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Testing the Accuracy of Low-Cost Data Streams for Determining Single-Person Office Occupancy and Their Use for Energy Reduction of Building Services

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Abstract

We explored methods of detecting occupancy in single-person offices using data already collected by the occupant's PC, or data from relatively cheap sensors added to the PC. We collected data at 15-second intervals for up to 31 days in each of 28 offices. A combination of low/no cost sensors (webcam-based motion detection, and keyboard and mouse activity) was much more accurate at detecting occupancy than a commercial ceiling-based passive infrared (PIR) sensor, and provided overall daytime accuracy >90%, with very low false negative rates. This enhanced detection performance would enable a reduction in the timeout periods for building service curtailment on space vacancy. For example, lighting switch-off timeout could be reduced from the current energy code standard of 20 minutes to less than 5 minutes, increasing energy savings potential by 25-45%. We then deployed this system in a proof-of-concept demonstration, using it to control lighting, heating, ventilation, and air conditioning (HVAC), and plug loads in a mock-up office environment. Tests were run over nine occupied days (six in cooling season, three in heating season). The system delivered energy savings of 15-68%, with no reported false negative errors.

Glossary of Terms and Abbreviations

Count	Total number of instances of sensor data, aggregated to the 15-second level.
TP	True Positives, instances when a sensor reports a space is occupied when indeed it is.
TN	True Negatives, instances when a sensor reports a space is not occupied when indeed it is not.
FP	False Positives, instances when a sensor reports a space is occupied when indeed it is not.
FN	False Negatives, instances when a sensor reports a space is not occupied when indeed it is.
Occupied (Occ)	Actual fraction of time office occupied = TP/Count
Accuracy (Acc)	Fraction of time a sensor correctly identifies occupancy status = (TP+TN)/Count
FPR	False Positive Rate =FP/(TN+FP)
FNR	False Negative Rate =FN/(FN+TP)
ESR	Energy savings ratio achieved by sensor system with 20-minute timeout.
MaxESR	Maximum energy saving ratio by switching off lights when office is unoccupied, compared to lights being on from first arrival to last departure

1. Introduction

The key to saving energy in buildings is to deliver building services only when and where they are needed, in the amount they are needed. Occupancy sensor technology and related controls have emerged from this observation. Occupancy sensors have been deployed at the room level to save energy primarily in ambient lighting systems [Williams et al., 2012; Galasiu et al. 2007], with the potential for energy savings with HVAC systems also emerging [Dong & Lam, 2011]. Energy savings of 20-50% are typically reported.

Given this success, occupancy sensors for lighting systems are now mandated in certain space types in many energy codes for new buildings [e.g. CCBFC, 2011]. However, penetration of this technology as a retrofit in existing buildings is low, and first-cost remains a tangible barrier. The goal of our research was to lower this cost barrier by extracting free or nearly-free occupancy information from an office PC platform. The attraction of a PC platform is that it is already in place in an office environment, and is already powered and networked.

Extracting occupancy data from systems not explicitly designed to deliver occupancy information has been termed “implicit occupancy sensing” [Melfi et al., 2011]. Examples of implicit occupancy data include: computer network activity [e.g. Kim et al. 2010], security card access systems [e.g. Ghai et al., 2012], detection of mobile devices at Wi-Fi access points [e.g. Jin et al. 2014], and PC-based sources such as keyboard activity, webcams, and microphones. These data streams may be supplemented by environmental sensors (e.g. temperature, humidity, light, sound), which are already present in some computing platforms, and are expected to become more widespread as wireless nodes lower in cost and become pervasive as part of the “Internet of Things” (IoT). Although these channels might provide limited accuracy in detecting occupancy independently, their aggregated data may carry more precision and robustness than any one high-end sensor [Dong & Lam, 2011; Dong et al., 2010; Tiller et al., 2009; Hailemariam et al., 2011; Ghai et al., 2012].

Many studies addressing alternative means of detecting occupancy were summarized in Shen & Newsham [2016]. However, few prior studies have focussed specifically on use of implicit data sources and supplemental environmental sensors in single-person office spaces, with no requirement for the occupant to carry hardware on their person.

Zhao et al. [2015] collected data in two offices over several weeks. Keyboard and mouse data were collected every 20 seconds along with data from supplemental sensors: PIR, chair pressure, door open/shut, lighting on/off, Wi-Fi connection, and GPS location. Bayesian Belief Networks were used to select the optimal fusion of sensor data, which typically involved keyboard, mouse and PIR data streams. Ground truth was derived from three extra PIR sensors and occupant diary entries. Overall accuracy exceeded 90%

Hailemariam et al., [2011] added light, sound, CO_2, current, and motion sensors to a single office cubicle; the motion sensor was mounted on the cubicle wall close to and facing the occupant. Data were aggregated at the 1-minute level and collected over one week. Ground truth occupancy was obtained from human transcription of video images. Using a decision-tree method, an overall detection accuracy of 98% was achieved.

Nguyen & Aiello [2012] used environmental sensors to infer not only office occupancy, but also the activity type (presence, absence, working with PC working without PC, and having a meeting). They relied on a pressure sensor in the chair, a ceiling mounted PIR sensor, and two acoustic sensors (one placed to register conversation and a second placed to register keyboard/mouse use). The user kept an activity diary every 5 minutes to provide ground truth. A test in a single office over five days yielded activity detection accuracy of 95%.

While not explicitly measuring the accuracy of an alternative occupancy sensing approach, Dalton & Ellis [2003] provided a very relevant application. They used a webcam with a simple face detection algorithm to determine if someone is looking at a PC display, and to switch off the display if no-one is looking at it. Their very short experiments suggested display energy savings of 12-30% compared to a fixed power saving mode enacted after five minutes of no PC activity.

We conducted a field study to test the accuracy of various data streams for determining the occupancy of offices, and determined a combination of PC-based sensor data streams that substantially outperformed the incumbent commercial technology. We then deployed the system in a full-scale demonstration to control several office systems (lighting, HVAC, miscellaneous/plug loads[1]) over multiple test days in heating and cooling seasons. This research is an advance over previous work in several important aspects:

- Data collection in more offices and over a longer time period
- More accurate ground truth recording
- Direct comparison to incumbent commercial technology
- Separate consideration of false positive and false negative error types
- Focus on accuracy during normal working hours only, when information is most relevant
- Demonstration of actual control of building services based on the new approach

[1] In an office setting, these are any electrical device powered from a conventional wall socket, and may include: computers, monitors, printers, fans, external speakers, supplemental space heaters, desk lights, coffee machines etc. [e.g. Mercier & Moorefield, 2011].

2. Better Occupancy Sensing

2.1 Methods & Procedures

2.1.1 Sensor and Data Description

We installed hardware and software on the PCs of volunteers who occupied single-person office spaces; we also installed additional hardware in these offices spaces. We recorded data from a variety of different sources that may indicate occupancy:

1. Keyboard and mouse activity. We recorded only if these devices had been used, not what was typed or clicked.
2. Webcam (external retrofit[2]). We mathematically derived pixel value differences in consecutive frames of down-sampled images[3], we did not record or store images.
3. Microphone (external retrofit[4], Phidgets 1133). We recorded only dB levels, not what was said.
4. Infra-red sensor (Omron D6T-44L). Low-res (4x4) pixel temperature map of the space.
5. Proximity sensor (MaxBotix EZ-1). Distance from sensor to nearest solid object.
6. Air Temperature and Relative Humidity (Phidgets 1125).
7. Light Level (Phidgets 1142).
8. PIR motion sensor (Phidgets 1111).
9. Commercial, PIR motion sensor (Manufacturer name/model withheld).
10. Pressure mat (United Security 925)[5]. This was used as "ground truth".

