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Publisher's version / Version de l'éditeur:
https://doi.org/10.1016/j.aei.2016.12.008
Advanced Engineering Informatics, 33, pp. 230-242, 2017-01-18

Leveraging Existing Occupancy-related Data for Optimal Control of Commercial Office Buildings: A Review

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Abstract: A primary strategy for the energy-efficient operation of commercial office buildings is to deliver building services, including lighting, heating, ventilating, and air conditioning (HVAC), only when and where they are needed, in the amount that they are needed. Since such building services are usually delivered to provide occupants with satisfactory indoor conditions, it is important to accurately determine the occupancy of building spaces in real time as an input to optimal control. This paper first discusses the concepts of building occupancy resolution and accuracy and briefly reviews conventional (explicit) occupancy detection approaches. The focus of this paper is to review and classify emerging, potentially low-cost approaches to leveraging existing data streams that may be related to occupancy, usually referred to as implicit / ambient / soft sensing approaches. Based on a review and a comparison of related projects / systems (in terms of occupancy sensing type, resolution, accuracy, ground truth data collection method, demonstration scale, data fusion and control strategies) the paper presents the state-of-the-art of leveraging existing occupancy-related data for optimal control of commercial office buildings. It also briefly discusses technology trends, challenges, and future research directions.

Keywords— occupancy detection; data fusion; commercial office buildings; energy conservation; HVAC control; lighting control

1. Introduction

According to United Nations Environment Programme's Sustainable Building and Climate Initiative (UNEP-SBCI), the building sector contributes up to 30% of global annual greenhouse gas emissions and consumes up to 40% of global energy [1]. Similar results were reported by the US Department of Energy [2]: buildings in the United States account for about 41% of national energy consumption. Among the total commercial building energy consumption in 2010, 39.6% was consumed by space heating, cooling and ventilation, 20.2% by lighting, 4.3% by water heating, and 30.5% by plug-in equipment loads. These systems and devices are essential to support commercial building operations and maintain occupant comfort. Among all the buildings, commercial office buildings are the largest in floor space and energy use in most countries [3].

It has been widely recognised that the key to saving energy in commercial office buildings is to deliver building services only when and where they are needed, in the amount that they are needed [4-6]. Since such building services are usually delivered to provide occupants with satisfactory indoor conditions, it is important to accurately determine the occupancy of building spaces in real time [7-9] in order to garner such energy savings. Therefore, occupancy detection has attracted a lot of attention for decades, particularly in the field of lighting control [10]; occupancy sensors have long-been deployed at the room level to save energy, primarily in electric lighting systems [11-14]. The potential for energy savings with HVAC (heating, ventilating, and air conditioning) systems is also emerging [15-22]. From these deployments, savings of 20-50% are typically reported. A study conducted by Gunay et al. [23] indicates that a 10-15% reduction in the space heating and cooling loads can be achieved just by applying individual temperature setback periods based on historical office occupancy patterns. Occupancy sensors for lighting systems have been mandated in certain space types in contemporary energy codes and standards (e.g., National Energy Code for Buildings in Canada [24], ASHRAE 90.1-2016 [25]). However, penetration of these technologies as retrofits in all eligible spaces in existing commercial buildings is low, and first cost remains a tangible barrier.

One possible solution that is emerging is to leverage data from existing systems, installed for some other purposes, to provide an indication of occupancy. According to two studies [26, 27], significant energy savings can be achieved by using the existing IT (Information Technology) infrastructure to enable energy savings in both IT (computers and networking) and non-IT infrastructure. Such occupancy information can be used by building control systems to reduce the energy consumption of lighting, HVAC, and other building systems [28, 29]. Occupancy detection can provide information to these building systems to allow them to operate proportionally to the number of occupants in the building [26, 30] and ultimately to optimize the building energy management through integrated optimal control of active and passive heating, cooling, lighting, shading, and ventilation systems [31].

In addition to direct energy and cost savings through real-time intelligent control of HVAC, lighting, and plug loads, detailed and accurate occupancy information may also be leveraged for other energy-saving applications, including occupant engagement and behaviour adjustment [32], achieving optimal demand response [33], optimizing energy storage, improving building energy simulation [34], enhancing building space modeling and utilization [35], supporting building planning and evacuation [36], and increasing building energy use forecasting accuracy [37]. Finally, there is some potential to lower building operation and maintenance costs. A study by the Electrical Power Research Institute (EPRI) found that while the increased on/off switching by occupancy sensors reduced fluorescent lamp life from 34,000 to 30,000 hours, it also dramatically increased lamp longevity (time in the socket between replacements) from 3.9 years for always-on lamps to 6.8 years by not wasting lamp life during unoccupied hours [38][1].

The objective of this paper is to review and classify emerging, potentially low-cost approaches to leveraging existing data streams that may be related to occupancy, usually referred to as implicit/ambient/soft sensing approaches. The rest of this paper is organized as follows. Section 2 defines building occupancy resolution and accuracy. Section 3 reviews conventional occupancy detection approaches. In addition, illustrative examples from the literature were provided to demonstrate the strengths and the weaknesses of these occupancy detection approaches. Section 4 provides a comprehensive review of implicit/ambient/soft sensor approaches. Section 5 presents some concluding remarks and briefly discusses future research and development directions.

[1] LED lighting technology lifetime is largely impervious to switching frequency, rendering this trade-off less important in new installations.

2. Building Occupancy Resolution and Accuracy

2.1 Building Occupancy Resolution

Different applications require different levels of building occupancy resolution and accuracy. Melfi et al. [26] proposed to measure the occupancy resolution in three dimensions (as shown in Figure **1**):

- Spatial (zone) resolution: Building, Floor, Room
- Temporal resolution: Day, Hour, Minute, Second
- Occupancy resolution:
  - Level 1: Occupancy: at least one person in a zone
  - Level 2: Count: how many people are in a zone
  - Level 3: Identity: who they are
  - Level 4: Activity: what they are doing

Another level (Level 5) may also be added to track where an occupant was before, as suggested by Labeodan et al. [39]. Such Level 5 information indicates the particular occupant's movement history across different zones in the building and is essential in the design of proactive comfort systems [40, 41]. However, this review focuses on the first four levels only.

