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An Overview of Real-time Occupancy Information Acquisition Method for Demand-driven Building Energy Management

Jiajing Liu^{a,b,*}, Hanbin Luo^{a,b}, Wenjin Zhang^{a,b}

^a*Dept. of Construction Management, School of Civil Engineering and Mechanics, Huazhong University of Science and Technology, Wuhan, Hubei, China*

^b*Hubei Engineering Research Centre for Virtual, Safe and Automated Construction, Huazhong University of Science and Technology, Wuhan, Hubei, China*

Abstract

Efficient building energy management needs to meet both energy savings and user comfort requirements, which relies on the accurate acquisition of occupancy information over time. In order to meet the data requirements of different building application environments, this paper reviews different sensor technologies based on the principle of obtaining occupancy information, and divides them into five categories, namely motion sensors, environmental sensors, radio frequency (RF) sensors, camera, and contextual sensors. A review of the fusion of multiple sensors that have been widely used for building occupancy detection in recent years has also been conducted. The pros and cons of the prior art are discussed in detail, thus future research can better fit the needs of different system control (such as heating, ventilation, and air conditioning (HVAC) and lighting systems) in different types of buildings.

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1. Introduction

Building sector consumed 40% of the global energy and produced one-third of the global greenhouse gases (GHG) both in developed and developing countries, according to the United Nations Environment Programme [1]. In order to maintain a comfortable indoor light and thermal environment, the inefficient operation of HVAC and lighting systems is a considerable energy waste. Although the occupancy level can vary over time, most of the current building control systems are designed according to the regulations, which assume that all spaces in the building maintain the maximum occupancy. In this case, the lighting and HVAC systems remain work when there is no occupant in the space; and when there are few people in the thermal zone, the maximum occupancy assumption could cause unnecessary energy consumption of HVAC system and make the occupants feel cold.

Building energy management based on occupancy information has great potential for energy saving while providing a comfortable indoor environment. Only with the application of individual temperature setback periods which analyzed

*Corresponding author: Jiajing Liu email: liu_jiajing@hust.edu.cn

by historical office occupancy mode, the space heating and cooling loads can be reduced by 10-15%. In [2], a proof-of-concept experiment was conducted in a mock-up office, the HVAC, lighting, and plug loads were controlled considering the presence of occupancy, and the result indicated that the system was able to deliver an energy saving of 15-68%. Li, et al. [3] adopted random forest to predict personal comfort based on the collection of occupant physiological and behavioural data, and the experiment conducted both in single and multi-occupancy spaces showed that comfort was expected to increase by 80%.

Dong, et al. [4] reviewed the statistical and data mining models for occupancy and behavior modelling, such as agent-based model and k-means clustering. However, for two days of the working day, the prediction methods based on the history data can be indistinguishable. To achieve optimal demand response, real-time occupancy information acquisition is essential. In recent years, there has been a surge of interest in the application of different sensor technologies to detect the presence, count, activities of occupants and support for demand-driven building energy control. The principle of sensors acquiring occupancy information determines their placement and accuracy. Since there are different data requirements for the controlling of different subsystems in different types of buildings, it is necessary to detail review the information acquisition and processing methods for further research.

This paper aims to classify and review emerging indoor occupancy information acquisition methods to serve efficient building energy management needs. According to the type of information acquired by the sensors and its relationship with occupants, we divided them into five categories, namely motion sensors, environmental sensors, RF sensors, cameras and contextual sensors. The following chapters are arranged as follows. Section 2 defines the resolution of building occupancy. Section 3 reviews the single and multi-type sensor fusions that capture occupancy information, detailing the occupancy information acquisition path and information processing methods. And finally, in section 4, some concluding remarks and briefly discusses on limitation and future work are presented.

2. Building occupancy resolution

The resolution demand of occupancy information for different application environments varies. Melfi, et al. [5] proposed to evaluate the resolution from three aspects, which are temporal, spatial and occupancy resolution, as shown in Figure. 1. To focus on the room level, from coarse to fine, the detection of occupancy information includes identifying whether the room is occupied, occupancy count, occupants' location and their trajectory and activities during a specific time. For large-scale commercial buildings, researches are prone to divide rooms into thermal zones, focusing on occupancy differences between regions, especially to detect whether space is occupied and the number of occupants[6, 7]. In contrast, for a space occupied by a few people, such as single offices or residential building, studies pay more attention to the fine-grained information to investigate the occupancy behavior. When it comes into time dimension, the time interval of information processing is closely related to the specific application[4].