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[2] We used an external webcam because not all PCs in the study group had internal webcams, but a future low-cost application would leverage ubiquitous internal webcams.

[3] Utilizing the Windows API, consecutive (40x30 pixel) images were captured every second from the webcam. The distance in RGB space between the two images for each image pixel was calculated:

$$\mathrm{d}(\mathrm{x},\mathrm{y})_{0-255} = \sqrt{((\mathrm{R}_2 - \mathrm{R}_1)^2 + (\mathrm{G}_2 - \mathrm{G}_1)^2 + (\mathrm{B}_2 - \mathrm{B}_1)^2)/3}$$

and a simple metric for motion detection was the maximum distance among all pixels.

[4] We used an external microphone because not all PCs in the study group had internal microphones, but a future low-cost application would leverage ubiquitous internal microphones.

Sensors 1-8 were already present in the PC, or were mounted to the PC monitor (Figure 1); Sensor 9 was mounted on the ceiling in a typical location for commercial use; Sensor 10 covered the majority of the most frequently occupied floor space in the office. The external webcam was connected to the PC via a dedicated USB port; other PC-based sensors that were not internal were connected to a data acquisition board, and then to the PC via a single USB port[6].

Data from all sensors were recorded and collated by custom software on each PC whenever the PC was switched on[7]. Data were recorded every 15 seconds, and were a statistical summary (e.g. Counts, Max, Min, Mean, Median) of raw data recorded at 1 or 5 Hz. The term “row” of data below refers to a single 15-second instance of data from one participant, that instance containing the statistical summary of data from all sensors.

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[5] Mat sensitivity was chosen to ensure that an empty chair or full briefcase would not trigger it.

[6] The radar sensor shown in Figure 1 was only installed on 15 of the sample PCs, and thus was not utilized in further analysis.

[7] The software continued to record data even if the host computer went into a “standby” or “sleep” mode.

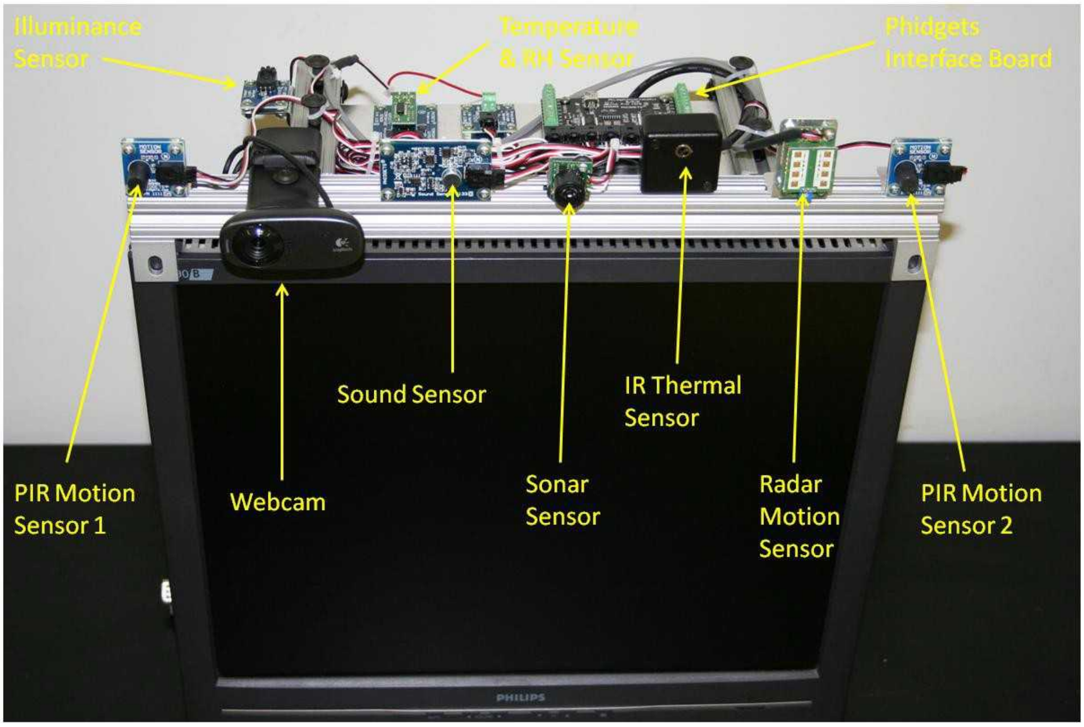

Figure 1 – Front view of sensors attached to PC monitor.

2.1.2 Participants and Data Collection Period

There were 28 participants in the study, located in three mixed-use buildings in Ottawa, Canada. Office ID codes and descriptions are shown in Table 1. Data collection occurred during July to October, 2013. Table 1 shows the number of days of raw (original) and final (cleaned) data available.

2.1.3 Data cleaning

We observed some instances when the pressure mat signal indicated extended occupancy though it was clear there was no-one present (e.g. overnight). This could occur if a very heavy object was placed on the mat or if the occupant's office chair was wedged under their desktop to apply continuous downward pressure. We removed entire days of data from all sensors if the day contained a period when the mat registered a continuous on signal for > 4 hours (considering it highly unlikely that an occupant would be seated for that long). Fewer than 10% of the days in the original dataset were discarded.

We removed all weekends and public holidays to avoid diluting the dataset with long periods when non-occupancy would be obvious and unchallenging for any sensor to detect. We also removed the first and last days of data collection for all offices. These were partial days, involving research staff installing/uninstalling equipment, and not representative of normal occupancy. These two steps combined resulted in about 25% of the days in the original dataset being discarded.

All rows of data (individual 15-second recordings) were removed if they occurred before the first ground truth presence (mat on) signal or after the last ground truth presence signal on a given day[8]. This was done to focus the dataset on periods of potential occupancy. Although only a small number of days of data were lost at this step (about 5% of the original data set), the total number of rows in the data set was almost halved.

Even after relatively conservative data cleaning choices, a large dataset remained: a total of >700,000 rows of 15-second data across >370 days. Further, all participants were retained in the sample, with no participant contributing fewer than 8 days /14,000 rows of data.

[8] e.g. if occupants did not switch off their computer when they left work at the end of the day.

Table 1. Days of data for each office, before and after data cleaning. The final column shows the percentage of time the ground truth pressure mat registered occupancy in the cleaned data set.

