Modeling occupancy distribution in large spaces with multi-feature classification algorithm

Wei Wang [a,b], Jiayu Chen [a,1], Tianzhen Hong [b,2]

[a] Department of Architecture and Civil Engineering, City University of Hong Kong, Y6621, AC1, Tat Chee Ave, Kowloon, Hong Kong

[b] Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA 94720, USA

Abstract:

Occupancy information enables robust and flexible control of heating, ventilation, and air-conditioning (HVAC) systems in buildings. In large-sized spaces, multiple HVAC terminals are usually installed to provide co-operative services for different thermal zones. Occupancy information for large spaces, such as people counts, determines the cooperation among terminals. However, a people count at room-level is not adequate to optimize HVAC system operation due to occupant movement within the room leading to uneven distribution of loads. Without an accurate knowledge of occupants' spatial distribution, uneven distribution of occupants often results in under-cooling/heating or over-cooling/heating in some thermal zones. Therefore, the lack of high-resolution occupancy distribution is often perceived as a bottleneck for future improvement in HVAC operation efficiency. To fill this gap, this study proposes a multi-feature based k-Nearest-Neighbors (k-NN) classification algorithm to extract occupancy distribution through reliable and low-cost Bluetooth Low Energy (BLE) networks. To demonstrate the proposed methods, an on-site experiment was conducted in a typical office of an institutional building. To validate the detection accuracy, the experiment outcomes were examined in three case studies, and one method based on City Block Distance (CBD) is used to measure the distance between detected occupancy distribution and ground truth and assess the results of occupancy distribution. The results show that the accuracy of CBD = 1 is over 71.4% and accuracy of CBD = 2 can reach 92.9%.

Keywords: HVAC loads, multi-feature classification algorithm, occupancy distribution, energy efficiency, occupancy-based control.

1*Corresponding author. tel.: +852 3442 4696; fax: +852 3442 0427.

e-mail addresses: jiaychen@cityu.edu.hk (Jiayu Chen)

2*Corresponding author. tel.: +1 (510) 486-7082.

e-mail addresses: thong@lbl.gov (Tianzhen Hong)

1. INTRODUCTION

A close estimation of operation procedure for a typical HVAC system usually focuses on thermal comfort load to provide hints on how energy conservation can potentially be achieved [1,2]. To optimize both thermal comfort and energy efficiency, researchers developed temperature-based demand-driven control strategies to adjust the operation of HVAC systems and achieve energy savings in large-sized rooms without zone divisions [3–5]. Lin and Claridge proposed a temperature-based Days Exceeding Threshold-Toa (DET-Toa) method to detect persistent small increases or decreases and assess the cooling or heating demand in a given period [3]. Zeng et al. developed a data-driven predictive model to balance temperature and air static pressure setpoint with actual demand to optimize HVAC operation [4]. Zhou et al. proposed a demand-based temperature control model with breathing level temperature sensors to eliminate data bias due to temperature vertical distribution [5]. In Zhou's work, a 20% to 30% reduction in supply airflow was estimated when the zone was fully or half-occupied in a large-sized room. This study was implicitly hampered without considering occupancy when estimating occupant-related loads in fully or partially occupied zones in large rooms.

Unlike regular-sized rooms, a large-sized office often serves a dense population and consumes more energy. In addition, occupancy in large spaces is difficult to predict due to diverse space functionality and occupants' preferences. As a result, the spatial distribution of occupants is often uneven and causes difficulties in efficient HVAC operation. Without knowing occupants' spatial locations, it inevitably results in under- or over-cooling/heating problems that mismatch the building service demand and supply [5]. Zone occupancy distribution has been mainly ignored or over simplified. A typical example is when a facility system runs at full capacity while there is no occupant in a thermal zone. To study zone occupancy level, previous studies have given an occupancy matrix analysis on how to map occupancy information into patches of physical space [6] and several studies [7–9] stressed the importance of zone occupancy. However, few accurate methods of how to detect occupancy level were discussed. Therefore, this study utilized a multi-feature k–nearest-neighbors' (KNN) classification algorithm to detect zone-based occupancy distribution with Bluetooth Low Energy (BLE) networks. An experiment for occupancy distribution estimation was conducted in one large-sized office room.

The main objectives of this study are as follows:

(1) It proposed a new approach to detecting the occupancy distribution in one large-sized room with BLE technology.

(2) It proposed a multi-feature KNN classification algorithm to profile zone occupancy distribution. A city block distance-based accuracy method was applied to assess the results of the detected occupancy distribution.

(3) Finally, it discussed the implications of using the occupancy distribution to improve building facility controls.

This study is organized as follows: Section 2 reviews and discusses some related works. Section 3 illustrates the zone-level thermal load based occupancy information. Section 4 presents the occupancy patch based multi-feature classification to detect occupancy distribution. The validation experiment and assessment index are introduced in Section 5. Section 6 shows the results of this study, and Section 7 discusses the implications, limitations, and future works of this study. Section 8 offers conclusion.

2. REVIEW OF OCCUPANCY STUDIES

2.1 Occupancy resolution

Occupancy information refers to the number- and time-based schedule of occupants in buildings. To quantify occupancy resolution, it was categorized at different scales. One of the most popular definitions was provided in [10]: (1) space, including building, floor, and room level; (2) occupants, including occupancy, count, identity, and activity level; and (3) time span, including days, hours, minutes, and seconds, which are illustrated in Fig. 1. In [11], there is another popular definition that includes presence, which is used to determine whether an occupant is present in a space; count, or the number of occupants present in a given space; location, meaning the occupants' exact physical position; track, which is the movement of occupants; and identity, which indicates who is in the room. While in large spaces or space conditioned by collaborative working air-conditioners, the "count" level in room spatial resolution is usually not accurate enough for HVAC control optimization. In the study [12], Du et al. proposed one method to optimize collaborative air-conditioners by finding the relationship between energy efficiency, temperature, and user location so that real-time "location" levels of occupant information can be used to optimize HVAC systems. However, on one hand, technology to find the accurate locations of occupants is currently undeveloped. On the other hand, HVAC systems cannot respond to such accurate temperature control in one exact location. Therefore, to address this limitation, this study proposes to add zone occupancy distribution to occupancy resolution, which is illustrated in Fig. 1. Zone occupancy level can be defined by the "count" level and "location" level of occupants, where it must find the number of occupants distributed in each thermal zone, but not the exact location of occupants in the zone, thus avoiding complex positioning algorithms. In the spatial resolution, zone level would be added to describe occupancy distribution information.

