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Implicit Occupancy Detection for Energy Conservation in Commercial Buildings: A Review

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***Abstract*—The key to saving energy in commercial buildings is to deliver building services only when and where they are needed, in the amount that they are needed. Given that building services are usually employed to provide occupants with satisfactory indoor conditions, it is therefore important to accurately detect the occupancy of building spaces in real time. This paper starts with some discussion on building occupancy resolution and accuracy as well as a brief introduction to traditional explicit occupancy detection approaches. The focus of this paper is on the review and classification of emerging, potentially low-cost approaches to leveraging existing data streams that may be related to occupancy, sometimes referred to as implicit / ambient / soft sensing approaches. About 40 related projects / systems are reviewed and compared in terms of occupancy sensing type, occupancy resolution, accuracy, ground truth data collection method, demonstration scale, data fusion and control strategies. It also briefly discusses technology trends, research challenges, and future directions.**

***Keywords*—commercial buildings; energy conservation; energy management; HVAC control; lighting control; occupancy detection**

I. Introduction

According to the US Department of Energy [41], 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 loads (including computers, electronics, refrigeration, cooking, and cleaning). These systems and devices are essential to support commercial building operations and maintain occupant comfort.

It has long been recognised that a key to saving energy in commercial buildings is to deliver building services only when and where they are needed, in the amount that they are needed. The first step towards this is to accurately detect the occupancy of building spaces in real time.

As a consequence of this understanding, occupancy sensors have been deployed at the room level to save energy, primarily in ambient lighting systems [2], [13], [44], with the potential for energy savings with HVAC (heating, ventilating, and air conditioning) systems also emerging [3], [9], [12], [27]. From these deployments, savings of 20-50% are typically reported. Given this success, occupancy sensors for lighting systems are now mandated in certain space types in many energy codes for new buildings (e.g., 2011 National Energy Code of Canada for Buildings). 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 use data from existing systems, installed for some other purpose, to provide an indication of occupancy. According to a recent report by Melfi et al. [33], 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 also be used by building control systems to reduce the energy consumption of air conditioning, lighting, and other building systems [14], [18]. Occupancy detection can provide information to these building systems to allow them to operate proportionally to the number of occupants in the building [33], [42] and ultimately to optimize the building energy management through integrated control of active and passive heating, cooling, lighting, shading, and ventilation systems [38].

In addition to direct energy and cost savings though real time intelligent control of HVAC, lighting, and plug loads, detailed occupancy information may also be leveraged for other energy-saving applications, including occupant engagement and behaviour adjustment, achieving optimal demand response, optimizing energy storage, and increasing building energy use forecasting accuracy. It may also help enhance building space utilization. Finally, there is potential to lower 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 [31].

The rest of this paper is organized as follows. Section II defines building occupancy resolution and accuracy. Section III reviews conventional approaches. Section IV provides a comprehensive review of implicit/ambient/soft sensor approaches. Section V presents some concluding remarks.

II. Building Occupancy Resolution and Accuracy

A. Building Occupancy Resolution

Different applications require different levels of building occupancy resolution and accuracy. Melfi et al. [33] proposed

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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
- Occupant 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

A room typically refers to a single office or a space with four full-height walls (e.g. conference room) or a large zone containing many cubicles. In the context of this paper, we may 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 [37].

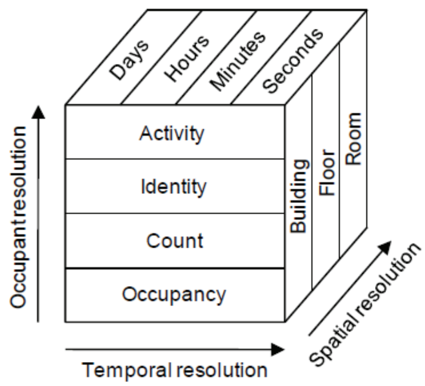

Figure 1. Occupancy resolution in three dimensions [33]

B. Building Occupancy Accuracy

Given a number of readings from a sensor and the ground truth (actual) occupancy, accuracy is the relative error of the measured value from the ground truth [33].

High levels of accuracy are important so that control strategies for the delivery of building services including lighting and HVAC can make correct decisions. However, the accuracy of occupancy information for building energy management may not be as important as that for the building security systems, for example. Further, high accuracy requirements usually bring high deployment cost. Therefore, an appropriate level of accuracy needs to be decided based on some ROI (return on investment) analysis.