ID	Office Type	Window in office	Days of data		Average Occupancy, %
			original	after cleaning	
01AR	Private	Yes	20	11	66.5
02AR	Private	Yes	13	9	49.9
03AR	Cubicle	No	15	13	76.4
04AR	Cubicle	No	16	14	57.1
05AN	Private	Yes	27	16	81.1
06AN	Cubicle	Yes	17	14	71.4
07AR	Private	Yes	24	11	72.5
08AN	Private	No	31	14	67.7
09AR	Private	Yes	16	14	81.3
10AN	Private	No	19	17	68.0
11AR	Private	No	18	16	52.5
12AR	Private	Yes	22	11	79.4
13AR	Private	Yes	26	15	60.4
14AN	Private	No	25	11	62.0
15AN	Private	Yes	17	11	57.6
16AN	Private	Yes	25	8	63.5
17CN	Private	Yes	22	15	60.6
18CR	Private	Yes	26	11	64.7
19CN	Private	Yes	17	15	79.1
20CR	Private	Yes	16	11	66.8
21DR	Cubicle	Yes	15	13	76.7
22DN	Private	Yes	25	10	43.0
23DN	Cubicle	Yes	23	21	32.1
24DR	Private	Yes	21	18	74.8
25CR	Private	Yes	24	16	66.5
26CR	Private	Yes	23	12	49.9
27CN	Private	Yes	31	16	76.4
28CN	Private	No	16	11	57.1
Total			590	374	65.7

Ensuring the accuracy of ground truth was key to further analyses. Any instances when the keyboard or mouse showed activity but the mat indicated no occupancy raised suspicions about the accuracy of ground truth[9]. Only 0.17% of data rows exhibited such a data combination. We also observed some ground truth state changes for only one 15-second period; i.e., a single row of non-occupancy among many rows of occupancy, or vice versa. Although this behaviour might be legitimate, it might also indicate a short-period lapse in correct mat functioning. From >700,000 rows of data we found only 1438 instances of single row state changes. Within these rows, if the mat indicated occupancy for a given 15-second period, but there was no keyboard or mouse activity, and both the PC-mounted motion sensors and webcam recorded low levels of activity then we considered there to be a stronger case that the mat had malfunctioned. This combination occurred for only 61 rows of data, or <0.01% of all rows. Similarly, if the mat indicated no occupancy for a given 15-second period, but there was keyboard or mouse activity, or either the PC-mounted motion sensor or the webcam recorded high levels of activity, there is the possibility of malfunction. This combination occurred for only 558 rows of data, or <0.1% of all rows. In summary, after initial data cleaning, residual ground truth errors are likely less than 1% of all data, and it is appropriate to treat the mat data as the standard to which all other sensors are compared.

2.2 Results & Discussion

In general, in the results below, ground truth mat data has been binarized. Mat data were normalized by dividing the number of readings within a 15-second period indicating occupancy by the total number of readings. A value >0.5 meant the whole 15-second period was considered occupied. Only 3.6% of all normalized mat recordings had a value other than 0 or 1.

Note also that although some results shown are from the entire cleaned dataset, many results are drawn from the final 10% of the dataset for each office. In deriving new occupancy detection approaches, the algorithm development methodology used the first 90% of the dataset for model training and the final 10% of the dataset for model testing.

[9] Although there are legitimate circumstances for such an observation – errors in the keyboard/mouse recording software, some types of remote login.

2.2.1 Descriptive occupancy data based on ground truth

Figure 2 shows the average occupancy profile over all offices and all days. The overall occupancy rate was 65.7%, with a peak of 69.3%. Occupancy exhibits a sharp rise in the morning, with a more extended departure "tail" in the late afternoon. As might be expected, there is a dip in occupancy around lunch time, however, this dip is not as pronounced as in other studies. This might be because work schedules at the study sites were more flexible than in other office-like workplaces, or because people took some lunch breaks in their office rather than another location. Table 1 also shows the mean occupancy for each office. There was considerable variation across offices and days, suggesting that we captured a wide range of schedules and job types in our study sample.

These observations are broadly in line with office occupancy profiles measured in other studies. For example, Rubinstein et al. [2003] used traditional occupancy sensors in 35 private offices to record occupancy every minute over a year (1999) in a large office building in San Francisco. Profiles on the two study floors showed a similar shape to Figure 2, with occupancy peaked at ~75% and ~80%, respectively. Duarte et al. [2013] used data from 629 PIR occupancy sensors in a large multi-tenant office building in Boise, Idaho. Data were collected over two years (2009-2011) and collated at the 1-minute level. The average profile for private offices was similar to Figure 2, with a peak occupancy of ~50%. Yang & Becerik-Gerber [2014] collected occupancy data from 28 private offices in a university office building in southern California. Occupancy was determined from a combination of sensors. They developed personalized occupancy forecasts, with peak occupancy typically 60-70%. Zhao et al. [2014] measured occupancy using wearable devices and PC activity data in 15 open-plan university offices over three months in 2013. The average weekday had peak occupancy ~68%. D'Oca & Hong [2015] recorded occupancy at 10-minute intervals in 16 private or semi-private offices in Germany over two years. They sought clusters of occupancy profiles rather than a single average, but three of four cluster profiles had a similar overall pattern to Figure 2, with a peak occupancy 60-65%.

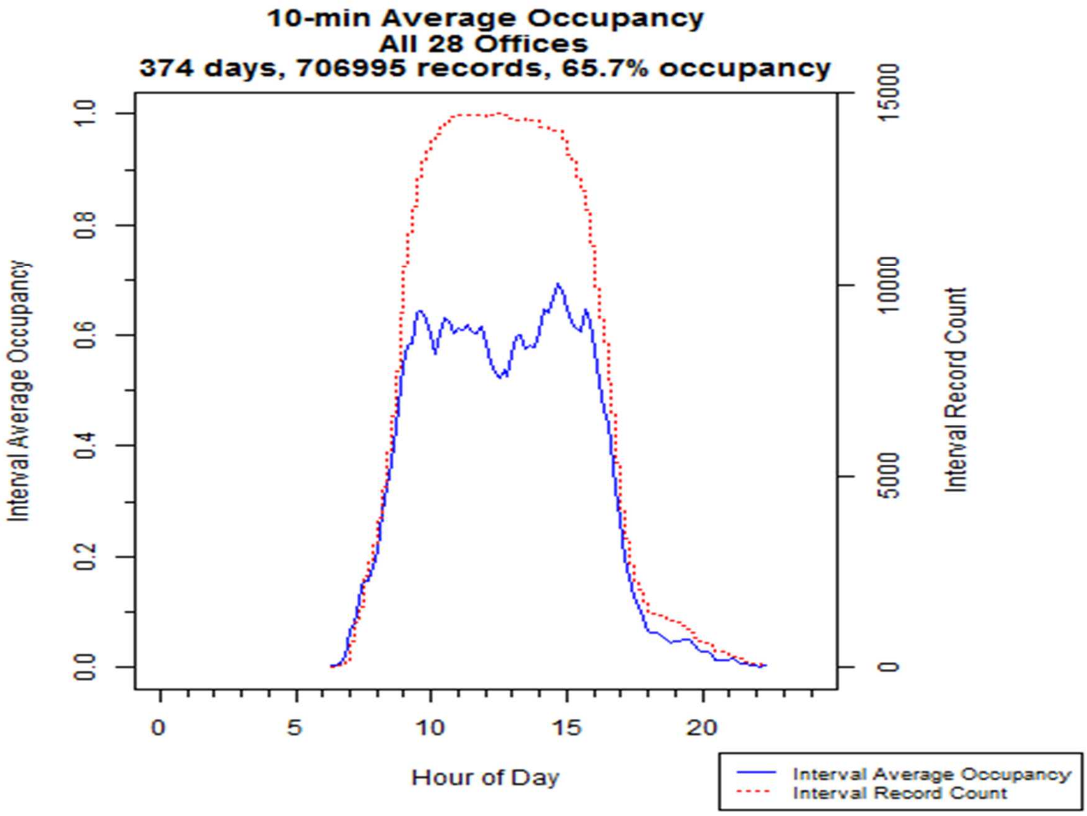

Figure 2 – The blue line (primary y-axis) shows occupancy averaged over all offices and all days, at 10-minute time resolution. The red line (secondary y-axis) shows the total number of data points contributing to each 10-min bin. (entire dataset).

