

An intelligent agent for determining home occupancy using power monitors and light sensors

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Abstract. Smart homes of the future will have a number of different types of sensors. What types of sensors and how they will be used depends on the behaviour needed from the smart home. Using the sensors to automatically determine if a home is occupied can lead to a wide range of benefits. For example, it could trigger a change in the thermostat setting to save money, or even a change in security monitoring systems. Our prototype *Home Occupancy Agent* (HOA), which we present in this paper, uses a rule based system that monitors power consumption from meters and ambient light sensor readings in order to determine occupancy.

Keywords: Smart Homes, Intelligent Agents, Occupancy Detection, Power Consumption, Ambient Light Sensors, Energy Conservation, Sustainability

1 Introduction

Research into *intelligent homes* has focused on a range of different issues, including *human-home* interaction [6], and occupant safety [10]. There remain some very basic issues, though, that play a key role to a wide range of smart home investigations [12, 11, 4, 5]. One of these basic issues is *how to detect if someone is at home*. The automatic determination of whether someone is home can be difficult, but has a number of exploitable benefits in terms of energy conservation, sustainability, and cost savings for the homeowner. Consider an intelligent agent (IA) that could turn down the heat by 2°C when no one is home. Such automatic behaviour could save the home owner money by lowering heating costs and could also save the home owner time, since (s)he would not need to (remember to) override the thermostat setting.

In general terms, the different factors we can monitor are: *consumption* (C) of power from appliances or devices; *environmental* (E) sources such as temperature, light levels, time/date, noise; and the *movement* (M) of individuals, and even air. All three of these factors are significant to determine home occupancy or activity patterns, but for our current study, we are only looking at the first two in any detail.

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Home Occupancy Agent (HOA) is our first single agent system prototype for a smart home. In this paper, we explore how different types of sensors can enable HOA to determine whether a home is occupied or unoccupied. We adopt a *bottom-up* approach; looking at each type of sensor in detail, first. In section 2 we introduce our centralized intelligent agent design. We then discuss the ideas behind monitoring power consumption (in section 3), and investigate ambient light sensors (in section 4). We introduce a *profile matrix* and discuss how to use it in conjunction with ambient light sensor readings to better determine household and room activity. In section 5, we describe our implementation of HOA in a *real home* using *off the shelf products* and report on our test results. We relate our research to similar studies in section 6, and provide some conclusions and directions for future research in section 7.

2 Intelligent Agent Design

Types of agents that will run in a smart home can be categorized as either centralized or localized agents. Moslehi notes that there is a *virtual hierarchy* and a *temporal dimension* to any agent system that needs to be developed for the smart grid [8, 9]. Both the smart home and the smart grid are similar in this way; they have a centralized server system, and localized controls and sensors.

Centralized agents will have a responsibility to collect and store localized sensor data on a continual, periodic basis. These agents can then report aggregations of this data and present them to the user either via the web or an in-home display (IHD). Whereas, *localized agents* monitor the sensory equipment directly connected to them and make localized intelligent decisions based on the data from the sensors they monitor. Agents will need to communicate with other agents within the home through a series of events, triggers, parameters, and alarms [8]. Note that we are proposing an agent that focuses on a more centralized approach. That is to say the agent will be running on a server and accessing data collected from local sensors via a database to make decisions. We do this to simplify our initial investigation. Another simplification for our initial implementation is that HOA will be a *rule-based* intelligent agent.

3 Power Consumption

When monitoring electric power consumption (C^E) for detecting occupant activity we look for spikes in kilowatt (kW) readings that correlate directly with occupants turning appliances on and off. Monitoring power consumption will be an ideal choice in the future due to high priority initiatives from electric utility companies who will be installing *smart meters* on every home (meaning data will be available to use and study).

It is useful to meter non-occupant triggered equipment such as heat pumps to get a more accurate activity determination and find a baseline kW reading for the home, called *rest of house* (C_R^E). Any spike above some *safe margin* (C_M^E) would be then considered occupant triggered activity. For example, our test

home had a $C_M^E = 0.9\text{kW}$ because the ambient consumption of the house (C_R^E) oscillated anywhere from 0.2kW to 0.7kW (due to fridges, freezers, electronics on stand-by mode). From the above observations we can derive the following formulae:

$$C_A^E = C_{A1}^E + C_{A2}^E + \dots + C_{Aa}^E . \quad (1)$$

$$C_R^E = C_T^E - C_A^E . \quad (2)$$

$$activity? = \begin{cases} true, & \text{if } C_R^E \geq C_M^E . \\ false, & \text{otherwise .} \end{cases} \quad (3)$$

In (1)-(3), C_T^E is the kW reading of the *whole house*, C_{A1}^E to C_{Aa}^E is a set of kW readings from occupant independent consumption activities (or appliances) that we want to filter out, and a is the number of filtered out activities (or appliances).

