CHAPTER 1

Literature Review

The proportion of elderly and mobility-impaired people is predicted to grow dramatically over the next century, leaving a large proportion of the population unable to care for themselves, and consequently less people able care for these groups. [5] With this issue looming, investments are being made into a variety of technologies that can provide the support these groups need to live independent of human assistance.

With recent advancements in low cost embedded computing, such as the Arduino and Raspberry Pi, the ability to provide a set of interconnected sensors, actuators and interfaces to enable a low-cost 'smart home for the disabled' that takes advantage of the Internet of Things (IoT) is becoming increasingly achievable.

Sensing techniques to determine occupancy, the detection of the presence and number of people in an area, are of particular use to the elderly and disabled. Detection can be used to inform various devices that change state depending on the user's location, including the better regulation energy hungry devices to help reduce financial burden. Household climate control, which in some regions of Australia accounts for up to 40% of energy usage [2] is one particular area in which occupancy detection can reduce costs, as efficiency can be increased dramatically with annual energy savings of up to 25% found in some cases. [4]

While many of the above solutions achieve excellent accuracies, in many cases they suffer from problems of installation logistics, difficult assembly, assumptions on user's technology ownership and component cost. In a smart home for the disabled, accuracy is important, but accessibility is paramount.

The goal of this research project is to devise an occupancy detection system that forms part of a larger 'smart home for the disabled', and intergrates into the IoT , that meets the following qualitative accessibility criteria;

- *Low Cost*: The set of components required should aim to minimise cost, as these devices are intended to be deployed in situations where the serviced user may be financially restricted.

- *Non-Invasive*: The sensors used in the system should gather as little information as necessary to achieve the detection goal; there are privacy concerns with the use of high-definition sensors.
- *Energy Efficient*: The system may be placed in a location where there is no access to mains power (i.e. roof), and the retrofitting of appropriate power can be difficult; the ability to survive for long periods on only battery power is advantageous.
- *Reliable*: The system should be able to operate without user intervention or frequent maintenance, and should be able to perform its occupancy detection goal with a high degree of accuracy.

To create a picture of what options there are in this sensing area, a literature review of the available sensor types and wireless sensor architectures is needed. From this list, proposed solutions will be compared against the aforementioned accessibility criteria to determine their suitability.

1.1 Sensors

To achieve the accessibility criteria, a wide variety of sensing approaches must be considered. It can be difficult to approach the board variety of sensor types in the field, so a structure must be developed through which to evaluate them. [20] proposes a 5-element human-sensing criteria that is very useful in defining broad quantitative requirements of sensors.

These quantitative requirements can be used to exclude sensing options that clearly cannot meet the requirements before the more specific qualitative accessibility criteria will be considered for those remaining sensors.

The quantitative criteria elements are;

1. *Presence*: Is there any occupant present in the sensed area?
2. *Count*: How many occupants are there in the sensed area?
3. *Location*: Where are the occupants in the sensed area?
4. *Track*: Where do the occupants move in the sensed area? (local identification)

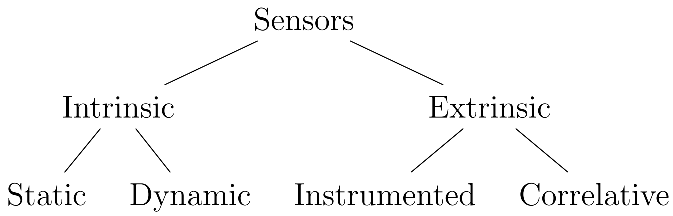

Figure 1.1: Sensor taxonomy

5. *Identity*: Who are the occupants in the sensed area? (global identification)

At a fundamental level, this research project requires a sensor system that provides both Presence and Count information. To assist with the reduction of privacy concerns, excluding systems that permit Identity will generally result in a less invasive system also. The presence of Location or Track are irrelevant to our project's goals, but overall, minimising these elements should in most cases help to maximise the energy efficiency of the system also.

[20] also proposes a measurable human trait taxonomy (see figure 1.1), which categorises different sensing systems in terms of what information they use as a proxy for human-sensing. We use this taxonomy here as a structure through which we group and discuss different sensor types.