Fig.1. Spatial-temporal properties of occupancy information

3. Monitoring technologies

In this section, a comprehensive review of the most popular occupancy information acquisition sensors and their fusions is conducted. According to the principle, they are divided into five categories, which are motion sensors, environmental sensors, RF sensors, camera, and contextual sensors.

3.1. Motion sensors

The motion sensor either emits stimuli and monitors any changes reflected back or acquires a signal from the moving object itself, including passive infrared sensors (PIR), ultrasonic detectors, and radar. Among them, PIR is one of the most commonly utilized devices for occupancy detection.

In nature, all objects including humans with a temperature above absolute (-273K) produce an infrared spectrum, and the wavelength of the infrared energy emitted by objects of different temperatures is not the same. PIR sensor itself does not emit any type of radiation while works by detecting the infrared rays emitted by the human body. It detects the presence of an occupant based on changes in infrared radiation produced by the movement of him. For instance, Dodier et al. [8] constructed a belief network with PIR sensors to detect the presence of occupants in the building. The sensor network was developed and deployed with three PIR sensors, which provide occupancy detection independently, and Bayesian probability theory was applied to determine occupancy. In [9], Duarte et al. analyzed the PIR motion sensor data to identify when the occupant arrived and left the office. Descriptive statistics and two-sample t-tests (95% confidence interval) were used to summarize the long-term occupancy diversity of different rooms, and the results showed that the measured diversity factors of the occupancy data significantly differ from the guidelines recommended by ASHRAE 90.1 2004. Wahl et al. [10] proposed a distributed sensors system based on PIR to detect the moving direction of occupants and estimate the number of indoor occupants. A pair of one-way PIR sensors were deployed, and a direction-based algorithm was applied to count the number. The probabilistic distance-based algorithm was used to select the start and end of the path, compensate for PIR masking-induced deletion errors, and improve the accuracy of the occupant detection. To reduce the cost of equipment costs, Labeodan et al. [11] managed to use a PIR sensor to complete the counting task. The motion patterns were extracted from the raw sensor data with an infinite hidden Markov model (IHMM), and applied to infer the number of occupants using basic statistical regression methods.

PIR sensor-based systems are low-cost and easy to install. However, the PIR sensor with poor penetrability can only detect moving occupants which within its field of view, and occupant information is confined to presence and number.

3.2. Environmental sensors

For one thing, it is necessary to ensure the sound, light, thermal environment and air quality for indoor occupants; for another, the presence of occupants can also act on the indoor environment. Based on this idea, the environmental sensor acquires occupancy information by sensing changes of environmental variables such as temperature, humidity and CO₂ concentration.

3.2.1 CO₂ sensor

The occupant as a source of carbon emissions will affect the concentration of CO₂ in the room. For instance, Cali et al. [12] used a dynamic detection algorithm based on the mass balance equation of indoor CO₂ concentrations to estimate the presence and quantity of occupants. They assumed that the air exchange rate of the doors and windows and the CO₂ produced by each occupant are constant. To smooth out short-term fluctuations and highlight long-term trends, a moving average based on a centred rectangular window function was used to filter the CO₂ concentration. Then, in different scenarios, the PM index and OM index were introduced to evaluate the algorithm. The results showed that the simulation algorithm has better performance when providing the position information of doors and windows.

In addition to dynamic physical models, CO₂-based statistical models have also been leveraged to describe the relationship between the CO₂ concentration and occupancy level.

To avoid the truncation error in deconvolution process, Jiang et al. [13] used the FS-ELM model for indoor occupancy estimation. Locally smoothed CO₂ data was applied to eliminate the effects of data peaks and an X-tolerance accuracy was introduced to evaluate the occupancy estimation performance. Considering the nonlinear relationship between CO₂ and occupancy level, Zuraimi et al. [14] compared the performance of dynamic mass balance model with support vector machines (SVM) and artificial neural network (ANN) models. A lecture hall for up to 200 people was used for a test. The results showed that the ANN and SVM models achieve higher prediction performance when compared with the physical model.

