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A Review of Existing Test Methods for Occupancy Sensors

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Abstract

One of the key new features of connected lighting systems (CLS) is their ability to collect data from various types of integral sensors and share that data with other lighting or building systems. Occupancy and vacancy sensors have been widely adopted as an energy-saving strategy in buildings, yet published test methods for reproducibly characterizing their performance remain few and limited in their sophistication. As a result, it has been difficult to predict the performance of such sensors in a specific application, and in practice, they frequently do not meet energy-savings expectations. Occupants at times remove or otherwise bypass occupancy sensors that hinder their work or otherwise do not perform as expected, thereby compromising the sensors' potential to reduce energy consumption. Poor performance can result from multiple causes – ranging from fundamental limitations of the sensor technology, to misconfiguration, to poor placement in the room or space. Innovative occupancy sensors, some of them combining multiple sensing technologies (i.e., multi-modal), have come on the market over the years, with claims of improved performance compared to their predecessors. However, in practice, their performance has neither differed enough from the performance of previous products to necessitate a test method that facilitated comparison between them, nor has it led to high deployment or high user satisfaction in human-occupied spaces with persistent presence. While the performance of both common and novel occupancy sensors has been the subject of many published research articles, the test methods that have been employed for them typically have been loosely described and have incorporated custom equipment or techniques that render them difficult to reproduce, or have been limited in their ability to fairly characterize devices that utilize varying sensor technology. The lack of a fully described, technology-agnostic test method that yields reproducible results across different implementations has been a barrier to the commercial success of new occupancy-sensor products, as users and specifiers who have been disappointed with previous products are often unwilling to take a chance with new ones. Motivated by a desire to fairly characterize new technologies that continue to enter the market and claim not only improved occupancy detection but, in some cases, additional capabilities (e.g., the ability to measure traffic or discern between different object types), this report presents the results of a literature review of recently published fully described test methods for characterizing occupancy-sensor performance, as well as research articles containing ad-hoc test methods. The review also identifies and consolidates test conditions for characterizing sensor performance in indoor spaces and identifies apparent test method gaps that need to be filled in order to evaluate emerging technologies and products. The identified test-method conditions are intended to enable the development of a future technology-agnostic test method that facilitates occupancy-sensor performance characterization more-accurately representing performance in buildings.

Keywords: occupancy sensors; vacancy sensors; motion sensing; spatio-temporal properties; test methods

1 Introduction

An important feature of connected lighting systems (CLS) is their ability to collect data from sensors and share that data with other lighting or building systems. The lighting industry has largely accepted the fact that occupancy and vacancy sensors are an effective energy-saving strategy (DiLouie, 2013). However, recurring investigations have observed that energy savings have fallen short of manufacturer claims, especially in general office spaces (DiLouie, 2013; Guo et al., 2010; Maniccia and Wolsey, 1998; Pacific Gas and Electric Company (PGE), 1997). This failure to meet energy-saving projections has been attributed to varying causes, including the occupancy sensor not being installed or maintained in accordance with manufacturer recommendations (PGE, 1997), manufacturer claims of typical performance that are either exaggerations (by as much as 83%; Maniccia and Wolsey, 1998) or not appropriate for a specific application, or occupants choosing to disable or remove underperforming sensors instead of reconfiguring or replacing them (PGE, 1997). Common causes of user dissatisfaction with occupancy sensors include false positives, false negatives, and a failure to commission the device in a manner suitable for the specific application. Some specifiers have expressed hesitation to employ occupancy sensing, because of poor experiences with previous deployments (Puleo, 1998).

As of 2017, it is estimated that only 6% to 10% of commercial buildings are equipped with occupancy sensors (Buccitelli et al., 2017; Yamanda et al., 2019), which is a limited improvement from 5% seven years earlier (Ashe et al., 2012). This increase was primarily due to large-scale adoption in the warehouse and storage sector between 2010 and 2015 (Ashe et al., 2012; Penning et al., 2016), which saw an increase from 1% to 34% during that period. Notably, these spaces are rarely occupied by people, and thus occupancy-sensor adoption is not necessarily indicative of user acceptability and performance in applications that typically have persistent human presence. Education and office (nonmedical) sectors, on the other hand, saw a decrease in adoption, from 9% to 8% and from 14% to 8%, respectively, evidence that historical performance issues continue to negatively influence adoption.

The annual energy savings currently generated by occupancy-sensor deployments are estimated to be somewhere in the neighborhood of 0.1 quads (Penning et al., 2016). The unrealized energy-savings potential in the commercial sector due to poor performance of installed occupancy sensors or a failure to deploy them properly is substantial. In one study, properly commissioned occupancy sensors were found to deliver an average increase of 13% in energy savings in new-construction buildings and an average increase of 16% in existing buildings (Mills, 2009), as compared to sensor performance prior to commissioning. If new, easier-to-commission technology increased sensor deployment an additional 6% to 10%, the potential annual energy savings would be an additional 0.116 quads, representing a reduction in annual commercial-sector lighting-energy consumption of almost 4.5% as of 2015 (Buccitelli et al., 2017). Occupancy sensors with breakthrough performance improvement might deliver energy savings multiple times this estimate. Occupancy sensors that are specified and commissioned in a manner more suited to their application, and that meet user expectations, could reasonably be expected to deliver greater energy savings and thereby reduce their financial payback periods.

2 Background

In order to discuss occupancy-sensor performance with clarity, terms that delineate basic occupancy-sensor capabilities need to be defined. In the current marketplace and literature, the terms "occupancy," "presence," and "motion" are widely used, at times interchangeably. "Occupancy" and "presence" are typically used to imply very similar occurrences – namely, that some defined space of interest is occupied by some object of interest (e.g., humans, animals, cars, bikes, or other specific objects, depending on the intended application of the occupancy sensor), or that some object of interest is present in some space of interest. Motion is simply the change in physical position of some object of interest. Most occupancy sensors deployed in buildings today utilize readily available and inexpensive passive infrared (PIR) sensors to detect motion, thereby using motion as a proxy for occupancy. This is not an uncommon characteristic of sensors in general; most do not explicitly detect or measure their intended parameter but, rather, detect or measure something that is related to it. The absolute status of a specific parameter is often referred to as the "ground truth"; sensor errors, whether they are systematic, random, false positives, or the result of some erroneous inference, are thereby failures to detect the ground truth. For the purposes of this literature review, the term "occupancy" will be utilized as an umbrella term, covering all properties of the detection of an object of interest in a space of interest. All occupancy sensors, therefore, attempt to determine one or more properties of the ground truth, such as whether an object has entered, exited, or is persisting in a space.

It is important to distinguish between occupancy properties and the means by which a sensing device measures or detects a change in an environmental condition that is related to occupancy. For example, to determine occupancy, a PIR sensor detects motion as changes in infrared radiation that is absorbed by its detection elements (Figure 1). In other words, PIR occupancy sensors can only detect occupancy when there is motion. While changes in occupancy may be determined in this manner, persistent occupancy cannot be determined by such a sensor if the infrared-emitting object remains still. Thus, when someone sits still at a desk for more than the timeout period of a PIR occupancy sensor, the sensor may incorrectly conclude that the area is no longer occupied, because the object is no longer moving across detection zones.

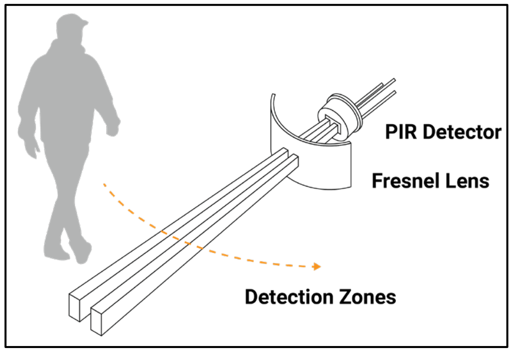

Figure 1. Operative principle of motion-oriented PIR occupancy sensors (reproduced from Steiner, 2016)

Previous research efforts have attempted to systematically categorize different observable properties of occupancy. As shown in Figure 2, Teixeira et al. (2010) established five "low-level spatio-temporal properties" for describing the performance of occupancy sensors: presence, count, location, track, and identity. Spatio-temporal properties are but one category of observable properties (Figure 3). Although at least one paper has made modifications to this categorization methodology (Labeodan et al., 2015), the modifications appear to be conflations of "behavioral properties" and "spatio-temporal properties."