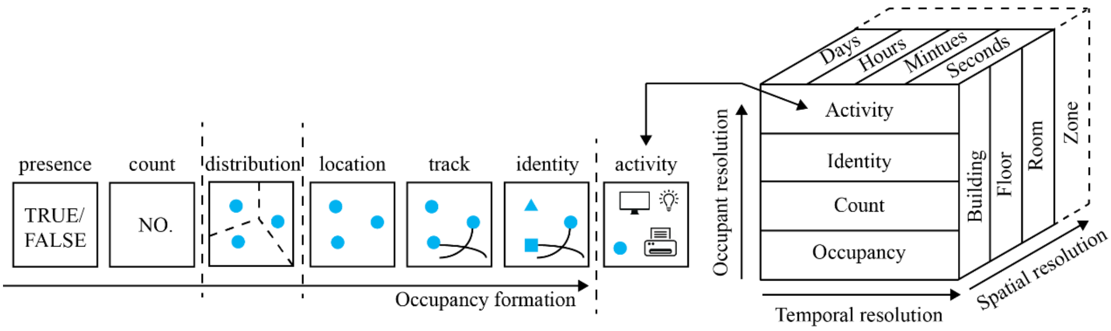

Fig. 1. Occupancy resolution, including occupancy distribution level

This occupancy resolution has some major benefits: (1) high occupancy resolution with low detection cost, (2) efficient control of multiple HVAC system terminals, and (3) energy saving and space management based on occupancy distribution preference.

2.2 Measurement of occupancy resolution

To acquire occupancy information at different levels, various sensor technologies and occupancy algorithms have been utilized to detect occupancy profiles and improve data resolution. The subsections 2.2.1 and 2.2.2 review some current, widely applied methods and studies for different occupancy resolutions.

2.2.1 Presence, count, and identity of occupancy studies

For the presence level, passive infrared (PIR) sensors, motion sensors, and lighting sensors can respond to occupants' presence/absence within their field-of-view [13], but these sensors are not able to detect stationary occupants [14]. Studies also employ building security cameras to receive building or room presence information and compile occupancy information [15–17]. Regarding count level, the ASHRAE standard 90.1-2007 [18] recommends designing diverse occupancy factors for different building types and this designed occupancy schedule is useful for size operation when actual data are unknown, but it might cause 40% of variation compared with the actual occupancy information [19]. To simulate occupancy, some researchers built an agent-based stochastic occupancy simulator and also provided a web application for occupancy information simulation and visualization [20–22]. Using CO_2 concentration, Wang et al. developed several dynamic CO_2-based models to estimate and predict occupancy in commercial buildings [23–25]. Jiang et al. proposed a feature-scaled extreme learning machine (FS-ELM) approach on CO_2 concentration to predict occupancy and reported 50% accuracy [26]. Some researchers also include CO_2 sensor data with other environmental sensors, such as temperature, humidity, lighting, and sound sensors, to improve occupancy estimation accuracy [27,28]. Diaz and Jimenez conducted an experiment on the power consumption of computers under occupancy variation estimated by CO_2, suggesting that CO_2 concentration is informative as a good indicator of occupancy [29]. These approaches are not ideal due to their constraints on time delay, high cost, and inaccuracy for indirect detection [30]. Some studies also utilized the existing Wi-Fi signal networks inside buildings to profile the number of occupants with Markov chain and artificial neural network algorithms, resulting in about 80% accuracy [31,32].

The "identity" level is also important in building energy-saving studies. Since occupants are the building energy end-users, providing information of energy use to occupants is an efficient feedback control method. For example, one residential eco-feedback study in [33] shows 10 % energy saving when providing users with historical consumption data. Normative comparison features have been recently added to eco-feedback systems to provide users and peers with socially contextualized feedback [34–36]. Identification can be sensed by cameras via image analysis, which is a traditional and effective tool. In recent years, the development of smart devices enables identification from one unique service set identifier (SSID) or the Mac address of smart devices [32]. However, as it is necessary to involve humans, such detections are correlated with ethical considerations and privacy concerns.

2.2.2 Location, tracking, and activity of occupancy studies

Location and tracking levels can usually be reported by RFID sensors using the spatial coordinates of occupants in an RFID network deployed space. Li et al. [1] found an average positioning accuracy of 88% for stationary occupants and 62% for mobile occupants when using active RFID systems, although the active network infrastructure is expensive [37]. Some researchers also investigated the application of motion sensors as walkaway sensing to track occupancy movement and behaviors, which achieves 96% and 95% average accuracies in offline and online modes [38]. At the computer science and artificial intelligence laboratory of Massachusetts Institute of Technology (MIT), Fadel Adib et al. have researched how to Radio Frequency (RF)-capture and WiTrack to track an occupant through walls with Wi-Fi signals and via body radio reflections [39]. However, it faces some constraints when cooperating with an HVAC system, such as high cost when detecting multiple occupants in a large space where Wi-Fi signal reflection will be distributed by other bodies and real-time tracking detection is not very applicable in HVAC controls.

The International Energy Agency's (IEA) Energy in Buildings and Communities (EBC) Programme Annex 66 project highlighted the significant roles of occupant behavior in a building performance study [40]. American Time Use Survey (ATUS), conducted by the U.S. Bureau of Labor Statistics provides access to records of respondents' activities and locations on a regular day [41]. Diao et al. [42] proposed to identify and classify occupants' activities with direct energy consumption outcomes and energy time use data through k-modes clustering, probability neural network, and inhomogeneous Markov chain model based on American Time Use Survey (ATUS) data. Researchers concluded that building energy use patterns could be observed and investigated with occupancy behavior information. Yu et al. [43] employed k-Means clustering analysis to examine the effects of different behavior patterns on energy consumption and revealed that four identified behavior clusters have significant attributes to some end-use loads, such as HVAC load. Sun et al. [44] defined five occupant activities measures in office buildings—lighting, plug load, thermal comfort criteria, HVAC control and window control—and simulated and analyzed their individual and integrated impact on building energy use. Table 1 gives an overview of related studies and typical sensing technologies for different occupancy resolution.

