Review: Energy-Efficient Smart Building Driven by Emerging Sensing, Communication, and Machine Learning Technologies

Qian Huang

Abstract—**As an integral part of smart grids and smart cities, nowadays smart building is one of the most promising areas of research to address the challenges of global environmental and energy sustainability. This review article introduces and outlines a variety of emerging information technologies, such as smart occupancy detection sensors, visible light communication for high-throughput communication and indoor positioning, and machine learning algorithms for multi-modal data fusion. These novel technologies have significantly promoted and accelerated the development of energy-efficient smart buildings in the future. The design requirements, features, and examples of these three emerging information technologies are discussed elaborately. Then, we provide insights and suggestions on how to integrate them properly with smart buildings. A design solution is envisioned to utilize these three technologies and to establish a platform dedicated to accurate occupancy counting towards energy efficient buildings. The envisioned system is portable, easy to use, highly-accurate, non-intrusive, low power, cost-effective, and self-adaptive to diverse and uncertain building environments.**

Index Terms— **smart building; occupancy detection sensor; visible light communication; machine learning algorithms**

I. Introduction

According to the statistics of the United States Energy Information Administration (EIA), residential and commercial buildings accounted for about 40% of total U.S. energy consumption in 2016. Electricity, natural gas, regional heat and fuel oil are the primary shares of building energy sources. HVAC (heating, ventilation, and air conditioning) equipment typically accounts for 50% of various energy usage sources. Energy-efficient smart buildings are considered as a viable energy-saving approach in [1-4], in which parameters related to the control of building energy consumption have been studied. As is well known in the research community, many existing buildings are energy-inefficient because of the lack of intelligent HVAC operations and building controls. As a result, a lot of energy is wasted, especially when buildings are completely unoccupied, or when the supplied ventilation flow exceeds its demand level. It is a daunting task and a costly process to adding intelligent building control functions directly to existing buildings through conventional building renovations and retrofit.

Fortunately, with the rapid advances in cutting-edge information technologies, such as user-transparent miniature smart sensors, high-speed reliable wireless communication, and big data analytics algorithms, the energy efficiency of existing buildings has been improved and cost-effective information technologies have been used. In some cases, multiple information technologies are embedded in wireless sensor networks or Internet of Things (IoT) prototypes, which are versatile and popular platforms [5]. In general, the reduction of building energy consumption requires multi-disciplinary research.

As depicted in Fig. 1, smart occupancy detection sensors, visible light communication, and machine learning algorithms work in conjunction with a building automation system (BAS) to collect real-time environmental data and respond to real-time events/requests. Data sensing, analysis, modeling, and decision-making processes are involved. Building automation systems are usually offered by HVAC equipment manufacturers, such as Johnson Controls, Siemens, Honeywell, and GE. By default, a BAS monitors and regulates the operation of HVAC equipment (such as heaters, coolers, fans, coils, etc.). For example, as shown in Fig. 1, the air temperature, pressure and flow, CO_2 concentration, and fan or damper status can be monitored in real-time from the user terminal of a BAS. From a sustainable perspective, an essential task of smart buildings is to maximize energy efficiency and reduce operating cost. To achieve this goal, the concept of demand-driven HVAC operation was proposed in [6-9], in which these information technologies collect and analyze real-time building environments and occupant activities with a negligible cost and little maintenance effort. In this way, the energy consumption of HVAC equipment is minimized while still keeping the "just-right" quality of service for building heating, cooling, and ventilation. In order to realize "just-right" assurance in the quality of building service, highly inter-disciplinary collective research efforts are needed, because it involves knowledge of electronic circuit theory, computer-aided design, system architecture, and signal processing algorithms. In order to harness the true benefits of these emerging technologies, it is absolutely necessary to deeply understand these new technologies and their interactions with HVAC/building operations. Therefore, three types of information technologies are selected and reviewed in this work. We envision the necessity and importance of designing smart buildings from a

Manuscript received December 10, 2017; revised July 13, 2018. Qian Huang is with the School of Architecture, Southern Illinois University, Carbondale, IL 62901 USA (phone: 618-453-1254; fax: 618-453-1129; e-mail: qhuang@siu.edu).

(Advance online publication: 28 August 2018)

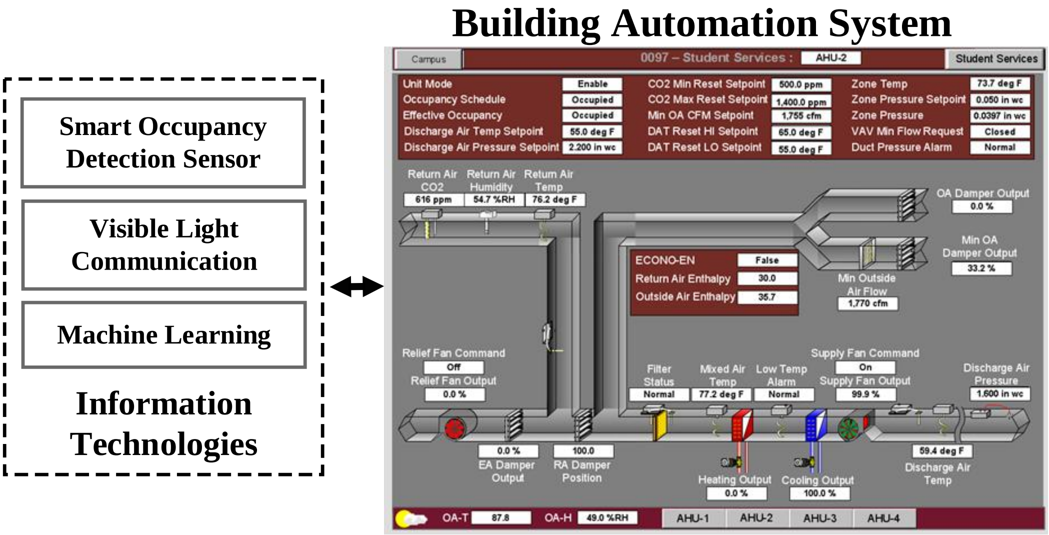

Fig. 1. Information technology-driven building automation system (BAS)

systematic and comprehensive design approach. The practical issues, challenges, and considerations are discussed on how to properly integrate them with energy-efficient smart buildings.

II. Emerging Information Technologies

In this section, three new information technologies are introduced and reviewed, namely smart sensors for building occupancy counting, Li-Fi for high-throughput wireless communication and indoor positioning, and machine learning algorithms for multi-modal data fusion. Next, we will describe how these three new information technologies can be seamlessly integrated and collaborated with building automation systems.

A. Smart Sensors for Building Occupancy Counting

Heating, cooling, and ventilation in buildings are very energy intensive. Traditional HVAC systems typically operate on a fixed schedule (for example, ON mode from 7 AM to 6 PM on weekdays and OFF mode on weekends), regardless of whether the building is vacant or occupied. It is predicted that if the real-time building occupancy is accurately perceptible in building automation systems, the energy consumption in HVAC operations is reduced by 30% [10].

In fact, the presence or absence of an occupant is relatively easy to detect in the case of a binary output signal ("occupied" or "vacant") generation. Accurate room occupancy counts or estimates are much more difficult than human presence detection. The awareness of the amount of occupancy quantity has led to a significant improvement in building energy efficiency, as the operation of HVAC equipment can be fine-tuned according to the exact number of occupants. For example, most commercial buildings today are equipped with variable speed fans for ventilation control. Depending on the number of residents in the HVAC thermal zone, HVAC equipment will provide residents with a "just-right" level of ventilation. In practice, it is difficult at any time to obtain the number of occupants in HVAC thermal zones. As a result, many buildings inevitably provide over-ventilation services and wastes energy. If smart occupancy detection sensors provide occupant quantity information for each HVAC zone, energy-efficient fine-grained HVAC service can be realized by dynamically and appropriately configuring the various thermostats and rotation speeds of fans.

According to the report from the U.S. Department of Energy [10], up to date, there are no such smart occupancy detection sensors available in the marketplace that can meet all the requirements mentioned in this report. These required features include cost-effective, high-precision, non-intrusive, privacy protection, reliability, ease of use, and adaptability to diverse and uncertain building environments. For instance, the expected system cost in [10] is within $0.08 per square foot. Occupants counting accuracy should have 95% long-term confidence, while the performance of existing designs is far below this goal. We can see that it is a great challenge to systematically investigate, design and implement novel occupancy detection sensors to satisfy most or all of these above performance requirements.

