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Wi-Fi based occupancy detection in a complex indoor space under discontinuous wireless communication: A robust filtering based on event-triggered updating

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ABSTRACT

Demand-driven control of building heating, ventilation and air conditioning (HVAC) and lighting systems warrants an attractive energy saving potential. A reliable and accurate occupancy detection technique should be available for estimating the demand. To this, many occupancy detection methods have been developed either based on physical sensors, cameras or information & communication technology (ICT). Wi-Fi based detection is one of the ICTs that uses Wi-Fi signals (e.g. from smartphones) to represent occupants. Nowadays, new smartphone models all have the battery-saving function that will switch off Wi-Fi communication in the idle mode, causing significant detection uncertainties. This challenge has not been addressed in the current Wi-Fi based occupancy detection methods that still assume or manipulate a continuous Wi-Fi communication. Moreover, most studies are conducted in relatively simple settings with small-scale occupancy that are far from a complex indoor space. Thus, this study investigates the Wi-Fi based occupancy detection in a complex indoor space with large occupancy. An event-triggered updating method is proposed to cater for the discontinuity in Wi-Fi communication of the smartphones. A location filter and a non-human media access control (MAC) address filter are proposed to screen out irrelevant Wi-Fi devices. The proposed event-triggered updating method is able to improve the detection accuracy from 77.3% to 96.8%. The proposed location filter and non-human MAC address filter prove to be effective in removing irrelevant outside and non-human devices. The proposed event-triggered updating method can be applied to existing installations with minimum cost regardless of the Wi-Fi communication continuity.

1. Introduction

Reducing the energy consumption of buildings is of utmost importance as buildings account for a significant portion (around 40%) of the primary energy use [1]. One major contributor of building energy consumption is building occupants, because (1) occupants generate heat and CO_2 which are closely related to cooling demand and fresh air demand [2] (2) the usage of appliances (e.g. lighting, radiators, fans, and printers); contributing to internal heat gain is occupant-driven [3] (3) the heat transfer through building envelopes (e.g. windows and doors); are affected by occupants' activities.

An accurate real-time occupancy detection technique is very useful in determining the actual cooling demand and the fresh air demand, and is also instrumental in the demand-driven control of HVAC systems [2,4]. A common phenomenon is that the HVAC system is set at a high capacity even in non-occupied or low-occupied periods [5,6], leading to energy wastage. With an accurate occupancy detection, a demand-driven control is able to determine the appropriate operation of a HVAC system. Previous studies show that about 20–50% of the building energy consumption could be saved with effective occupancy detection [7–9]. A coordinated control based on the zonal occupancy information can also be applied to enhance the operation efficiency and thermal comfort [10–12].

Many technologies have been developed recently to improve the accuracy in occupancy detection. They can be broadly divided into three categories: (1) physical sensors; (2) cameras; and (3) information & communication technology (ICT). Environmental parameters obtained by physical sensors, such as CO_2 concentration, temperature, relative humidity and dust concentration, have been used to infer the occupant number [13–15]. They all exhibit time delays in reflecting the occupant number because of the process of air mixing. The time delay is even severe when sensors are placed far away from occupants (e.g. at

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return air ducts). Besides, environmental parameters can only provide a coarse occupancy resolution in both spatial and temporal aspects. The infiltrations through building envelopes will also introduce measurement errors. Other physical sensors, such as sound sensor, ultrasonic detector, chair sensor and smart meter, cannot provide detailed occupancy information [16,17]. The additional cost of installing these sensors also limits their applications in demand-driven HVAC control.

Camera-based occupancy detection is generally the most accurate method, and thus is commonly used to provide the ground truth occupancy [18]. However, they often demand high computation power, are liable to privacy intrusiveness, and are suffered from illumination interference [2,16,19]. The deep learning algorithm developed recently is able to achieve a high accuracy occupant recognition [20]. Yet the image processing algorithms involved require powerful desktop computers and privacy issues remain intact. Some studies make use of the depth camera to protect privacy in occupancy detection [21,22]. So far, the depth camera is not equipped for large-scale occupancy situation, and the installation incur significant extra cost.

The recent advances in ICT open new opportunities in occupancy detection, and would complement the traditional occupancy detection techniques in many aspects [23,24]. The ICT-based techniques generally have higher detection accuracy and occupancy resolution as compared to physical sensors. These techniques include Wi-Fi [25], Bluetooth Low Energy (BLE) [26], RFID, etc. Wi-Fi based detection is a promising option due to several reasons. First, Wi-Fi is massively deployed in wireless local area networks (WLAN), almost available in nearly all buildings nowadays [6,16,27]. Second, Wi-Fi almost has no delay in detecting occupants, which warrants a fine temporal resolution [6]. Third, Wi-Fi based detection can also provide location and other occupant-related information (e.g. tracking and behavior) in addition to occupancy, which enables a more flexible [19,28] and personalized control [29]. Therefore, many studies have made use of Wi-Fi in occupancy detection, with a reported accuracy ranging from 80 to 95% [6,30,31]. Nevertheless, most Wi-Fi based studies are only limited to well-controlled experimental scenarios. Their effectiveness in real-life applications has not been completely investigated.

Previous Wi-Fi based occupancy detection studies, as summarized in Table 1, either used a continuous Wi-Fi communication by disabling the battery-saving function ([30]) or assumed a continuous Wi-Fi communication. The condition of discontinuous Wi-Fi communication due to the battery saving function has not been addressed. Such battery-saving function is a standard function in recent versions of iOS and Android operating systems. When a stable Wi-Fi connection between the smartphone and an access point (AP) is established, the Wi-Fi communication frequency will be downgraded to save battery life [30]. Hence the Wi-Fi connection between the Wi-Fi devices and the AP is discontinuous even when Wi-Fi function is turned on [30,32]. Evidently, significant errors in Wi-Fi based occupancy detection would result if such smartphone operation characteristics are not addressed [30].

Most previous studies validated their methods in relatively simple settings (e.g. laboratory and office), with small number of occupants (presented in Table 1 and [33]) that remained relatively stationary in the room [6,31]. This is far from a real complex indoor space that comprises a complicated occupancy, with many short-term visitors with chaotic behaviors. Occupants may loiter outside or pass by the detection area, resulting in irrelevant Wi-Fi devices being included. Large number of occupants enter and exit the room within a short period would also create a dynamic occupancy situation. The study on how to filter out the irrelevant Wi-Fi devices under a dynamic and irregular occupancy situation is a core issue that has not been well investigated. The performance of a Wi-Fi based occupancy detection on a large occupancy scale in actual occupancy situation has yet to be studied. Many non-human Wi-Fi devices may exist in the indoor space, such as wireless printers, cameras and smart home appliances. These devices must also be identified and effectively excluded from the Wi-Fi based occupancy detection mechanism.

Hence, this study aims to develop (1) a Wi-Fi based event-triggered updating method to handle the condition of discontinuous Wi-Fi communication of the smartphone; (2) a location filter based on received signal strength (RSS) threshold to exclude irrelevant "outside" Wi-Fi devices; and (3) a MAC address filter to screen out non-human devices. The proposed Wi-Fi based occupancy detection approach is evaluated in a real-life scenario with large occupancy scale.

