"Converging Redundant Sensor Network Information for Improved Building Control"

Technical Progress Report

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Abstract

Knowing how many people occupy a building, and where they are located, is a key component of building energy management and security. Commercial, industrial and residential buildings often incorporate systems used to determine occupancy, however, current sensor technology and control algorithms limit the effectiveness of both energy management and security systems.

This topical report describes results from the first phase of a project to design, implement, validate, and prototype new technologies to monitor occupancy, control indoor environment services, and promote security in buildings. Phase I of the project focused on instrumentation and data collection. In this project phase a new occupancy detection system was developed, commissioned and installed in a sample of private offices and open-plan office workstations. Data acquisition systems were developed and deployed to collect data on space occupancy profiles. Analysis tools based on Bayesian probability theory were applied to the occupancy data generated by the sensor network. The inference of primary importance is a probability distribution over the number of occupants and their locations in a building, given past and present sensor measurements. Inferences were computed for occupancy and its temporal persistence in individual offices as well as the persistence of sensor status. The raw sensor data were also used to calibrate the sensor belief network, including the occupancy transition matrix used in the Markov model, sensor sensitivity, and sensor failure models. This study shows that the belief network framework can be applied to the analysis of data streams from sensor networks, offering significant benefits to building operation compared to current practice.

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1 Introduction

1.1 Background

Knowing how many people occupy a building, and where they are located, is a key component of building energy management and security. Commercial, industrial and residential buildings often incorporate systems used to determine occupancy, however, relatively unsophisticated sensor technology and control algorithms limit the effectiveness of both energy management and security systems.

This topical report describes progress and initial results from a three-phase project to design, implement, validate, and prototype new technologies to monitor occupancy, control indoor environment services, and promote security in buildings. More effective building services will be facilitated through more extensive occupancy sensing systems, and more sophisticated analysis of sensor data, which in this project are achieved by:

- Development of low-cost distributed sensor networks. The delivery and management of building indoor environment services (e.g., lighting, heating, air conditioning, security), will be improved if control systems are based on systems of multiple independent distributed occupancy detectors, instead of relying on single points of occupancy detection, and;
- Development of new analysis methods and control algorithms to treat data arising from distributed sensor networks. Collecting information from a network of sensors is only advantageous if accompanied by a rational analysis framework that can be used to make inferences about occupancy from the resulting data stream. Our approach to the analysis of information collected by multiple related and redundant sensors is based on Bayesian probability theory. In particular, a class of graphical probability models, called belief networks, are applied to the raw data for the purposes of prediction, diagnosis, and calculation of the value of information in building systems, and apply this information to building control.

The primary motivation for this work stems from commercial building electricity consumption. Currently, commercial building electricity consumption is enormous. Commercial buildings contribute a substantial 13% or 12.1 out of 96.6 quadrillion Btu ("quads") to the total U.S. primary energy consumption (EIA/DOE, 2000; Little, 1999). Aggravated primarily by an immense surge in the use of office equipment combined with the associated demand for cooling energy, electricity is responsible for 80% of the end-use primary energy consumption in commercial buildings, more than 150 million metric tons of carbon emissions per year, and $60 billion of utility cost (Little, 1999). Harnessing the efficiency potential in current and future construction will be instrumental in attenuating the growth of energy consumption and demand as well as the nation's dependency on an uninterrupted supply of fossil fuels.

The equipment and systems providing thermal comfort and indoor air quality for commercial buildings consume 42% of the total energy used in buildings. Energy use and utility cost can be reduced significantly by increasing the efficiency of this equipment, by distributing thermal energy more efficiently and by more closely meeting the needs of building occupants. The energy efficiency of system components for heating, ventilating, and air-conditioning (HVAC) has improved considerably over the past 20 years. For example, shipment-weighted energy efficiency ratios of unitary air conditioners in the United States have increased by 54% (ARI, 1999). The average efficiency of centrifugal chillers improved by 36% and the efficiency of the best chillers increased by 50% (American Standard, 1999). With similar improvements in the efficiencies of boilers, motors, fans, and pumps, outstanding opportunities exist for reducing energy use and cost in commercial sites. Yet, these opportunities still depend on effective building operations: e.g., services are still wasted if an unoccupied space is being conditioned.

Illumination systems are also an integral and important component of building systems: they interact with and affect other building systems, and are essential to a productive working environment. Brodrick, Rivest, Kendall and Ryan (1999) have estimated that lighting systems account for approximately 7% of the energy consumed in the U.S., and that lighting is responsible for about 26% of commercial building energy use. Lighting systems have consequently been a focus for successful energy saving campaigns.

In addition to the electrical energy consumption of lighting systems, lighting systems also generate heat. In most modern offices, internal heat gains outweigh heat losses to the outside, even in winter, resulting in a year-round cooling load on the building. Switching lights off when they are not being used, especially during daytime, will reduce the building system cooling load. Finally, and perhaps most important, the cost savings associated with reductions in electricity use and building cooling may be less important than the avoided capital costs associated with HVAC, chiller or electrical distribution upgrades that will be required to meet rising demand for electrical power in new and existing buildings. Better lighting control may therefore also provide a significant capital-cost avoidance opportunity for building owners and managers.

With occupancy accurately known, both in time and in space, it also becomes possible to develop operational strategies for building response to external or localized internal threats: accurate occupancy information in large multistory buildings could allow for the targeted allocation of emergency personnel and resources in situations where every second counts.

1.2 Current Approaches to Occupancy Detection

Commercially available technologies currently used to detect occupancy for energy management and security are limited by relatively unsophisticated sensor technology and control software: it is still a challenge to ensure that lights and other services are switched off when spaces are unoccupied.

These systems use passive infrared (PIR) and/or ultrasonic technologies, signaling space occupancy based on changes in the temperature or sound profile of the space. In energy management applications, the occupancy sensor functions as a timer, sending a signal to a switch that turns off electrical power after a defined period of time has elapsed during which no signal has been received from the detector (e.g., switch lights off when the space has been unoccupied for 5 minutes). In security applications, an "armed" system initiates a security call immediately upon receiving a signal from a single detector.

There is a growing literature that addresses the effectiveness of occupancy sensors for controlling office ambient lighting systems, and other studies have evaluated the effectiveness of occupancy-based switching for power management of office equipment (Audin, 1999; Floyd, Parker, McIlvaine & Sherwin, 1995; Jennings, Rubenstein, DiBartolomeo & Blanc, 2000; Maniccia, Burr, Rea & Morrow, 1999; Maniccia et al., 2001; Richman, Dittmer & Keller, 1996; Tiller & Newsham, 1993; Todesco & Robillard, 1995; Siminovitch & Page, undated; Von Neida et al., 2001). This work shows that occupancy sensors reliably deliver significant energy and demand savings in infrequently or unpredictably occupied spaces, such as washrooms, stairwells, corridors, storage areas (e.g., Todesco & Robillard, 1995), and mail carrier sorting stations (e.g., Siminovitch & Page, undated). Comparable savings have eluded general office applications, and occupancy sensors have not achieved as wide use as other energy-saving lighting technologies (Von Neida et al., 2001). There are often significant differences between actual observed savings (up to 43% reductions) and industry estimated savings (up to 70% reductions) that result from the application of single point occupancy detection systems.

