IoT-based Occupancy Monitoring Techniques for Energy-Efficient Smart Buildings

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***Abstract*—With the proliferation of Internet of Things (IoT) devices such as smartphones, sensors, cameras, and RFIDs, it is possible to collect massive amount of data for localization and tracking of people within commercial buildings. Enabled by such occupancy monitoring capabilities, there are extensive opportunities for improving the energy consumption of buildings via smart HVAC control. In this respect, the major challenges we envision are 1) to achieve occupancy monitoring in a minimally intrusive way, e.g., using the existing infrastructure in the buildings and not requiring installation of any apps in the users' smart devices, and 2) to develop effective data fusion techniques for improving occupancy monitoring accuracy using a multitude of sources. This paper surveys the existing works on occupancy monitoring and multi-modal data fusion techniques for smart commercial buildings. The goal is to lay down a framework for future research to exploit the spatio-temporal data obtained from one or more of various IoT devices such as temperature sensors, surveillance cameras, and RFID tags that may be already in use in the buildings. A comparative analysis of existing approaches and future predictions for research challenges are also provided.**

***Index Terms*—Big data, data fusion, data mining, energy efficiency, hidden Markov model (HMM), HVAC, localization, Markov chain, occupancy monitoring, positioning, position estimation, WLAN, WiFi, wireless location estimation.**

I. Introduction

Smart buildings are becoming a reality with the integration of Building Management Systems (BMS) [1] with an underlying monitoring and communication infrastructure that consists of smart devices such as sensors, cameras, RFIDs, meters, and actuators. These smart devices, along with the communication infrastructure, are referred to as Internet of Things (IoT). The BMS manage various crucial components of the buildings such as heating, ventilating, and air conditioning (HVAC), gas, lighting, security system, and fire system, and it can communicate with the IoT devices.

With the availability of IoTs in commercial buildings, building occupants and environment can be monitored in real time. In this way, we can have real-time access to occupancy counts in different zones of the building and even locate most of the users carrying a wireless device. This real-time occupancy status information can be used in a variety of applications controlled by the BMS. For example, the smart building systems of the future can adjust their *energy consumption* by intelligently controlling the HVAC, and respond promptly to any potential issues that can put the building off its track to carbon neutrality [2], [3]. In addition to energy issues, real-time occupancy tracking may also help rescuing survivors in case of emergency response applications [4]. The security or fire system can benefit from this information through the BMS. Finally, this information may also be used to improve building surveillance and security, and help in better deploying the wireless communication infrastructure for fulfilling ubiquitous throughput guarantees throughout the buildings.

Due to such advantages of occupancy detection/monitoring, many approaches have been proposed in the literature by considering the use of different devices, assumptions, and goals. These approaches have certain drawbacks with respect to accuracy, cost, intrusiveness, and privacy. Accuracy, cost and intrusiveness are inter-related in the sense that with the increased cost, you can deploy additional devices (such as various sensors, RFIDS, cameras) and increase the accuracy of the system while at the same time increase the intrusiveness. Therefore, a wise method to reduce costs is to rely on the existing infrastructure as much as possible. This automatically addresses the intrusiveness issue since there will be no need to deploy additional devices inside the rooms, and additional applications on the users' devices. Nonetheless, this raises the question of accuracy which may be severely affected.

This paper provides an analysis of the existing approaches and help address the aforementioned issue by promoting the use of multi-modal data fusion that will be collected from the existing IoT network. A data fusion process could improve the accuracy of occupancy detection while maintaining a low intrusiveness. By exploiting the synergy among the available data, information fusion techniques can filter noisy measurements coming from IoT devices, and make predictions and inferences about occupancy status. Specifically, we first analyze the variations of the problem and the available IoT devices and then survey the existing works with respect to these assumptions. We analyze their abilities to address the issues of accuracy, cost, intrusiveness and privacy. We finally consider data fusion approaches and investigate how these techniques can be exploited to come up with more advanced occupancy monitoring techniques that can significantly reduce the energy consumption of the building HVAC systems.