Next, we examined the frequency of various lengths of occupancy and absence, aggregated across all offices and days, as shown in Figure 3[10]. For practical control to save energy, it is the longer events that have a greater importance. The number of around five absences per day for absences longer than five

[10] Our first look at these data showed that the frequency of very short events was high and could have been inflated by non-genuine single row state changes (described above). To correct for this potential (and minor) ground truth error, we ran a script that (temporarily) modified the binarized ground truth value: a single row state change was recoded to match the state of the rows on either side, so a sequence of 11110111, became 11111111, and so on. This was done for these frequency calculations only, and not for the analyses in other sections.

minutes agrees with earlier data in a different office area of one of the study buildings [Galasiu & Newsham, 2009].

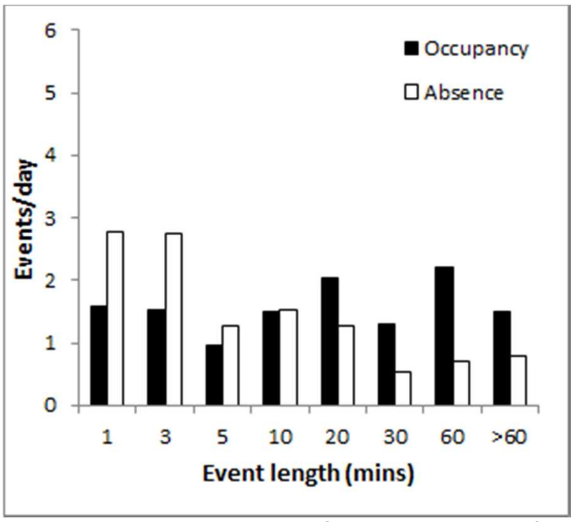

Figure 3 – Frequency of various lengths of occupancy and absence, aggregated and averaged across all offices and days. Event length 1 = events of less than 1 minute duration, Event length 3 = events between 1 and 3 minutes duration, and so on. (entire dataset).

From these data we made initial estimates of energy savings potential, if building systems were controlled based on ground truth data. We considered savings for switching lighting systems limited to fully on and fully off states. Lighting is straightforward in that it obviously only needs to be on during occupancy. Savings for plug loads might be considered similar to lighting, although some plug loads (e.g. those based on electronics) might need to be maintained in a partial-off state to facilitate appropriate restart when the occupant returns. HVAC savings are more complex, as pre-conditioning prior to occupancy is needed to avoid comfort penalties.

The theoretical maximum lighting energy savings assume lighting is switched off immediately upon detecting vacancy, and switched back on again immediately when detecting occupancy[11]. However, any

[11] In spaces with daylight the approach now required by energy codes is auto-off, manual-on, so the occupant on re-entry might decide that there is adequate daylight and electric lighting is not necessary. However, for our

inaccurate detection of vacancy (false negatives) results in lights switching off with an occupant in the space, causing substantial dissatisfaction. Therefore, lighting control systems typically employ a safety factor, or timeout period, such that vacancy must be detected continuously for a given period before lights are switched off. Current energy codes specify a maximum timeout period for occupancy control of 30 minutes, with new code revisions lowering this to 20 minutes [ASHRAE, 2010; CCBFC, 2011]. In Table 2 below we present calculated savings for various timeout periods, based on our ground truth data, aggregated across all offices and days. These calculations show that savings may increase substantially if the timeout period is reduced, as has long-been recognised (e.g. Von Neida et al. [2001]; Richman et al. [1996]; Maniccia et al. [2001]; Dikel & Newsham [2014]). This signals the potential for additional savings with more reliable methods of detecting occupancy that allow timeout periods to be lowered without elevating the risk of false negatives.

Table 2. Calculated lighting energy savings (%) based on ground truth data, aggregated across all offices and days, for various timeout periods.

	Timeout period (mins)						
	30	20	10	5	3	1	0
Potential Lighting Energy Saving	13.3	17.0	22.4	26.6	28.9	32.0	34.3

2.2.2 Ceiling-based PIR sensor as comparison

Although our PIR installations were not optimized for each office, we submit that this is also true for commercial installations. However, in a commercial installation poor performing set-ups would likely be remedied[12]. Therefore, it may be more appropriate to compare a new sensor approach to the better-performing ceiling PIR installations, rather than the average.

calculations we will consider the “worst case” situation of a space without other light sources.

[12] Or sabotaged by an irritated occupant! And such a re-installation would not be without cost and irritation.

Figure 4 shows the performance of the ceiling PIR sensor compared to ground truth (mat) in each office individually[13] and at the 15-second level. The results show a wide range of performance across offices. False positives were relatively few. Overall accuracy was poor, as a result of the very high rate of false negatives, in other words, in many PIR installations the sensor did not reliably "see" the seated occupant for the majority of occupied time. Despite their growing deployment, few studies have looked at the accuracy of PIR sensors in actual installations, and those that have often observe disappointing performance. For example, in the studies quoted by Williams et al. [2012] the savings from actual installations, although frequently conducted in highly-curated environments, were on average 25% lower than those from simulations. Tiller et al. [2010] observed very different sensing accuracy from three identical occupancy sensors installed on three walls of the same office, and all sensors reported substantially lower occupancy than ground truth (human observers). NLPIP [1998] performed extensive laboratory testing of occupancy sensors from multiple vendors, using a robotic arm to test the response of the sensors to motion within the claimed sensor coverage area. They found many sensors unresponsive to small- and medium-sized motion triggers. Priyadarshini & Mehra [2015] also note the PIR sensors are relatively insensitive to motion that is not perpendicular to the direction of view of the sensor, and that they are particularly prone to false negatives.

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[13] Note, data from the ceiling PIR sensor was normalized and binarized in the same way as the mat data; our data shows that over all data rows, only 1.1% of normalized PIR recordings had a value other than 0 or 1.