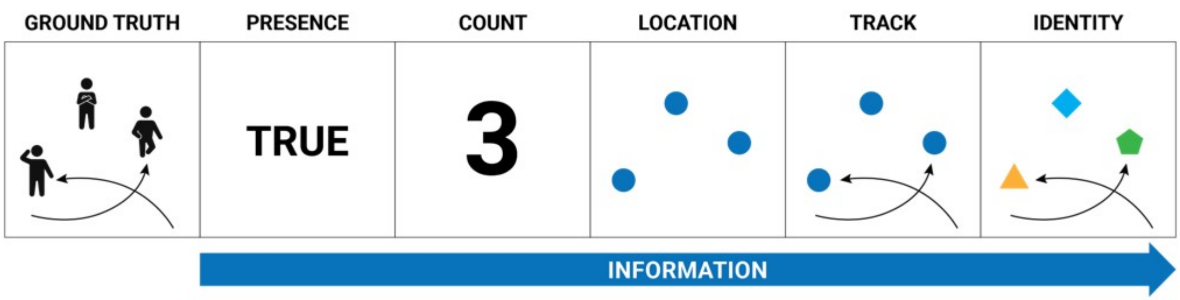

Figure 2. Spatio-temporal properties of occupancy sensors (reproduced from Teixeira et al., 2010)

Teixeira et al. (2010) arranges the five spatio-temporal properties in a hierarchy (presence → count → location → track → identity) according to how much information is required to determine them. The ability to detect hierarchically higher properties at any point in time is claimed to be strictly dependent on the ability to detect hierarchically lower properties at that point in time. For example, a small office lighting system containing four luminaires that can share data from their luminaire-integrated PIR occupancy sensors may be able to accurately detect the presence, number (count), position (location), and movement (track) of objects in that space at one moment in time. However, if the system is unable to accurately determine location at some subsequent moment it time, it can no longer accurately determine movement (track).

The use of multiple sensing devices is a common technique for improving performance; the availability of a greater volume of raw data can deliver improved accuracy or reproducibility or enable the determination of properties that the sensors could not discern individually. For example, while a single sensor might be able to determine the distance between itself and an object of interest but not be able to place the object on a two- or three-dimensional location grid, data from multiple sensors, together with the analytical technique of triangulation, can enable the multi-sensor system to determine the location of the object in two- or three-dimensional space. If a multi-device system uses PIR sensors to determine presence, their inability to accurately determine persisting occupancy compromises the ability of the system to accurately determine all higher-order properties.

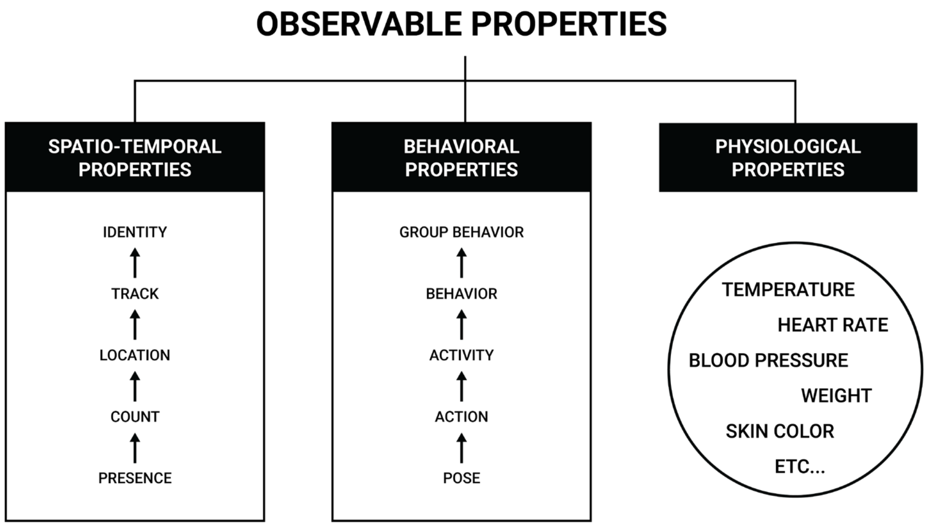

Figure 3. Observable properties of occupancy sensors (reproduced from Teixeira et al., 2010)

3 Scope

Test methods that accurately identify higher-performing occupancy sensors and aid in specifying products that are well-suited to an application may accelerate deployment and the realization of energy savings by removing the barrier of trial-and-error experimentation. A previous literature review established the need for a technology-agnostic means of predicting the ability of occupancy sensors to deliver lighting-energy savings (Guo, 2010). This article reviews active (i.e., not deprecated), fully described test methods for characterizing occupancy-sensor performance, and research articles containing ad-hoc test methods; extracts and consolidates test conditions for characterizing sensor performance in indoor spaces; and identifies apparent test-method gaps that might need to be filled in order to evaluate emerging technologies and products. Fully described test methods include step-by-step instructions for setting up the test, executing test procedures, collecting and reporting data, establishing ground truth, and interpreting results. Ad-hoc test methods fail to specify one or more of these aspects; often, they simply mention some key parameters of the test method, and do not provide enough information for the method to be faithfully reproduced. Addressing the identified test-method gaps is hypothesized to produce more-accurate and technology-agnostic characterizations of occupancy-sensor performance, thereby improving product specification, user acceptance, and adoption. This literature review should not be considered a complete or exhaustive compilation of journal articles characterizing occupancy sensors. Rather, the reviewed articles are representative of research published over the past 20 years.

Since occupancy and vacancy sensors have historically employed the same sensor technologies (varying only in the post-sensing control that they derive from the detected change in state), the methods used to characterize their performance were evaluated concurrently. The scope of this literature review was limited in several ways. Test methods that characterize technologies requiring the use of tags (i.e., the attachment of a radiofrequency identification [RFID] tag, cell phone, or other device to a target) were considered out of scope. Studies utilizing solely theoretical models or statistical analysis, or otherwise lacking a physical implementation of a test method, were also excluded. Test methods that characterize occupancy sensors requiring regular manual intervention to ensure proper function were excluded due to their ability to be disabled by frustrated occupants, and mobile occupancy-sensor systems (e.g., robots or drones) were excluded due the impracticality of these devices for architectural applications.

This literature review categorizes test methods that characterize occupancy-sensor performance by the five spatio-temporal properties described by Teixeira. Methods that attempt to characterize behavioral and physiological properties are excluded, as achieving the five spatio-temporal properties is the focus of the architectural lighting industry. Particular attention is paid to the spatio-temporal property under test, the test conditions, and the sensor technology. To simplify reporting, we classified test conditions into the following categories: doorways and hallways, enclosed room, false stimuli, furniture obstruction, more than one sensing device, multiple illuminances, multiple stimuli sources, and other obstructions. We also classified sensor technologies into the following categories: air quality; industrial, scientific and medical (ISM) radiofrequency band; infrared; mechanical; other radiofrequency; and visible light.

4 Fully Described Test Methods

Throughout the architectural lighting industry, occupancy-sensor performance has historically been characterized by identifying and describing detection areas, as shown in Figure 4, for the two dominant technologies (ultrasonic and PIR) in theoretical three-dimensional space. These device-level, space/application-agnostic detection areas, or zones, have typically been simplified into a two-dimensional representation in occupancy-sensor specification sheets, examples of which are shown in Figure 5 for a sensor that utilized a single sensing technology, and in Figure 6 for a dual-technology sensor. Performance characterization has typically been carried out by the sensor manufacturer, using a simulation model or an ad-hoc (i.e., not standardized or fully described) test method. Some limitations of this approach include:

- The limited ability of simulation models to capture real-world performance anomalies
- The potential for inconsistent performance characterization that results from test-method variations
- An inability to capture the performance impacts of space characteristics (e.g., ceiling height, ambient temperature) and obstructions (e.g., walls, barriers)

