Improved occupancy detection accuracy using PIR and door sensors for a smart thermostat

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Abstract

It is important to investigate the occupancy levels in buildings in order to achieve accurate and meaningful building simulations results. Thus, research on buildings occupants' behavior has been conducted in various institutions, including the International Energy Agency (IEA) annex 66. In this paper, we studied the use of passive infrared (PIR) sensors along with a door sensor to ensure the accuracy of occupancy detection in the built environment. This experimental study was conducted in a testbed setting to determine the appropriate locations and number of PIR sensors needed to improve the accuracy of occupancy detection. An occupancy detection algorithm was suggested to improve the performance of the developed system. The study result indicated that a PIR sensor located on a wall provides more accurate detection rate compared to those located on the ceiling or on the wall beside the door. In terms of the optimal number of PIR sensors to be used, the accuracy of detection improved as the number of sensors increased. It is found that an accuracy rate of 91.5% (number of occupants: 1 to 6) was obtained when using all four sensors together. When the suggested occupancy algorithm was applied, an improved occupancy detection accuracy rate of 99.8% was achieved (number of occupants: 1 to 6), while using one PIR sensor located on the wall and a door sensor together in this specific study. Thus, applying the algorithm allowed to obtain accuracy rates better than when four sensors were used together.

Introduction

Occupant behaviour in buildings is associated to a high uncertainty in building simulation results. Since the capture and measure of occupant behaviour is hard in the real world, in a building simulation domain, assumptions are made for the number of people and time of occupancy in a built environment.

Recently, various sensors have been used for detecting occupancy and occupants' behavior, such as passive infrared (PIR) sensors, CO or CO_2 sensors, lighting sensors, energy consumption meters, infrared sensors, cameras, videos, etc. Sarkar et al (2008) used a video camera to control the lighting systems and harvest daylight in a room setting. In addition, Lymberopoulos et al (2008) proposed the BehaviorScope system for interpreting the occupant's activity using camera networks. The study by Wang (1998) employed CO_2 sensors to detect occupancy and determine the ventilation rate depending on the indoor CO_2 concentration. Smart meters to measure electricity consumption could also be used for occupancy detection. Kleiminger (2013) collected the electricity consumption data using ground truth occupancy information for five households over 8 months period, and achieved an occupancy detection accuracy rate of over 80%. Furthermore, Tapia (2004) installed 77 state changes sensors in a home to detect occupancy behavior**.** The household living patterns were sufficiently structured in the study. Xia and Aggarwal (2013) utilized a video camera to study the human activities by applying deep spatio-temporal interest points (DSTIP) and depth cuboid similarity feature (DCSF). Additionally, Kwapisz et al (2010) used phone-based accelerometers to recognize the occupants' activities, such as walking, jogging, climbing, stairs, sitting, and standing. To detect occupancy more effectively, machine learning could be utilized with various sensors. Shih (2014) developed a monitoring system to detect occupancy continuously using image based depth sensor and programmable pan-tilt-zoom (PTZ) camera with a support vector machine (SVM) model. Jusitn and Brandon also proposed an occupancy prediction model using Mitsubushi Electric Research Lab(MERL) motion detector by combining the Markov Chain (MC) model.

In this study, PIR sensors (passive infrared sensors) are used as one of the simplest and most cost effective approaches to detect occupancy rates. In addition, the privacy related issues are eliminated by avoiding the use cameras or videos. However, this method involves some detection errors. For the purpose of this study, PIR sensors and door sensors are combined together to improve the detection accuracy. An algorithm was also applied in combination with the PIR and door sensors and an experiment was set to test this approach.

Method

In this study, we conducted experiments in a testbed that set in the university building. The testbed is an enclosed chamber that consists of PIR sensors set in different locations, a door sensor, Variable Refrigerant Flow (VRF) system, a heat recovery ventilator, a humidifier, a dehumidifier, a floor heating system, a dimming system, an automatic blind, and a building monitoring and control system. These systems are interconnected and operated using building automation and control networks (BACnet). BACnet is an ASHRAE, ANSI, and ISO 16484-5 standard protocol for building automation and control systems (Bushby, 1997). The monitored data are stored in a workstation and used to determine the presence of people using an occupancy detection algorithm. A web-based camera is also installed in the testbed to visually check the presence of people and their behaviors. Four PIR sensors were installed along with one door sensor for this experiment. The positions of sensors are shown in Figure 1, and the Figure 2.