These failures are due to design limitations that result in false or inappropriate switching, and failure to detect small motion in the area covered by a given detector. For example, the National Lighting Product Information Program (NLPIP) Specifier Report on Occupancy Sensors described 23 commercially available occupancy detectors, and performance data for 18 of these devices. NLPIP showed that many of the detectors tested did not respond to a movement trigger occurring within the coverage area claimed for the device (NLPIP, 1998). These performance failures can be traced to a design limitation that affects all current occupancy detection systems. These systems attempt to regulate the lighting in a local area (i.e., a single workstation or private office), by responding to activity occurring over a larger area (i.e., several workstations or passersby in a corridor). The zone that is viewed or monitored by any single detector is usually larger than the zone controlled by that detector. For example, a single occupancy detector will often respond to the presence of passersby and/or air streams coming from office equipment cooling fans operating within the field of view of the detector. Energy savings will be compromised because the probability is low that the area viewed by a single detector will remain vacant long enough for the lights to be switched off. Consequently, lights in these areas are switched off less frequently than they would be in a washroom, for example. Further exacerbating this problem is the wide variation in office layouts, which means that a generic solution using current technology is unlikely.

1.3 Sensor Network Instrumentation and Data Collection

Our proposed solution to this set of challenges is to use multiple, inexpensive distributed detectors that together function as a system, rather than a single, more expensive detector. A system based on multiple distributed detectors, with appropriate analysis and control algorithms, will ensure that controllers respond exclusively to local conditions within the coverage area. Instead of relying on fewer, more complex sensors, we have chosen to deploy a greater number of simple sensors, and extract the occupancy information from these multiple sensors through a more complex inference algorithm.

The project incorporates three distinct phases. Phase I of the project, described in this topical report, focused on Instrumentation and Data Collection. In this phase of the project, we conducted field trials to collect the raw data required to identify promising combinations of new and existing low cost sensors and other sources of information that we expect will improve occupancy detection and indoor environment system control effectiveness. A new occupancy detection system was developed, commissioned and installed in a sample of private offices and open-plan office workstations. Data acquisition systems were developed and deployed to collect data on space occupancy profiles. The data collected in the first phase provides the foundation for the work planned in Phases II and III.

In Phase II, new control algorithms will be developed based on the application of belief network analysis to the data collected in the first phase, to identify an optimal combination of sensors for control system application. Phase II will be completed over the second 12 month project period. In Phase III (also 12 months in duration) a prototype control system will be developed based on the work of the first two phases. The prototype system will be field tested in a private office, an open-plan office, and a classroom. Pending the successful completion of the project, in consultation with our industrial partners, we expect to turn the prototype system developed in Phase III into a tangible commercial product.

This topical report describes the development of a novel distributed occupancy detection system in a small sample of private offices and workstations, and associated data analysis strategies and methods. This occupancy detection system uses three traditional PIR occupancy sensors aimed at occupied areas in the work space. These three detectors were complemented by a sensor that determines when the telephone is off-hook (i.e., a telephone conversation is in progress). Each device provides an independent measurement of occupancy. Together, the combination of three measurements provides a converging and redundant sensor network.

Equally important as the physical sensor network is the analysis framework that is applied to these data to determine occupancy. We have proposed to apply analysis tools based on Bayesian probability theory to the occupancy data generated by the sensor network. The inference of primary importance is a probability distribution over the number of occupants and their locations in a building, given past and present sensor measurements.

While the project plan defers data analysis until the second phase of the project, we were able to apply the proposed analysis framework to a small sample of sensor network data collected early in the project. Inferences were computed for occupancy and its temporal persistence in individual offices as well as the persistence of sensor status. The raw sensor data were also used to calibrate the sensor belief network, including the occupancy transition matrix used in the Markov model, sensor sensitivity, and sensor failure models. This pilot analysis shows that the belief network framework can be applied to the analysis of data streams from sensor networks, offering benefits to building operation compared to current practice.

2 Executive summary

This project is based on the simple idea that it makes good sense to switch off building services (lighting, ventilation, miscellaneous electrical plug loads) when spaces are unoccupied. Current building practice incorporates many environmental control features: occupancy detectors that switch lights on and off, and centralized building energy management and control systems are two examples. However, sensor technology and control algorithms limit the effectiveness of current systems. For example, it is still a challenge to ensure that lights are switched off in unoccupied spaces.

More effective indoor environmental control and building management will be facilitated through more extensive sensing, and more sophisticated analysis of sensor data. More extensive sensing means the development and deployment of low-cost distributed sensor networks, in contrast to current technology that relies on single points of occupancy detection. More sophisticated analysis of sensor data means the development of an analysis framework that can be applied to a sensor network data stream to make accurate inferences about space occupancy.

Phase I of the project, described in this topical report, focused on Instrumentation and Data Collection. In this phase of the project, we conducted field trials to collect the raw data required to identify promising combinations of new and existing low cost sensors and other sources of information that we expect will improve occupancy detection and indoor environment system control effectiveness.

An occupancy detector sensor network was developed and deployed in a sample of 30 private offices and 30 open-plan workstations, all located in the Peter Kiewit Institute at the University of Nebraska, Omaha NE. This occupancy detection system uses three traditional PIR occupancy sensors aimed at occupied areas in the work space. These three detectors were complemented by a sensor that determines when the telephone is off-hook (i.e., a telephone conversation is in progress), and a thermocouple mounted in the cushion of the occupant's chair. Each detector provides an independent measure of occupancy. Together, the combination of detectors provides a converging and redundant sensor network.

With the exception of the chair thermocouple (each of which was connected to a standalone data logger mounted on the underside of the chair), all other occupancy detectors located in each work area were connected to a personal computer-based data acquisition system. This data acquisition system polls each occupancy detector in every office once every second, writing a single character to a text file to indicate whether or not each respective detector was sending a signal to indicate occupancy (a "0" indicates no signal from the detector, and a "1" indicates a signal-and assumed occupancy- from the detector). The data are written to a text file on the hard disk drive of the computer collecting the data.

All 60 work areas were monitored for a two month period, over the fall and winter of 2004-2005. A pilot study, using data collected from 2 private offices over May-June 2004, was completed to evaluate the utility of the proposed analysis framework.

The data collected in Phase I will be used in Phase II to compare the occupancy patterns and energy savings that would result if the indoor environment systems in the spaces studied in Phase I were controlled by any single detector, versus combinations of multiple detectors. We will also analyze the information collected by multiple related and redundant sensors within the context of Bayesian probability theory. Specifically, belief network analysis will be applied to the raw data collected during the first phase. This analysis will identify optimal sensor combinations for improved control system performance and space occupancy determination. The outcome of this phase will be new analysis algorithms based on belief networks, which optimize the performance of control systems based on measurements collected from converging and redundant sensor networks.

3 Experimental

Phase I of the project focused on instrumentation and data collection. In this phase a new occupancy detection sensor network was developed, commissioned and installed in a sample of private offices and open-plan office workstations. Data acquisition systems were developed and deployed to collect data on space occupancy generated by the sensor network.

3.1 Sensor Network

A sensor network consisting was deployed in each work area (i.e., private office or cubicle workstation). This sensor network uses three traditional PIR occupancy sensors aimed at occupied areas in the work space. These three detectors were complemented by a sensor that determines when the telephone is off-hook (i.e., a telephone conversation is in progress), computer activity monitoring software, and a thermocouple mounted in the cushion of the occupant's chair. Each detector provides an independent measure of occupancy. Together, the combination of detectors provides a converging and redundant sensor network. Each detector will be briefly described in turn.

Figure 1 depicts the PIR sensor used in the project. This sensor is purchased as a self-assembly kit. Although it is possible to purchase assembled sensors, we will assemble the kits ourselves. The sensor circuit incorporates several sensitivity adjustments that may offer more flexibility than can be achieved with off-the-shelf units sold by home renovation and construction retailers. Three sensitivity controls are offered by the kit: one to adjust the detector sensitivity itself, a second to adjust the sensitivity of the circuit to daylight, and a third to adjust the duration of the pulse when the PIR sensor is triggered.