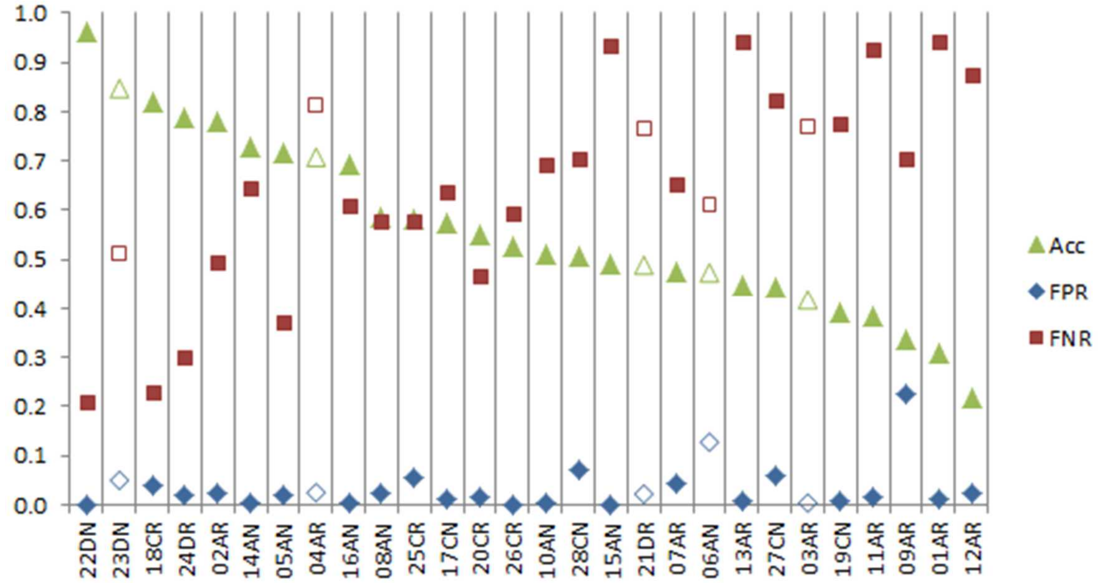


Figure 4 – Performance of the ceiling PIR sensor compared to ground truth (mat) in each office individually, at the 15-second level (i.e. no timeout). Offices rank-ordered by overall accuracy. Unfilled symbols indicate cubicle offices. (10% testing data).

Table 3 shows the effect of various timeout period lengths on ceiling PIR performance metrics for all offices collectively (count-weighted). It also indicates a dramatic reduction in FNs with increasing timeout, associated with a dramatic increase in FPs (because any timeout period added after a genuine departure is considered as a false positive occupancy).

Table 3. Ceiling PIR metrics for various timeout periods (0 min timeout indicates15-second data). (10% testing data).

	Timeout period (mins)						
All offices	30	20	10	5	3	1	0
Acc	0.7363	0.7516	0.7585	0.7430	0.7178	0.6527	0.5593
FPR	0.6518	0.5490	0.3980	0.2746	0.2069	0.1077	0.0275
FNR	0.0554	0.0871	0.1574	0.2475	0.3227	0.4759	0.6626

Figure 5 illustrates the effect of the 20-minute timeout for a single example office. The 15-second PIR data features many FNs (Tiller et al. [2010] report similar data at the 1-second level), and an FP episode (around 13:10 on the second day). Application of the 20-minute timeout to the PIR data eliminates most FNs, but introduces more FPs.

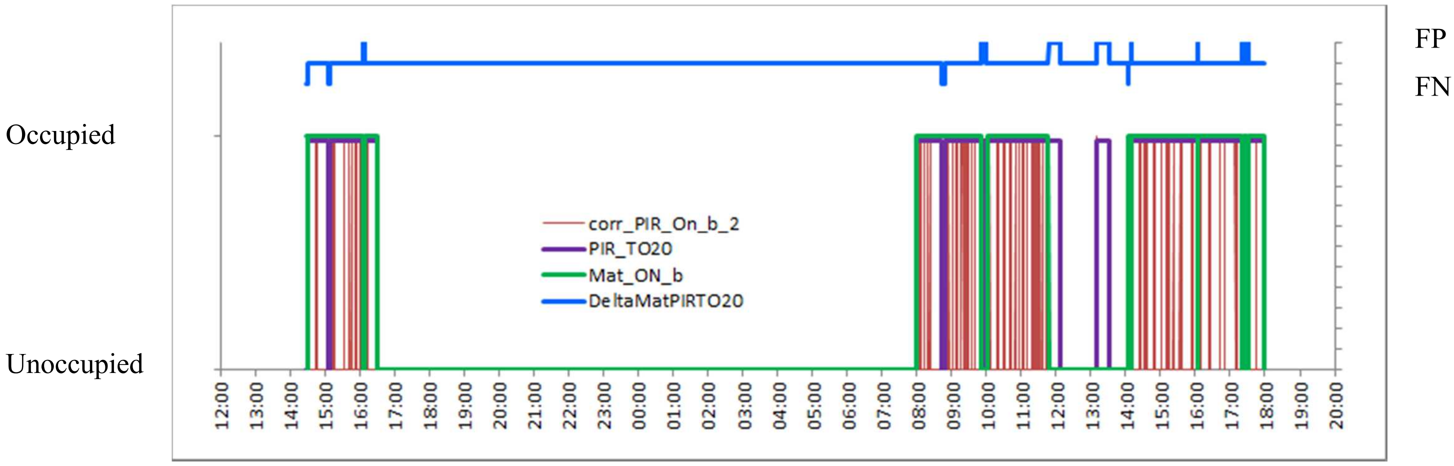


Figure 5 – Typical data set for office 19CN, showing raw 15-second data (green: ground truth; red: PIR response), the application of a 20-minute timeout to the PIR data (purple), and the resulting errors vs. ground truth (blue). (10% testing data).

This analysis provides guidelines for performance targets for an alternative sensor package. False negatives represent the biggest barrier to satisfactory technology adoption, therefore, the false negative ratio (FNR) is our primary performance target. Given current North American energy codes, a maximum timeout period of 20 minutes is allowable for incumbent technology. Therefore, we propose that the appropriate target FNR for an alternative sensor package should be that achieved by the ceiling-based PIR motion sensors with a 20-minute timeout – the goal is that the alternative sensor package achieves this FNR with a shorter timeout, thus enhancing energy savings. Given the discussion above we propose using the upper quartile of the seven offices with the best performing PIRs, chosen according to their overall accuracy following the application of a 20-minute timeout, to provide the FNR target.

2.2.3 Choice of alternative/implicit occupancy sensors

We began by comparing the accuracy of each sensor's output vs. ground truth. This simple analysis indicated that the webcam was a good single indicator of occupancy. The PC-mounted motion sensor and sonar were also promising. Some IR channels also performed well, but this sensor was not practical overall. The mouse and keyboard were not good performers by themselves, although they deliver no FPs, they cannot detect the presence of someone doing something other than computer work; this suggests they might be good in combination with another sensor.

Many advanced analysis methods and sensor combinations were possible. We chose to focus on "good enough", parsimonious methods that were easily interpretable, using sensor packages that are low-cost and practical. Thus, we chose keyboard+mouse+webcam representing sensors already in place for most new computing platforms[14].

