Building Occupancy Estimation and Detection: A Review

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Abstract

Building occupancy is of great importance for energy efficient control of buildings. A large number of works have been developed for the estimation and detection of building occupancy. In this paper, we present a comprehensive review on building occupancy estimation and detection. The estimation and detection systems are divided into different categories based on the involved sensors. Since the fusion of multiple sensors is widely adopted for building occupancy estimation and detection, a review on the systems based on different combination of sensors is also performed. Then, we conduct a comparison of different sensor types for the estimation and detection of occupancy. Finally, some potential future research directions are indicated based on current progresses of the systems.

Keywords: Occupancy estimation, occupancy detection, sensor, fusion

1. Introduction

Buildings consume around 40% of total energy in the world to provide a comfortable and healthy indoor environment for occupants [1]. Due to the energy crises and the conciseness of sustainable development, more and more attention has been paid on energy efficient buildings. To achieve this objective, building occupancy information is one of the key components [2, 3]. For

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instance, the presence and absence of occupants will determine the operation time of HVAC (Heating, Ventilation, and Air Conditioning) systems in buildings [4, 5]. Meanwhile, the number of occupants in a thermal zone will indicate the cooling or heating load of this area. Some occupancy driven building climate control systems have been presented in the literature to save energy and provide a comfortable indoor environment. Agarwal et al. proposed a low cost system to accurately detect the presence and absence of occupants in offices, and they showed that the system can achieve an energy saving from 10% to 15% with the detected occupancy information [6]. Yang and Becerik-Gerber demonstrated that the HVAC system is able to save up to 9% of the energy if occupancy based HVAC schedules are utilized [7]. In [8], Wang et al. proposed a predictive control algorithm for building environmental control based on occupancy information. They showed a reduction of around 40% of energy usage for buildings without compromising thermal comfort and air quality. Occupancy information also determines the operation time of lighting systems [9, 10]. Leephakpreeda indicated a potential energy saving of lighting systems from 35% to 75% with the proposed occupancy based lighting control [11]. A survey of occupancy based lighting control systems can be found in [12]. Moreover, the occupancy presence information is important for building security management and the occupancy distribution in buildings is also vital in emergency evacuations.

To achieve accurate building occupancy estimation and detection, many types of sensors have been involved when considering different applications. For example, passive infrared (PIR) sensors can be used to detect the presence and absence of occupants in an office [13]. With cameras, we are able to obtain the number of occupants in a room [14]. Based on CO_2 sensors, we can obtain a rough estimation of occupancy [15]. Different sensors have unique properties and limitations for building occupancy estimation and detection. Therefore, we intend to categorize different occupancy estimation and detection solutions based on different types of sensors.

Since building occupancy estimation and detection are active and hot topics in the past decades, and to our best knowledge, no comprehensive reviews have been made to compare and summarize different solutions for them, in this paper, we attempt to perform a qualitative overview for building occupancy estimation and detection. Meanwhile, we also summarize and compare different solutions on some basic criteria, such as cost, performance and limitations. Finally, some potential research directions are highlighted for further research. In what follows, occupancy estimation means to estimate the number or range of occupants; and occupancy detection refers to detecting the presence and absence of occupants for an area.

The paper is organized as follows: Section 1 presents the background and motivation of this review. Section 2 comprehensively reviews current solutions for occupancy estimation and detection with different sensor types and the fusion of sensors. Section 3 compares different type of sensors for occupancy estimation and detection to give a clear guideline on the selection of sensors. Section 4 presents some potential future research directions to encourage more research efforts on this area. Section 5 concludes this work. A schematic overview of this paper can be found in Figure 1.

2. Occupancy estimation and detection with different types of sensors

In this section, we perform a comprehensive overview of current solutions for building occupancy estimation and detection with different sensor categories. Meanwhile, we also review some systems for occupancy estimation and detection with the fusion of multiple sensors.

2.1. PIR

The PIR sensors can detect the infrared radiation changes caused by the movement of subjects. Therefore, they are able to detect the motion of occupants, indicating the presence of occupants. Some occupancy detection systems have been developed using PIR sensors. Dodier et al. proposed a sensor belief network for occupancy detection with PIR sensors [13]. In their system, three PIR sensors were deployed to sense the presence of occupants independently. Then, Bayesian probability theory was leveraged to infer the presence

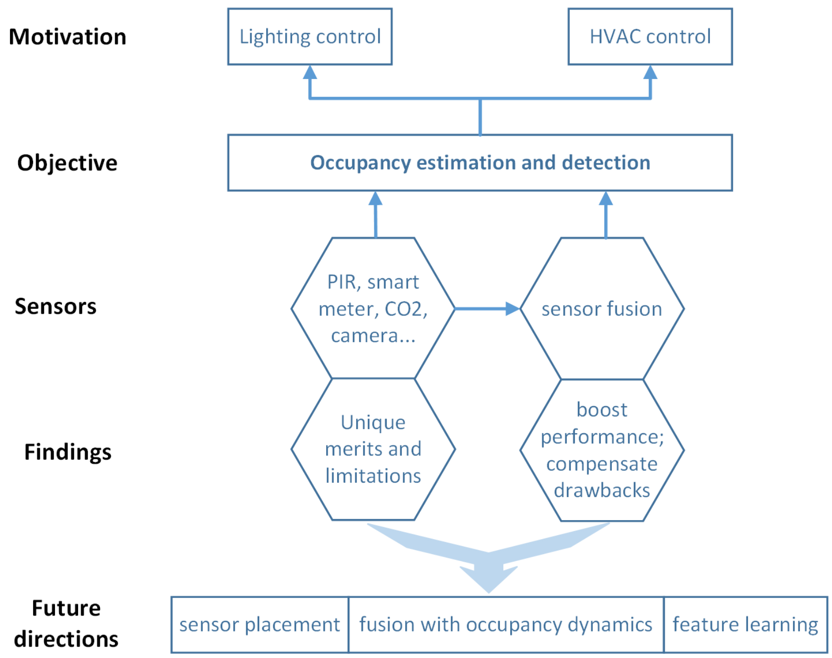

Figure 1: An overview of the paper.