Since the kits are unassembled, we can configure the circuit board as required for our application. For example, initial work suggests that we may not require the "on/off" toggle switch that is included with the kit, and we may mount the LED indicators at another location so they better fit inside a plastic container. Figure 1 depicts the two sides of one of the assembled kits.

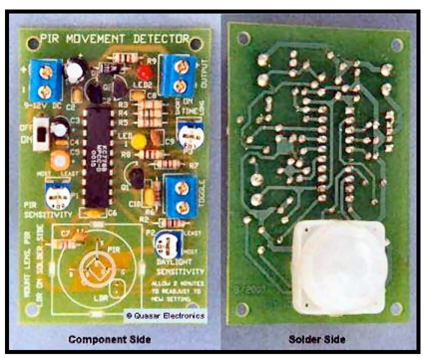


Figure 1: Assembled passive infrared sensor detector kit

The output from each detector is connected to the digital input of a computerized data acquisition system (DAS), described below.

A circuit was developed to indicate when the telephone handset is "off hook", and is therefore being used (i.e., a telephone conversation is in progress, and therefore the workstation or office being monitored is presumably occupied). This circuit is very unobtrusive (connected to the telephone system using an inexpensive telephone-jack "splitter"), and it uses the change in voltage supplied to the telephone to signal that the handset is off hook. The signal from this circuit is also connected to the digital input of the DAS.

Computer keyboard and mouse activity were monitored using a custom client-server software application. The client software resides on the host computer and monitors keyboard and mouse activity. The server software resides on another computer connected to the same network. The server polls every client every second, and writes the activity status of each client to a text file.

Finally, chair temperature was monitored using a type-T thermoucouple, mounted in the chair cushion, connected to a standalone datalogger that was fastened to the underside of the chair using Velcro and secured firmly in position using duct tape. The dataloggers used are manufactured by the Onset Computer Company, model number HOBO U12-014. One of these dataloggers is depicted in Figure 2.

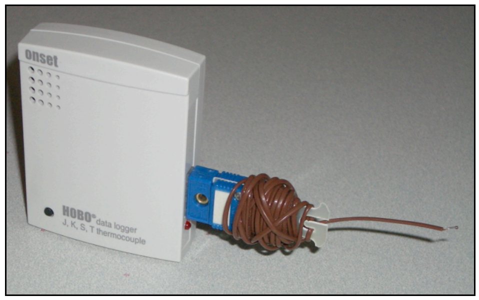


Figure 2: Temperature datalogger and thermocouple

Each datalogger supports a single-channel thermocouple connection (the protruding wire at the right side of the figure), via a subminiature connector (depicted in the figure as the input jack connected to the body of the datalogger body). These dataloggers support 12-bit resolution, 43,000 measurements memory capacity, automatic cold-junction compensation, direct USB Interface, and a 1-year battery life. Chair temperature is polled by the datalogger once every three minutes. Data are manually retrieved from the datalogger at the end of the two month monitoring period.

3.2 Data Acquistion System

The three PIR sensors and the telephone sensor in each work area were connected to a USB PC-based data acquisition system manufactured by Data Translation, model number DT9806. The electrical signals from the PIR sensor and telephone sensor outputs were connected to the digital inputs on the DT9806 terminal block. The data acquisition and control software was developed using the Data Translation Measure Foundry graphical programming environment. This data acquisition system polled each connected device every second, writing a single character to a text file to indicate whether or not each respective detector was sending a signal to indicate occupancy (a "0" indicates no signal from the detector, and a "1" indicates a signal – and assumed occupancy – from the detector).

Figure 3 depicts the DAS deployed to collect data from the cubicle workstations. A similar system was used to collect data from the sample of private offices.

Figure 3: Computerized DAS

The terminal blocks connecting wires delivering signals from individual sensors to the data acquisition system are on the left side of the desk, next to the computer monitor. The sensor network in each work area is connected to the data acquisition system using CAT 5 ethernet cable, which contains 4 pairs of conductors. The signal from each of the four detectors uses one of the wire pairs.

Figure 4 depicts the components of the data acquisition system. On the detector side (left side of the figure), the insulation on the CAT 5 cable is stripped away, leaving four pairs of conductors, each of which is connected to one of the sensors (3 passive infrared detectors and a circuit to indicate whether the telephone is off-hook). This detector assembly is prepared and fully tested before installation in the work area. The right side of the figure shows a longer CAT 5 cable connected to the detector assembly using a coupler, which is circled in figure 3. This longer cable represents the connection to the data acquisition system, which uses identical CAT 5 cable passed through the ceiling plenum back to the room hosting the data acquisition system.

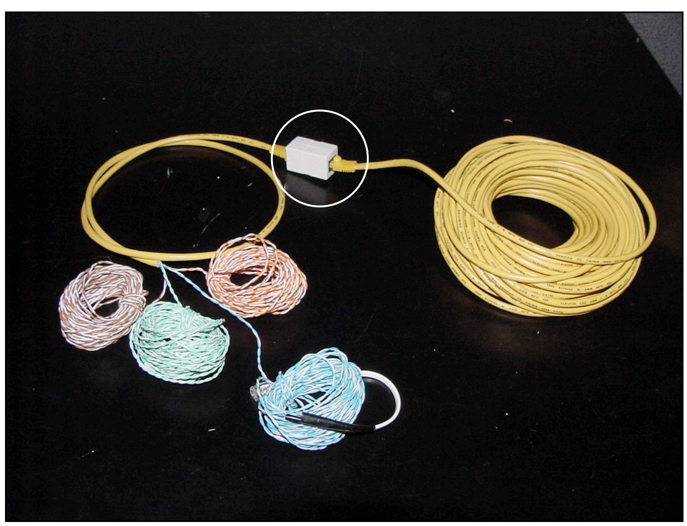


Figure 4: Data acquisition wiring assembly

By separating the detector assembly from the longer wire run to the data acquisition system, wire can be pulled through the plenum to each office or work area independently of the detector assembly. This allows us to proceed with data acquisition system installation and commissioning more rapidly, and with less inconvenience to subjects. Quality control and fault detection and repair are also improved since the detector assembly is fully tested before installation, and it is also possible to independently test the continuity of the longer wire runs from the detector assembly to the data acquisition system, which had been a problem in earlier work described in previous monthly reports.

This DAS is different than originally proposed, and has slowed data collection. Our initial plan was to use a standalone DAS consisting of time-of-use data loggers in each work area or office, with each data logger connected to a single occupancy detection measurement point. This would have required considerable manual labor to retrieve the raw data from each logger, followed by significant data pre-processing to transform the raw data collected by each logger into a format suitable for analysis. Further, the standalone system does not allow for real-time display and analysis of data, which is planned under the third phase of the project.

We revised this initial plan extensively, to increase the flexibility and efficiency of data collection and subsequent analysis. This strategy is more efficient, because raw data are collected in the form required for the analyses planned in Phase II. No post-processing is required before data can be analyzed. Second, it allows the project team to monitor data acquisition in real time, and diagnose and correct any problems immediately, which is not possible with standalone data loggers. Finally, the experience gained implementing and deploying this kind of data acquisition system will be valuable in completing the work planned under Phase III of the project, when we expect to develop a prototype occupancy detection system that will need to interface with existing building management and control systems.

3.3 Sample of Work Areas Studied

Occupancy was studied in a sample of 30 private offices and 30 cubicle workstations, all located at the University of Nebraska's Peter Kiewit Institute, in Omaha NE. Each of the 30 private offices is occupied by a university faculty or staff member: each private office is occupied by a single faculty or staff member, and is about 3.3 meters by 4 meters (10 feet by 12 feet). The statistical basis for selecting 30 of each work area was the Central Limit Theorem of inferential statistics, which states that as long as the sample size is large (at least 30), the distribution of sample means will be normal (Gaussian), even if the population distribution is not normal. Accordingly, conclusions drawn from these samples will be statistically valid.