A room typically refers to a single office or a space with four full-height walls (e.g., an office or a conference room) or a large zone containing many cubicles. In the context of this paper, we also consider a cubicle as a room if it has independent sensing and control.

We will use this classification of occupancy resolution throughout the paper when reviewing existing technologies and solutions. A slightly different, but compatible classification scheme can be found in [42].

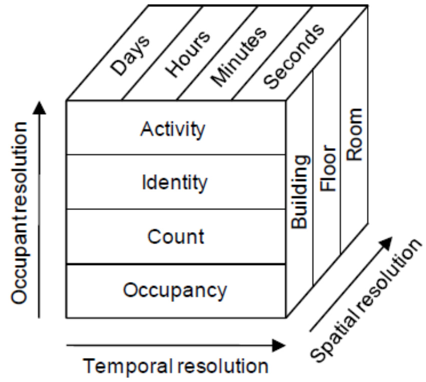

Figure 1: Occupancy resolution in three dimensions (modified from Melfi et al. [26])

2.2 Building Occupancy Accuracy

Occupancy detection accuracy can be defined as the proximity of measured value (usually based on a number of readings from a sensor) to the ground truth (actual) occupancy.

High levels of occupancy detection accuracy are important for building control systems to make correct decisions for the delivery of building services. However, the accuracy of occupancy information for building energy management may not be as important as that for building security systems, for example. Further, high accuracy requirements usually bring high deployment cost. Therefore, an appropriate level of accuracy needs to be determined based on some return on investment analysis.

Different types of occupancy detection errors have different implications. In the domain of building energy management, false negatives (concluding there is no one in the zone when, in fact, the zone is occupied) are more problematic than false positives (concluding there is someone in the zone when, in fact, the zone is unoccupied). For example, a false negative might lead to lights being automatically switched off. Particularly, incorrect vacancy detections in lighting controls can lead to occupant annoyance, and in many cases occupants place an opaque material to cover the surface of motion detectors [43]. Figure 2 presents an example from a private office space in an academic building in Carleton University.

Figure 2: An example where the occupant taped over the motion detectors (taken from [44] credit: Sara Gilani).

Although a system inclined towards false positives will waste energy, a system inclined towards false negatives will lead to occupant annoyance, which often results in automatic controls and sensors being sabotaged [45] and a reduction in energy savings in the long run. This concern with false negatives means that conventional occupancy sensing systems often have long timeout periods (15-60 minutes), meaning that the system must detect no occupancy for the entire timeout period, to have a high confidence there is no occupancy, before engaging in control actions. This reduces the risk of occupant annoyance, but also lowers energy savings potential.

3. Conventional Occupancy Detection Approaches

PIR sensors are the most common sensor type used in commercial buildings to detect human presence. They detect movements from changes in the infrared-radiation impinging on them [46]. Given that movements are discrete-events, in practice a delay value (e.g., 15 to 60 min) is heuristically selected to avoid incorrect vacancy detections during immobility. After movement detection, the space is assumed occupied for this delay period. The uncertainties in occupants' activeness (frequency of detectable movements), office layouts and sensor positioning play a nebulous role over the reliability of PIR sensors. As discussed earlier, these uncertainties force controls technicians and programmers to select conservatively long delay values – which diminish the energy savings potential. For example, Gunay et al. [45] investigated the impact of the PIR sensor delay decisions on the accuracy of occupancy detections at three different sensor locations in a shared office space. Against ground-truth occupancy data, the accuracy was quantified with two different metrics: (1) presence accuracy is the correctly detected fraction of the occupied periods (i.e., true positives) and (2) absence accuracy is the correctly detected fraction of the unoccupied periods (i.e., true negatives). As shown in Figure **3**, when the PIR sensor delay values are too small, even brief periods of immobility are interpreted as absence periods. As a result, false absence detections are very common particularly at delay values smaller than 15 to 20 min. However, as the PIR sensor delay values get larger, false presence detections become common. At 60 min delay, more than 20% of the unoccupied periods were falsely interpreted as occupied. From a controls point of view, this causes a reduction in the potential energy savings.

After numerous experiments, Nagy et al. [47] showed that for lighting controls the optimal PIR time delay is the one with which 95% of the occupied periods can be correctly detected. For example, for the illustrative example shown in Figure **3**, the optimal PIR delay is between 15 and 20 min – depending on the location of the sensor. However, Nagy et al. [47] demonstrated that optimal delay values in different space types can differ by a factor of five (4 to 20 min), and they developed a method for selecting the optimal delay value by looking at the distribution of the frequency of movement detections. Upon this method, Gunay et al. [45] created a recursive algorithm to select the optimal delay values inside a controller and verified its accuracy in a controls laboratory.

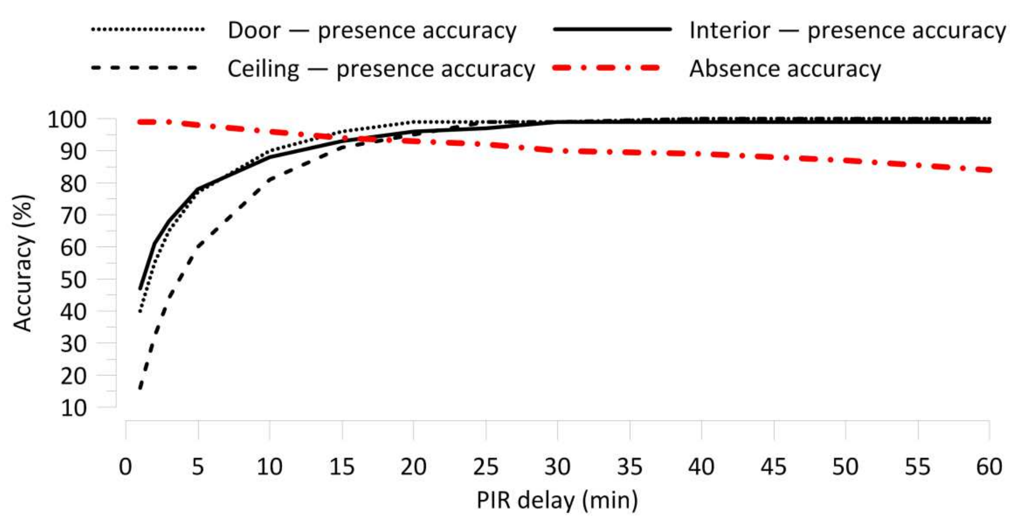

Figure 3: Accuracy of presence and absence detections using PIR sensors in a shared office space. Three different PIR placement options were studied: facing the door, facing the interior space, and on the ceiling. The figure was modified from Gunay et al. [45].