and absence of occupants in a zone. Duarte et al. monitored long-term occupancy diversities of different rooms using PIR sensors [16]. They analyzed the detected occupancy patterns and compared their method with the standardized occupancy diversities in ASHRAE 90.1-2004 [17]. It turns out that real occupancy patterns have a large difference with the standardized occupancy diversities which are widely used in energy simulation tools. In [18], Liu et al. proposed an occupancy detection system using PIR sensors. A Hidden Markov Model (HMM) with expectation-maximization was applied for occupancy detection. Some other works directly view the active state of PIR sensors as the presence of occupants to formulate the statistical model of building occupancy [19, 20].

PIR sensors can also be used to estimate the number of occupants. Wahl et al. presented an occupancy counting system based on pairs of PIR sensors which can detect the moving directions of occupants [21]. A simple direction-based algorithm and a probabilistic distance-based algorithm were proposed for occupancy estimation with the movement directions of occupants. Raykov et al. applied a single PIR sensor to estimate the number of occupants in a room [22]. Firstly, they extracted motion patterns of occupants from raw sensory data using an infinite HMM model. Then, the extracted patterns were applied to estimate the occupancy using statistical regression models.

A summary on PIR sensor based occupancy estimation and detection systems is shown in Table 1. PIR sensors are of low cost and easy to be deployed in environments. However, one limitation of the PIR sensor is that it can only detect the motion of occupants, which means that the static occupants will be missing.

Table 1: A summary on PIR sensor based occupancy estimation and detection systems

Reference	Detection	Estimation	Methodology
[13]	√		Bayesian probability theory
[16]	√		activity detection
[18]	√		HMM
[21]		√	direction-based and distance-based algorithms
[22]		√	statistical regression model

2.2. Smart meter

Power consumption which can be measured by using smart meters is able to reflect the interactions between indoor occupants and appliances. Therefore, building occupancy information can be inferred from power consumption data. However, the relationship between occupancy and power consumption data is not straightforward, and sometimes very difficult to model. Machine learning approaches are a good choice for modeling this complicated relationship.

Chen et al. proposed an occupancy detection system using smart meters [23]. By analyzing the changes of statistical metrics of power data, they can detect the events of occupancy presence using a thresholding method. Then, a clustering algorithm was utilized to combine nearby events to form a continuous trace of occupancy. Kleiminger et al. exploited electricity meters as occupancy sensors for occupancy detection [24]. Since the raw electricity consumption data is not indicative for occupancy presence and absence, they derived some more representative features. The classifiers of Support Vector Machine (SVM), K-Nearest-Neighbors (KNN), HMM and thresholding were employed for classification. In their another work [25], Kleiminger et al. attempted to improve the performance with a larger dataset. First of all, they augmented the number of features from 10 to 30. Then, a feature selection algorithm of sequential forward selection and a dimension reduction algorithm of principal component analysis (PCA) were employed to obtain more abstract features. Finally, classification algorithms, i.e. SVM, KNN, HMM, thresholding and Gaussian mixture model (GMM), were leveraged for final occupancy detection. Similarly, Akbar et al. presented an occupancy detection system based on electricity consumption measured by smart meters [26]. They applied the machine learning algorithms of KNN and SVM with different kernels for occupancy detection. A high accuracy of 94% can be achieved by the KNN algorithm.

Ground truth of occupancy data for supervised learning is sometimes difficult to obtain. Therefore, Becker and Kleiminger proposed an occupancy detection system with smart meter data using unsupervised learning methods [27]. They investigated three unsupervised learning algorithms, i.e. HMM, geometric moving average (GeoMA) and PageHinkley test (PHT), and compared with several supervised learning algorithms. In [28], instead of using supervised learning for occupancy detection, Tang et al. proposed a non-training approach, i.e. sparse human action recovery with knowledge of appliances (SHARK), for occupancy detection using smart meter data. Firstly, they formulated appliance power models with appliance mode switching and constrains as an optimization function. Then, appliance states and human actions can be decoded from the optimization function. Finally, the occupancy can be inferred from the recovered human actions with some defined rules. Jin et al. developed an occupancy detection system with smart meter data [29]. Since ground truth data is difficult to collect, they focused on the problems when no data or limited labeled data is available for model learning. Two algorithms of nonintrusive learning (NL) and transfer learning (TL), were formulated for these problems. The NL method attempts to infer the occupancy schedule with only power consumption data, and the TL method intends to learn a model with the data from a group of similar homes. Both methods achieved good performances with no training data or limited training data.

We summarize smart meter based occupancy estimation and detection systems in Table 2. Smart meter data is non-intrusive for occupants and without additional cost. But, it can only detect the presence and absence of occupants, rather than the more advanced information of occupant number.

Table 2: A summary on smart meter based occupancy estimation and detection systems

Reference	Supervised	Unsupervised	Detection	Methodology
[23]	√		√	thresholding and clustering
[24]	√		√	thresholding, SVM, KNN and HMM
[25]	√		√	thresholding, SVM, KNN, HMM and GMM
[26]	√		√	HMM, GeoMA and PHT
[27]		√	√	SHARK
[28]		√	√	rule based algorithm
[29]		√	√	NL and TL

2.3. Environmental sensors

Environmental sensors including CO_2, temperature, humidity, light and pressure are widely available in modern building LHVAC (lighting, heating, ventilation, and air-condition) systems [30]. Since occupants will directly influence indoor environments, environmental sensor readings can be a good indicator for building occupancy. Many advanced works can be found for building occupancy estimation and detection using environmental sensors. Among all the environmental sensors, CO_2 has been shown to be the most effective sensor for occupancy estimation and detection [31, 32]. Some researchers only apply the CO_2 data for the estimation and detection of building occupancy, while the others use multiple environmental sensors.