Table 1. Overview of typical occupancy sensing technologies and example studies

Occupancy resolution	Example studies	Sensing technologies	Applications

Presence	Dodier et al. [13]; Benezeth et al. [14]; Zou et al. [17]	PIR, Video/Camera, Switch (e.g. Door), RFID, Wi-Fi/Bluetooth	To control on/off operation for lighting, HVAC, and other systems.
Count	Wang et al. [23–25]; Jiang [26]; Wang [31,32]	PIR, Video/Camera, Switch (e.g. Door), RFID, CO2, Consumption sensing (e.g. Energy), Wi-Fi/Bluetooth	To facilitate demand based controls for HVAC and other systems
Identity	Chen et al. [32,34]	Video/Camera, RFID, Wi-Fi/Bluetooth	To facilitate individual feedback based energy saving
Location	Li et al. [1]	Video/Camera, RFID, Wi-Fi/Bluetooth	To provide indoor positioning which can be potentially used in building controls
Tracking	Soltanaghaei et al. [38]; Fadel Adib et al. [39]	Video/Camera, RFID, Wi-Fi/Bluetooth	To provide indoor positioning which can be potentially used in building controls
Activity	Diao et al. [42]; Yu et al. [43]; Sun et al. [44]	Video/Camera, Switch (e.g. Door), Consumption sensing (e.g. Energy)	To provide individual activity patterns with potential targeted comfort solution and energy savings

3. ZONE-LEVEL THERMAL LOAD ESTIMATION BASED ON OCCUPANCY

Fig. 2 shows the scheme of a typical zone-based thermal load distribution in a VAV system. In this scheme, this room has been divided into four zones and each zone is commonly served by one VAV terminal unit/box. In the cooling process of the HVAC operation, it usually needs to eliminate the occupant-related and non-occupant-related thermal loads, the former of which contains ventilation load, heat gained from occupants and equipment operated by occupants, and which—crucially—determines the operation of the HVAC system to guarantee indoor air quality and thermal comfort level in the occupied zones. The non-occupant-related load includes the load from air infiltration, envelope, and so on. The following interpretation of two types of HVAC loads is illustrated at the room level and zone level.

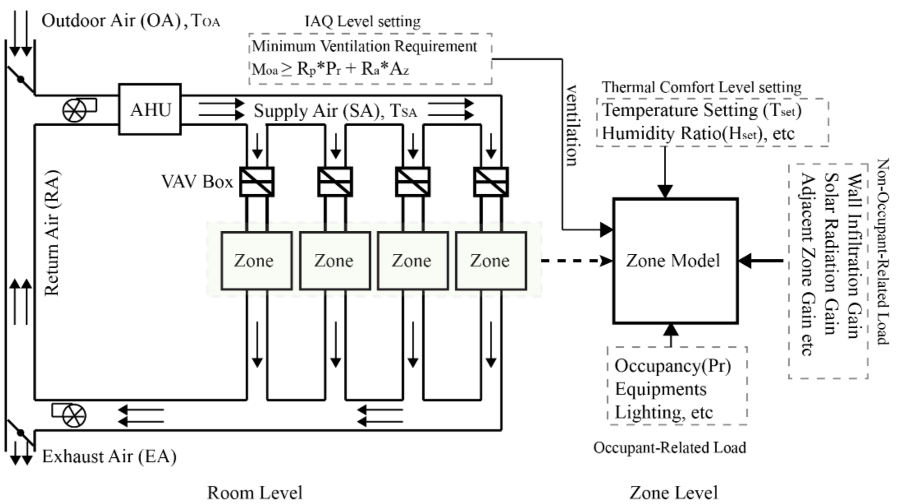

Fig. 2. Energy loads at the zone level and room level for a VAV system

At the room level and zone level, the non-occupant-related load ($Q_{nor}\text{¿}$ is generated by heat transfer across the building envelope depending on weather conditions:

$$Q_{nor,i}=Q_{inf,i}+Q_{adj,i}+Q_{surf,i} \tag{1}$$

$$Q_{inf,i}=m_{inf,i}*C_p*\left(T_{\text{¿},i}-T_{air}\right) \tag{2}$$

$$Q_{adj,i}=m_{adj,ij}*C_p*\left(T_{\text{¿},i}-T_{\text{¿},j}\right) \tag{3}$$

$$Q_{surf,i}=A_{surf,i}*K_{surf}*\left(T_{\text{¿},i}-T_{air}\right) \tag{4}$$

$$Q_{nor,r}=\sum Q_{nor,i} \tag{5}$$

The occupant-related load $\overset{Q}{\underset{\text{¿}}{(\text{¿¿¿})}}$, which includes internal gain from occupants and equipment operated by occupants. At the zone level,

$$Q_{gain,i}=\sum_{P_r} Gp+\sum_{P_{eq}} G_{eq}+\sum G_{other} \tag{6}$$

$$Q_{z,i}=Q_{nor}+Q_{gain,i} \tag{7}$$

While G_{eq} contains computers, water heaters, lights etc., the operation schedules of which usually rely on the schedule of occupancy.