1.1.1 Intrinsic traits

The first set of sensors discussed are sensors detecting intrinsic traits. Intrinsic traits are those which can be sensed that are a direct property of being a human occupant. Intrinsic traits are particularly useful, as in many situations they are guaranteed to be present if an occupant is present. However, they do have varying degrees of detectability and differentiation between occupants. Two main subcategories of these sensor types are static and dynamic traits.

Static traits are physiologically derived, and are present with most (living) occupants.

One key static trait that can be used for occupant sensing is that of thermal emissions. All human occupants emit a large amount of thermal radiation in both resting and active states. The heat signatures of these emissions could potentially be measured with some apparatus, counted, and used to provide Presence and Count information to a sensor system, without providing Identity information. Once such paper that proposes this is [4], which uses a type of thermal sensor known as an Infrared Array Sensor (IAR) . This sensor is much like a camera, in that it has a field of view which is divided into "pixels"; in this case an 8×8 grid of detected temperatures. This sensor is mounted on an embedded device on the roof, along with a Passive Infrared Sensor (PIR) , and uses a variety of classification algorithms to detect human heat signatures within the raw thermal and motion data it collects. Such a system achieves Root Mean Squared Error ≈ 0.35 persons. There are few drawbacks with this approach.

Another static trait is that of CO_2 emissions, which, like thermal emissions, are emitted by human occupants in both resting and active states. By measuring the buildup of CO_2 within a given area, one can use a variety of mathematical models of human CO_2 production to determine how many occupants there are likely in a space to have that amount of CO_2 produced. This was trialled as part of a sensor fusion in [11], within the context of an office environment, achieving a $\approx 94\%$ accuracy. Such a sensing system could provide both the Presence and Count information, and exclude the Identity information as required. However, a CO_2 based detection mechanism has serious drawbacks, discussed in [7]; the CO_2 feedback mechanism is very slow in nature, taking hours of continuous occupancy to correctly identify the presence of people. In a residential environment, occupants are more likely to be moving between rooms than an office, so the system may have a more difficult time detecting in that situation. Similarly, such systems can be interfered with by other elements that control the CO_2 buildup in a space, like air conditioners, open windows, etc. This is also much more of a concern in a residential environment compared to the studied office space, as the average residence can have numerous such confounding factors that cannot easily be controlled for.

The final static trait discussed is actual visual identification, achieved through the use of video or still-image cameras and advanced image processing algorithms. Video can be used in occupancy detection in several different ways, achieving different levels of accuracy and requiring different configurations. The first use of video, discussed in [6] is the use of video as a "optical turnstile"; the video system detects potential occupants and the direction they are moving in at each entrance and exit to an area, and uses that information to extrapolate the number of occupants within the turnstiled area; this system has up to a 94% accuracy. However, the main issue with such a system applied to a residential environment is the system assumes that there will be wide enough "turnstile areas", corridors of a fairly large area that connect different sections of a building, to use as detection zones. While such corridors exist in office environments, they are less likely to exist in residential ones.

The second use of video is a ceiling-based video system [18], it uses advanced image processing algorithms to count the number of people in the captured area.

This system achieves a specificity of $TP/(TP + FP) \approx 97\%$ and a sensitivity $TP/(TP + FN) \approx 96\%$ (TP = true positives, FP = false positives, FN = false negatives). Such a system could be successfully applied to the residential environment, as both it and the "optical turnstile" model provide Presence and Count information. However, these systems also allow Identity to be determined, and are thus very invasive. Such invasive systems have serious privacy concerns, and thus are less readily considered.

Dynamic traits are usually products of human occupant activity, and thus can generally only be detected when a human occupant is physically active or in motion.

The first discussed dynamic trait based system is [12], an ultrasonic system that uses clusters of such sensors above doorframes to detect the height and direction of potential occupants travelling between rooms. This acts as a turnstile based system, much like [6], but augments this with an understanding of the model of the building to error correct for invalid and impossible movements brought about from sensing errors. This system provides an overall room-level tracking accuracy of 90%, however to achieve this accuracy, potential occupants are intended to be tracked using their heights, which has privacy implications. The system can also suffer from problems with error propagation, as there are possibilities of "phantom" occupants entering a room due to sensing errors.