The idea of installing micro-scale environmental sensors in buildings is not new, and carbon dioxide sensors, motion detectors, and thermometers are commonly used. Fig. 2 shows a temperature map acquired by the distributed sensors in an office building. Real-time temperature value of each HVAC thermal zone can be successfully monitored from a BAS terminal. Fig. 3 plots the return water temperature, supply water temperature, and water volume rate of the same office building for three consecutive days. Obviously, these data points vary significantly with time and depend on indoor activities of building residents. According to the report from the U.S. Department of Energy [10], the next generation of smart buildings is more intelligent and can accurately count how many people are in an HVAC thermal zone in real time. In order to support this attractive feature, autonomous sensor systems need to collect considerably rich and diverse data that detail what is happening in buildings. Existing sensor systems have limited ability to meet this need. As a result, the main challenge in smart sensor systems is to improve accuracy, functionality, reliability, and flexibility with strict constraints of cost and size. The cost constraint ensures their

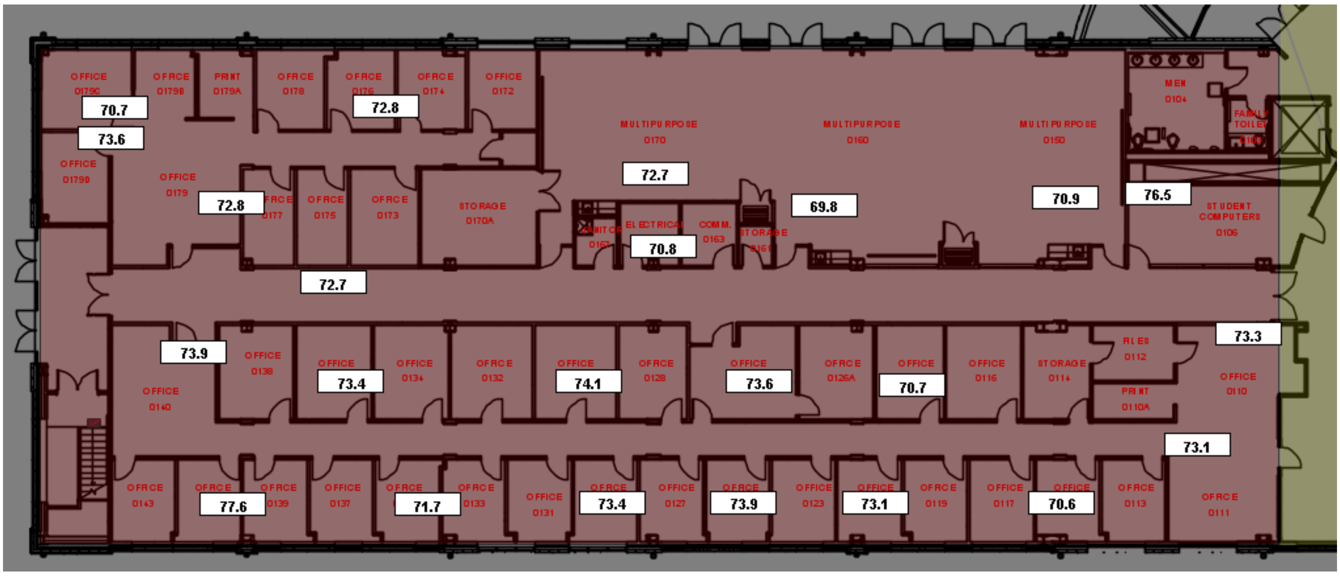

Fig. 2. A temperature map collected by distributed sensors in an office building captured from a BAS of Johnson Controls

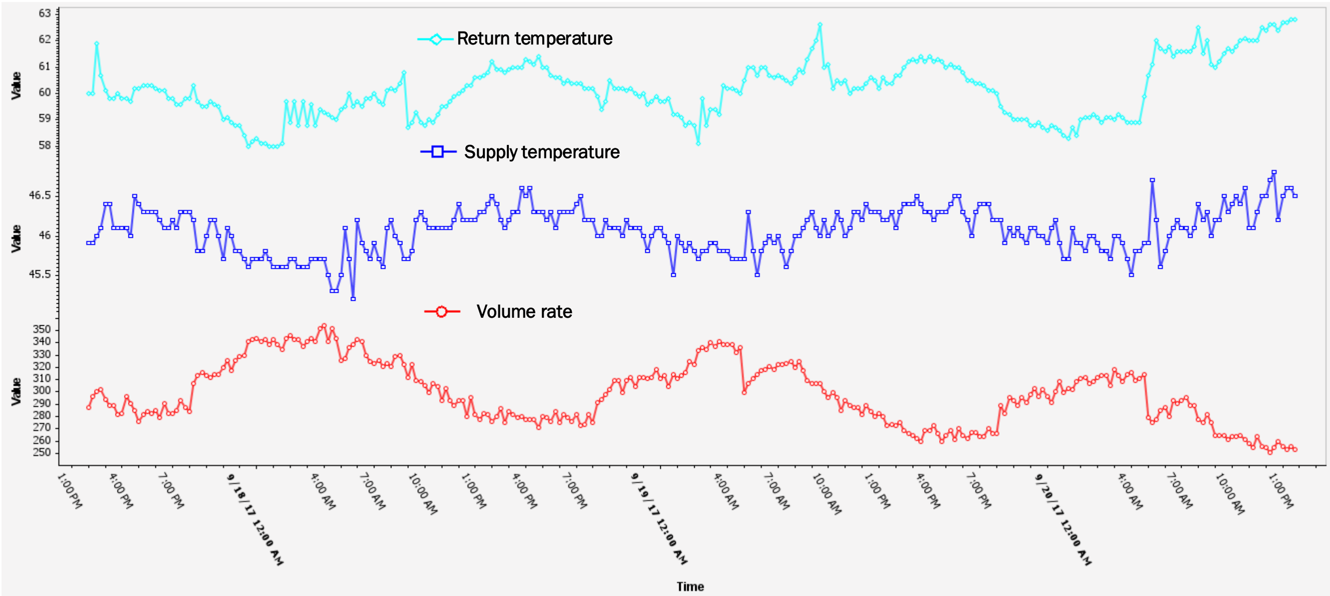

Fig. 3. Collected sensor data from an office building captured from a BAS of Johnson Controls

scalability in various building applications, while the size constraint helps to achieve user-transparency and user-convenience.

Many types of environmental sensors have been used to detect room presence status or occupancy number [11]. Passive infrared (PIR) motion sensors are commonly installed in restrooms or hallways to automatically turn on/off fans or ceiling lights to save energy. As the output of a PIR motion sensor is binary, indicating the presence or absence status, it is not possible to give accurate numbers of people [6, 12]. Later, radio-frequency identification (RFID) and other wearable wireless devices (*e.g.*, Bluetooth, UWB receivers) have been demonstrated for coarse-grained occupancy detection. However, since each RFID tag or wearable device is associated with and carried by a particular person, human privacy and security concern are the primary problems [7, 12]. Building residents or users do not want to be tracked or monitored, so they are very reluctant to wear RFID tags or wearable devices. Speech recognition and acoustic processing are potential techniques for predicting building occupancy information [13-15]. Audio-based occupancy processing is not expensive, because the basic hardware resources needed only contain microphones and microcontrollers. Collected audio signals from microphones are processed by algorithms running in microcontrollers. Yet, acoustic detection is rarely adopted for stand-alone occupancy detection, because (a) sound waves from non-human sources in a building can trigger false detections, and (b) the detection easily fails when an HVAC zone is occupied and there is no sound made by persons. Acoustic-based occupancy detection is therefore useful in quiet offices than noisy places such as supermarkets, shopping malls, or restaurants. In addition, video or image cameras are presented to monitor building occupancy [9, 16-17]. However, cameras cannot be placed in any position due to the limitations of the line of sight. If people move out of the viewing area of a camera, this method does not work at all. If a large number of cameras is installed in an HVAC thermal zone, the resultant hardware costs are very high. Moreover, since daily activities of building users/residents are recorded by cameras, the issue of user privacy is a big obstacle to its widespread deployment. Furthermore, the room occupancy number can be predicted based on the indoor carbon dioxide level, which is linear with the number of inhabitants in a space [18-19]. Despite the low-cost and non-intrusive advantages, the level of carbon dioxide fluctuates with the HVAC operations, such as ventilation settings, door and window opening status, and placement of CO_2 sensors, so the exact relationship between CO_2 level and occupancy information varies case by case. Especially when an occupant leaves a room, the CO_2 concentration starts to drop after a long time, which reduces the sensitivity of occupancy detection.

We presented hybrid CO_2 and light smart sensors in 2016, which improves occupancy detection accuracy while maintaining a small-size and low-cost solution [20]. Unlike video/image cameras, which capture and record clearly the daily behaviors of building residents, the light sensors only report the illuminance level of lighting situations, and hence privacy protection is no longer a concern. The cost of a light sensor is only $4, which is much cheaper than cameras. In [17], experimental measurements in an office building showed the full functionality of such hybrid CO_2 and light smart sensors. Later, other researchers and we proposed to study the response of CO_2 level, temperature, and humidity to deduct the room occupancy quantity [21-22], while light, CO_2, temperature and humidity sensors are used in [23]. In June 2017, an active infrared (AIR) smart sensor was reported to monitor doorway traffic and calculate the room occupancy number in [24]. A 5-minute proof-of-concept video demonstration is recorded and available to watch at https://sites.google.com/site/chaolushomesite/. Fig. 4 depicts the concept of active infrared occupancy counting using highlighted key components. Fig. 5 shows the picture of a programmed Lattice iCEstick FPGA board to implement a proposed AIR sensor. The dimension of the FPGA board is only 4.6 inches by 1.5 inches, so it enables good user transparency. The total power consumption of this FPGA board is several milliamps, so a typical rechargeable battery (2000mAh) is capable to support several months of operation. An infrared receiver (*i.e.*, RX) FPGA board and an infrared transmitter (*i.e.*, TX) FPGA board are needed and fixed on each side of a door opening. Therefore, as shown in Fig. 6, two TX boards and two RX boards are respectively attached to the left and right sides of the door frame. Powered by a long-life battery, each TX board sends an infrared stream to its aligned RX board. In this way, two separate infrared streams are established in parallel. Each RX board is cabled to a Raspberry Pi 3 module. When an object (*e.g.*, a person) walks through this door opening, infrared streams are blocked and interrupted by this human body. Once a signal blocking event is detected by an RX board, the blocking event and its occurrence time are notified to a Raspberry Pi 3 module via cable connections. By comparing the occurrence time of events reported by two RX boards, the moving direction of an object can be determined. Then, the Raspberry Pi 3 module calculates and updates the real-time occupancy quantity, which is instantaneously observed by building automation systems or building owners/users

.