Due to the high variability and slow response of CO₂ sensors, it is difficult to reliably correlate CO₂ levels with actual occupancy. As the occupancy rate increases, the inevitable delay in CO₂ concentration increases.

3.2.2 Multiple sensors

In addition to CO₂ sensors, other environmental sensors such as humidity, temperature, light, and pressure are also applied to provide occupancy information while monitoring the indoor environment, as shown in Table 1. Studies have shown that when CO₂ features are included, better detection performance can be obtained. However, it is worth noting that some researchers also use environmental sensors to detect occupant activities when associated with room information[15].

Table 1. Multi-environment sensor fusion system for occupancy information

Reference	Sensors	Occupancy resolution	Spatial solution	Methodology	Remarks
[16]	CO ₂ , humidity, temperature, light	Presence	Room	LDA, CART, RF	A proper selection of features together with an appropriate classification model have an important impact on the accuracy
[17]	CO ₂ , humidity, temperature, light	Presence	Room	HMM	The HMM with features through CO ₂ achieves the best detection performance
[18]	CO ₂ , humidity, temperature, pressure	Count	Room	Wrapper based ELM	Pressure sensors are meaning for occupancy estimation
[19]	CO ₂ , humidity, temperature, pressure	Count	Room	Filter-wrapper based ELM	Ranges of occupants are defined
[20]	CO ₂ , humidity, temperature, pressure	Count	Room	HFS-ELM	Combining dynamic and static features to form a feature selection framework
[21]	CO ₂ , humidity, temperature	Count	Room	Wrapper based KNN and LDA	KNN performs better than LDA
[22]	CO ₂ , humidity, temperature, pressure	Count	Room	IHMM-MLR	The temporal dependency is captured for different instances
[23]	CO ₂ , humidity, temperature, pressure	Count	Room	Particle filter	
[24]	CO ₂ , humidity, temperature, pressure	Count	Room	LRF	Automatically learn useful features from time and frequency domains
[15]	CO ₂ , humidity, temperature	Activity	Room		
[25]	CO ₂ , humidity, temperature, and air pressure	Count	Room	CDBLSTM	

3.3. RF sensors

RF sensor-based systems include WiFi, Bluetooth, radio-frequency identification (RFID), Global Position System (GPS), ultra-wideband (UWB) and ZigBee. These systems are widely used owing to their flexible, efficient, and wide coverage, which are usually associated with location information.

3.3.1 WiFi

In recent years, with the wide availability of WiFi infrastructure in building and the ubiquitous WiFi-enabled mobile devices (MDS), leveraging routers along with MDs carried by occupants for occupancy detecting becomes feasible.

Wang and Shao [26] developed a WiFi-based Navizon indoor triangulation system for occupancy detection based on the number and location of WiFi devices in the university library. The energy waste pattern was identified through data association rule mining, and the correlation rules were evaluated by the Apriori algorithm. Considering the privacy issues, Zou et al. [27] proposed a new WiFi-based non-intrusive occupancy sensing system (WinOSS), which can provide accurate occupancy information, including occupancy presence, counting and trajectory. Routers were used to scan WiFi-enabled smartphones indoor to capture the data packets and signal strength (RSS) value. The MAC address of MDs was used as identification of occupant. Then, the Online Sequence Extreme Learning Machine (OS-ELM) algorithm was applied to infer occupancy information. To solve the possible detection error that caused by the WiFi-enabled devices not connected to the network, Wang, et al. [28] proposed a WiFi probe-based Dynamic Markov Time-Window Inference (DMTWI) model based on time series and random characteristics of the measured WiFi signal to predict the number of occupants automatically. Comparing with the traditional SVR and ARMA model, the results showed that the WiFi probe can reduce the detection fluctuation effectively.