Section 2 introduces the Wi-Fi operation characteristics of smartphones. Then, the event-triggered updating method and the MAC address filter will be presented. Section 3 presents the experimental setup, while the results and discussions are detailed in Section 4. Finally, conclusions are given in Section 5.

2. Method

2.1. Wi-Fi operation characteristics of smartphones in indoor space

A WLAN is a wireless computer network that links devices by wireless communication to form a local area network (LAN) within a designated area, such as a home or a building complex. Wi-Fi is the most popular technology for WLAN based on the IEEE 802.11 standards. The AP enables nearby Wi-Fi devices to access a wired network. A typical Wi-Fi network connection schematic is shown in Fig. 1. Common Wi-Fi enabled devices are smartphones, tablets, laptops, printers (with Wi-Fi function), etc.

This study aims to detect the Wi-Fi connection of smartphones for the estimation of occupancy, with the assumption that everyone would carry a smartphone nowadays [36,37]. Table 2 summarizes the Wi-Fi operation modes of smartphones. As shown in Fig. 2, when a person enters a room, the smartphone carried by the person will connect to an AP inside the room. When connection is established and with the screen-off (or locked), the smartphone Wi-Fi signal transmission frequency would be downgraded to save the battery life (e.g. 10 mins per transmission). In other words, smartphones in normal mode with screen-off will "disappear" from a Wi-Fi based occupancy detection algorithm that is scanning for smartphones. The scan mode of the smartphone will be activated again at the boundary of adjacent AP service area (shadow area in Fig. 2). This is because when an occupant exits a room, the smartphone will disconnect from the AP in the original room due to the separation distance and/or the attenuation of physical partitions, and then enter the "scan mode" looking for new AP. A smartphone can be detected continuously in the "scan mode" when the Wi-Fi signal is actively broadcasting in high frequency (e.g. 5 s). In summary, the transition of an occupant between rooms or zones can always be detected, while a person remaining in a room or a zone is not always detectable.

Based on this Wi-Fi operation pattern, an event-triggered updating method is proposed to overcome the problem of non-continuous Wi-Fi communication (see Fig. 3). It is assumed that each room contains at least one AP, as this is an usual engineering practice to have at least one AP in a medium-size physical-partitioned room (assuming 25 occupants) [38].

2.2. Event definitions and event threshold

The occupant transitions are described by the ideas of 'states' and 'state transitions'. As defined in Table 3, states of occupants can be 'inside' or 'outside' an AP service area, while the state transitions of occupants can be 'entering' or 'exiting' an AP service area. The occupants' movement within a certain AP service area is not considered as a state transition in this study.

An "event" is defined as a state transition [39]. Two events are defined by a commonly used threshold-based form [40,41], namely, "entering" and "exiting" events, similar to Ref. [35]. The RSS value that measures the power presented in a received radio signal can be used to

Table 1
Brief summary of recent Wi-Fi based occupancy detection studies.

Author/Year	Paper Title	Aims	Testing Environment	Occupancy scale (type)	Remarks
Wang et al./2018 [6]	Occupancy prediction through Markov based feedback recurrent neural network (M-FRNN) algorithm with WiFi probe technology	Predicting occupancy profiles based on Wi-Fi	office	14–19 (long-term residents)	● experimental scenarios; ● small occupancy scale; ● discontinuous Wi-Fi communication not mentioned.
Zou et al./2018 [31]	Device-free occupancy detection and crowd counting in smart buildings with WiFi-enabled IoT	Counting occupants by Wi-Fi	conference rooms	4–11 (not specified)	● experimental scenarios; ● small occupancy scale; ● short experimental period.
Zou et al./2018 [25]	WinLight: A WiFi-based occupancy-driven lighting control system for smart building	Developing an occupancy-driven lighting control system based on Wi-Fi	laboratory	27 (staff volunteers)	● dedicated application installed to ensure a continuous Wi-Fi communication; ● not for temporary visitors; ● limited applications.
Mohamed et al./2017 [34]	Effectiveness of using WiFi technologies to detect and predict building occupancy	Investigating both CO_2 concentration and WiFi counts as indicators for occupancy	classroom	80 (students)	● outside and non-human Wi-Fi devices not excluded; ● discontinuous Wi-Fi communication not mentioned.
Zou et al./2017 [19]	Non-intrusive occupancy sensing in commercial buildings	Counting and tracking occupants by Wi-Fi	laboratory and office	32 (research staffs)	● experimental scenarios; ● Wi-Fi of smartphones is forced to turn on during the experiment.
Wang et al./2017 [32]	Modeling and predicting occupancy profile in office space with a Wi-Fi probe-based Dynamic Markov Time-Window Inference approach	Profiling occupancy in offices through Wi-Fi probe	office	28 (long-term occupants)	● outside Wi-Fi devices are ignored; ● discontinuous Wi-Fi communication is not mentioned.
Zhao et al./2015 [35]	Virtual occupancy sensors for real-time occupancy information in buildings	Detecting real-time occupancy using GPS location and Wi-Fi	office	7 (staff volunteers)	● dedicated Android application installed to read the Wi-Fi data; ● not for temporary visitors; ● limited applications; ● valid for private office rooms with single occupant only.

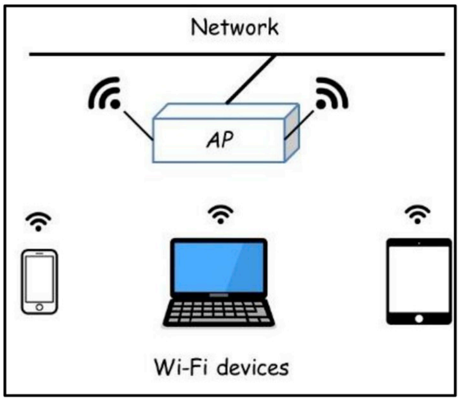


Fig. 1. Wi-Fi network connection schematic.

estimate the distance between the transmitter and receiver. The log-distance path loss model is described as

$$PL(d) = P_t - P_r = PL(d_0) + 10\gamma log_{10}\frac{d}{d_0} + X_\sigma \tag{1}$$

$PL(d)$ is the total path loss at distance d in decibel (dB)
P_t is the transmitted power in decibel-milliwatt (dBm)
P_r is the received power in dBm (also the measured RSS value)
$PL(d_0)$ is the path loss at the distance d_0 in dB
d_0 is the reference distance (usually 1 km or 1 mile)
d is the length of the path
γ is the path loss exponent which is environment-dependent
X_σ is a zero-mean Gaussian random variable in dB for the attenuation caused by flat fading

From equation (1), it is obvious that RSS value does not change linearly with the distance, and is a function of obstructions and object materials. The RSS value is usually a negative value measured in dBm, with a typical negative value ranging from 0 dBm (extremely good signal) to −110 dBm (extremely poor signal). A larger RSS value means a shorter distance to an AP or Wi-Fi detection node. The "entering" and "exiting" events are represented quantitatively by the changes in RSS value as described below.