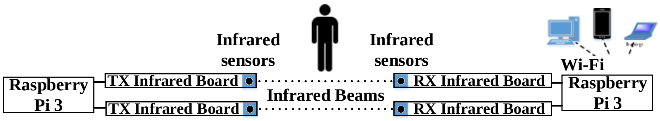

Fig. 4. The concept of active infrared occupancy counting with highlighted key components [24] (this figure is owned by me)

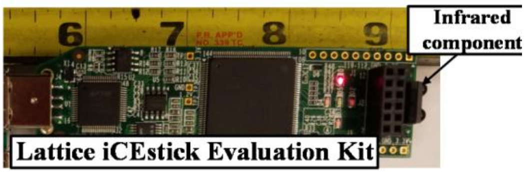

Fig. 5. Picture of a programmed FPGA board to implement an AIR sensor

Fig. 6 shows the experimental setup for testing this system in an office building. The proposed AIR smart sensor is implemented using the Lattice iCEstick evaluation kit [25]. The researchers conducted a four-week lab measurement and validated the gate monitoring module with a success rate of 97%. The 3% failure rate is caused by the temporal noise or signal interference in this study. This problem can be mitigated by using a robust custom circuit board to improve system reliability and noise immunity. From an implementation cost perspective, the hardware price for the proposed design in Fig. 4 is about $300, which is equivalent to about $0.02 per square foot and is also 75% lower than the requirement by the U.S. Department of Energy [10]. Note that all the design codes for FPGA configuration are stored in a micro-SD card. Customers only need to plug this SD card into the SD slot of Raspberry Pi. Customers do not need the prerequisite knowledge for programming.

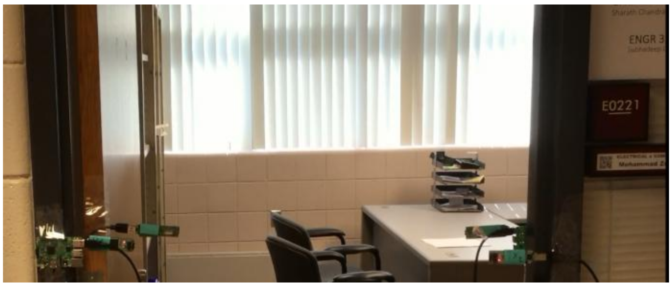

Fig. 6. Experimental setups and testing near an office door frame

In Table I, existing smart building occupancy detection sensors are summarized and compared in terms of the detection mechanism, implementation cost, detection accuracy, and privacy protection. In order to achieve better user transparency and scalability, it is attractive to reduce cost, system size, and power consumption of smart occupancy detection sensors. These sensors are typically powered by batteries. Ambient energy harvesting techniques have been presented to scavenge environmental energy and to extend battery life. Thus, the need for regular battery replacement is eliminated. Ambient thermal gradients and indoor lighting illuminance are commonly collected to sustain the operation of these sensor nodes. Prior researchers have validated the idea of using indoor energy harvesting to power wireless sensors [26-28]. Due to the ultra-low-power feature of the FPGA board, the battery life is expected to exceed 3 years. According to the report from the U.S. Department of Energy, the total sensor system cost in [10] is no more than $0.08 per square foot. Image camera and CO_2 sensors are relatively expensive. In contrast, RFID, PIR motion, acoustic, and active infrared sensors are more cost-effective. Among all the existing sensors reported, the active infrared sensor has a high occupancy counting accuracy, which is much better than its counterparts in Table I. Light, CO_2, and active infrared sensors are ideal choices for personal privacy and security protection. Active infrared detection sensors only perceive the arrival and departure of the building occupants into and out of an HVAC thermal zone. Since the proposed active infrared sensor in [24] does not collect any image/RF/radar signals, it well protects the privacy of building occupants.

TABLE I
SUMMARY AND COMPARISON OF SMART OCCUPANCY COUNTING SENSORS

Reference Number	Detection Mechanism	Low Cost	High Counting Accuracy	Privacy Protection
[6]	Passive infrared	×	×	×
[7-8]	RFID	√	×	×
[9]	Camera	×	×	×
[12]	RFID +PIR	×	×	×
[13]	Acoustic	√	×	×
[14]	Acoustic	√	×	×
[15]	Acoustic	√	×	×
[16]	Camera	×	×	×
[17]	Camera	×	×	×
[18]	CO_2 level	×	×	√
[19]	CO_2 level	×	×	√
[20]	CO_2+light	×	×	√
[21-22]	CO_2+humidity +temp	×	×	√
[23]	CO_2+ humidity+ temp+light	×	×	√
[24]	Active infrared	√	√	√

B. Visible Light Communication for High-Throughput Communication and Indoor Positioning

With the increasing popularity of ultra-high-definition (UHD) televisions and cameras, such as 4K or 8K resolution, real-time high-throughput data communications are highly desirable in smart buildings in the future. For example, when broadcasting TV or movies via Netflix, it is recommended to use 25 Megabits per second of internet bandwidth to ensure good quality of services [29]. On the other hand, establishing the reliability of network communications is a key issue, because communication networks are venerable for malicious attacks [30]. Hence, it is a challenge to offer high-throughput wireless data communication at low-cost overhead. Visible light communication, also known as Li-Fi (Light Fidelity), is one of the most promising wireless communication technologies [31-33]. Most people are aware of Wi-Fi, which uses radio-frequency electromagnetic waves as the wireless communication medium and has a throughput in the range of Mbps. Due to its high throughput (*e.g.*, Gbps), Li-Fi is a supplement to Wi-Fi for indoor wireless data communication. Li-Fi has limited coverage and cannot support mobility as Wi-Fi. On the contrary, Wi-Fi offers a wide range of coverage, enabling network connectivity with moderate mobility. Thus, based on the needs of customers, it is very useful to combine both Li-Fi and Wi-Fi technologies for mixed data communication or indoor localization [4, 34-35].

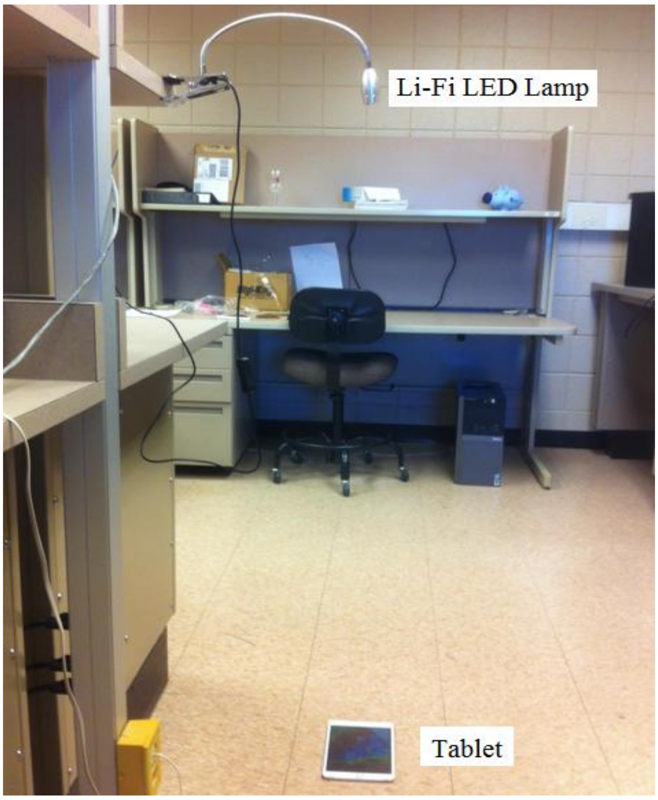

Figure 7. Li-Fi communication setups in an office building [35] (this figure is owned by me)

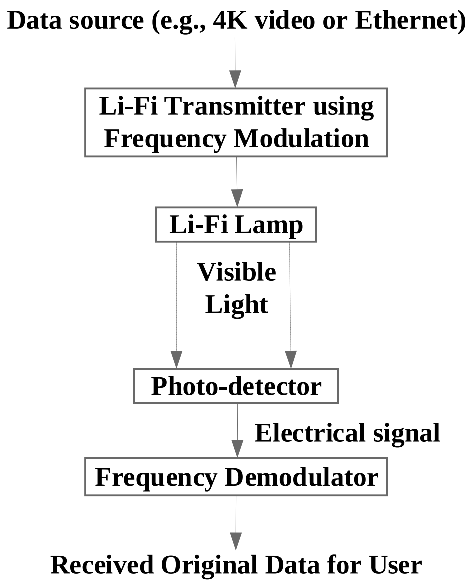

Figure 8. Flowchart of Li-Fi signal processing for experiments in [35] (this figure is owned by me)

Fig. 7 shows the experimental test setup for Li-Fi data communications in an office building. Fig. 8 illustrates a flowchart of Li-Fi signal processing involved in this study. The Li-Fi transmitter is an electronic circuit that uses frequency modulation to encode input data. The signal to control the Li-Fi bulb was measured using an oscilloscope, as shown in Fig. 9. Therefore, under the control of this signal, the Li-Fi lamp is turned on and off accordingly. Note that the visible light is used for dual purposes: room lighting and data transmission. The Li-Fi receiver includes a miniature photo-detector and a frequency demodulator. Based on the photoelectric effect, the photo-detector converts the received visible light signal into an electrical signal. Then, the user can retrieve the received raw data after inverse frequency modulation. In summary, a Li-Fi reuses existing lighting infrastructure to provide indoor lighting and high-throughput data communication capabilities.