Different types of accuracy errors have different implications. In the domain of building energy management control, false negatives (concluding there is no one in the zone when, in fact, the zone is occupied) are more problematic that 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 leaving a person in darkness. 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 [24] and a reduction in energy savings in the long run. Heschong Mahone Group [24] refers primarily to photo-sensors for daylight harvesting being sabotaged when the lighting control they provided was unsatisfactory, but we expect a similar mechanism to apply to unsatisfactory occupancy sensors, e.g., the anecdote of people waving at a motion sensor in a darkened bathroom is very common. This concern with false negatives means that conventional occupancy sensing systems often have long timeout periods (15-30 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.

III. CONVENTIONAL APPROACHES

Three types of motion detectors have been commercially available for a long time for occupancy detection: passive infrared (PIR), ultrasonic (acoustic) emitters, and microwave emitters. They are combined with various devices to make six types of occupancy sensors:

- Passive infrared (PIR) detector
- Active ultrasonic detector
- Passive ultrasonic detector
- Microwave occupancy detector
- Combined PIR and ultrasonic detector
- Combined PIR and microwave occupancy sensor

Conventional occupancy sensors such as PIR sensors and acoustic sensors output a binary value indicating whether people are in the area being monitored. These data are often used for lighting control. Typically, a single sensor is deployed to determine control over an entire zone.

CO_2 sensors are more commonly used for controlling the operation of HVAC systems in response to occupancy [30]. The level of CO_2 in a space correlates with the number of occupants (because respiration is the main source of CO_2 in buildings), and standards typically require minimum levels of ventilation air per person. However, CO_2 sensors have low levels of precision, and there is considerable time lag between the entrance of a person into a space and a resulting substantial change in ambient CO_2 concentration.

Because of the uncertainty associated with the determination of occupancy using single-point sensing, a network of linked, cheaper conventional occupancy sensors [7], [40] 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.

These conventional occupancy detection approaches have a number of limitations:

- Cost: A high-quality, wired, standalone occupancy sensor can cost $200 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 without information on count, identity, and activity.
- False detection: a shadow or a flash (e.g., headlight from a passing car) can trigger PIR sensors; any other noises can trigger acoustic 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.

IV. Implicit / Ambient / Soft Sensing Approaches

A. Overview

Extracting occupancy data 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" [33], soft sensing [15], [39], or ambient sensing [30].

Sources of implicit occupancy data include data that are already collected but not used for building control purposes, and data which are potentially available, but not yet collected. In the former category are things like computer network traffic, security card access systems, and detection of mobile devices at Wi-Fi access points. In the latter category are things like keyboard and mouse activity, 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 system, and thus come at little or no incremental cost. Although these individual channels might have limited accuracy independently, their aggregated data may carry more precision, and certainly more robustness, than any one high-end sensor [8]-[9], [15], [18], [40].

Melfi et al. [33] 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 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., CO_2, light, relative humidity, and temperature) or sensor networks (e.g., RFID and ZigBee-based wireless sensor networks) rather than conventional PIR or acoustic sensors. About 60% of projects / systems we reviewed fall in this category. This paper focuses on the more novel Tier I and Tier II approaches.

Table I summarizes various implicit sensing approaches (Tiers I & II only) proposed and developed in the literature. Table II provides an overview of the same projects as listed in Table I 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		
Research Group with References	**DHCP/ ARP**	**Outbound phone calls**	**Access badge, codes**	**WiFi-based**	**IP Traffic**	**Instant Msg, Calendar**	**Key-board, Mouse**	**Webcam**	**Bluetooth**
Melfi et al. [33]	x	x	x				x		
Ghai et al. [15] ; Thanayankizil et al. [39]			x	x		x			
Oldewurtel et al. [36]						x			
Ekwevugbe et al. [10]			x						
Dodier et al. [7]		x							
Hay et al. [23]			x						
Kushki et al. [29]				x					
Chintalapudi et al. [4]				x					
Balaji et al. [3]				x					
Kim et al. [28]					x				
Jin et al. [26]				x					
Dalton and Ellis [6]								x	
Harris and Cahill [22]									x
Conte et al. [5]									x
Dong et al. [8]							PC activity		