However, require all occupants to carry a WiFi-enabled smartphone is not the case in real life. To solve this problem, Liu et al. [29] inferred the total number of people walking in a given space based only on the WiFi received signal strength (RSS) measurements between a pair of fixed transmitter/receiver antennas, and no need for occupants to carry MD. A motion model was used to simulate the effects of blocking line of sight (LOS) and scattering effects. By putting the two components together, a mathematical expression was established to represent the relationship between RSS measurements and occupancy. Finally, occupancy was inferred from the calculation of Kullback-Leibler divergence. However, RSS suffers from fluctuations greatly. Chen and Ahn [30] proposed a crowd counting system based on CSI Doppler spectrum analysis acquired by a single wireless receiver. The system used an exhaustive search feature selection strategy to reduce the number of features and improve the overall accuracy of the classification. This method can only provide a rough estimate of occupancy when the number of people is greater than 2. In [31], Zou et al. proposed a device-free occupancy detection and crowd scheme using commercial WiFi to support Internet of Things (IoT) devices. By measuring the shape similarity between adjacent time series CSI curves, an effective signal-based trend index occupancy detection scheme was developed. Finally, an information-based feature selection scheme was used to select the most representative features which are sensitive to human motion, and a crowd counting classifier based on transfer kernel learning (TKL) and information fusion was proposed to calculate the number of occupants in space.

In sum, the indirect system relies on the detection of MDs, but sometimes the occupant may not turn on the WIFI service or a single occupant may carry multiple MDs. The direct system is confined by the estimate of the number of mobile occupants while ignoring the stationary one.

3.3.2 Multi-sensor networks

The availability of WiFi and BLE sensors in smartphones makes it easy for users to carry potential positioning capabilities in their pockets, and research tends to combine the two to explore more accurate and reliable occupancy information, as shown in Table 2.

Table 2. Multi-RF sensor fusion system for occupancy information

Reference	Sensors	Occupancy resolution	Spatial resolution	Methodology	Remarks
[32]	WiFi, BLE	count	Zone	KNN	Uneven occupancy distribution leads to high energy saving potential
[33]	WiFi, BLE	count, location	Floor	DFT, Particle Filter	

3.4. Camera

Cameras for security monitoring are widely installed in public buildings, which also provide a solution for the acquisition of occupancy information. Benezeth et al. [34] proposed a vision-based algorithm to detect human presence and characterize activity with static cameras. Firstly, the objects variation was detected using the background subtraction algorithm. Secondly, the moving objects were tracked based on interest points. Finally, multiple cascades of boosted classifiers were applied for occupant identification. To alleviate privacy issues, Diraco et al. [35] presented a computational framework for occupancy detection and profiling based on pure depth data. The Gaussian average background model was applied to estimate the depth distance in crowded scenes. A semi-supervised version of the complete linkage agglomerative clustering was proposed to improve the localization in depth data. Then, the occupancy detection was implemented by means of an ensemble classification technique based on Real AdaBoost. In [36], Zou et al. proposed an occupancy detection algorithm combining the cascaded classifiers and emerging machine learning technology. The pre-classifier employed three frame difference algorithm to search for motion windows and used the HOG-SVM module to filter non-head regions quickly. Then, the main classifier utilized a convolution neural network (CNN) to classify head windows. Finally, the clustering analyzer employed K-means clustering to fuse the sequence frames to improve accuracy. If the interior layout is compact, it may cause head blockage or overlap. Petersen et al. [37] proposed an occupancy detection system based on Kinect camera installed at the room entrance. An image-based unsupervised image processing technique was proposed to determine whether a person enters or leaves a room within the camera field of view according to different moving directions of occupants.

Generally, camera-based occupancy systems have high accuracy and were commonly used to obtain ground truth. However, it still has many limitations, such as the need of large data storage, high computational complexity and interference with privacy issues.

3.5. Contextual sensors

Contextual sensors refer to entities in space such as chairs, keyboards and mice, which can be in direct contact with occupants to obtain occupant information. As shown in Table 3, a few studies that only based on chairs have made some attempts.

Table 3. Contextual sensor system for occupancy information

Reference	Sensors	Occupancy resolution	Spatial resolution	Methodology	Remarks
[11]	Chair	Count	Room	Thresholding	
[38]	Chair	Count	Room	Control algorithm	Mechanical-switch sensors perform better than strain and vibration sensors; Chair sensors perform better than PIR sensors

3.6. Sensor fusion

Since the occupancy information coming from one kind of sensor may unreliable, there is a tendency for researchers to investigate the application of multiple sensors to increase coverage and extract higher levels of occupancy information that cannot be obtained by a single sensor. Sensor fusion technology usually has the ability to measure fine-grained human activities and improve the accuracy of occupancy detection based on the characteristics and advantages of different sensors. However, it does not mean that more sensors in the occupancy detection systems have better performance.