"Entering event" is defined as "the occupant is previously outside and later moving inside (both conditions should be satisfied)". RSS values that are all "inside" is not regarded as an "entering event". In terms of RSS values, the "entering event" is defined as

$$\boldsymbol{Event_{entering}} = \left\{ <\boldsymbol{RSS^i_{t_p}}, \boldsymbol{RSS^i_{t_q}}> \mid \boldsymbol{RSS^i_{t_p}} < \sigma,\ \boldsymbol{RSS^i_{t_q}} \geq \sigma \right\} (\boldsymbol{for}\ \ \forall\ \boldsymbol{i} \in [1,2,\ldots,\boldsymbol{n}]) \tag{2}$$

t_p is the previous time, t_q is the later time, i is the Wi-Fi node index from 1 to n, σ is the RSS threshold to distinguish "inside" device and "outside" device.

"Exiting event" is defined as "the occupant is previously inside and later moving outside (both conditions should be satisfied)". In terms of RSS values, the "exiting event" is defined as

$$\boldsymbol{Event_{exiting}} = \left\{ <\boldsymbol{RSS^i_{t_p}}, \boldsymbol{RSS^i_{t_q}}> \mid \boldsymbol{RSS^i_{t_p}} > \sigma,\ \boldsymbol{RSS^i_{t_q}} \leq \sigma \right\} (\boldsymbol{for}\ \ \forall\ \boldsymbol{i} \in [1,2,\ldots,\boldsymbol{n}]) \tag{3}$$

The threshold of the RSS ("σ") is subjected to many geographical influencing factors [42]. A proposed on-site RSS value and position measuring scheme is adopted to calibrate the RSS threshold.

2.3. Wi-Fi based event-triggered updating method

An "inside MAC list" is created to compute an "inside Wi-Fi device" count (see Fig. 3). Based on the defined events, the proposed event-triggered updating method updates the "inside MAC list" whenever an event occurs. If an event occurs, the "inside MAC list" will be updated; otherwise the "inside MAC list" remains the same.

The non-human MAC address filter is included in the detection flowchart. A location filter is embedded in the event definitions based on a RSS threshold. The procedures of the flowchart are described as follows:

1. Input Wi-Fi raw data in the form of a set of MAC address and RSS data pairs.
2. Re-sample the Wi-Fi raw data if needed (e.g. re-sample in 5 or 10 min).
3. Filter out the non-human MAC addresses based on a pre-defined non-human MAC address list (see Section 2.4).
4. Check if the "inside MAC list" is empty.
   - 4.1 if it is empty, identify the entering events and create an "inside MAC list";
   - 4.2 if it is not empty, identify both the entering and exiting events, and compare the identified MAC addresses with the "inside MAC list".
     - 4.2.1 Update the "inside MAC list" by adding the "entering" MAC addresses that are not present in the current "inside MAC list";
     - 4.2.2 Update the "inside MAC list" by removing the "exiting" MAC addresses that are present in the current "inside MAC list".
5. Output the "inside MAC list" and the inside MAC count. Go to the next time step.

The "inside MAC list" will be reset to blank at the start of a day. In step 4.2.1, the "entering" MAC addresses that are not present in the current "inside MAC list" is regarded as newly entered MAC addresses, which will be added into the "inside MAC list". In step 4.2.2, the "exiting" MAC addresses that are present in the current "inside MAC list" mean that the MAC addresses exit the room, which will then be removed from the "inside MAC list".

2.4. Non-human MAC address filter

Printers, routers, desktops, wireless cameras, etc., that are Wi-Fi enabled are classified as non-human devices, their operation characteristics are summarized in Table 4. A non-human device "appears frequently", "appears at non-occupied hours" and "remains stationary". Any detected Wi-Fi devices that satisfy these conditions will be put in

Table 2
Various Wi-Fi operation modes of smartphones.

	Wi-Fi function turned on		Wi-Fi function turned off
	Normal mode (connected with a specific Wi-Fi network)	Scan mode (not connected with a specific Wi-Fi network)	
Screen-on	High-frequency signal transmission (e.g. 5 s)	High-frequency signal transmission (e.g. 5 s)	No signal transmission
Screen-off	Low-frequency signal transmission (e.g. 10 mins)		

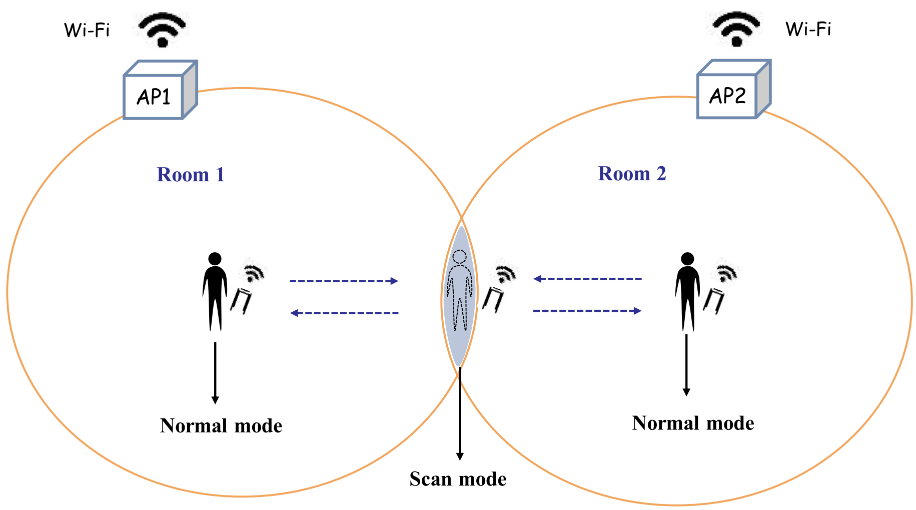


Fig. 2. A schematic of Wi-Fi operation modes of smartphones.

(Orange circle represents an effective service area of an AP)

the non-human device list. The non-occupied hours are determined from the actual room occupancy profile. The non-human device list is further counter-checked with the MAC address list of manufacturers (based on IEEE Registration Authority) [43].

3. Experimental setup

3.1. Basic information of the test room

A university lecture theater (LT) is chosen for the evaluation of the performance of the proposed Wi-Fi-based occupancy detection algorithm. The area of the LT is about 200 m^2 (14.5 m by 14 m) without windows, with a maximum capacity of 200 seats. Two APs from *Aruba Networks* are located in the LT, as shown in Fig. 4. Fig. 5 shows the floor plan of the LT. The LT has two main entrances (with two doors for each entrance). An audio-visual control room is situated between the two

Table 3
States and state transitions of occupants.

States	State transitions
(1) inside the AP service area (2) outside the AP service area	(1) entering event: from outside to inside (2) exiting event: from inside to outside

Table 4
Classification criteria of non-human devices.