At the room level, the VAV box in the zone should provide enough conditioned air in case the thermal comfort requirement and the amount of air supplied by the AHU system should equal to the total amount of air that is delivered by all VAV boxes. So,

$$E_{v,i}=m_{z,i}*C_p*\left(T_{\text{¿}}-T_s\right)=Q_{z,i} \tag{8}$$

$$M_r=\sum m_{z,i} \tag{9}$$

$$E_{V,r}=\sum E_{v,i} \tag{10}$$

ASHRAE standard recommends minimum ventilation requirements, and in recognition of the fact that indoor air pollutants are generated by both building occupants (and their activities) as well as by the contents (e.g., furniture) of a building, the ventilation requirements include both a people component (to dilute contaminants from people and their activities) and an area component (to dilute contaminants from non-occupant-related sources that are more related to floor area than the number of people) [45]. Outdoor airflow required in the breathing zone of the occupied space or spaces in a zone should be determined:

$$m_{OA} \geq R_p * P_r + R_a * A_r \tag{11}$$

Then,

$$E_{AHU,r} = Q_{vent,r} = m_{OA} * \left(h_{OA} - h_{¿}\right) \tag{12}$$

For the whole system, the objective is to minimize the total energy consumption of the two main energy consumers in an HVAC system under the conditions of satisfying occupant-related thermal comfort and indoor air quality requirements.

$$min\left(E_{V,r} + E_{AHU,r}\right) \tag{13}$$

In HVAC, occupants usually perform as the regular building energy end-users. If real-time occupancy information is available, the building energy load at zone level or building level can be illustrated in detail in occupant-related loads, such as human thermal gains or energy usage for associated appliances. On one hand, those occupant-related loads can be calculated without any delay and the HVAC operation system can be guided by occupancy-driven control modes. On the other hand, unoccupied zones can be defined so that non-occupant-related load can be avoided at the same time in the unoccupied zones. Building energy savings can be evaluated by considering turning off HVAC operation, or maintaining higher temperature and lower ventilation rates for the unoccupied zones.

4. OCCUPANCY PATCH BASED MULTI-FEATURE CLASSIFICATION

In practice, for ease of building HVAC system operation, large spaces are normally divided into multiple thermal zones. Each thermal zone can have its own occupancy information and implement independent system settings. This study propose to develop a novel multi-feature classification algorithm based on BLE network signals to acquire zone-level occupancy distributions. With such information, the building HVAC system can adept an occupancy-driven control mechanism to avoid energy wastes. To capture occupancy distribution, the physical room space can be divide into small patches; thus, instead of occupancy coordination, this study is specially designed to map occupancy information into the patch level. The proposed method includes three major steps.

4.1 Step 1: Signal fingerprinting implementation

To detect occupancy distribution, the signal fingerprinting method was applied to create reference points, which has been widely used in several indoor localization studies [46–48]. Implementing signal fingerprinting can avoid signal fluctuation and then map signal feature with geographical locations. This study utilized vertices of patches as the signal fingerprinting points. One example of the signal fingerprinting points selection can be found in Fig. 3. Ideally, each physical location will own one unique and differentiable signal fingerprint feature, and the higher the distinction is, the greater the accuracy is.

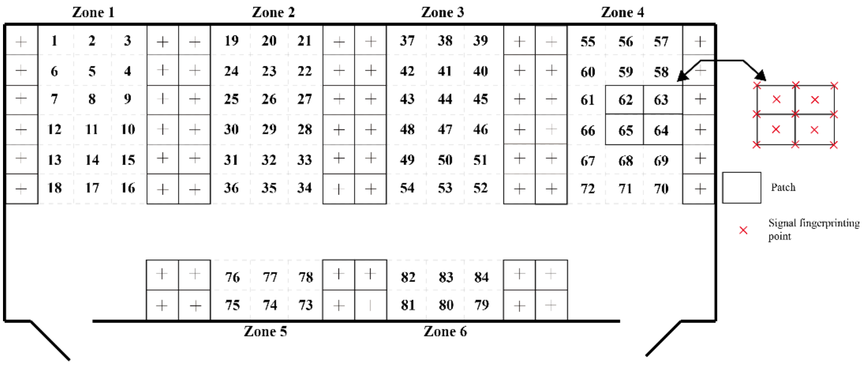

Fig. 3. Patches indices in the office room.

4.2 Step 2: Signal feature extraction

After implementing signal fingerprinting points, the signal strength of all points should be measured with the signal source of the Bluetooth Lower Energy (BLE) technology in this study. One popular device to transmit the BLE signal is iBeacon, which is a protocol developed by Apple and introduced at the Apple Worldwide Developers Conference in 2013 [49,50]. iBeacon can also be used with an application as an indoor positioning system, which helps smartphones determine their approximate location or context [51,52]. Implementing more fingerprinting points or increasing the number of signal sources can enhance the robustness and accuracy of an algorithm; however, it is time-consuming and the cost is higher. To enhance performance, two pieces of information from iBeacon sources can be used in this study: (1) received signal strength indicator (RSSI) and (2) approximate location range (LR). The iBeacon devices could not only tell the receivers' RSSI value but also distinguish a possible location range for receivers away from iBeacons. When iBeacon is installed, measurement of signal fingerprinting points includes both RSSI and LR. Suppose there are n signal sources,

$$\{S_1, S_2, \ldots, S_j, \ldots, S_n\} \tag{14}$$

Supposing Z location ranges have been picked, for the signal source S_j, the location ranges (LR) could be formulated as:

$$LR_j^1 \in ¿ \tag{15}$$

$$LR_j^2 \in ¿ \tag{16}$$

$$LR_j^z \in \text{¿} \tag{17}$$

Where, $LR_j^1, LR_j^2, \ldots, LR_j^z$ mean the location range 1 ($LR^1\text{¿}$, 2 ($LR^2\text{¿}$ and z ($LR^z\text{¿}$ of signal source S_j . The $S_{j,min}$ and $S_{j,max}$ mean the minimum and maximum value of the signal source S_j . The location ranges' illustration of other signal sources would be the same as the signal source S_j .

Therefore, each signal fingerprinting point would be assigned two important features. For fingerprinting point x_p , the feature vector *F* can be formatted

$$\text{¿} S_1(x_p), LR_1(x_p), \ldots, S_j(x_p), LR_j(x_p), \ldots S_n(x_p), LR_n(x_p) > \text{¿} \tag{18}$$

Where, $S_j(x_p)$ is the RSSI value from signal source S_j for fingerprinting point x_p .

For fingerprinting point x_p , we can attain the feature and target patch:

$$F = \text{¿} S_1(x_p), LR_1(x_p), \ldots, S_j(x_p), LR_j(x_p), \ldots S_n(x_p), LR_n(x_p) > \rightarrow f(x_p) \tag{19}$$

Where *F* and $f(x_p)$ are the feature vector and is the target patch of x_k .

Those two features from different signal sources can efficiently equip reference points and occupant information with differentiable location information. The location range can help point out the approximate area inside a room, which can reduce the complexity of occupancy distribution detection; for example, one occupant can be located in one or two estimated thermal zones. RSSI information can further estimate maximum possible patches to get occupancy distribution information.