The paper is organized as follows. In the next section,

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we define the variation of occupancy problems and describe the available IoT devices along with the classification of approaches in the literature. The following sections are dedicated to each of these classes. Finally we provide a list of future challenges and conclude the paper.

II. Problem Definitions and Classifications

There are a number of variations when we refer to *Occupancy Monitoring* problem. These are interrelated but depending on the goal of the application, in the past, various forms of the problem are studied. We show them in the form of subset/superset relationships in Fig. 1.

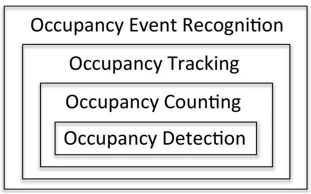

Fig. 1: Occupancy monitoring problems.

- **Occupancy Detection**: This problem studies whether a space is occupied or not at a given time. This is typically in the form of binary answers which does not tell how many people exists if the space is occupied. The spaces considered here are typically offices or private spaces. Occupancy detection of the public spaces (e.g., meeting rooms, aisles, cafeterias), on the other hand, is more challenging. Typically, these public spaces can either be monitored via other means (e.g., cameras) or by default considered occupied for HVAC applications.
- **Occupancy Counting**: The goal of this problem is to determine the total number of people in a building at a given time. There are two versions of this problem: First, counting all the people in the whole building. Second, counting people based on some predefined zones. The zones can be defined, for example, using HVAC zones, offices, or WiFi access point (AP) coverage areas. The granularity of the zones differ in most of the studies.
- **Occupancy Tracking**: This problem can be considered as the superset of the all of the above problems. It not only detects people, but also counts, locates, and tracks them. The solutions to this problem can utilize the well-known user localization algorithms that run on the network side rather than the user devices.
- **Occupancy Event/Behavior Recognition**: This problem is mostly related with the activities of the users once they are detected at certain locations. The activities can be individual or collective. Through occupancy event/behavior recognition, the behavior analysis of the individuals can be done and used for intelligent HVAC control.

When investigating these problems, researchers relied on several network and IoT devices. These can also be classified into the following categories in order to assess the cost and intrusiveness of the approaches [5].

- *Tier-1*: Approaches which rely on the existing WiFi infrastructure without any addition of hardware or software.
- *Tier-2*: Approaches which additionally require new software to be installed on APs or client devices.
- *Tier-3*: Approaches which requires new hardware/software deployment. This category can either aggregate several IoT devices or use one of the other IoTs such as sensors or cameras.

In this paper, we survey the existing occupancy monitoring approaches based on the tiers above. Specifically, Tier-1 and Tier-2 are considered under WiFi-based occupancy monitoring. Tier-3 can be divided into several classes, where we will survey sensor-based and camera-based occupancy monitoring techniques in this paper. The approaches that fused data from several IoTs will also be reviewed under data fusion based occupancy monitoring techniques.

III. WiFi-based Occupancy Monitoring

Most of the early building HVAC actuation systems are based on the occupancy data collected from sensors and cameras, which are deployed specifically for HVAC systems. Obviously, there is a major cost associated with the hardware, and the design, setup and maintenance of the data collection network. In this regard, Erickson et al. [6] report an expense of $147 K for just the hardware for a three floor building, and wireless motion sensors are estimated to cost over $120 K for a five floor building testbed. In addition to hardware cost, the inconvenience of deployment and the maintenance issues make it unattractive for commercial building owners to invest on the deployment of smart technologies for energy-efficiency purposes. Therefore, there is a research trend recently towards the use of existing communication infrastructure, such as the widely available WiFi AP infrastructure in buildings.