Criteria	Characteristics
appears frequently	Wi-Fi devices that are present round the clock (24 h)
appears at non-occupied hours	Wi-Fi devices that exist in non-occupied hours
remains stationary	Wi-Fi devices that are not moving over time

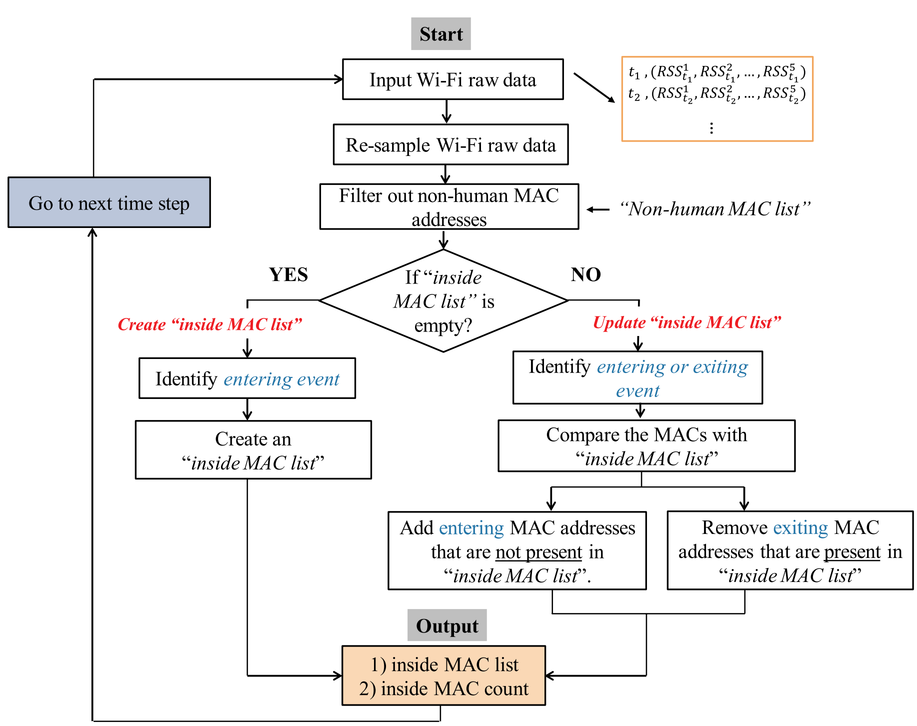


Fig. 3. Flowchart of Wi-Fi based event-triggered updating method.

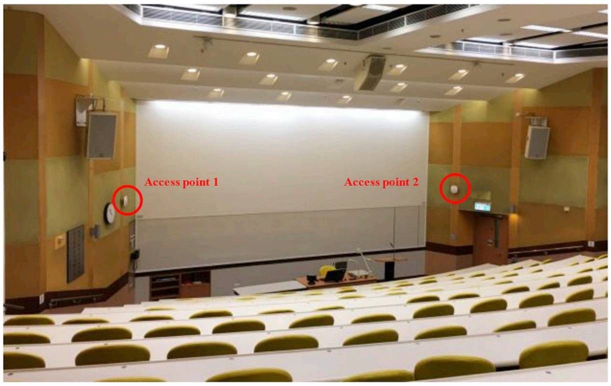


Fig. 4. Locations of Wi-Fi access points in the LT.

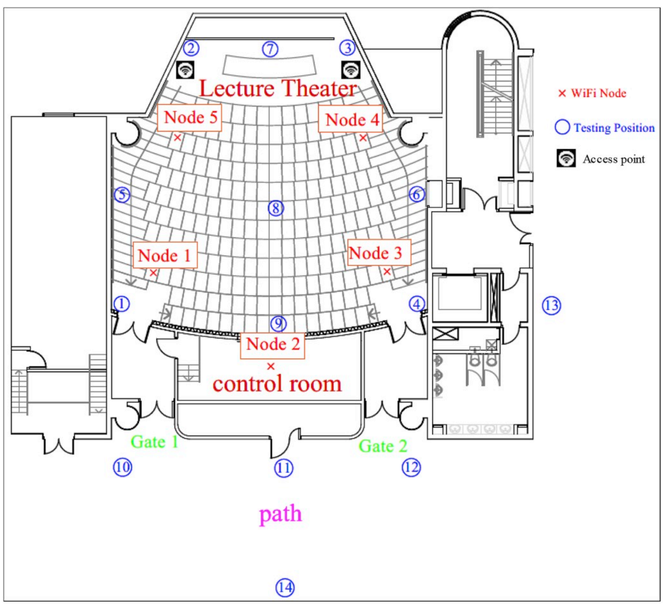


Fig. 5. Floor plan of the LT.

entrances. Outside the LT is a main university concourse for people to access other lecture theatres and university facilities. People may pass by, loiter outside, enter or exit the LTs, ensuring a complex and dynamic occupancy environment.

3.2. On-site calibration of the RSS threshold

An onsite calibration scheme is adopted to calibrate the RSS threshold, as elaborated in Table 5. The empirical RSS threshold takes all the influencing factors affecting RSS value in the LT into account.

Positions inside and outside the LT are to be measured, especially near the boundary. As indicated in Fig. 5, Position 1 to 9 are inside the LT and position 10 to 14 are outside. Three RSS values were recorded for each position, which are then averaged to get a representative RSS value.

Table 5
Calibration scheme of the RSS threshold.

Setup
- set up Wi-Fi detection nodes in the detection area - record the MAC address of the Wi-Fi device
Procedure
Step 1: put the Wi-Fi device at a specific location Step 2: login in the Accuware server and record the RSS Step 3: repeat Step 1 and 2 at various locations (inside and outside the detection area) Step 4: determine an empirical relationship between RSS values and locations Step 5: determine the event threshold of RSS

3.3. Experimental setup

This study assumes that occupants in an educational building will always switch on the Wi-Fi function of their smartphones and that each person carries one smartphone only. This assumption is valid in that occupants in educational buildings tend to use the free high-speed Wi-Fi service considering that the local mobile data service charge is relatively high.

One-week experiment was carried out from May-07 to May-13, 2018, including weekdays and weekends. Normal activities, such as lectures or examinations, were undergone in the experimental period. Wi-Fi data, including MAC addresses and RSS values (dBm), were collected from the "Accuware Wi-Fi location monitor" system. Although the existing APs (or routers) can be used to collect the Wi-Fi data, separate Wi-Fi detection nodes are used in the experiment to avoid causing disturbance to the existing Wi-Fi service. The "Accuware Wi-Fi location monitor" can locate, track, and monitor people, which works well with all Wi-Fi enabled devices without the need of installing mobile apps. The detection nodes are "OM2P Open Mesh" Access Points with a detection range of 75–150 ft (22.86–45.72 m) indoor (including 3–4 walls).

Five Wi-Fi detection nodes were installed in the LT (Fig. 5), labelled as Node 1 to 5. One of the nodes served as the gateway to connect with the Internet, other nodes are set as repeaters. The Wi-Fi detection interval in the system is set at 5 s. A Wi-Fi device will be detected only when data is transmitted. There may be transmission delays in the actual operation, the observed maximal detection interval is 15 s in the employed system. Thus, a Wi-Fi device might also be detected every 15 s. The Wi-Fi raw data was downloaded from the *Accuware* server in the form of comma-separated values (CSV) data files, which contains a Unix time index, a MAC address, and several RSS values from various detection nodes. The actual occupancy in the experiment period was captured by surveillance cameras and counted manually to serve as the ground truth.