2.2.4 Data fusion with genetic programming

Machine learning and computational intelligence provides a wide variety of approaches for data-driven model discovery [Solomatine & Ostfeld, 2008]. We performed initial experiments using decision trees and random forests, but focused on genetic programming (GP) [Koza, 1989, 1992, 1994], which has been successfully applied to a wide variety of fields (e.g., to generate new integrated circuits, antennas and controllers in circuit design [Koza et.al, 2003]). The variant of GP used here is Gene Expression Programming (GEP) [Ferreira, 2001, 2006]. Consequently, models emerged from a two-stage process: (i) a computational intelligence data driven model learning phase, and (ii) a model selection phase determined by criteria specified by human experts with application domain knowledge. The specific tool used in stage (i) was described in Valdés et al. [2007].

The first 90% of the timespan of data from each office was used as a training dataset, with the remaining 10% (typically around 1.5 days per office) as a testing dataset; results are reported based on performance against the testing dataset. For each sensor in our candidate sub-set (normalized, standardized) min, max, mean, and standard deviation metrics for each 15-sec timestep were potential predictors, with no interaction terms.

[14] We also explored an option with an additional, PC-mounted motion sensor. However, overall, the additional cost and system complexity did not offer a compensatory improvement in system performance.

The evolutionary process started with a randomly generated population of candidate functions. Many different genetic operators were applied in each generation, including mutation, recombination, inversion, and transposition. The particular individual (analytical function model) affected by the operator, and which part of its chromosome was affected, was determined randomly according to a collection of probabilities applied to the genetic operators.

In each run, the population size was fixed at 30 individuals, which were modified over 1000 generations. Up to 8 genes (function terms) were allowed per individual, the function set within genes that operated on predictors was limited to {+, -, *, ^2} and genes were linked by simple addition. We conducted 4500 such runs, using different fitness criteria (e.g. based on resulting overall accuracy, FNs, FPs) across these runs, and chose the best performing function at the end of each run. This generated a list of 4500 candidate functions. The final models were picked by rank-ordering these candidate functions according to application-relevant performance parameters, in particular FNs, and also according to the simplicity of the function, judged by a domain expert.

The final model chosen was designated #2043, shown below.

Model #2043:

```
14.54+3*z_Keyboard_ON_n+4*z_Mouse_ON_n+z_WebCam_Max+z_WebCam_StdDev
(threshold = 9.0)
```

where, the prefix "z_" indicates a standardized value, and the suffix "_n" indicates a normalized value. If the model yields a value greater than the threshold at a given timestep then occupancy is predicted. Note, a further simplification of the function might be possible by combining the data from the keyboard and mouse into a single data channel representing "tactile interaction with the computer". Whether this is effective, without negatively affecting the overall accuracy, is a topic for future work.

2.2.5 Ceiling PIR vs. alternative sensor performance

Model #2043 had an overall accuracy on 15-sec data >90%, substantially better than the overall accuracy of the ceiling PIR sensors. To estimate the enhanced energy saving potential compared to the upper quartile of the ceiling PIR sensors, we took the count-averaged FNR for the PIR sensors with a 20-minute timeout (Table 4, 0.0064) and for each office looked at the timeout needed with Model #2043 to achieve the same FNR. We did this for all 28 offices, and for the 7 upper quartile PIR offices.

Table 4 compares overall performance metrics for ceiling PIR and Model #2043. The superior performance of the new occupancy sensing system is clear, with substantially improved accuracy and higher energy savings potential over a PIR with 20-minute timeout, even in offices representing the upper quartile of PIR performance. The only metric where Model #2043 performed worse is average FNR for the upper quartile offices. This is because there is one office in seven where Model #2043 performs less well than the PIR, and this performance is poor enough (FNR>9%) that its inclusion in the average drags down the average overall. Average performance of Model #2043 in the other six offices is much better (Acc.=0.9221; FPR=0.0194; FNR=0.0037, and timeout <1 min.).

Table 4. Key performance metrics for PIR sensors with a 20-min timeout, and for Models #2043 with a timeout chosen in each office to yield an FNR <= 0.0064. (10% testing data).

	PIR		Model #2043	
	All 28 offices	Offices in PIR Upper quartile	All 28 offices	Offices in PIR Upper quartile
Mean Timeout (mins)	20	20	8.7	4.6
Accuracy	0.7516	0.8872	0.8812	0.9507
FPR	0.5490	0.3635	0.2919	0.1117
FNR	0.0871	0.0064	0.0258	0.0228
Actual Occupancy	0.6507	0.7020	0.6507	0.7020
ESR, %	21.4	19.4	26.4	28.1
MaxESR	0.613	0.652	0.756	0.942

Figure 6 illustrates the effect of the 1-minute timeout on Model #2043 for the same example office in Figure 5. In this case, the 15-second data was virtually coincident with the ground truth. This indicates a much more accurate occupancy sensing system than with the PIR. With a 1-minute timeout applied to Model #2043 in this office all FNs were eliminated. And the better sensing accuracy and reduced timeout resulted in fewer FPs.

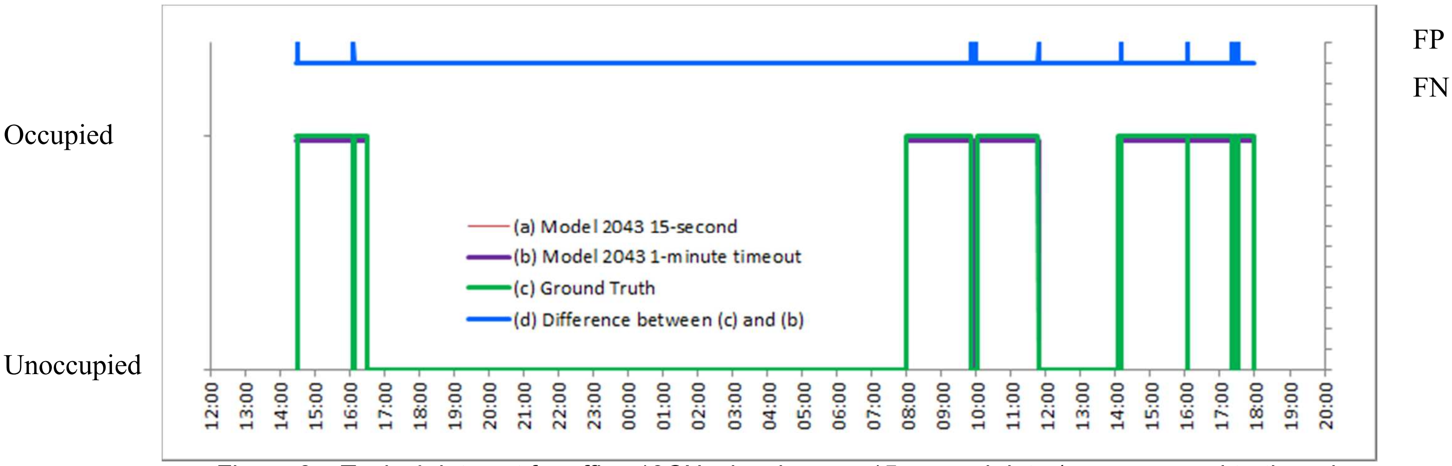


Figure 6 – Typical data set for office 19CN, showing raw 15-second data (green: ground truth; red: Model 2043), the application of a 1-minute timeout to the Model 2043 data (purple), and the resulting errors vs. ground truth (blue). (10% testing data).