2.3.1. CO_2 sensors

Ansanay-Alex developed a simple occupancy detection system using the changes of CO_2 concentrations [33]. This simple method can only detect the presence and absence of occupants. Since indoor CO_2 concentrations are related to the number of occupants and the ventilation level, based on the mass balance equation of indoor CO_2 concentrations, Wang and Jin presented a dynamic detection method for occupancy detection [34]. They compared the proposed method with the steady-state detection method in [35]. Cali et al. applied the same dynamic detection algorithm in [34] for occupancy detection under different conditions such as the rooms with and without ventilation [36]. They also employed the information of the positions of doors and windows to enhance the performance of occupancy detection. Weekly et al. proposed a partial differential equation-ordinary differential equation (PDE-ODE) algorithm to model CO_2 concentrations in a conference room for occupancy estimation [37]. They performed a controlled experiment to tune model parameters and conducted two additional experiments with different number of occupants to validate the performance of their proposed method. Jin et al. applied the same algorithm in [37] for occupancy estimation using CO_2 sensors [38]. All these approaches above are based on the modeling of CO_2 concentrations to detect and estimate building occupancy.

Szczurek et al. provided a simple method to estimate the number of occupants using the statistical pattern matching [39]. They directly estimated the occupancy level in a time window of half an hour based on the statistical indices of CO_2 concentrations, such as autocorrelation function and correlation coefficients. This method can easily provide a rough estimation of mean occupancy level in a long time horizon, i.e. half an hour, which is too long for real-time control of LHVAC systems. Due to the high complexity of indoor CO_2 concentrations, an explicit modelling of CO_2 concentrations in terms of the number of occupants is difficult and inaccurate. An alternative solution is to use data-driven approaches which directly model the relationship between inputs and outputs using some general models, such as machine learning algorithms. Zuraimi et al. compared dynamic physical models and machine learning approaches of SVM, prediction error minimization (PEM) and artificial neural networks (ANN) in building occupancy estimation using CO_2 concentrations [40]. Experiments in a room with up to 200 occupants showed that machine learning approaches of ANN and SVM perform the best. Jiang et al. proposed a feature scaled extreme learning machine (FS-ELM) algorithm for building occupancy estimation using CO_2 measurements [15]. A locally smoothed strategy for CO_2 data was presented to further improve the performance of the model. They also presented a criterion of x-tolerance accuracy for performance evaluation. In [41], Rahman and Han conducted a comparison of neural network and Bayesian Markov chain Monte Carlo (MCMC) for occupancy estimation using CO_2 data in a room. Both models can yield a satisfactory performance under certain conditions. Ebadat et al. designed a gray-box model to capture the CO_2 dynamics of a new room with the data collected from another room [42]. The regularized deconvolution model in [43] was employed to estimate building occupancy for the new room. Alam et al. investigated the uncertainties of using ANN for occupancy estimation with CO_2 data [44]. They used simulation studies with different occupancy profiles and airflow schemes to determine the optimal parameters of their proposed occupancy estimation system. Some useful conclusions were made, which can be treated as a guideline for occupancy estimation using ANN with CO_2 concentrations.

The CO_2 based systems for building occupancy estimation and detection are summarized in Table 3. The main issue of occupancy estimation and detection using CO_2 concentrations is that the estimation results are always with a time delay from the real building occupancy due to the slow spread of CO_2 in environments.

Table 3: A summary on CO_2 based occupancy estimation and detection systems

Reference	Detection	Estimation	Methodology
[33]	$\surd$		thresholding
[34, 36]	$\surd$		dynamic detection methods
[37, 38]	$\surd$		PDE-ODE
[39]		$\surd$	statistical pattern matching
[40]		$\surd$	dynamic physical models, SVM, PEM and ANN
[15]		$\surd$	FS-ELM
[41]		$\surd$	neural network and Bayesian MCMC
[42]		$\surd$	gray-box model
[43]		$\surd$	regularized deconvolution model
[44]		$\surd$	ANN

2.3.2. Multiple sensors

In addition to CO_2, other environmental sensors such as temperature, humidity, light and pressure are also useful in detecting and estimating building occupancy. Candanedo and Feldheim proposed an occupancy detection system using environmental sensors of CO_2, light, temperature and humidity [10]. Three learning algorithms, i.e. linear discriminant analysis (LDA), classification and regression trees (CART) and random forest (RF), were employed for detection. They concluded that a satisfactory occupancy detection performance can be achieved with proper selections of features and learning algorithms. Assuming that the ground truth occupancy is not available, Candanedo et al. evaluated the HMM algorithm for occupancy detection using the same sensors [32]. The HMM with different combinations of features were tested. They concluded that the HMM with features from CO_2 can achieve the best detection performance. Considering temporal dependencies of environmental time series data, Ertuğrul presented a recurrent ELM approach for occupancy detection [45] using the same sensors in [10]. Kraipeerapun and Amornsamankul proposed modified stacking schemes with duo output neural network for occupancy detection with environmental sensors of CO_2, light, temperature and humidity

[46]. The proposed approach contains two stages. In the first stage, multiple neural networks were trained and their outputs were concatenated as inputs for the second stage. In the second stage, two different detection techniques were proposed for occupancy detection.

It is more challenging to estimate the number or the range of occupants using environmental sensors. Since the raw sensory data is noisy and not representative for occupancy estimation, researchers intend to apply feature engineering which is a widely used technique for machine learning models [47]. Feature engineering consists of two components, i.e. feature extraction and selection. Feature extraction is to generate some informative representations for the raw data based on domain knowledge; feature selection is to choose some features that are more informative based on certain criteria.