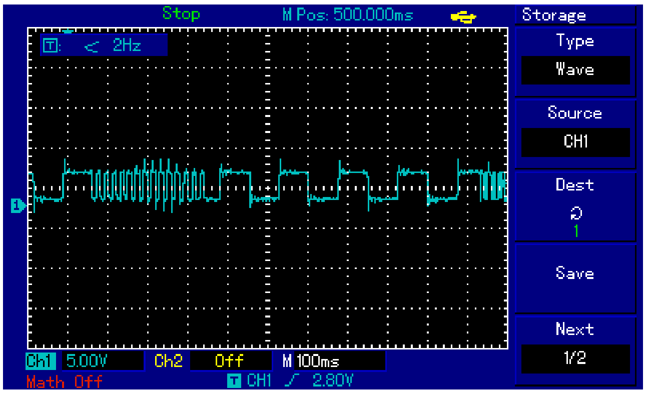

Figure 9. Measurement results of frequency modulated signals in Li-Fi communication

Table II summarizes data communication throughputs for various Wi-Fi standards and Li-Fi records [36-38]. We can see that the throughput of Li-Fi is much higher than that of Wi-Fi. This feature enables ultra-high speed wireless data communication in future bandwidth-limited smart buildings.

TABLE II
SUMMARY OF THROUGHPUT OF INDOOR COMMUNICATION METHODS

Standard	Maximum data throughput (Mbps)
Wi-Fi 801.11b	11
Wi-Fi 802.11a	54
Wi-Fi 802.11g	54
Wi-Fi 802.11n	600
Wi-Fi 802.11ac	1,300
Li-Fi [35]	2,000 or 4,000
Li-Fi [36]	32,000
Li-Fi [37]	11,900

Visible light communication also refines the accuracy of indoor localization [35]. When people live in buildings, their trajectories reflect daily activities and personal intentions. For example, the location of a person in a shopping mall, hospital, or library can help building owners understand the behaviors of their customers and then provide location-based services or assistance. Based on each user's history and preferences, user-oriented services, such as room lighting and temperature control, door or window openings, can be triggered automatically. In addition to improving customer loyalty and business sales, indoor location-based services can also enhance customer experience, productivity, and comfort [39-41]. Furthermore, taking into account of high-precision indoor position of occupants, a building automation system (BAS) is capable to offer highly-efficient heating, cooling, ventilation, and lighting services. For example, if an occupant stays in the kitchen of a residential building, the ventilation rate and temperature control in bedrooms may be somewhat relaxed. The ventilation fans or air valves in bedrooms can be turned down or even completely off. In this way, the energy consumption of the entire HVAC operation is significantly reduced. Due to inaccurate indoor positioning may have a negative impact on business performance and customer loyalty, many researchers are trying to minimize indoor positioning errors. The Wi-Fi-based indoor positioning technology is widely adopted. It is based on measuring Received Signal Strength Indication (RSSI) that reflects the received power level at the antenna. Ideally, the received power level is inversely proportional to the distance between the receiver and the transmitter. Yet, due to complex signal reflections, multipath and interference with indoor obstacles (e.g., walls, windows, or furniture), the received Wi-Fi signal strength shows a large variation [42]. Recently, several efforts have been made to resolve the issue of relatively large errors in indoor positioning [43-51]. A Li-Fi assisted calibration approach has been proposed to improve the accuracy of Wi-Fi- based indoor localization method [35]. It was reported that the integration of Li-Fi into Wi-Fi indoor positioning improves the positioning accuracy by 80%, compared to a Wi-Fi alone method. Moreover, in order to solve the problem of locating overlapping areas in Li-Fi positioning systems, Li-Fi with a gray-coded identification was presented in [51].

TABLE III
SUMMARY OF EXISTING INDOOR LOCALIZATION METHODS

Reference Number	Mechanism	Low Cost	High Positionin g Accuracy
[35]	Wi-Fi + Li-Fi	√	√
[43]	Wi-Fi with multiple mobile terminals	×	×
[44]	Wi-Fi + particle swarm optimization	√	×
[45]	Wi-Fi + cellular network signal	√	×
[46]	Bluetooth low energy beacons	√	×
[47]	Wi-Fi + Bluetooth	√	×
[48]	Wi-Fi + neural network algorithm	√	×
[49]	Camera	×	√
[50]	RFID	√	×
[51]	Li-Fi + Gray-coded identification	×	√

Table III summarizes existing indoor localization methods in the literature, including Wi-Fi with Li-Fi, Wi-Fi with multiple mobile terminals, Wi-Fi with particle swarm optimization (PSO), Wi-Fi with cellular network signal, Bluetooth low energy beacons, Wi-Fi with Bluetooth, Wi-Fi with neural network algorithms, camera, RFID, Li-Fi with Gray-coded identification. Among these methods, Wi-Fi with Li-Fi, camera, and Li-Fi with Gray-coded identification lead to high positioning accuracy. Since using cameras for indoor localization is expensive and unfriendly for privacy, Li-Fi technology is viable, high-performance, and cost-effective.

C. Machine Learning Algorithms for Building Presence or Occupancy Estimation

Once raw data sensing and acquisition is completed from building environmental sensors, the subsequent process is data fusion and analysis. A huge amount of diverse data, including temperature, carbon dioxide, humidity, sound, and image, needs to be handled effectively. For real-time decision-making applications, these large data sets require automatic data analysis and adaptive signal processing [2]. Fig. 10 shows an observational view of a computer service lab, where a video camera is used to monitor real-time room

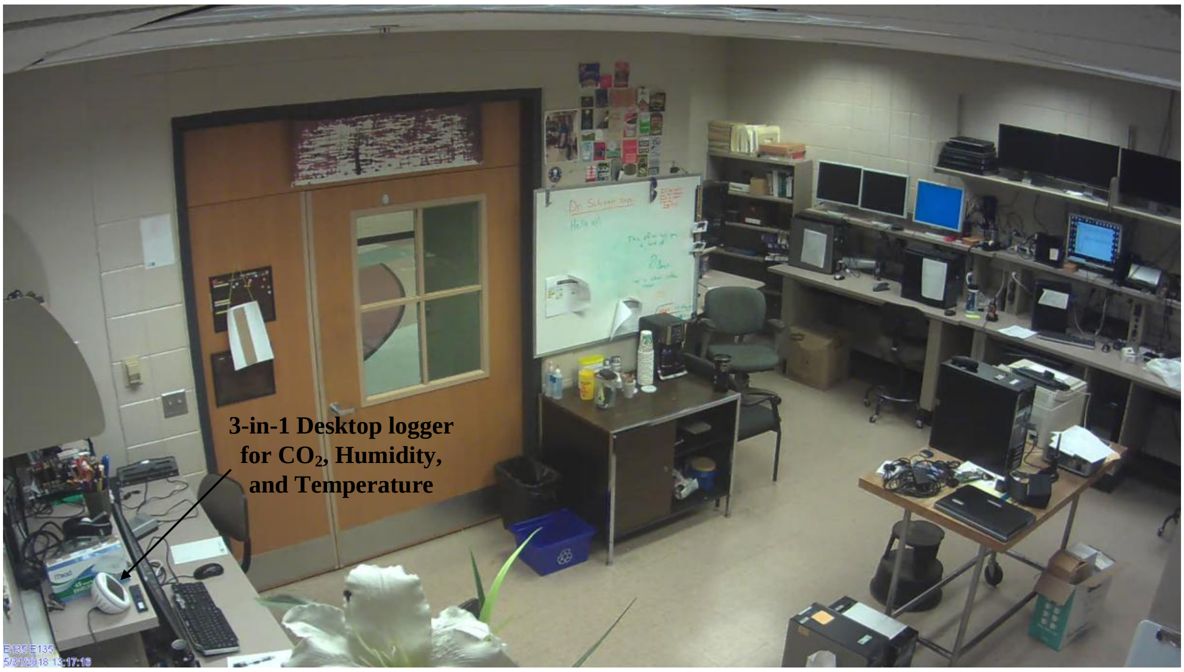

Figure 10. An observational view of a computer service lab using a video camera to monitor real-time room occupancy information