Cubicle workstations are distributed through several individual rooms, as follows: Room 1 - fourteen workstations; Room 2 - four workstations; Room 3 - six workstations; Room 4 - four workstations, and; Room 5 - four workstations. These rooms are occupied by graduate students.

Each workstation supports three PIR detectors, aimed at the cubicle occupant and the immediate area around the workstation, computer activity monitoring software, and a chair cushion thermocouple. Since all these work areas are used and occupied by graduate students, we expect longer and more irregular occupancy than would be typical for a private office occupied by faculty or staff.

Rooms 1 and 2 contain traditional cubicles in a larger open-plan space, as depicted in Figure 5. PIR detectors are mounted on wall and cubicle partitions in these two rooms.

Figure 5: View of room containing 14 cubicle workstations (left panel), and close-up view of two cubicles workstations in this room (right panel)

Figure 5 shows two views of Room 1, containing 14 cubicle workstations. The left panel shows a view of this room from the northeast corner, looking toward the southwest. The right panel depicts a representative view of two of the cubicle workstations that are contained in this room. Room 2, containing 4 workstations, has a similar configuration consisting of four cubicles separated by partitions.

The remaining rooms contain adjacent workstations located in a single open space, as depicted in Figure 6. Each workstation consists of a desk and an overhead filing bin. Two PIR detectors are mounted at the top of the pillars supporting the overhead filing bin (circled in the right panel of Figure 6), oriented so each detector faces the desk area. A third PIR detector faces outward into the room, and is mounted along the center of the bottom edge of the filing bin.

The data acquisition system collecting PIR occupancy signals from all five rooms is located unobtrusively in Room 1 (depicted in Figure 3).

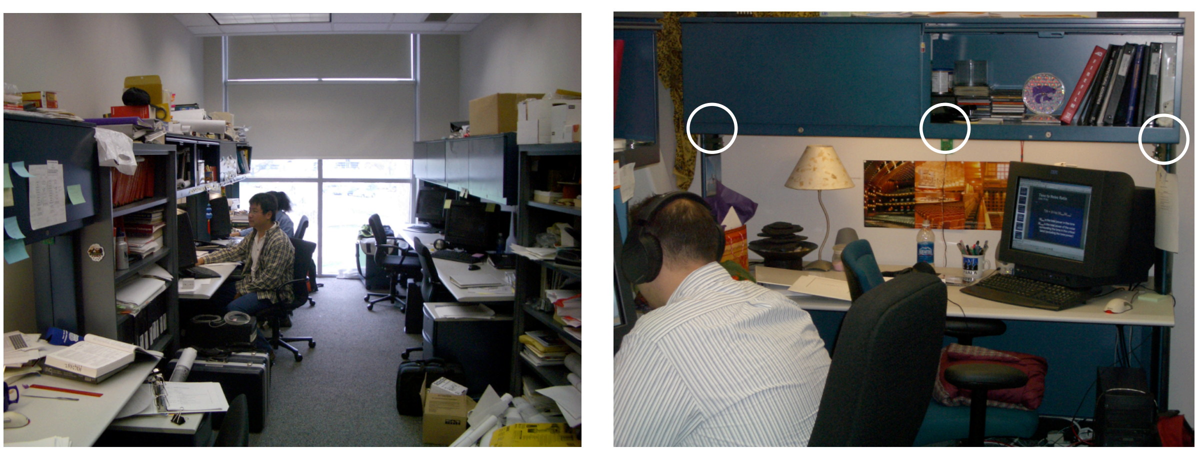


Figure 6: Graduate student work area (left panel). Detail showing mounting location of PIR sensors (circled in the right panel)

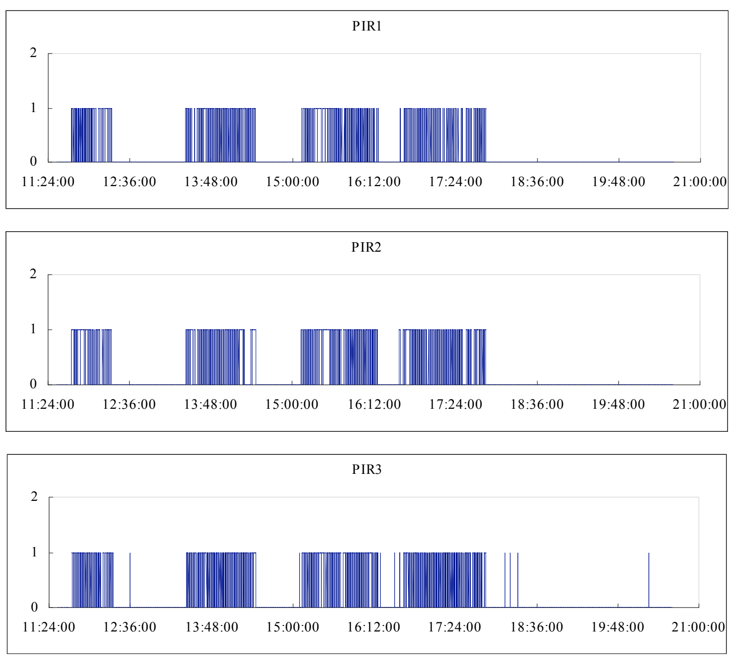
4 Results and Discussion

This section discusses preliminary results collected over two time periods. The first data set (Pilot Data Set #1) was collected from a single private office over a single day in early winter 2004. This limited trial was to verify the feasibility of the alternate data collection method using computerized DAS rather than deploying standalone systems. Although of limited duration, this trial showed that data collected using this alternate method would be relatively easy to analyze, and provided hints that the approach to occupancy measurement using multiple detectors will ultimately bear fruit.

The second data set (Pilot Data Set #2) was more extensive, collected from two private offices over a longer time period during the spring of 2004. A preliminary belief network analysis was successfully applied to these data to verify the applicability of this analysis technique. Each data set will be described in turn.

4.1 Pilot Data Set #1

These data were collected from a single private office over a single day in early winter 2004. The sensor network consisted of three PIR occupancy detectors, a detector that sensed when the telephone handset was "off hook", and software to monitor activity at the computer keyboard and mouse. No chair thermocouple was used. The PIR sensors were mounted on the walls of the office, as follows: PIR1 was mounted on the north wall; PIR2 was mounted on the east wall of the office; and PIR3 was mounted on the south wall, facing the door. The three PIR sensors and the telephone sensor were connected to the same DAS hardware as described above. Figure 7 shows PIR and telephone sensor network activity over a portion of a single day.



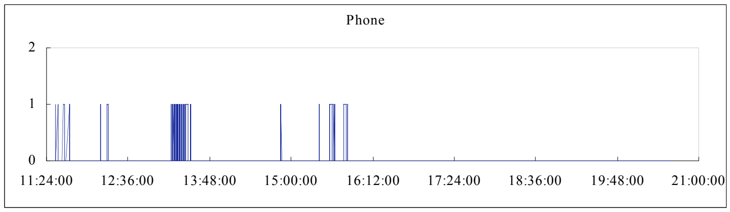


Figure 7: PIR and telephone sensor network activity as a function of time of day

Figure 8 depicts computer activity over the same day. Recall that the program writes a "0" when it detects no activity during the previous second, a "1" if it detects keyboard or mouse activity the previous second, and a "2" if it cannot determine the status of a client (the user has logged off the computer, shut it down, or the computer no longer has the monitoring software installed).