PIR motion detectors require a direct line-of-sight. Oftentimes, a single motion detector cannot have a direct line-of-sight to all occupants in an office space. For example, Figure 4 presents a 17 m^2 shared office space with three commercial PIR sensors. Any of the three PIR sensors alone cannot provide a full coverage of this small office space. Similar findings were reported by others [48]. This is partly because of the room geometry and the furniture layout.

But, other contextual factors may force control technicians to choose rather suboptimal locations for PIR sensors. Within a building controls network, PIR sensors are often built-in inside control interfaces such as thermostats or light-switches and mounted on vertical surfaces, or they are mounted on ceilings as standalone sensors. When they are built-in inside control interfaces, the design purpose of the control interface dictates where the PIRs are placed. For example, the light-switches in commercial buildings are typically placed about 100 cm above the floor level. For thermostats, this value is about 150 cm. Thus, the same motion sensor placed inside a wall thermostat rather than a light switch would tend to have a lesser coverage of a seated occupant. Within a wall thermostat (which contains a thermistor sensor), a PIR sensor needs to be placed away from terminal HVAC units and exterior walls. The controls technicians are often expected to make such decisions during the installation with little, if any, guidance.

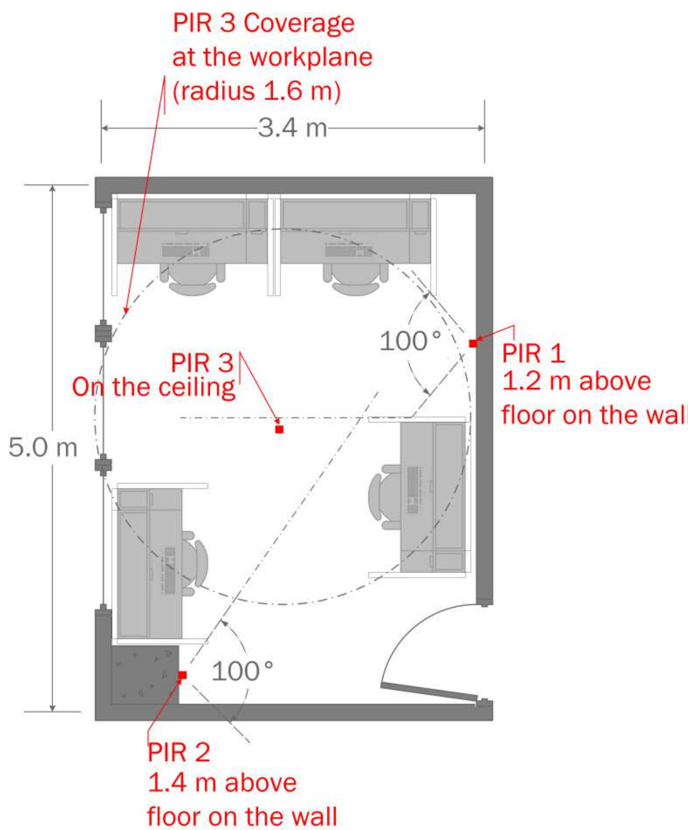

Figure 4: An illustrative example for the coverage of three PIR sensors in a small shared office space. The figure was modified from Gunay et al. [45].

Ultrasonic sensors – similar to PIRs – detect human movements, and thus suffer from the same types of limitations as the PIR sensors with the exception that they were reported to be more sensitive to the motion of inanimate objects (e.g., blowing curtains) [49]. In an early study, Maniccia [50] reviewed 23 commercially available ultrasonic and PIR sensors. Of them, 18 failed to detect movements with the manufacturers claimed coverage range. Almost two decades after this study, there is no evidence whether this remains as a valid issue.

Note that both PIR and ultrasonic sensors are motion detectors. They output only a binary signal upon movement detection, and thus they fail to detect the number of occupants using a space. The building controls industry has begun to integrate CO_2 sensors inside wall thermostats. The CO_2 generation rate of a sedentary occupant is about 0.3 L/min [51]. Thus, a single occupant in a hypothetical perfectly airtight and unventilated 15 m^2 office space can increase the CO_2 concentration by about 350 ppm/hour. The CO_2 sensors render the potential to infer the number of occupants in a space by filtering out occupants' influence on the CO_2 concentration of the office spaces. In the reviewed literature, this was done via simple physical models assuming perfectly mixed indoor air [52-54].

Although the early attempts to estimate the whole-building occupancy by taking CO_2 readings at the air-handling unit's supply and return air were successful [53], estimating the spatial distribution of occupancy at the zone level were found to be challenging [54]. Transport of CO_2 emitted by occupants is a transient process. Depending on the office furniture layout and the distance between occupants and the CO_2 sensor, the influence of occupants on the sensor's readings will lag. Although room specific anecdotal observations were reported for the time lag values in the literature (e.g., Arora et al. [54] 30 min or Dong and Andrews [55] 20 min), the variables such as ventilation rate and style (e.g., displacement or mixing ventilation), room size, window/door positions can affect the CO_2 transport rate (by changing the process from diffusion to advection). Furthermore, estimating occupants' influence on CO_2 sensors' readings may require auxiliary information from ventilation airflow rate and CO_2 concentration, door position and corridor CO_2 concentration, and air permeability of the envelope and outdoor CO_2 concentration. As a result, CO_2 sensors have been treated as a secondary source of information after the PIR or ultrasonic sensors [55-57]. They were used to complement PIR sensors for cases in which a direct line-of-sight to the motion of all occupants is not possible [57].

Because of the uncertainty associated with the determination of occupancy using single-point sensing, a network of linked, cheaper conventional occupancy sensors [10, 46] was proposed to offer more accurate and robust occupancy measurement, and greater energy savings than that which can be achieved with a single sensor. Wired sensors may be replaced by wireless sensors (therefore wireless sensor networks or WSN) to further reduce the deployment and maintenance costs.