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	Occ. Accu.	Ground Truth	Demo Scale	Data fusion & control strategies	Remarks
Melfi et al. [33]	Level 1/2	Room	Minutes	89%	Manual recording	2 buildings		Focus on accuracy analysis
Ghai et al. [15]; Thanayankizil et al. [39]	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. [36]	Level 1/2	Zone, Room	Days			20 persons for 5 years (simulation)	Model Predictive Control	Simulation only, no physical tests
Ekwevugbe et al. [10]	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. [7]	Level 1	Room	Seconds			2 offices 2 days	Belief network	Cheap sensor approach, wired sensor network
Hay et al. [23]	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. [29]	Level 3	Floor, Zone						WiFi based indoor positioning
Chintalapudi et al. [4]					Theoretical value for analysis	No demo		Conceptual proposal on WiFi-based ad-hoc localization use ranging & sectoring devices
Balaji et al. [3]	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. [28]	Level 1/2	Zone	Seconds			Lab setting		IP traffic + power monitoring. Simulation & analysis only.
Jin et al. [26]	Level 1	Room	Seconds	89%	Manual	5 cubicles	A zero-training algorithm	Focused on power monitoring to infer occupancy
Dalton and Ellis [6]	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.
Harris and Cahill [22]	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. [5]	Level 1/2/3	Room	Seconds	83~84%		3 rooms, 1,000 samples	k-NN, decision trees	BLE (Blow Low Energy), modified iBeacon protocol
Dong et al. [8]	Level 2	Floor	Minutes	65~90%	Networked cameras	A large open-plan 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.

B. *Explicit or Implicit Occupancy Sensing*

Among about 40 projects / systems we reviewed, only a small number of projects / systems use the existing IT infrastructure to collect occupancy information (as listed in Table I). More researchers have proposed and developed systems using supplementary devices and systems including Wireless Sensor Networks [8], [22], [25], [30], [35], [45], [46], sensor arrays [1], [18], RFID (Radio-frequency identification) [2], [32], [48], different motion sensors [10], [30], [35], [46], and other dedicated sensors [1], [20], [35]. Other interesting efforts include applying particulate matter sensors to infer the local movement of occupants [43]; using individual power monitoring data to enhance presence detection [26]; 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 [47]; and using only relative humidity to detect the human presence by adjusting the threshold, sampling window and size [19].

C. *Sensors / Data Sources Use*

Among all the projects / systems being reviewed, almost every project or system uses only one sensing approach or source for occupancy data collection, with very few exceptions [15], [27], [33]. A recent study by Khan et al. [27] 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).

D. Occupancy Resolution

A majority of the systems reviewed detected occupancy at Level 1 (yes or no) and Level 2 (counting numbers of people). Among all the systems, only five systems detected occupancy at Level 3 (identity) and only two at Level 4 (activity). Related to spatial resolution, most systems detected occupancy at the Room or Zone level. In terms of temporal resolution, almost all the reviewed studies have been focused on exploiting short-term (in the range of minutes or seconds) occupancy information for increasing energy efficiency in buildings.

E. Occupancy Detection Accuracy

Most reviewed systems report an overall accuracy of 80%-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. 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 Erickson et al. [11]. However, very few efforts have been reported on the separation of error types.

F. 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 [8], [12]-[13], [21], [33]-[34].

G. 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 automation systems. Various approaches have been reported for data fusion and control strategies including:

- Classification approaches by Ghai et al. [15];
- K-means Clustering by Augello et al. [2];
- Adaptive Neuro-Fuzzy Inference approach by Ekwevugbe et al. [10];
- Belief Network based approaches by Dodier et al. [7] and by Tiller et al. [40];
- Bayesian Networks by Harris and Cahill [22];
- Support Vector Machine (SVM) by Zhen et al. [48];
- Markov Chain Model by Erikson et al. [12];
- Hidden Markov Models by Dong et al. [8], Han et al. [20], Lam et al. [30];
- Sensor-Utility Network by Meyn et al. [34];
- Decision Trees by Hailemariam et al. [18].

Most of these data fusion methods are mentioned in the literature review section of many papers, but it is rare to compare different data fusion approaches on the same data set.

H. 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 [9], [16], 20-30% for lighting control [17], and about 20-30% for computer power management [21].

V. CONCLUDING REMARKS

This paper presents a comprehensive review and classification of implicit occupancy sensing approaches by leveraging data streams from existing IT infrastructure. About 40 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 high-enough occupancy accuracy for efficient building energy management (savings of 20-50% for controlled systems are typically reported) with lower costs compared to traditional explicit sensing approaches. However, the development of systems is in the early stages only, 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 Clouding Computing and the so-called Internet of Things, the IT infrastructure will likely provide even more sources of implicit occupancy information, while emerging Big Data analytics technologies promise to make implicit occupancy information more useful in various applications to save energy, reduce building operation and maintenance cost, and ensure occupant comfort and safety.

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, security card access systems). Effort 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.

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