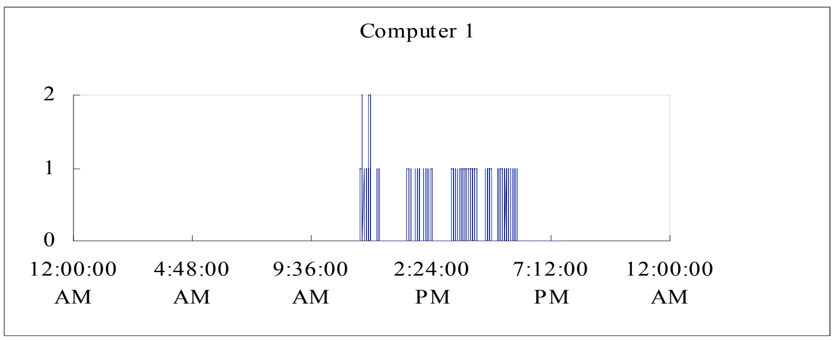
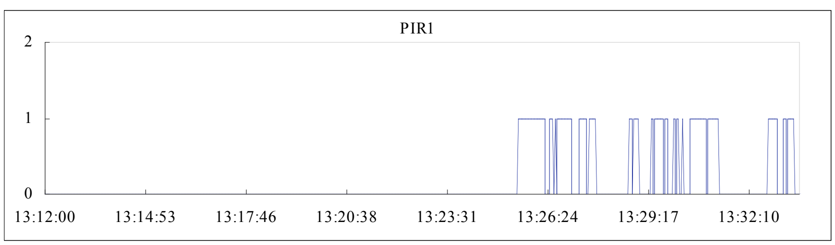
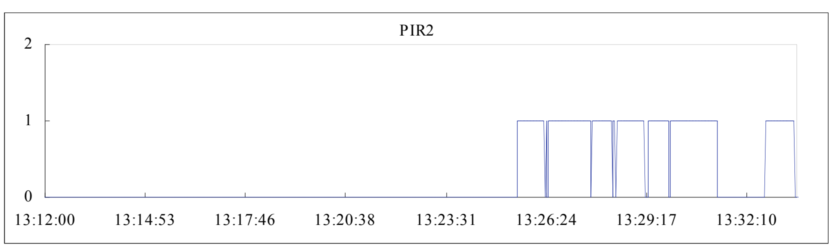


Figure 8: Computer activity as a function of time of day

Figure 9 shows data from the PIR and telephone sensors extracted from a 20 minute interval on the same day.





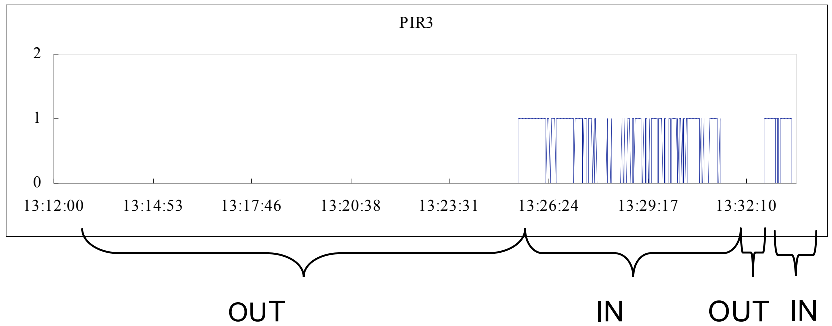


Figure 9: PIR sensor network activity and office occupancy status (occupant is OUT or IN) over 20 minute interval

Figure 9 shows that there are differences in the performance of the three PIR detectors that is not as apparent in Figure 2, as a result of the different time scales used in the two figures. The response rate for PIR3, the detector facing the office door, is greatest, as expected, and the other two detectors exhibit different response rates. Thus we expect that the application of the belief network paradigm to these data will be fruitful. For example, it may be possible to use sensor position and detector response rate to estimate the number of occupants in addition to simply determining whether or not a space is occupied.

Finally, Figure 10 shows data from the same time interval from the telephone sensor. In Figure 7, it appears as if the telephone was used for a long interval sometime between 12:36 and 13:48. Further detailed inspection of the raw data shows this not to be the case. When an incoming caller leaves a phone message, the telephone system sends a regular single-second pulse to the telephone handset to flash the "message waiting" light. Removing this single second pulse from the raw data file produces the telephone usage data profile that appears as the bottom panel of Figure 10.

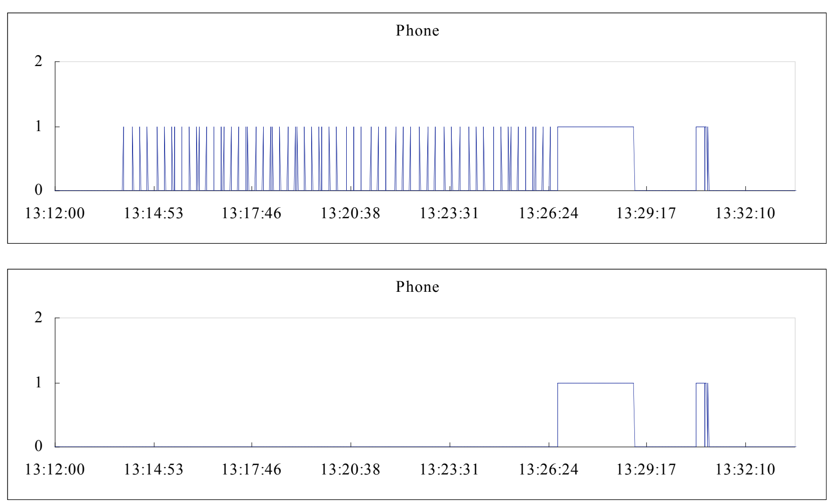


Figure 10: Telephone sensor network activity over 20 minute interval

4.2 Pilot Data Set #2

A sensor network was assembled and tested in two private offices, for a period of 22 consecutive days during spring 2004. The offices were occupied by faculty members from the Architectural Engineering program at the University of Nebraska's Peter Kiewit Institute, located in

Omaha, NE. The sensor network consisted of three PIR occupancy detectors, a detector that sensed when the telephone handset was "off hook", and software to monitor activity at the computer keyboard and mouse. No chair thermocouple was used. The PIR sensors were mounted on the walls of the office, as follows: PIR1 was mounted on the north wall; PIR2 was mounted on the east wall of the office; and PIR3 was mounted on the south wall, facing the door. The three PIR sensors and the telephone sensor were connected to the same DAS hardware as described above.

4.2.1 An Occupancy Sensor Belief Network

In this section we present a belief network to model occupancy in a building. This belief network has been implemented and tested using Pilot Data Set #2. For the purpose of exposition, we limit discussion to a model of just two rooms.

The belief network shown here is capable of answering questions about building occupancy, both by individual space and in aggregate. It is also useful for answering secondary questions such as the status (functioning or otherwise) of sensors represented in the belief network.

We have constructed this belief network to take into account several specific dependencies among the variables relevant to occupancy. The variable of central importance is the number of occupants in a room. The total number of occupants in all rooms is just the sum of the numbers in each room (Figure 11). It is known that the number of occupants persists over time (Figure 12). If someone is present now, it is probable that someone will be there a short time from now. Likewise, if no-one is there now, it is probable there will be no-one a short time from now. Sensor measurements depend on the number of occupants (Figure 13). Each sensor responds in its own way to the presence or absence of occupants. Each type of sensor has a different kind of probability distribution conditional on occupancy, and each particular sensor of a given type may have different parameters. There may be any number of sensors in a given space; the sensors may be of any type, and two spaces can have different kinds and numbers of sensors. A sensor may respond to occupancy in different ways depending on its status (Figure 14). Status in this context means functioning correctly, or malfunctioning in one or more ways. The probability of malfunction is a useful by-product of the main occupancy calculation.