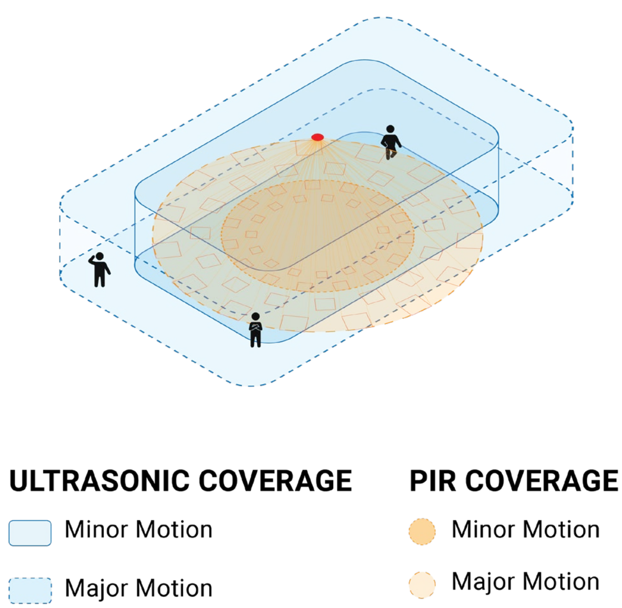

Figure 4. Example of a PIR and ultrasonic multi-technology occupancy-sensor detection pattern (reproduced from DOE, 2016)

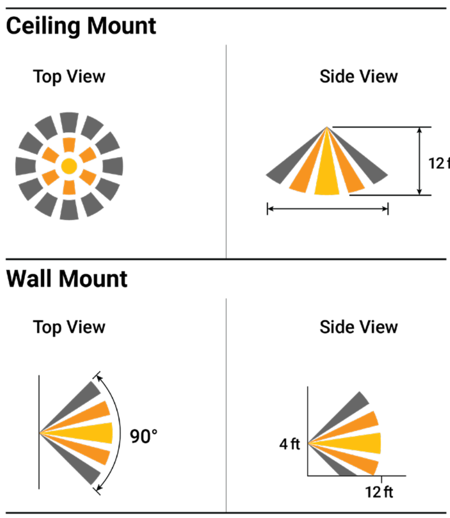

Figure 5. Example of a common PIR occupancy-sensor detection pattern (reproduced from DOE, 2016)

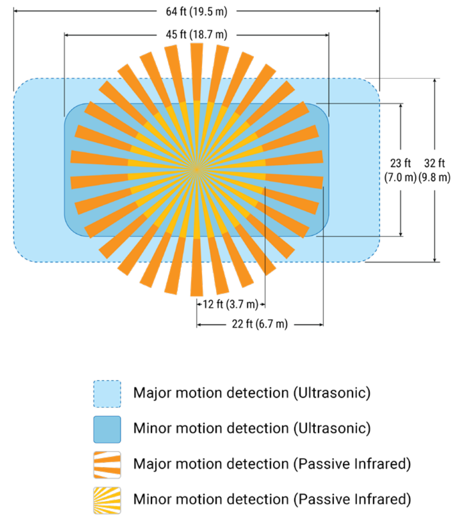

Figure 6. Example of a common PIR and ultrasonic multi-technology occupancy-sensor detection pattern (reproduced from Lutron, 2019)

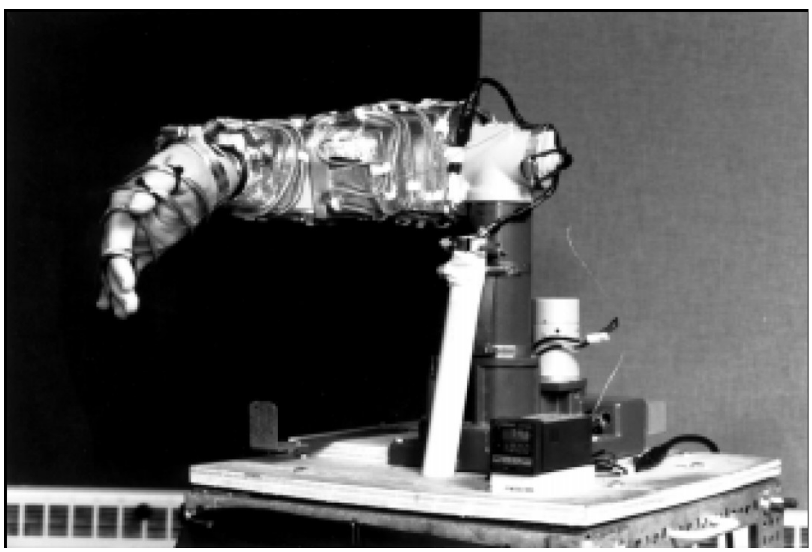

Figure 7. Robotic arm apparatus utilized in the Lighting Research Center test method (reproduced from Maniccia and Wolsey, 1998)

The present literature review only found two existing test methods that fully (or near-fully) describe how to characterize the ability of sensors to evaluate any of the spatio-temporal properties of occupancy. About 20 years ago, Maniccia and Wolsey (1998) of the Lighting Research Center (LRC) developed a test method for characterizing PIR occupancy-sensor performance, which used human subjects to evaluate the ability of a sensor to detect "major motion" and used a robotic arm, shown in Figure 7, to create two specific test conditions, referred to as "minor motion" and "moderate motion." This test method was used to characterize a variety of sensors on the market at the time and demonstrated that most of their performance claims were exaggerated. However, the LRC test method was never standardized or adopted by the market. Some limitations of that method include:

- A limited description of test-method procedures, which rendered the method difficult to fully reproduce or develop further

- Utilization of a test setup that included equipment (e.g., the robotic arm) that was neither readily available on the market nor well described and specified

- An inability to capture the performance impacts of space characteristics (e.g., ceiling height, ambient temperature) and obstructions (e.g., walls, barriers)

Shortly after the LRC test method was published, in the year 2000, the National Electrical Manufacturers Association (NEMA) developed a test method for characterizing PIR occupancy sensors, which was subsequently revised in 2005, 2011, and 2016 (NEMA, 2005; NEMA, 2016). While NEMA refers to the test method as a standard, it was not developed using an accredited standards-development process such as that facilitated by the American National Standards Institute (ANSI). The NEMA test method is conducted in a specified open area divided into 3-foot square "cells," with no obstructions. Sensor performance is characterized under two conditions (major and minor motion), and performance is documented graphically, as shown in Figure 8. Mounting height of the sensor is per the manufacturer's instructions or, in the case of high-bay sensors, is provided by the test method. Major-motion stimulus is created when a human subject who meets specific height, weight, and clothing requirements travels through cells parallel to either the x or y axis. If travel in either direction on the x or y axis successfully stimulates the occupancy sensor, the test is considered a success for that cell. The results of major-motion testing are indicated in Figure 8 as hatched squares. Minor-motion stimulus is created by placing a loosely defined robotic arm in a test cell and recording whether the occupancy sensor responds to stimulation by the apparatus. Detection areas where the sensor can detect the stimuli are shown as dark shaded squares in Figure 8. While NEMA considers a 45° motion of the robotic arm as "minor motion" (NEMA, 2016), the LRC defined this as "moderate motion" and movement of the hand at the wrist as "minor motion" (Maniccia and Wolsey, 1998). The performance data produced by the NEMA test method are relative to a specific area and are thus application-oriented, providing an advantage to predictive models of performance commonly used on product specification sheets, as shown in Figures 5 and 6. While some research studies reference and utilize the method in its original form or as inspiration to characterize occupancy sensors (Caicedo and Pandharipande, 2012; Yavari et al., 2016; Lowes, 2018; Papatsimpa and Linnartz, 2018), it is rare to find test results that utilize it in product specification sheets. Limitations of the NEMA test method include:

- Development by a single stakeholder group (lighting manufacturers), without formal input and review by other key stakeholders (e.g., users), and thereby not compliant with an accredited standards-development process

- Utilization of a test setup that included equipment (e.g., the robotic arm) that was neither readily available on the market nor well described and specified

- An inability to adequately characterize sensors that utilize technologies other than PIR, such as ultrasonic sensors, which rely on reflections off walls in a room to perform well

- An inability to characterize sensors that utilize approaches requiring two or more sensor elements to perform up to their full potential

- An inability to capture the performance impacts of obstructions (e.g., walls, barriers)