WiFi APs have been used extensively for indoor localization in the past [7]–[10]. These works, however, focus on individual user localization, assuming that an individual carries a wireless device and in most cases an app on the user's device is needed. Nevertheless, some of these works can still be leveraged in occupancy monitoring. For instance, fingerprinting-based training schemes can be employed to localize people when the RSSI values of these users can be obtained from the APs or log files. As an example, the approach in [11] proposes using RSSI values extracted from APs to locate people and hence the occupancy. The idea is to install a packet analyzer at each AP and capture each incoming packet via *tcpdump*. The packets are forwarded to a central computer via SSH connection to extract MAC addresses and the corresponding RSSI values. The authors use a coarse-grained localization (i.e., based on zones) which is inspired from the idea of passive localization of rogue access points [12].

Another recent work that focuses on coarse-grained localization is reported in [13]. The authors solely utilize WiFi APs along with the users' smartphones to build a system in the Department of Computer Science at UC San Diego. The basic source of user information is the Authentication, Authorization and Accounting (AAA) WiFi logs which is augmented with metadata information such as occupant identity, WiFi MAC address and AP location within the building to improve the accuracy of occupancy detection further. The authors show that the proposed system can be easily integrated with building HVAC system and can actuate it effectively. Based on the experiments conducted for 10 days on 116 occupants, the authors show that the proposed approach infers occupancy correctly for 86% of the time, with only 6.2% false negative occupancy detections in personal spaces. The inaccuracies are mostly attributed to aggressive power management by smartphones which stops their WiFi connections temporarily. The authors report savings of 17.8% in the HVAC electrical energy consumption through this technique.

There are other works that somewhat utilizes WiFi but complements it with other information. Ghai et al. [14] use a combination of WiFi signals, calendar schedules, personal computer activity and instant-messaging client status to infer the occupancy within cubicles with an accuracy of up to 91%. However, the algorithms have been evaluated for just 5 volunteers, and do not evaluate scalability. Similarly, the work in [15] complements data from APs with sensors and cloud-based calendars to estimate the occupancy in buildings to be used in emergency response. The WiFi-based approach uses an intrusion detection tool, namely SNORT, to analyze HTTP traffic and identify mobile devices that are connected. Once the MAC address of a device is identified, the AP it is connected to is used to get the zone of the mobile device. This information is then used along with sensors and room schedules to come up with an estimate of the occupancy in the building. The work in [5] used the WiFi users' DHCP leases to infer the occupancy information. Additionally the authors looked at other options such as PC Monitor software, PIR sensors etc. The results indicated that PIR sensors that are attached to computer monitors provide the best accuracy. DHCP approach had issues since a user may get connected to different APs when walking in different locations which may not necessarily indicate its actual zone. We note that none of these approaches measure energy-efficiency improvement since their focus is just the improvement of the accuracy of occupancy monitoring.

IV. Camera-based Monitoring

Camera-based people counting research can be classified into three: a) count the number of people by extracting features that would describe body parts of a person, b) track moving regions/pixels and cluster pixels based on their trajectories to yield one cluster per person, and c) extract features and use them to estimate the number of people directly by regression [16]. Counting people directly may be challenging due to partial/complete object occlusion [17] and difficulty to locate and analyze the window(s) having a person (or people) [17]. Tracking moving trajectories may help to overcome the occlusion problem, but it has to deal with the complexity of different motion paths observed by different parts of a moving body and intersecting paths of multiple people [17]. Regression methods may help to count directly but they do not provide information about where people actually are. Regression methods may not help fusion of data from multiple sensors directly since they only yield the count.

The body parts that are usually used for counting people are face [18], head [19], head-shoulder [20], upper-body, and skeleton [21]. An important number of algorithms rely on motion information (assumes that people should move for counting). However, there are also indoor or outdoor environments where people may have little to no motion. Examples include people waiting at long lines at airports [22] or students studying at a desk in a library. In such cases, approaches relying on motion would not yield desirable outcomes for people counting.