The second dynamic trait system is based upon a PIR connected to a transmitter of some description. A solely PIR based system is used within [11], with the motion of the sensor being averaged over several different time intervals, and fed into a decision tree classifier. This PIR system alone produced a $\approx 98\%$ accuracy. However, such a system, due to only motion detection capabilities, can only provide Presence information, and is unable to provide Count information.

1.1.2 Extrinsic traits

The second set of sensors discussed are sensors detecting extrinsic traits. Extrinsic traits are those which are actually other environmental changes that are caused by or correlated with human occupant presence. These traits generally present a less accurate picture, or require the sensed occupants to be in some way "tagged", but they are generally also easier to sense in of themselves.

The sensors in this category have been divided into two subcategories for our purposes that are not discussed in [20]. The first of these categories is instrumented approaches; these require that detectable occupants carry with them some device that is detected as a proxy for the occupant themselves.

The most obvious of these approaches is a specially designed device. [16] uses RFID tags placed on building occupant's persons and a set of transmitters to triangulate the tags and place them within different thermal zones for the use of the HVAC system. For stationary occupants, there was a detection accuracy of $\approx$ 88%, and for occupants who were mobile, the accuracy was $\approx$ 62%. Such a system could be re-purposed for the residence, however, these systems raise issues in a residential environment as it requires occupants to be constantly carrying their sensors, which is less likely in such an environment. Additionally, the accuracy for this system is not necessarily high enough for a residential environment, where much smaller rooms are used.

To make extrinsic detection more reliable, [13] leverages a device human occupants are likely to carry around; wifi enabled smart phones. They propose the *homeset* algorithm, which uses the phones to scan the visible wifi networks, and from that information estimate if the occupants are at home or out and about by "triangulating" their position from the visible wifi networks. This solution does not provide the fine-grained Presence data that we need, as it is only able to triangulate the phone's position very roughly with the wireless network detection information.

[3] also leverages smart phones to determine occupancy, but in a more broad enterprise environment: Wireless association logs are analysed to determine which access points in a building a given occupant is connected to. If this access point falls within the radio range of their designated "personal space", they are considered to be occupying that personal space. This technique cannot be applied to a residential environment, as there are usually not multiple wireless hotspots.

Finally, [10] uses specifically the GPS functions of the smartphone to perform optimisation on heating and cooling systems by calculating the "travel-to-home" time of occupants at all times and ensuring at every distance the house is minimally heated such that if the potential occupant were to travel home, the house would be at the correct temperature when they arrived. While this system does achieve similar potential air-conditioning energy savings, it is not room-level modular, and also presupposes an occupant whose primary energy costs are from incorrect heating when away from home, which isn't necessarily the case for this demographic.

The second of these subcategories are correlative approaches. These approaches analyse data that is correlated with human occupant activity, but does not require a specific device to be present on each occupant that is tracked with the system.

The primary approach in this area is [14], which attempts to measure elec-

	Requires		Excludes	Irrelevant	
	Presence	Count	Identity	Location	Track
<u>Intrinsic</u>					
Static					
Thermal	✓	✓	✓	✓	
CO_2	✓	✓	✓		
Video	✓	✓	✗	✓	✓
Dynamic					
Ultrasonic	✓	✓	✗		✓
PIR	✓	✗	✓		
<u>Extrinsic</u>					
Instrumented					
RFID	✓*	✓	✓	✓	
WiFi assoc.˜	✓*	✓	✗	✓	
WiFi triang.˜	✓*	✓	✗		
GPS˜	✓*	✗	✓	✓	
Correlative					
Electricity	✓*	✗	✓		

*Doesn't provide data at required level of accuracy for home use.
˜Uses smartphone as detector.

