination with each other?*
- *How can existing infrastructure in the home be used and/or modified to develop a home Indoor Positioning System?*

Over the 10 years since the Global Positioning Systems (GPS) 'Selective Availability'[27] was discontinued, Outdoor Positioning Systems have become ubiquitous with the inclusion of GPS receivers in Smart Phones, Car Navigation Systems, and Cameras. The extension of the outdoor positioning capabilities offered in these devices to positioning indoors, where the signal from the GPS satellites becomes too weak to be used usefully, requires different technology solutions

This part of the paper provides a summary of the various solutions to the problems facing Indoor Positioning. It is structured as follows:

- **Classification of Indoor Positioning Systems:** Introduces the taxonomy used to organise Indoor Positioning Systems, and the evaluation framework used to summarise the effectiveness of the solutions is introduced.
- **Indoor Positioning System Survey:** A survey of Indoor Positioning research and commercial products classified and evaluated according to taxonomy and evaluation framework.
- **Indoor Positioning System Technology Selection:** This section summarises the primary technology choice for the project.

Classification of Indoor Positioning Systems

Indoor Positioning Systems can be grouped using the following classifications: System Architecture, Technology, and Techniques.

Location System Architectures

Using a layered style of architecture the Location System Architecture can generally be broken into 3 layers [25], [28], [29]:

- **Location Sensors:** Different Location Technologies are used to collect data on the users and their devices. The Location Sensor layer can classified as either Active or Passive [28] . Active sensor networks require the user to participate by carrying a device or wearing a tag. Passive networks don't require any direct participation by the user. Additionally, the layer can also be divided into Network and Dedicated Infrastructure and Infrastructure-less based approaches [29]. Network based approaches make use of existing network infrastructure whilst Non-Network approaches require dedicated equipment for positioning. Infrastructure-less approaches do not require any fixed infrastructure to determine position.
- **Location Rules Engine:** The Location Rules Engine takes the raw Sensor Data and converts it into Spatial, Network, or Descriptive Location information. The system topology for the rules engine can be divided into the following four categories [30]:

- Remote Positioning: The network completes the positioning calculations.
    - Self-Positioning: The mobile unit completes the positioning calculations.
    - Indirect Remote Positioning: The mobile unit completes the positioning calculations and passes to the network for action.
    - Indirect Self-Positioning: The positioning calculations are completed by the network, as passed to the mobile unit for action.

  Functions supported by this layer include Measurement (transcription of raw sensor data into location measurement), Fusion (time stamped location and tracking of individual targets), and Arrangement (rules for proximity between two or more objects and translation between different co-ordinate systems) [25].
- **Location Application:** These applications use the information created by the lower levels to create context sensitive applications, e.g. Triggering of a wandering alert based on time, previous and current location information, and potentially rules provided by the user. [25]
  Note: Location Applications will not be used to categorise Indoor Positioning Systems and are included here for completeness.

Location Technologies

The technologies that underpin the Sensor Layer can generally be categorized as Optical, Audio, Electromagnetic Radio Waves, and Inertial based technologies. In addition, a small number of solutions use Electrical Inductance or Air Pressure sensors to determine location.
As noted in the architecture section, the solutions which use these technologies either make use of existing network infrastructures or have dedicated equipment which can be deployed, either based on a static infrastructure (e.g. GPS Satellites) or which are infrastructure-less (e.g. Inertial Sensors).

Location Techniques

Techniques for determining location have a long history, starting with contextual navigation based on landmarks, moving through the use of Compass and Celestial bodies, and on to modern navigation techniques using Radio waves, Cellular Networks, and Satellite-based navigation. The techniques used for Indoor Positioning often used fixed references in a manner similar to traditional navigation techniques and can be grouped as follows [25], [30], [31, Ch. 3].

- **Angulation:** The angles at which signals arrive at the receiver from two or more reference points (base stations) are measured, and these measurements are used to create a system of equations which can be solved to find the position of the receiver. The angle of arrival can either be measured using a directional antenna or by measuring the phase properties of the signal.
- **Dead Reckoning:** The new position is calculated based on the history of movement associated with the target. The movement history is based on a set of vectors that define the heading and distance moved. The new position is calculated relative to a starting position, which is ideally a known reference point.

- **Lateration:** Lateration is a technique used to determine position based on the range from three or more reference points. The range from reference points can be based on the time it takes for the signal to travel from the reference point to the target (the range is then the time taken multiplied by the speed of the medium used to transmit the signal). Once multiple ranges have been found the position can be calculated by determining the intersection of circles or hyperbola defined by the reference point and range measurements.
- **Proximity:** A basic method for locating a target, proximity techniques use the immediacy of the target to a reference point, and this can be done either based on the assumption that the underlying technology has limited range (e.g. for RFID tags) or by measuring the Received Signal Strength from a number of reference points and selecting the strongest.
- **Scene Analysis:** Mathematical matching techniques are used to find the best match to the data previously captured, and this match is then used to position the target. For example, Radio Frequency-based scene analysis, also known as Fingerprinting, positions the target by comparing the observed received signal strengths with a database of previously captured information which has been mapped to locations.

Evaluation Criteria

It has been understood for some time that performance of location systems cannot solely be based on Accuracy [32]. The qualitative evaluation criteria defined by Liu and Darabi [30] will be used to assess surveyed solutions; the criteria includes accuracy, precision, complexity, robustness, and cost:

- **Accuracy:** Is a statistical measure of the error between the reported position by the system and the ground truth, and is normally represented by the mean distance error.
- **Precision (or repeatability):** Is a statistical measure of the distribution of the reported position without reference to a ground truth.
- **Complexity:** Complexity is an attempt to qualify the hardware and software challenges required to set up the Indoor Positioning System, including the need for specialist equipment and the computational overhead of the location algorithms required to support the solution.
- **Scalability:** Scalability of the solution needs to be reviewed from two dimensions:
    - How well does the solution scale to support multiple devices?
    - How well does the solution scale to support and wider geographic areas?
- **Robustness:** How well does the solution function if there is a partial or total loss of the signals available from the reference point/base stations – can it continue to provide location information, and to what level is the accuracy and precision impacted?
- **Cost:** The upfront installation and running costs for the positioning system are considered.

Indoor Positioning System Survey

The following section summarises a number of important solutions to Indoor Positioning, including Inertial Navigation, Optical, Ultrasound, Infrared, RFID, Bluetooth and WiFi. This is not an exhaustive list and other solutions including Sound and **Electrical Inductance**[33] have also been proposed.

Inertial Sensors

As Micro Electro Mechanical systems have become cheaper it has been possible to add Accelerometers, Gyroscopes, Barometers and Magnetometers to portable and wearable devices, and this has spurred on significant interest in the use of these cheap sensors for Indoor Positioning.

Commercial Products: Sense Platform's FreeMotion library [34] allows access to processed MEM sensor data to provide context awareness and positioning to other applications on android phones.

Use within Elder Care Domain: D'Souza et al. used inertial sensors in conjunction with wireless nodes to track patients with dementia in a elder care home [35].

Classification

Taxonomy	User Participation	Sensor Infrastructure	Technolo gy	Technique
Classificati on	Active	Infrastructure-less	Inertial	Dead Reckoning

Overview

The user is required to carry a device, containing inertial measurement sensors, which may be either fixed to the body in a strap-down configuration (e.g. a sensor attached to the foot, or waist with known configuration [36]) or unconstrained (e.g. a smart phone [37]).

Although inertial navigation does not mandate any additional infrastructure, all positions estimated are relative to each other and an initial fix may be required. This can either be done manually or by using existing GPS, WiFi, or other Radio Frequency technology. The following sensors are most commonly used for Inertial Navigation:

- Accelerometers - for Step Detection and Step Length calculation
- Gyroscopes - for Step Detection and Heading estimation
- Magnetometer (Compass) - for Heading estimation
- Barometer – to determine vertical position (building floor or geographic terrain matching)

The basic technique for positioning targets using Inertial Sensors is Pedestrian Dead Reckoning (PDR). PDR typically involves 3 key activities, these being Step Detection, Step Length Estimation, and Heading or Change in Heading Estimation [38]. Various solutions have been proposed for Step Detection including Peak Detection [39] and Zero Crossing [36]. The information used is generally based on accelerator data and is treated as a noisy signal with steps like low-pass filters being applied to remove higher frequency changes in acceleration, which are not related to the act of walking. Step Length can either be derived statically, as a function of the person's height and sex, or dynamically, using either the vertical hip displacement as a proxy for step distance or step frequencies which have been shown to be well-correlated with walking speed and therefore step length [38], [40]. Finally, Headings can be derived from integrating the signals from gyroscopes to get an estimate of Heading Change along with signals from magnetometers to provide absolute Heading information [20].

Harle [38] highlights a number of areas of future research for Inertial based systems including:

- **Unconstrained Sensor Site:** Mobile devices offer unique opportunities and challenges for Inertial-based systems. Solutions must cope with changing sensor orientation and the possibility that the phone is not facing the direction of movement.
- **Battery Power Requirements:** When implementing solutions in portable devices consideration needs to be given to the draw on the battery. Optimisation techniques to reduce the use of the Accelerometer, Gyroscope and Magnetometers will also need to be developed.
- **Processing Power:** In a similar way to battery life, the utilisation of mobile device CPUs needs to be considered. Most of the current solutions are based on desktop computing, and consideration needs to be given on how signal processing and particle filter algorithms can be optimised for use on mobile devices.

Evaluation

Criteria	Rating	Description
Accuracy	0.6-1.5 meters ~1% of Journey Length [41]	Accuracy depends largely on the position of the Inertial Sensors (sensors mounted on the foot provide the best accuracy as the drift error can be reset). In addition, correct/probabilistic algorithms such as map-matching using particle filters can be applied to further increase accuracy. The best accuracy reported is based on a journey through a 3 story building with a foot-mounted INS with particle filter applied to align the position with the known building constraints. [42] Other accuracy ranges are based on the Survey completed by Harle, again based on additional map-matching processes. [38]
Precision	95%	Precision is affected by similar constraints as accuracy. Additional processing on top of the initial sensor-capture can improve the precision. The recorded precision is based on the same set up as the accuracy.
Complexity	Low	The integration of MEMS into devices means that they are readily available commercially, with little or no additional infrastructure to implement.
Scalability	Low	Typically, errors in positioning are reported at 3%-10% of distance travelled. The sensors can only position one person at a time.
Robustness	Low	The solutions are subject to drift as errors in the various sensors are compounded over time. This can be addressed by various additional computation approaches such as map filtering. [42, Ch. 5]
Cost	Low	MEMS are low cost and are incorporated into many commercially available devices. There are no upfront costs for infrastructure, as devices can communicate data over existing communications networks.

Computer Vision

The robotics community pioneered the concepts of computer vision, and in the late 1990's the first research into how vision could be used to support pedestrian and augmented-reality applications was completed [43]. Two types of solutions are explored in research - ego-motion using a mobile sensor and static camera tracking moving objects.

Commercial Products: None identified.

Use within Elder Care Domain: Zouba et al. used video cameras in conjunction with a selection of binary sensors (e.g. door contacts) to categorise activities of daily living [44].

Ego-motion

Classification

Taxonomy	User Participation	Sensor Infrastructure	Technology	Technique
Classification	Active	Infrastructure-less	Optical	Scene Analysis

Overview

Computer Vision-based solutions based on ego-motion require the target to carry a camera, either by hand or attached to the body [45]. Imaging sensors of varying degrees of quality are used. Supplementary equipment such as lasers or IR projectors can be used as noted above to provide markers. Images captured are resolved to a location either by matching images to pre-stored building models and/or images, by coded markers, or via the projection of markers using infrared or lasers. [45]

Chen [46] summarises the various Scene Analysis techniques used Image processing as:

- Line detection - Canny Edge Detection, Hough Transform
- Corner Detection - Harris Corner Detection
- Vanishing point calculation
- Feature Detection - Scale Invariant Feature Transform - SIFT
- Optical Odometry – Similar to dead reckoning explored in the previous section, but based on changes in consecutive images. [45]
- Simultaneous Location and Mapping - SLAM
- Random Sample Consensus – used to reduce the impact of errors on visual calculations.

Scene analysis information can then be used to search a reference database of images, or geo models, and/or compare successive images. The latter allows for a relative position to be calculated based on no prior information about the environment.

Evaluation

Criteria	Rating	Description
Accuracy	<1cm – 30cm	High levels of accuracy can be achieved using Vision-based systems, with industrial applications achieving sub-centimetre accuracy. Mobile phone-based solutions have reported accuracy of around 1 - 30cm. [45]
Precision	Not Reported	In general precision is not reported, however for the mobile phone-based solution reported error rate if no features were occluded was in excess of 90% for the report accuracy of 30cm. [47]
Complexity	Medium	A reference model has to be built, and either the site needs to be surveyed or reference markers with known locations have to be placed into the environment as part of the deployment of the solution. The algorithms used to determine features tend to be computationally heavy and require reworking for use on portable devices [46]
Scalability	High	The visual solutions (certainly for pedestrian positioning) scale well in both the density of supported targets and the size of the area it is possible to cover. [45]
Robustness	Low	Light, camera quality, and speed of movement can all degrade the performance of a vision-based solution. It is possible to address this but at the cost of increased computing power.
Cost	Low (Industrial applications High)	The costs of the solutions range from <£20 to >£10K dependent on the type of camera selected. In general, pedestrian tracking solutions are low cost. [45]

Static Camera

Classification

Taxonomy	User Participation	Sensor Infrastructure	Technology	Technique
Classification	Passive	Dedicated Infrastructure	Optical	Scene Analysis & Angulation

Overview

Typically with Static Camera-based positioning the target does not need to actively participate in the positioning process. However, to increase the robustness of the solution the target is fitted with a marker, for example the Robot monitored by Boochs et al. [48]. Imaging sensors of varying degrees of quality are used in conjunction with supplementary equipment such as LED markers [48], and these sensors are deployed at fixed positions in the area to be monitored.

Positioning techniques used by Static Camera solutions include:

- Background Subtraction – Targets in the room are identified by measuring the mean & variance for each pixel in an empty room, and any changes from this are used to trigger the identification of a target 'blob' [43], [49]
- Blob Connection – The blobs detected are joined together to create the target [43].
- Colour Analysis – The colour composition of targets is analysed and used to track the targets
- Triangulation is used to estimate depth by capturing the image from two or more cameras with known positions

Evaluation

Criteria	Rating	Description
Accuracy	<1cm – <1m	High levels of accuracy can be achieved using Vision-based systems, with industrial applications achieving sub centimetre accuracy. [42, Ch. 2.1.2.5 Vision] Other solutions such as the EasyLiving [43] project and the low cost solution proposed by Tappero [49] achieve sub-meter accuracy.
Precision	Not reported	In general precision is not reported and, in a number of cases, cannot be guaranteed because the solution is susceptible to sudden changes in the lighting or partial occlusion of targets.
Complexity	Medium-High	The installation of the solutions can range from simple deployment of low-cost images sensors to the management of multiple camera arrays and precise control of markers. Software to process images and compensate for errors involves some computationally heavy algorithms.
Scalability	High	The visual solutions (certainly for pedestrian positioning) scale well in both the density of supported targets and the size of the area it is possible to cover. [45]
Robustness	Low	Light, camera quality, and speed of movement can all degrade the performance of a vision-based solution. It is possible to address this to certain extent, but at the cost of increased computing power.
Cost	Low (although Industrial applications can be High)	The costs of the solutions range from <£20 to >£10K dependent on the type of camera selected. In general pedestrian tracking solutions are low cost. [45]

Infrared

Infrared was the basis for one of the earliest Indoor Positioning Systems, the Active Badge developed by the Olivetti Research Laboratory in the early 1990's [50], and it still remains the archetype for Active Infrared location systems. The solution was limited to providing symbolic positioning based on proximity to a IR beacon and was affected by fluorescent lights and sunlight which prevented the signal from being identified [28]. Passive Infrared systems are used to detect presence in a number of research papers and commercial offerings, specifically in the security, building automation, and tele-health domains. Passive Infra systems are explored further below.

Commercial Products: Irisys use thermal imaging technology to provide solutions such as people counting, security, and health care, while the ambient assisted-living proposition is at the time of writing still in the research phase [51].

Use within Elder Care Domain: Campo et al. used passive infrared sensors to monitor the activities of daily living of a elder person in a care home [23].

Classification

Taxonomy	User Participation	Sensor Infrastructure	Technology	Technique
Classification	Passive	Dedicated Infrastructure	Electromagnetic Radiation - Infrared	Proximity/ Angulation

Overview

The target's body heat generates infrared electromagnetic radiation, which can be used to trigger the infrared sensors. [52]
Note: Human skin temperature is 23-34°C, and at this temperature the maximum radiation emittance lies in the near infrared spectrum. [53]
Dedicated Infrared sensors are deployed in known fixed positions to capture heat emitted by the targets, and these sensors can be pyroelectric, microbolometer, or thermopiles [52], [54].

- Pyroelectric sensors are low-cost, but when used in motion detectors they can only detect changes in temperature.
- Microbolometers array are arrays of thermally isolated temperature dependant resistors and are used in infrared cameras. However, they are costly and require their temperature to be carefully managed.
- Thermopile sensors can be produced as low-resolution line and array sensors. They are low-cost and can detect objects with temperatures different to the ambient temperature. The main current application is for contactless temperature measurement.

Simple Passive Pyroelectric sensors are suitable for detecting motion in proximity to the detector, and as such can be used with simple proximity detection [55]. A number of extensions to basic proximity detection have been proposed, including

zone-tracking to estimate location [56], [57] and enhancements with other positioning technologies, including Zigbee radio, & pressure mats [55], [58]
The use of Angulation has been researched using multiple Thermopile imaging arrays enhanced with probabilistic-based filters to support tracking of multiple targets [53]

Evaluation

Criteria	Rating	Description
Accuracy	<1m, Room Level	Reported accuracy for solutions have been around the 30cm mark, where multiple sensors or thermo sensor arrays have been used [53]
Precision	Not Reported	Precision is not reported in the papers surveyed
Complexity	Medium-High	Sensors need to be installed and in some cases calibrated to ensure that algorithms output is optimised
Scalability	Low	Current research topics are dealing with multiple occupants in a single room [52] . The solution scales well for positioning indoors, but due to the short range nature of Infrared additional infrastructure will need to be installed
Robustness	Medium	Infrared can be interfered with by changes in ambient temperature, targets that remain motionless (dependant on the sensor used), and ambient heat sources, e.g. lamps and heating – these are currently areas for further research [52]
Cost	Low	Infrared sensors are widely available and used as part of existing commercial offers for home security.

Radio Frequency Identity (RFID)

Radio Frequency Identity (RFID) was originally designed as a contactless low-energy replacement of smart card systems. RFID facilitates the automatic identification of targets and so the technology is used extensively in access control, supply chain and logistics, and for key-less entry into cars. Because it is based on Radio Waves, RFID can also be used to locate the target it identifies, and this along with the low cost of the component parts, low power consumption, and effective range and simplicity has meant that it has become the mainstay of commercial Real Time Location Systems over the past 10 years [46, Ch. 4], [59, Ch. 8].