A study that purely utilizes a camera sensor network on the ceilings of offices is reported in [6], [23]. The cameras use lightweight algorithms in order to do background extraction and object recognition before the data is sent to a data server. The occupancy model considers inter-room relationships over time, which are captured through real-world data. In particular, the multi-variate Gaussian probability density function for the occupancy vector $\boldsymbol{O}_h = [\mathbf{r}_1, ..., \mathbf{r}_m]$ at an hour h is defined as

$$p(\boldsymbol{O}_h;\boldsymbol{\mu}_h, \boldsymbol{\Sigma}_h) = \frac{1}{(2\pi)^{n/2}|\boldsymbol{\Sigma}|^{1/2}} \times \exp\left\{\frac{1}{2}(\boldsymbol{O}_h - \boldsymbol{\mu}_h)'\boldsymbol{\Sigma}_h^{-1}(\boldsymbol{O}_h - \boldsymbol{\mu}_h)\right\} , \quad (1)$$

where $1 \leq h \leq 24$ is the hour in a day, $\mathbf{r}_i$ is a vector of occupancy for room i ($1 \leq i \leq m$) (captured every second within the hour h), $\boldsymbol{\mu}_h = (\mu_1, ..., \mu_m)$ is a vector that includes the average occupancy counts in each room during hour h, and $\boldsymbol{\Sigma}_h$ is the covariance matrix obtained from $\boldsymbol{O}_h$. For a given occupancy realization, using (1), it is possible to calculate the probability of an occupancy pattern in different rooms in the future.

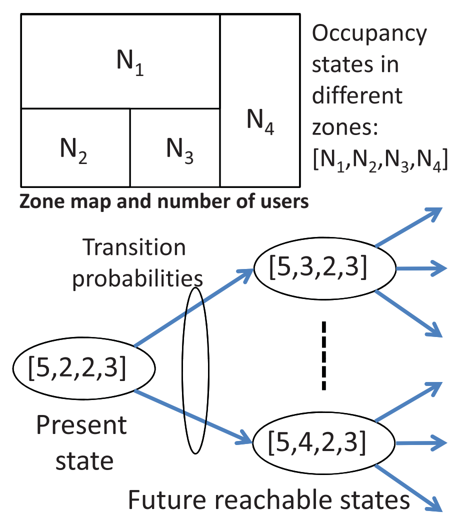

Fig. 2: Markov chain building occupancy model, with states represented by a sequence that holds the number of users in different zones.

The multi-variate Gaussian model (MVGM) in (1), while takes into account temporal and inter-room correlations, does not account for previous user behavior, nor does it capture the information about the rarely used zones. In order to address these shortcomings, [23] further introduces a Markov Chain model. In particular, the states of the Markov chain are the occupancy at each zone ($[s_1, ..., s_m]$ for m zones), where the transition from one state to a different state depends only on 1) the current state, and 2) time (see Fig. 2). With L denoting the largest number of occupancy count in a zone, then, there may be a total of L^m states in the Markov chain, with many of the transition probabilities being equal to zero due to infeasibility to move between certain zones. The transition probabilities are captured through training data. Two variations are also discussed in [23] for more effective operation: closest distance Markov chain and blended Markov chain.

V. Sensor-network based Occupancy Monitoring

Most of the initial works in occupancy monitoring considered deploying special sensors within the building in order to detect presence. While sensors are typically used to complement the other approaches, there were some works which solely used sensors. For instance, Dodier et al. [24] proposed a Bayesian belief network comprising of three PIR sensors and a telephone sensor to probabilistically infer occupancy. Occupied state of individual offices/rooms was modeled with a Markov chain. Their system had a detection accuracy of 76%, but was unable to count the number of occupants.

In [25], [26], three machine learning techniques are used to process the data from a sensor network, which collects the feature information about the CO_2, lighting, temperature, humidity, motion, and acoustic signals in the environment. In particular, support vector machine, neural network, and hidden Markov model (HMM) are used to obtain occupancy information from the estimated features. Experimental results show that the HMMs model the number of occupants in a zone more realistically, as 1) it can discount sudden short changes in the occupancy level, and 2) it can maintain a constant occupancy level during static periods. In another related work [27], [28], features extracted from acoustic, lighting, motion, and CO_2 sensors are used to capture occupancy patterns using hidden semi-Markov models. Experiments conducted in a one-week interval show that the proposed approach yields 92% accuracy in estimating the number of occupants in a room which can accommodate up to 7 people.