4.3 Step 3 Occupancy classification algorithm based on multiple signal features

With features, several classification algorithms in machine learning disciplines can mathematically and automatically train and learn occupancy distribution, such as Artificial Neural Networks (ANN), Support Vector Machine (SVM), Decision tree, k-Nearest Neighbors (k-NN) algorithms, and so on. Some of these algorithms have been widely used in occupancy studies. This study applied the k-NN classification algorithm to map occupancy information into indoor areas since the k-NN algorithm has two considerable benefits: (1) it uses distance to determine closeness between instances, which is easily available for signal strength and makes it very efficient; (2) and it ultimately determines the classification performance using k nearest instances, while k nearest instances can help map occupants' distribution in high-priority patches. For example, we can pick up 3 nearest patches among k nearest instances to sense which area occupants might occupy. For demand-based HVAC control models, the high-priority occupied areas are vital for determining the operation of HVAC terminals. To refine the occupancy distribution information in each thermal zone, the k-NN algorithm is adopted to estimate the most likely zone that an occupant belongs to. However, when a room is divided into patches, the number of patches will be relatively high. In Fig. 3, for example, the number is 84. If the number of targets to learn in k-NN algorithm is large, the accuracy of the results will be reduced. Therefore, three steps were applied in this study to approach occupancy distribution information.

Firstly, this study used the location range feature to reduce the learning target. The location range feature vector ($\langle LR_1(x_p), LR_2(x_p), \ldots, LR_j(x_p), \ldots, LR_n(x_p) \rangle$) was applied firstly to the training algorithm, and the location range feature vector was to reduce the targets where the objects possibly were. The number of patches after reduction was selected as 2k. Then, Euclidean distance was used to calculate closeness between points to train the k-NN algorithm, and it can be expressed:

$$d(x_i, x_j) = \sqrt{\sum_{r=1}^{N} \left(F_r(x_i) - F_r(x_j)\right)^2} \tag{20}$$

Where the $d(x_i, x_j)$ is the Euclidean distance between two instances, x_i and x_j. N is the total number of attributes of feature vector and r is the r th attribute of feature vector.

To learn occupancy distribution, the learning function that is widely applied is,

$$\hat{f}(x_q)\Big|_{LR} \leftarrow \underset{v \in V}{argmax} \sum_{i=1}^{k} \delta\left(v, f(x_i)\right) \tag{21}$$

Where $\hat{f}(x_q)\Big|_{LR}$ is the estimated result of object x_q using the LR feature. k is the number of selected nearest neighbors. Function $\delta(\cdot)$ is defined as auxiliary and when a = b, $\delta(a, b) = 1$, or $\delta(a, b) = 0$.

Secondly, this study determined the k nearest patches by using the RSSI feature vector ($<S_1(x_p), S_2(x_p), \ldots, S_j(x_p), \ldots, S_1(x_p)>$), and we added the weight to refine the occupancy distribution information,

$$\hat{f}(x_q)\big|_{RSSI} \leftarrow \underset{v \in V}{argmax} \sum_{i=1}^{k} w_i \delta\left(v, f(x_i)\right) \tag{22}$$

$$w_i = \frac{1}{d(x_q, x_i)^2} \tag{23}$$

Where $\hat{f}(x_q)\big|_{RSSI}$ is the estimated result of object x_q using the RSSI feature vector. w_i is the distance weight.

Finally, in k nearest samples, we defined three maximum possible patches that the occupant is located in

$$p_1 = \frac{1}{k} * N_1 \qquad p_2 = \frac{1}{k} * N_2 \qquad p_3 = \frac{1}{k} * N_3 \tag{24}$$

Where, N_1 , N_2 , and N_3 donate the frequency of first, second, and third closest patches that an occupant possibly occupies, respectively, in k nearest patches. p_1 , p_2 , and p_3 donate the possibilities of first, second, and third closest patches that an occupant occupies, respectively.

5. VALIDATION EXPERIMENT

5.1 Experiment setup

In validation, we chose one experiment area in one general office room in an institutional building, showed in Fig. 4. This office area is located in the City University of Hong Kong, Hong Kong, and the area contains office desks, computers, partitions and so on. From the network setting in Fig. 4, six iBeacons were installed in the location to create overlapping signal networks. After ascertaining signal sources, signal fingerprinting methods were implemented in the experiment area for the office room, and it was sequenced by setting 180 fingerprinting points from Zones 1 to 4, and 90 fingerprinting points from Zone 5 to 6, respectively, shown in Fig. 4. All the signal sources had been tested for reception, and all the signal references could be reached in this room. To eliminate the influence caused by fluctuation of the signal, RSS of all points in the experiment would be recorded and averaged by three times. The information about the room and iBeacon is included in Table 1.

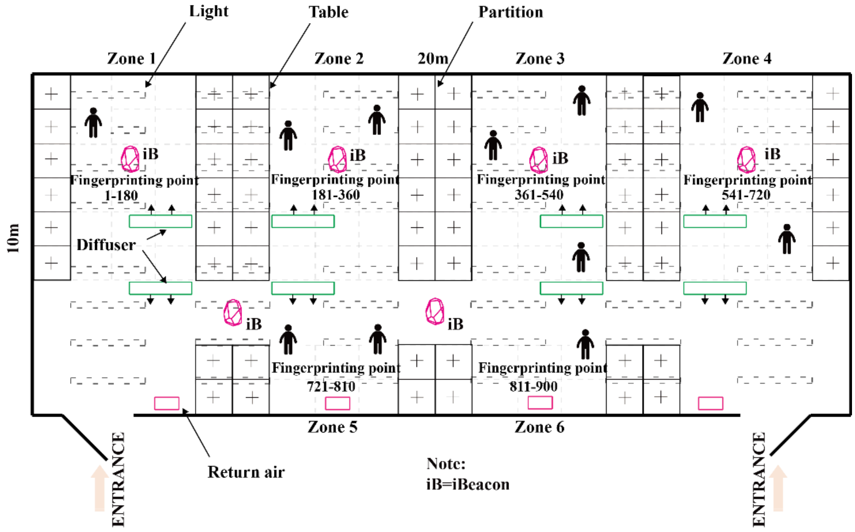

Fig. 4. The schematic view of an office room area in this experiment.