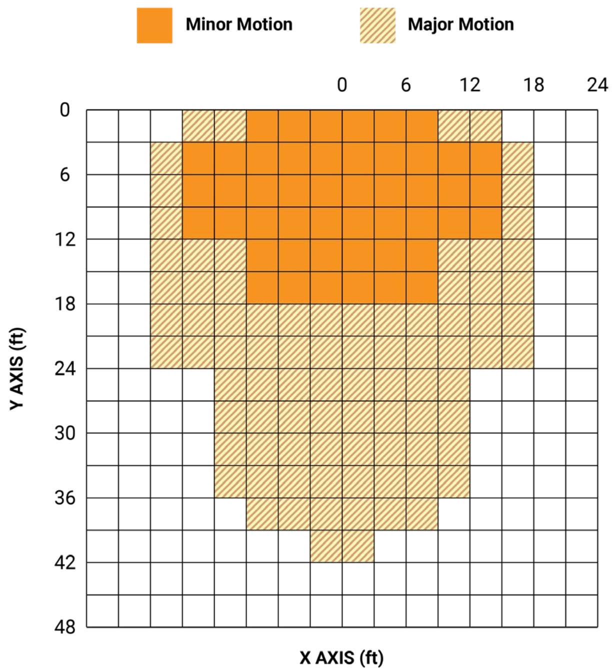

Figure 8. Example coverage diagram for a wall-mounted occupancy sensor (reproduced from Steiner, 2016)

5 Ad-Hoc Test Methods

The previous section reviewed two test methods that fully describe how to characterize the ability of sensors to evaluate the most basic spatio-temporal property of occupancy (i.e., presence). Both test methods were primarily developed to characterize the performance of a predominant market-available and deployed product: a single sensing device that utilizes PIR and/or ultrasonic technology intended to be installed in, and monitor, a single defined area. Neither test method has been standardized nor widely adopted by the lighting or building industry. In recent years, however, new technologies have been developed or adapted for use in occupancy characterization and promise new capabilities and improved performance compared with their historical counterparts. In some instances, these approaches simply use more than one sensing device per zone or room and analyze data from the set of devices to deliver improved performance. While many of these new technologies and products promise improved presence detection, some promise the ability to characterize additional spatio-temporal properties. For example, camera-based systems that can characterize all five spatio-temporal properties continue to come down in cost, and wireless communication technologies that are commonly used in buildings have been adapted to produce three-dimensional models of objects, locate them in space with an accuracy of 1 cm, and differentiate between different objects (Wang et al., 2018).

As new technologies and approaches have become available and increasingly viable, several research studies have endeavored to characterize their performance. Given the significant limitations of the LRC and NEMA test methods, these efforts have largely necessitated the improvisation of test methods tailored to the claimed capabilities of specific sensing technologies or approaches. The remainder of the present literature review attempts to identify and assess such research studies that utilize improvised, or ad-hoc, test methods to characterize the performance of occupancy sensors, regardless of sensor technology, quantity, or distribution in space. Test methods varied significantly and appeared to be tailored for characterizing the specific sensor or sensing system under investigation.

Given the different approaches to defining states of presence taken by NEMA and Maniccia, additional attention is paid to how that spatio-temporal property is evaluated. Specifically, test conditions for presence are categorized according to one of five possible states: major motion, minor motion, hand motion, stillness, and absence. Major motion is defined, in accordance with the NEMA test method, as a human subject traveling at a speed of approximately 4 feet per second (NEMA, 2016). To avoid confusion with existing terminology used in nearly all existing industry technical documentation for occupancy sensors, the present review uses the NEMA definition of minor motion, while movement of the hand at the wrist is referred to as "hand motion." While NEMA (2016) requires 45° motion of a robotic arm along a single axis to produce minor motion, this review considers as minor motion a human arm performing a similar movement at the elbow. Hand motion is defined in accordance with the LRC method as 45° motions of the hand at the wrist, with fingers extended (Maniccia and Wolsey, 1998). Stillness is defined as presence of a human subject whose movement does not rise above the thresholds defined by hand (and, by definition, minor and major) motion. Lastly, absence requires all human subjects to be outside of the detection range of all occupancy sensors under evaluation.

None of the ad-hoc test methods found in journal articles were fully described. Specified test conditions are highlighted, research intent and questions are considered, and research-results analyses are used to postulate additional details about the test conditions and related categorizations.

5.1 Presence

Nine research studies, published between 2009 and 2018, were found to contain test methods that attempted to characterize the ability of a sensor or sensing system to determine presence (Tarzia et al., 2009, Caicedo and Pandharipande, 2012; Weekly et al., 2013; Yavari et al., 2013; Ang et al., 2016; Yavari et al., 2016; Luppe and Shabani, 2017; Lowes, 2018; Papatsimpa and Linnartz, 2018). Presence detection enables the analysis of space utilization and thereby facilitates the repurposing or reconfiguration of spaces to maximize their utilization and possibly reduce the energy consumption of supporting building resources, such as lighting and heating, ventilation, and air conditioning (HVAC) systems, by reducing the space that they need to serve. While presence is still the most common spatio-temporal property claimed by occupancy sensors currently on the market and deployed in the built environment, these studies identify and demonstrate the continued need for improved presence detection, due to the prevalence of false negatives when occupants are still or only perform hand motions for extended periods.

Tarzia et al. (2009) investigated how a laptop, located on a desk in a room of unspecified size, could be configured to operate as an ultrasonic sensor. A software application was developed to run in the background and leverage the integrated speakers and microphone, both of which are found in most laptops and are capable of ultrasonic frequency emission and detection. Human subjects performed a defined series of activities at the desk, which resulted in all five states of presence. However, performance of the sensor system was primarily characterized as a function of behavioral (e.g., typing, reading, writing) rather than spatio-temporal properties.

Caicedo and Pandharipande (2012) conducted only major, minor, and hand-motion testing of an ultrasonic sensor mounted on the ceiling in the center of an enclosure measuring 6 m in length, 4 m in width, and 3 m in height. The sensor was comprised of a transmitter and an array of four co-located linear receivers.

Weekly et al. (2013) investigated the potential relationship between particulate matter and presence by placing a set of eight particulate-matter sensors along a single open-office walking path near the floor. The walking path was defined by cubicle and open-office walls. Test conditions evaluated major motion and absence. Performance was evaluated by comparing the sensor system output to a high-accuracy particulate-matter reference sensor and a ground truth established by a video camera.

Another study that focused on radiofrequency technology as a means for detecting occupancy evaluated a quadrature Doppler radar system that utilized two antennae out of phase by 90° and placed horizontally 1 m from a chair and at an unspecified height (Yavari et al., 2013). To evaluate stillness and absence conditions, a human subject was then seated in the chair, and to evaluate major-motion conditions, the subject moved within a half-meter of the chair. A fan was also placed in front of the radar system as a test of resistance to false positives. Yavari et al. (2016) later continued this work, incorporating elements of the NEMA test method by placing a 2.4-Ghz antenna in a room whose dimensions were 3.5 m by 4.5 m. The floor was divided into 3 ft × 3 ft squares, and the temperature and humidity were controlled. Two experiments tested the sensor's ability to detect stillness, with both a mechanical device and a human subject generating human-respiration stimuli.

Ang et al. (2016) integrated sensors that measured illumination, ambient temperature, relative humidity, barometric pressure, audible sound, and carbon dioxide in a single sensor cluster installed in a private office of unspecified dimensions. Presence was determined via various algorithms that utilized data from the sensor cluster. Test conditions again evaluated for basic human subject presence and absence. The performance of the cluster was evaluated by comparing its output to a ground truth established by reviewing data collected by an online web-based computer logging system, power data from wall-plug meters, a PIR motion sensor, and a door-open-or-closed sensor.

Combinations of sensor technologies have also been investigated for presence detection. Luppe and Shabani (2017) combined PIR, ultrasonic, and carbon-dioxide sensors into a single desk-mounted cluster suitable for an office cubicle of unspecified size. Readings were taken from the carbon-dioxide sensor when the cubicle was vacated, to establish baseline conditions. Presence was determined via various algorithms that utilized data from the sensor cluster. Test conditions evaluated for basic human-subject presence (i.e., not specifically major, minor, or hand motion), stillness, and absence.

Lowes (2018) compared the performance of PIR to a single video sensor in high-bay applications. Typical PIR sensors were used for calibration. The video sensors were mounted at varying heights between 12 ft and 60 ft, major-motion stimulus was provided by a human subject, and minor-motion stimulus was provided by a robotic arm. Although hand-motion stimuli, stillness, and absence conditions were not assessed, performance was evaluated at varying high-bay illuminance levels to determine its impact on the accuracy of the video sensors.