Commercial Products: Multilux [60] and Zebra [61] are two examples of commercial RFID-based Real Time Location Systems (RTLS)

Use within Elder Care Domain: Kim et al. proposed an RFID based solution to monitor activities of daily living for an elder living at home.[62]

Classification

Taxonomy	User Participation	Sensor Infrastructure	Technology	Technique
Classification	Active	Dedicated Infrastructure	Electromagnetic Radiation – Radio Waves	Proximity Lateration Angulation Scene Analysis

Overview

The majority of the solutions available or proposed in literature are Active, requiring the target to carry a reader or a tag.
There are limited research papers on Device-free Passive systems, which position people based on the interference they create in an existing RFID network [63]. A dedicated infrastructure made up of one or more of the following components Readers (also known as interrogators), Controllers, and Tags (also known as transponders) [46, Ch. 4] is required to be deployed. RFID systems use Low Frequency (LF), High Frequency (HF) and Ultrahigh Frequency (UHF) bands. Two types of interaction occur between tags and readers: inductive coupling is used as a basis for communication for LF and HF, while UHF based systems tend to use Propagation coupling.
Tags can be Active or Passive referring to how they are powered. Active tags have their own power source whilst Passive tags use the energy from the magnetic or electromagnetic fields created by the reader. Passive tags have a reading range of up to 10m, whilst active tags can be read over a range of several hundred meters [46, Ch. 4].
The infrastructure has two main topologies - mobile Reader with fixed Tags and mobile Tags with a fixed reader [62].
Multiple techniques can be used with RFID systems to estimate location. The basic approach is to use Proximity, and this can be done either at choke points (e.g. doors), or within cells based on the range of the RFID solution or Zones of influence identifying where reader footprints overlap [46, Ch. 4], [59].

Lateration can be used to determine the position of a target based by using Time of Arrival, Time Difference of Arrival, or Received Signal Strength (RSS) measurements to determine the distance of the target from three or more readers. Angulation is used with directional antenna built into two or more readers to determine the location of a tag. Finally, scene analysis can be used using RSS fingerprints to estimate the location of the user [46, Ch. 4], [64].

Evaluation

Criteria	Rating	Description
Accuracy	<1m – 3m	RFID positioning has been constantly improving from 3m in the early SpotOn solution [65] to recent papers highlighting an accuracy of 62-168cm [66], and a number of papers summarized by Fortin-Simard et al. [67] suggest sub 10cm accuracy is possible in the laboratory. Recent papers on Device Free Passive solutions have reported accuracy of 0.4-1.4m [68].
Precision	Not reported	Precision is not generally reported as defined.
Complexity	Low-Medium	Readers and/or tags need to be deployed and arranged. RFID infrastructure is a well-understood technology. Configuration of tags as landmarks and calibration of the system is required for a number of solutions, in particular where scene analysis is used. The air interface and API for Real Time Location Systems using RFID are covered by two BSI Standards [69], [70].
Scalability	High	By varying the tags from passive to active, the RFID positioning solutions can scale from meter level to several hundred meters, although this does require significant investment in the deployment of large numbers of Readers. The algorithms used can be computationally heavy, which results in time to fix locations that can be multiple seconds. Optimisation of some of the algorithms is being explored in recent papers [71].
Robustness	High	The Technology used is mature and well understood. UHF does not perform well in the presence of metal and liquid, which may interfere with the strength of signals received, and therefore reduce accuracy of the overall solution[59, Ch. 11].
Cost	Low	Passive tag-based tracking with a limited number of beacons is a minimal investment. The cost of passive tags can be less than £0.20.

Bluetooth

Ericsson initially conceived Bluetooth as a low-cost, low-power RS-232 wireless replacement solution, and as such it is connection orientated. The network topology for Bluetooth, known as a piconet is based on a peer-to-peer communications within a proximity network[1], which allows the formation of personal area networks and allows federation of personal devices such as tablets, headphones, and mobile phones. Bluetooth is readily available in modern phones and as such has been the focus of a number of papers and Thesis that utilize the technology for positioning. One of the more exciting developments was recent the launch of Bluetooth Low Energy in 2010. Bluetooth Low Energy is a new technology and is currently the lowest possible power-consuming wireless technology that can be built [72]. The Bluetooth Low Energy technology has the concept of presence detection using a connectionless advertiser-scanner model. There are now some commercial products becoming available, e.g. iBeacons, Tòd, however there appears to be limited open research into the use of Bluetooth Low Energy for Indoor Positioning [73].

Commercial Products: indoo.rs [74] & estimote [75] offer a Bluetooth-based positioning Software Development Kit for iOS based on iBeacons (Apple's implementation of the Bluetooth 4.0 standard). Both of these solutions use a Self-Positioning rules engine.
Zonith [76] offers a 'Classic' Bluetooth-based Real Time Location System, based on Bluetooth beacon approach where the location rules engine uses the Remote.

Use within Elder Care Domain: Kelly et al. used classic Bluetooth with Remote Assisted rules engine to track the movement of an elder around the home [77].

Classification

Taxonomy	User Participation	Sensor Infrastructure	Technology	Technique
Classification	Active	Dedicated Infrastructure	Electromagnetic Radiation – Radio Waves	Proximity Lateration Scene Analysis

Overview

The target has to carry a mobile phone or a Bluetooth peripheral (e.g. headset, watch, bracelet) [78]. This Bluetooth-enabled device typically interacts with a network of beacons that are set up at known locations. Low cost beacons have been created from Bluetooth headsets, powered USB hubs and cooking foil, the latter used to reduce the footprint of the cells to allow for finer grain positioning [79].
Bluetooth uses the unlicensed industrial, scientific and medical radio band of 2.4 GHz (ISM) to manage carrier contention. It utilises two key schemes both based on the clock of the device taking the role of master within the piconet, which ticks at 312.5μs intervals

- Slot-based protocol; the master device transmits on even slots and receives packets from slave devices in odd slots. Packets are allowed to be 1, 3 or 5

[1] When two devices come into range they can form a communications link.

slots in length, but the start of the packet communication always conforms to the even/odd rule.

- Frequency Hopping Spread Spectrum; this is a process of rapid switching between radio frequency channels in a pseudo-random sequence. Bluetooth breaks the available spectrum into 79 channels (in the majority of countries), and channels are selected based on the sequence defined by the Master device's device address and clock value.

RSSI is the predominant metric used to determine the position for Bluetooth positioning systems, and the simplest model is where the Bluetooth beacon with the highest RSSI is selected, and location is reported as a proximity to the cell [46, Ch. 13]. Lateration is generally approached by measuring RSSI from a number of beacons and calculating distance based on path loss formulas [78], [80]. Scene Analysis in the form of RSSI fingerprinting can be used to determine the position of a target. However, because Bluetooth is a mobile ad-hoc network, the RSSI fingerprints are subject to significant change and need to be made more robust using probabilistic algorithms [81].

Wang et al. [78] summarise the difficulties using other methods such as Angle of Arrival (low-cost Bluetooth devices don't have antenna arrays) and time of Arrival (no time synchronisation in Bluetooth standard) based on the constraints of the Bluetooth standard.

Evaluation

Criteria	Rating	Description
Accuracy	2-5 meters	Accuracy reported for Bluetooth is generally between 2-5 meters [46, Ch. 3], [78], although as noted it can take up to 10 seconds to generate the information required by the discovery process to position the target.
Precision	N/R	Not reported
Complexity	Low-Medium	The components that make up a Bluetooth locating network are in general commodity items. There is a dedicated infrastructure that needs to be deployed and mapped at the beginning of the process, but in general the Bluetooth beacons are maintenance-free once deployed.
Scalability	Medium	Bluetooth has limited range and therefore infrastructure needs to be deployed every 15-20 meters to achieve the accuracy highlighted.
Robustness	Medium	The key challenges for using Bluetooth for positioning are the length of time it can take to discover devices and enquiry, which can take up to 10 seconds [59, Ch. 11], the robustness of this process, and the reliability of the RSSI value, which is vendor specified and can vary based on interface. It should be noted that Bluetooth LE should address the discovery issue and supports advertiser-scanner topologies over a reduced set of channels [82]. Advertisements can be broadcast at intervals between 20ms and 10.28 seconds depending on the application, and scanners can be configured either to periodically or constantly scan. The other important difference is that the advertisement packet can contain useful data such as Transmitted power, and RSSI, as well as the device identity [73, Ch. 13.2].
Cost	Low	Bluetooth is a mature standard-based technology with a low-power footprint.

Wi-Fi

WiFi is at the time of writing the most prevalent method for determining location indoors, with providers such as Google, Apple (with the recent purchase of WiFiSlam), Skyhook, Navizon, Ekahau, Qubulus and Indoo.rs all offering WiFi-based indoor positioning products. The use of WiFi signals is attractive, as the vast majority of smartphones have WiFi capabilities and WiFi signals are now ubiquitous in both private and public spaces.

Commercial Products: See Qualbus blog for a current list of WiFi based solutions [83].

Use within Elder Care Domain: Chandrasekharapuram et al. proposed a solution to track elderly/patient location within the home using WiFi Fingerprinting. This solution appears to pre-date the majority of other WiFi development, which has subsequently seen a number of commercial offerings made available [84]. There are a number of Healthcare sector-related solutions, such as Aeroscout, that specialise in tracking staff and patients using WiFi tags [85].

Classification

Taxonomy	User Participation	Sensor Infrastructure	Technology	Technique
Classification	Active/Passive	Infrastructure Reuse	Electromagnetic Radiation – Radio Waves	Proximity Lateration Scene Analysis

Overview

Targets typically carry a WiFi-enabled device (e.g. Mobile Phone) or tag (e.g. ekahau WiFi Tags). In addition, a smaller set of research has been completed using the interference a human body has on WiFi signals to create Device Free Passive positioning systems [86]–[88].

One of the key benefits of WiFi positioning solutions is that they are built to utilise the existing WiFi networks deployed in public and private buildings. There are two key system topologies, including a Client-based topology, which reuses the WiFi and processing capabilities inherent in modern smart phones to determine the position based on the WiFi signals that are being received by the mobile station. Alternatively, the network-based topology uses the WiFi signal information collected from base stations to determine the position of a target using a centralised location server.

Wireless LANs utilise the 2.4 GHz[2] unlicensed ISM radio bands. The network topology of a Wireless LAN is made up from Basic Service Sets (BSS), which are collections of nodes that can communicate with each other in the Service Area defined by the radio coverage of each of the nodes. Basic Service Sets can either be Independent (Ad-hoc), used to create peer-peer networks for a short period of time, or Infrastructure BSS, which use Access Points to manage all communications within Basic Service Set. The simplest technique to employ is based on proximity, where the target's location is associated with the location of the infrastructure node with the

[2] Some versions of the 802.11 standards allow the use of 5 GHz radio band

strongest Received Signal Strength (RSS) [59]. Trilateration can be used once the distance of the target from the WiFi infrastructure nodes has been established. Distances can be estimated by using path loss models and Received Signal Strength [89] Time of Arrival [90].

Evaluation

Criteria	Rating	Description
Accuracy	1-5m	WiFi-based Indoor Positioning Systems have a reported accuracy of 1-5m [28], [59]. Note: 5m is considered to be the cut-off point for being able to support in room positioning
Precision	50%	The accuracy reported for WiFi-based systems is around 50% for the high-end accuracy figure and 95% for the lower accuracy figure [28], [59].
Complexity	Low	WiFi solutions can be deployed over the top of existing architecture; for fingerprinting or landmark-based models additional training activities need to be undertaken as part of the solution deployment.
Scalability	Medium-High	Client-based architectures scale both in terms of the number of devices supported and the area that can be covered. Devices do not need to be attached to a network to use it to determine a location.
Robustness	Medium	There are two main issues that affect the robustness of WiFi solutions. The first is that path fade models which use RSSI do not always provide an accurate distance, due to external environmental effects such as multipath fading and aliasing. The second is that RSSI fingerprinting models need to deal with dynamic environments where the scene analysis for a particular location can change with the addition of new access points, or even just the number of people in the location at any one point in time.
Cost	Low	WiFi solutions can be deployed without any additional investment in hardware. The Network Interface Cards present in most handheld devices are capable of reading RSSI values, and this, coupled with the ubiquitous WiFi access points, mean that this is a cost-effective method of indoor positioning for both commercial and private properties.

Indoor Positioning Technology Selection

A summary of the findings from the survey is presented below: -

Technology	Accuracy	Precision	Complexity	Scalability	Robustness	Cost	User Participation	Sensor Infrastructure	Technology	Technique
Inertial Sensors	0.6-1.5 meters	0.95	Low	Low	Low	Low	Active	Infrastructure-less	Inertial	Dead Reckoning
Computer Vision (Active)	<1cm – 30cm	Not Reported	Medium	High	Low	Low (Industrial applications High)	Active	Infrastructure-less	Optical	Scene Analysis
Computer Vision (Passive)	<1cm – <1m	Not reported	Medium-High	High	Low	Low (although Industrial applications can be High)	Passive	Dedicated Infrastructure	Optical	Scene Analysis & Angulation
Infrared	<1m - Room Level	Not Reported	Medium-High	Low	Medium	Low	Passive	Dedicated Infrastructure	Electromagnetic Radiation - Infrared	Proximity/ Angulation
RFID	<1m – 3m	Not reported	Low-Medium	High	High	Low	Active	Dedicated Infrastructure	Electromagnetic Radiation – Radio Waves	Proximity Lateration Angulation Scene Analysis
Bluetooth	2-5 meters	N/R	Low-Medium	Medium	Medium	Low	Active	Dedicated Infrastructure	Electromagnetic Radiation – Radio Waves	Proximity Lateration Scene Analysis
WiFi	1-5m	0.5	Low	Medium-High	Medium	Low	Active/Passive	Infrastructure Reuse	Electromagnetic Radiation – Radio Waves	Proximity Lateration Scene Analysis

The information gathered for each of the technologies was then qualitatively evaluated against the requirements described in Part II using a Pugh Matrix [91]. The weightings for the identified criteria were derived from the consultations with the various health care professionals and the subsequent literature review. It should be noted, however, that they represent the author's own views.

A summary of the analysis is shown in the table below:

Requirement Id	Criteria (Weight)	Inertial Sensors	Computer Vision (Passive)	Infrared (Thermopile Arrays)	RFID	Bluetooth	WiFi (Passive)
F.01	**Sub-Room Accuracy (+)**	+	++	o	o	-	-
F.02	**System must not require action from User (++)**	--	++	++	--	-	++
F.03	**Identification of Stationary Targets (o)**	+	+	o	+	o	o
F.05	**Support for Multiple Targets (o)**	--	++	o	++	+	-
NF.01	**Real Time Reporting (o)**	o	+	+	++	+	+
NF.02	**Cost of Technology Deployment (+)**	+	o	+	o	+	o
NF.07	**Retrofit of Sensors into Existing Homes (+)**	++	o	o	o	+	+
NF.08	**Acceptability of Sensors (++)**	-	--	+	-	o	+
	Rank	**6**	**3**	**1**	**5**	**4**	**2**

Key {-- → 1, - → 2, o → 3, + → 4, ++ → 5}

The three passive solutions of Computer Vision, WiFi, and Infrared achieved similar scores. Device Free Passive localisation-using WiFi was marked down on support for Multiple Targets, as this had not been achieved in the papers reviewed [88]. Computer Vision scores highly on the functional areas but suffers from a lack of acceptability to care users and Public Sector Health Professionals, as cameras are viewed as a significant invasion of privacy.
Infrared Thermopile arrays, cheap low-resolution sensors, which, like Passive Infrared sensors can be retrofitted into existing properties with relative ease, emerged as a well-balanced trade-off between functional and non-functional constraints. The sensors work without the need for ambient light and therefore can function at night, require no Care User actions, and can be deployed in all areas of the house.

These Thermopile arrays form the basis for the technology used in the rest of this paper.

Part IV: Indoor Positioning System Design

Related research questions:

- *How can the Indoor Positioning System be used to determine the location of a person within a building?*

This section provides an overview of the design of the Indoor Positioning System developed as part of this project. It is structured as follows:

- **Solution Architecture**: Provides an overview of the key components and interfaces involved in the solution and its placement in relation to the Context Aware Telecare Applications (which as noted are outside the scope of this work).
- **Component Design**: This section provides some background theory and design overview for each of the components identified in the Solution Context

Solution Architecture

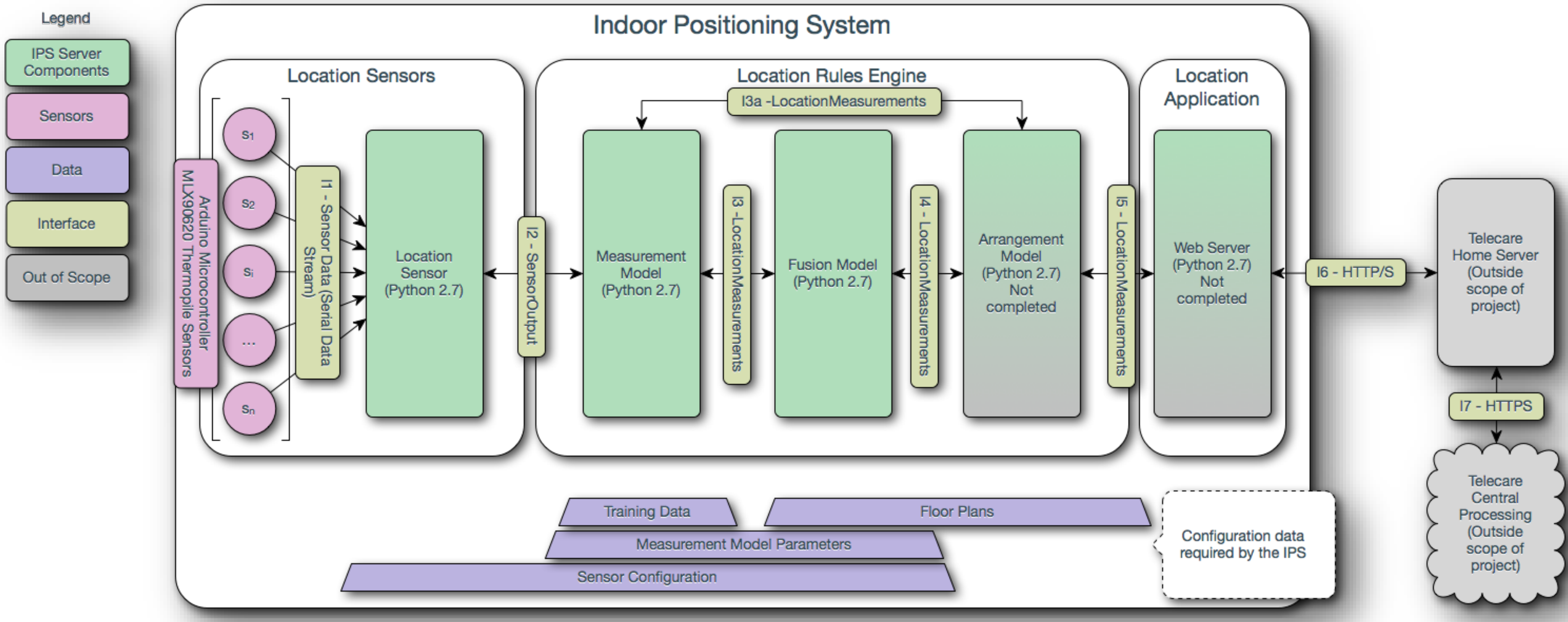


Figure 1 Solution Architecture Diagram

The Indoor Positioning System design proposed as part of this project is based on the three following layers [25], [28], [29]:

- **Location Sensors Layer:** This layer has two key components: -
    - The physical location sensors that for this project will be developed using thermopile arrays. The Location Sensor Layer defines the Hardware and Firmware required to make the sensors work. This hardware and firmware allow the sensors detect temperature differences in the environment and pass this the observed information over a simple serial connection using JSON [92] as the serialisation format.
    - The design of a software representation of the Location Sensors. This layer is responsible for the collection and encapsulation of sensor output that is passed to the upper layers of the Indoor Positioning system.
    - Key interfaces in this layer are: -
        - I1 – Sensor Data which is streamed over a serial interface from the individual sensors to the Location Sensor software in the IPS server
        - I2 – SensorOutput – python objects which represent the sensors readings are passed to the Location Rules Engine
- **Location Rules Engine:** This Software layer is responsible for a number of key activities:
    - turning the Sensor Output from the Sensor Layer into Location ***Measurements.***
    - the ***Fusion*** of multiple location measurements into a single location.
    - the ***Arrangement*** of location events into reference co-ordinates.
    - Key interfaces in this layer are: -
        - I2 – SensorOutput – See above
        - I3 – AngularMeasurement; Python objects representing the angular location measurement for objects which have been detected is passed from the Measurement Model to the Fusion Model.
        - I3a – AngularMeasurement: The angular location measurements are passed to the Arrangement Model for storing and presentation to the Location Application domain
        - I4 – Positioning Location Measurements calculated by the Fusion Model measurement model are passed to the Arrangement layer for presentation to external systems
        - I5 – The various Location Measurements are stored by the Arrangement Model and presented relative a frame of reference on demand to the Location Application Layer.
- **Location Application Layer:** This layer is responsible for the ***Presentation*** of location information to the Telecare applications, for incorporation into a wider context-aware application and support for ***Configuration*** of the application. It provides access to location history and can be configured to notify the target applications, based on events that occur in the notification layer. The key interfaces from this layer are HTTP Restful Web services serialised using HAL/JSON [93].