VI. Data Fusion For Occupancy Tracking

Indoor occupancy tracking accuracy can be improved significantly by using data fusion techniques to simultaneously utilize the information collected at different types of sensors, such as cameras, radio receivers, and occupancy detection sensors (CO_2, PIR, etc.). In this section, data fusion techniques recently introduced in the literature in the context of occupancy monitoring will be briefly summarized.

A data fusion based occupancy monitoring technique that uses information from a variety of sensors is introduced in [29]. Each collection of sensor devices is integrated into an Arduino microcontroller with WiFi support, and they are mounted close to entrance door in a room at a height of 1.5 m. For data fusion, a radial basis function (RBF) neural network is used at an Arduino device, which takes multiple sensory information as inputs, and outputs an occupancy count in a room, in the form of a number between $0 - 10$. The sensory inputs can be instant variables (e.g., lighting, sound, CO_2 concentration, temperature), count variables (e.g., motion count over the last minute), and average variables (sound average over 5 seconds and 5 minutes). Based on the data collected with one minute sampling rate over 20 consecutive days in two laboratory rooms, up to 88% occupancy monitoring accuracy is reported in [29].

In another related work, data fusion technique that relies on an adaptive neural-fuzzy inference system (ANFIS) is presented in [30]. The authors use the data collected from humidity, illuminance and temperature sensors (all of which are logged every five minutes), as well as the data from CO_2 and volatile organic compound (VOC) sensors (both logged every two minutes) to estimate the occupancy pattern using the ANFIS approach. Based on the measurement data, a significant correlation has been reported between the occupancy pattern and the building energy consumption. Therefore, along with the other sensory data, building energy consumption data is also used in the ANFIS data fusion technique for occupancy monitoring.

Meyn et al. [31] improved occupancy detection accuracy by using a sensor network comprising CO_2 sensors, digital video cameras, and PIR detectors, as well as historic building utilization data for occupancy estimation at the building level. The system used a receding-horizon convex optimization algorithm to infer occupancy numbers which is an extension of Kalman filter. Their system detection accuracy reached 89%. However, it was not able to estimate occupancy numbers at the room level.

A technique for fusing the information from Bluetooth and WiFi technologies for improved indoor localization is proposed in [32]. Using Bluetooth measurements, the zone where the desired user is located is identified. Subsequently, the fingerprint based WiFi localization technique is applied to find the user's location considering only the fingerprints within the given zone. Reported results in [32] show that an average localization accuracy of 2.32 m can be obtained when both are used simultaneously, compared to 2.69 m localization error when only WiFi is used for localization.

A client-side data fusion technique for combining information from wireless LAN access points and a camera vision system available at the client is introduced in [33]. Initially, a database of feature points corresponding to camera image sequences obtained at different locations in a building is generated. During real-time localization, first, a tentative client location is estimated by using the received wireless LAN signals and a sparse Bayesian learning technique. This location is then used to search the natural feature points in the image database to improve the localization accuracy. In [34], the signals from 2.4 GHz and 5 GHz WiFi APs are combined at the client side for a more accurate localization through particle filters. Furthermore, data fusion with accelerometer and gyroscope are used to enhance the position estimates.

A comprehensive survey on information fusion techniques in general for wireless sensor networks is presented in [35], which studies: 1) multi-sensor inference techniques including Bayesian inference, Dempster-Shafer inference, fuzzy logic, neural networks, abductive reasoning, and semantic information fusion; 2) multi-sensor estimation techniques including maximum likelihood (ML), maximum a posteriori (MAP), and least squares (LS) estimation, moving average filter, Kalman filter, and particle filter; and 3) multi-sensor feature map techniques involving occupancy grids and network scans.