We also explored occupancy detection models that did not use the webcam in order to investigate the trade-off between privacy gain and performance loss. Instead of the webcam we used the PC-mounted motion sensor. Derived Model #2494 yielded acceptable accuracy and parsimony. Its performance at the 15-sec data level compared to the earlier models with the webcam, and to the ceiling PIR sensor, is shown in Table 5. However, although the motion sensor does not have the same privacy concerns as the webcam, unlike the webcam, a motion sensor is not present in most PC systems, thus it would carry a small incremental cost.

Model #2494:

9.68+5*z_Mouse_ON_n+2*z_Motion1_Max+2*z_Keyboard_ON_n

Table 5. Performance of Models #2043 and #2494 vs. ceiling PIR, at the 15-sec data level, over all offices. (10% testing data).

	Model number		PIR
	#2043	#2494	
Accuracy	0.9023	0.8857	0.5593
FPR	0.0975	0.1130	0.0275
FNR	0.0978	0.1150	0.6626

3. Control Demonstration

3.1 Methods & Procedures

We deployed Model #2043 occupancy detection in a proof-of-concept demonstration, linking it to the control of various building services and equipment in a mock-up office environment (Figure 7). Colleagues were invited to occupy the test office for one full day. They were free to work on whatever tasks they wished. Participants were encouraged to bring their own laptop on which the occupancy sensing algorithm and control software were installed[15].

[15] If they did not have their own laptop, a laptop was provided for them.

Figure 7. Test office within where control proof-of-concept was performed.

We deployed a variety of timeout and restoration conditions to different devices under control, as shown in Table 6. We covered the window in the test space with a blind to ensure that the electric lighting would be needed during occupancy, but residual daylight was sufficient for basic visibility if electric lighting was off. To limit the potential for FPs generated by large changes in daylight, we required the model to predict a majority in five contiguous 15-second samples to indicate occupancy before the system went into occupied mode. However, to allow for instant-on for the plug loads we implemented an override to Model #2043, which allowed for occupancy detection at the 5 Hz sampling rate for mouse and keyboard activity, or very large changes in the webcam pixel values, when the prior detected condition was no occupancy. Timeout criteria (to avoid FNs) were applied following the last detected occupancy in order to shift the system into vacant mode.

Table 6. Devices under control, and their timeout and service restoration condition.

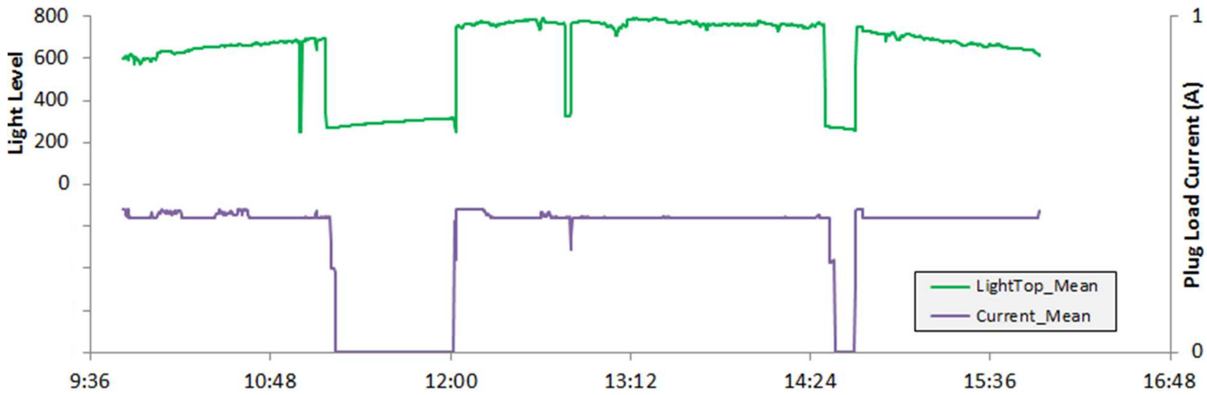
	OFF timeout (mins)	ON, restoration condition	Measured power draw (W)
Light	2	Manual	80
Monitor	4	Instant	15
Thermostat	(setback) 5	After 1 min. occupancy	n/a
Plug Load	6	Instant	33

Control of the light, thermostat, and plug loads were actuated via an Insteon wireless network, in which control signals generated from Model #2043 were relayed via a USB dongle on the occupant's laptop to remote Insteon devices (dongle – 2448A7, light switch – part # 2477S, thermostat – part # 2441TH, recessed smart plug – part # 2663-222). Control of the supplementary computer monitor was achieved via the Windows™ internal API.

We installed additional equipment to provide a physical confirmation of the specified control actions, including a temperature sensor, light sensor and clamp-on plug load sensor (manufactured by Phidgets). The plug load sensor measured the current on the controlled circuit which supplied both the fan and supplementary computer monitor. The temperature sensor was positioned at the HVAC supply outlet in the test office floor. Participants were asked to comment on any FNs or FPs they observed, during occupancy, or after returning from a period of absence, respectively.

3.2 Results & Discussion

Figure 8 shows an example of the data from one summer test day. There were two periods of extended vacancy, one beginning around 11:00, and the second around 14:30. There were a few very short periods where the system also recorded no occupancy, and the participant confirmed these to be accurate. Also, there were no short spikes in occupancy during longer vacancy periods that are indicative of FPs.