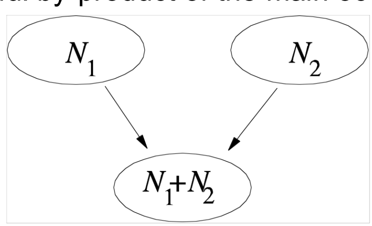


Figure 11: The number of persons in a collection of spaces, or in an entire building, is derived from the number of persons in each individual space

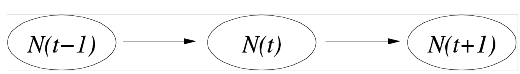


Figure 12: The number of persons in a space persists over time. What is known about the occupancy at this time can inform us about the occupancy at preceding and succeeding times

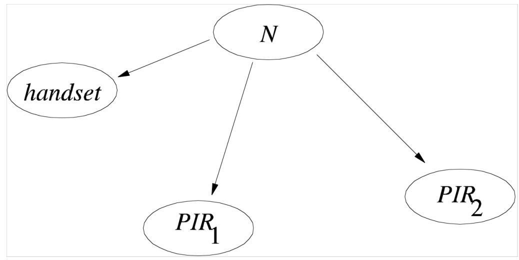


Figure 13: Observable variables are conditional on the number of persons in a space

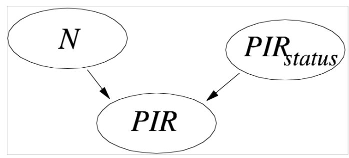


Figure 14: The observed value of the PIR sensor is conditional not only on the actual number of occupants, but also on the status of the sensor (functioning correctly)

Combining the interrelated dependencies shown in Figure 11 through Figure 14 yields a belief network that takes all these factors into account, as shown in Figure 15. Usually a reported value will be known for each sensor, although the value will have little effect on the computed belief if it appears the sensor is malfunctioning. Occasionally some other values may be known, for example, if verified by service personnel. There is no requirement that the set of reported values be the same at all times, but any additional information will be taken into account to sharpen the belief about unobserved variables

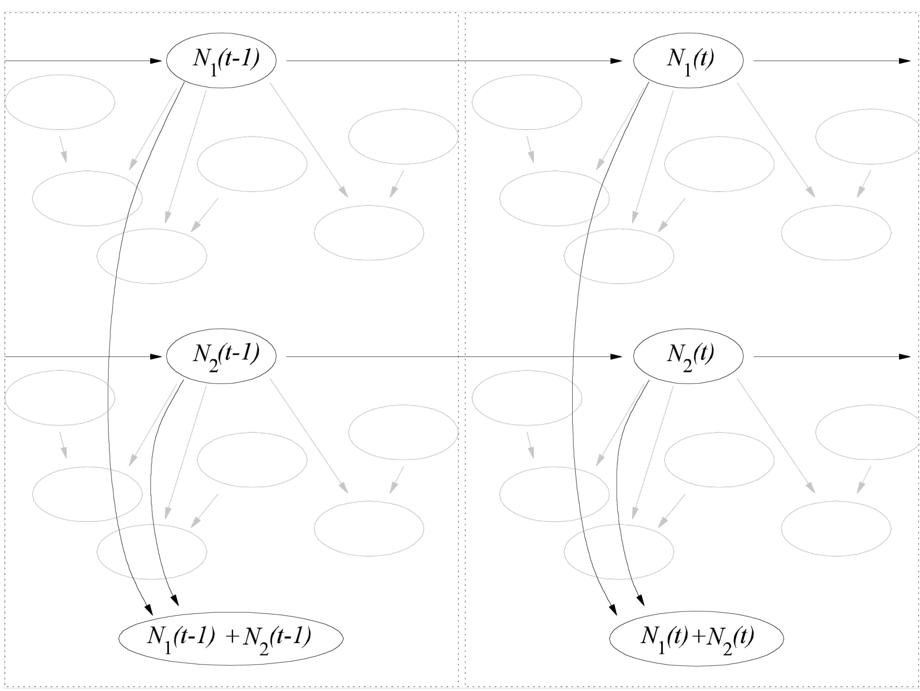


Figure 15: Two slices of a belief network to model occupancy in a building, combining the effect of occupancy on observable variables, a model for each sensor, total occupancy as a function of occupancy in each space, and temporal dependence of occupancy from one time slice to the next

Some known temporal and spatial dependencies have been omitted from the diagrams to avoid crowding. We will now describe these briefly.

Some temporal dependencies are omitted, namely the persistence of sensor status (as a malfunctioning sensor tends to continue malfunctioning), and the persistence of physical variables (as the rate of change in humidity, temperature, and carbon dioxide concentration is a function of the air mass balance in a space).

There may also be spatial dependencies which are not accounted for. For example, humidity and temperature within the building may be a function of ambient humidity and temperature, an influence shared by all spaces within the building. Occupancy sensors with overlapping fields of view illustrate another kind of spatial dependence. Finally, sensors may share some common parameters. For example, all sensors of a particular design may share a common calibration parameter. It remains to be seen whether it is necessary to account for all of these additional dependencies in order to build an effective and accurate model for occupancy.

4.2.2 Computation of Inferences in Sensor Belief Networks

The sensor belief network was implemented using a software program, called RISO, developed by one of the authors. RISO is an implementation of inference in distributed, heterogeneous belief networks (Dodier, 1999). RISO is written in Java for greater cross-platform portability. RISO carries out computation of posterior distributions using Pearl's polytree algorithm (Pearl, 1988), which applies only to belief networks without loops. For belief networks with loops, there is an implementation of Gibbs sampling (Gelman et al., 2003) for RISO.

There are several software implementations of belief network inference available. Generally speaking, there are algorithms which are applicable to different types of distributions. Exact algorithms for loopy belief networks containing only discrete or Gaussian distributions are known. For all other cases, some degree of approximation is often necessary. Gibbs sampling is a widely-used approximation method applied to problems for which exact solutions are known. However, as a Monte Carlo method, Gibbs sampling is relatively slow, and yields an empirical distribution (histogram or other approximation) instead of an identifiable algebraic distribution. Among the implementations of Gibbs sampling, BUGS (Gilks et al., 1994) is widely used.

4.2.3 Calibration of Sensor Belief Network

The belief network described in Section 5.2.1 contains several free parameters which describe the relations among variables. For example, the sequence N(t-1), N(t), N(t+1) forms a Markov chain, and the detailed behavior of the chain is governed by its transition matrix.

Occupancy transition matrix: The transition probabilities have been estimated from PIR sensor data. As there is no unambiguous record of arrivals and departures (which could be provided by a human monitor, say, or a video camera), occupied and unoccupied states have been imputed from the available data according to these two rules. (1) If at least two of the three PIR sensors fire, it is assumed that someone is present. (2) If someone is assumed present at a certain time, and also present less than 60 seconds later, it is assumed that someone was present during the intervening interval. These heuristics enable an initial statistical analysis. A more accurate analysis will become possible with unambiguous "ground truth".

In a Markov model, the probability of transition out of a state is equal to the inverse of the expected sojourn time. Thus, transitions probabilities can be estimated from observed sojourn times. Expected sojourn time in the imputed occupied state is estimated as 564 seconds based on 22 days of data collected May 11, 2004 through June 1, 2004. Expected sojourn time in the imputed unoccupied state is estimated as 379 seconds, ignoring unoccupied states longer than 5000 seconds. (There are a small number of very long unoccupied states, since the building is largely unoccupied during the night, and there were apparently some vacation days when no occupancy events were observed. A transition model which takes time of day and calendar into account will more accurately describe the modeled system.)