Table 1. Room specifications of the experiment office.

Room specifications	
Size of room	20 m (length) x 10 m (width) x 3 m (height)
Maximum operation schedule	From 07:30 to 23:00
Conditioning system	DOAS and fan coil
Maximum occupants	25 (during experiment)
Sensor information	
iBeacon type	Proximity Beacon
Battery life	2 years
Sensing range	70 meters
Sensing context	SSID (service set identifier) Mac address RSSI (received signal strength indicator) Proximity region Motion

5.2 Results assessment

To assess the performance of the occupancy distribution algorithm, this study adopted the one City Block Distance (CBD)-based accuracy method. The CBD method represents distance between points in a city road grid by examining the absolute differences between coordinates of a pair of objects. In this study, we used the distance to represent how detected patch location was away from the ground truth patch location. Fig. 5 shows the illustration of CBD application in the occupancy distribution study. When CBD is 0, it means the detected patch matches very well with the actual patch. When CBD is 1, it means the detected patch is adjacent to the actual patch.

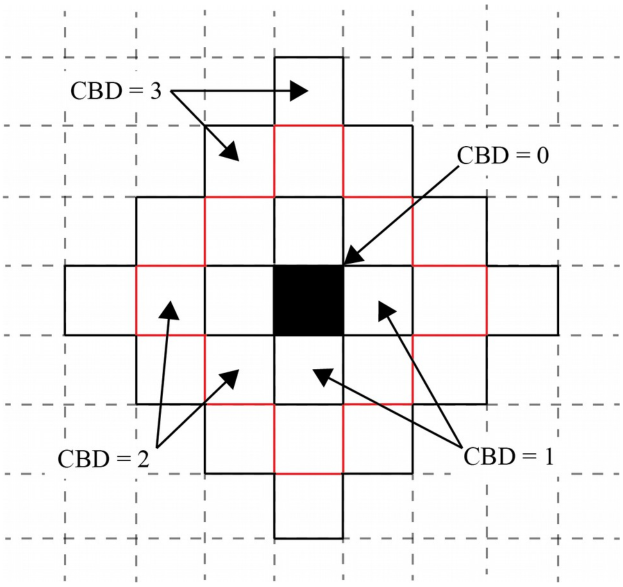

Fig. 5 The illustration of the City Block Distance-based accuracy.

We can define the CBD-based accuracy methods using Eq. 25,

$$\tau(CBD, x) = \frac{\sum_{1}^{M} X(CBD, x)}{M} \tag{25}$$

while

$$X(CBD, x) = \begin{cases} 1, CBD \leq x \\ 0, CBD > x \end{cases} \tag{26}$$

Where, $\tau(CBD, x)$ is the accuracy of the CBD method;

x is the acceptable tolerance level;

M is the sampling size.

6. RESULTS

6.1 Detected occupancy distribution

Occupancy density map data is used as the training dataset in the k-NN classification algorithm, by which occupants are classified into approximate occupancy distribution in a thermal zone. In terms of the HVAC system, this study would find out which HVAC terminal serves the occupants. As discussed in the methodology section, occupancy distribution could be determined using the k-NN classification algorithm. This study picked up three typical cases of office occupancy distribution at three different office times in a typical day: 10:00am, 1:00pm and 4:00pm. Since the received signal strength of devices would fluctuate in a small range, the proposed algorithm introduced ways to find the maximum probability area of the occupant. This study took three maximum possible patches that each occupant is located in using Eq. 24. The ground truth was captured by camera and referred to the actual occupancy distribution by mapping where occupants sat. Fig. 6-8 show the occupancy distribution ground truth and detection results of the three cases.

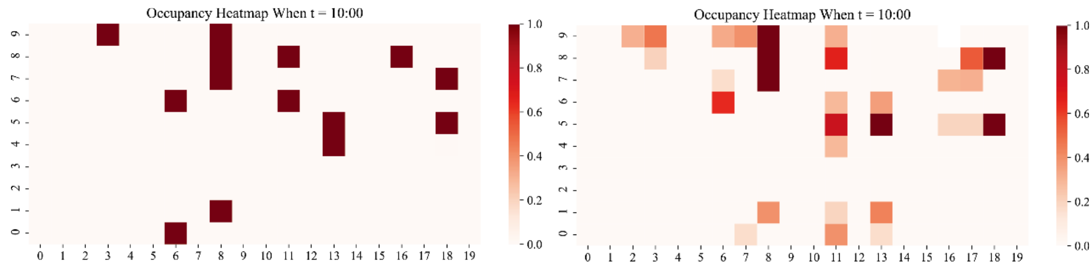

Fig. 6. Occupancy distribution ground truth (left) and result (right) in Case 1 (10am).

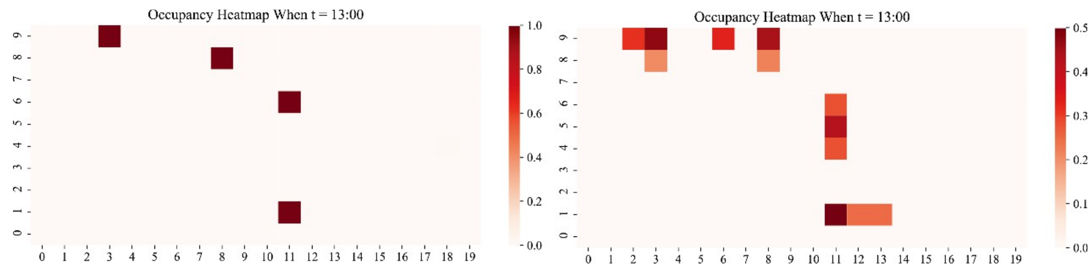

Fig. 7. Occupancy distribution ground truth (left) and result (right) in Case 2 (1pm).