Component Design

Location Sensors – Physical Sensors

Thermal Radiation, Thermocouples and Thermopiles.

The atoms which materials are composed of are in motion, and this motion causes collisions and bonding to occur within the material. The transfer of internal energy from an object to its surroundings caused by this motion is in the form of electromagnetic waves, and when the electromagnetic waves are detected as heat or light it is called Thermal Radiation [94, Ch. 1], [95].
The wavelength with the highest power that is emitted by a body is a function of the body's temperature and can be calculated using Wien's law [52]

$$\lambda_m = \frac{2898\mu m°K}{T} \qquad \text{(IV-1)}$$

The maximum emittance for human skin at a temperature of 34ºC or 307ºK is 9.44μm, which falls into the long-wave infrared division. The temperatures relevant for indoor positioning, between 0ºC and 70ºC, all lie within this long-wave infrared division which is suitable for thermal imaging [52], [95].

Thermocouples are simple sensors comprised of a two dissimilar materials joined near to a measurement point and a reference point. The electromotive force generated by a Thermocouple is proportional to the temperature difference at the two reference points and is given by Seebeck's law [96].

$$E_{AB} = (S_{AB})(\Delta T) \qquad \text{(IV-2)}$$

Where E_{AB} is the electromotive force measured in Volts, S_{AB} is the Seebeck coefficient, and ΔT is temperature difference of the Hot and Cold junction.

Historically several thermocouples were connected in series to increase the size of the electromagnetic force and thus increase the sensitivity of the sensor; these large sensors were literally piles of thermocouples and hence the name Thermopile. Semi-conductor technology has allowed this cumbersome and expensive process to be reduced in size and cost, thus making thermopiles an feasible sensor to be used outside of the laboratory [97].

The formula for calculating the theoretical temperature reported by a thermopile pixel has been adapted from the work done by Troost in his thesis '*Presence detection and activity recognition using low-resolution passive IR sensors'* [98]: -

$$T_p(u,v) = \frac{\sum_{i=1}^{N} T_{obj}\,(i)\left[A_{obj}(i) \cap A_{pixel}(u,v) \cap \left(\vartheta(i)\right)^C\right]}{A_{pixcel}} \qquad \text{(IV-3)}$$

Where $A_{obj}(i)$ is the area of the polygon presented to the sensor by the object, $T_{obj}\ (i)$ is the temperature of the object and $A_{pixel}(u,v)$ is a polygon describing the pixel.

The occlusion polygon $\vartheta(i)$ can be calculated by creating the union of all the other polygons representing objects in in the current scene, which are closer to the sensor than the selected object.

$$\vartheta(i) = \bigcup_{j=1}^{i-1} A_{obj}(j) \tag{IV-4}$$

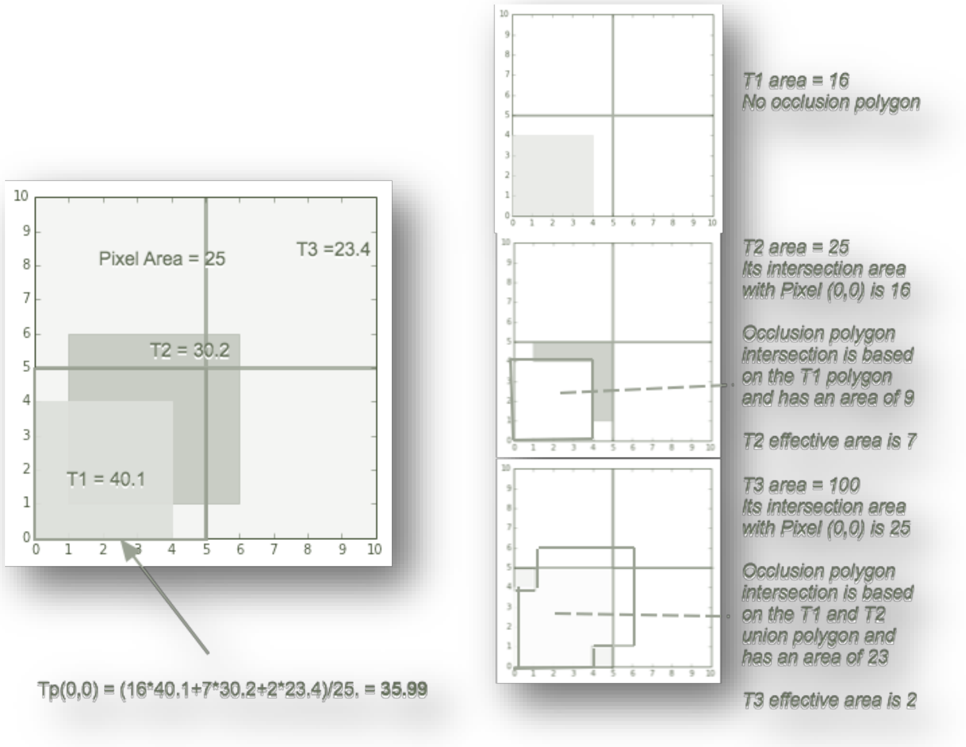


Figure 2 Pixel Temperature Calculation

Sensor Hardware Design

The following figure provides a schematic for the sensor hardware design[3]

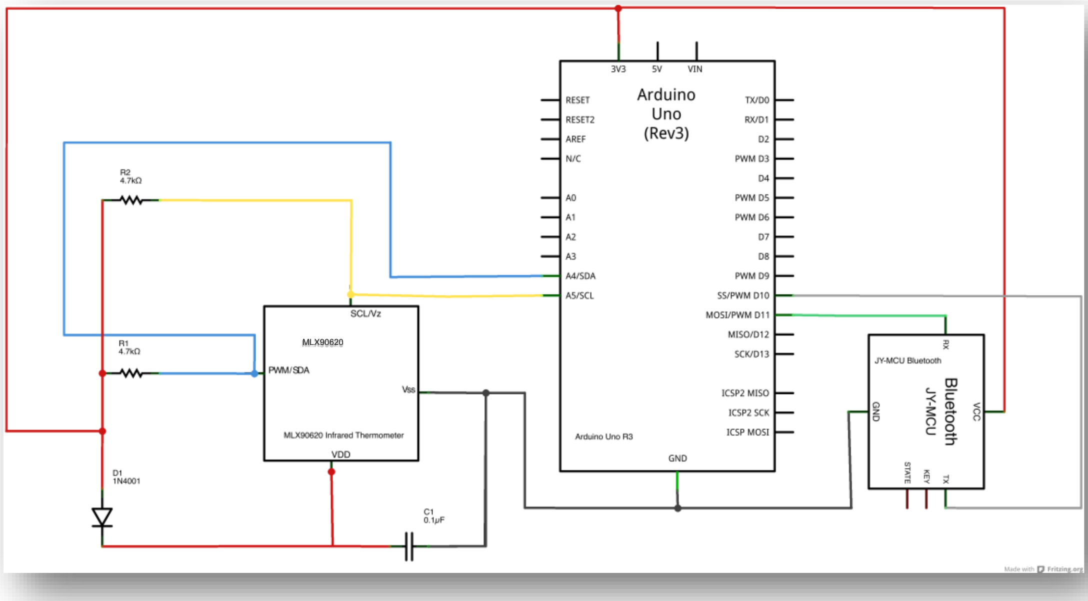


Figure 3 Thermal Sensor Electronic Circuit Design

The Sensors were constructed using the following key components:

- **MLX90620 Sensor**: Thermopile Sensor from Melexis used to read temperatures of remote objects.
- **Arduino Uno R3**: The Microcontroller responsible for retrieving the MLX90620 Sensor readings and serialising and sending them to the Location Rules Engine Server.
- **JY-MCU**: Low-cost Bluetooth Board used to create wireless serial connection to the Location Rules Engine.

The sensors' Serial-based output can be collected over a wired USB connection or wireless Bluetooth connection to the JY-MCU

[3] The wiring for the MLX90620 was informed by [99], [123].

MLX90620 Sensor Component

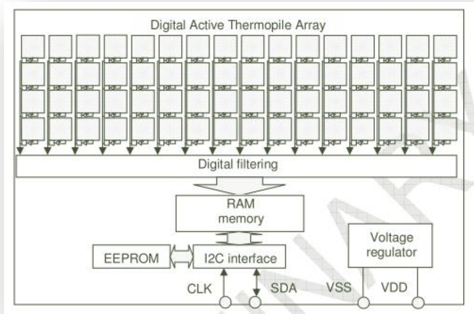


Figure 4 MLX90620 Block Diagram [99]

As noted this project uses the Melexis MLX90620 16x4 Thermopile Array. The sensor was selected as it provides a good trade-off in terms of cost, the number of elements in the array, the frame rate, power requirements, and availability in the UK [99].

It can detect temperatures between -40ºC and 85ºC and the model selected has a 60º Field of View [99]. The Melexis White Paper shows the sensor detecting multiple human beings at ranges greater than 8m [100].

The results from the 64-thermopile sensors are stored in the device RAM for querying over an I2C Serial Interface. The calibration information required to read accurate temperatures from the MLX90620 is stored in a separately addressable EEPROM.

Sensor Software Design

The Sensor Software has been written using Arduino C, and is based on the example code provided by Spark Fun electronics [101].

The MLX90620 Data Sheet [99] provides an overview of the principal of operation which is used to drive the functional steps of the algorithm implemented on the Arduino microcontroller:

Set Up

- Power on Reset (POR) is initiated and the process waits for 5ms.
- Calibration data is read from the EEPROM.
- Complete Error Checks on I2C Bus using 'Oscillator Trim Value'.
- The EEPROM POR/Brown Out Flag is set to true.

Main Loop

- Data is read from the RAM for the selected sensors (for this project all 64 sensors are read).
- The ambient Temperature is calculated.
- The Temperature for each sensor is calculated using the calibration data retrieved from the EEPROM and the current ambient Temperature. (This calculation ensures that errors generated by thermal gradient across the thermocouples and electronic noise is corrected.)

The Main Loop is repeated and the POR/Brown Out Flag is detected every 2 seconds. If it is marked as False the refresh rate is reapplied to the Main Loop and the process continues.

The firmware produces output over the Arduino Serial interface once every 8th of a second. The output is formatted using JSON and has the following structure *{ "Ta":Number, "To":[Number*64]}.*

Where Ta is the ambient temperature and To is the readings from the sensor array, as per the Sensor data sheet, the position of the Thermopile Sensor can be determined from the To array using the formula

$$Pix(\mathrm{i}, j) = To[\, i + 4j] \qquad \text{(IV-5)}$$

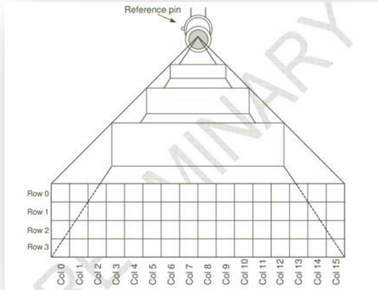


Figure 5 MLX90620 Thermal Array Configuration [99]

Location Sensors – Software Layer

The Location Sensor layer encapsulates the physical sensors and provides Sensor Output to the upper layers of the Indoor Positioning System.
It is responsible for making serial connections (over USB or Bluetooth) to the sensor hardware, managing the collection, processing, and formatting of sensor output.

Software Design

The sensor layer has been implemented in Python 2.6 on a Mac OSX operating system. The class model for the Location Sensor layer has been derived from the Semantic Sensor Network Ontology around the Stimulus-Sensor-Observation design pattern [102] and the domain meta-model define by Al Mamum et al. [103].

Class Model

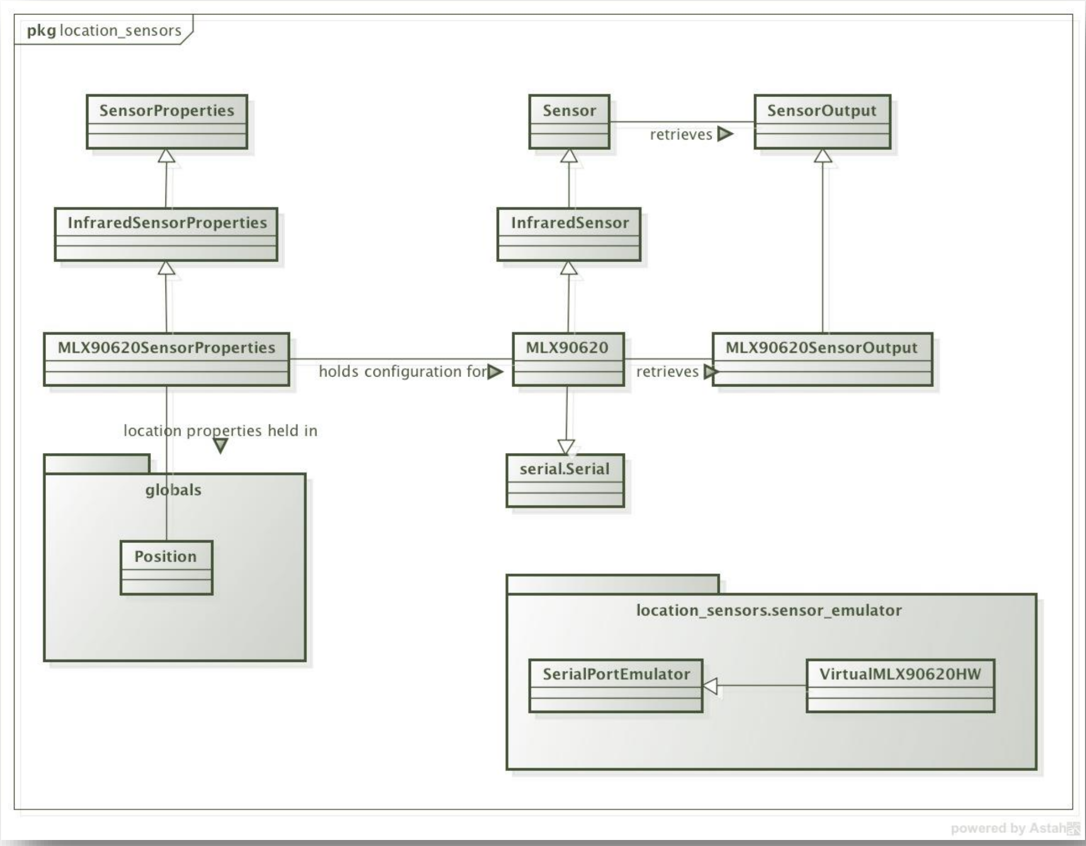


Figure 6 Location Sensors Class Model

The core objects are MLX90620, MLX90620SensorProperties, and MLX90620SensorOutput. The MLX90620 object is responsible for collecting the sensor output, using the data connection information held in the SensorProperties class.

The layer also includes a hardware emulator to facilitate testing of the IPS system without the need for installing physical devices. This virtual hardware class opens a serial connection by creating a tty file buffer in the form '/dev/ttys00' on the Mac OSX platform, and then uses stored sensor readings to write the tty file at the same rate as the MLX90620 sensors.

See the Interaction Model section below, for details of the major methods and properties.

Interaction Model

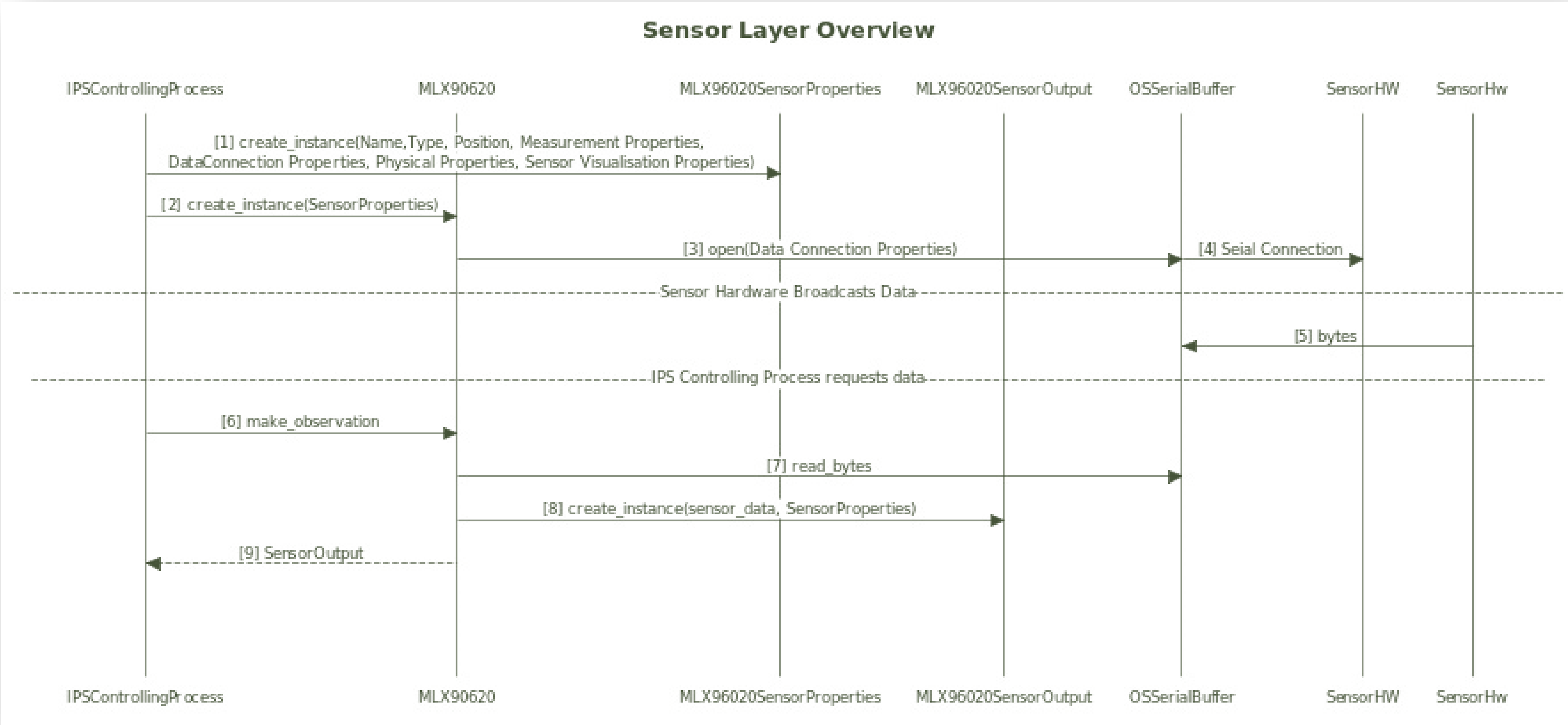


Figure 7 Location Sensors Sequence Diagram

The sequence diagram above provides a summary of the key processes that occur in the sensor layer.