The weaknesses of the conventional occupancy detection approaches can be summarized as follows:

- Cost: A high-quality, wired, standalone occupancy sensor can cost US$150 or more to be installed. Wireless devices may offer lower installation costs, but are not completely reliable regarding data communications, and must be powered by batteries (that eventually need to be changed), or by energy-scavenging systems that add cost and have their own reliability issues.
- Field of view (restricted to visual line of sight): if there is any object between the sensor and the occupant, the occupancy cannot be detected.
- Low occupant resolution: at Level 1 with limited information on count, identity, and activity.
- False detection: a shadow or a flash (e.g., headlight from a passing car) can trigger PIR sensors.
- Robustness: if the single sensor fails, drifts out of calibration, or is physically compromised, control for the zone becomes sub-optimal or is lost entirely.

4. Implicit / Ambient / Soft Sensing Approaches

4.1 Overview

Extracting and leveraging occupancy information from systems already in the building for other primary purposes, rather than from those explicitly designed to collect occupancy information, has been termed implicit occupancy sensing [26], ambient sensing [57], or soft sensing [58, 59].

Sources of implicit occupancy information include data that are already collected but not used for building control purposes, and data that are potentially available, but not yet collected. In the former category are things like computer network traffic, security card access systems, elevator usage, and detection of mobile devices at Wi-Fi access points. In the latter category are things like keyboard and mouse activities, webcams, and PC microphones. The advantage of implicit occupancy sensing is that these sensors are already present for other purposes, are powered and capable of communication so that they can be accessed by the building control systems, and thus come at little or no incremental cost. Although these individual channels might have limited accuracy independently, their aggregated data may result in higher accuracy, and certainly more robustness, than any one high-end sensor [16, 48, 56, 58, 60].

Melfi et al. [26] proposed a three-tier classification of implicit occupancy sensors:

- Tier I requires no modification to existing systems other than a collection and processing point.
- Tier II involves the addition of software to existing infrastructure to make existing occupancy-related data available.
- Tier III involves the addition of software and hardware to introduce new sources of occupancy data to existing systems.

We will use this three-tier classification for review and comparison of various implicit occupancy sensing approaches developed in the research literature. Note that Tier III approaches are essentially similar to the conventional approaches, with the exception that they use other types of sensors (e.g., light, relative humidity (RH), temperature, and physical pressure) or sensor networks (e.g., Radio-frequency identification (RFID) and ZigBee-based wireless sensor networks) rather than conventional motion detectors and CO_2 sensors. About 60% of the projects / systems being reviewed fall in this category.

Table 1 summarizes various implicit sensing approaches proposed and developed in the research literature. Table 2 provides an overview of the same projects as listed in Table 1 in terms of occupancy resolution, accuracy, demo scale, data fusion and control strategies.

Table 1: Implicit occupancy sensing: summary of prior studies in the research literature.

	Tier I						**Tier II**				**Tier III**			
Research Group with References	**DHCP/ ARP**	**Outbound phone calls**	**Access badge, codes**	**WiFi-based**	**IP Traffic**	**Instant Msg, Calendar**	**Key-board, Mouse**	**Webcam**	**Microphone**	**Bluetooth**	**RFID**	**Motion Sensors**	**Special purpose sensors**	**Wireless Sensor Networks**
Melfi et al. [26]	x	x	x				x							
Ghai et al. [58]; Thanayankizil et al. [59]			x	x		x								
Oldewurtel et al. [61]						x						x		
Ekwevugbe et al. [62]			x									x	RH, light, VOC, CO_2, sound, pressure mats	
Dodier et al. [46]		x										x		
Hay and Rice [63]			x											
Kushki et al. [64]				x										
Chintalapudi et al. [65]				x										
Balaji et al. [15]				x										
Kim et al. [66]					x								Circuit power monitor	
Jin et al. [67]				x									Plug load sensor, sonar, accelerometer	
Ruiz-Ruiz et al. [36]				x										
Zhao et al. [68]				x			x	x		x		x	Chair sensors	
Dalton and Ellis [69]								x						
Huang et al. [70]									x					
Harris and Cahill [71]										x				x
Conte et al. [72]										x				x
Dong et al. [56]							PC activity						With existing IT infrastructure	x
Zhen et al. [73]											x			
Li et al. [41]											x			
Augello et al. [11]											x		RH, light, temperature	
Lam et al. [57]												x	CO, CO_2, TVOC	x
Nguyen and Aiello [74]												x	Pressure (chair), acoustic	x
Yang et al. [19]												x	RH, light, temperature, CO_2,	x
Khan et al. [18]												x	RH, light, temperature, sound	x
Dong et al. [16]												x	RH, temperature, light, CO_2	
Polese [75]													Image processing occupancy sensor	
Labeodan et al. [39, 76]													Chair sensors	
Jazizadeh and Becerik-Gerber [77]													Light intensity sensors	x
Liao et al. [78]													Beam-break sensors	
Meyn et al. [79]													Camera, CO_2	

	Tier I						Tier II				Tier III			
Research Group with References	**DHCP/ ARP**	**Outbound phone calls**	**Access badge, codes**	**WiFi-based**	**IP Traffic**	**Instant Msg, Calendar**	**Key-board, Mouse**	**Webcam**	**Microphone**	**Bluetooth**	**RFID**	**Motion Sensors**	**Special purpose sensors**	**Wireless Sensor Networks**
Wu and Clements-Croome [80]													RH, temp, light	x
Tiller et al. [48]												x		Wired SN
Dedesko et al. [81]													Beam-break sensors, CO_2	
Erickson et al. [82]													Wireless Camera	
Erickson et al. [17]													Wireless Camera	
Harle et al. [83]													Ultrasonic 3D tracking	
Benezeth et al. [84]													Camera	
Hailemariam et al. [29]													RH, temperature, light, AC current	Sensor array
Attar et al. [85]													RH, temperature, light, AC current	Sensor array
Han et al. [86]													RH, temperature	
Han et al. [87]													CO_2, PIR, RH	
Pandharipande and Caicedo [88]													Ultrasound array sensor	
Agarwal et al. [21]													PIR + door sensor	x
Weekly et al. [89]													Particulate matter sensor	
Yavari et al. [90]													Doppler Radar	
Arora et al. [54]													Illuminance, RH, PIR, power consumption, door contact, CO_2	
Gunay et al. [45]								x					PIR, door contact, CO_2	
Philipose et al. [91]											x			
Ramoser et al. [92]								x						
Brackney et al. [93]													Image processing occupancy sensor	
Milenkovic and Amft [94]													PIR, ultrasound range finders, and plug-in equipment load	

Table 2: Occupancy resolution, accuracy, demo scale, data analysis, and control strategies used by implicit occupancy sensing studies in the research literature.