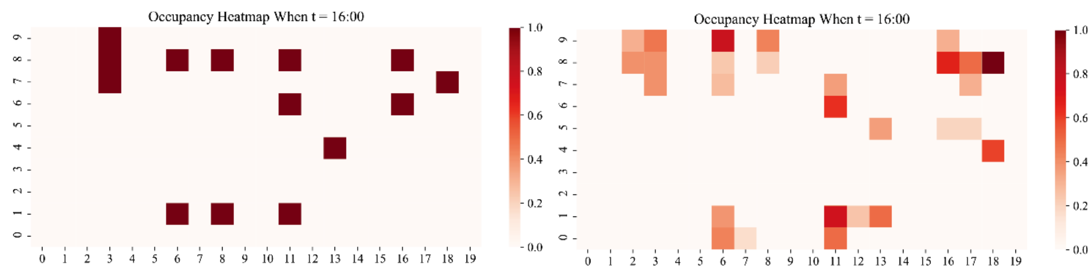

Fig. 8. Occupancy distribution ground truth (left) and result (right) in Case 3 (4pm).

Observing the result at time 10:00am, zone 6 in the ground truth is unoccupied, whereas from the detection results, there are two occupants possibly located in zone 6. The results at 13:00pm show strong accuracy of occupancy distribution detection in the thermal zone, and zones 4 and 5 are unoccupied, which can inform whether to close or maintain minimum supply air from VAV boxes in such areas for occupancy-based demand control. From the aspect of thermal comfort control mode, conventional controls usually recognized the temperature of mixing air at the return air location as the representative temperature to adjust cooling/heating air supply amount. One application with significant potential is using occupancy distribution to recommend the better representative temperature closer to actual occupancy thermal comfort.

6.2 Assessment of results

This study applied the City Block Distance-based accuracy method to assess performance of a multi-feature k-NN classification algorithm. Since CBD >= 4 is not available in the experiment field, only four acceptable tolerance levels of CBD are considered: CBD = 0, CBD = 1, CBD = 2, and CBD =3. Meanwhile, once CBD > =4, the occupancy distribution resolution may not be suitable for the HVAC system to sense occupancy load in the corresponding zone. Fig. 9 shows the results of the City Block Distance-based accuracy method in Case 1, Case 2, Case 3, and the entire room. It can be seen that the accuracy usually is very low, even at zero, when it requires the detected patch to equal actual patch (CBD =0). The best performance of 100% accuracy exists in Zone 2 in Case 1, where CBD = 0 when there are occupants. Although 100% accuracy—i.e., CBD = 0—exists in Zone 1 in Case 1, Zone 1, Zone 4, and Zone 5 in Case 2, the total number of occupants in such cases occurred only once. Considering CBD = 1, or that the maximum tolerance is one patch, we can find that accuracy increases significantly. The accuracy in most zones can reach 100%, except for in Case 3, where the accuracy of Zone 3 is about 33.3%. However, although the accuracy will increase when CBD is higher, the occupancy resolution will decrease. In the entire room, seen at the right-bottom of Fig. 9, the accuracy of CBD = 0 is about 64.2%, 50%, and 42.9% in Case 1, 2, and 3, respectively. The accuracy of CBD = 1 is about 71.4% in Case 3 while it reaches 85.7% and 100% in Case 1 and Case 2, respectively. With reference to Fig. 5, when CBD =1, the occupant can be detected in the nearest patch, and such occupancy distribution resolution is still reliable for HVAC control as the terminals of HVAC can adjust the thermal comfort around the areas if the feedback control signal, such as temperature, can be accurately measured. If we increase the value of CBD, zooming into the detection area, the accuracy will increase substantially, which can be found to be over 92.9% in Fig. 9.

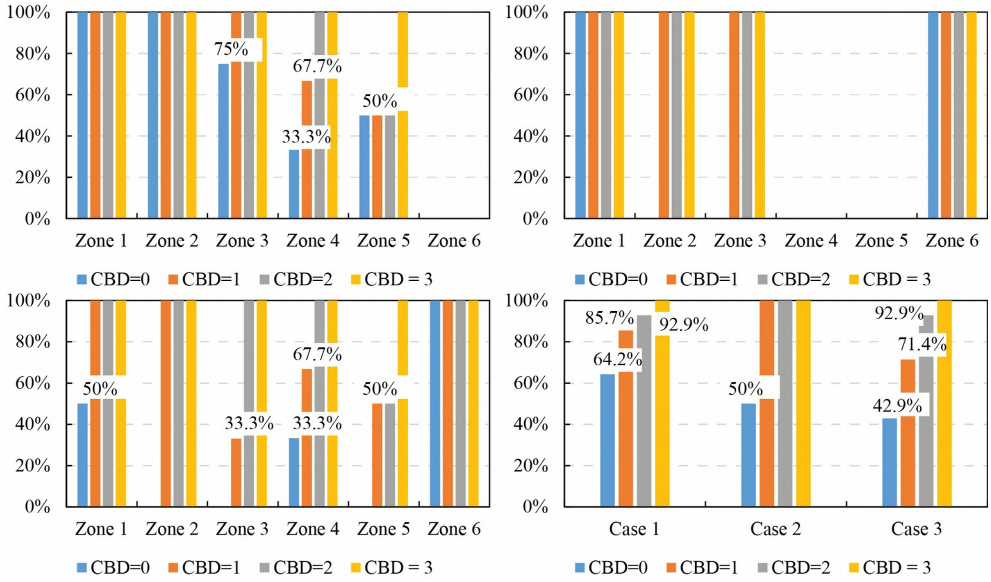

Fig 9. Results of City Block Distance-based accuracy in Case 1 (left-top), Case 2 (right-top), Case 3 (left-bottom), and total room (right-bottom).

7. IMPLICATIONS AND LIMITATIONS

While studying building energy performance, researchers and building managers have begun to recognize the importance of understanding building occupants' behavior patterns. A surge of interest in building occupants and their behavior has spurred considerable research, but aspects of occupant behavior are still treated in a highly simplistic manner [53]. This study can be recognized as an essential step forward in the collection of representative occupant resolution and occupancy distribution in thermal zones. In the proposed method, firstly, signal strength distribution had a crucial performance in determining occupancy distribution. The experiment field was divided into six zones and each zone was further divided into small patches with features created using the signal fingerprinting method. In our study, each zone was defined by the physical partitions in the experiment field, and serves as a thermal zone with one independent-controlled HAVC terminal. The patches were selected and illustrated by workstations of users in the field. In real-world applications, zones can be identified by (1) physical division, or (2) areas served by independent-control HVAC terminal. Patches can be determined by the workstation of each user in the field. Secondly, this study extracted two important features using the classification algorithm—RSSI and Location Range. The two features can help apply efficient classification in search of the patches where occupants are. The proposed algorithm focuses on revealing the most possible patches in the zone level of occupancy information in a large-space room and benefits the operation of multiple HVAC terminals. Moreover, the City Block Distance-based accuracy method is utilized in this study to facilitate results assessment of occupancy distribution by determining accuracy under the acceptable tolerance.