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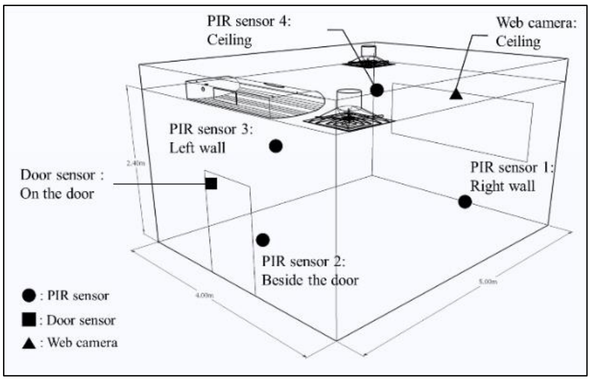

Figure 1. The position of the PIR, door sensor and the web camera

Figure 2. The appearance of PIR, door sensor and Web camera

In this study, experiments were conducted to examine:

1. The accuracy of occupancy detection depending on locations and the numbers of PIR sensors.
2. The accuracy of occupancy detection of a suggested algorithm using PIR sensors and a door sensor.

These experiments were conducted based on two-case to examine the difference in the accuracy rate based on the number of occupants. The experiment for each case was conducted for 24 hours (00:00 – 24:00). In Case 1, the occupancy level of the testbed ranged between one to six people. During the experiment, the room was occupied for 9 hours 24 minutes. In Case 2, there was only one occupant in the testbed, the room was occpuied for 10 hours 1 minutes during the experiment. In both cases, the participants were sitting at desks and doing their work freely. Additionally, they were free to come and go based on their personal schedules. The number of people over the experiment time is shown in Figure 4 and Figure 5.

Figure 3. Two-case scenario Experiment settings (Left: Case 1, Right: Case 2)

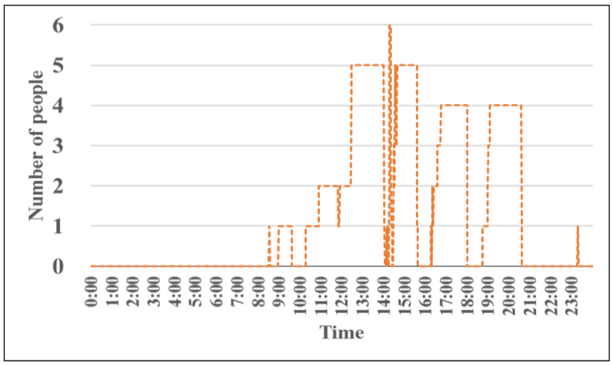

Figure 4. Change of the number of people over time (Case 1)

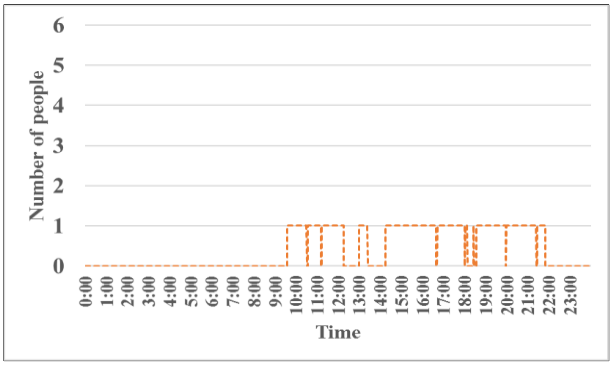

Figure 5. Change of the number of people over time (Case 2)

Result

Accuracy Detection according to the location

As shown in Table 1, the accuracy of the PIR sensors is calculated by comparing the actual room status data and the PIR sensor output data. First, when the testbed is occupied, the accuracy increased when there is a signal from the PIR sensor. On the other side, the accuracy decreased when there is no signal from the PIR sensor (Error 1). Second, when the testbed is empty, the accuracy increased when there is no signal from the PIR sensor, while it decreased when there is a signal from PIR sensor (Error 2).