4 Ambient Light Sensors

When monitoring ambient light (E^L) sensors for detecting occupancy we look for illuminance spikes measured in lux (lx). By placing ambient light sensors in various rooms, these spikes can correlate directly with occupants turning lights on and off in different rooms. For example, from the data collected in our test home, we observed that light levels were dramatically different in each room.

A room's light levels lack *smoothness* that can be attributed to sunlight levels changing from clouds (not occupant activity) or open and shut blinds (a sign of occupant activity). A *profile matrix* becomes part of the solution because any lux spike may or may not be considered occupant activity. For example, a lux spike in a dark north facing room during the day would be activity but that same spike in a bright south facing room would not.

$$activity(n)? = \begin{cases} true, & \text{if } E_n^L \geq PM(n,p) . \\ false, & \text{otherwise .} \end{cases} \quad (4)$$

In (4), let PM be the 2D *profile matrix* indexed by *sensor position* (n), and the *day period* (p), E_n^L be the lux reading from the ambient light sensor at n .

5 Experimentation Setup and Evaluation

We implemented HOA in a *real home* using *off the shelf products*. Ambient light sensor and power meter data were collected over a ZigBee home area network (HAN) at 15 minute intervals. Weather [1] and day period [2] data sets were retrieved from external third party websites. We collected data from January 22 to August 28 (2010) for a home in Burnaby, Canada. HOA analyzed the

historical data looking to see if anyone was home or not. Results from HOA were then compared to the expected/correct results (what actually happened) using the standard precision-recall methods.

Determining occupancy by **power consumption** yielded an **f-score of 1.000** (precision score of 1.000, recall score of 1.000). This accuracy is not surprising, particularly if you are able to cancel out background consumption from known non-occupant triggered events as the threshold value in equation (3).

Determining occupancy by **ambient light sensors** yielded an **f-score of 0.943** (precision score of 0.926, recall score of 0.962). This did work very well. A more detailed examination found there were 19 out of 219 days where the day’s precision or recall scores were below 80% due to unusual light levels and sensors not being optimally placed (a limitation due to the design of the sensor).

6 Related Work

Current research revolves around identifying what the occupant is doing. PlaceLab [11, 6] and MavHome [4, 5] both use sensors as a commodity. We are interested in a slightly different approach. We want to use the least amount of sensors at the least cost possible to determine occupancy. Since each sensor consumes energy, it would *not* be beneficial if the cost of running a smart home system was more than the amount of savings the system could realize. We fully agree with MavHome’s objective to *minimize operation cost* [5].

We feel the use of real homes is important in evaluating the performance of IA systems (as does PlaceLab [11, 6]). Sensors should be ubiquitous. We do not see wearable sensors (like RFID gloves [10]) as part of the solution. Currently, wearable sensor technology is cumbersome and not practical. Wilson *et al* [12] discuss why wearable sensors are not appropriate for people with disabilities. Cameras and microphones as sensors have also been used in PlaceLab [6]. We feel that these types of sensors are too costly and too intrusive as Abascal [3] has pointed out.

Ambient light sensors in a home are susceptible to small changes in lighting levels. Mohamaddoust *et al*’s system only acted on changes of 50lx [7]. This is far greater than the level we have observed in our test home where light sources can change by as little as 3lx. Light from the sun and atmospheric changes had a dramatic effect on our ability to evaluate light levels, and is an important factor to consider. Mohamaddoust *et al* state the same for their LACS specifications but later on when testing do not consider these scenarios [7]. This again stresses the importance of testing research in a real home.

7 Conclusions and Future Work

With our key constraint of using a minimal number of inexpensive sensors, we were able to use power consumption and ambient light sensors to accurately detect home occupancy. Seasonal effects (e.g. summer, winter) and environment effects (e.g. light bulbs burning out thus changing light levels) can have performance

impacts on the correctness of determining occupant activity. Identifying the *weak spots* of each the type of sensor is critical in identifying what different complementary sensors are needed to be deployed in future research.

There are many directions that we can take HOA. A high priority item for us is to incorporate a *learning-based* algorithm to complement our *rule-based* ones. Adding more intelligence presents opportunities to explore *Reinforcement Learning*, and *multi-agent systems* or distributed intelligence. We feel that ultimately it would be better if more than one sensor could be used to determine occupancy activity as a way to confirm that the activity is truly from the occupant. For example, a power spike in the kitchen could be confirmed as activity because the motion sensor was triggered as the occupant moved.

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