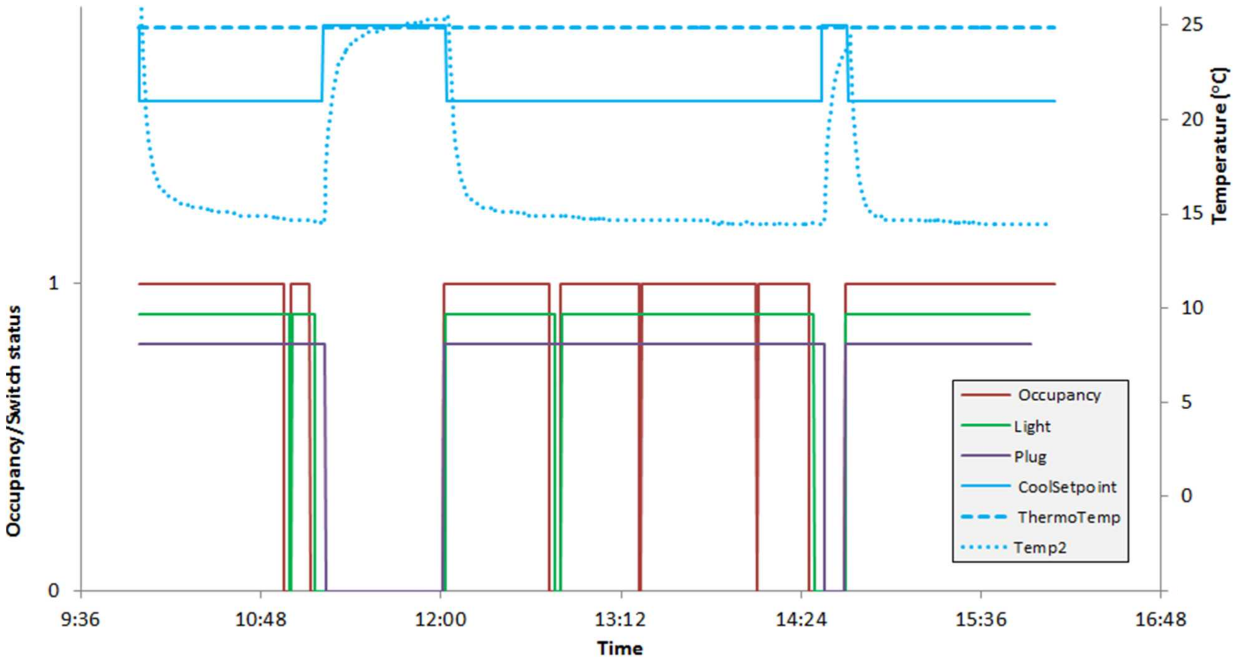


Figure 8. Data from September 4th, 2015. Lower chart shows occupancy as detected by Model #2043, and the switch status transmitted to the light switch and smart plug (left y-axis, any value >0 indicates "on"). This chart also shows the cooling mode setpoint transmitted to the thermostat, the local air temperature reported by the thermostat, and the temperature ("Temp2") at the HVAC supply outlet (right y-axis). Upper chart shows the horizontal light level recorded in the office (left y-axis), and the current measured on the controlled smart plug (right y-axis).

As designed, the thermostat in cooling mode went to its setback temperature of 25 °C five minutes after occupancy was no longer detected. This switched off the air conditioner, such that the air temperature measured at the HVAC supply outlet rose rapidly; this was quickly reversed when occupancy was restored[16]. The measured light level reflected the recorded occupancy and associated control signals faithfully. Drops in light level (down to the level provided by residual daylight) as the electric lighting

[16] Note, the air temperature measured at the thermostat showed very little sensitivity to air conditioner status. We are not sure if this was because the sensor was faulty, if the air conditioner was undersized, or due to the location of the thermostat relative to HVAC outlets.

was switched off during the longer periods of vacancy were obvious. Because the light switching had the shortest timeout period (2 minutes), there were also some short duration light level drops associated with the reported shorter-term absences[17]. The measured current also followed the occupancy and related sensor signals as expected. Four minutes after occupancy was no longer detected, the current dropped from 0.4 A to 0.25 A when the monitor was switched off. Two minutes later, the fan plug load was turned off, and the current dropped to 0 A.

The dates and times of the various test days are shown in Table 7, along with the measured energy savings compared to an uncontrolled setting. The energy savings obviously depend heavily on the individual occupancy schedules on any given day, but the percentage savings were substantial, ranging from 15-68%[18].

Table 7. Test days for the algorithm-based occupancy detection system to control various building services, and the resulting energy savings.

Participant	Date	Time Span (approx.)	HVAC mode	Energy Saving, %*		
				Lighting	Plug Load**	HVAC***
01	2015-07-21	0900-1700	Cool	59.6	46.6	51.9
02	2015-08-12	1400-1630	Cool	51.9	48.3	33.7
03	2015-09-02	1000-1630	Cool	31.5	30.4	30.9
04	2015-09-04	1000-1600	Cool	20.0	15.6	16.6
05	2015-09-08	1100-1600	Cool	36.6	33.8	26.1
06	2015-09-09	0930-1600	Cool	60.6	47.3	48.4
07	2015-12-17	0930-1600	Heat	25.3	21.2	22.6
08	2015-12-18	0900-1630	Heat	37.5	35.7	36.3
09	2015-12-22	1000-1830	Heat	67.8	63.0	63.9

* Calculated over period from first occupancy to last occupancy or plug load timeout, whichever comes last, compared to always on during occupancy.
** Slightly conservative in energy terms as this assumes the 6 min. fan timeout, whereas the monitor is also controlled on the same plug with a slightly shorter, 4 min. timeout.
*** Savings only counted if furnace not calling for heat/cool during setback.

[17] The residual daylight leaking around the blind imposed a time-dependent pattern on the total light level.

[18] The energy use of the sensor system itself was minimal, with a power draw < 2W, so inconsequential compared to the savings it can facilitate.

4. General Discussion on Deployment Scale-up

This study demonstrated great potential to employ data sources not currently used to detect office occupancy to accurately indicate occupancy, and thus to support building control optimization and enhance energy saving opportunities. Nevertheless, the work was limited to single-person offices with static computing platforms. There are several issues to be considered when contemplating broader application in offices. Among these are:

- Multi-person, open-plan offices: in a shared office space the keyboard and mouse data would remain accurate and associated with the person assigned to a specific desk. However, at any one desk there would be substantial background webcam activity due to the presence of other occupants in and around other desks. This would likely lower the accuracy of algorithms based on our current methods, with particular risk to increasing false positives. More sophisticated webcam data processing may be necessary. Testing in such a context should be explored in future research.
- Mobile computing: in many workplaces mobile laptops, tablets and other computing devices are displacing traditional, fixed computing platforms. As long as these are associated with the desk and associated systems in the office they are being used in, and as long as they have input devices equivalent to a keyboard and mouse and have a webcam, our approach should work. Of course, our approach only works while a fixed or mobile computing device with these properties is active. Workplaces in which computing devices are absent/off will require another occupancy detection method.
- Building system integration: in our work we customized the integration between the occupancy detection method and the controlled building systems. Protocols to integrate IT and building automation systems (BAS) are not yet seamless, and industry developments in this direction are required if buildings are to take full advantage of the coming IoT. Common to all advanced control systems, on-going maintenance of software, user databases etc. is essential to long-term success.
- Privacy: in one sense, this technique does not infringe further on privacy than already-accepted methods of occupancy detection. Energy codes require occupancy sensors for lighting control in single-person offices already, and to the systems that support conventional sensors thus indicate whether a person is in their office or not, and with networked systems this data is increasingly

visible beyond the state of the lighting in the office itself. However, our method utilizes a webcam, and requires the camera to be on constantly. Although the pixel resolution required can be downgraded such that most actual privacy issues are not relevant, the perceived privacy concerns might be more difficult to assuage. In such cases people may resort to taping over webcams as they tape over conventional occupancy sensors when they do not provide the desired functionality. Nevertheless, technology and associated applications are continuing to eat away at the level of continuous visual monitoring and social norms are changing, and continuously-recording media devices might become commonplace for other reasons.

5. Conclusions

These results suggest that there is great potential to leverage currently unused data sources to support building controls and enhance energy saving opportunities. This offers a very cost-effective way for energy-efficiency in buildings to be increased, especially in retrofit scenarios. Such opportunities are likely to grow as the "Internet of Things" propagates and the density of data gathering devices in the built environment increases dramatically.

Specifically, a combination of keyboard/mouse activity and pixel changes in a webcam image proved to be a much better occupancy sensor than incumbent commercial technology (ceiling-based PIR). More effective occupancy sensing supports shorter timeout periods for lighting (and plug load and HVAC) control, leading to savings potentially 25-45% higher than current energy code controls.

Subsequent testing of this approach in a full-scale proof-of-concept demonstration in a mock-up office delivered perfect occupancy sensing and energy savings of 15-68% on lighting, HVAC, and plug loads.

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