Research Group with References	**Occupancy Resolution**	**Spatial Resolution**	**Temporal Resolution**	**Accuracy**	**Ground Truth**	**Demo Scale**	**Data fusion & control strategies**	**Applications**	**Remarks**
Melfi et al. [26]	Level 1/2	Room	Minutes	89%	Manual recording	2 buildings			Focus on accuracy analysis
Ghai et al. [58]; Thanayankizil et al. [59]	Level 1/2/3	Floor, cubicles		90%	Manual recording	5 people for 6 weeks on a floor	Classification, Regression		Classification is much better than Regression
Oldewurtel et al. [61]	Level 1/2	Zone, Room	Days			20 persons for 5 years (simulation)	Model Predictive Control		Simulation only, no physical tests
Ekwevugbe et al. [62]	Level 1/2	Building areas	Minutes			A building area	Adaptive Neuro-Fuzzy Inference		Indoor climatic variables, indoor events and energy data obtained from a non-domestic building to infer occupancy patterns
Dodier et al. [46]	Level 1	Room	Seconds		Manual & camera	2 offices 2 days	Belief network		Cheap sensor approach, wired sensor network
Hay et al. [63]	Level 3/4	Floor, Room	Seconds			A building			Study on apportioning the total energy consumption of a building to individual users to provide incentives to make reductions
Kushki et al. [64]	Level 3	Floor, Zone							WiFi based indoor positioning
Chintalapudi et al. [65]					Theoretica l value for analysis	No demo			Conceptual proposal on WiFi-based ad-hoc localization use ranging & sectoring devices
Balaji et al. [15]	Level 1/2/3	Zone	Seconds	86%	Manual recording	1 building, 10 days			WiFi + smartphone for occupancy detection; applied for HVAC control
Kim et al. [66]	Level 1/2	Zone	Seconds			Lab setting			IP traffic + power monitoring. Simulation & analysis only.
Jin et al. [67]	Level 1	Room	Seconds	89%	Manual	5 cubicles	A zero-training algorithm		Focused on power monitoring to infer occupancy
Ruiz-Ruiz et al. [36]	Level 1/2	Buildings	Seconds			A large hospital, 2 weeks		Building planning, evacuation	Use sole measurement of WiFi signals from peoples' devices to estimate the density of people in the hospital for building planning purpose (e.g., evacuation).
Zhao et al. [68]	Level 1	Room, Zoom	Seconds	97%	Manual	2 rooms, 2 weeks	Bayesian Networks	HVAC control	Two types of virtual occupancy sensors: room level virtual occupancy sensors are composed of physical occupancy sensors, chair sensors, keyboard, and mouse; working zone-level virtual occupancy sensors based on real-time GPS location and Wi-Fi connection from smart devices.
Dalton and Ellis [69]	Level 4	Room	Seconds		Simulated	1 laptop			Face monitoring instead of keyboard and mouse detection for screen saver control. Average power saving 10~30% based on a few experiments.
Huang et al. [70]	Level 1/2	Room	Seconds	90%+	Simulated	1 room		HVAC control	Use audio processing techniques (i.e., speaker recognition and background audio energy estimation) to estimate room occupancy (i.e., the number of people inside a room)
Harris and Cahill [71]	Level 1	Device	Seconds	80%		6 user trails, each for a week	Bayesian Networks		Context-aware desktop PC power management by detecting Bluetooth phone. Trade-off between energy saving by shutting off a device and the waiting time (user satisfaction) for starting up.
Conte et al. [8]	Level 1/2/3	Room	Seconds	83~ 84%		3 rooms, 1,000 samples	k-NN, decision trees		BLE (Blow Low Energy), modified iBeacon protocol

Research Group with References	Occupancy Resolution	Spatial Resolution	Temporal Resolution	Accuracy	Ground Truth	Demo Scale	Data fusion & control strategies	Applications	Remarks
Dong et al. [56]	Level 1/2	Floor	Minutes	65~ 90%	Networked cameras	A large open office area for 90 days	Hidden Markov Models, NN, SVM		Open-plan office building with wireless ambient sensing, wired CO_2& IAQ sensing; wired camera network for ground truth.
Zhen et al. [73]	Level 3	Floor, Zone, Room	Seconds	93%	Manual recording	1 person with 4 tags moving in 12 zones	Support vector machine	Lighting control	Active RFID-based lighting control
Li et al. [41]	Level 1/2	Floor, Zone	Seconds	88% stationary; 62% mobile	Manual recording	One floor within an educational building		HVAC control	RFID-based occupancy detection
Augello et al. [11]	Level 1/2/3	Room	Seconds			1 room with 2 people & 1 open area	K-means clustering	Lighting control	Sensor mining to profile user behavior patterns. Potential for agent-based implementation. RFID for presence detection.
Lam et al. [57]	Level 1/2	Floor	Minutes	80%	Video camera	2 bays of a large open workspace for 57 days	SVM, Hidden Markov Models (HMM), ANN		Various classification methods including SVM, NN, and HMM used to count the number of occupants in an open office environment.
Nguyen and Aiello [74]	Level 1	Room	Minutes	95%		1 room 5 days			Simple sensors (but moderate-to-high cost)
Yang et al. [19]	Level 1/2	Room	Minutes	86~89% trained 63~66% generic	Manual on a mobile device	Three-story building for 20 days	Radial basis function neural network	HVAC control	A occupancy estimation model built on a combination of nonintrusive sensors
Khan et al. [18]	Level 1/2	Room	Seconds ~ hours	92~95%	Camera & manual	10 days	SVM, k-NN	HVAC and lighting control	Combined environmental sensors & contextual info; Hierarchical Occupancy estimates with decision confidences
Dong et al. [16]	Level 1/2	Room, Zone	Minutes	83%	Networked cameras	One zone with multiple rooms			Findings: important sensors for the accurate occupant behavior pattern prediction are CO_2, acoustics and motion.
Polese [75]	Level 1	Room	Seconds	99.57%		A few hours		HVAC and lighting control	Developed a new image processing occupancy sensor to replace a PIR sensor.
Labeodan et al. [39, 76]	Level 1/2	Room	Seconds	87~99%		1 chair, 1 day		HVAC and lighting control	Experiments with chair sensors using sensing techniques based on strain, vibration and a mechanical-switch for occupancy detection in an office space.
Jazizadeh and Becerik-Gerber [77]	Level 1/2	Room	Minutes			A few rooms	Machine learning	HVAC control (not implemented)	Extract device info from IFC model; ambient sensors to monitor lighting systems; devices/ appliances to send their energy consumption info to the server for HVAC decisions
Liao et al. [78]	Level 1/2	Room, Zone	Minutes			One room with one person			Agent-based simulation of occupant behavior for modeling and estimating occupancy in commercial buildings
Meyn et al. [79]	Level 1/2	Zone, Building	Minutes	89% at building, 79% at zone	Recorded video	A building with multiple floors/zones	Senor-Utility-Network		Senor-Utility-Network: estimation based on sensors, prior knowledge of building utilization & building network structure
Wu and Clements-Croome [80]	Level 1/2	Room, Zone	Seconds			Existing dataset	Clustering algorithms		Data mining for temperature, RH, and lighting distribution, rather than on occupancy detection,