Table 1.1: Comparison of different sensors and project requirements

tricity consumption and use such data to determine Presence. Electricity data was measured at two different levels of granularity; the whole house level with a smart meter, and the consumption of specific appliances through smart plugs. This data was then processed by a variety of classifiers to achieve a classification accuracy of more than 80%. Such a system presents a low-cost solution to occupancy, however it is not sufficiently granular in either the detection of multiple occupants, or the detection of occupants in a specific room.

1.1.3 Analysis

From these various sensor options, there are a few candidates that provide the necessary quantitative criteria (Presence and Count); these are thermal, CO_2 , Video, Ultrasonic, RFID and WiFi association and triangulation based methods. All sensing options are compared on Table 1.1.

In the context of our four qualitative accessibility criteria, CO_2 sensing has several reliability drawbacks, the predominant ones being a large lag time to receive accurate occupancy information and interference from a variety of air conditioning sources which can modify the CO_2 concentration in the room in unexpected ways.

Video-based sensing methods suffer from invasiveness concerns, as they by design must have a constant video feed of all detected areas.

Ultrasonic methods have particular issues with reliability when a user falls outside the prescribed height bounds of normal humans. Wheelchair bound occupants, a core demographic of our proposed sensing system, would be incompatible with such an approach. Their wheelchair may also interfere with height measurement results. Ultrasonic methods also provide weak Identity information through height detection.

RFID sensing also has several drawbacks, predominantly being that it is difficult value proposition to get residential occupants to carry RFID tags with them continuously. Another drawback is that the triangulation methods discussed are too unreliable to place occupants in specific rooms in many cases.

WiFi association is not granular enough for residential use, as the original enterprise use case presupposed a much larger area, as well as multiple wireless access points, neither of which a typical residential environment have.

WiFi triangulation is a good candidate for the residence, as there are most likely neighbouring wireless networks that can be used as virtual landmarks. However, it suffers from the same granularity problems as WiFi association, as these signals are not specific enough to pinpoint an occupant to a specific room.

For smartphone based approaches generally, it is also more difficult in residential environments to ensure that occupants are carrying their smartphones with them at all times. Another issue with smart phones is that they represent an expense that the target markets of the elderly and the disabled may not be able to afford.

Finally, we have thermal sensing. It provides both Presence and Count information, as it uses occupants' thermal signatures to determine the presence of people in a room. It does not however provide Identity information, as thermal signatures are not sufficiently unique with the technologies used to distinguished between occupants. Such a sensor system is presented as low-cost and energy efficient within [4], is non-invasive by design and can reliably detect occupants with a very low root mean squared error. For our specific accessibility criteria, thermal sensing appears to be the best option available.

1.2 Thermal sensors

Above we concluded that thermal sensors are the best candidates for this project. In this section we discuss the thermal sensing field in more detail.

A primary static/dynamic sensor fusion system in this field is the Thermosense system, [4] a PIR and IAR [1] used to subdivide an area into an 8×8 grid of sections from which temperatures can be derived. This sensor system is attached to the roof on a small embedded controller which is responsible for collecting the data and transmitting it back to a larger computer via low powered wireless protocols.

The Thermosense system develops a thermal background map of the room using an Exponential Weighted Moving Average (EMWA) over a 15 minute time window (if no motion is detected). If the room remains occupied for a long period, a more complex scaling algorithm is used which considers the coldest points in the room empty, and averages them against the new background, then performs EMWA with a lower weighting.

This background map is used as a baseline to calculate standard deviations of each grid area, which are then used to determine several characteristics to be used as feature vectors for a variety of classification approaches. The determination of the feature vectors was subject to experimentation, with the differences at each grid element too susceptible to individual room conditions to be used as feature vectors. Instead, a set of three different features was designed; the number of temperature anomalies in the space, the number of groups of temperature anomalies, and the size of the largest anomaly in the space. These feature vectors were compared against three classification approaches; K-Nearest Neighbors, Linear Regression and an a feed-forward Artificial Neural Network of one hidden later and 5 perceptions. All three classifiers achieved a Root Mean Squared Error (RMSE) within 0.38 ± 0.04. This final classification is subject to a final averaging process over a 4 minute window to remove the presence of independent errors from the raw classification data.