4. Experimental results and validation

4.1. Calibration results of the RSS threshold

Figs. 6 and 7 present the mean values of the measured RSS values at inside positions and outside positions respectively. For the inside position 1 to 9, most RSS values are between −50 and −75 dBm; they are all greater than −80 dBm. For outside position 10 to 14, the RSSs are all smaller than −88 dBm. Thus, a RSS value of −84 dBm, the average of −80 dBm and −88 dBm, is adopted as the event threshold for separating inside and outside positions.

4.2. Raw data of Wi-Fi device count

Fig. 8 shows the raw data of Wi-Fi device count, representing the unique visitor numbers in each 10 min interval. One Wi-Fi device count is one device detection in a 10-min interval. The same Wi-Fi device is counted again if it is detected in the succeeding interval.

It is observed that the Wi-Fi device count is relatively low (between 100 and 300) on Sunday simply because there was no class in the University on Sundays. From Monday to Saturday, the Wi-Fi device count is between 200 and 900. Given that the maximum capacity of the LT is only 200 seats, a detected raw Wi-Fi device count well exceeding the LT capacity implies that irrelevant Wi-Fi devices were detected. The excessive Wi-Fi count is very likely due to the busy people traffic outside the LT as well as the existence of Wi-Fi enabled stationary

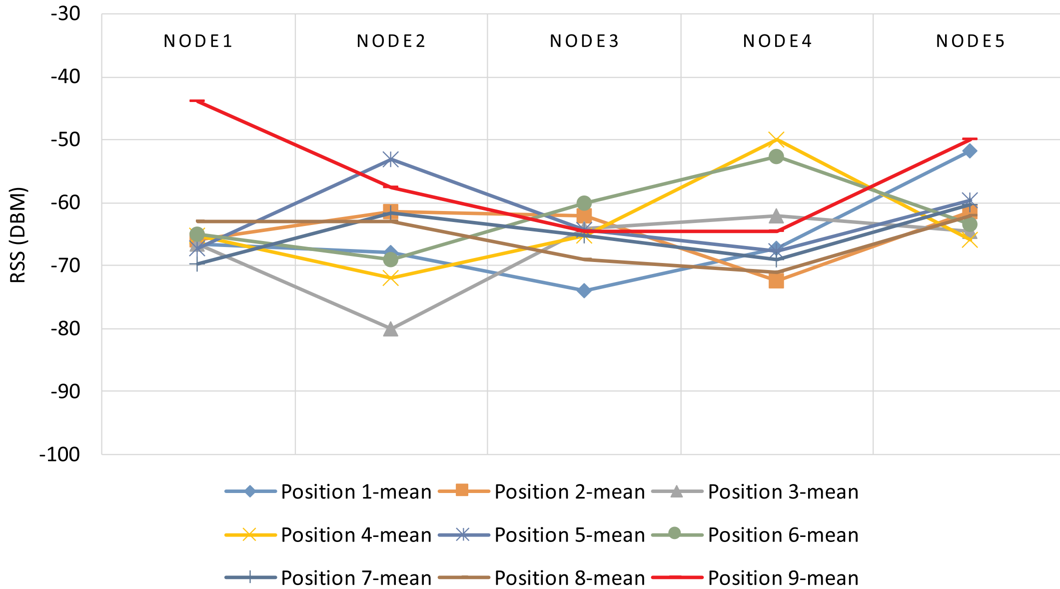


Fig. 6. RSS values of inside positions.

equipment.

From Fig. 8, it can be seen that some Wi-Fi devices were detected during the non-scheduled operation period of the LT (8:00 to 8:30 and 22:30 to 23:00). These Wi-Fi devices are probably stationary equipment inside/nearby the LT with Wi-Fi function.

4.3. Identification of non-human MAC addresses

Based on the classification criteria in Table 4, the quantitative classification criteria for a non-human device are summarized in Fig. 9(a). One-week Wi-Fi data prior to the experimental period was collected for the identification of non-human MAC addresses. It is found that 80 MAC addresses appeared 1000 time or more, in which 30 MAC addresses were present 5 days or more. Moreover, 22 MAC addresses were found to be present in non-occupied hours (e.g. 8:00–8:30 and 22:30–23:00) and their positions did not change over time (i.e. with a stable RSS value). The identification procedures of non-human MAC addresses are summarized in Fig. 9 (b).

A *non-human MAC list* containing 22 MAC addresses is created (Table 6). A quick reference to the IEEE Registration Authority website [44] confirms that the MAC addresses belong to Wi-Fi routers or network devices.

4.4. Experimental results

Fig. 10 compares (1) the actual occupants count captured by the surveillance cameras; (2) the occupants count by the conventional Wi-Fi based detection using periodic updating; and (3) the occupants count by the proposed event-triggered updating method. As the LT was not occupied on two days, the experimental results of the other five days are discussed. All the occupancy data are sampled at a 10-min interval.

The raw data shows a Wi-Fi count of around 200–900 (Fig. 8), which includes inside occupants' devices, outside occupants' devices and non-human devices. After removing the outside and non-human devices, the detected occupant count is reduced to around 10–100 (Fig. 10). As there are only 22 MAC addresses in the non-human MAC list, the majority (around 90%) of detected Wi-Fi devices in the raw data is outside the LT. For instance, at 13:50 on 7-May, there were 897 unique devices (in Fig. 8) in the raw data. In Fig. 10, at 13:50 on 7-May, only 45 Wi-Fi devices are detected. Thus, the 830 devices that are outside the LT. are caused by the heavy people traffic in the university concourse. From Fig. 10, it can be seen that occupants entered and

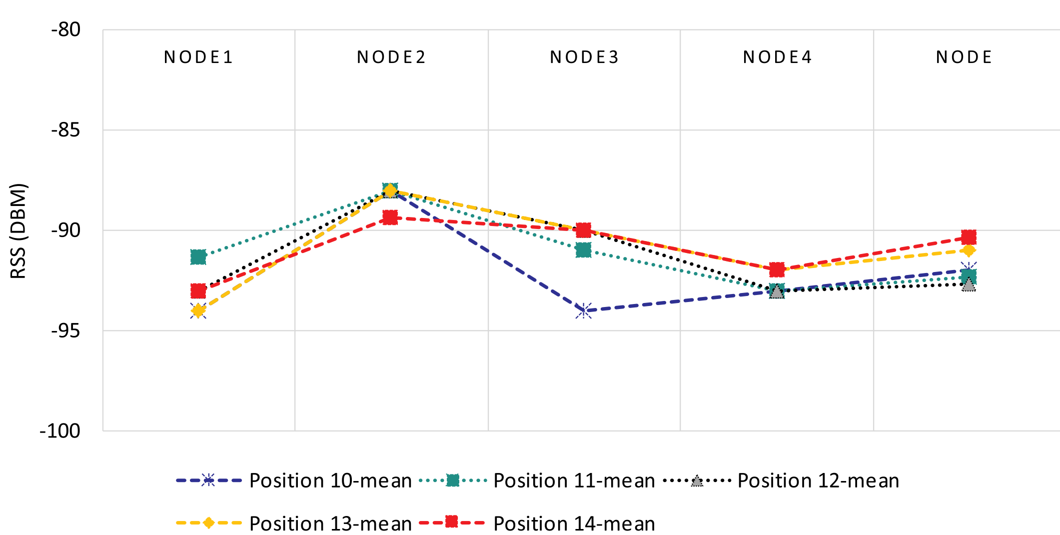


Fig. 7. RSS values of outside positions.