Research Group with References	Occupancy Resolution	Spatial Resolution	Temporal Resolution	Accuracy	Ground Truth	Demo Scale	Data fusion & control strategies	Applications	Remarks
Tiller et al. [48]	Level 1	Room	Seconds	88%			Belief network	Lighting control	Wired sensor network for improved lighting system control
Dedesko et al. [81]	Level 1	Room	Seconds		Manual	10 patient rooms			A method that utilized data from CO_2 and beam-break sensors to characterize time-varying occupancy and occupant activity in a hospital environment.
Erickson et al. [82]	Level 1/2	Zone, Building	Seconds	80%	3 webcams (3 images every 2 s)	A large multi-function building	Multivariate Gaussian models	HVAC control	Wireless sensor network for data collection. Multivariate Gaussian and agent based models for occupancy prediction. 14% energy reduction from HVAC.
Erickson et al. [17]	Level 1/2	Zone, Building	Seconds		7 cameras covering 10 areas	A large building for a few days	Markov chain model	HVAC control	Changed modeling approach from the above work. 42% Annual energy saving based on simulations & analyses.
Harle et al. [83]	Level 1/2	Room, Zone	Seconds	95%	Ultrasonic location system	50 rooms, 40 people, 60 days.			Using an existing ultrasonic location system. Lighting energy reduction of 50% based on estimation & analysis.
Benezeth et al. [84]	Level 1/2	Room	Seconds	97%	Recorded videos	Proof-of-concept tests			Vision-based system for human detection and activity analysis.
Hailemariam et al. [29]	Level 1	Room	Minutes	98%	Camera	One cubicle, one person, 7 sensors, days	Decision Trees		Decision Trees method for data analysis. It improves the detection accuracy with motion sensors alone, but the accuracy reduces with multiple sensor types.
Attar et al. [85]	Level 1	Room, Zone	Minutes			One cubicle data, zone visualization			Focusing on time-based visualization of thermal values linked to as-built BIM.
Han et al. [86]	Level 1	Room	Seconds	92%		One sensor, three persons, 27 hours			Use only the relative humidity to detect the human presence by adjusting the threshold, sampling window and size.
Han et al. [87]	Level 1/2	Room, Zone	Seconds	81%	Manual recording	A lab with 6 people for 3 weeks	Autoregressive Hidden Markov Model		Compared with classical Hidden Markov Model and Support Vector Machine.
Pandharipande and Caicedo [88]	Level 1/2	Room	Seconds			A test office room for a short period		LED control	Ultrasound array sensor. Specifically, for LED control, considered both occupancy and daylight distribution. OK to consider two people that are very close as one object.
Agarwal et al. [21]	Level 1	Room	Seconds		Manual recording	10 rooms, 10 days		HVAC control	Errors are mostly caused by the door sensor which assumes occupancy if the door is open.
Weekly et al. [89]	Level 1	Small area	Seconds	66%	Camera	One sensor, 8 hours			Use low-cost (<$8) particulate matter sensor to infer the local movement of occupants.
Yavari et al. [90]	Level 1	Room	Seconds		Piezo-electric chest belt	One sensor , couple of minutes			A Doppler radar sensor is used to detect human presence by extracting respiratory and heart signals while the human subject is at rest and moving at different activity levels.
Arora et al. [54]	Level 2	Room	Minutes	65%	Recorded videos	One room, five days	Decision Trees		Decision Trees method for data analysis. It ranks the information gain from individual sensors. The method appears promising for classifying presence, however low-accuracy detecting the number of occupants in the room.
Gunay et al. [45]	Level 1	Room	Minutes	95%	Recorded videos	One room, two months			Different complementary sensors such as CO_2, door contact, and webcam-based computer vision were used to improve presence detections using PIRs.

Research Group with References	**Occupancy Resolution**	**Spatial Resolution**	**Temporal Resolution**	**Accuracy**	**Ground Truth**	**Demo Scale**	**Data fusion & control strategies**	**Applications**	**Remarks**
Philipose et al. [91]	Level 3/4	Room	Seconds						Anecdotal observations reported for a method to detect occupant position and activity type by using RFID tags and Bayesian filtering using existing activity models. Accuracy of the method was not quantified.
Ramoser et al. [92]	Level 3/4	Small area	Seconds						Using the surveillance camera records, occupants' locations were detected. Limited preliminary are promising but accuracy was not quantified.
Brackney et al. [93]	Level 2/3	Room	Seconds	94%	Recorded videos	One cubicle, several days			Preliminary results from a new computer vision-based sensor. It conducts computations required for image processing locally and images are not stored. This may alleviate the privacy concerns pertaining to other camera-based occupancy detection solutions.
Milenkovic and Amft [94]	Level 2/3	Room	Minutes	Presence 87% People count 78%	Manual recording	One shared office and one single office, 100 hours	Layered hidden Markov models		Layered hidden Markov models were trained with 30 h worth of data for presence detection and with 50 h worth of data for people count detection. The models were shown to detect presence accurately. Activity type detection and people count detection accuracies were less than 80%.