Masood et al. presented an occupancy estimation system with environmental parameters, i.e. CO_2, temperature, humidity and pressure, using the ELM algorithm [48]. Owing to the extremely fast learning speed of ELM, they proposed an ELM based wrapper method for feature selection. Experiments showed that their proposed ELM-based wrapper method outperforms the popular filter methods. They also concluded that the rarely used pressure sensors are meaningful for occupancy estimation. In another work, Masood et al. proposed a filter-wrapper hybrid feature selection method with ELM to estimate the ranges of occupants which are defined as zero, low, medium and high [49]. Firstly, they applied a relative information gain approach to rank all features, and then employed an incremental search to select the best features for occupancy estimation. Moreover, they also presented a hybrid feature-scaled ELM which contains a novel feature layer for dynamic feature extraction to estimate occupancy using the same environmental sensors in [50]. The conventional static features were selected using a filter method. Then, the selected static features were combined with the dynamic features to form a new feature set for selection using a wrapper method. In this way, they can guarantee both the fast speed and high accuracy. Szczurek et al. presented an occupancy estimation system using CO_2, temperature and humidity data [51]. A wrapper based method was applied for feature selection and two learning algorithms of KNN and LDA were leveraged for estimation. In their experiments, they investigated the occupancy estimation with individual sensor data and the fusion of multiple sensor data. The authors found that the classifier trained by KNN is much more effective than that designed by LDA. Liu et al. proposed a two-stage ELM approach for occupancy estimation using environmental sensors of CO_2 and temperature [52]. In the first stage, an ELM algorithm was applied to obtain local representations for the raw features. Then, in the second stage, a linear SVM was employed to map the obtained local representations to the number of occupants.

Due to the Markov property of building occupancy dynamics [53, 54], the HMM model has been shown to be effective for occupancy estimation and detection [31, 32]. However, conventional HMM has some limitations, such as fixed transition probability matrix and simple mixture of Gaussian for emission probabilities. Chen et al. proposed an inhomogeneous HMM with multinomial logistic regression (IHMM-MLR) for building occupancy estimation using CO_2, temperature, humidity and pressure [55]. They applied the inhomogeneous transition probability matrices to capture occupancy properties at different time instances, and utilized the multinomial logistic regression with environmental sensor measurements to generate the emission probabilities. Online and offline IHMM-MLR algorithms were designed for different applications. Another system to improve occupancy estimation with occupancy properties was presented in [56]. The authors fused the conventional data-driven approaches with the well developed occupancy models which can reveal occupancy properties for occupancy estimation and detection using multiple environmental sensors of CO_2, temperature, humidity and pressure. An inhomogeneous Markov model was employed to capture occupancy dynamics. The data-driven models included ELM, SVM, ANN, CART, KNN, and LDA. A particle filter was formulated for the fusion of the occupancy model and the data-driven approaches to estimate building occupancy. Ebadat et al. proposed a regularized deconvolution model for the modeling of occupancy levels with environmental sensor measurements, i.e. CO_2 and temperature [43]. They also took the regularity of occupancy pattern into consideration by introducing a fused lasso estimator into the optimization function.

Most of previous works are based on manual feature extraction which requires domain knowledge and sometimes may miss some implicit features. To solve this problem, Zhu et al. proposed an occupancy estimation system with a local receptive fields (LRF) based feature learning in both time and frequency domains using environmental sensors, i.e. CO_2, temperature, humidity and pressure [57]. The LRF with random weights can automatically learn useful features from time and frequency domains and applied these features for occupancy estimation. Deep learning is also a powerful tool for automatic feature learning [58]. Liu et al. proposed an occupancy detection system using a sparse auto-encoder (SAD) for automatic feature learning with environmental sensors of CO_2, light, temperature and humidity [59]. The SAD is able to learn features from raw environmental sensor data. Then, the features are fed into classifiers of softmax, SVM and liblinear for final occupancy detection. Chen et al. proposed a convolutional deep bi-direction long short-term memory (CDBLSTM) approach for occupancy estimation using the sensory data of CO_2, temperature, humidity and pressure [60]. A convolutional network was applied to learn local robust features from the raw sensory data. Then, a DBLSTM network was employed to learn high-level features and encode temporal dependencies into features for final estimation. Experimental results showed the superior performance of their proposed approach for occupancy estimation and detection.

We summarize the systems for occupancy estimation and detection using multiple environmental sensors in Table 4. Environmental sensors are widely available and non-intrusive for occupancy estimation and detection. But they suffer from the problems of limited performance and delayed estimation.

2.4. Camera

Due to the high precision, the cameras are also popular for building occupancy estimation and detection. With a multi-camera system, Fleuret et al. provided a method to estimate the locations of all indoor individuals, which can

Table 4: A summary on multiple environmental sensor based occupancy estimation and detection systems

Reference	sensors	Detection	Estimation	Methodology
[10]	CO_2, light, temperature, humidity	√		LDA, CART and RF
[32]	CO_2, light, temperature, humidity	√		HMM
[45]	CO_2, light, temperature, humidity	√		recurrent ELM
[46]	CO_2, light, temperature, humidity	√		stacking schemes
[48]	CO_2, temperature, humidity, pressure		√	wrapper based ELM
[49]	CO_2, temperature, humidity, pressure		√	filter-wrapper based ELM
[50]	CO_2, temperature, humidity, pressure		√	hybrid feature-scaled ELM
[51]	CO_2, temperature, humidity		√	wrapper based KNN and LDA
[52]	CO_2, temperature		√	two-stage ELM
[55]	CO_2, temperature, humidity, pressure		√	IHMM-MLR
[56]	CO_2, temperature, humidity, pressure		√	particle filter
[43]	CO_2, temperature		√	regularized deconvolution model
[57]	CO_2, temperature, humidity, pressure		√	LRF
[59]	CO_2, light, temperature, humidity	√		SDA
[60]	CO_2, temperature, humidity, pressure		√	CDBLSTM