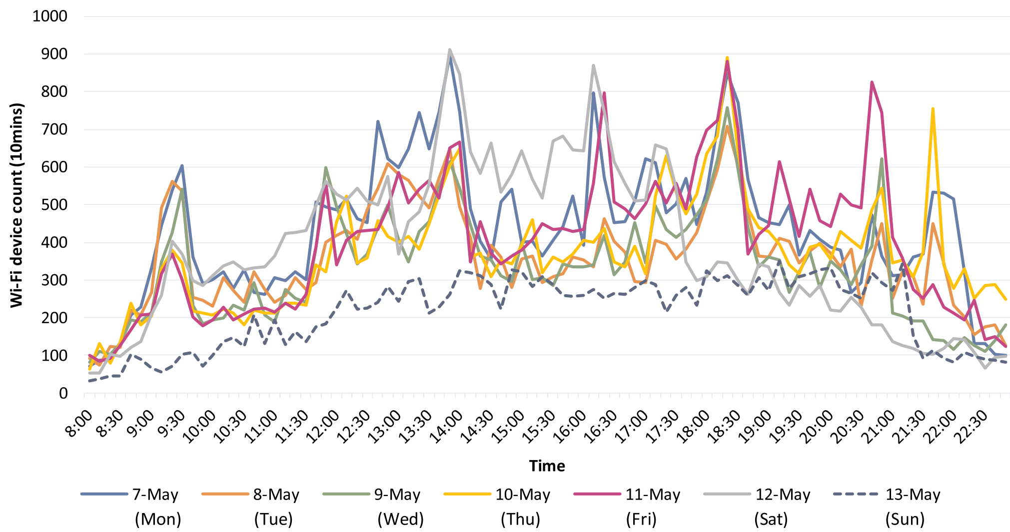


Fig. 8. Wi-Fi device count in one week (unique visitor per 10 min).

exited the LT in a relatively short period (i.e. 10–20 min). In occupied periods, the actual occupancy remained stable for a duration of around 2–3 h, in agreement with normal class durations of a university.

Based on the conventional Wi-Fi based periodic updating method, the detected occupant count is close to the actual occupancy during the occupants' entering or exiting periods. This is expected as smartphones were in scan mode at these instants, making all the Wi-Fi enabled smartphones detectable. However, after the occupants have settled in the LT, the occupant count showed a significant drop, and then followed by a period in which the occupant counts showed obvious fluctuations without a clear pattern. Evidently, smartphones are in the normal mode, with the Wi-Fi communication frequency downgraded for saving battery life. However, when the smartphone is un-locked, or some mobile applications trigger the Wi-Fi communication, the smartphones are detected. Thus, the randomness of Wi-Fi communication frequency in occupied periods results in fluctuations of Wi-Fi counts. Obviously, the conventional Wi-Fi based periodic updating method showed significant detection errors in occupied periods.

By using the proposed Wi-Fi based event-triggered updating method, the detected occupant count matched closely with the actual occupancy under all conditions. In particular, the proposed approach performed extremely well in occupied periods, showing very stable counts. Moreover, occupancy changes during the occupied periods were closely tracked, as can be seen on 8-May and 12-May (Fig. 10). The main reason is that the occupant count will only be updated when entering or exiting events are detected. Outside the occupied periods, the conventional periodic updating method and the proposed event-triggered updating method produced similar results.

As shown in Fig. 11, the mean absolute error (MAE) is significantly reduced from 6.4 to 24.7 in the conventional periodic updating method to 2.0–3.1 in the proposed event-triggered updating method. The average MAE reduction is 84%. Table 7 also compares the detection accuracy of the two methods. The average detection accuracy of the conventional periodic updating method and the proposed event-triggered updating method is 77.3% and 96.8% respectively.

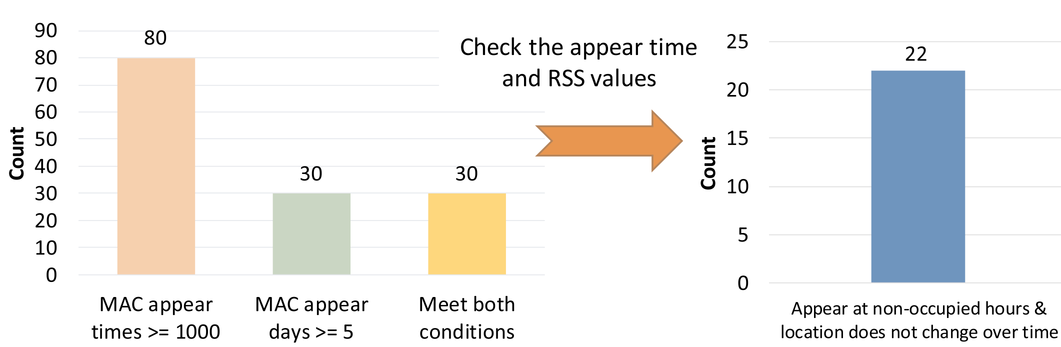
4.5. Discussions

4.5.1. Implications

A practical challenge of Wi-Fi based occupancy detection is that Wi-

Condition	Quantitative expression
appear frequently	MAC appear times (in one week) ≥ 1000
appear at non-occupied hours	MAC appears at $8:00-8:30$ am and/or $22:30-23:00$ pm
location does not change over time	varirion of RSS value $\in [-3,+3]$

(a)



(b)

Fig. 9. (a) Quantitative classification criteria of non-human MAC addresses; (b) Identification of non-human MAC addresses.

Table 6
Identified non-human MAC addresses.

MAC address	Manufacturer	MAC address	Manufacturer
00246Cxxxxx0[a]	Aruba Networks	84D47Exxxxx9	Aruba Networks
00246Cxxxxx5	Aruba Networks	84D47ExxxxxA	Aruba Networks
3052CBxxxxxD	Liteon Tech. Corp.	84D47Exxxxx0	Aruba Networks
40E230xxxxxD	Aruba Networks	84D47Exxxxx3	Aruba Networks
40E3D6xxxxx0	Aruba Networks	84D47Exxxxx9	Aruba Networks
40E3D6xxxxx2	Aruba Networks	A8BD27xxxxx0	Hewlett Packard Enterprise
40E3D6xxxxx0	Aruba Networks	A8BD27xxxxx3	Hewlett Packard Enterprise
84D47Exxxxx0	Aruba Networks	A8BD27xxxxx0	Hewlett Packard Enterprise
84D47Exxxxx0	Aruba Networks	A8BD27xxxxx3	Hewlett Packard Enterprise
84D47Exxxxx2	Aruba Networks	A8BD27xxxxx8	Hewlett Packard Enterprise
84D47Exxxxx3	Aruba Networks	D05349xxxxxF	Liteon Tech. Corp.

