Developing a robust system for occupancy detection in the household

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Abstract

This is the abstract.

Keywords: keyword, keyword
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Contents

Abstract ii

Acknowledgements iii

1 Introduction 1

2 Literature Review 2

2.1 Sensors 3

2.2 Thermal sensors 5

2.3 Architecture 6

3 Methods 7

4 Results 8

5 Discussion and Conclusion 9

A Original Honours Proposal 10

A.1 Background 10

A.2 Aim 11

A.3 Method 12

A.3.1 Hardware 12

A.3.2 Classification 12

A.3.3 Robustness / API 13

A.4 Timeline 13

A.5 Software and Hardware Requirements 14

A.6 Proposal References 15

List of Tables

2.1 Comparison of different sensors and project requirements 5

List of Figures

CHAPTER 1

Introduction

CHAPTER 2

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 [1] and Raspberry Pi, [2] the ability to provide a set of interconnected sensors, actuators and interfaces to enable a low-cost 'smart home for the disabled' 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 [3] 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' that meets the following 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.

2.1 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. [8] proposes a 5-element human-sensing taxonomy that is very useful in considering the broad requirements of sensors for this research.

The taxonomic elements are;

1. *Presence*: Is there anyone present in the sensed area?
2. *Count*: How many people are there in the sensed area?
3. *Location*: Where are the people in the sensed area?
4. *Track*: Where do the people move in the sensed area? (local identification)
5. *Identity*: Who are the people in the sensed area? (global identification)

These elements are particularly useful when it comes to comparing the different qualities of sensors, and to determine which sensors are useful for our particular purpose. 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.

[8] also proposes a measurable human trait taxonomy, which we use in this literature review as a structure through which we describe different sensor types.

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 human. Intrinsic traits are particularly useful, as in many situations they are guaranteed to be present if a human is present. However, they do have varying degrees of detectability and differentiation between people. Two main subcategories of these sensor types are static and dynamic traits.

Static traits are physiologically derived, and are present with most (alive) humans.

One key static trait that can be used for human sensing is that of thermal emissions. All humans 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. This sensor is much like a camera, in that it has a field of view which is divided into 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 present 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 people there are likely in a space to have that amount of CO_2 produced. This was trialled as part of a sensor fusion in [7], 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 [6]; the CO_2 feedback mechanism is very slow in nature, taking hours of continuous occupancy to correctly identify the presence of people. In a home environment, people are more likely to be moving between rooms than an office, so the system may have a more difficult

	Requires		Excludes	Irrelevant	
	Presence	Count	Identity	Location	Track
Intrinsic					
Static					
Thermal	✓	✓	✓	✓	
CO_2	✓	✓	✓		
Video	✓	✓	✗	✓	✓
Dynamic					
Ultrasonic	✓	✓	✗		✓
PIR	✓	✗	✓		
Extrinsic					
Instrumented					
RFID	✓	✓	✓	✓	
Smart phone	✓	✓	✗	✓	
GPS	✓	✗	✓	✓	
Correlative					
Electricity	✓	✗	✓		
Network	✓	✗	✓		

Table 2.1: Comparison of different sensors and project requirements

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 home environment compared to the studied office space, as the average home can have numerous such confounding factors.

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

2.2 Thermal sensors

A primary static/dynamic sensor fusion system in this field is the Thermosense system, [4] a PIR and Infrared Array Sensor (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.

[1] Phillips GridEYE; approx \$30

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.

Using the Melexis MLX90620 (*Melexis*)

2.3 Architecture

CHAPTER 3

Methods

CHAPTER 4

Results

CHAPTER 5

Discussion and Conclusion

APPENDIX A

Original Honours Proposal

Title:	Developing a robust system for occupancy detection in the household
Author:	Ash Tyndall
Supervisor:	Professor Rachel Cardell-Oliver
Degree:	BCompSci (24 point project)
Date:	August 15, 2014

A.1 Background

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. [6] 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 [1] and Raspberry Pi, [2] the ability to provide a set of interconnected sensors, actuators and interfaces to enable a low-cost 'smart home for the disabled' 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 [3] 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. [8]

Significant research has been performed into the occupancy field, with a focus on improving the energy efficiency of both office buildings and households. This is achieved through a variety of sensing means, including thermal arrays, [5] ultrasonic sensors, [11] smart phone tracking, [12][4] electricity consumption, [13] network traffic analysis, [15] sound, [10] CO2, [10] passive infrared, [10] video cameras, [7] and various fusions of the above. [16][15]

A.2 Aim

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' that meets the following accessibility criteria;

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- *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.