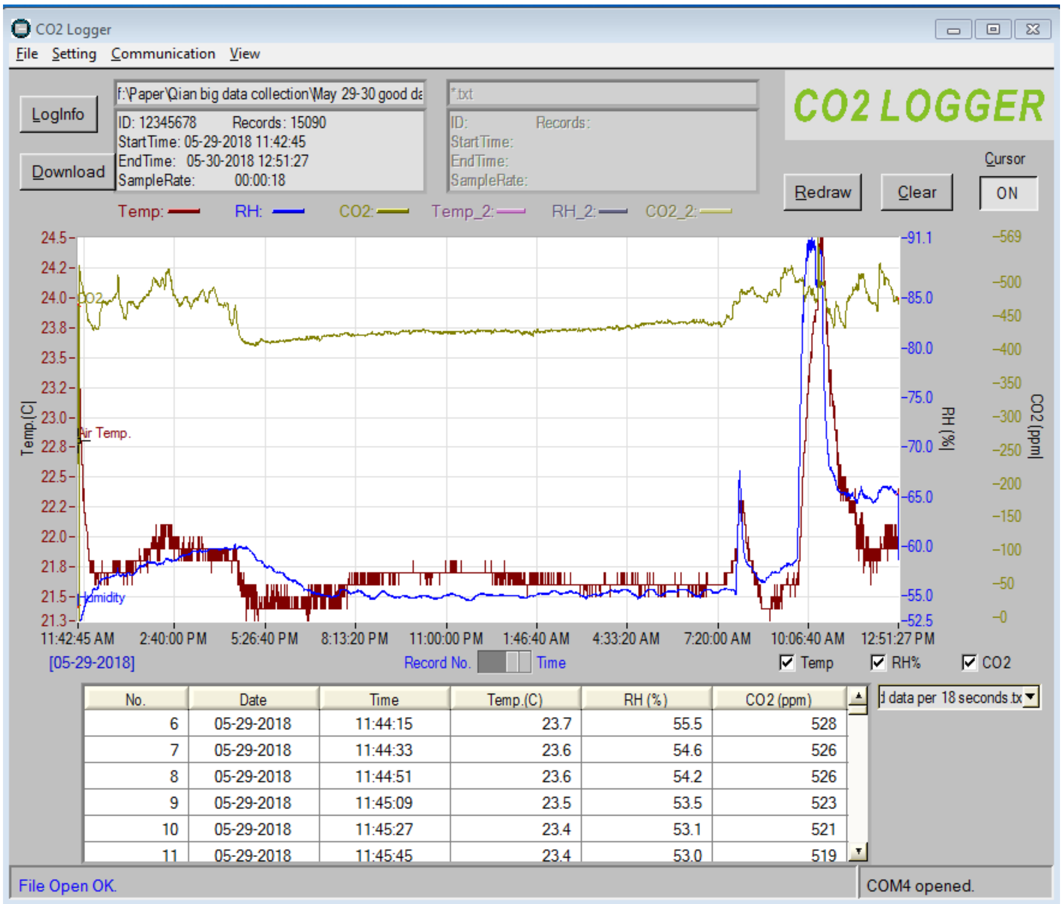

Figure 11. Collected 15,090 data points for CO_2, humidity and temperature

occupancy information. As indicated in the lower left corner, a 3-in-1 desktop logger is configured and placed on the desk to record the values of CO_2 concentration, humidity, and temperature. Fig. 11 shows the plot of 15,090 data points for one day, assuming a sampling rate of every 18 seconds.

The true room occupancy count can be observed from watching video recording files. Recognizing and retrieving complex patterns hidden behind these data sets by machine learning algorithms is demanded. Data fusion solutions for various sensors are growing. In complex buildings of varying types, structures, or geometries, the data collected from environmental sensors are not always reliable due to temporary noise or signal interference. In addition, raw sensor data often exhibit substantial uncertainty in patterns, since the activities and behaviors of building occupants are usually unpredictable. Therefore, raw sensor data need to be analyzed by signal processing algorithms that correlate the measured sensor data with building occupancy numbers. Due to the large data volume, it is extremely difficult to extract the essential patterns of occupancy from raw sensor data. A lot of useful information is hidden, so it is hard to discover and determine the occupancy characteristics. Hence, the research challenge is how to efficiently analyze and utilize these massive data points to make correct decisions and actions, such as adjusting HVAC configuration profiles and set-points. Recently, machine learning algorithms have been proposed to analyze environmental sensor data to monitor room occupancy. Machine learning is a set of technologies that automate big data processing by developing a set of rules. However, these conventional machine learning methods have limitations in non-stationary environments, and suffer from relatively large errors in the time domain.

Deep machine learning (*e.g.*, deep neural network) rapidly becomes a powerful tool for high-dimensional data analysis and automatic feature/pattern extraction. As shown in Fig. 12, a set of criteria rules needs to be manually extracted by designers in machine learning, while deep machine learning automatically grasps the relevant features to solve problems. Therefore, the deep learning algorithms support self-learning and calibration without manual intervention. Compared with traditional machine learning, deep machine learning is more advanced for complex problems. Deep machine learning has been widely used in various applications, such as imaging recognition, energy market price forecasting, speech and language translation, and self-driving cars [52-53].

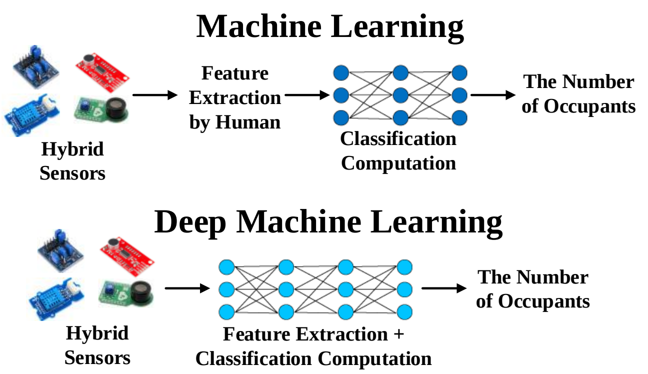

Figure 12. Concepts of applying Machine learning and deep machine learning algorithms for building occupancy counting

Unlike traditional general-purpose processors (*i.e.*, CPUs or GPUs) whose computation is based on instruction flow and data stream, deep neural networks (DNNs) are composed of a large number of neurons as basic computing units, and computations are realized through interconnected neuron networks with a certain topology. A deep neural network has weak instruction streams, and its performance is dominated by the number of neurons and the network topology. This large-scale on-chip interconnection structure poses a great challenge to the design of embedded neural network chips. Fig. 13 illustrates these typical neural network topologies. Modern deep learning neural networks are mainly based on these basic topologies or their mixture. Deep learning algorithms are computation-intensive and memory-intensive, so they require a large number of computational units and memory cells. Rapid reading and writing a large amounts of weighted data is expected in these deep convolutional neural networks, such as LeNet-5 [54], AlexNet [55], VGG [56], GoogLeNet [57], and ResNet [58]. Therefore, it is difficult to program deep neural networks on resource-limited embedded systems. At present, deep learning neural networks strongly rely on cloud computing. However, even though rapid advances in high-resolution video compression [59-61], this remote learning and processing of neural networks limit them in many scenarios, especially for real-time applications.

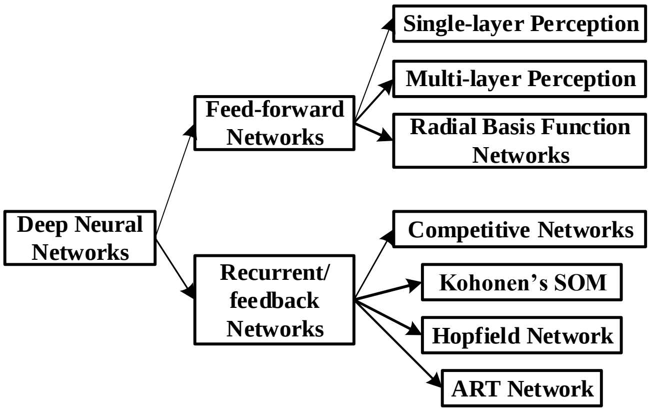

Figure 13. Existing basic neural network topologies.

In order to realize and enhance the data processing capability of DNNs on embedded platforms or mobile terminals, people have started to optimize and compress deep learning neural network models. For example, the researchers in [62] have reduced AlexNet by 35 times from 240MB to 6.9MB, and squeezed the VGG-16 by 49 times from 552MB to 11.3MB. Due to these optimizations, the computational speed of DNNs has been increased by 3-4 times in [63]. Later, the researchers in [64] proposed a light-weight CNN model by resizing convolutional dimensions and reducing pooling functions. Compared to AlexNet, the required size of model parameters are reduced by 50 times from 240MB to 4MB. In [65], if the data width is reduced from 32 bits to 8 bits, the model size can be further compressed to only 0.92Mb, equivalent to 258 times comparing to the original model size. Besides, its top-5 accuracy on ImageNet is not reduced at all.
These studies provide useful references for us to implement real-time embedded DNN processing technology. In [66-69], another concept of stochastic computing was introduced to largely reduce the hardware complexity of various deep neural networks. In order to meet real-time processing and low power consumption, the computational complexity of deep neural networks needs to be reduced without sacrificing recognition or classification performance. So far, several methods have been developed and reported in the literature, including reduction of the number of nodes in neural network layers, sparse matrix coding, replacement of large convolution kernels by multiple small convolution kernels, and the storage and sharing of weight parameters.

Machine learning or deep machine learning algorithms have been applied to predict occupancy presence/quantity and show promising results. In [70], Support Vector Machine

(SVM) was used to analyze the occupancy features and activity patterns in buildings. In [71], using a Radial Basis Function (RBF) neural network, the cross-estimation tests produce an occupancy prediction accuracy of 66%. In another study [72], a random neural network model was developed to understand the relationship between occupancy rate and CO_2 concentration, indoor temperature, and room humidity. The accuracy for occupancy presence detection was reported as 87.4%. In [73], a low-cost and non-intrusive sensor network was deployed in an office. The selected multi-sensory features were determined using an artificial neural network (ANN) with an estimation accuracy of 84.6%. In [74], based on multiple types of sensor data, the researchers studied three statistical classification models (hidden Markov chains) for occupancy detection. Instead of investigating the number of occupants, the researchers discovered a high degree of accuracy to examine whether an office is occupied or not. In [75], PIR sensors were combined with machine learning algorithms to estimate the room occupancy. Based on PIR sensors and microprocessors, machine learning models were presented to estimate the presence of occupants. This work validated the feasibility of running machine learning algorithms on these Internet of Things (IoT) platforms. Later, clustering and regression models were developed in [76] to predict occupancy estimates. In [77], Extreme Learning Machine (ELM) was presented and modified for building occupancy quantity estimation. Machine learning or deep machine learning has its own drawbacks. For example, as described in [70], machine learning algorithms tend to produce noisy and unstable results over time. This is because machine learning models treat training data as independent, thus ignoring the cross-correlation of multi-sensor data.