Table 1: Variation in PIR sensor accuracy based on the output

Room status	PIR output	Change of accuracy
Absence	Signal	Decreased (Error 1)
	No signal	Increased
Occupied	Signal	Increased
	No signal	Decreased (Error 2)

Table 2: Accuracy of occupancy detection based on the location and number of people

Sensor	PIR sensor number	Total time (Minute)	Result					
			Case 1 (Number of people: 1~6)			Case 2 (Number of people: 1)		
			Error 1 (Minute)	Error 2 (Minute)	Accuracy (%)	Error 1 (Minute)	Error 2 (Minute)	Accuracy (%)
PIR	1 (Right wall)	1440	11	324	76.7	2	544	62.1
	2 (Door)		14	369	74.4	1	600	58.3
	3 (Left wall)		11	183	88.9	0	541	62.4
	4 (Ceiling)		14	352	74.6	1	583	59.4
	1 + 2		17	242	82.0	2	542	62.3
	1 + 3		16	131	89.8	2	518	63.9
	1 + 4		17	235	82.5	1	535	62.8
	2 + 3		19	142	88.9	1	536	62.7
	2 + 4		19	277	79.4	2	579	59.7
	3 + 4		17	152	88.3	0	535	62.8
	1 + 2 + 3		20	105	91.3	2	517	64.0
	1 + 2 + 4		20	197	84.9	2	534	62.8
	1 + 3 + 4		28	113	90.2	2	514	64.1
	2 + 3 + 4		21	126	89.8	2	533	63.0
	1 + 2 + 3 + 4		25	97	91.5	2	513	64.2

The results of the experiment are shown in Table 2. When only one sensor was used, PIR sensor 3 indicated the highest accuracy rate among the PIR sensors in the testbed in both cases. When listed in order from the highest to the lowest, the observed accuracy rates of the PIR sensors in both cases showed the same order as below:

1. Sensor 3 (Left wall): 88.9%, 62.4%
2. Sensor 1 (Right wall): 76.7%, 62.1%
3. Sensor 4 (Ceiling): 74.6%, 59.4%
4. Sensor 2 (Beside the door): 74.4%, 58.3%

Accuracy Detection according to the location

When multiple PIR sensors were used, it was assumed that there was someone in the testbed if one of the four sensors has an output value. This assumption is to solve Error 2 (Occupancy, No signal), which occurs more frequently than Error 1 (Absence, Signal) as shown in the Table 1 and 2. In Case 1, when considering the number of sensors, the detection accuracy was improved as the number of sensors increased. As listed in Table 3, as each sensor was added, the observed accuracy detection rates were improved by an average of 6.5%, 3.9%, and 2.4%, respectively (see the average improvement rates). However, some cases showed lower accuracy levels despite using more sensors. For example, as shown in Table 2, the accuracy was 84.9% when using PIR sensor 1, 2, and 4 together, which was 4.0% lower than using only the PIR sensor 3 (88.9%). Thus, the accuracy of the sensor that installed at the proper position was better than using three sensors together. These results indicate that the location of the PIR sensor is more important than the number of sensors in order to accurately detect occupancy. In terms of errors, Error 1 was increased as each sensor was added. This is because it makes false assumption that there was someone in the testbed even if only one sensor gave a wrong signal. However, the total accuracy had been improved because of offsetting Error 1 by improving Error 2. In Case 2, as shown in Table 4, the average improvement rates were 1.8%, 1.1%, 0.7% as each sensor was added. These values were not significant compared to Case 1. In other words, the number of sensors does not have much effect on the accuracy level when few occupants are present.

Table 3: Average accuracy based on the number of sensors (Case 1)

Sensor	Number of PIR sensors	Case 1 (Number of people: 1~6)	
		Average accuracy (%)	Average improvement rate (%)
PIR	1	78.7	-
	2	85.2	6.5
	3	89.1	3.9
	4	91.5	2.4

Table 4: Average accuracy based on the number of sensors (Case 2)

Sensor	Number of PIR sensors	Case 2 (Number of people: 1)	
		Average accuracy (%)	Average improvement rate (%)
PIR	1	60.6	-
	2	62.4	1.8
	3	63.5	1.1
	4	64.2	0.7

Accuracy according to the number of people

Considering the number of people in the testbed, the PIR sensors were highly accurate when there were several occupants. As shown in Figure 6 and Figure 7, the difference in accuracy between Case 1 and Case 2 is due to the frequency of the PIR sensor output. When there were few people in the testbed, the PIR sensor output decreased. This is because the sensors could not detect the occupants correctly due to the slight amount of motion that was missed by the sensors (e.g., people at rest or asleep). The results of this experiment show that it is difficult to accurately measure occupancy rates solely using PIR sensors.