4.2 Explicit or Implicit Occupancy Sensing

Among more than fifty projects / systems being reviewed, only a small number of them use the existing IT infrastructure to collect occupancy information (as listed in Table 1). Many researchers have proposed and developed systems using supplementary devices and systems including Wireless Sensor Networks [19, 56, 57, 71, 74, 77, 80, 95-98], sensor arrays [29, 85], RFID (Radio-frequency identification) [11, 41, 73, 91], different motion sensors [19, 57, 62, 74], and other dedicated sensors like chair sensors [74, 76], image processing occupancy sensors [93], RH and temperature sensors etc. [29, 85, 86]. Other interesting efforts include applying particulate matter sensors to infer the local movement of occupants [89]; using individual power monitoring data to enhance presence detection [54]; utilizing a Doppler radar sensor to detect human presence by extracting respiratory and heart signals while the human subject is at rest and moving at different activity levels [90]; and using only RH to detect the human presence by adjusting the threshold, sampling window and size [86].

4.3 Sensors / Data Sources Use

Among all the projects / systems being reviewed, most projects / systems use only one sensing approach or source for occupancy data collection, with some exceptions [16, 26, 29, 45, 54, 56-58, 78]. For example, Dong et al. [16] employed a combination of motion, sound, RH, temperature, light, and CO_2 sensors and found that important sensors for the accurate occupant behavior pattern prediction are CO_2, acoustics, and motion. Hailemariam et al. [43] used various types of sensors including motion, RH, temperature, light, and AC current, though their results showed that additional sensors do not help to improve detection accuracy when using decision trees. Lam et al. [57] deployed a wide array of sensor types including various gas sensors, sound pressure level, illuminance, PIR, RH, and temperature in an open office environment to detect occupancy count. Similarly, to detect the occupancy count in a shared office space, Arora et al. [54] employed illuminance, RH, PIR, power consumption, door contact, and CO_2 sensors. Melfi et al. [26] is one of the early studies that investigated occupancy detection using the existing IT infrastructure including computer networking, phone calls, access badges, as well as computer usage through keyboard and mouse activities. Ghai et al. [58] is another example of using only context sources that are commonly available in commercial buildings such as area access badges, Wi-Fi access points, Calendar and Instant Messaging clients.

A recent study by Khan et al. [18] investigated the combination of environmental sensing and contextual information to produce Levels 1 and 2 occupancy estimates with some promising results. However, there has not been any rigorous investigation of multiple sensors and/or multiple data sources, as well as the combination of implicit sensing (using the existing IT infrastructure) and explicit sensing (e.g., using motion sensors). Another recent study by Newsham et al. [99] explored the viability of detecting occupants' presence at the one-person office or cubicle level through various contextual information such as keyboard and mouse activities, webcam, microphone, proximity sensor, air temperature and relative humidity sensor, and pressure mat (for the ground-truth). Through a case study, they demonstrated that occupancy information can be retrieved more accurately with these low-cost and readily available sensing technologies than with traditional PIR motion detectors.

4.4 Occupancy Resolution

A majority of the systems being reviewed provided occupancy detection at Level 1 (yes or no) and Level 2 (counting numbers of people). Among more than 50 systems reviewed, only 11 detected occupancy at Level 3 (identity) and only three at Level 4 (activity). Related to spatial resolution, most systems detected occupancy at the room or zone level. Li and Becerik-Gerber [41] listed six different occupancy detection technologies that can locate occupants in the indoor environments at a higher spatial resolution. These technologies are the indoor global positioning systems [100], inertial navigation systems [101], a network of PIR motion detectors [102], ultra-wide band positioning systems [100], wireless local area networks [103], and RFID tags [104]. In terms of temporal resolution, almost all the reviewed studies focused on exploiting short-term (in the range of minutes or seconds) occupancy information for increasing energy efficiency in buildings.

4.5 Occupancy Detection Accuracy

Most reviewed systems report an overall accuracy of 80 to 98% which is believed to be high-enough for building automation. Note that accuracy here is typically in the context of a heavily curated pilot / research study, and one could expect accuracy in a longer-term commercial implementation in multiple space types and with a variety of user types to be lower. As argued by many researchers, the accuracy requirement is really dependent on various control applications. For example, for lighting automation, Nagy et al. [105] observed that even 90%

accuracy in detecting presence can cause substantial occupant dissatisfaction – e.g., lights switch off automatically upon false vacancy detection. Later, they showed that a minimum of 95% accuracy should be achieved, if the occupancy detections are intended for lighting automation. Depending on the purpose of the occupancy detections, larger presence prediction errors can be acceptable. For example, incorrect detection of vacancy periods for HVAC control, may not cause a noticeable thermal discomfort given that buildings respond to thermal loads slowly. Since high accuracy requirements also bring high implementation cost, the key is to have high-enough accuracy with minimal cost, at the same time ensuring occupant comfort and protecting occupant privacy. As described above, any analysis of occupancy accuracy in the context of building systems control should discriminate between false positives and false negatives. For example, the false positive rate could be greater than 20% according to three studies [45, 82, 106]. However, very few efforts have been reported on the separation of error types. Further, some studies have inflated accuracy by including overnight periods when, in commercial settings, extended vacancy is self-evident and detection is not challenging.

4.6 Demo Scale

Almost all reported systems are at the proof-of-concept stage, and most have been demonstrated at the very small scale only over short time periods in a limited number of spaces. There have been a few exceptions of studies at the building level over a period of a few months [12, 17, 19, 56, 79, 83, 99, 106].