The Thermosense approach presents the state of the art in the field of sensing with IAR technology. Using a similar IAR system along with those types of classification algorithms should yield useful sensing results which can be then integrated into the broader sensor system.

[1] Phillips GridEYE; approx $30

REST	
Application	CoAP
Transport	UDP
IP / Routing	IETF RPL
Adaptation	IETF 6LoWPAN
Medium Access	IEEE 802.15.4e
Physical	IEEE 802.15.4-2006

Table 1.2: Proposed protocol stack

1.3 Architecture

Beyond specific sensor design and occupancy detection algorithms, a large emphasis of this project is to create a system that is correctly architected to operate as a useful Thing in a real-world IoT environment, as the key advantage of Things is the "disruptive level of innovation" [1] brought about by their ability to be combined in ways unforeseen (yet still enabled) by their creators. This architecture involves careful consideration of the embedded hardware that will drive the system, as well as the communications protocols utilised between the sensor and devices interested in the sensor's information.

1.3.1 Protocols

In an ideal environment, the sensor systems used will communicate with each other wirelessly. As the system has low power requirements, it is important to prioritise those protocols and architectures that minimise power usage while still enabling the necessary wireless communication. The system will also ideally exist in a system with other identical sensors (one for each room in a residence), thus it is important to prioritise those protocols which allow multiple identical sensor systems to coexist on the same network without conflict, and to be uniquely addressable and identifiable. In recent years, many developments have been made in the IoT arena, with standards emerging specifically designed for low-power embedded devices to communicate between themselves and bigger systems that address these and other unique needs, across the entire protocol stack.

[17] proposes a protocol stack that aligns with the above requirements, the key advantage of which is being that an implementation of that stack is completely standardised, based on TCP/IP, uses the latest IEEE and IETF IoT standards, and is free from proprietary protocol restrictions (unlike ZigBee 1.0 devices, for instance). Table 1.2 shows the full stack proposed. The key components of this

proposal are the introduction of CoAP at the application layer, RPL at the IP / Routing layer and 6LoWPAN at the Adaptation layer.

Above the application layer, [8] proposes the use of Representational state transfer (REST) over Web Services Descriptive Language / Simple Object Access Protocol (WS-*) as a method of exchanging information between sensor systems. Their data suggests that REST is easier to use than WS-* , and the key advantage of a WS-* based approach is its ability to represent much more complex data and abstractions, which are unnecessary in this project's situation.

Constrained Application Protocol (CoAP) [15] is an application layer protocol designed to replace HTTP as a way of transmitting RESTful information between clients. The chief advantage of CoAP over HTTP is it compresses the broad-strokes of the HTTP feature set into a binary language that is much more suitable for transmission over low-bandwidth and low-power links, such as those discussed here.

IPv6 Routing Protocol for Low-Power and Lossy Networks (RPL) [21] is a routing protocol designed for low power environments, allowing low power nodes to create and maintain a mesh network between themselves, allowing, among other things, the routing of packets to a "root" node and back again. RPL is particularly suited to the routing situation of our proposed architecture, as individual sensors do not need to communicate with one another, but rather report back to a larger node (further discussed in subsection 1.3.2).

IPv6 over Low power Wireless Personal Area Networks (6LoWPAN) [19] is a compression and formatting specification to allow IPv6 packets to be sent over an 802.15.4 based network. Optimisations are found in the reduction of the size of 6LoWPAN packets, IPv6 addresses as well as redesigning core Internet Protocol algorithms so that they can run with low power consumption on participating devices.