[a] Part of the MAC address is concealed for the sake of privacy.

Fi communication of smartphones is discontinuous due to battery saving function. While previous studies always assume a continuous Wi-Fi communication, this study proposes an event-triggered updating method to tackle discontinuous Wi-Fi communication by detecting occupant transitions. The updating of occupant count does not depend on the Wi-Fi communication frequency. The proposed approach has been tested in a complex indoor space under a real-life scenario. Results show that the proposed Wi-Fi based event-triggered updating method greatly reduces the detection MAE by 84% in average. Comparing with the conventional periodical updating method, the average occupancy detection accuracy is improved from 77.3% to 96.8%.

In addition, the experimental results show that up to 900 Wi-Fi devices were detected in a 10-min interval with around 100 occupants. As a comparison, in a previous Wi-Fi based study [6], around 40–50 Wi-Fi devices were detected in one day with 14–19 actual occupants. A study by Yang et al. [45] tested the occupancy detection in a large lecture room with the capacity of 200 people, where they investigated camera-based and CO_2-based methods. Thus, this work could be the first one in investigating the large-scale Wi-Fi occupancy detection in a complex environment with large number of detected devices in a short period. Results demonstrate that the outside and non-human devices would contribute to a significant portion of the detected Wi-Fi devices. Therefore, a location filter is developed based on a calibrated RSS threshold to classify the inside and outside Wi-Fi devices. A MAC address filter is also developed based on common characteristics of non-human machines. Results show that the two filters are effective in screening out irrelevant Wi-Fi devices.

As Wi-Fi networks are widely available in modern buildings, the Wi-Fi based occupancy detection has a great application potential. The implementation cost of the proposed solution is only minimum when separate Wi-Fi detection nodes are to be used. There is even no implementation cost if the firmware of the existing AP is permitted to update for Wi-Fi signal detection (as implemented in Ref. [25]). That means the proposed detection method can be readily applied in existing Wi-Fi networks for the improvement of detection accuracy without additional cost.

The proposed Wi-Fi based occupancy estimation approach can also be used for predicting cooling demand and indoor air quality, and can be incorporated into demand-driven HVAC or lighting control to enhance energy saving, e.g., controlling the fresh air supply volume [10] or lighting [25]. Since the APs or routers are connected with the Internet, cloud-based computing for building-level [46] or building-cluster-level [47] occupant-based demand-driven energy management and coordination can be implemented conveniently.

The proposed entering and exiting events will also be useful for the following applications:

- to help saving energy in public buildings where occupants are not the bill payer [48], reminders on turning off lighting and HVAC can be sent to occupants' smartphones through Wi-Fi connections when exiting events are detected;
- since an exiting event is also an entering event for an adjacent zone (or room), the occupant count information of several adjacent zones (or rooms) can be updated collectively. That makes the computation of occupancy detection in multiple zones more efficient; and
- the occupant-related events can be integrated into the building evacuation and route optimization functions [49,50].

4.5.2. Application considerations, limitations and future work

If separate Wi-Fi detection nodes are to be used, the covering range of the deployed Wi-Fi detection nodes should be larger than that of APs in the detection area. Otherwise, smartphones in their scan mode cannot be detected by the Wi-Fi detection nodes as they are outside the range. There is no such problem if APs are used for Wi-Fi signal detection.

The study has the following application considerations and limitations.

- First, this study tackles the problem of discontinuous connection of the Wi-Fi operation pattern of smartphones. Other Wi-Fi devices (e.g. laptops) may have different operation patterns, and a general suggestion is that new events should be defined and tailored for accordingly. Hence, the usefulness of the proposed Wi-Fi based detection method would rely on having a proper understanding of the Wi-Fi operation pattern of the specific application scenario.
- Second, the proposed Wi-Fi based detection method relies on capturing the Wi-Fi communication between smartphones and the existing APs. For an AP that covers several rooms, only zone-level occupant count can be provided. In virtually partitioned zones without physical walls, the RSS-threshold based method may misinterpret an outside device located closer to the detection node as an inside device. In this case, RSS-based positioning algorithms that utilize at least three detection nodes should be used to estimate room-level occupancy [51].
- Third, detection errors appear when (1) a single occupant has multiple Wi-Fi devices [16], or (2) occupants leave the smartphone behind. For (1), multiple devices can be distinguished by recognizing the interaction patterns between users and devices [32]. For (2), the significance varies with application scenarios. In a public space, such a case rarely happens since occupants have to take care of their personal belongings. In office environments, occupants may be separated from their smartphones. If the separation duration is significantly long, data fusion approach incorporating other detection techniques (e.g. cameras or motion sensors) may be necessary to enhance the occupancy detection accuracy [16,33].
- Forth, different device models may have different Wi-Fi chips and antennas, termed as “device heterogeneity”, which will affect the measured RSS values. The reported RSS difference due to the smartphone heterogeneity is around 2–6 dBm [52]. In our study, this magnitude of RSS difference does not affect the RSS threshold