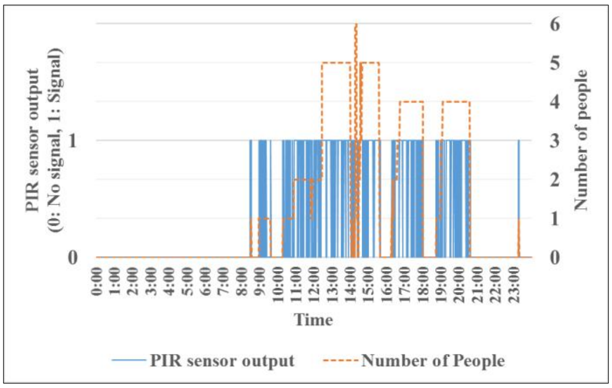

Figure 6. The frequency output of the PIR sensor 3 and the actual number of occupants (Case 1)

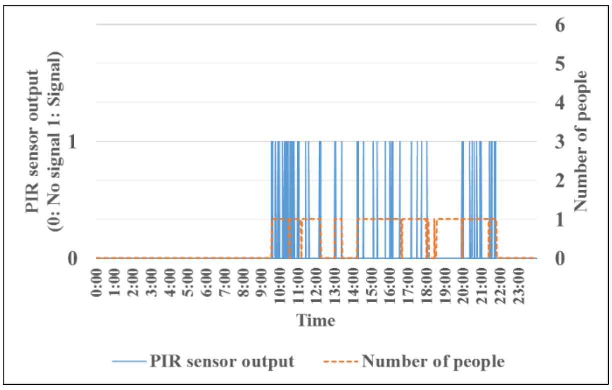

Figure 7. The frequency output of the PIR sensor 3 and the actual number of occupants (Case 2)

Occupancy detection algorithm

In order to improve the accuracy of PIR sensors, we could assume that someone is staying in the space for a certain period of time after detecting the output value of a PIR sensor. This approach is applied to wide range of occupancy sensors in the market, however, these occupancy sensors are mainly used for lighting control in toilets or fitting rooms. This strategy is used to compensate for the inability of the PIR sensor to detect occupancy when occupants are not moving. For the purpose of the experiments, it was assumed that people remained in the room for 30 minutes after a PIR sensor detected occupancy. Additionally, the 30 minute time period was renewed after each time a PIR sensor detected a motion. However, the issue with this approach is that the 30 minutes assumption remains valid even when all people have left the room and the room is empty. In other words, when a PIR sensor detects occupancy due to motion for leaving the room, an incorrect assumption is made for an extra 30 minutes. Figure 7 and Figure 8 show the occurrence of errors caused by the 30 min occupancy assumption.

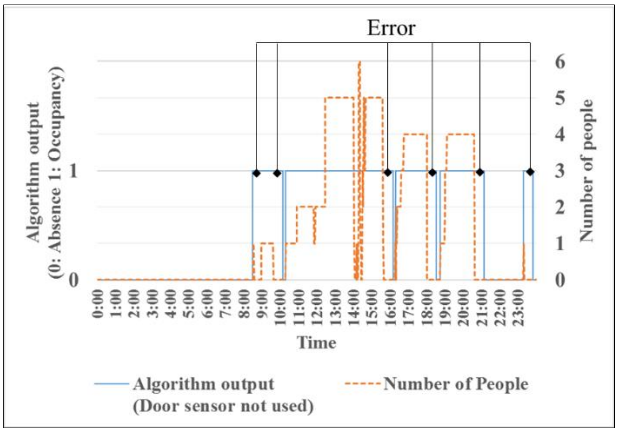

Figure 8. The error of PIR sensor 3 due to the 30-minute occupancy assumption (Case 1)