In a study conducted by Papatsimpa and Linnartz (2018), a large room with unspecified dimensions was used to investigate the performance of a set of four microwave radar sensors ceiling-mounted 2.7 m above the floor. A human subject provided a series of major- and minor-motion stimuli at various locations within a grid created inside a 4 m × 4 m area bounded by the sensors. Within the room was a desk where the human subject also conducted minor-motion activities. Although there were pillars within the room, all activity was restricted to the area between them, so that obstructions were not a functional aspect of testing.

5.2 Count

Eight research studies, published between 2007 and 2018, employed test methods that attempted to characterize the ability of a sensor or sensing system to count the number of occupants in a space (Zappi et al., 2007; Yokoishi et al., 2012; Zhang et al., 2012; Shih and Rowe, 2015; Petersen et al., 2016; Chen et al., 2017; Yang et al., 2017; Whitworth et al., 2018). While the detection of presence is the most fundamental occupancy-sensor capability that can be translated into energy savings, additional benefits and perhaps energy savings can be realized if a sensor is also able to count the number of occupants in a space. While knowledge of the number of occupants is not usually useful for lighting systems, it might be leveraged to generate energy savings for HVAC systems, as air circulation requirements vary with the number of people occupying a space. Further, the ability to count or understand that more than one object is present in a space is considered a prerequisite for detecting object location, which can be useful for lighting systems. For example, if an occupancy sensor in a large conference room could detect that all or most of the occupants are in the front half of the room, the lights in the rear of the room might be dimmed or turned off.

Zappi et al. (2007) developed a sensing system capable of determining the quantity and direction of human subjects through a hallway by mounting three PIR sensors along the wall at 2.3 m in height, each with a modified field of view of 34°. The sensors were placed in a row, with a center-to-center separation of 80 cm and were focused towards a center point of the hallway. Test conditions consisted of one to three human subjects walking through the hallway in series and side-by-side.

Yokoishi et al. (2012) installed four PIR sensors in a large (15.3 m × 6.4 m) room. Two sensors were mounted in opposite corners, and one sensor was mounted in the vicinity of the wall-ceiling interface, somewhere along each long (15.3 m) wall. The sensors were focused towards the middle of the room, such that the field of view of each sensor overlapped with the field of view of at least one other sensor. Performance was investigated via multiple short-term targeted experiments and, more broadly, over three months of normal room use. False negatives were specifically evaluated in targeted experiments by instructing one to five room occupants to remain motionless for at least four hours. While it can be assumed that performance during normal room use was evaluated by comparing sensor-system output to some means for establishing the actual number of room occupants, mechanisms for determining ground truth were not described.

Occupancy counting was investigated by Zhang et al. (2012) and Petersen et al. (2016) by placing a Microsoft Kinect over a doorway and analyzing the infrared video data. The overhead doorway orientation was chosen to reduce the possibility that the video sensor could capture and recognize individual faces, thereby preserving occupant privacy. Test conditions consisted of varying numbers and ages of human subjects walking in series at varying distances or side-by-side. In some cases, subjects were instructed to change directions, raise their hands, or contact other subjects and either continue in the same direction or reverse direction.

Shih and Rowe (2015) investigated the ability of a two-component (i.e., separate transmitter and receiver) ultrasonic sensing system to count occupants in a conference room with maximum occupancy of 10, a lecture hall that seated up to 24, and an auditorium that seated up to 150. Multiple transmitters and a single receiver were installed in each of the three rooms at four different locations around the room, including the sides, middle, and front. The transmitters and receivers were ceiling-mounted at unspecified locations within the room, at least 1 m from any wall. Performance was investigated on specific days of normal operation by comparing sensing-system output to a ground truth established by reviewing data collected by a video camera. Actual occupancy was determined via video camera review at least 100 times during each evaluation day. Somewhere between five and 10 different occupancy levels were chosen by the researchers from among the set of 100 validations for characterization of the sensing-system accuracy. The maximum number of occupants identified during any evaluation day was approximately 55 (in the auditorium, based on a graph reading). Environmental variables (including open/closed doors, open/closed windows, and furniture location) were specifically controlled for, to determine their impact on sensor performance. The systems were periodically recalibrated to an empty room, and transmitters in the classroom and lecture hall were reconfigured multiple times to resolve crosstalk between them.

Chen et al. (2017) utilized a combination of humidity, temperature, air pressure, and carbon-dioxide sensors to estimate occupancy, with a similar focus on preserving privacy. Occupancy was estimated via various algorithms that utilized data from the sensor cluster. Instead of calculating specific occupant counts, the sensor system determined which of four occupancy ranges was present in the room: zero, low (one to six occupants), medium (seven to 14 occupants), and high (greater than 14 occupants). Occupancy ranges were pre-established according to the room occupancy limitations. Performance was evaluated by comparing sensor-system output to a ground truth established by reviewing data collected by video cameras placed at each doorway.

Yang et al. (2017) reversed the operation of LEDs to utilize them as sensors that might be easily integrated into luminaires. Sixteen such LED sensors were mounted on the 2.5 m high ceiling of a 5 m × 6 m active laboratory populated with desks and cubicles. The sensor system was utilized to count the number of occupants in cells measuring 1.25 m × 1.25 m. Performance was investigated via specific test conditions, as well as over six months of normal laboratory use. Controlled test conditions included asking up to 20 volunteers to either create a "static pattern," in which they sat or stood at arbitrary locations, or to create a "dynamic pattern," in which each volunteer walked or ran freely in the laboratory. Participants were encouraged to conduct work, change posture, etc., during both cases, and as a result, the "static pattern" may have included minor motion and hand motion. Performance during normal laboratory use was discussed anecdotally; no mechanism for determining ground truth was described.

Whitworth et al. (2018) mounted two mechanical human-respiration simulators on a desk 1 m from a single Doppler radar sensor. The mechanical simulators generated unique respiration frequencies, thereby simulating two different humans sitting side-by-side with a center-to-center separation of 0.8 m. The mechanical simulators were turned on and off to create test conditions with two, one, and zero occupants.

5.3 Location

Five research studies, published between 2003 and 2016, were found to contain test methods that attempted to characterize the ability of a sensor or sensing system to locate occupants in a space (Yang et al., 2003; Hnat et al., 2012; Beltran et al., 2013; Labeodan et al., 2015; Hammoudi et al., 2016). Many lighting systems are designed using task-ambient principles, whereby some portion of the system is designed to provide ambient lighting during defined hours of operation, and another portion is designed for use only when specific tasks are being performed in specific locations. For example, in an open office space, ambient lighting might be designed to facilitate navigation throughout the space, while task lighting illuminates specific desk surfaces only when occupants are working there. The task lighting in many task-ambient systems requires manual operation. Having to manually activate the task lighting sometimes results in reduced occupant satisfaction. Failure to activate task lighting sometimes results in reduced occupant performance. Failure to turn off task lighting when no longer necessary results in wasted energy consumption. The use of occupancy sensors to activate task lighting in specific locations offers the potential to improve occupant satisfaction and performance and reduce energy consumption. HVAC systems that understand the location of occupants in a space can similarly realize energy savings to the degree that their output can be moderated by zone or space.

Yang et al. (2003) distributed eight video cameras, mounted at a height of 4 ft from the floor surface, around the perimeter of a 12-ft-square room, to detect occupant location. The video feeds were reduced to black-and-white bitmaps in which a white pixel represented an object appearing within the camera's field of view. Occupancy and three-dimensional location were generated by combining data from all eight video feeds. Test conditions for evaluating the ability of the full eight-camera system to count included scheduling the room entrance and exit of up to 12 human subjects, who were subsequently allowed to move about uncontrolled. In order to evaluate the ability of a seven-camera system to locate occupants in the room, four occupants could move about the room and, at times, stood in place. System performance was compared with a ground truth established by human-researcher review of the video feed recorded by the eighth camera.