easily provide the number of indoor occupants [61]. Benezeth et al. proposed a vision based occupancy estimation and detection system [62]. The detection of an occupant consists of three steps, i.e. background subtraction, tracking and recognition. Erickson et al. applied cameras to obtain building occupancy which is leveraged to develop an occupancy model [63]. They then integrated the developed occupancy model into building control systems to save energy. Liu et al. presented an occupancy estimation system based on vision cameras at the entrances and inside a room [64]. Two different static vision algorithms were employed to estimate occupancy in the room, and a motion based approach was adopted for occupancy detection at the entrances. They fused the estimation results of the entrances and the room using a dynamic Bayesian network approach for final occupancy estimation. A more advanced work can be found in [14]. The authors proposed a cascade framework for building occupancy estimation using cameras. Firstly, they applied a pre-classifier to filter out non-head areas. Then, a convolution neural network (CNN) was employed to classify head windows. Finally, a clustering algorithms performed a fusion of consecutive frames for more robust head detection. A high estimation accuracy, i.e. up to 95.3%, can be achieved with their proposed approach. By counting the entering and leaving of occupants in a room using unsupervised image processing techniques, Petersen et al. presented an occupancy estimation system using the camera at the entrance of a room [65]. Tomastik et al. utilized the cameras at each portal of the zone to obtain the movements of occupants among the zones of a building [66]. They also developed a non-linear stochastic state-space model with the movements of occupants for occupancy estimation in emergency egress.

Table 5 presents a summary on camera based occupancy estimation and detection systems. Generally, with cameras, an indoor occupancy counting system with a high accuracy can be designed. Hence, for many other occupancy estimators, cameras were commonly used to obtain the labeled data and ground-truth [15, 48, 49, 56]. Occupancy estimation using cameras often provides relatively accurate results but it also suffers some issues, such as high computational complexity, the influence of illumination conditions and privacy concerns.

Table 5: A summary on camera based occupancy estimation and detection systems

Reference	Estimation	Methodology
[61]	√	location estimation
[62]	√	background subtraction, tracking and recognition
[63]	√	background subtraction and manual counting
[64]	√	dynamic Bayesian network approach
[14]	√	CNN and clustering
[65]	√	unsupervised image processing techniques
[66]	√	non-linear stochastic state-space model

2.5. WiFi

Due to the widely availability of WiFi signals in indoor environments, WiFi can be a good candidate for occupancy estimation and detection. Nowadays, smartphones are widely available for occupants. Thus, the number of smartphones can be treated as an indicator of the number of occupants in a given space. Balaji et al. presented an occupancy estimation system based on the existing WiFi infrastructure [67]. Instead of using complex WiFi based localization algorithms, they developed a coarse-grained localization approach based on the connected access point with metadata information and occupancy patterns. Lu et al. proposed a room-level occupancy inference system based on commodity WiFi [68]. Firstly, the system obtained a snapshot occupancy by matching the received signal strength (RSS) measurements with the measurements of anchors in different zones. Then, the estimation performance was enhanced by the use of temporal correlations of consecutive snapshot occupancy and historical occupancy data. In [69], Zou et al. presented an occupancy estimation system using a WiFi based indoor localization technique [14]. Instead of collecting WiFi RSS on smartphones, they applied routers to scan WiFi enabled smartphones in indoor environments. A localization algorithm of online sequential ELM was utilized to infer the occupancy information. Similarly, Wang et al. presented a different occupancy inference system using WiFi scanning [70]. A dynamic Markov time-window inference (DMTWI) approach which models occupancy dynamics as a Markov process was proposed for occupancy estimation. The authors compared the approach with conventional methodologies of support vector regression (SVR) and auto-regressive moving average (ARMA).

It is assumed in all of these works that each occupant would carry a smartphone with WiFi enabled. However, this is not always true in real life. Under the principle that WiFi RSS managements between a pair of WiFi transmitter and receiver will be influenced by occupants between them, Depatla et al. attempted to directly estimate occupancy based on WiFi power measurements [71]. Firstly, they modeled the impact of blocking the line of sight and scattering effects. Then, a mathematical expression was formulated between the RSS and the occupancy by combining the two components. The final occupancy estimation was achieved by using Kullback-Leibler divergence with the formulated mathematical expression. Another direct occupancy estimation system using WiFi was presented in [72]. The authors applied a refined information of WiFi, i.e. channel state information (CSI). First of all, they defined a percentage of nonzero elements (PEM) in CSI matrix as features for occupancy estimation. Then, a grey Verhulst model was leveraged for occupancy estimation with the designed features.

A summary on WiFi based occupancy estimation and detection systems is shown in Table 6. One merit of WiFi based systems is that WiFi signals are widely available in indoor environments. But the limitations of WiFi based systems are obvious. The indirect systems attempt to detect the number of smartphones. Some issue will be encountered for these systems. For example, the occupants may have multiple smartphones, or they may not turn on WiFi for their smartphones. The direct systems can only estimate the number of moving occupants, which means the static ones would be missing.

Table 6: A summary on WiFi based occupancy estimation and detection systems

Reference	Indirect	Direct	Estimation	Methodology
[67]	√		√	coarse-grained localization approach
[68]	√		√	snapshot matching
[69]	√		√	online sequential ELM
[70]	√		√	DMTWI
[71]		√	√	Kullback-Leibler divergence
[72]		√	√	grey Verhulst model

2.6. BLE

Bluetooth low power (BLE) is widely available in modern smartphones and is quite energy efficient compared to classical Bluetooth technologies and WiFi. Researchers intend to estimate the number of smartphones to know the number of indoor occupants by using BLE. Conte et al. proposed an occupancy estimation system using iBeacon which is built upon BLE technology [73]. They modified iBeacon protocol to make it more accurate and efficient for occupancy detection. Two algorithms, i.e. KNN and decision tree (DT), were employed to classify occupants into different rooms based on the received signal strength indicators (RSSIs) from different iBeacons. They attempted to further enhance the performance of the occupancy estimation using iBeacon in [74]. A smoothing algorithm to obtain the stable features for classification was presented. Then, a SVM algorithm was leveraged to classify occupants into different rooms. Similarly, Filippoupolitis et al. also applied a SVM algorithm for occupancy estimation using BLE beacons [75]. Instead of using the raw RSSI values, they extracted some statistical features for occupancy classification. In their another work, with the same features, they explored a larger area with three learning algorithms of SVM, KNN and logistic regression (LR) for occupancy estimation using BLE beacons [76].