TABLE IV
SUMMARY OF MACHINE LEARNING ALGORITHMS FOR BUILDING OCCUPANCY PRESENCE/NUMBER ESTIMATION

Reference Number	Machine Learning Approach	Occupancy Presence Detection	Occupancy Number Counting	High Accuracy
[70]	SVM	×	√	×
[71]	RBF neural network	×	√	×
[72]	Random neural network	√	√	×
[73]	Artificial neural network	×	√	×
[74]	Hidden Markov model	×	√	×
[75]	Hidden Markov model	√	×	×
[76]	Clustering + Regression	×	√	×
[77]	Extreme learning machine	×	√	×

Table IV lists existing machine learning and deep machine learning approaches for building occupancy presence/number estimation. It is observed that even though several machine learning algorithms support occupancy counts, their accuracy is not very high (usually less than 90%). Consequently, in order to overcome this challenge and obtain high-precision occupancy estimates, we envision to develop big-data-driven deep neural network (DNN) algorithms. Using these DNN algorithms does not require the creation of explicit and comprehensive feature models for occupancy counts. We also envision exploring cost-effective and energy-efficient DNN algorithms and hardware implementations for end-to-end computing – from raw sensor data all the way to the final output of occupancy counts. Therefore, these DNN algorithms may operate in collaboration with future smart occupancy detection sensors together to achieve low complexity, low power consumption, high precision, and self-adaptive to diverse and uncertain building environments. We believe all the involved processes for data acquisition, communication, and computation should be performed within smart buildings, so there is no need for cloud or server computing.

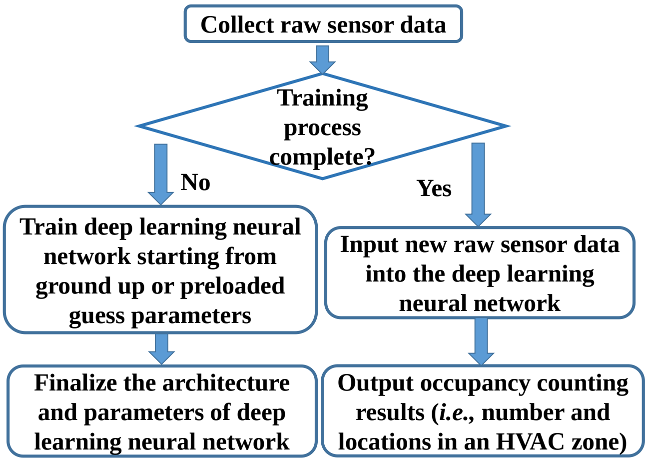

Figure 14. The proposed flowchart of using a DNN to perform end-to-end computation for building occupancy counting

As shown in Fig. 14, there are two stages for DNN end-to-end computation: a training phase and a computation phase. The motivation for training is to determine the parameters for a DNN. After completing the training phase, a DNN acts as an end-to-end computing engine. A DNN needs to be large enough to have a capacity to tune-up to a useful computation, but it is simple enough that its computation time does not exceed the assigned time limit. As a result, a DNN architecture needs to be simplified to reduce computational complexity. After defining a DNN architecture, its parameters are tuned by the multi-sensor data. The inherent limitations of DNN algorithm are long training time and a large amount of training data. Based on the amount of training data points, parameter optimization may take several days or even weeks, but the computation itself (from the raw inputs to the output) takes a fraction of a second. If parameter training starts from scratch, a large number of training samples are required, hence a long training time often limits its practical deployment. To address this challenge and enhance system flexibility, two parameter optimization methods (*i.e.*, starting from scratch or preloading of guessing parameters) are supported in this project. If customers have enough time to optimize the DNN parameters, the original sensor data collected on-site will be stored and used for training. Or, if customers want a shorter training time, they can inform the system designers of some building knowledge (such as building type, location, and application) in advance. Then, before sending to the customers, a set of guessing parameters matching with the building to be deployed is preloaded as existing DNN parameters. This set of guessing parameters is derived from many buildings with similar type, architecture, and size. Thus, this set of guessing parameters is very likely to maintain the general characteristics of the building, and can be used as a semi-trained value. When such a DNN starts field operation, all parameters will be updated over time. This training method significantly improves the learning speed, quality, and versatility of the resulting solution.

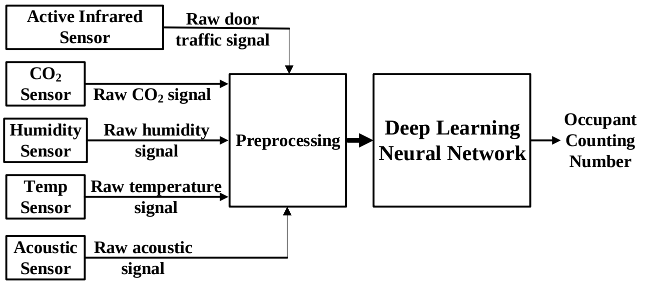

Figure 15. The proposed overall diagram of signal processing using DNN

Fig. 15 illustrates the overall diagram of proposed signal processing algorithm for building occupancy counting. The raw sensor data of door entry/exit, carbon dioxide, humidity, temperature, and acoustic are digitalized and preprocessed. Data preprocessing includes timestamp synchronization, deletion of outliers, and handling missing values. Next, the information of preprocessed multi-sensor data is fed to a deep neural network (DNN), which outputs the accurate number of occupancy. After the start of this design, the task of collecting sensor data is immediately carried out. Indoor environmental information is collected by individual sensors. Meanwhile, room occupancy information will be extracted manually or from surveillance cameras installed in these buildings. All these data samples will be fed into a deep neural network algorithm to train the relevant parameters. Upon completion of the training phase, on-site experiments are carried out in these buildings to test the accuracy of occupancy count.

D. Overview of Smart Building Collaborated with Selected Information Technologies

The combination of three information technologies leads to a hybrid smart sensor platform with deep machine learning algorithms for accurate occupancy counting towards energy-efficient buildings. The proposed platform consists of multiple types of inexpensive heterogeneous sensors that collect a wealth of environmental data points. As shown in Fig. 16, active infrared, temperature, acoustic, and CO_2 sensors are distributed and work collaboratively in each HVAC thermal zone. Specifically, personnel entry and exit to an HVAC zone are detected and monitored by active infrared sensors, which have been developed and tested in the preliminary experimental study in [24] and show great potential for accurate observation of door traffic in real time. In the preliminary study, it was found that deploying the proposed active infrared sensors in office buildings resulted in a low probability of false count due to temporary noise or signal interference. Therefore, in order to further improve the precision of occupancy detection, we envision to fuse and analyze these heterogeneous sensor data to correct this minor false counts obtained by active infrared sensors.

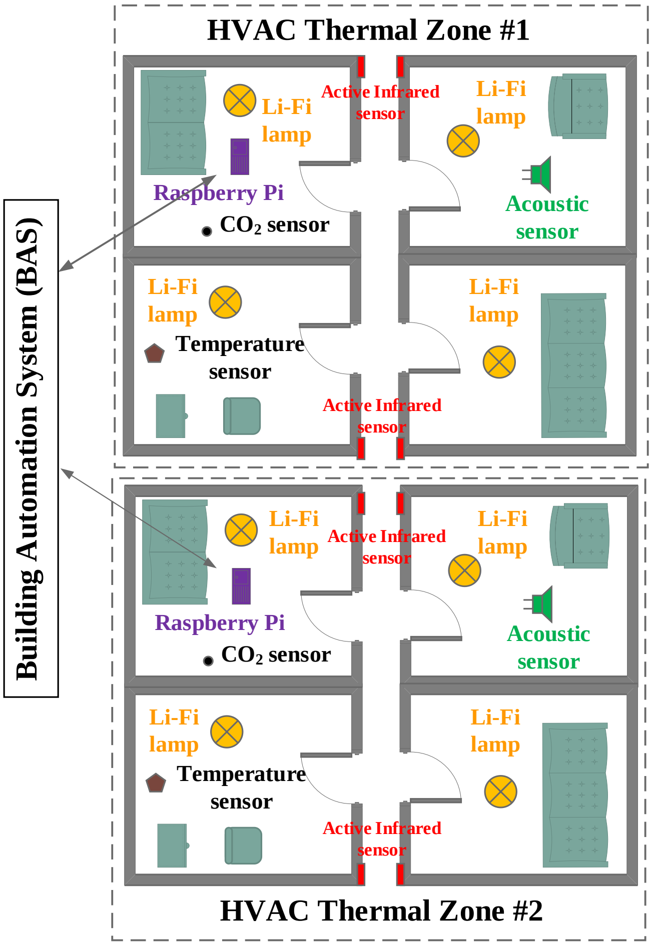

Figure 16. Overview of the proposed smart building collaborated with three information technologies

Due to its superior performance in multimodal data processing, deep neural network (DNN) algorithms are supposed to extract the cross-correlation patterns hidden behind multi-sensor data. The traditional DNN algorithms are very complex and power consuming, so it is not feasible to run traditional DNNs on cost-effective hardware, which consists of only a quad-core microprocessor and limited memory size. Here, we envision to investigate low-complexity, energy-efficient DNN implementation in the Raspberry Pi module to achieve fast end-to-end computation of building occupancy information. The future research efforts should be paid to simplify the traditional DNN algorithms and their corresponding software implementation. This DNN-based smart sensor platform supports automatic learning and calibration without human intervention. The built-in Wi-Fi server in a Raspberry Pi module provides Wi-Fi service for these heterogeneous sensors and the building automation system. In addition, building users can access the built-in Wi-Fi server to view real-time building occupancy quantity. Through Wi-Fi service, real-time building occupancy information is obtained and guides the BAS to dynamically control operation of HVAC equipment.