1.3.2 Devices

In addition to the protocol stack used, how these nodes relate to each other is also an important consideration. Part of what will inform these decisions are the requisite processing power and internet connectivity required to successfully execute all elements of the sensing system. [15] provides a helpful system to consider this, by describing three classes of resource constrained devices that would benefit from CoAP , and each can provide different levels of security for an IP stack;

- *Class 0*: "not capable of running an RFC-compliant IP stack in a secure

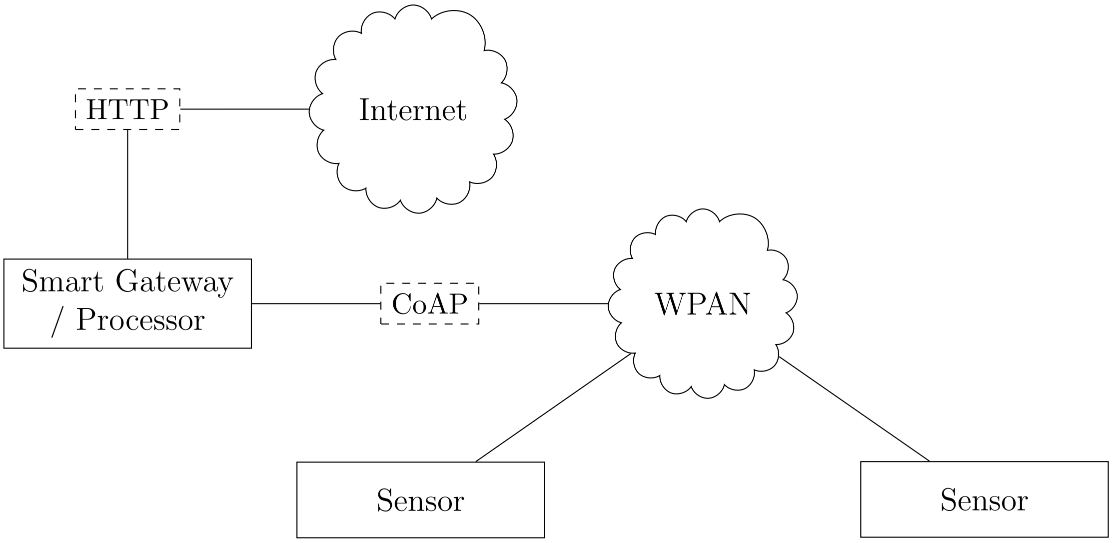

Figure 1.2: Proposed system architecture

manner. They require application-level gateways to connect to the Internet."

- *Class 1*: Able to connect to the internet with some "integrated security mechanisms". Are unable to employ full HTTP with TLS.
- *Class 2*: Normal Internet nodes, able to use the full HTTP stack with TLS.

The devices that we propose the sensors will connect to are the likes of the Arduino, which can be generally classified as class 0 or possibly class 1 devices. Due to their insecurity and difficulty running a fully fledged IP stack, [9] proposes the use of a "Smart Gateway" system to bridge the wider internet and these sensor systems. This gateway would be able to communicate with the sensor systems over CoAP and 802.15.4 , as well as receive API requests via HTTP from a traditional TCP/IP network to forward on to these sensors.

The Thermosense paper [4] proposes several different algorithms to process the raw sensing data into the occupancy estimates (further discussed in section 1.2 on page 9), all of which are fairly computationally expensive. Because of this, it would be non-trivial to implement these algorithms on the embedded sensing devices themselves. This problem is already resolved in our proposed system, as the aforementioned "Smart Gateway" can easily also take on the task of processing the raw sensor data into estimates which it can relay to interested parties over its HTTP-based API. A visualisation of this proposed system can be seen in figure 1.2.

1.4 Research Gap

Throughout this discussion of the area of wireless occupancy sensors within the IoT it can be seen that there is a clear research gap within the area of occupancy. No group could be found who has assembled an occupancy sensor that optimises these ares of Low Cost, Non-Invasiveness, Energy Efficiency and Reliability into a architected software and hardware package that can be integrated like any other Thing into the IoT .

This is a key research area, because, as we have previously discussed, the true "disruptive level of innovation"[1] the IoT provides can only be realised once a novel idea has been properly packaged as a Thing, rather than as a research curiosity. Packaging something as a Thing requires careful consideration of the best sensing systems, the best hardware to run those systems on, the best protocols to allow these Things to communicate, and the best device architecture to enable that communication. The state of the art in all these areas have been discussed throughout this literature review.

A key part of enabling the "smart home for the disabled" is creating a set of Things that can improve quality of life for those people. We believe the proposed Thing has clearly demonstrated this potential.

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