If occupancy is described by a Markov chain, the sojourn time in any state should be exponentially distributed. Indeed, histograms of empirically determined sojourn times shown in Figure 16 to Figure 18 are approximately exponential for both occupied and unoccupied states. However, the histogram for the unoccupied state has a greater number of lengthy sojourns than is expected from an exponential model. This defect is due to ignoring time of day and calendar information in the transition model.

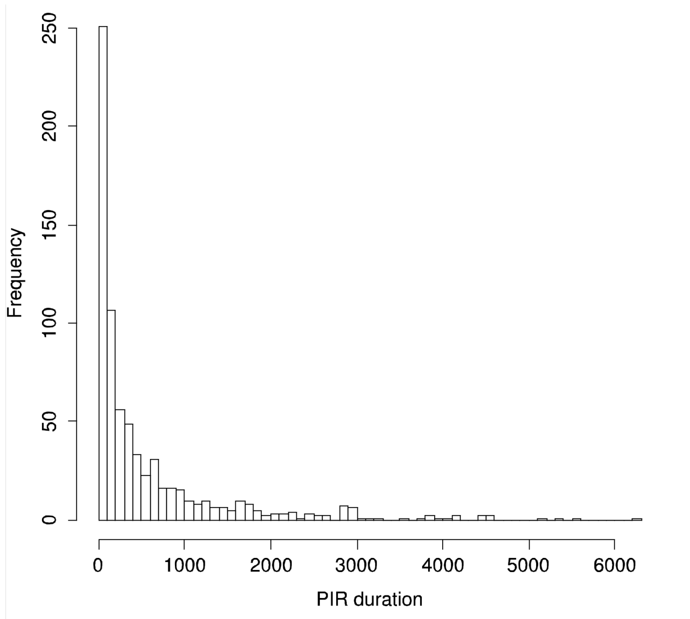


Figure 16: Duration of presence, both rooms aggregated, data collected May/June 2004. 717 intervals of continuous occupancy, assuming gap between events greater than 60 seconds for the purpose of imputing occupancy. 50 bins in histogram

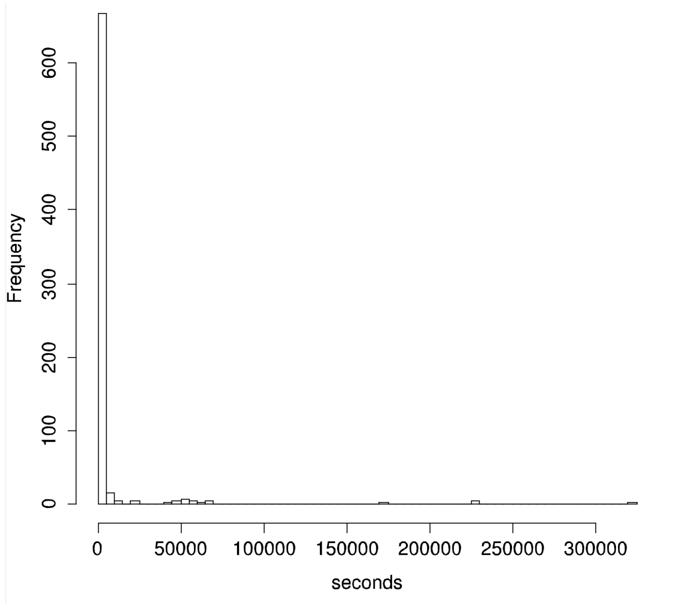


Figure 17: Duration of absence, both rooms aggregated, data collected May/June 2004. 719 intervals of continuous absence, assuming gap between events greater than 60 seconds for the purpose of imputing occupancy. 50 bins in histogram

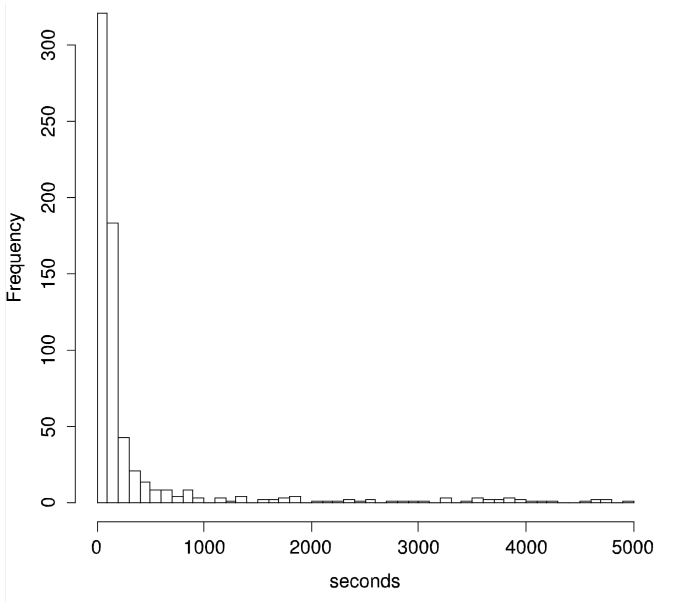


Figure 18: Duration of absence less than 5000 seconds, both rooms aggregated, data collected May/June 2004. Same data as in Figure 8, excluding intervals greater than 5000 seconds. 668 intervals

PIR sensitivity: To judge from PIR sensor data, some PIR sensors are more sensitive to occupancy than others. This behavior may be due to mounting position and direction, or to adjustment factors or other differences; for the purpose of analysis of occupancy, the reason for the difference may not matter.

It is observed that in room 1, PIR 1 is less sensitive than PIR 2, and PIR 2 is less sensitive than PIR 3. In room 2, PIR 1 is less sensitive than PIR 2 and PIR 3, and the latter two are equally sensitive. The average firing rates for each sensor in the presence and absence of occupancy are reported below.

Table 1: Average PIR firing rates for Room 1

Room 1	Present	Absent
PIR 1	0.497	0.000322
PIR 2	0.581	0.000360
PIR 3	0.726	0.00402

Table 2: Average PIR firing rates for Room 2

Room 2	Present	Absent
PIR 1	0.242	0.0000149
PIR 2	0.847	0.00281
PIR 3	0.848	0.00326

As the PIR firing events are assumed to be Poisson distributed, these average values are therefore the parameters of the Poisson distribution for each PIR.

Telephone handset sensors: From the observed data, it appears that the telephone handset sensors function exactly as designed. The signal is 1 if and only if the handset is off the hook, and 0 otherwise.

Failure models for sensors: No sensor failures are recorded in the available data, but failure is far from impossible. It is assumed at present that if a sensor (PIR or handset) has failed, its output is 0. The failure probability is assessed a priori as 1%. More complex failure models will certainly be useful.

4.2.4 Analysis of Typical Occupancy Patterns using Belief Networks

In this section we will consider some scenarios in which inference is useful and interesting.

One person in an office: Suppose in Room 1, we observe PIR 1 fires and PIR 2 does not. These are the only data (the telephone handset sensor is not observed in this example). From these data we calculate p(occupancy) equal to 0.804. If PIR 2 fires, as well as PIR 1, we find p(occupancy) increases to 0.998. If the telephone is off the handset, p(occupancy) increases yet again to 1: the handset cannot be off the hook if nobody is there, and if the handset sensor malfunctions, it cannot send a positive signal. Thus there must be someone present.

Temporal persistence of occupancy: Suppose we observe, at a particular instant, PIR 1 fires, PIR 2 fires, and the handset is not off the hook. Over the following time slices, in the absence of further observations, we see that the calculated p(occupancy) decreases slowly.