In this proposed design (Fig. 16), since all the processes of sensor data acquisition, communication, and computation are performed locally, this smart sensor system is self-contained. Being the most computationally intensive part, deep machine learning algorithms are run in Raspberry Pi modules to find data cross-correlation and improve the occupancy counting. No cloud or server computation is involved. Furthermore, based on the Li-Fi assisted indoor positioning technique [35], this design also provides a spatial distribution of occupants across an HVAC zone. This unique feature allows the building automation system to adjust the ventilation rate of each air diffuser. As a result, the HVAC system can be more energy efficient.

III. CONCLUSION

Energy-efficient smart building is a key contributor to low-carbon, sustainable society. In this work, we envision that three emerging information technologies will provide creative solutions to promote the development of smart buildings, which require demand-driven energy-efficient operation of HVAC equipment. Specifically, smart occupancy detection sensors, visible light communication for high-throughput communication and indoor positioning, and machine learning algorithms for multi-modal data fusion are reviewed and discussed. Through comparison with traditional technologies, advantages and drawback of these emerging technologies are highlighted. Finally, a design solution is proposed to utilize these three technologies and build a platform dedicated to accurate occupancy counting towards energy-efficient buildings. Such an integrated design solution is expected to enable end-to-end computation with favorable features of user transparency, low cost, good privacy, and high precision of occupancy count.

REFERENCES

[1] M. Moreno, B. Ubeda, A. Skarmeta, M. Zamora, How can we tackle energy efficiency in IoT based smart buildings? *Sensors.* vol. 14, pp. 9582-9614, 2014.

[2] M. Manic, K. Amarasinghe, J. Rodrigeuz-Andina, C. Rieger, "Intelligent buildings of the future: cyberaware, deep learning powered, and human interacting," *IEEE Industrial Electronics Mag.* vol. 10, pp. 32-49, 2016.

[3] S. Feng, P. Setoodeh, S. Haykin, "Smart home: cognitive interactive people-centric internet of things," *IEEE Commun. Mag.* vol. 55, pp. 34-39, 2017.

[4] Q. Huang, C. Lu, K. Chen, *Big Data Analytics for Sensor-Network Collected Intelligence*, 1st ed.; Elsevier: Aalborg, Denmark, pp. 225-240, 2017; ISBN: 9780128096253.

[5] H. Ghayvat, S. Mukhopadhyay, X. Gui, N. Suryadevara, "WSN-and IOT-based smart homes and their extension to smart buildings," *Sensors.* vol. 15, pp. 10350-10379, 2015.

[6] Y. Agarwal, B. Balaji, R. Gupta, J. Lyles; M. Wei, T. Weng, "Occupancy-driven energy management for smart building automation," In Proceedings of ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building, pp. 1-6, 2010.

[7] N. Li, G. Carlis, B. Gerber, "Measuring and monitoring occupancy with a RFID based system for demand-driven HVAC operations," *Automation in Construction.* vol. 24, pp. 89-99, 2012.

[8] C. Rohrig, D. Heb, F. Kunemund, "RFID-based localization of mobile robots using the received signal strength indicator of detected tags," *Engineering Letters*, vol. 24, no. 3, pp338-346, 2016.

[9] V. Erickson, Y. Lin, A. Kamthe, R. Brahme, A. Surana, A. Cerpa, M. Sohn, S. Narayanan, "Energy efficient building environment control strategies using real-time occupancy measurements," In Proceedings of ACM workshop on Embedded Sensing Systems for Energy Efficiency in Buildings, pp. 19-24, 2009.

[10] DOE Sensor FOA. Available online: https://arpa-e-foa.energy.gov/#FoaId2d3f7530-bdc3-4090-ae7c-0d5ca8584e07

[11] T. Labeodan, W. Zeiler, G. Boxem, Y. Zhao, "Occupancy measurement in commercial office buildings for demand driven control applications-a survey and detection system evaluation," *Energy and Buildings*. vol. 93, pp. 303-314, 2015.

[12] F. Manzoor, D. Linton, M. Loughlin, "Occupancy monitoring using passive RFID technology for efficient building lighting control," In Proceedings of International Workshop on RFID Technology, pp. 83-88, 2012.

[13] S. Uziel, T. Elste, W. Kattanek, D. Hollosi, S. Gerlach, S. Goetze, "Networked embedded acoustic processing system for smart building applications," In Proceedings of Design and Architectures for Signal and Image Processing, pp. 349-350, 2013.

[14] B. Kelly, D. Hollosi, P. Cousin, S. Leal, B. Lglar, A. Cavallaro, "Application of acoustic sensing technology for improving building energy efficiency," *Procedia Computer Science*, vol. 32, pp. 661-664, 2014.

[15] Q. Huang, Z, Ge, C. Lu, "Occupancy estimation in smart buildings using audio-processing techniques," In Proceedings of International Conference on Computing in Civil and Building Engineering, pp.1413-1420, 2016.

[16] Y. Benezeth, H. Laurent, B. Emile, C. Rosenberger, "Towards a sensor for detecting human presence and characterizing activity," *Energy and Buildings.* vol. 43, pp. 305-314, 2011.

[17] H. Ahmed, B. Faouzi, J. Caelen, "Detection and classification of the behavior of people in an intelligent building by camera," *Inter. J. Smart Sensing Intelligent Syst*. vol. 6, pp.1317-1342, 2013.

[18] Z. Sun, S. Wang, Z. Ma, "In-situ implementation and validation of a CO_2-based adaptive demand-controlled ventilation strategy in multi-zone office building," *Building and Environment.* vol. 46, pp. 124-133, 2011.

[19] N. Nassif, "A robust CO_2-based demand-controlled ventilation control strategy for multi-zone HVAC systems," *Energy and Buildings.* vol. 45, pp. 72-81, 2012.

[20] C. Mao, Q. Huang, "Occupancy estimation in smart building using hybrid CO_2/light wireless sensor network," *J. Applied Sciences and Arts*. vol. 1, article 5, 2017.

[21] Q. Huang, C. Mao, Y. Chen, "A compact and versatile wireless sensor prototype for affordable intelligent sensing and monitoring in smart buildings," In Proceedings of International Workshop on Computing in Civil Engineering, Seattle, pp. 155-161, 2017.

[22] A. Szczurek, M. Maciejewska, T. Pietrucha, "Occupancy determination based on time series of CO_2 concertation temperature and relative humidity," *Energy and Buildings.* vol. 147, pp. 142-154, 2017.

[23] L. Candanedo, V. Feldheim, "Accurate occupancy detection of an office room from light, temperature, humidity and CO_2 measurements using statistical learning models," *Energy and Buildings.* vol. 112, pp. 28-39, 2016.

[24] K. Rodriguez, N. Whetstone, S. Habel, Q. Huang, C. Lu, "Rapid Internet of Things (IoT) prototype for accurate people counting towards energy efficient buildings," *Journal of Information Technology in Construction*, under review, 2018.

[25] Lattice iCEstick evaluation kit. Available online: http://www.latticesemi.com/icestick

[26] C. Lu, V. Raghunathan, K. Roy, "Efficient design of micro-scale energy harvesting systems," *IEEE J Emerg Selected Top Circ Syst.* vol. 13, pp. 254–66, 2011.

[27] Q. Huang, C. Lu, M. Shaurette, "Feasibility study of indoor light energy harvesting for intelligent building environment management," In Proceedings of International High Performance Buildings Conference, 2010.

[28] Q. Huang, C. Lu, M. Shaurette, R. Cox, "Environmental thermal energy scavenging powered wireless sensor network for building monitoring," In Proceedings of International Symposium on Automation and Robotics in Construction, pp. 1376-1380, 2011.

[29] Netflix bandwidth recommendation, https://help.netflix.com/en/node/306

[30] Y. Bangash, Q. Abid, A. A, Y. Salhi, "Security issues and challenges in wireless sensor networks: a survey," *IAENG International Journal of Computer Science*, vol. 44, no.2, pp135-149, 2017.