Table 4. Multi-type sensor fusion for occupancy information

Reference	Sensors	Occupancy resolution	Spatial resolution	Methodology	Remarks
[39]	PIR, keyboard, mouse, WiFi, GPS	Presence	Zone	Bayesian belief network	
[40]	CO ₂ , temperature, smart meter	Presence	Building	HMM	Without the need of ground truth data
[2]	PIR, keyboard, mouse, webcam	Presence	Room	Occupancy sensing algorithm	PC data can get more accurate occupancy information than PIR sensor
[41]	PIR, noise, CO ₂ , VOC	presence	Room	plug-and-play detection method	CO ₂ sensor has the best performance when applied in a room; A combination of PIR and VOC is better for an apartment
[42]	PIR, CO ₂ , temperature, humidity, illumination, CO	Count, Activity	Zone	SVM, ANN, HMM	Important sensors for occupant pattern prediction are CO ₂ , acoustics and motion;
[43]	PIR, CO ₂ , double-beam, pressure mats, acoustic	Presence, count	Zone	CRF	Different combinations of sensors are evaluated in four different types of room
[44]	CO ₂ , energy consumption	Count	Room	CART, HMM	
[45]	CO ₂ , camera	Count	Room	Massive conservation equation	Cameras were used under good illumination condition, otherwise, CO ₂ sensors were utilized
[46]	PIR, sound, CO ₂ , temperature, humidity, VOC	Count, Activity	Building	ANN	
[47]	PIR, door, CO ₂ , electric meter	Identity, Activity	Room	Multinomial logistic regression model	Distinguish between three occupancy status of away, active, sleep
[48]	Thermal, camera	Presence, Activity	Zone	Background subtraction, ROI based segregation models	The thermal sensor overcomes the main shortcoming of PIR sensors

4. Discussion

The occupancy level at which a sensor perceives depends on how it obtains information. Take the environmental sensor as an example, since the CO₂ sensor can sense the changes of indoor CO₂ concentration, it can be used to estimate the number of occupants based on the rate at which a single occupant exhales CO₂. Economics and privacy are important measures to decide whether a program to be adopted. As can be shown in Table 5, Explicit sensors require additional devices, while implicit sensors can rely on existing infrastructure in the building. The development of computer vision technology has enhanced the ability to extract information from images, however, its invasiveness has greatly limited the application scenario.

Table 5. The characteristic of different sensor systems

Sensor type	Occupancy resolution	Infrastructure	Privacy
Motion sensors	Count	Explicit	Nonintrusive
Environmental sensors	Count	Implicit/Explicit	Nonintrusive
RF sensors	Location	Implicit	Intrusive
Camera	Activity	Implicit/Explicit	Intrusive
Contextual sensors	Count	Implicit	Nonintrusive

As can be seen from the studies reviewed, the number of occupants is most concerned by researchers in terms of occupancy levels. If take the occupant identity into account, the accumulation data of him can be applied for personalized service since an individual has a preference for the indoor environment. What's more, occupancy behavior can also be leveraged to reduce energy consumption, such as opening a window. In [49], the study reconfigured the occupant sub-areas based on similar arrival and departure times.

For different kinds of buildings, due to the defects of occupancy tracking method, the immaturity of occupied information processing method, the difference in energy consumption control methods, the control target cannot be fully realized. Thus, there is still a lot of work can be done to obtain real-time occupancy information for demand-driven building energy management.

5. Conclusion

For demand-driven building energy management, select a proper occupancy information acquisition method is the first step since different sensors have different characteristics. This paper reviews different sensor technologies based on the principle of obtaining occupancy information, and divides them into five categories, namely motion sensors, environmental sensors, RF sensors, camera, and contextual sensors. There is also a tendency for researchers to investigate the feasibility of multi-sensor fusion applications. Although great progress has been made, studies still haven't paid enough attention to the specific application environment when test the performance of sensor technologies. Besides, more robust data processing method like deep learning can be explored with the accumulation of data. To provide a more personalized service, occupancy information can be used to model the occupancy behavior characteristics.

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