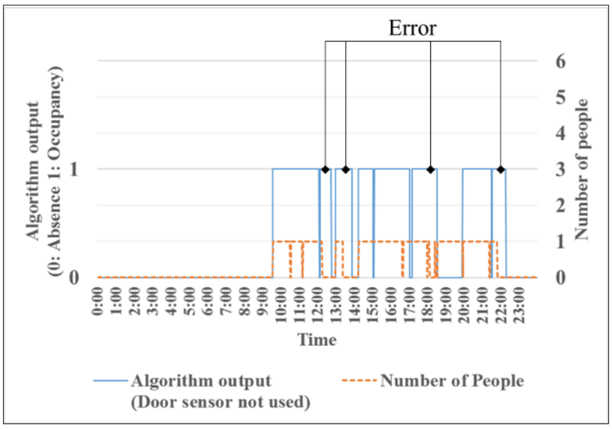

Figure 9. The error of PIR sensor 3 due to the 30-minute occupancy assumption (Case 2)

To solve this problem, an occupancy detection algorithm using PIR and door sensors was developed (Agarwal et al, 2010). In this algorithm, a door sensor is used to check the status based on the door being opened or closed. If there was a change in the status of the door, then it was assumed that the occupancy state changed as defined by three case scenarios: Case 1: occupied → unoccupied, Case 2: unoccupied → occupied, Case 3: occupied → occupied. Case 2 and Case 3 are satisfied by applying the 30 min assumption for the PIR sensor, since people remain in the room. However, for Case 1, errors could develop as discussed above, where the room will remain unoccupied, yet the PIR sensors will provide output data indicating occupancy for another 30 minutes. Thus, a technique to cancel this assumption when the status of the door changed was implemented. After canceling the assumption, the PIR sensor output was checked to determine if someone was still present in the room. Then, a reset for the assumption time is needed if an output value is provided by the PIR sensor. On the other hand, if there is no output value, the room will be considered empty. In the earlier study, the room is considered occupied when the door is open. It represents a typical office environment where occupants are staying while the door is opened. However, this assumption is not appropriate for the case when the door opens while the room stays unoccupied. This is the situation caused by absent-minded occupants, but in many cases, the door opens for a while due to short-term leaves. Within this context, we updated and modified the occupancy algorithm based on the assumption that no occupant is present when the door is opened. The flow chart of this occupancy detection algorithm for the testbed is shown in Figure 9. There is a delay time of 10 seconds after canceling the occupancy assumption time. This is the time needed to prevent errors caused by the PIR sensor's pulse duration.

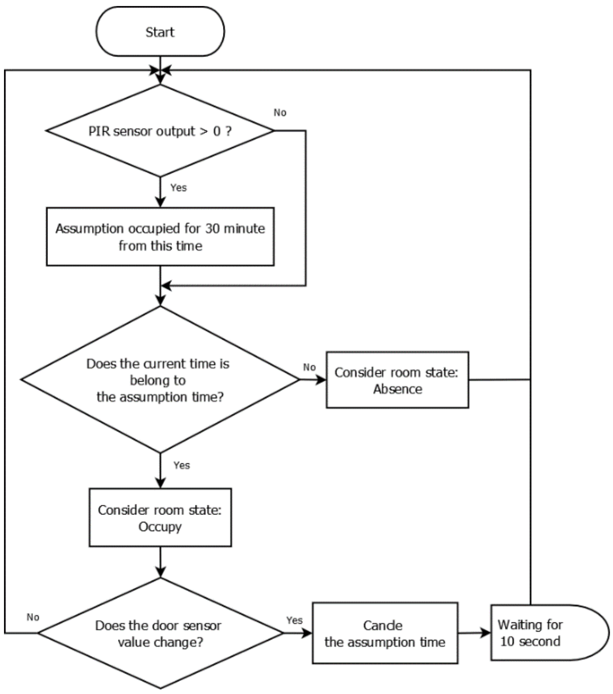

Figure 10. The flow chart of an occupancy detection algorithm

The results of the experiments using the new occupancy detection algorithm are shown in Table 4. The algorithm is applied for only PIR sensor 3 to compare the accuracy rate using all PIR sensors mentioned above. In Case 1, an experiment that applied the 30 minutes occupancy assumption time without using the door sensor showed 2% decrease in the accuracy rate because of the occupancy detection error caused by the assumption time. However, Case 2 showed an increased detection accuracy of 22% due to applying the 30-minute assumption time. When we applied both the assumption time and a door sensor with the suggested algorithm, the detection accuracy was increased to 99.8% and 90.1% in each case, respectively. This result showed a higher accuracy rate compared to the previous experiments, in which four PIR sensors were used at the same time.