Hnat et al. (2012) installed a door-open/-closed sensor, a PIR sensor, and an ultrasonic sensor at the top of all door jambs in a home. A total of 43 of these sensor clusters were installed in four different homes for periods of six to 18 months. Each sensor cluster was calibrated for its mounting height, which varied across installed doors. Three short-term experiments were conducted. Single human subjects passed from room to room in the home, at varying distances from each side of the door jamb, until a minimum of 500 doorway passages occurred. Sensor performance was compared with a ground truth established in two ways. Human subjects were required to self-report their location via a hand-held touch-screen device by selecting which room they were in as they transitioned from room to room. They also wore a battery-powered device that allowed their location to be tracked via a well-established, custom-developed radiofrequency-based "tag" tracking system installed throughout the home (Lorincz and Welsh, 2005).

Beltran et al. (2013) integrated a PIR sensor and a thermal camera in a single sensor cluster to explore their combined ability to distinguish between motion and presence and to detect occupant location. A single sensor cluster was installed on the ceiling in an open space at a mounting height of 3 m, where it was estimated to have a coverage area of 2.5 m × 2.5 m. Test conditions that facilitated evaluation of the cluster's ability to detect presence and location were seemingly utilized but not defined. Performance was evaluated by comparing sensor output with some means for establishing occupant location, which was documented for at least three different rooms. However, the mechanisms used to determine ground truth were not described.

Labeodan et al. (2015) placed wireless pressure sensors within the cushions of 25 chairs in a 650 ft^2 conference room to determine both the occupancy and location of seated human subjects. Performance was evaluated during normal use of the conference room and compared with a ground truth established on specific days, in varying ways. Sensor performance over a one-day evaluation period was compared with occupant presence (but not location) estimated by a calendar application that was used to schedule the room. Occupant quantity and location (but not seated or standing position, nor wall-facing orientation) were manually recorded by human researchers at 30-minute intervals over the course of another day and were again compared with sensor outputs.

One study that took place in an outdoor environment rather than indoors was reviewed due to its novel use of a video camera. Hammoudi et al. (2016) mounted the camera inside a parked car and pointed it out the rear window to locate available parking spaces. While the authors postulated scenarios where the camera might be mounted in a more traditional fixed location (e.g., on a streetlight pole), they did not actually evaluate any such scenarios. In an analogous indoor space, ceiling-mounted cameras might detect available desks in an office hoteling environment. The camera had to be trained to identify specific parking spaces in the monitored space. The camera system was evaluated under normal operation, and the performance of the algorithm used to detect open spaces was compared with a ground truth determined by a human-researcher review of video from the same camera. Test conditions included variable daylight and weather conditions and traveling human pedestrian and vehicle obstructions.

5.4 Track

Nine research studies, published between 2003 and 2018, were found to contain test methods that attempted to characterize the ability of a sensor or sensing system to track occupants in a space (Gopinathan et al., 2003; Cucchiara, 2005; Prati et al., 2005; Hao et al., 2006; Akhlaghinia et al., 2008; Kamthe et al., 2009; Jia and Radke, 2014; Pan et al., 2014; Depatla and Mostofi, 2018). Tracking most fundamentally facilitates the monitoring and review of individual paths through a space, for security and related purposes. Over time, the analysis of tracked paths can yield additional benefits, including traffic analysis that might suggest ways to redesign spaces to reduce transit time and congestion, and preemptive action based on historical patterns. For example, the analysis of tracked paths for specific individuals might, over time, be used to predict the likelihood of them entering a particular room (e.g., their private office) and turn the lights on just prior to their approach to the doorway, instead of waiting until they have entered the room. Such capabilities enable what has been termed a predictive ambient intelligence environment (Akhlaghinia et al., 2008), which is considered the third generation of smart environments (Martin, 2006). In such environments, building systems anticipate occupant needs and take appropriate action in a reliable, unobtrusive manner. Such systems might learn over time, and leverage their understanding of occupant behavior and needs to deliver persistent energy savings for all adaptive-lighting strategies.

Gopinathan et al. (2003) and Hao et al. (2006) conducted similar studies in which four sensor clusters, each comprised of eight PIR sensors arranged in a circular pattern and facing outward, were mounted at a height of 2 m and used to track movement. Gopinathan et al. (2003) installed the sensor clusters so as to monitor a 1.6 m × 1.6 m space, and separately tracked the movement of both a human subject and a robot carrying an object warmed to a temperature of 320 K, or 116.3 °F – which is greater than that of the human body. The remotely controlled robot moved at constant velocity of 32 cm/s along a defined path. Hao et al. (2006) installed the sensors in a 9 m × 9 m room and tracked a human subject walking back and forth along the room's diagonal. Further, Hao et al. (2006) improved the algorithms used to track activity, and modeled the relationship between tracking accuracy and the economic cost of improved lensing and electronic components.

Cucchiara (2005) and Prati et al. (2005) explored different performance aspects of a system comprising six PIR sensors and four video cameras, with partially overlapping fields of view, installed along an outdoor double-height walkway beneath a building. Three of the video cameras were aimed at fixed locations, while one had pan-tilt-zoom functionality. PIR sensors were installed in targeted locations that were outside the cameras' fields of view. The pathway contained large column obstructions within the camera fields of view. System performance was seemingly evaluated under normal operation, although some documented human-subject walking paths appeared to be prescribed. Ground truth was established by human-researcher review of the camera feeds.

Akhlaghinia et al. (2008) installed four PIR sensors in a small home with four spaces to characterize space occupancy. Sensor data was collected during 15 business days of normal home use by a single occupant. The performance of the sensor system was evaluated by comparing the PIR sensor data with a ground truth established by a set of light, energy, and gas-flow sensors that were also installed in the home. Learning algorithms were applied to the PIR sensor data to predict future occupancy.

Kamthe et al. (2009) placed 16 low-resolution video cameras along the ceilings of public corridors in a university engineering office building. The raw video feeds were analyzed locally, and were not recorded, to minimize privacy concerns. Human-recognition algorithms identified generic human subjects and transmitted their location and time to a central server, which analyzed the aggregate dataset to discern the path of occupant travel. The output of this sensor system was compared with a ground truth established by review of recorded video feeds from two low framerate (10 frames per second), 640 × 480 resolution network web cameras.

Jia and Radke (2014) mounted a single time-of-flight infrared video camera on the ceiling and explored the potential for arrays of single-pixel, privacy maintaining, time-of-flight sensors distributed throughout a room to accurately track people. To simulate a variety of single-pixel time-of-flight sensor spacings in a test environment, the video frames were down-sampled. The time-of-flight infrared video camera was installed in an 18 m × 14 m × 2.5 m laboratory that included some office space, including desks and chairs as obstructions within the sensor's field of view. Test conditions included six human subjects entering the lab, walking around, sitting down, standing up, standing close to each other, grouped together around the conference table and in front of the experimental bench, and leaving the room.

Pan et al. (2014) installed three geophones on the floor of a commercial building hallway measuring 6 ft in width and 42 ft in length, and monitored the ground vibrations created by the footsteps of human subjects wearing either sneakers or high heels. The geophones had to be calibrated to the floor materials and to identify each type of step (e.g., a human subject wearing sneakers versus heels). Two test conditions were defined. In the first, single human subjects walked through the hallway along one of three paths predefined by footstep markers placed on the floor to control path and stride length. Each of the three paths was traversed 10 times. In the second test condition, two human subjects separately entered two adjacent doors, one leading to a carpeted room and one leading to a stairwell, or both subjects entered the same door and one exited soon thereafter. Performance was determined by analyzing the processed sensor data and comparing it with a ground truth established by the predefined paths, and via a human researcher who observed the test subjects and pressed a button on a recording device each time a step was completed, to determine walking speed.

Depatla and Mostofi (2018) installed a set of four 2.4-GHz Wi-Fi wireless access points (WAPs) in three pathways (an indoor hallway, an outdoor walkway, and a grocery aisle) and utilized an algorithm that analyzed variations in the signal strength between WAPs on opposite sides of the pathway (i.e., resulting from human-subject presence) to estimate the number of people traveling down the pathway as well as their travel direction and speed. Two WAPs were installed on each side of the pathway, approximately a half-meter apart from each other and a half-meter off the ground. Test conditions varied by pathway. Up to 20 human subjects, wearing varying types and amounts of clothing and sometimes carrying devices such as headphones or cell phones, walked together through the indoor hallway and outdoor walkway. In one set of experiments, human-subject walking speed was uncontrolled. In a second set of experiments in the indoor and outdoor walkways, human subjects were trained to take 0.3 m, 0.8 m, and 1.6 m steps (or double-steps), and their walking speed was regulated using a mobile application that produced an audible chirp every second, thereby facilitating prescribed walking speeds of 0.3 m/s (slow), 0.8 m/s (normal walking), and 1.6 m/s (fast). Human subjects entered and exited the indoor hallway and outdoor walkway from defined sides and were permitted to move in whatever direction they desired while they were in the pathway. In some test conditions, pathway occupancy was fixed (i.e., entrance and exit were controlled), while in other conditions, human subjects could enter and exit at will. Movement of human subjects in the grocery aisle occurred during normal operation and was therefore completely unconstrained in speed and direction. Further, subjects pushed grocery carts through the aisle, carrying varying types and amounts of objects. Sensor output in all instances was compared with a ground truth established by human-researcher observation.