[31] V. Arya, P. Priya, P. Omanakuttan, S. Baby. Li-Fi: the future technology in wireless communication. *Inter. J. Advanced Research in*

Electrical, Electronics and Instrumentation Engineering. vol. 4, pp. 2340-2343, 2015.
[32] M. Saaid, L. Wattisuttikulkij, Y. Zhao, P. Sangwongngam, "Visible light communication: opportunities, challenges and channel models. *Inter. J. Electronics & Informatics.* vol. 2, pp.1-11, 2013.
[33] H. Burchardt, N. Serafimovski, D. Tsonev, S. Videv, H. Haas, "VLC: beyond point-to-point communication," *IEEE Communications Mag.* vol. 52, pp. 98-105, 2014.
[34] X. Wu, M. Safari, H. Haas, "Access point selection for hybrid Li-Fi and Wi-Fi networks," *IEEE Trans. on Communications,* PP, 1, 2017.
[35] Q. Huang, Y. Zhang, Z. Ge, C. Lu, "Refining Wi-Fi based indoor localization with Li-Fi assisted model calibration in smart buildings," In Proceedings of International Conference on Computing in Civil and Building Engineering, pp.1358-1365, 2016.
[36] C. Lee, C. Zhang, M. Cantore, R. Farrell, S. Oh, T. Margalith, J. Speck, S. Nakamura, J. Bowers, P. Denbaars, "2.6GHz high-speed visible light communication of 450 nm GaN laser diode by direct modulation," In Proceedings of IEEE Photonics Society Summer Topical Meeting Series, pp. 112-113, 2015.
[37] T. Koonen, J. Oh, A. Khalid, K. Mekonnen, M. Vega, Z. Cao, E. Tangdiongga, "2D beam-steered high-capability optical wireless communication. In Proceedings of IEEE Photonics Society Summer Topical Meeting Series, pp. 132-133, 2016.
[38] M. Islim, R. Ferreira, X. He, E. Xie, S. Videv, S. Viola, S. Watson, N. Bamiedakis, R. Penty, I. White, A. Kelly, E. Gu, H. Haas, M. Dawson, "Towards 10 Gb/s orthogonal frequency division multiplexing-based visible light communication using a GaN violet micro-LED," *Photonics Research.* vol. 5, A35, 2017.
[39] J. Liu, T. Chen, J. Bao, J. Kim, J. Wang, "Location technology-based mobile shopping service systems," *Inter. J. Hybrid Information Technology.* vol. 5, pp. 133-142, 2012.
[40] N. Greene, L. Hand, "Location-based services: an important building block to enhance the customer experience," White paper, CISCO; 2014.
[41] W. Kuo, Yung-Sheng Chen, Kui-Tai Cheng, and Tai-Wei Lu, "Signal strength based indoor and outdoor localization scheme in Zigbee sensor networks," *IAENG International Journal of Computer Science*, vol. 43, no.1, pp55-64, 2016.
[42] R. Henniges, "Current approaches of Wi-Fi positioning," TU-Berlin, pp. 1-8, 2012.
[43] T. Kitasuka, T. Nakanishi, A. Fukuda, "Wireless LAN based indoor positioning system WIPS and its simulation," In Proceedings of IEEE Pacific Rim Conference on Communications, Computers and Signal Processing, pp. 272–275, 2003.
[44] X. Chen, S. Zhou, "Improved Wi-Fi indoor positioning based on particle swarm optimization," *IEEE Sensors J.* PP. 1, 2017.
[45] M. Mahamud, M. Chowdhury, "Indoor location system with Wi-Fi and alternative cellular network signal," *Inter. J. Multimedia and Ubiquitous Engineering*. vol. 10, pp. 59-70, 2015.
[46] Y. Zhuang, J. Yang, Y. Li, L. Qi, N. Sheimy, "Smartphone-based indoor localization with Bluetooth low energy beacons," *Sensors.* vol. 16, pp. 596, 2016.
[47] G. Blasio, A. Arencibia, C. Garcia, J. Molina, C. Gil, "Study on an indoor positioning system for harsh environments based on Wi-Fi and Bluetooth low energy," *Sensors*. vol. 17, pp. 1299, 2017.
[48] E. Mok, B. Cheung, "An improved neural network training algorithm for Wi-Fi fingerprinting positioning," *J. Geo-Information.* vol. 2, pp. 854-868, 2013.
[49] T. Tsai, C. Chang, S. Chen, "Vision based indoor positioning for intelligent buildings," In Proceedings of International Conference on Intelligent Green Building and Smart Grid, 2016.
[50] S. Saab, Z. Nakad, "A standalone RFID indoor positioning system using passive tags," *IEEE Trans. on Industrial Electronics.* vol. 58, pp. 1961-1970, 2011.
[51] J. Gao, F. Yang, X. Ma, "Indoor positioning system based on visible light communication with gray-coded identification," In Proceedings of International Wireless Communications and Mobile Computing Conference, pp. 899-903, 2017.
[52] J. Ramiez, M. Chacon, J. Chacon, "Artificial neural image processing applications: a survey," *Engineering Letters*, vol. 20, no. 1, pp68-80, 2012.
[53] C. Costa, M. Santos, "Big data: state-of-the-art concepts, techniques, technologies, modeling approaches and research challenges," *IAENG International Journal of Computer Science*, vol. 44, no. 3, pp285-301, 2017.
[54] Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol., 86, pp. 2278-2324, 1998.
[55] A. Krizhevsky, I. Sutskever, G. Hinton, "Imagenet classification with deep convolutional neural networks," Advances in Neural Information Processing Systems, pp. 1097-1105, 2012.
[56] K. Simonyan, A. Zisserman, "Very deep convolutional networks for large-scale image recognition,"arXiv preprint arXiv: 1409.1556, 2014.
[57] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich, "Going deeper with convolutions," In Proceedings of IEEE Conference on Computer vision and Pattern Recognition, pp. 1-9, 2015.
[58] K. He, X. Zhang, S. Ren, J. Sun, "Deep residual learning for image recognition," In Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, pp. 770-778, 2016.
[59] M. Chen, Y. Zhang, C. Lu, "Efficient architecture of variable size HEVC 2D-DCT for FPGA platforms," *International Journal of Electronics and Communications*, vol. 73, pp. 1-8, 2017.
[60] G. Pastuszak, A. Abramowski, "Algorithm and architecture design of the H.265/HEVC intra encoder," *IEEE Trans. Circuits Syst. Video Technol*., vol. 26, pp. 210-222, 2016.
[61] Y. Zhang, C. Lu, "A highly-parallel hardware architecture of table-based CABAC bit rate estimator in HEVC intra encoder," *IEEE Trans. Circuits Syst. Video Technol*., in preprint, 2018.
[62] S. Han, H. Mao, W. Dally, "Deep compression: compressing deep neural networks with pruning, trained quantization and Huffman coding," In Proceedings of International Conference on Learning Representations, pp. 1-14, 2016.
[63] F. Iandola, S. Han, M. Moskewicz, K. Ashraf, W. Dally, K. Keutzer, "SqueezNet: AlexNet-level accuracy with 50× fewer parameters and < 0.5dB model size," In Proceedings of International Conference on Learning Representations, pp. 1-13, 2016.
[64] M. Rastegari, V. Ordonez, J. Redmon, A. Farhadi, "XNOR-Net: imagenet classification using binary convolutional neural networks," In Proceedings of European Conference on Computer Vision, pp. 1-17, 2016.
[65] T. Dettmers, "8-bit approximations for parallelism in deep learning," arXiv preprint arXiv: 1511.04561, 2016.
[66] B. Brown, H. Card, "Stochastic neural computation. I. Computational elements," *IEEE Trans. on Computers*, vol. 50, pp. 891-905, Sep 2001.
[67] P. Ting, J. Hayes, "Stochastic logic realization of matrix operations," In Proceedings of Euromicro Conference on Digital System Design, pp. 356-364, Aug 2014.
[68] V. Lee, A. Alaghi, J. Hayes, V. Sathe, L. Ceze, "Energy-efficient hybrid stochastic-binary neural networks for near-sensor computing," In Proceedings of Design, Automation & Test in Europe Conference and Exhibition, pp. 13-18, 2017.
[69] Y. Xie, S. Liao, B. Yuan, Y. Wang, Z. Wang, "Fully-parallel area-efficient deep neural network design using stochastic computing," *IEEE Trans. on Circ. and Syst. II*, vol. 64, pp. 1382-1386, 2017.
[70] J. Ortega, L. Han, N. Whittacker, N. Bowring, "A machine learning based approach to model user occupancy and activity patterns for energy saving in buildings," In Proceedings of Science and Information Conference, pp. 474–482, 2015.
[71] Z. Yang, N. Li, B. Gerber, M. Orosz, "A multi-sensor based occupancy estimation model for supporting demand driven HVAC operations," In Proceedings of Symposium on Simulation for Architecture and Urban Design, no. 2, 2012.
[72] A. Javed, H. Larijani, A. Ahmadinia, D. Gibson, "Smart random neural network controller for HVAC using cloud computing technology," *IEEE Trans. on Industrial Informatics.* vol.12, pp. 351-360, 2017.
[73] T. Ekwevugbe, N. Brown, V. Pakka, "Real-time building occupancy sensing for supporting demand driven HVAC operations," In Proceedings of International Conference for Enhanced Building Operations, 2013.
[74] Y. Raykov, E. Ozer, G. Dasika, A. Boukouvalas, M. Little, "Predicting room occupancy with a single passive infrared sensor through behavior extraction," In Proceedings of International Joint Conference on Pervasive and Ubiquitous Computing, pp. 1016-1027, 2016.
[75] C. Leech, Y. Raykov, E. Ozer, G. Merrett, "Real-time room occupancy estimation with Bayesian machine learning using a single PIR sensor and microcontroller," In Proceedings of IEEE Sensors Applications Symposium, pp. 1-6, 2017.
[76] O. Shih, A. Rowe, "Occupancy estimation using ultrasonic chirps," In Proceedings of ACM International Conference on Cyber-Physical Systems, pp. 149-158, 2015.
[77] C. Jiang, M. Masood, Y. Soh, H. Li, "Indoor occupancy estimation from carbon dioxide concentration," *Energy and Buildings.* vol. 131, pp.132-141, 2016.

Qian Huang received the Ph.D. degree in Building Construction Management department of Purdue University, West Lafayette, Indiana, in 2013. Starting from August 2015, Dr. Huang is a tenure-track assistant professor in School of Architecture at Southern Illinois University Carbondale, Illinois, USA. Her research interests include information technology for building monitoring and control, wireless sensor network, energy harvesting, big data analytics on smart buildings. Dr. Huang has published more than 20 international conference and journal papers in these areas.