- **Step 1:** The controlling process creates an instance of the MLX90620SensorProperties object holding the configuration, for an MLX90620 sensor this includes the following key attributes:
  - Name – ID of the sensor within the IPS system
  - Location – the co-ordinates, heading, and reference frame for the position of the sensor
  - Connection Information - including Serial Port Name and Time Out
  - Sensor Information – Thermopile array size and shape, sensor effective range, and field of view

  The MLX90620SensorProperties object on instantiation creates the geometric properties for the sensor, including the sensing area boundary. For an MLX90620 this is defined by the field of view (*ø*), sensor range (*r*), sensor position (*x,y*), and sensor heading (*h*), and the resulting sensing area is a circle sector. The key geometric properties of the sensor are highlighted in the figure below. The sensing area is stored as a polygon within the SensorProperties object.

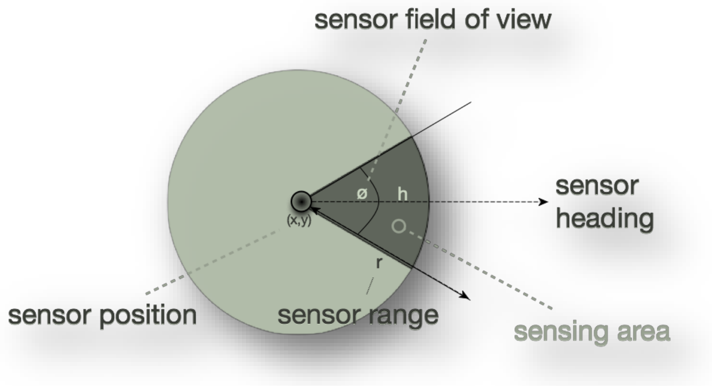


Figure 8 Sensor Geometric Properties

- **Step 2:** The controlling process creates a Sensor object (in the case of this project an instance of the MLX90620 class) passing the Sensor Configuration to it.
- **Step 3/4:** Using the Connection Information in the sensor configuration the object opens a serial connection to the physical sensor on the Mac OSX, which is a tty file interface - e.g. *'/dev/tty.Node1-DevB'*. This connection opens the serial interface to the sensor, and the tty file acts as a buffer for the bytes streamed over the serial interface
- **Step 5:** The MLX90620 sensor continually broadcasts temperature readings over the serial interface in the format as described in the previous section, e.g. *{ "Ta":22.51, "To":[25.32,23.92,21.64,22.83,24.90,22.76,22.27,22.23,23.69,21.41,21.41,22.27,24.49,22.35,21.91,21.81,26.74,27.90,26.12,25.65,28.40,27.56,26.66,26.34,26.78,26.13,26.85,27.02,26.39,26.73,26.51,26.20,27.11,27.71,27.09,26.91,26.82,26.46,26.79,27.31,26.87,26.88,27.25,27.02,28.05,26.94,27.73,27.51,29.84,32.56,31.06,26.87,49.50,54.52,42.13,27.81,46.43,49.13,36.60,25.53,25.66,25.38,24.92,21.41]}*

- **Step 6/7:** The request from the controlling process to make an observation triggers the class to retrieve the sensor output from the Serial buffer.
  Note, the sensor class can be configured to flush the buffer first, to ensure the latest temperature is read.
- **Step 8/9:** The temperature readings are parsed to ensure correct formatting and that all the data for a reading has been retrieved (this is done by validating the JSON object) and the validated readings are used with the sensor properties to create a SensorOutput object. The SensorOutput object can be used to present the data in various formats including:
  - **Flat array:** The data can be returned as a flat array, arranged as per the original data provided from the sensor.
  - **Shaped array:** The data can be returned aligned with the shape of the physical sensor, as defined in equation (IV-5)
  - **Interpolated array:** The shaped temperature data is well suited to interpolation, due to the way Thermopile outputs reflect the stimulus in the environment - i.e. the temperature of the array is the average temperature of all the objects which fall into the area covered by the cell.

  The figure on the next page provides an overview of the different views of the sensor data available from the SensorOutput object, as well as an overview of the method used to calculate them.

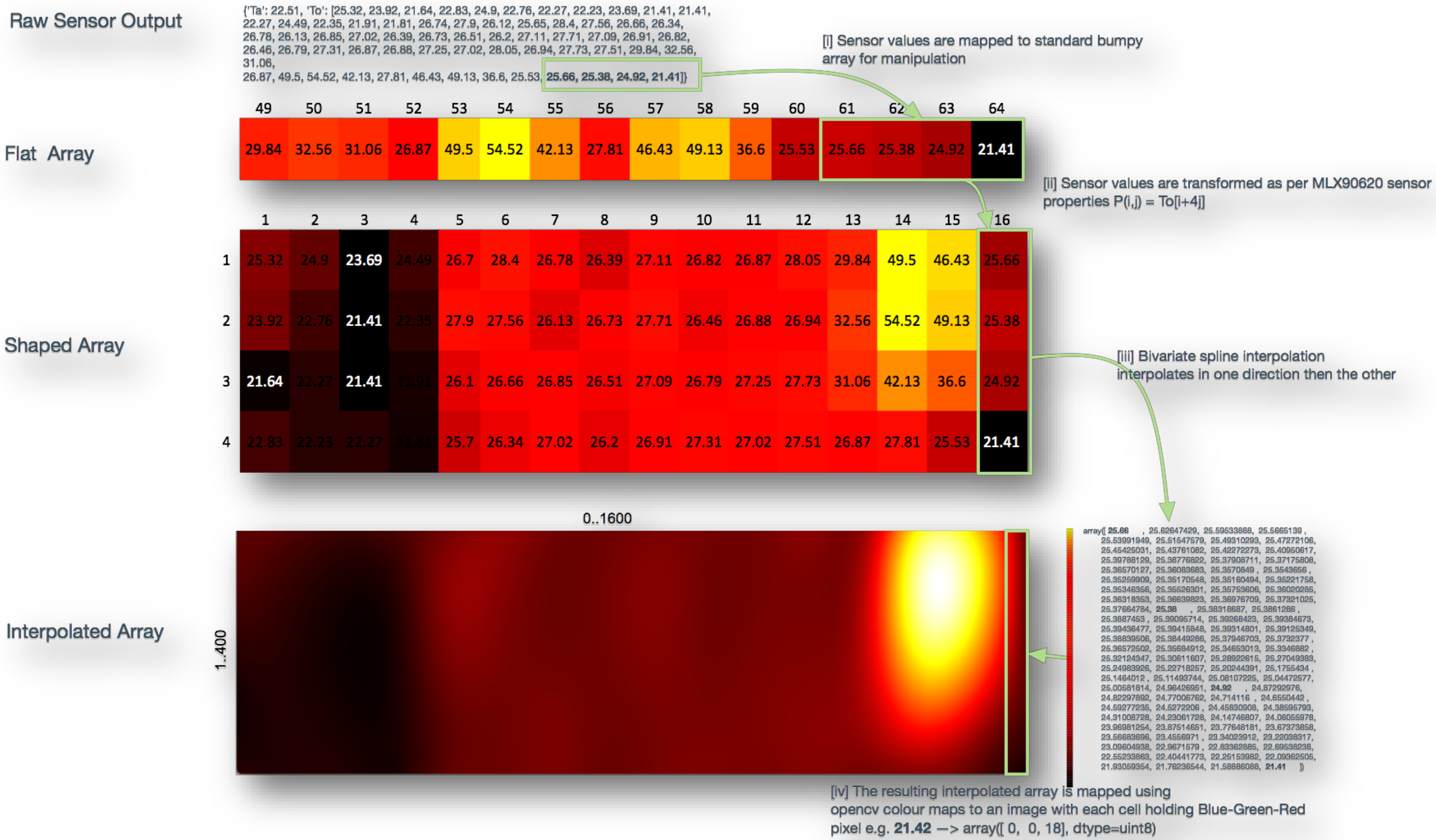


Figure 9 Sensor Output Visualisation

Location Rules Engine – Measurement Model

The Location Rules Engine has been implemented in Python 2.6 on a Mac OSX operating system.

The measurement model takes the sensor output generated by the Infrared sensors and turns it into a location measurement. As discussed in Part III, the two key Location Techniques available to Infrared-based positioning systems are Angulation and Proximity.

Proximity Measurements are the simpler of the two Location Techniques applicable to infrared sensors - if the sensor detects an object we can infer that the object must be in the sensing area of that sensor (defined by the location, range, and field of view of the sensor). The sensor's properties can then be used to provide information about the location of the object.

In addition, due to the physical nature of the Thermopile arrays it is possible to deduce the Angle of Arrival of the temperature readings, and thus calculate a line through the sensor and the object, and infer that the object must be somewhere along this line within the sensing area.

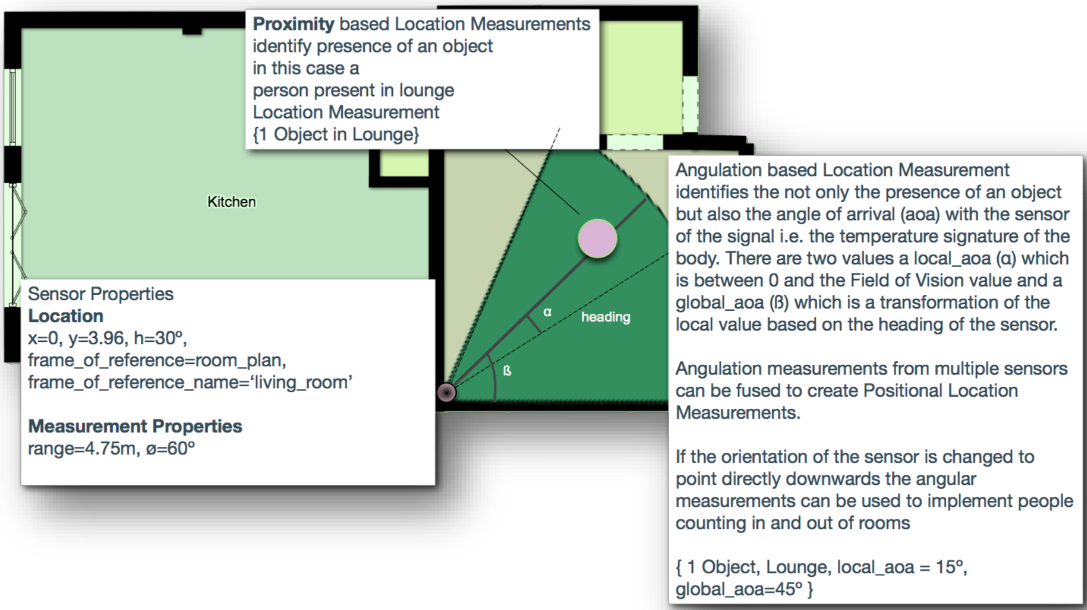


Figure 10 Location Measurements with Infrared Sensors

If the sensors are orientated appropriately (i.e. on the ceiling facing directly down), the angular measurement generated by the sensors can be used at Choke Points [59, Ch. 8,9] to facilitate People Counting [51, p. people–counting] in and out of building portals (e.g. doors).

Thermopile Array Measurement Model Theory

The theory used in this chapter is adapted from the excellent MSc Thesis by M. Troost and the subsequent reviewed paper issued by Ignacio et al. [98], [104].

The measurement model postulates that the temperatures detected by the thermopile sensor array cells are independent and identically distributed random variables. Therefore an object with a temperature varying between T_0 and T_1 can be identified from the background temperature readings using Bayesian probabilistic algorithms, which is similar to the Occupancy Grid Map approaches used in robotics [105]–[109]. This probabilistic function represents the mapping from the measurement space $V = \mathbb{R}^N$ to the decision space $D = \mathbb{R}^K$ [98, Ch. 6.2], [108].

$$f: V \rightarrow D \qquad \text{(IV-6)}$$

The function used in this paper preserves the dimensions of the measurement space i.e. $N = K$, and the function can be represented as:

$$z = [t_1, \dots t_N] \in V: f(t_i) = P(o|t_i) \qquad \text{(IV-7)}$$

Where each member of D represents the probability that the cell in the array is occupied, based on the temperature reading presented by the sensor.

Given that an object is present or not we can rewrite (IV-7) using Bayes Theorem and the law of total probability to get:

$$P(o|t_i) = \frac{P(t_i|O)P(o)}{P(t_i|O)P(o) + P(t_i|\bar{O})P(\bar{o})} \qquad \text{(IV-8)}$$

Derivation of P(ti|o)

Troost proposed a discrete Probability Mass Function to describe the probability of reading a temperature, given an object with a temperature range [T_{min}, T_{max}] is present, and the equation is used here without alteration; bw is the bin width used with the discrete function
[98, Ch. 6.2].

$$F(t_i|o) = \begin{cases} 0, & t_i < T_{min} \\ \frac{t_i - T_{min}}{T_{max} - T_{min}}, & T_{min} \leq t_i \leq T_{max} \\ 1, & t_i > T_{max} \end{cases} \qquad \text{(IV-9)}$$

$$P'(t_i|o) = F\left(t_i + \frac{bw}{2} \middle| o\right) - F\left(t_i - \frac{bw}{2} \middle| o\right) \qquad \text{(IV-10)}$$

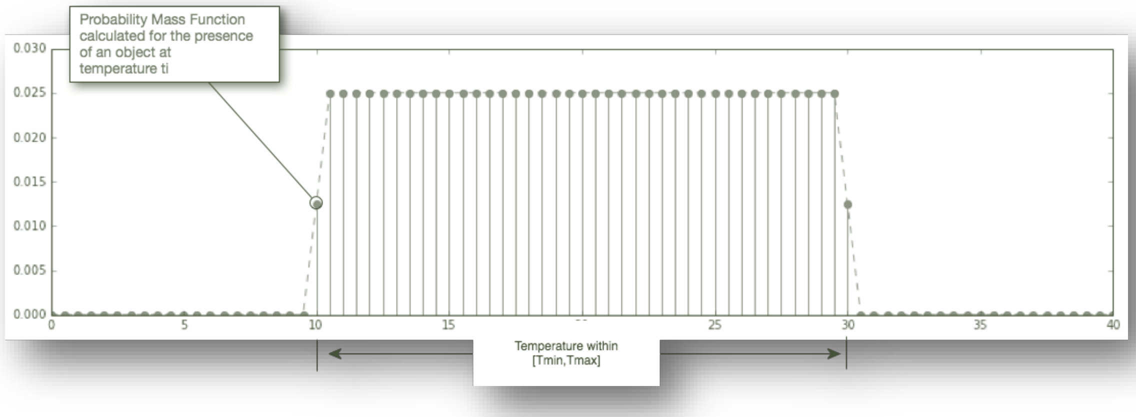


Figure 11 Example of P'(t_i|o) for [T_{min}=10,T_{max}=30] and bw=0.5

Derivation of P(ti | ō)

The derivation of the probability of receiving a particular temperature based on an object not being present is based on the observation that temperature readings produced by a thermopile array are normally distributed based on the temperature reading of background objects in the sensing area. The following diagram shows the distribution of temperature readings based on running the sensor in an unoccupied room for 2 minutes.

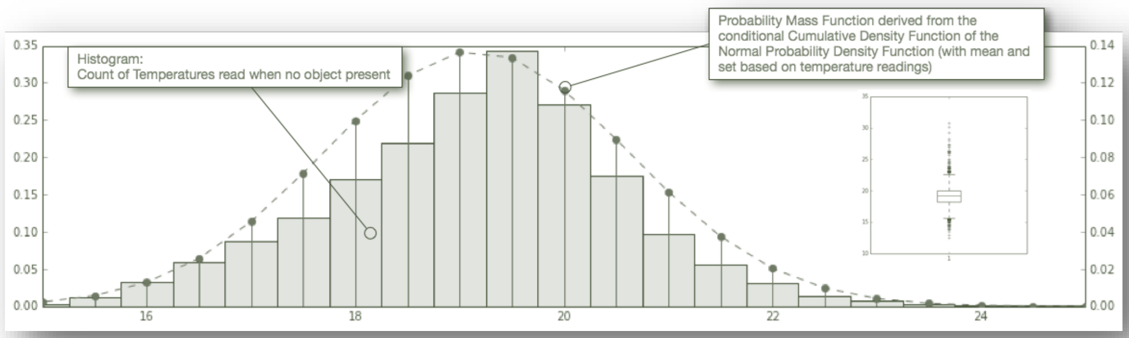


Figure 12 Fit of Normal Distribution to Background Temperature Readings

When first experimenting with the sensors, there appeared to be a reasonable fit for applying a Gaussian distribution to the background temperature distribution , which was in line with previous investigations into similar capabilities by Troost et al. Based on this assumption the Measurement model uses a Gaussian distribution using the mean and variance for the sensed pixel temperatures to determine the probability of getting a temperature in a cell if the object is not present. See Wikipedia article on Gaussian distribution for details[110].

Resulting P(ti | ō) Function

The resulting function $P(o|t_i)$ (IV-8) is sensitive to the probability that an object is not present. The example results show the results for $P(\bar{o})$ = [0, 0.2, 0.4, 0.6, 0.8, 1] a sensor temperature mean of 19.8 and a body with [T_{min}, T_{max}] = [10,30]; The Measurement model uses $P(\bar{o})$ which is provided as part of the model set up; This parameter is then updated based on the proportion of cells which are deemed to be unoccupied while the sensor is running.

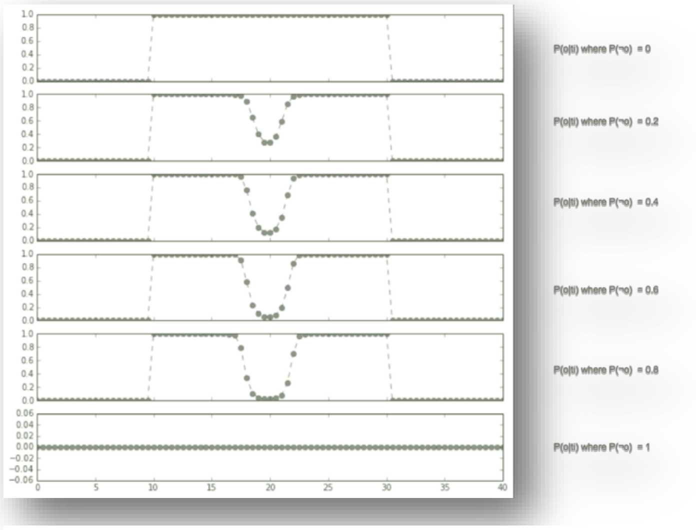


Figure 13 Example Results for $P(o|t_i)$

Notes:

- It was not possible to use the ambient temperature, as per Troost et al., as this was significantly different and started to diverge from the average temperature readings as the sensor housing heated during use. Instead, a running average and variance for the sensed pixel temperatures is maintained throughout the operation of the sensor.
- Towards the end of the project it was noted that larger sets of training temperature data do not always follow a Gaussian distribution, as within the majority of the individual cells the distribution of readings does remain normal. The effect this has on the accuracy of the sensors will be reviewed during the experimentation phase.

Occupancy Grids & Log Odds

Occupancy grids have long been used as an approach to solve Simultaneous Location and Mapping (SLAM) problems in robotics. They represent the environment as a grid of independent variables, each of which reflect the probability that the part of the environment they represent is occupied [106]. They have also been used for Pedestrian detection using infrared sensors by Linzmeier et al. [108].

Here, rather than using the occupancy grid to map an environment, we use the technique to determine if there is an object within a defined temperature range occupying the field of view of for the sensor - i.e. the sensor itself becomes the grid. The common approach of using a recursive Bayes rule via log odds is used [106]. Odds are simply the ration between the probability of a something happening and it's complement.

$$od(A) = \frac{p(A)}{p(\neg A)} \qquad \text{(IV-11)}$$

The formula for calculating the log odds for a cell at time tm (l_i^{tm}) is given as: [98], [106], [108]

$$l_i^{tm} = \log\frac{P(o_i|t_i^{tm})}{1-P(o_i|t_i^{tm})} + \log\frac{1-P(o_i)}{P(o_i)} + l_i^{tm-1} \qquad \text{(IV-12)}$$

Note: The range for log odds is (-∞, ∞), and it is useful to bound the log odds to a defined range to prevent long response times if the cell has been occupied or unoccupied for significant amount of time.