This study could improve the flexibility of operation for HVAC systems and achieve energy-saving objectives, especially in large-sized rooms where refined occupancy distribution captures more attention in eliminating the uneven load distribution. Meanwhile, this study might also provide more potential accessibility to HVAC control mechanism studies. With more accurate occupancy information available in buildings, more efficient occupancy-driven HVAC operation optimization strategies can be implemented. For example:

(1) To illustrate occupancy-related room energy consumption distribution: occupants play an important role for accounting HVAC system loads and assessing the efficiency of HVAC system operation [30,54–56]. Once the occupancy distribution information is acquired for one room, occupancy-related room energy consumption distribution can be accessible. That information could direct coordinated control modes of HVAC systems. For example, a VAV system can make adjustments to VAV boxes to deal with a different load in zone level, or if one zone is overloading, then VAV box in the zone with non- or low-occupant-related load can serve as an alimentative zone.

(2) To facilitate occupancy-driven demand HVAC control modes: some researchers have argued that the supply air volume can be controlled according to occupancy information in each room. Instead of being based on the maximum design

occupancy, the air volume should be dynamically controlled to meet demand for the detected occupancy requirement [57,58]. Once occupancy distribution is detected, it could benefit demand-based control modes by the occupancy-driven operation.

(3) To provide specific identification for occupancy-based feedback control: HVAC feedback control methodology has been studied in many researchers' work, and by providing real-time energy feedback to occupants, researchers observed up to a 46% reduction in consumption in residential buildings and prove its potential in energy consumption [33,35,59]. Therefore, besides acquiring occupancy distribution, occupancy-specific identification is still important for potential occupancy-based feedback control. Identifying and labeling occupants could enrich occupancy distribution information.

(4) To identify the building occupied preference information: if the occupancy detection could efficiently profile room occupancy distribution so that occupants prefer to stay in the featured zones, then the system could learn the trend of occupancy or the fixed location of occupancy. With the occupied time schedule, the pattern recognition would associate the occupancy preference with energy needs and proactively operate for optimal energy consumption [1].

(5) To increase efficiency and flexibility of control modes: identifying the occupied zones could not only control the occupied zone with actual load, but also maintain at least minimum air flow or even close the device in the occupied zones. On the other hand, it is a potential of the HVAC system to integrate occupancy-based control methods with current popular controls systems, such as temperature-based thermal control methodology [5] and CO2-based outdoor air control systems [60–62]. It could increase the efficiency and flexibility of traditional control modes.

Still, this study has limitations that might be resolved in future research. First, the room-level cooling load in this research is estimated by linear addition of all subzones. In practical operation, the supplied flows from multiple air vents will interfere with each other through a nonlinear heat transfer process. Therefore, future research should adopt more sophisticated fluid-dynamic models that consider such superimposed effects. Second, obstacles in the positioning networks could result in inaccuracy in the location detection. These building components could potentially disturb the stability and accessibility of the received signals [63]. Therefore, a more stable and complicated positioning algorithm needs to be employed to identify potential problems and future improvements to positioning accuracy. Third, in the proposed system, it commonly collects Mac address information from occupants, yet for occupants' privacy, this tag might be impermissible and should be protected. This issue could not be avoided in the research on positioning tasks. To gain permission for this type of study, protecting privacy or defining a new tag must receive more attention in future work. Fourth, this study does not consider the impact of physical layout, space type, space size, or the BLE signal source distribution in zones. In this study, the signal distribution of BLE sources are utilized to map the physical thermal zones. Also, the fingerprint collection is an important issue to determine robustness of algorithm under different sizes of fingerprints. Therefore, there is a need for further validation considering various combinations of space types, sizes and layout. An additional need is to collect more ground truth data (occupancy distribution) in such spaces for algorithm validation. Under the International Energy Agency's (IEA) Energy in Buildings and Communities (EBC) Program, the Annex 66 project concludes with the importance of data collection—including occupant sensing, data acquisition, and ground truth validation—when measuring occupant behavior [40]. Although BLE sensors are cheap (about $10 each in our experiment) and easy to install, it is still a great challenge when applying BLE sensors to large-sized buildings. Collecting data and running data analytics are complicated and time-consuming if signal fingerprinting method is used, as is ground truth validation for occupancy distribution. Finally, future work can study methods and applications using the derived occupancy distribution information to improve HVAC control and validate potential energy savings.

8. CONCLUSIONS

In HVAC controls, occupancy behavior is the key to developing models, in particular for the improvement of controls and operations that reduce energy use and increase occupant comfort. The study has illustrated the HVAC load at room level and zone level to provide the foundation of demand-based operation in HVAC systems. BLE technology was chosen in the occupancy distribution detection as a demand-driven signal. In order to increase the robustness of the algorithm, another feature, location range, was applied, in addition to the received signal strength. The multi features-driven k-NN classification algorithm was utilized to define room occupancy distribution, illustrated by the heatmap. In the on-site experiment, six iBeacons were installed and signal fingerprinting methods were applied. To validate the detection accuracy, the experiment outcomes were examined in three case studies, and one City Block Distance (CBD)-based method is used to measure the distance between detected occupancy distribution and ground truth, and to assess the results of occupancy distribution. The results show accuracy of CBD = 1 is over 71.4% and accuracy of CBD = 2 can reach 92.9%. The results showed that the accuracy of CBD = 0 is about 64.2%, 50%, and 42.9%. Though the core of this research is focused on determining occupancy distribution and then controlling supply air in VAV systems, such demand-driven control systems can also be extended to other building service systems and enable more sophisticated control design.

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