VII. Comparative Analysis and Future Predictions

Table I summarizes the existing occupancy monitoring approaches in terms of the used infrastructure and techniques applied. The table indicates that most of the existing works relied heavily on sensor's which need to be specially deployed. While different techniques are used based on artificial intelligence, machine learning and statistics, multi-modal data fusion was not applied in most of the works. Combination of WiFi, sensors, cameras and other resources at the same time was not investigated at all. The analysis of these helps us to determine a number of future trends in the area of smart buildings:

- *Exploiting IoT within the Buildings*: With the proliferation of IoT devices and technologies, there is a great potential to exploit their communications for occupancy monitoring. In addition to smart phones, the upcoming years will witness the use of wearable sensors, glasses, watches and RFIDs on objects. If one can collect the signals emitting from these devices, they can help increase the accuracy of occupancy monitoring significantly.
- *Using Existing WiFi Infrastructure*: There is a grown interest on infrastructure-based occupancy monitoring for zero costs and intrusiveness. Typically, the goal is to only rely on the WiFi and user's wireless devices to get zone level occupancy information and then complement this information with other IoT devices, if any, in order to further increase the granularity of occupancy information.
- *Using Localization*: While zone-based coating of people provides a coarse-grained occupancy detection, the exact number and location of the people are still needed for especially shared spaces in the buildings. Indoor localization has the potential to reduce the zone of detection enough for occupancy inference in shared spaces [13]. Thus, there is a need to integrate localization with the existing monitoring systems to significantly increase the energy gains.
- *Multi-modal Data Fusion*: In order to increase the accuracy and reduce the costs, fusing data coming from multiple sources within the building is another important trend. As mentioned, with the maturing of IoT technologies, there will be additional sources that can provide additional data for fusion. The techniques in [35] can be adapted for various buildings with different IoT devices.
- *Privacy Preservation*: While most of the occupancy monitoring approaches focus on the people count and do not track the individuals, accurate occupant tracking may pose challenges regarding privacy. The existing techniques for user localization privacy are mostly based on the mechanisms applied at client side. New privacy mechanisms are needed to be applied to occupancy tracking.

VIII. Conclusion

In this paper, we surveyed and analyzed the existing efforts for occupancy monitoring in smart buildings for energy-efficiency purposes. Specifically, we first identified the problem types that are related to people occupancy. We also discussed the past research that solely focused on using sensors and cameras. Finally, we investigated the current efforts where IoT comes into picture with the involvement of smart phones, motion sensors and WiFi APs. The existing approaches indicated a trend towards the use of existing IoTs that are available within the buildings. With the goal of using minimal hardware and software costs, future smart buildings have a great potential to save energy by employing smart control strategies on HVAC through the help of data collected via IoT. We concluded the paper by identifying major future trends in this emerging area.

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TABLE I: Review of existing literature on occupancy modeling and monitoring for smart buildings.

Approach	WiFi	Sensor	Camera	Other	Techniques Used	Fusion	Privacy
[11]	X	-	-	TCP Dump	Passive Localization	No	None
[13]	X	-	-	AAA WiFi Logs	Zone-based Localization	No	Hiding MACs
[14]	X	-	-	Calendars	Regression & Classification	Yes	None
[15]	X	X	-	Cloud Schedules	Histogram	Yes	None
[5]	X	X	-	DHCP Leases	Simple Counting	No	None
[6], [23]	-	-	X	-	Markov Chain	No	Infrared Camera
[24]	-	X	-	Telephone sensors	Bayesian Network	No	N/A
[25], [26]	-	X	-	-	Machine Learning	No	N/A
[29]	-	X	-	-	Neural Network	Yes	N/A
[30]	-	X	-	-	Neural Fuzzy Inference	Yes	N/A
[31]	-	X	X	Building utilization data	Extended Kalman Filter	Yes	None

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