See figure on the next page for an example of the occupancy calculations using the Sensor Data introduced in the previous Location Sensors section.

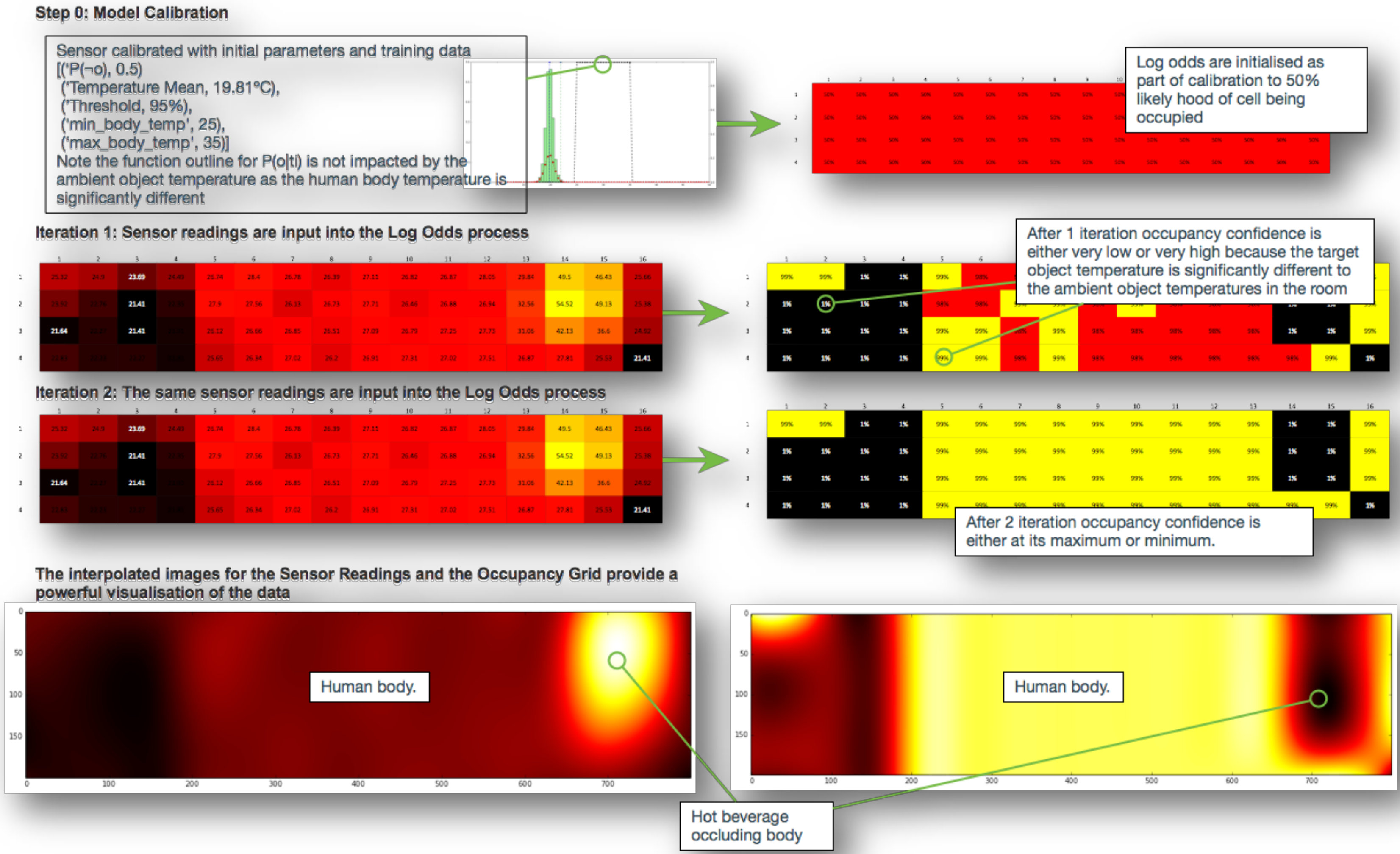


Figure 14 Example Grid Occupancy Calculations

Object Tracking and Angle of Arrival Calculations

The Measurement Model exploits the fact that the Thermopile Sensor Output can be treated as an image to identify objects and calculate the angle of arrival. The occupancy grid is manipulated using opencv [111] image manipulation libraries to extract polygon outlines of the regions of the sensor that are defined as occupied[4]. The bounding circles of the resulting polygons are inspected and any that overlap are merged into a single larger object.
To simplify the Fusion layer later, the final step is to single out the single largest object for tracking. The centres of these circles are used to determine the Angle of Arrival.

The Angle of Arrival is calculated using the following formula, where fov is the field of view for the sensor and scale is a scaling factor when processing the images:

$$AoA = \frac{fov}{2} - x.fov.scale \qquad \text{(IV-13)}$$

The figure below provides an example of the 'image' processing completed on the occupancy grid.

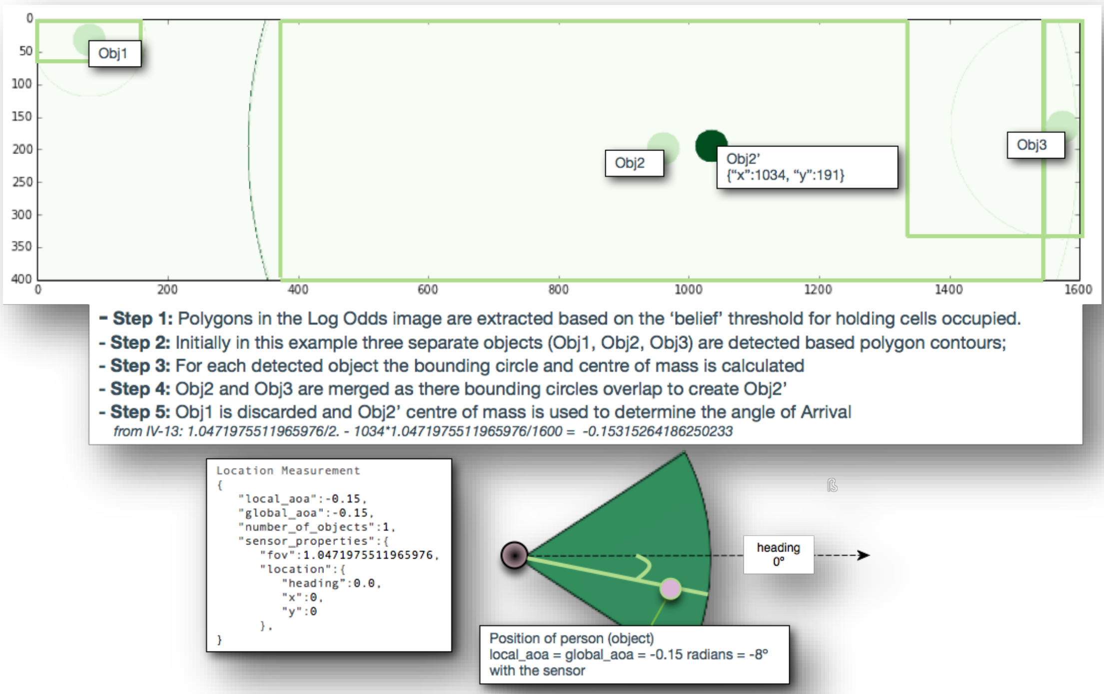


Figure 15 Object Tracking Matrix

[4] A cell is defined as occupied once its odds exceed a 'belief' threshold, which is set as part of the model instantiation.

Class Model

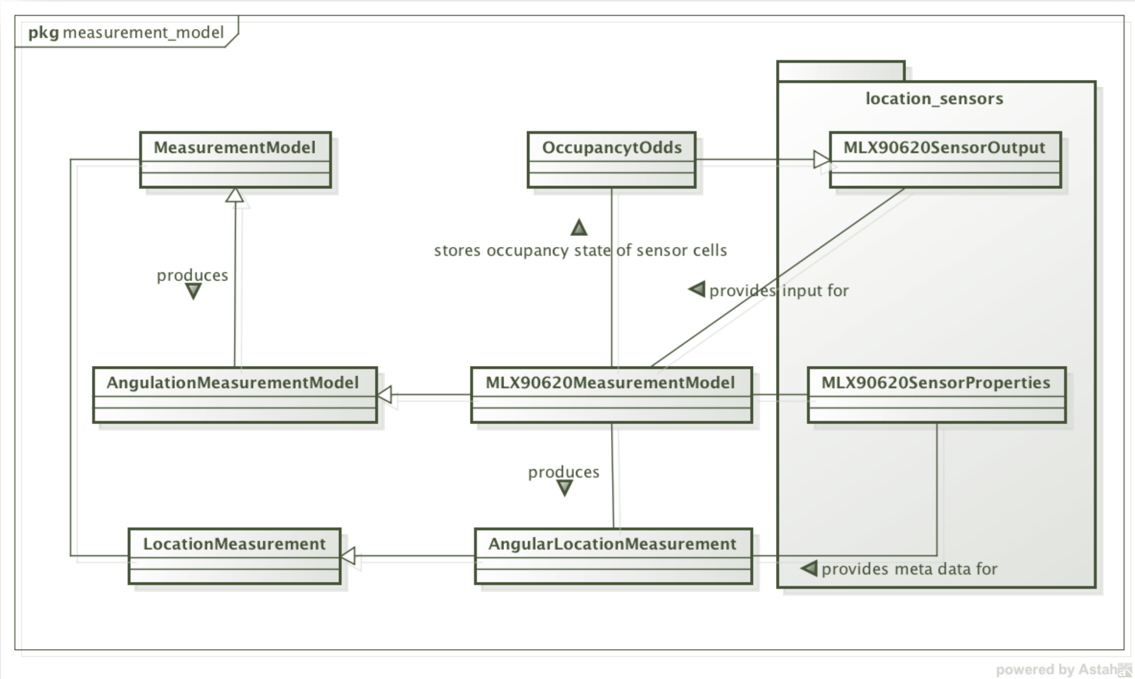


Figure 16 Measurement Model

The core class in the Measurement Layer is the MLX90620MeasurementModel. Its methods calculate the probability that an object (specifically in for this paper a person) is present and estimates the centre of mass of the detected person, and based on this information produces an Angular Location Measurement.

- **MLX90620MeasurementModel:** Measurement model designed specifically for the MLX90620 Infrared sensor key methods are:
  - calibrate_sensor_model: Creates the core information required to calculate the log odds of a sensor cell being occupied.
  - reset_prob_o_bar: The method allows for the P(ō) value to be reset to its originally provided value.
  - initialise_log_odds: This method facilitates a reset of the Log Odds matrix.
  - create_location_measurement: This core method facilitates the production of an AngularLocationMeasurement object based on the provided sensor data.
  - visualise_mode: This method provides an overview of the key probability statistics set up during the calibration process.
- **AngularLocationMeasurement:** A data structure object, it holds the Local Angel of Arrival and Sensor Information, including Location Information for the measurement. It is able to translate between local and global Angle of Arrival on demand.
- **OccupancyOdds:** This object stores the state of the occupancy grid for use by the measurement model.

Interaction Model

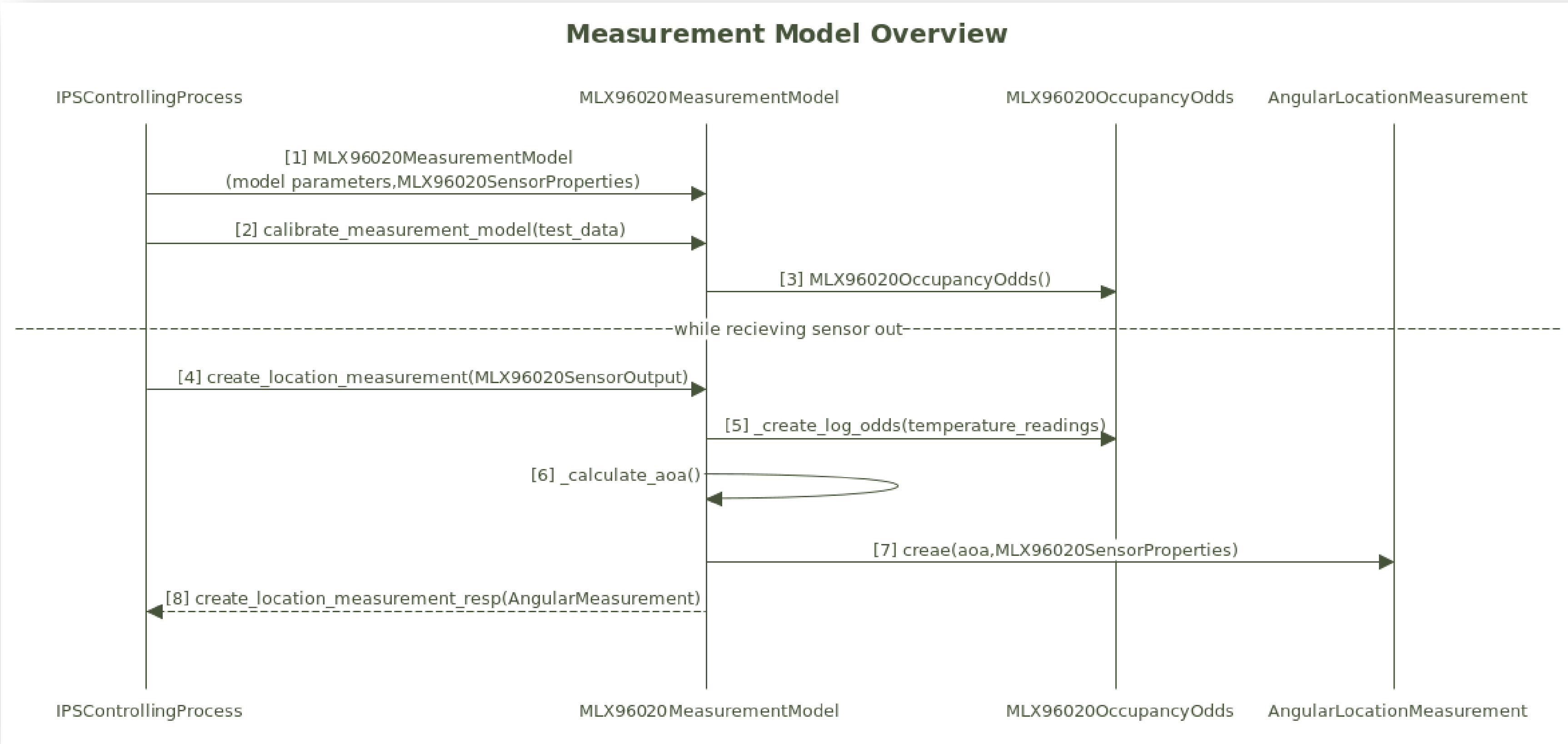


Figure 17 Measurement Model Interaction Model

Key steps for producing the Angular Location Measurement are highlighted below.

- **Step 1:** The Measurement Model's instantiated key parameters include:
  - **min_body_temp**: the minimum temperature of the object that is to be detected set to 25 based on empirical results and from the results and information published by Ng and Elert [112], [113].
  - **max_body_temp**: the maximum temperature of the object that is to be detected set to 35 based on same sources as above.
  - **training_data_file:** raw sensor data captured with no objects present, which allows the initial calibration of the sensor to be completed.
  - **object_prob_threshold**: The belief parameter that an object is present based on the log odds – currently set to 95% based empirical results.
  - **prob_o_bar:** Probability that an object is not present – initially set to 0.50 until data captured by the sensor is updated proportionally to the number of sensor cells classed as un-occupied. Note: cells are classed as unoccupied if the log odds for the cell are below $1 - \text{object\_prob\_threshold}$.
- **Step 2/3:** The sensor is calibrated using the initial parameters and training data, and the key output of this step is the calculation of the attributes needed to calculate the log odds for each sensor cell. Training data is loaded; temperature bins are created, and the log odds matrix is initiated.
- **Step 4-7:** The controlling process requests n location measurement to be made which triggers the log odds and angle of arrival processes described in the Thermopile Array Measurement Model Theory section.
- **Step 8:** The measurement model returns a location measurement to the calling process.

Location Rules Engine – Fusion Model

The Location Rules Engine Fusion Model has been implemented in Python 2.6 on a Mac OSX operating system.

The fusion model takes multiple location measurements and mergers them to improve accuracy. In this project, Angular Location Measurements produced for infrared sensor arrays in the Measurement Model layer are merged to produce a Positional Location Measurements.

The core underlying principle for this fusion model is Triangulation [114], whereby the position of an object is derived from the Angle of Arrival of the signal it produces at two or more known reference points. If the distance between two sensors is known (l) the position of the object can be inferred from the angle of incidence the object makes with the two sensors (α, β). Using the following formula:

$$d = \frac{l \sin(\alpha)\sin(\beta)}{\sin(\alpha+\beta)} \qquad \text{(IV-14)}$$

The following figure provides an example of the calculations required to infer the position of an object from two angular location measurements.

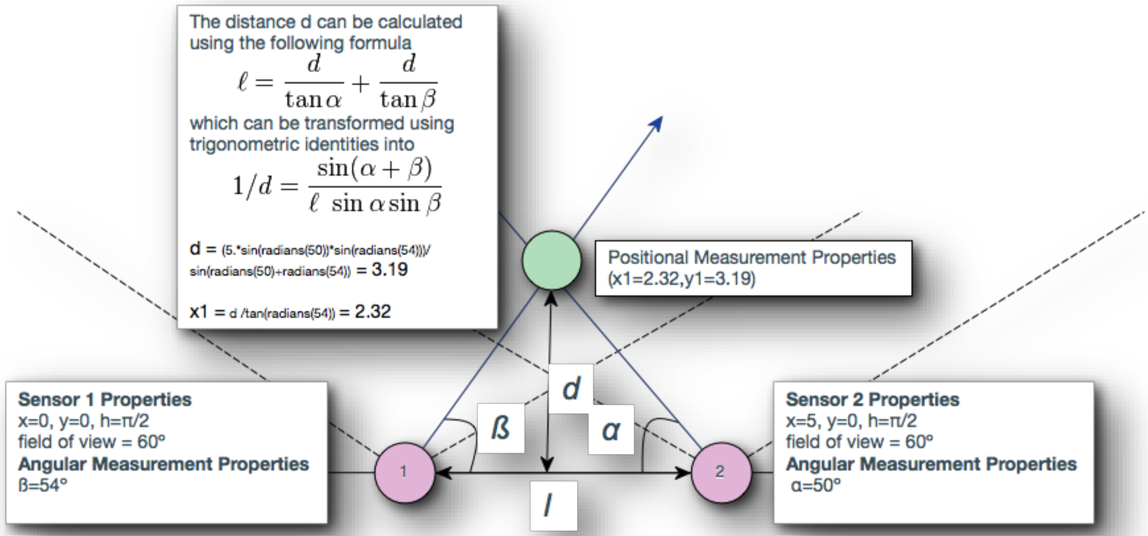


Figure 18 Deriving Positional Location Measurements by Angulation

The angulation approach has been used directly by Sayeef et al. [115]. Conversely to cope with problems such as tracking, occlusion and to improve the overall accuracy of the location measurements it is common in practice to use a form of Bayes filter [54].

Fusion Measurement Theory

Particle Filter

In the same fashion as the log odds methodology used to determine the Angular measurement in the Measurement Model section, a Bayes filter is applied to the various angular measurements to determine a belief about the position of tracked objects. This belief can be represented as:

$$bel\big(x_{t)}\big) = P(x_t|z_{1,..}z_t) \qquad \text{(IV-15)}$$

A number of filter options are available including Kalman Filter, Occupancy Grid (used in the Measurement Model Section) and Particle Filters [116].