Table 4: Accuracy rates of the occupancy detection using combined PIR and door sensors

Sensor	PIR sensor number	Accuracy (%)	
		Case 1 (Number of people: 1~6)	Case 2 (Number of people: 1)
PIR sensor (without assumption time)	3	88.9	62.4
PIR sensor (with 30 minutes assumption time)		86.9	84.4
PIR + Door sensor (with 30 minutes assumption time)		99.8	90.1

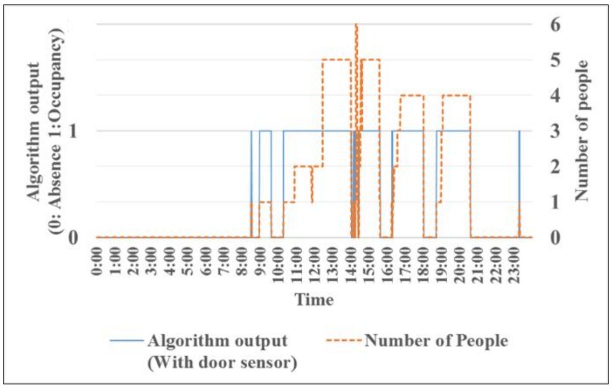

Figure 11. Improvement in occupancy detection when using PIR sensor 3 and a door sensor (Case 1)

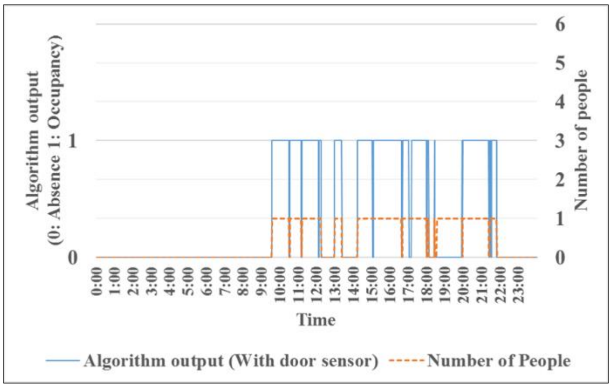

Figure 12. Improvement in occupancy detection when using PIR sensor 3 and a door sensor (Case 2)

Discussion

The results of the experiments show that the occupancy detection algorithm along with a door sensor could be used to improve the occupancy detection accuracy rates of the PIR sensors. In future research, we will expand our study as follows:

- Developing more accurate occupancy patterns in various types of buildings by applying the occupancy detection algorithms combined with the low cost sensors. The results will contribute to reduce the uncertainty associated with the buildings occupants' behavior simulations.
- The suggested approach can be applied to the operation of the air conditioning or ventilation systems. Smart thermostats can adopt the occupancy detection algorithm for advanced control of indoor environmental devices.
- The use of the occupancy detection algorithm can also be expanded to cover various occupant activities, such as sleeping patterns.

Conclusion

In this paper, we conducted a study to improve the occupancy detection methods in order to achieve more accurate and meaningful results from the building occupants' behavior simulations. We utilized PIR sensors to detect occupancy in a testbed setting, where the experiments conducted to investigate the proper locations and number of sensors. The results showed that a sensor installed on a wall provided a more accurate detection rate compared to those located on the ceiling or beside the door. In terms of the number of PIR sensors, the detected accuracy rates were slightly improved as the number of sensors increased. However, some cases showed lower accuracy rates despite using more sensors.

When the suggested occupancy detection algorithm was applied to the PIR and door sensors, an improved occupancy detection accuracy rates of 99.8% (when the number of occupants is 1 to 6) and 90.1% (when the number of occupants is: 1) were achieved. These values were higher than the case when four PIR sensors were used at the same time. These results prove that the accuracy of occupancy detection in a built environment could be improved by applying occupancy detection algorithms to low cost sensors.

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