5.5 Identity

While tracking can be used to infer, through analysis of historical patterns, the likely actions of a particular occupant, knowledge of occupant identity could increase the likelihood of choosing the correct action (and thereby occupant satisfaction) in predictive ambient intelligence environments (Akhlaghinia et al., 2008). If occupant identity is associated with other occupant characteristics (e.g., age) or preferences (e.g., low-ambient, high-task lighting), then additional energy savings might be realized by providing unique lighting conditions that meet those needs, as opposed to conditions that meet typical or average needs. Further, identity can be coordinated with authorization and safety systems to determine whether occupants are present in spaces they do not have permission to be in. The ability to discern human from nonhuman objects (e.g., robots) may be able to provide additional energy savings, security features, and other non-energy benefits.

Akhlaghinia et al. (2010) followed up their 2008 work with PIR sensors by exploring the ability of sensor systems to track and identify human subjects carrying an identifying object such as a security access card or other form of “tag.” Three different systems were evaluated: one comprising four Zigbee wireless mesh radios, and two systems each comprised of four active RFID readers. Such approaches have been well-proven in subsequent years using varying wireless radio technologies, whereby a “tag” containing one instance of a wireless radio can be located and tracked by triangulating its location relative to that of wireless radios of known location. This technique has been widely used to track the movement of cellular devices with active Wi-Fi or Bluetooth radios.

Two research studies, published between 2005 and 2012, contained test methods that attempted to characterize the ability of a sensor or sensing system to identify occupants in a space without the use of tags. Establishing human identity without utilizing a “tag” tracking approach remains a challenging area of research and development. However, some studies have demonstrated ability to identify occupants by utilizing forms of inference. Tao et al. (2012) installed a dense network of 43 PIR sensors in a 15 m × 8.5 m laboratory and inferred occupant identity from behavior patterns, such as travel to one's desk upon entry to a room. Test conditions involved groups of occupants, ranging in number from five to 23, either entering the room at the same time and returning to their workstations (if they had one), or working normally in the laboratory. Lorincz and Welsh (2005) were able to distinguish between human and nonhuman objects in a 1,742-square-meter computer-science building by detecting the characteristic radiofrequency signature produced by objects when within the detection range of 20 custom-developed 433/916 MHz radios. The system was trained via the collection of 482 reference signatures captured over a wide range of environmental conditions, including proximity to a hallway or a room, room-door state (i.e., open or closed), time of day (to account for solar radiation and building occupancy), and radio component manufacturer. While it can be assumed that performance was evaluated by comparing sensor-system output with some means for establishing actual room identity, mechanisms for determining ground truth were not well described.

6 Discussion

A total of 33 studies containing ad-hoc test methods for characterizing occupancy-sensor performance were examined in this literature review. All were published after the LRC test method was released in 1998 and the initial version of the NEMA test method was released in 2000. One of the 33 studies (Lowes, 2018) was conducted in accordance with the NEMA method, while three others (Caicedo and Pandharipande, 2012; Yavari et al., 2016; Papatsimpa and Linnartz, 2018) utilized parts of it.

A total of six unique technologies were utilized in the reviewed studies: air quality; industrial, scientific, and medical (ISM) band radiofrequency; infrared; mechanical; other radiofrequency; and visible light (Figure 9). Of the studies that evaluated sensor systems (i.e., systems comprised of more than one device), some utilized arrays of identical or similar devices, while others utilized devices based on different sensing technologies (i.e., multi-modal). Twenty-seven of the studies evaluated a sensor or sensing system that utilized a single technology. Only six studies explored the use of more than one sensing technology. Infrared sensors were the most frequently (13 studies) evaluated. Systems utilizing radiofrequency technologies were always evaluated independently, perhaps due to their promise of being able to discern all five spatio-temporal properties.

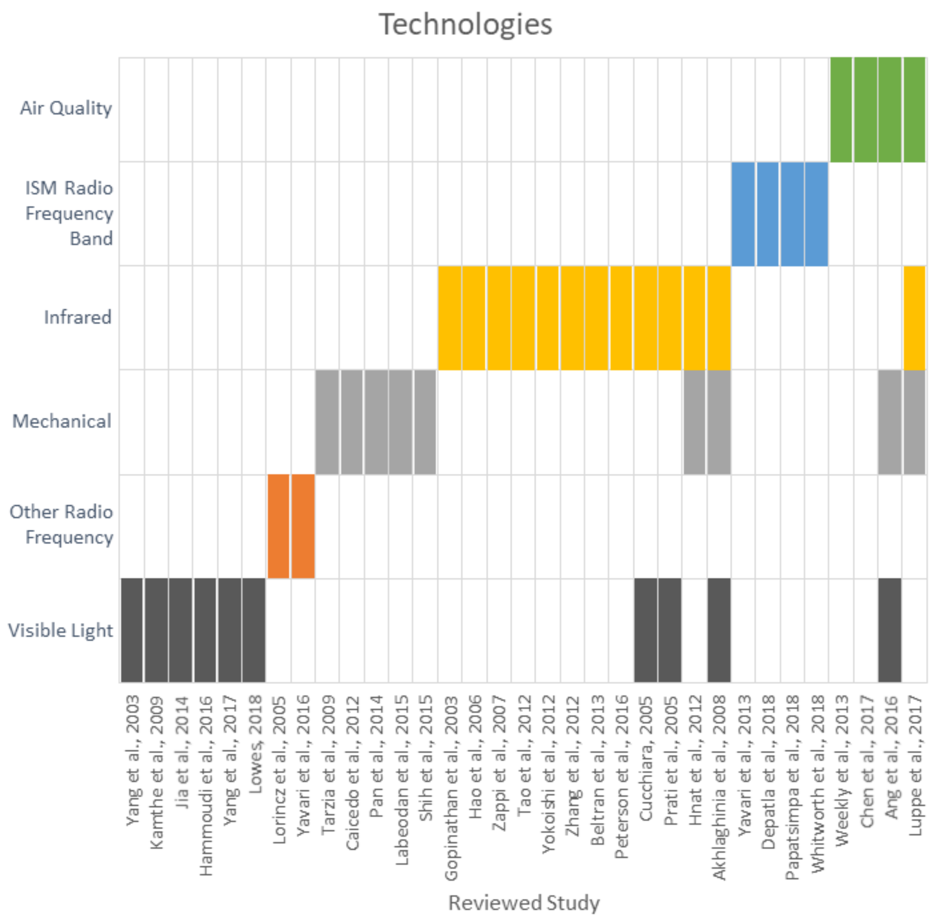

Figure 9. Occupancy-sensor technology utilized in reviewed studies

Thirty-two studies contained unique test conditions that went beyond those found in the LRC and NEMA methods, both of which were designed to evaluate a single sensing device installed in an open room with no doors, furniture, or obstructions, and with a single human subject or single robotic arm to create stimuli. As shown in Figure 10, 23 of the examined studies evaluated a sensor system comprised of more than one sensing device, 18 tested resilience to false stimuli, 20 utilized an enclosed room, 16 utilized doorways or hallways, 19 utilized furniture obstructions, 19 utilized other obstructions, and six tested at multiple illuminances. Twenty-three of the studies contained test conditions that utilized multiple human subjects or robots to stimulate the sensor or sensing system.