Sensor status inference: Suppose we observe PIR 1 fires, PIR 2 does not, and the telephone handset is off the hook. p(occupancy) is computed as 1, since someone must be present. What about PIR 2? The probability that it is malfunctioning is computed as 0.027. This can be compared to the prior probability of malfunction, which is specified in the belief network as 0.01. Although the malfunction probability is still small in absolute terms, it is larger than the prior probability; if someone is present, PIR 2 usually fires (though not always).

Explaining away office occupancy: If there are two causes for an observed consequence, and something is known about one cause that accounts for the observation and explains away the other cause. "Explaining away" is the term typically applied in belief networks to the flow of information from one parent to another via downstream evidence. In the occupancy belief network we have described, suppose that in office 1, PIR 1 fires, while in office 2, both PIR 1 and PIR 2 fire. In the absence of any further evidence, the calculated probability of occupancy is computed as nearly 1 in office 1 and in office 2. However, suppose that it is known that there is exactly one person present. This information is represented by setting the occupancy total N1+N2 equal to 1. Now the probability of occupancy in office 1 falls to just 0.025, while the probability of occupancy in office 2 is still 0.975. Because office 1 and office 2 are tied together via their common child, the total occupancy, the stronger evidence of occupancy in office 2 has an effect on office 1. Interactions between events in different offices are not explicitly represented in the belief network, but rather such interactions are consequences of the laws of probability applied to the local dependencies stated directly by the belief network.

5 Conclusions

Phase I of this project focused on instrumentation and data collection. In this project phase a new occupancy detection system was developed, commissioned and installed in a sample of private offices and open-plan office workstations. Data acquisition systems were developed and deployed to collect data on space occupancy profiles. Analysis tools based on Bayesian probability theory were applied to the occupancy data generated by the sensor network. The inference of primary importance is a probability distribution over the number of occupants and their locations in a building, given past and present sensor measurements. Inferences were computed for occupancy and its temporal persistence in individual offices as well as the persistence of sensor status. The raw sensor data were also used to calibrate the sensor belief network, including the occupancy transition matrix used in the Markov model, sensor sensitivity, and sensor failure models. This study shows that the belief network framework can be applied to the analysis of data streams from sensor networks, offering significant benefits to building operation compared to current practice. This Topical Report concludes with a discussion of the prospects and merits of sensor networks and probabilistic inference for the sensor network approach advocated in this work.

5.1 Experienced and Expected Difficulties

The most serious obstacle to the use of graphical probability models in occupancy detection is the difficulty, inability, or lack of expertise needed to express domain knowledge in probabilistic form. Although the range of applications is broad, the required skill is not yet widely cultivated. Ideally, every detail known to domain experts will be expressed in some way in the belief network model.

Some computational problems have been encountered. The software implementation is not memory efficient and the total memory allocation approaches the physical memory of the test machine (512 megabytes) after processing several hundred time slices. Also, there is a problem which manifests itself as the detection of a loop in the belief network, even if there is no such loop. As the latter problem also appears after several hundred slices are processed, it may be a symptom of the memory allocation problem.

Inferences which require downstream evidence be taken into account are computed by Gibbs sampling. This is much slower, by orders of magnitude, than inferences which can be computed by the polytree algorithm alone.

5.2 Possible Improvements

There are some aspects of the problem domain which are recognized but not yet expressed in the belief network. Chief among these is the dependence of occupancy on the time of day and the calendar. Ideally the occupancy transition matrix would show greater probability of transition into the occupied state during the day and on weekdays, and lower probability at night and on weekends and holidays.

The dependence on time of day can be determined empirically, but the dependence on calendar information will likely be determined by making reasonable assignments based on the prevalent calendar at the work site. Conceivably, the transition matrix for a particular room could be tailored to the personal calendar of the customary inhabitants.

A secondary consideration is distinguishing the number of people in an area, as opposed to only distinguishing presence from absence. The model has placeholders for parameters to describe the dependence of sensor observations on multiple occupants, but the necessary statistical analysis has not been carried out. Some progress can be made by assuming that people move independently and therefore the total PIR firing rate is somewhat less than the sum of the firing rates for each person. The total PIR firing rate is "somewhat less" than the sum because two movements at the same time are recorded as a single event.

Weak dependencies between occupancy in different rooms could be taken into account in the present model. For example, if most rooms in a building are occupied, that should increase the probability that any one room will be occupied, as people may move from one area to another. Also, there is relatively weak evidence in the form of whole-building cooling load, as the cooling load generally increases with the number of people in the building, all other parameters being constant.

The ability of the belief network to model sensor status would be substantially increased by taking temporal persistence of sensor state into account. At present it is assumed that the sensor status in one time slice is not directly dependent on sensor status in the previous time slice. This is unrealistic, since if a sensor is malfunctioning, it tends to continue malfunctioning. Unfortunately, taking status persistence into account will introduce loops into the belief network and make inference computations more difficult.

5.3 Merits of Sensor Networks and Probabilistic Inference

We expect this approach to occupancy detection will produce benefits in several areas: improved occupant acceptance of control systems; electrical energy and demand savings, and; enhanced safety, security and comfort for building occupants. Each of these will be discussed in turn.

Attention to human factors is crucial to the performance of control systems. Users will quickly disable energy-saving features if they are inconvenienced in any way. Research on energy-efficient shower-heads, for example, suggests that at least 10 to 15% of users will replace a newer more efficient shower-head with the older technology it replaced, often within the first week after the new device was installed (Hickman & Warwick, 1994; Manclark, 1991). If users disable occupancy detectors due to poor perceived performance, energy savings will be less than expected. We believe that systems based on multiple detectors and information sources will achieve greater savings with less inconvenience to occupants.

Previous research provides information on the energy and demand savings that can be achieved by applying occupancy sensors to lighting control, and other studies have evaluated the effectiveness of occupancy-based switching for power management of office equipment. Von Neida et al. (2001) have summarized industry estimates of potential savings arising from the application of occupancy sensors in private offices as ranging from between 13-70%. In open-plan offices, these estimates ranged from between 15-35%. A companion paper (Maniccia, Tweed, Bierman & Von Neida, 2001) reports observed savings of between 27-43% in private offices.

Tiller and Newsham (1993) compared the effects of reminder stickers versus automated power management for desktop office equipment. At one site stickers were installed reminding users to switch off computers when not in use. Computer on-time was reduced by 14%, and mean peak demand by 7%; how-ever, these savings were not maintained over time. This reduction is comparable to that found by Rea, Dillon and Levy (1987), who found that switch plate stickers reminding users to turn off lights produced savings of 15%, and these savings also diminished with time. An occupancy-based power management device that automatically switched off computers and peripherals after a specified period of inactivity was installed at a second site. Tiller and Newsham (1993) found that computer on-time was reduced by 63%, and mean peak demand due to computers was reduced by 35%; the on-time of video display terminals was reduced by 82%; savings were maintained over time.

More accurate detection of space occupancy will improve the performance of occupancy-based control systems. We expect, therefore, that the deployment of new technologies to manage and control building energy systems could save up to 70% in private offices, and up to 35% in open-plan offices. Clearly, further improving the performance of control systems with the help of the proposed system is a significant contribution to the responsible and efficient operation of commercial buildings.

Finally, building security will also be enhanced through more accurate occupancy detection using sensor networks. For example, a dynamically updated building occupancy map stored on an offsite internet servers, updated in real time, would let emergency services know how many occupants are in a building, and where they are located.

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7 List of Acronyms and Abbreviations

ARI	American refrigeration institute
DOE	United States Department of Energy
EIA	Energy Information Administration
HVAC	Heating, ventilating, and air-conditioning
NLPIP	National Lighting Product Information Program (located at the Lighting Research Center, Rensselaer Polytechnic Institute)
PIR	Passive infrared

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