Particle filters were selected as they tend to scale well for tracking, as they concentrate computational effort on areas of the state space with the highest probability that the object is present and can support a non-linear and non-Gaussian systems [116], [117].

Particle filters are a sequential Monte Carlo method, which uses discrete random measures to estimate probability distributions [118, Ch. 7] We create a random set of particles Np and associated weights (based on an importance sampling function):

$$\{x_i(t), w_i(t)\}; i = l, \dots N \qquad \text{(IV-16)}$$

The particles are samples from an unknown state space and the weights represent the fitness to the target distribution. The figure below shows in principle how the particles represent their suitability (weight) to represent a positional location, similar to that worked out trigonometrically above.

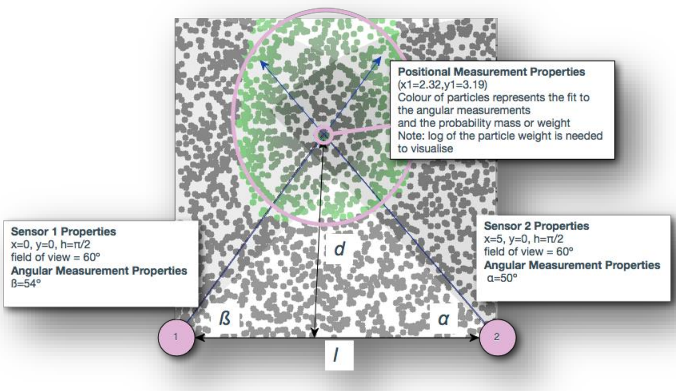


Figure 19 Particle Weights for Positional Measurement

The importance sampling function initially selected is a Gaussian distribution; this will be reviewed along with the sensor noise (distribution sigma) during the experimental stage of the project.

The Regularized Particle Filter [118, Ch. 7.5] is used with Jitter[5]. After the particles are initialised at random points in the target state space, the particle filter iterates through the following steps: -

- **Step t_1:** The particles are moved based on their speed and position and random jitters are applied to ensure that population of particles remain diverse
- **Step t_2:** The particles are resampled with a probability based on their weights i.e. those particles with a better fit have a larger probability of being reselected (see the Map Matching below for additional steps in this process)

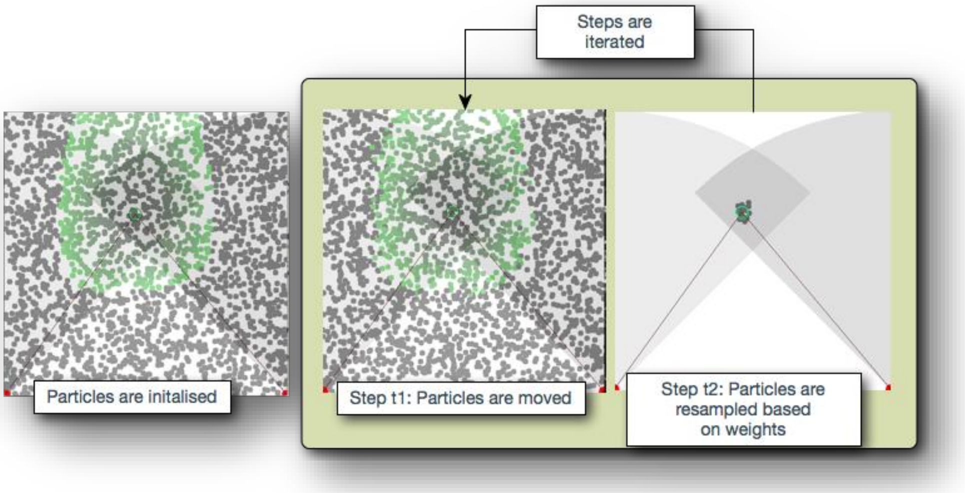


Figure 20 Particle Filter Iteration Steps

Map Matching

Prior knowledge of the locales spatial geometry can provide useful information when calculating the weights of the particles. For example, it is not possible for an object to be inside the walls of a building, and it is less probable that a particle inside the range of a sensor that has not detected any objects represents an accurate guess of the objects location.

The particle filter can be used in conjunction with a map of the location being monitored. Any particles that after the movement in **Step t_1**, which end up in an improbable location have their initial calculated weights reduced thus reducing the probability of the particle being resampled in **Step t_2**. The parameters used to manipulate the weight of these particles will be optimised during the experimental stage of the project.

To facilitate the incorporation of spatial data into the Fusion Measurement model a small script was written to extract key features such as floors, rooms and walls from a standard floor plan.

[5] Also know as roughening

The figure below outlines the basic steps taken to extract metadata about a building from the floor plan images. The steps included the use of opencv to analyse a standard floor plan, the extraction of key polygons such as walls and floors and finally storing the extracted features as geoJSON [119].
The stored data can be extracted and manipulated to provide a polygon that defines the useable portion of the floor or room plan.

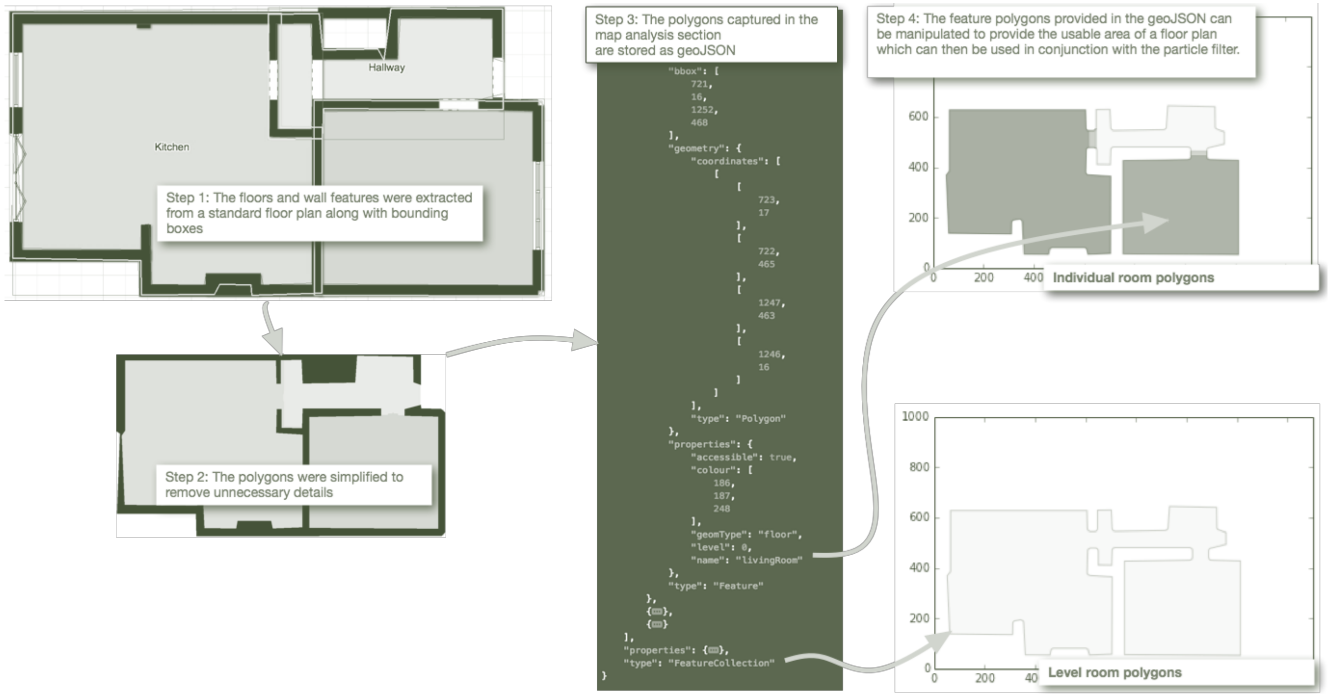


Figure 21 Floor Plan Analysis

Class Model

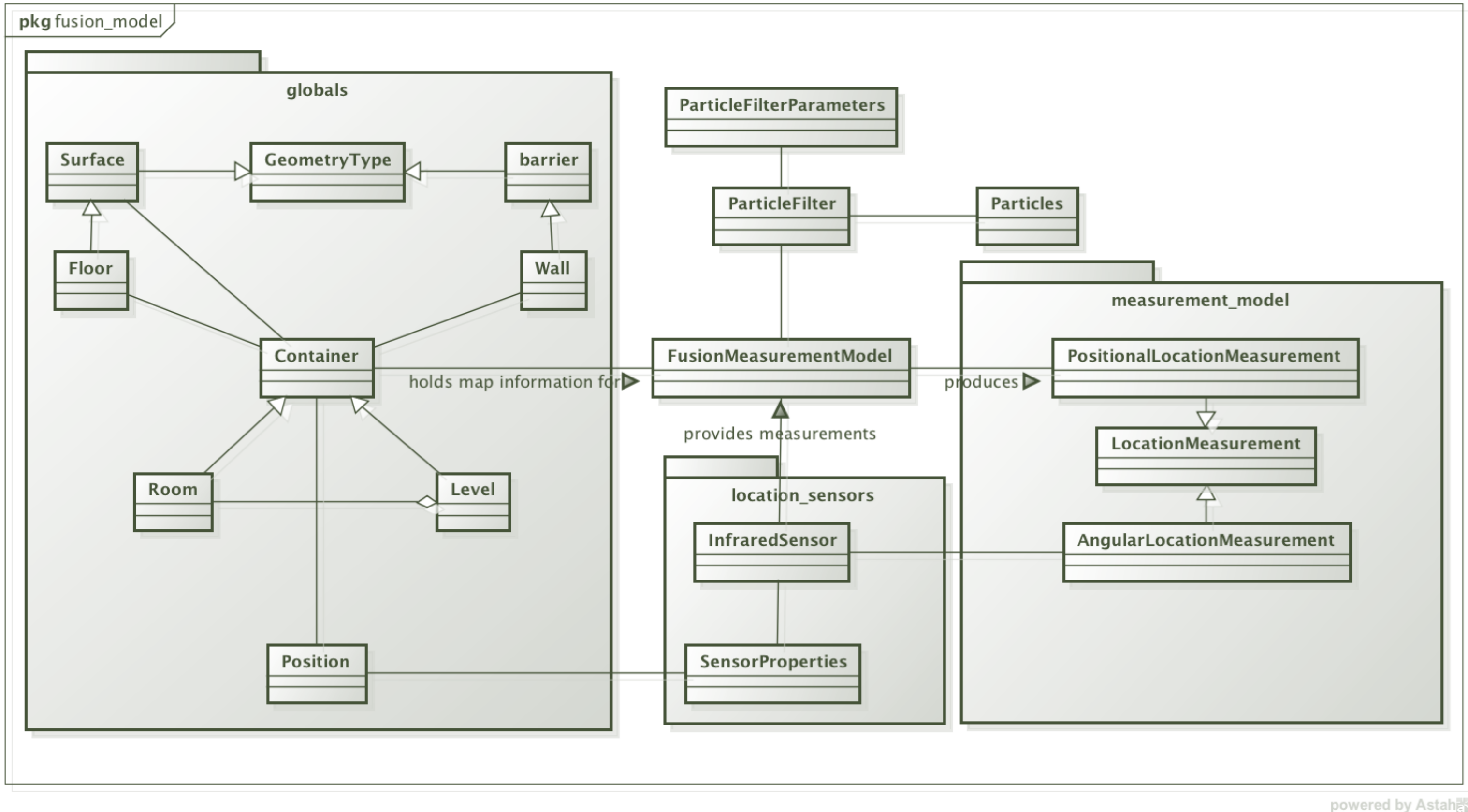


Figure 22 Fusion Measurement Model

The Fusion Measurement Model (FusionMeasurementModel) is the core class responsible for setting up the particle filter (ParticleFilter) with important configuration data such as; useable floor space, associated sensors and measurement noise.

The Fusion Measurement Model (FusionMeasurementModel) uses the angular location measurement (AngularLocationMeasurements) produced by the measurement model described in the previous section of this paper with the particle filter to produce a Cartesian location measurement (PositionalLocationMeasurement).

The main attributes and methods of the remaining classes are listed below: -

- **ParticleFilter:**
  Key parameters include
  - number_of_particles: the number of particles which will be used to represent the hidden position distribution
  - world_dimensions, world_usable_area: the map information used to inform the particle filter resampling method.
  - sensor_noise: the variation in the angular location measurements produced by the MLX90620 Infrared sensor

  Key methods include:
  - create_particles: A function which creates the initial distribution of particles
  - move_particles: which moves the particles and calculates new AnguarLocationMeasurements
  - resample_particles: this method evaluates the fitness of the particles and resamples them
- **Particle:** This object is used to represent individual particles, it has methods such as move, sense, calculate_weight that are controlled by the ParticleFilter.
  Note: It can also be used as a robot to simulate the particle filter results without the need for physical sensors being deployed
- **Container:** This class represents rooms, floor plans and buildings. When initialised it creates appropriate surfaces such as floor, walls and useable areas from the geoJSON provided as an argument during the instantiation process. It is based on the indoor semantic ontology summarised by Worboys [120]
- **Surface:** The surface class is used to represent floors, and useable areas of the floor plans. On instantiation the geoJSON objects are provided as arguments are processed and appropriate geometrical and object metadata created [120]
- **Barrier:** Barriers are used to represent in accessible areas of the floor plan in this project just walls have been considered. In similar manner to Surfaces the barrier on instantiation use the geoJSON provided as arguments to create appropriate geometrical and metadata [120]

Part V: Conclusions

This part of the paper provides a summary of the findings of the Project and is structured as follows:

- **Project Summary:** This section provides a general summary of the project findings and conclusions.
- **Project Objectives Evaluation**: Presents a review of the progress made towards meeting the project objectives set out in the extended project proposal[121].
- **Reflections and Further Work:** Highlights further work, either identified as part of the project proposal or discovered during the course of the project, which would merit further attention.

Project Summary

The aim of this project was to explore the criteria an Indoor Positioning System would need to meet in order to support a Telecare package, and then to develop a prototype Indoor Positioning System suitable for assisting the elderly to remain in their homes.

Part II Requirements

The project started with a broad review of the drivers and context for Telecare and Telehealth, including interviews with Senior Social Care Nurses and a Senior Manager from the private care sector. These interviews were supplemented with a review of the literature produced by the various telecare organisations, the government, and research and developments centres. All of these sources highlight significant interest from both the Private and Public Social Care sectors in the development of Technology to help support an increasing aging population to remain independent and engaged in the community [4].

Important ethical considerations when developing tracking technology for vulnerable people were identified, especially concerns over 'tagging' vulnerable adults. The solution selected attempts to balance the needs of privacy, autonomy, and safety by:

- Not requiring active participation of the care user, therefore avoiding any stigmatisation which can be attached to tagging and social alarms
- Avoiding the privacy issues associated with computer visions systems. It is not possible to identify targets using thermopile array sensors' low-resolution images, however the images can be used to detect position with the possibility of using the generated images to identify position.

The project reviewed future trends in telecare, identifying the likely convergences of Telecare and Telehealth, and the emergence of 3rd Generation telecare solutions based on open standards.

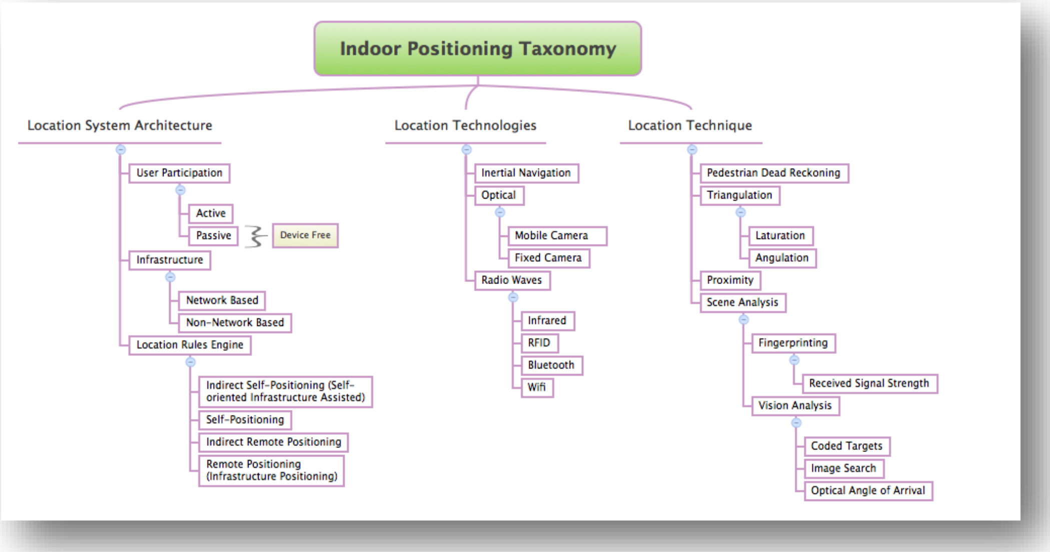
The role of Indoor Positioning applications as a core sub-component was identified and used to influence the system design [18], ensuring the Indoor Positioning System developed could be integrated into a wider Ambient Assisted Living application using open web standard.

The information gained from investigation was used to formulate a number of high-level constraints/requirements that an Indoor Positioning System for the Elderly in the home should comply with, including the need to be able to identify care users location at sub room level. Key use cases were identified for 2nd and 3rd Generation Telecare systems where Location is an important to the derivation context, and therefore action by the wider system including:

- Triggering the activation of lights when a care user starts moving around at night to help reduce the risk of falls [22].
- Monitoring Activities of Daily Living, e.g. Preparing Food, Sleeping, Hygiene [5].

Part III Technology Survey and Selection

The project then moved on to complete a review of available Indoor Positioning technologies and research. A classification system for Indoor Positioning Systems was developed and summarised in the following figure.



This taxonomy was used in conjunction with an evaluation framework adapted to address the requirements and constraints identified in the requirements documentation process from frameworks proposed by Liu and Darabi [30].

The review was organised by location technology, and a subset of available technologies was selected based on their prevalence in literature or relevance to the requirements highlighted in the earlier part of the project[6], the criteria considered were accuracy, precision (or repeatability), scalability, robustness, and cost

The information gathered for each of the technologies was then qualitatively evaluated against the requirements described in Part II of the paper, with Thermopile Arrays emerging as the technology of choice. A summary of the advantages and limitations of the choice of technology is presented below.

[6] A more complete review of technologies can be found in Mautz's Habilitation Thesis [41].

Advantages: Infrared Thermopile arrays are cheap low-resolution sensors, which, like Passive Infrared sensors, can be retrofitted into existing properties with relative ease. They allow sub room level positioning, have low energy requirements, don't invade privacy in the same way that a computer vision system might be perceived to, work without the need for ambient light and therefore can function at night, require no Care User actions, and can be deployed in all areas of the house.

Limitations: Infrared can be interfered with by changes in ambient temperature and ambient heat sources, such as lamps and heating, and objects such as polished aluminium with a low emissivity can generate infrared reflections creating false object detections. Also, like computer vision targets, objects can be occluded by other objects which are closer to the sensor, and objects which are too close together can lead to the two objects being classified as one due to the low resolution of the sensors [54], [98].

Part IV – Design & Build

The design and build phase of the project started with the drafting of an Indoor Positioning system context which would allow low-cost assimilation into a broader 3rd Generation Telecare system.

An Architectural design for the Indoor Positioning Server was proposed, based on a layered architecture approach adapted from the work completed by Deak, Gu and Hightower [25], [28], [29]. Restful Web services, which utilise design patterns proposed by Kelly [93], were proposed as an open interface which would allow rapid integration with different 3rd Generation Telecare Applications.

The design process then moved on to the procurement of Thermopile Sensors, and a number of suppliers were reviewed including Irisys, Heimann, Panasonic and Melexis. In the end the Melexis MLX90620 sensor was selected, based on availability in the UK and cost (the prototyped sensors cost around £60 in total) [99]. The basics of thermopile arrays and electrical engineering were researched in literature, industry white papers, various open source projects, and Arduino notice boards and product data sheets for MLX90620. [96], [97], [99], [100], [122], [123] .