Success in this project would involve both

1. Devising a bill of materials that can be purchased off-the-shelf, assembled without difficulty, on which a software platform can be installed that performs analysis of the sensor data and provides a simple answer to the occupancy question, and

2. Using those materials and softwares to create a final demonstration prototype whose success can be tested in controlled and real-world conditions.

This system would be extensible, based on open standards such as REST or CoAP, [9][14] and could easily fit into a larger 'smart home for the disabled' or internet-of-things system.

A.3 Method

Achieving these aims involves performing research and development in several discrete phases.

A.3.1 Hardware

A list of possible sensor candidates will be developed, and these candidates will be ranked according to their adherence to the four accessibility criteria outlined above. Primarily the sensor ranking will consider the cost, invasiveness and reliability of detection, as the sensors themselves do not form a large part of the power requirement.

Similarly, a list of possible embedded boards to act as the sensor's host and data analysis platform will be created. Primarily, they will be ranked on cost, energy efficiency and reliability of programming/system stability.

Low-powered wireless protocols will also be investigated, to determine which is most suitable for the device; providing enough range at low power consumption to allow easy and reliable communication with the hardware.

Once promising candidates have been identified, components will be purchased and analysed to determine how well they can integrate.

A.3.2 Classification

Depending on the final sensor choice, relevant experiments will be performed to determine the classification algorithm with the best occupancy determination accuracy. This will involve the deployment of a prototype to perform data gathering, as well as another device/person to assess ground truth.

A.3.3 Robustness / API

Once the classification algorithm and hardware are finalised, an easy to use API will be developed to allow the data the device collects to be integrated into a broader system.

The finalised product will be architected into a easy-to-install software solution that will allow someone without domain knowledge to use the software and corresponding hardware in their own environment.

A.4 Timeline

Date	Task
Fri 15 August	*Project proposal and project summary due to Coordinator*
August	Hardware shortlisting / testing
25–29 August	*Project proposal talk presented to research group*
September	Literature review
Fri 19 September	*Draft literature review due to supervisor(s)*
October - November	Core Hardware / Software development
Fri 24 October	*Literature Review and Revised Project Proposal due to Coordinator*
November - February	*End of year break*
February	Write dissertation
Thu 16 April	*Draft dissertation due to supervisor*
April - May	Improve robustness and API
Thu 30 April	*Draft dissertation available for collection from supervisor*
Fri 8 May	*Seminar title and abstract due to Coordinator*
Mon 25 May	*Final dissertation due to Coordinator*
25–29 May	*Seminar Presented to Seminar Marking Panel*
Thu 28 May	*Poster Due*
Mon 22 June	*Corrected Dissertation Due to Coordinator*

A.5 Software and Hardware Requirements

A large part of this research project is determining the specific hardware and software that best fit the accessibility criteria. Because of this, an exhaustive list of software and hardware requirements are not given in this proposal.

A budget of up to $300 has been allocated by my supervisor for project purchases. Some technologies with promise that will be investigated include;

Raspberry Pi Model B+ Small form-factor Linux computer
Available from `http://arduino.cc/en/Guide/Introduction`; $38

Arduino Uno Small form-factor microcontroller
Available from `http://arduino.cc/en/Main/arduinoBoardUno`; $36

Panasonic Grid-EYE Infrared Array Sensor
Available from `http://www3.panasonic.biz/ac/e/control/sensor/infrared/grid-eye/index.jsp`; approx. $33

Passive Infrared Sensor
Available from various places; $10–$20

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