Table 7 summarizes the BLE based occupancy estimation and detection systems. The major issue for BLE based occupancy estimation is that occupants may not turn on the Bluetooth of their smartphones. Moreover, the deployment of BLE beacons in indoor environments requires extra cost and maintenance.

Table 7: A summary on BLE based occupancy estimation and detection systems

Reference	Raw data for features	Features extraction	Estimation	Methodology
[73]	√		√	KNN and DT
[74]		√	√	SVM
[75]	√		√	SVM
[76]		√	√	SVM, KNN and LR

2.7. Other sensors

A large number of other sensors have also been used for occupancy estimation and detection. Labeodan et al. proposed a fine-grained occupancy estimation system in a conference room using chair sensors [77]. A simple thresholding method is enough to detect the occupied/unoccupied states of a chair. The total occupancy can be derived from the number of chairs to be occupied. Pan et al. proposed to use sparsely deployed ambient vibration sensors for occupancy estimation in buildings [78]. Firstly, they detected footstep events from noisy vibration sensor measurements. Then, a localization module was implemented to localize these footsteps. Finally, they tracked these localized footsteps with structural information and updated the occupancy. Yang et al. proposed an occupancy inference system using light-emitting diodes (LED) sensors [79]. The rationale is that occupants in the view of ceiling-mounted LED array will cause perturbations into diffuse reflections from the floor in the form of snapshots. A SVR algorithm was utilized for occupancy estimation using these snapshots. In [80], Shih and Rowe developed an ultrasonic sensor based occupancy estimation system. First of all, an ultrasonic tweeter transmitted ultrasonic chirps across a frequency range, and a microphone recorded the reverberation characteristics over time. Then, a clustering model and a regression model were presented to estimate occupancy based on the measured reverberation characteristics. Li et al. presented an radio-frequency identification (RFID) based occupancy estimation system [81]. A KNN algorithm was applied to localize each RFID tag corresponding to each occupant in an environment based on the RSS vector of the tag. Then, the occupancy can be inferred with the locations of tags. Fadhlullah and Ismail proposed the use of Zigbee sensors to estimate occupancy levels, i.e. low, medium and high [82]. They placed three Zigbee tags in a zone to continuously report the RSSI to a Zigbee coordinator. Then, a rule based algorithm was presented for occupancy estimation using the RSSI data. Quan et al. presented an occupancy counting system based on the impulse radio ultra-wideband (IR-UWB) sensor [83]. A simple thresholding method was leveraged to detect the number of occupants passing through a gate using the value of IR-UWB. After that, the occupancy of a room can be easily derived. Another work in [84] presented a theoretical framework for occupancy counting using target backscattering of UWB. The authors developed two methods, i.e. individual-centric and crowd-centric, for occupancy estimation. The individual-centric method utilizes a maximum a posterior algorithm for counting with model order selection. The crowd-centric approach directly relies on some low-level features which is more computationally efficient.

We summarize the occupancy estimation and detection systems using other sensors in Table 8. All these systems are required to use specific devices for occupancy estimation, which limits their usability.

Table 8: A summary on other sensor based occupancy estimation and detection systems

Reference	Sensor	Estimation	Methodology
[77]	chair sensors	√	thresholding
[78]	vibration sensors	√	localization based method
[79]	LED	√	SVR
[80]	ultrasonic sensor	√	clustering and regression models
[81]	RFID	√	KNN
[82]	Zigbee	√	rule based algorithm
[83]	UWB	√	thresholding
[84]	UWB	√	individual-centric and crowd-centric models

2.8. Sensor fusion

Each sensor has some unique properties and limitations for occupancy estimation and detection. The fusion of multiple sensor types can boost the performance of occupancy estimation and detection by taking advantages and compensating limitations of each sensor. Many advanced works have been developed in the literature.

Zhao et al. presented an occupancy detection system in two situations, i.e. room level and working zone level [85]. In the room level, the physical sensors of PIR and virtual sensors of keyboard and mouse were utilized for the detection of presence and absence. In the working zone level, WiFi and GPS were employed to detect the states of individual occupant including leaving, coming, working and not working. The Bayesian belief network with expectation-maximization algorithm was applied for the detection.

Chaney et al. presented an occupancy detection system based on sensor fusion of smart meter, temperature and CO_2 [86]. A HMM algorithm was utilized for learning and detecting occupied and unoccupied states without the need of ground truth data. The Dempster-Shafer theory which was applied for sensor fusion can provide the emission probabilities for the HMM algorithm. Their approach is also able to handle the problem of missing data.

Wang et al. combined video camera with CO_2 concentrations to estimate occupant number [8]. Considering the privacy issue, the camera was installed at the entrance of a room. It detected room occupancy by counting the occupants moving into or out of the room. When illumination condition is poor, the estimation error will accumulate. Then, a CO_2 based occupancy estimation model using massive conservation equation was formulated to detect occupant number and eliminate the accumulative error caused by the video system.

Zhang et al. presented to estimate building occupancy with the fusion of CO_2 and power consumption data using statistical modeling [87]. Firstly, they extracted some features from CO_2 based on physical diffusion model. Statistical distribution with two models, i.e. maximum a posteriori probability (MAP) estimation of HMM and multiple-hypothesis sequential probability ratio test (MSPRT), was applied to deal with occupancy estimation with limited training data.