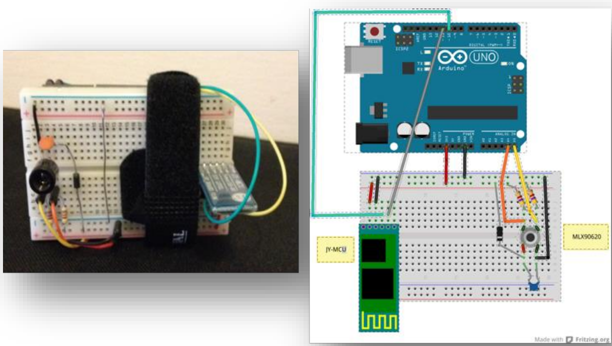


Figure 23 Example Prototype Sensor

A number of sensors were constructed using the Arduino microcontroller and JY-MCU Bluetooth Module, and an Arduino sketch was adapted from the code made available by Seidle [101] to facilitate a simple serial connection between the constructed sensors and the Indoor Positioning System.

The framework for an Indoor Positioning System, based on the architectural packages identified at the beginning of the design phase, was developed using Python 2.6 as a rapid prototyping tool. Various Software Engineering techniques and patterns were used, including Object Orientated Programming, and Layered Architecture and the Python PEP 8 Style guide [124] was followed during the development of the application.

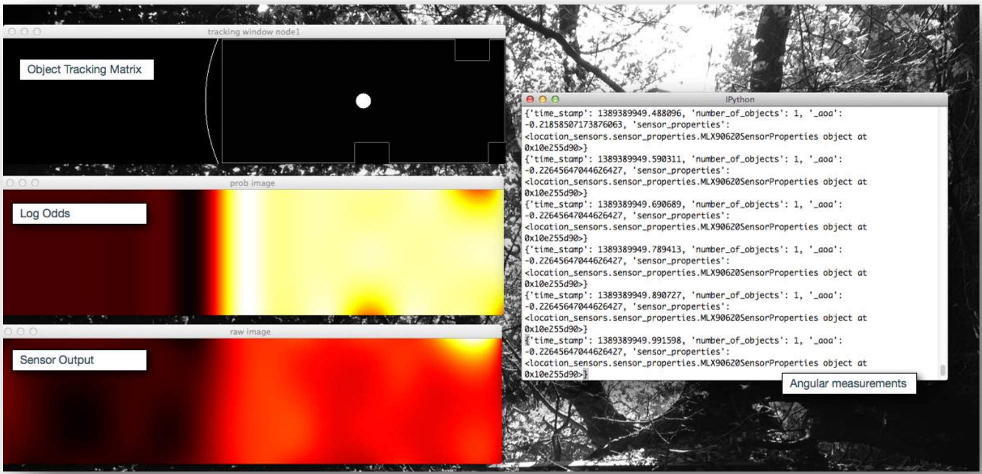


Figure 24 Real Time Object Identification and Visualisation

The Sensor and Location Rules layers (specifically the Measurement and Fusion models) of the application architecture were the development focus.
The Semantic Sensor Network working group's final report heavily influenced the application domain model, and it aligned well with the architectural proposal for the system.

Finally, a number of location techniques and algorithms were explored and implemented within the Location Rules Layers, including:

- Grid Occupancy & Log Odds [98], [105]–[109], [125].
- Computer Vision Object Identification and representation using contours, patches, and centroids [111].
- Particle filters.
- Map matching.

The resulting system is capable of passively calculating Proximity and Angular Location Measurements based on the output of the Thermopile arrays.
These coarse measurements can be fused together to create a more precise Positional Location Measurement, which can facilitate sub-room localisation within the home.

Project Objectives Evaluation

The research proposal for this project proposed a number of objectives, which should be met by the project. This section provides a review of the status of the core objectives for the project and highlights where further work is required.

- *Complete and document a critical review of Indoor Positioning System solutions - the review will include implementation and evaluation of prototypes for different location technologies and techniques.*
  Status: Complete
  The Part III of this report provides a substantial review of Indoor Positioning Systems, and proposes a framework for the categorisation and evaluation of the different technology options available.
- *Identify key constraints/requirements for a Home Indoor Positioning System to support Elder Care.*
  Status: Complete
  Part II of this report highlights the context and high level requirements which would need to be satisfied to produce an effective Home Indoor Positioning System which could then be incorporated into a 2nd/3rd Generation Telecare system.
- *Produce, design, and develop a Home Indoor Positioning System to assist the Elderly to remain in their home, based on requirements and constraints captured.*
  Status: Partially Complete
  Part IV of this report contains an overview of the design and development of a Home Indoor Positioning System
  Note: The design for the Arrangement Model layer has been proposed, but this part of the application has not been developed.
- *Assess the effectiveness of the developed Indoor Positioning System by Completing controlled experiments such as taking fixed paths through the home and assessing the accuracy of the Indoor Positioning System*
  Status: Outstanding
  A key section missing from this report is the Implementation Results section. This section should contain a discussion of the effectiveness of the developed Indoor Positioning System. The evaluation work will be completed and submitted as an addendum to this report.
- *Reviewing the accuracy against similar solutions identified as part of the literature review*.
  Status: Complete
  Part III of this report provides an overview of current research and products, along with the reported accuracies for the positioning systems which have been developed.

Conclusion and identification of future work

The project set out to understand how an Indoor Positioning System could be used to support Social Care, and to explore the techniques and technologies which could be used to implement such as system.

The project produced original work that whilst it does not cover new areas of knowledge, is incremental to information found in the existing literature.

- Part II: Provides a distillation of the broad challenges faced by Social Care, is enhanced with information available from the industry and from literature, and also from interviews with a number of senior Social Care professionals, to define the placement of Indoor Positioning in relation to this challenge, and it proposes a number of high level requirement and constraints.
- Part III: Provides an abridged view of a number of key Indoor Positioning technologies and proposes a taxonomy for classifying them as well as a framework for evaluation.
- Part IV: Builds on the theory explored in Part III, and while the techniques used to develop the Object identification model are basic and common practice in their respective source fields, the application of Computer Vision to thermopile array is novel.

Further Work

The following section provides an overview of the different areas which might be considered for further work:

- **Part II - Interaction Design:** The implementation of Indoor Positioning Systems and wider Telecare platforms needs useable and positive experience if it is deliver its promised benefits. It would therefore be advantageous to complete a Human Computer Interaction study to understand how elements such as system set up, maintenance, data collection and reporting should manifest themselves for care users, informal carers, and the members of the Social Care multidisciplinary team [126].
- **Part III – Indoor Mapping**: Representation of indoor space is a key element in a successful Indoor Positioning System. Different approaches have been proposed, including semantic and spatial, and these different approaches can be useful in presentation and communication of tracking information, but need further work to investigate how the floor plan might be represented [120].
- **Part III & IV Tracking** - Development of an Indoor Positioning System that can identify individuals in the home [86]. Further investigation into emerging technology like capacitive floor tiles, which have the potential to track and identify people passively [33].
- Alternatively, leveraging the likely convergence of Telehealth and Telecare technologies over the next few years with the fusion of an active Location Sensor layer with the existing passive one - a good technology choice for this would be the new low-energy Bluetooth standard [82].
- **Part IV Alternative Technology** – Development, implementation, and comparison of two or more location technologies to determine which is the best fit for the requirements identified - e.g. Computer Vision or Device Free Passive WiFi location sensor & measurement models could be developed.

- **Part IV –Development of Use Cases**: The application could be extended to include support for one or more of the Social Care use cases identified in Part II, which would require the Indoor Positioning System to be integrated into a context aware computing environment such Homer or OpenAAL [127], [128]
- **Part IV – Indoor Positioning System Enhancements:** There are a number of engineering areas which merit further work to enhance the existing design work, including:
    - *Location Sensors*: The application of Signal-processing techniques to the temperature data, to remove electrical noise and fluctuations from the data, while still tracking changes in the temperature of objects.
    - *Location Sensors*: The MLX90620 sensors allow for sleep mode, where if no objects are detected the power consumption can be reduced. This capability is not currently used and it would be interesting to explore how the power consumption of the unit could be optimised, as this would facilitate the cost-effective and potentially wireless installation of the sensors into existing properties.
    - *Location Sensors:* The current Serial Interface works well for demonstrations, although it would be beneficial to facilitate automatic discovery of sensors - approaches using such as using semantic web services have been proposed by Lanthaler et al. for the automatic discovery and integration of sensors [129].
    - *Location Rules Engine:* The fusion of multiple types of sensor, e.g. Ultrasound ranging device and the Thermopile areas, would be an appealing exercise to see how additional measurements could be used to improve the accuracy of the developed system.
    - *Location Rules Engine:* Development of a Indoor Positioning System that can support multiple persons in the home [86]. This would require object-tracking to be implemented in both the measurement and fusion layers and would result in some of the key requirements identified in Part II of the project being delivered.
    - *Location Rules Engine*: Configuration to allow the sensors' rotation to be modelled in 3 dimensions, as opposed to the current 2 dimensional orientations, which would facilitate the possibility of including people-counting and therefore room-level location measurements into the developed Indoor Positioning System.

(Word Count 17261)

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Appendix A - Terminology

Terms commonly used when describing positioning system are as follows:

- **Location vs. Position**: Location and Position are used interchangeably in this report, reflecting that they are largely synonyms. [20]
- **Types of Location**: The concept of location can be usefully broken down into the following subcategories[28], [130, Sec. 2.1]:
  - *Spatial Location*: In a navigation context positions are described using a Spatial Position based on a co-ordinate system (X,Y,Z), where each part of the vector fixes the position in a particular dimension. A co-ordinate system is identified by its origin, orientation, and scale. Global Spatial location requires a datum that defines the shape of the earth and the origin & orientation of the co-ordinate system and a projection which projects the 3 dimensional earth onto a 2 dimensional map. Spatial Location forms the basis for mapping of descriptive locations, e.g. (51.7505°N, 0.3275°W, 108M).
  - *Descriptive Location*: In everyday life location is described relative to a geographic or man-made object, (e.g. I am on platform 1 of the St Albans Railway Station). This descriptive location is based on defining a relationship between two or more people and/or objects and it enables people to orientate themselves and navigate the environment.
  - *Network Location*: In communication networks the location of a device in relation to the topology of the network is key for routing information, e.g. a Phone Number or an IP address. In wireless networks the location of a mobile station is defined relative to the base station it is connected to.
- **Target**: Target is used to denote the device, person, robot, or tag that the positioning system is trying to locate.
- **Ground Truth:** Ground Truth is the actual position of the Target using the Spatial Location system that the Location System is operating [20].

Appendix B – Social Care Interview Mind Maps

The information captured during the interviews with the Social Care professionals is presented as series of mind maps below, the first introduces the scope of the interviews; notes taken for each of the sections then follow this introduction.

Overview

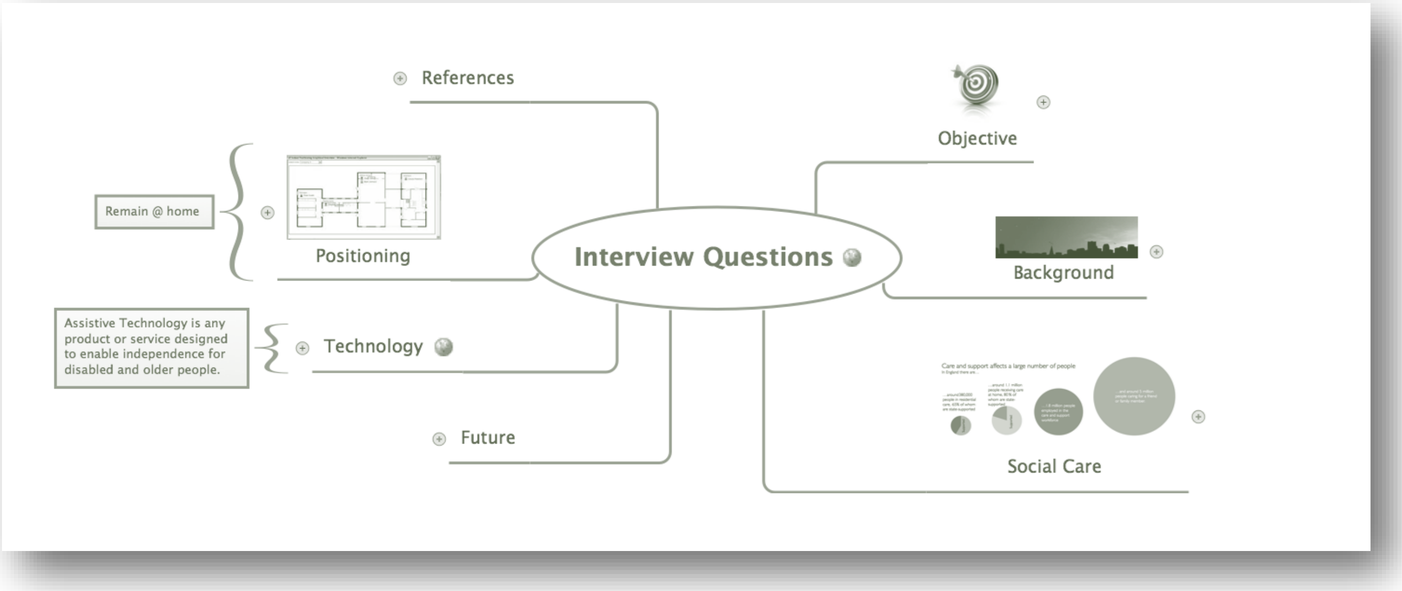

Figure 25 Interviews – Agenda Mind Map

The interviews started with my objectives for both the interview and the project. The background of each of the interviewees along with the technology used in their current roles was then discussed, followed by their views on the current challenges for Social Care. The interview moved on to cover the future and how technology might help address some of the Social Care challenges identified. The interview finished by capturing their thoughts on the usefulness of location information in the Social Care environment.

Background

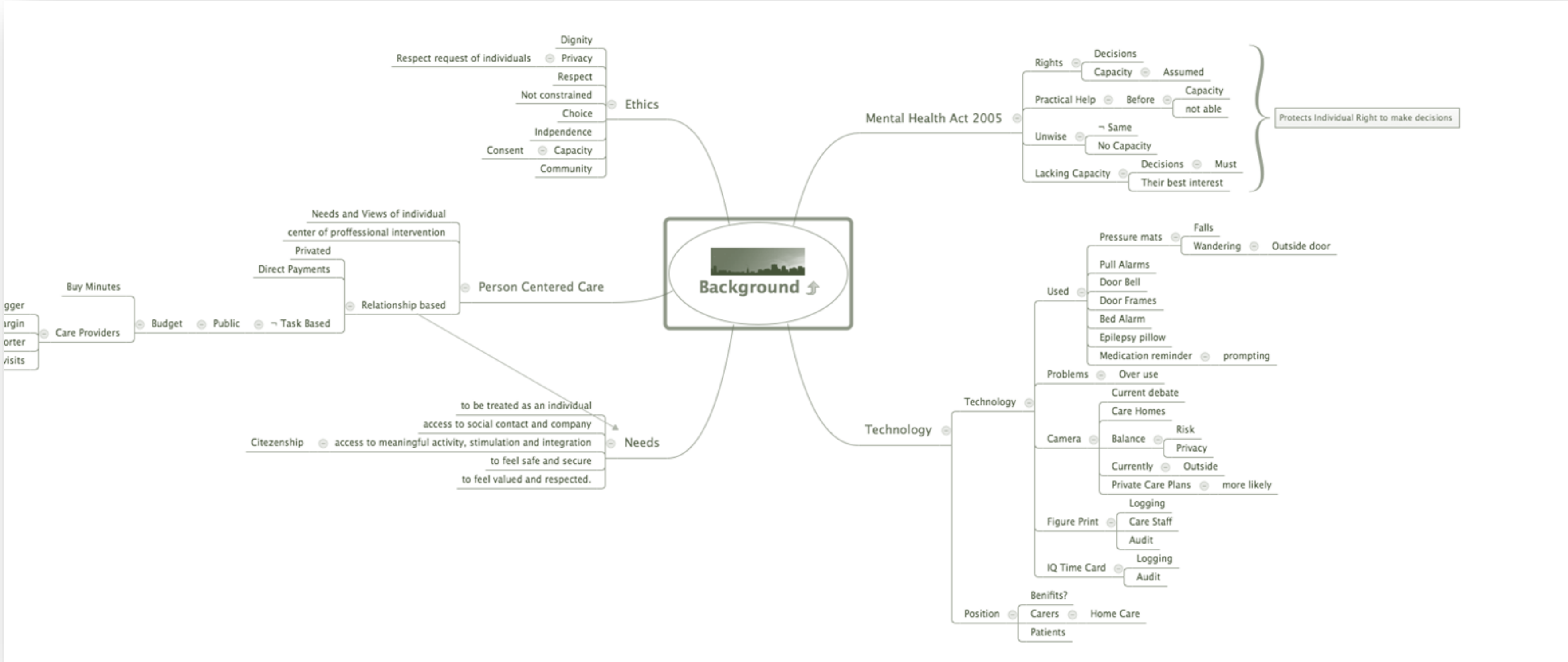

Figure 26 Interviews – Background Mind Map

This section of the interview covered a range of subjects from the Mental Health Act to the types of technology used within different Social Care environments. A passionate focus on users needs, dignity and the ethics involved in Social Care was consistent across all 3 interviews.

Social Care

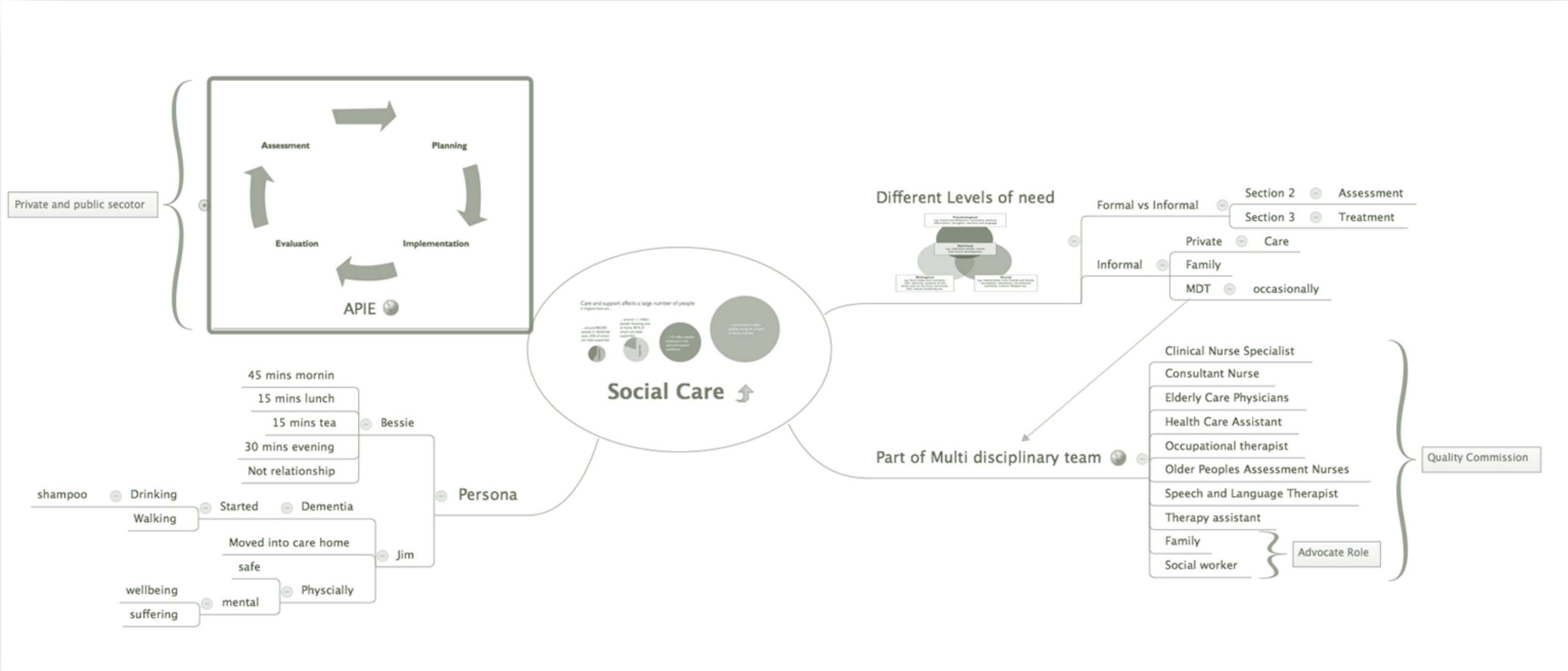

Figure 27 Interviews - Social Care Mind Map

The interviewees provided an overview of the Social Care system. An overview of the assessment process (APIE) that is used to determine the risks associated and formulate tailored care plans for users was provided. The problems caused by the current public sector system along with the impacts of an elder having to leave their own home to be placed into a care facility was explained with the use of personas.