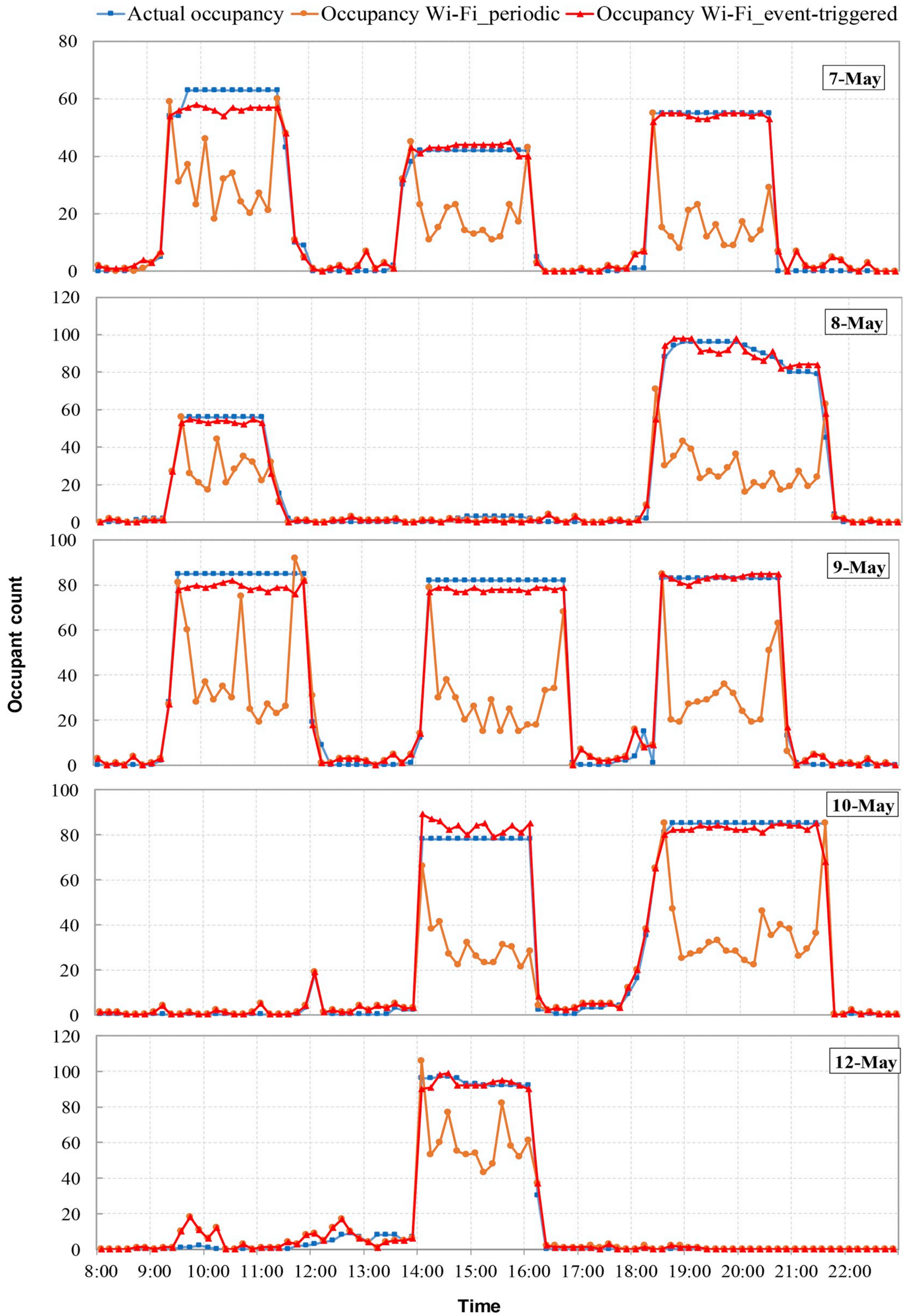
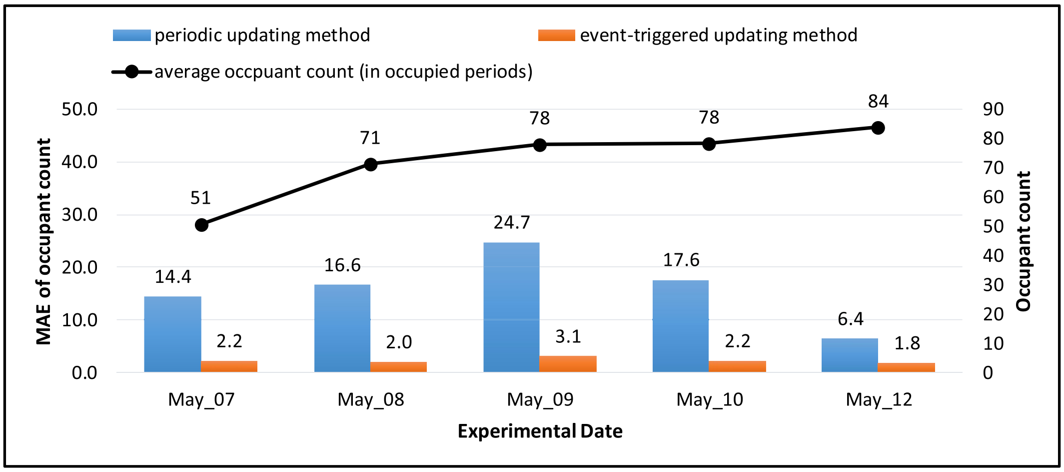


Fig. 10. Comparison of Wi-Fi based occupancy detection approaches.

determination because of the following reasons: (1) the minimal measured RSS difference between "inside" and "outside" devices is 8 dBm at detection node 2, and is even larger at other detection nodes. The RSS difference, mainly due to the obstruction of concrete walls, is sufficient to offset the device heterogeneity error of 2–6 dBm; (2) the large RSS difference is caused by different device types, and the RSS difference is up to 20 dBm even at the same location [53]. Different models of the same device type have small RSS difference [53], which may not affect the RSS threshold determination in this study. In case that the device heterogeneity does cause a significant RSS difference, methods such as the rank-based Wi-Fi fingerprinting [54], the automatic calibration and the calibration-free methods [55] could be pursued.

- The MAC address data of occupants should be protected to preserve



MAE reduction	May_07	May_08	May_09	May_10	May_12	Mean
	85%	88%	88%	88%	72%	84%

Fig. 11. Mean absolute error (MAE[#]), average occupant count and MAE reduction %.

#: $MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}$ (x_i *is the observed value*, y_i *is the estimated value*, n *is the number of data*)

Table 7
Detection accuracies of periodic updating and event-triggered updating.

	May-07	May-08	May-09	May-10	May-12	Average
periodic updating	71.7%[a]	76.7%	68.3%	77.5%	92.4%	77.3%
event-triggered updating	95.7%	97.2%	96.1%	97.2%	97.9%	96.8%

[a] The MAE divided by the average occupant count.

privacy. A dynamic MAC masks or data encryption should be used to serve this purpose.

Data fusion techniques have been studied intensively in order to improve detection accuracy and reliability [16] in Table 4 and [56] in Table 2. They normally make use of physical sensors, such as CO_2, temperature, humidity, light and pressure [16], due to their low-cost and availability. As mentioned before, physical sensors have limited occupancy resolution and are subjected to delay. Recently, data fusion techniques based on Wi-Fi and environmental sensors for occupancy detection have been developed [56]. Results show that the fused approach can improve the detection reliability but may not the accuracy. However, the discontinuous Wi-Fi communication of smartphones is still not discussed in their studies [57]. Since a reliable and accurate data source is critical for data fusion, the presented work can be regarded as a ground work for tackling discontinuous Wi-Fi communication and is instrumental for further researches on Wi-Fi based data fusion occupancy detection techniques.

5. Conclusion

This study reveals the practical challenges when applying the Wi-Fi-based occupancy detection in real-life complex environment. The discontinuous Wi-Fi communication of smartphones presents a practical challenge in occupancy detection. Outside and non-human Wi-Fi devices may also bring in irrelevant or unwanted Wi-Fi communications. To tackle these challenges, an event-triggered updating method is proposed to handle the discontinuous Wi-Fi communication. A location filter is developed based on a calibrated RSS value to exclude the outside Wi-Fi devices. A MAC address filter is developed based on operation characteristics of non-human devices to screen out Wi-Fi enabled stationary equipment. One-week experiment has been conducted in a university lecture theater to verify the proposed method. Experimental results confirm the effectiveness of the proposed event-triggered updating method in handling the discontinuous Wi-Fi communication. The developed filters are also effective in excluding outside and non-human Wi-Fi devices. Comparing with the conventional Wi-Fi based periodic updating method, the average detection accuracy improves from 77.3% to 96.8%. The proposed Wi-Fi based event-triggered updating method can be applied to Wi-Fi networks of new or existing buildings with minimum cost regardless of the Wi-Fi communication continuity. This study reveals that the event-triggered Wi-Fi based occupancy detection approach is effective when applying to institutional or university buildings. The practicality of the proposed Wi-Fi based detection method in other building usages or room occupancy behaviors should be further investigated. Since Wi-Fi only may not handle every complicated scenario, the proposed method can be integrated into a data fusion approach to enhance the detection reliability and accuracy.

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