Wang et al. proposed a spiking neural network (SNN) for occupancy estimation using sensor fusion [88]. They applied five different sensors including CO_2, humidity, PIR, RFID and WiFi. An unsupervised Hebbian algorithm was utilized for model learning of SNN.

Ekwevugbe used the sensors of temperature, humidity, VOC, CO_2, sound and PIR for occupancy estimation [89, 90]. Firstly, they extracted some relevant features from raw sensory data. Then, a genetic correlation feature selection algorithm was presented to select optimal features. Finally, an ANN algorithm was applied to estimate the number of occupants with these optimal features.

Yang et al. exploited temperature, humidity, CO_2, light, sound and motion for occupancy estimation [91]. A radial basis function (RBF) neural network was used to estimate occupancy with preprocessed sensor data. In addition to these sensors, they also included the door status in [92] for occupancy estimation. In this work, a PCA was utilized to determine the importance of each sensor. Then, a back-propagation (BP) ANN algorithm was applied to estimate the number of occupants with several most important features. For their another work in [93], they used the same sensors for occupancy estimation. Firstly, the contribution of each sensor was evaluated using the information gain theory. Then, six machine learning algorithms, i.e. SVM, ANN, KNN, DT, naive Bayesian (NB) and tree augmented naive Bayesian (TANB), were employed for occupancy estimation and detection using the selected sensors.

Ai et al. presented a modified HMM algorithm, i.e. auto-regressive HMM, for building occupancy estimation using sensor fusion of PIR, CO_2, temperature, humidity, air-velocity, global thermometer, and reed switches [94]. The auto-regressive HMM can take correlations of sensors into consideration. Therefore, it can achieve better performance than conventional HMM in their experiments.

Arora et al. presented an occupancy estimation system by fusing a large number of sensors including temperature, humidity, CO_2, illumination, PIR, door state and power consumption [95]. Firstly, they extracted some statistical features from the raw sensory data. Then, a feature selection was performed by the use of information gain theory. Finally, the number of occupants was identified using a DT algorithm with the selected features. For their another work in [96], they also included a microphone which can detect the acoustic level of the room. The same feature selection method was applied. The learning algorithms of DT and RF were employed to estimate the number of occupants.

In [97], Zikos et al. developed an occupancy estimation system with multiple sensors such as double-beam, pressure mats, acoustic, PIR and CO_2. They presented an efficient learning algorithm of conditional random fields (CRF) for occupancy estimation with different combination of sensors in four different types of rooms.

In [98, 31], the authors proposed to estimate occupancy using a large number of sensors including CO_2, temperature, humidity, illumination, carbon monoxide (CO), total volatile organic compounds (TVOC), small particulates (PM2.5), acoustics and motion [98]. Firstly, they extracted some statistical features from the raw data. Then, the information gain theory was applied to select the most informative features for estimation. Finally, machine learning algorithms of ANN, SVM and HMM were employed to identify the occupancy.

A summary on occupancy estimation and detection systems using sensor fusion is presented in Table 9.

Table 9: A summary on sensor fusion based occupancy estimation and detection systems

Reference	Sensor	Detection	Estimation	Methodology
[85]	PIR, keyboard, mouse, WiFi, GPS	√		Bayesian belief network
[86]	CO_2, smart meter, temperature	√		HMM
[8]	CO_2, camera		√	massive conservation equation
[87]	CO_2, smart meter		√	HMM and MSPRT
[89, 90]	temperature, humidity, VOC, CO_2, sound, PIR		√	ANN
[91]	temperature, humidity, CO_2, light, sound, PIR		√	RBF neural network
[92]	temperature, humidity, CO_2, light, sound, PIR, door status		√	ANN
[93]	temperature, humidity, CO_2, light, sound, PIR, door status		√	SVM, ANN, KNN, DT, NB and TANB
[94]	CO_2, temperature, humidity, air-velocity PIR, global thermometer, reed switches		√	auto-regressive HMM
[95]	temperature, humidity, CO_2, illumination, PIR, door state, smart meter		√	DT
[96]	temperature, humidity, CO_2, illumination, PIR, door state, smart meter, microphone		√	DT and RF
[97]	double-beam, pressure mats, acoustic, PIR, CO_2		√	CRF
[88]	CO_2, humidity, PIR, RFID, WiFi		√	SNN
[98, 31]	CO_2, temperature, humidity, illumination, CO, TVOC, PM2.5, acoustics, PIR		√	ANN, SVM and HMM

3. Discussion

We have compared all the sensors in Table 10 based on some evaluation metrics including existing infrastructure, cost, privacy issue, detection accuracy, estimation accuracy, and limitations. These evaluation metrics are of great importance for practitioners to select one solution to suit their particular application. If the selected sensor type is one of the existing infrastructures for a building, there will be no cost for the solution. Otherwise, the cost of sensors will sometimes be a major concern in real applications. Meanwhile, the performance of occupancy detection or estimation, i.e. detection or estimation accuracy, is vital, which will determine the performance of the entire system, such as occupancy based lighting and HVAC control systems [11, 6]. Another important issue that one should address for an application is the privacy concern which has been considered in [99] where a privacy-enhanced architecture for occupancy driven HVAC control has been developed. Different sensors have their unique properties and limitations for occupancy estimation and detection. For example, PIR sensors are low cost and easy to deploy, but they probably provide wrong detection results if occupants are static. Environmental sensors are available in many modern buildings, but they provide a low estimation accuracy with some delays caused by the diffusion of environmental parameters. RFID can provide an accurate occupancy estimation and detection, but it is intrusive for users and will miss visitors who do not take an RFID tag. For different applications, a careful selection of a particular sensor for occupancy estimation and detection is required. For instance, the chair sensor is a good option for occupancy driven control in a classroom or meeting room. The PIR sensor is widely used in occupancy driven lighting control for restrooms.