The Future Trends and Technology

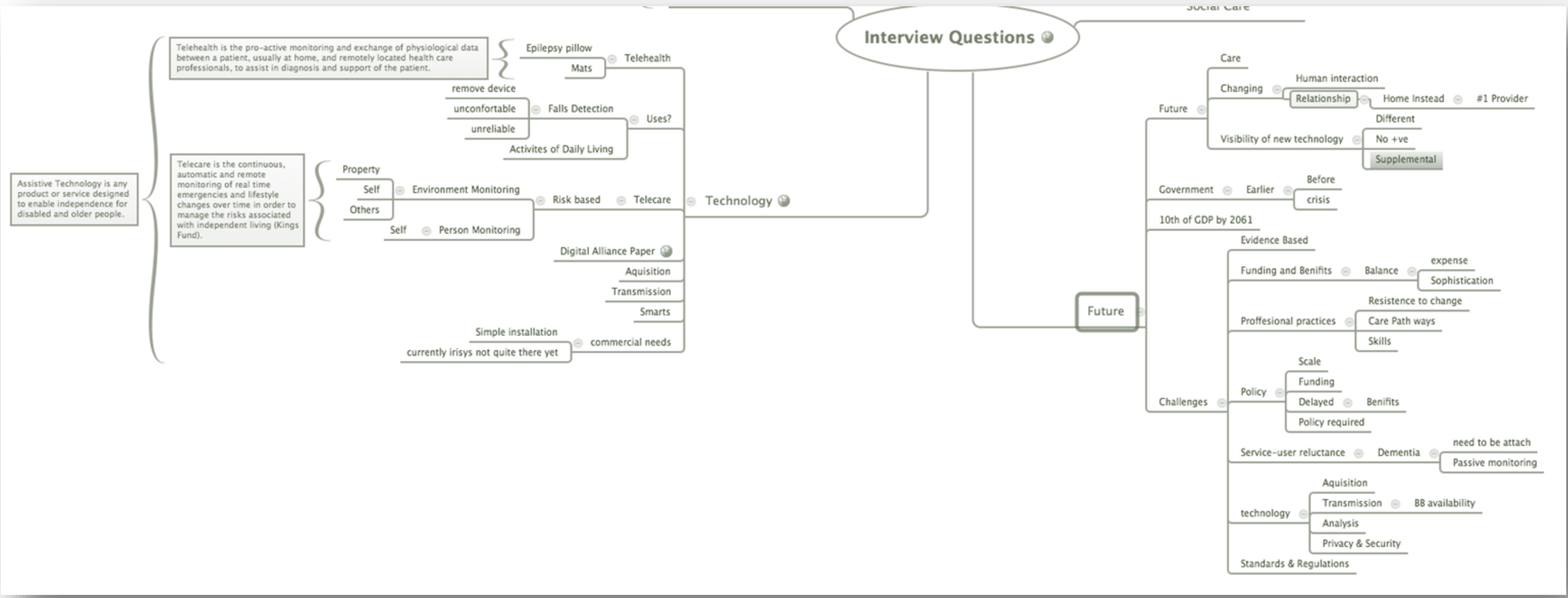

Figure 28 Interviews - Future of Telecare Mind Map

The future section of the interview discussed some of the challenges created by an aging population, touching on the areas covered by Sethi et al. in their the Trends and Issues in Community Telecare paper [16]. It then moved on to technology the views about how Telecare might be used to complement existing services.

Indoor Positioning

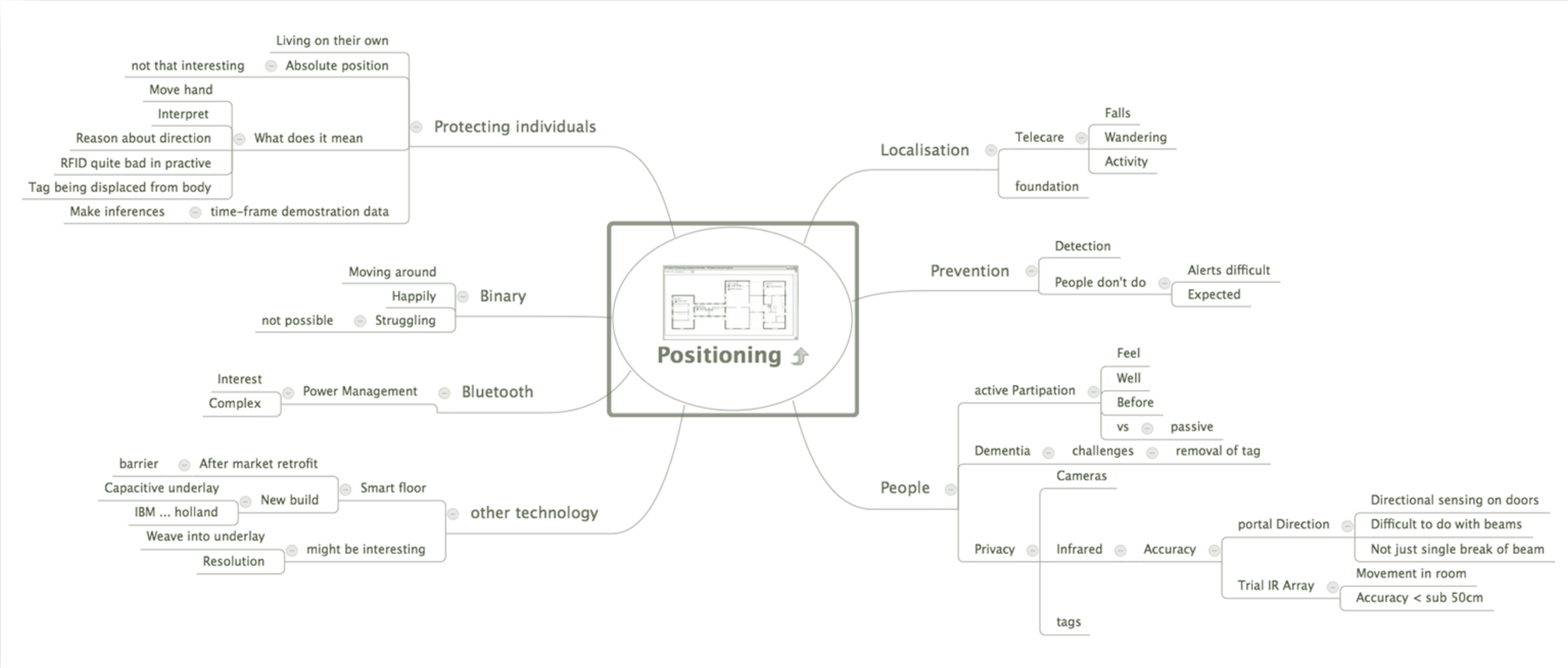

Figure 29 Interviews - Indoor Positioning

The final section of the interview covered indoor positioning, highlighting the balance of privacy and risk, as well as the problems with the active participation of care users, who suffer from dementia.

Appendix C – Code Structure Overview

The code is structured as per Python PEP 8 style guide [124] and aligned with the architectural model described in Part IV of the paper. This appendix provides and overview of the key directories to aid review of the code

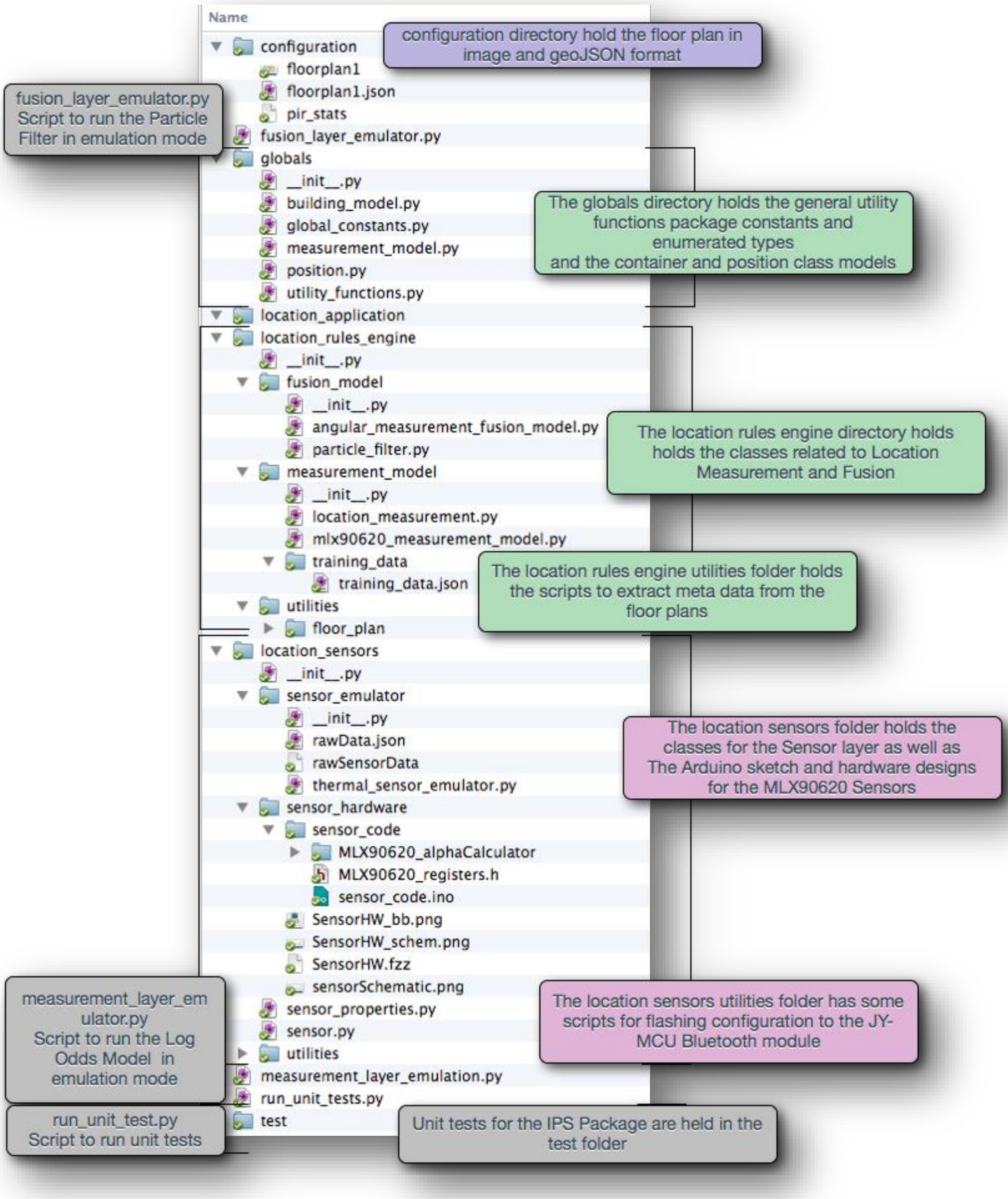

Figure 30 Code Directory Structure

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Addendum 1 –Design Update & Revised Code Structure

This addendum provides a brief overview of key design changes made since the formal submission of the project and a review of the revised code structure made available for the project demonstration

Design Changes

The most significant design change made since the submission of the project is the refactoring of the core objects in the Measurement and Fusion Models to use the Observer Pattern [1, Ch. 5]. This pattern allows models to subscribe to sensor output and facilitates a '1 to many relationship' between output and models, most importantly between the Measurement Model and Fusion Models. Conceptually the design allows for multiple measurement models to be applied to the same sensor output, for measurement model output to be incorporated into multiple fusion models and for fusion models to act as input into further fusion models.

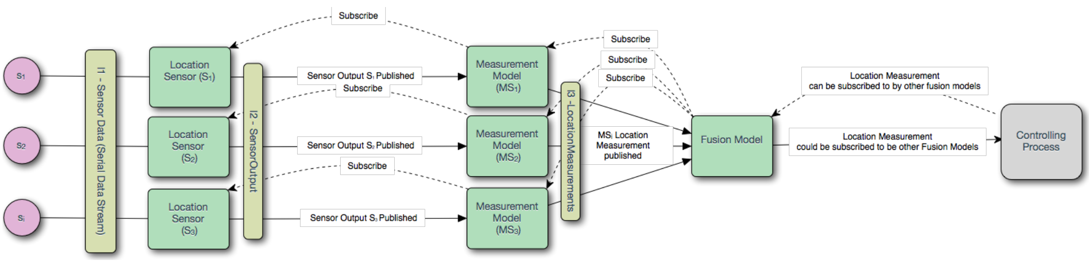

Figure 1 IPS Measurement Model Observer Pattern - Architecture Overview

This design change is reflected in the following class model for the Fusion Model.

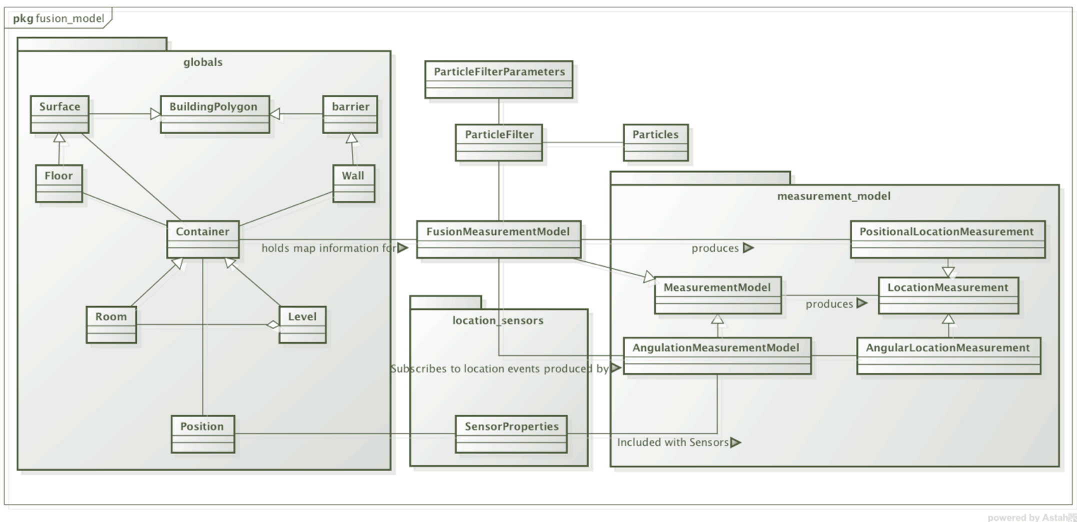

Figure 2 - Revised Fusion Class Model

The Fusion Measurement Model now subscribes to Location Measurement Events produced by the Angular Measurement Model. The base MeasurementModel class has the subscription to relevant location measurement events built into its instantiation method. Lastly a new method to publish measurement events has been developed.

In addition to the domain model changes, the application has been updated to write the output from the connected sensors and active measurement models along with any system wide messages to log files.

Code Structure

The code structure remains as per Appendix C of the Final Project Report; new elements developed for the demonstration are highlighted in the figure below

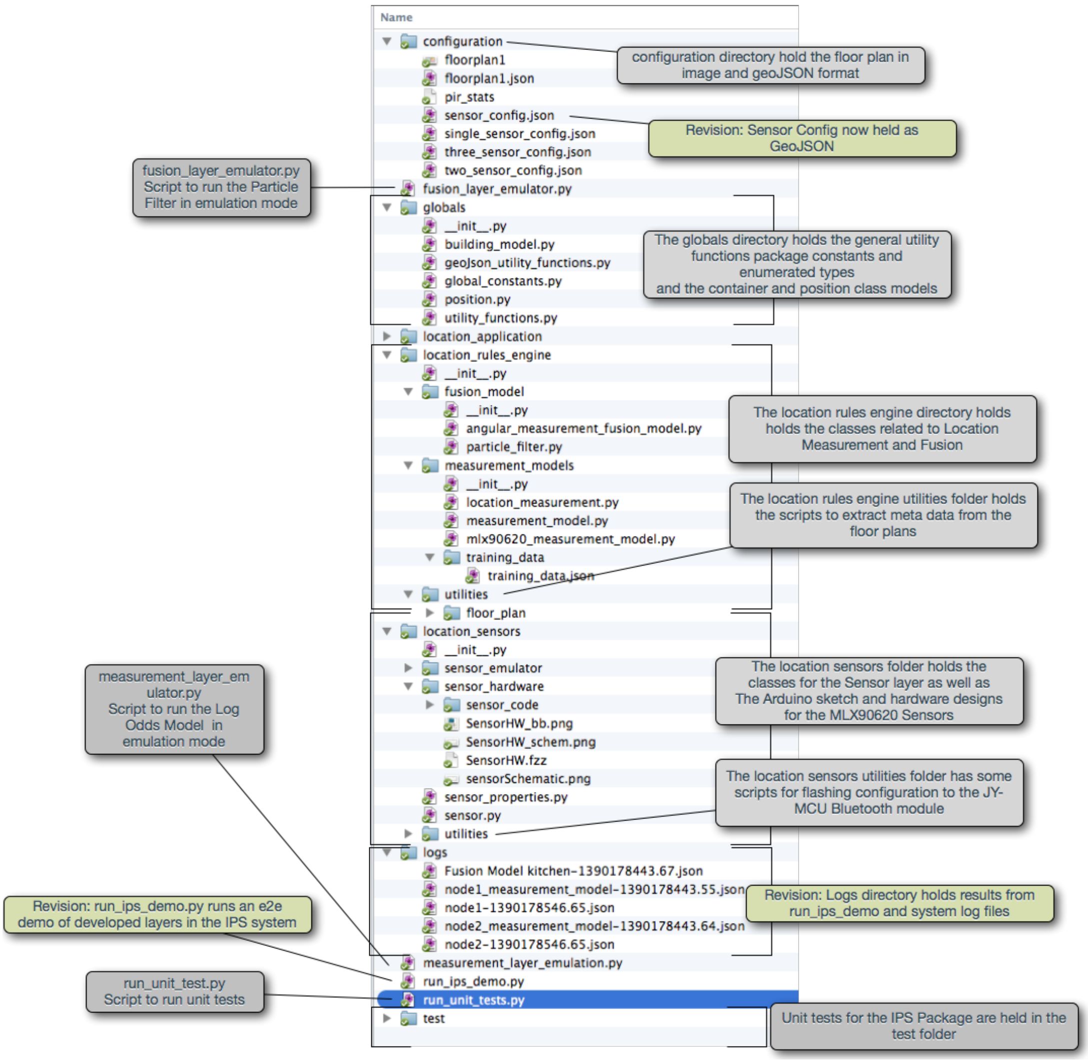

Figure 3 Code Directory Structure

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