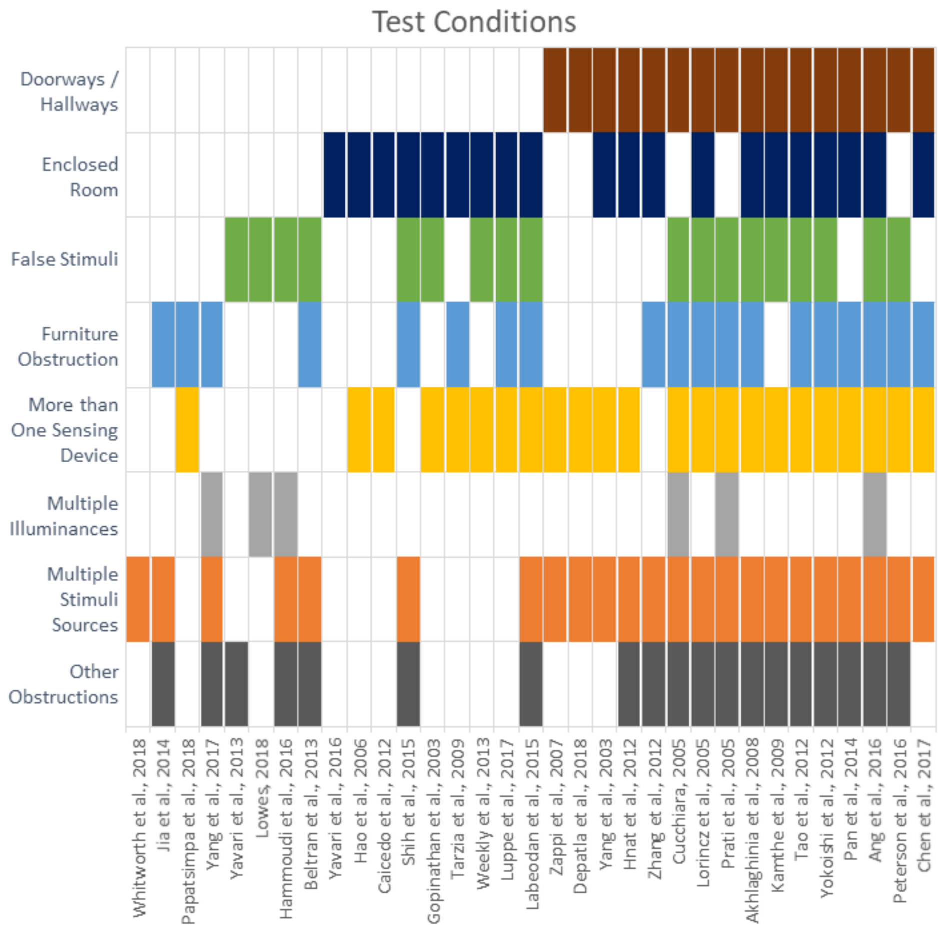

Figure 10. Test conditions utilized in reviewed studies

The five spatio-temporal properties were explored via defined test methods to widely varying degrees, as summarized in Figure 11. The ability to detect only presence was evaluated most frequently (in nine studies). Presence and count were evaluated in eight studies, presence through location was evaluated in five studies, presence through track was evaluated in nine studies, and two studies evaluated all spatio-temporal properties. Most, but not all, studies of sensors or sensing systems that utilized infrared technology were susceptible to presence-detection loss characteristic of PIR sensors when a stimulus remained still. In such instances, evaluation of other spatio-temporal properties beyond presence was compromised when presence detection was lost, as the ability to detect each property is dependent on successful detection of the lower property or properties. As shown in Figure 11, the detection of spatio-temporal properties beyond presence was compromised by presence-detection loss in six out of a total 33 studies. Identity was the least-frequently explored property. Only one of the studies was able to characterize for identity detection, by using inference from traffic patterns (Tao et al., 2012).

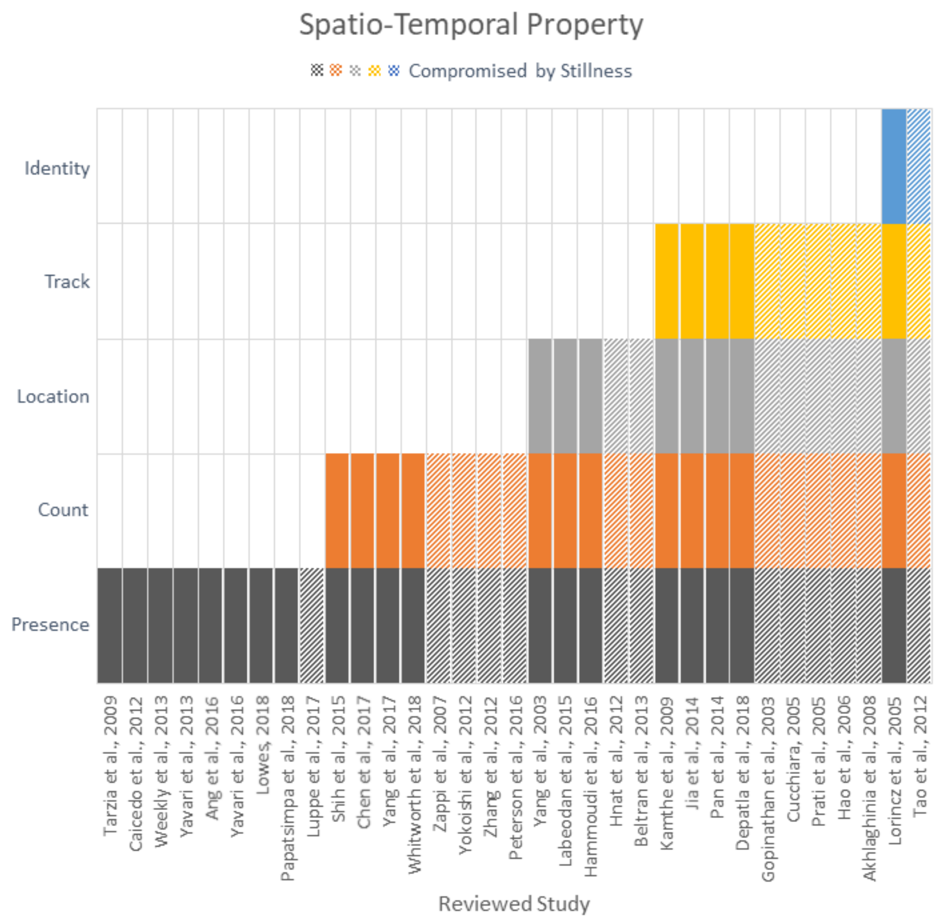

Figure 11. Spatio-temporal properties investigated in reviewed studies

7 Suggestions for Future Test-Method Development

This review evaluated literature that contained fully described or ad-hoc occupancy-sensor test methods, and categorized those methods according to which spatio-temporal properties they were able to discern, which states of presence were stimulated in the characterization of presence, and which unique test conditions were utilized during characterization. No fully described test method capable of evaluating all five temporal properties and stimulating all five states of presence was identified. Most of the reviewed literature contained ad-hoc test methods for characterizing a specific occupancy-sensor technology. A wide variety of unique test conditions was identified. Given the growing number of technologies being developed and adapted, alone and in combination, for the detection of occupancy, and their increasing success in discerning spatio-temporal properties beyond presence, the development of test methods that are more capable, replicable, and fully described appears warranted.

The authors suggest that future research leverage the unique test conditions identified in this literature review towards the development of a technology-agnostic, fully described test method for characterizing emerging occupancy sensors. The following test-method requirements are suggested for characterizing occupancy sensors targeting the indoor environment:

- Evaluate multiple spatio-temporal properties – including presence, count, location, and, if driven by stakeholder demand, track, and identity.
- Evaluate the five states of presence – major motion, minor motion, hand motion, stillness, and absence.
- Utilize human subjects or a well-defined and calibrated stimulus that does not require unique, one-of-a-kind equipment.
- Facilitate configuration flexibility for multi-device sensing systems.
- Control environmental conditions (e.g., temperature, humidity, illuminance) that may cause occupancy-sensor performance to vary, or repeat testing at various environmental conditions to characterize performance in dynamic environments.
- Utilize an enclosed room, sized appropriately for the sensing system under test.
- Utilize obstruction simulations that can be easily reproduced and do not require unique, one-of-a-kind equipment.
- Utilize sources of false stimuli that are based on known weaknesses, can be easily reproduced, and do not require unique, one-of-a-kind equipment.
- Define ground truth using a means that is clearly demonstrated to be of higher accuracy than the sensing system under test.

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