Each sensor contains some advantages and limitations for occupancy estimation and detection. To enhance the performance, the fusion of multiple sensor types is a wonderful choice. Multiple types of sensors can compensate each other. In [8], the authors fused the camera at the entrance with CO_2 sensors. In the daytime with good illumination condition, the camera can count the oc-

Table 10: Comparison of different sensors

Sensor	Existing infrastructure	Cost	Detection accuracy	Estimation accuracy	Privacy issue	Limitations
PIR	no	low	high	low	no	miss static occupants
Smart meter	yes	no	medium	N.A.	no	miss occupants not using appliance
Environmental	yes	no	medium	low	no	delay detection
Camera	yes	no	high	high	yes	illumination condition
WiFi	yes	no	high	high	partial	need to turn on WiFi
BLE	no	medium	high	high	partial	need to turn on Bluetooth
Chair sensor	no	high	high	high	no	miss standing subjects
Vibration	no	high	high	medium	no	scalability; maintenance
LED	yes	no	high	medium	no	maintenance
RFID	no	medium	high	high	partial	inconvenient; miss visitors
Zigbee	no	medium	high	high	partial	inconvenient; miss visitors
UWB	no	high	high	low	no	poor performance in crowded environments

cupancy based on the occupants moving into or out of a room, which may have accumulated error. In the midnight with poor illumination condition and low occupancy, the CO_2 sensors can achieve a good performance for occupancy estimation, and the results can be used to eliminate the accumulated error of the camera based system. When we design an occupancy estimation and detection system, a proper fusion of multiple sensor types will boost the performance of the system.

For a particular type of sensor, many occupancy estimation and detection algorithms have been developed. However, the comparison of different algorithms is sometimes difficult. In computer vision and nonintrusive load monitoring communities, some benchmark datasets such as Imagenet [100] and BLUED [101] have been released for the comparison of different algorithms in these areas. For occupancy estimation and detection, we can also find some popular datasets, for instance, the ECO [24] and SMART* [23] datasets in smart meter based occupancy estimation and detection. With these benchmark datasets, different occupancy estimation and detection algorithms can be evaluated and compared, which will better promote the development of this research field.

4. Potential future directions

Even though great progresses have been achieved in the literature for building occupancy estimation and detection, the performance is still far from satisfactory for some applications. Some potential future directions will be discussed in this section.

4.1. Sensor placement

An optimal combination of sensors is of great importance for building occupancy estimation. The authors in [31] applied an information gain theory to investigate the importance of each sensor for occupancy estimation. The performance of the system can be enhanced with the data from more important sensors. However, the optimal placement of sensors which will determine the coverage, cost and performance of sensing systems [102] has not been explored. The authors in [55] leveraged on three environmental sensor sets in a room for occupancy estimation. The three sensor sets are intuitively deployed in the environment. They evaluated the impacts on position and number of sensors in experiments. The conclusion is that the position and number of sensors is vital for building occupancy estimation. Few works have been done to investigate the optimal sensor placement for the task of building occupancy estimation and detection. A systematic and theoretic analysis of optimal sensor placement is an urgent and challenging task where further research is required.

4.2. Fusion with occupancy dynamics

Occupancy time series has some unique properties. A number of researchers have explored the modeling of occupancy dynamics [53, 54]. A review on occupancy modeling can be found in [103]. This occupancy dynamics can be helpful for the estimation of real-time building occupancy. Ebadat et al. incorporated a simple property of occupancy dynamics, i.e. piece-wise constant, into their proposed inverse optimization function for building occupancy estimation [43]. They achieved a better performance than traditional approaches without this simple occupancy property. In [56], the authors proposed to fuse an occupancy model with conventional machine learning approaches using a particle filter for occupancy estimation. They improved the performance of machine learning approaches by the fusion with the occupancy model. These works clearly demonstrate that occupancy dynamics is meaningful to enhance the performance of building occupancy estimation and detection. But, how to optimally combine conventional occupancy estimation approaches with occupancy dynamics is still an open problem.

4.3. Feature learning

In the previous works, most of researchers apply manual feature engineering to improve the performance of shallow machine learning algorithms for building occupancy estimation and detection. However, manual feature engineering will inevitably lose some inherent key features. Owing to the powerful automatic feature learning capability, deep learning has been successfully applied to many challenging applications, such as image processing [104] and nature language processing [105]. The authors in [60] attempted to use a deep learning approach for building occupancy estimation. Firstly, they applied a convolutional network to extract local robust features, and then employed a deep bi-directional LSTM network for high-level feature learning. The experimental results indicated the superiority of their proposed deep learning approach for building occupancy estimation and detection. With the development of sensing and communication technologies, more sensor data will be available for learning. Deep learning will be a good tool to analyze these big data for occupancy estimation and detection from scratch without human intervention.

5. Conclusion

In this paper, we performed a comprehensive review on occupancy estimation and detection. We categorized the systems based on the use of different sensors, such as PIR, smart meter, environmental sensors, camera, WiFi, BLE, and others. The fusion of multiple sensors was also reviewed. We then conducted a comprehensive comparison and discussion of different sensors for building occupancy estimation and detection based on some evaluation metrics including existing infrastructure, cost, privacy issue, detection accuracy, estimation accuracy, and limitations. We can conclude that different sensors have different merits and limitations. For a particular application that requires the estimation or detection of occupancy, we can select the sensors based on these evaluation metrics. Besides, sensor fusion tends to perform better because different sensors will compensate the drawbacks of each other. Therefore, a combination of multiple sensor types is also a good option. At the end of this review, we presented some potential future research directions, i.e. sensor placement, fusion with occupancy dynamics and feature learning, for the estimation and detection of building occupancy. Some initial works have been done in these directions. But the current results are far from satisfaction. More efforts should be given on these potential research directions.

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