4.7 Data Fusion and Control Strategies

Having knowledge regarding occupancy and being able to accurately predict usage patterns will allow significant energy-savings by intelligent control of lighting and HVAC systems. However, with the massive amount of data being collected using various occupancy detection systems, it is very challenging to process the collected data efficiently and effectively in real-time in order to provide accurate inputs into building control systems. Various approaches have been reported for data fusion and control strategies including:

- Classification approaches by Ghai et al. [58];
- K-means Clustering by Augello et al. [11];
- Adaptive Neuro-Fuzzy Inference approach by Ekwevugbe et al. [62];

- Belief Network based approaches by Dodier et al. [46] and by Tiller et al. [48];
- Bayesian Networks by Harris and Cahill [71] and Zhao et al. [68];
- Support Vector Machine (SVM) by Zhen et al. [73];
- Markov Chain Model by Erikson et al. [17];
- Hidden Markov Models by Dong et al. [56], Han et al. [87], Lam et al. [57];
- Layered hidden Markov models by Milenkovic and Amft [94];
- Sensor-utility Network by Meyn et al. [79];
- Decision Trees by Hailemariam et al. [29] and Arora et al. [54].

Most of these data fusion methods are mentioned in the literature review sections of many papers, but it is rare to find a comparison of these different data fusion approaches on the same dataset.

4.8 Applications

While most reported efforts on occupancy detection are still purely on feasibility studies on various devices, systems, and technologies, a few applications have been demonstrated for HVAC control, lighting control, and computer management. For those that did engage in energy management, they were generally successful in illustrating the energy savings potential, with savings of 15-20% for HVAC control [16, 107], 20-30% for lighting control [10], and about 20-30% for computer power management [83].

With the innovations in sensing technologies, the focus in occupancy detection research has diverted to tracking occupants' position and activities from monitoring spaces (to infer anonymous occupancy information). For example, Li and Becerik-Gerber [41] and Philipose et al. [91] employed RFID tags, Milenkovic and Amft [94] used ultrasound range finders mounted on computer monitors, and Nguyen and Aiello [74] monitored occupancy through pressure sensors placed on seats. Tracking individuals – in lieu of monitoring spaces – brings about heightened privacy concerns [108]. And, arguably it will provide limited benefits for the operation of existing buildings because of the course-granularity of the HVAC and lighting equipment control. As Li and Becerik-Gerber [41] reported, a large portion of the occupancy detection literature has been generated by computer scientists and electrical engineers. As a consequence, the focus has been on developing new sensing technologies without acknowledging the application specific requirements and constraints of indoor occupancy sensing. Occupancy sensing for indoor climate control (e.g., HVAC and lighting) should be tailored in recognition of the granularity of HVAC and lighting zoning and numerous contextual factors such as privacy and the interior design [43].

Occupancy sensing technologies that provide information at Level 1 and 2 (i.e., zone level presence and occupant count) may still cause substantial privacy concerns. The privacy issues may be exacerbated, particularly for the computer vision based occupancy detection technologies, if the images are stored and processed in a central server. Brackney [93]'s image processing occupancy sensor is embedded on a device with limited computational power, and each sensor can process images locally in real-time and output an occupancy state signal that can be interpreted by a commercial building controller. This may alleviate some of the concerns-related with the occupants' privacy.

Implicit occupancy sensing also means using data that are not originally intended for controls-oriented applications inside an automation and controls network. This will bring about integration challenges. For example, after demostrating the theoretical feasibility of using Wi-Fi as a proxy to the occupancy in the Univesity of British Columbia library, Henderson [109] discussed the challenges to integrate the existing IT and controls infrastructures. Similarly, access control, despite being a promising source of occupancy information [58], is seldom integrated to the HVAC and lighting controls. In addition, HVAC and lighting controls are rarely integrated with each other in existing buildings [106]. These issues bring about hidden capital and labour costs, and thus represent a major barrier against the wider usage of indoor climate control with implicit occupancy sensing.

5. Concluding Remarks and Future Research Directions

This paper presents a comprehensive review and classification of implicit occupancy sensing approaches by leveraging occupancy related data streams from existing IT infrastructure. About fifty related projects / systems have been reviewed and compared in terms of occupancy sensing type, occupancy resolution, accuracy, ground truth data collection method, demonstration scale, data fusion and control strategies. Implicit occupancy sensing has the potential to provide acceptable occupancy accuracy for efficient building energy management through optimal delivery of building services (including lighting, heating, ventilating, and air conditioning) with lower costs compared to traditional explicit sensing approaches. However, the development of implicit occupancy sensing systems is still in the early stages, and considerably more work is necessary to demonstrate a large-scale, robust and persistent deployment. For example, optimum combinations of sensors and data sources need to be identified, along with the most efficient and accurate data fusion and analysis approaches.

With the recent fast development and deployment of Mobile/Cloud Computing and the Internet of Things (IoT), the IT infrastructure will likely provide even more sources of implicit occupancy information and more opportunities for combining occupancy related sensors and data sources to support building occupancy determination with less cost, and for mutually-supportive applications beyond energy savings. For example, sensors deployed for access control or for fire safety purposes can provide useful occupancy information, and accurate occupancy information from implicit sources can be useful to support building evacuation planning as well as emergency response and rescue. The challenges are to develop efficient occupancy determination algorithms under easy-to-use Big Data analytics platforms. In this direction, data semantics and interoperability is another major challenge.

On the development and commercialization side, there will be a trend to develop more intelligent and accurate but less expensive occupancy sensors that can be connected to the building control systems (lighting, HVAC, and plug loads), in the short-term through wired connections, but in a few years all wirelessly through an IoT environment. Such occupancy sensors will soon be embedded into IT equipment (computers and monitors etc.) and fire alarm devices.

Despite the potential for more efficient building operations, the exploitation of some implicit data sources may understandably raise privacy concerns among building occupants (e.g. webcams, image processing occupancy sensors, security card access systems). Efforts will need to be expended to develop methods to engage such data in a way that preserves appropriate privacy in a transparent manner and demonstrates value to the occupant, otherwise deployment of such systems will be compromised.

Acknowledgment

The work presented in this paper was supported by the ecoENERGY Innovation Initiative (EcoEII) administered by Natural Resources Canada (NRCan), by the National Research Council Canada’s High Performance Building Program, and the Conservation Fund of the Independent Electricity System Operator (formerly Ontario Power Authority)

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