Occupant Activity Detection in Smart Buildings: A Review

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Abstract

Building management systems (BMS) in smart buildings are supposed to support the optimization of energy and resources consumption, while ensuring basic users' comfort. A common and effective optimizing strategy is to detect, with high accuracy, room occupancies, events, and activities that occur within a building, to accordingly control the energy usage. Several approaches have been implemented to achieve this goal, combining many technologies (e.g., sensor networks, machine learning techniques) as well as new data sources (e.g., sensed data, social networks) allowing to better detect occupant activities. In this context, the purpose of this study is twofold: (i) identify existing solutions related to capturing occupant activities and events to better manage energy usage and provide occupants' comfort, and (ii) pin down the lessons to learn from existing approaches and technologies in order to design better solutions in this regard. We do not pretend to give an exhaustive revision, but throughout this review, we aim at showing that several data can significantly enrich the typology and content of information managed to detect occupant activities and highlight new possibilities in terms of activities diagnosis and analysis to generate more opportunities in optimizing the energy consumption and providing comfort in smart building.

Keywords

Sensor Networks, Multimedia Sensors, Smart Buildings, Energy Saving, Occupancy Detection, Occupant Activities Detection, Data Analysis.

1. Introduction

Nowadays, advancements in low-cost sensor technology, wireless networks, electronic devices, as well as new powerful data processing methods have fostered the emergence of intelligent Building Management Systems (BMS) [1]. These latter are describing today's buildings as *complex systems*, embedding several subsystems (heating, ventilation, air-conditioning systems, lighting systems, etc.) and actors/occupants with different behaviours and needs, aiming to optimize energy and resources usage, while ensuring basic users comfort [2]. To do so, several data sources need to be analyzed, such as: (i) Data related to buildings (physical features, purpose, etc.); (ii) Data related to building equipment (lighting, temperature, heating, etc.); (iii) Data concerned to activities and occupancy (events, number of people, etc.); and (iv) Data from occupants (interests, preferences, etc.).

Data related to buildings and equipment have been exploited in most of the existing BMS solutions. However, they have some common limitations related to do not consider individual needs of occupants (which are heterogeneous) and their various activities which cannot be treated as a whole. A better strategy is to detect the activities occurring within a building in order to fine-tune energy and resources usage. This strategy is proven to be very effective if events, activities, and building occupancies can be detected accurately [3]. In order to achieve this goal, several approaches have been implemented by combining various technologies (e.g., sensor networks, machine learning techniques) as well as by enriching the BMS data with new data sources (e.g., Internet of Things, social networks).

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In this context, we survey technologies and studies in the literature, with twofold aims: (i) analysing existing solutions related to capturing occupant activities and events to better manage the energy usage and provide occupant's comfort; and (ii) pin down the lessons to learn from existing solutions in order to design better solutions in this regard. We do not pretend to have an exhaustive revision, but throughout this study, we aim at showing that several data can significantly enrich the typology and content of information managed to detect occupant activities. We highlight new possibilities in terms of activities analysis to generate more BMS opportunities, for energy saving and occupants' comfort.

2.Related Reviews

General comparative studies of the most popular occupancy and occupant activities detection techniques are presented in extensive surveys focused on discussing its significance impact on energy use in the context of smart buildings. However, apart from referring older works, they have only a partial overlap with our target topics. In this section, we present some of the most recent general studies and highlight the difference with our work.

Some studies focus on surveying sensor-based activity recognition system [4][5]. In these studies, the sensing techniques are mainly divided into two categories: Video Sensor based Activity Recognition (VSAR) and Physical Sensor based Activity Recognition (PSAR). PSAR is in turn subdivided in two subcategories: Wearable Sensor based Activity Recognition (WSAR) and Object Usage based Activity Recognition (OUAR). For each category, authors present some common application areas, most used recognition techniques, and most used type of sensors. However, they do not cover their use in the context of buildings nor their impact on energy saving.

Other studies are dedicated to review the most common systems considered to detect occupancy in smart buildings [3, 6, 7, 8, 9] These works describe the fine-grained occupancy information in terms of spatial–temporal properties, such as *presence, location, count, activity, identity*, and *track*. In [6, 7, 9], most popular occupancy measurement techniques based on sensors, are described and compared. Authors of [3], classify the systems to obtain these properties in terms of: (i) the *method*, according to the need of wearable devices or based on passive sensors; (ii) the *function*, that classifies the systems in individualized system, if they have the capability of identifying and tracking individual building occupants, and non-individualized systems, if they only have the ability of providing occupancy information without user identity information or exact location in the building; and (iii) the *infrastructure*, that distinguishes the occupancy detection systems between explicit systems, whose unique purpose is to measure occupancy in the building, and implicit systems, which provide occupancy information along with another primary function. In [7, 8], besides the comparison among sensors used in occupancy detection, authors also present a summary of studies focused on occupant-centric building controls. Authors of [8] found that most occupant-centric applications for building control are related to real-time reactive response to occupancy, individual occupant preferences, individual behaviours/activities, and prediction of occupancy/behaviours; while in [7], mathematical tools for occupancy estimation are studied and compared. In general, these works present and evaluate sensor systems according to the spatial-temporal properties and the classification aspects. They are focused on the evaluation of systems for occupancy measuring and activity recognition only from the point of view of the sensors involved. In our work, besides these aspects, we also review the most recent technologies beyond the sensor types.

Others studies are concentrated in surveying occupancy and occupant activities modelling methodologies and the perspectives of energy saving and activity recognition, regardless data acquisition techniques [10, 11, 12, 13]. In [10, 13], different methodologies to model occupant behaviour are presented and classified according their research objectives, as: agent-based models, statistical analysis models, data mining approaches, stochastic-based process models, rules-based models, and other methods. In [13], authors present a biographical database of documents related to methods for modelling occupants presence and actions. Even though these studies present a quite well review of modelling and processing methodologies in the context of building energy use, they lack in considering sensor technologies for data acquisition. In [11], it is presented a useful research review of studies, whose main effort is focused on integrating the occupants behaviour into building energy simulation tools, with the aim of reducing the performance gap between predicted and real energy consumption. To the best of our knowledge, the work presented in [12] is one of the most complete. Besides the occupancy modelling techniques and systems classification, it also considers sensors technologies. However, none of these surveys consider more recent approaches, such those based on crowd-sourcing, Big Data, and semantic web approaches.

3.Review Process

In order to analyze most popular and recent studies related to occupant activities detection, we followed a review process consisting of three steps: (i) search of works dealing with detection of occupancy and occupant activities in smart buildings; (ii) select relevant articles; and (iii) elaborate a comparative analysis based on a proposed set of criteria.

For the first step, the search was done on the search engine of Google Scholar, which provides links to scientific repositories such as IEEE Xplore, ACM, and Springer. The search was based on tags that included the keys ”smart buildings” and ”occupant activity detection”, combined with tags related to the technologies, such as ”Sensor networks”, ”Multimedia Sensor networks”, ”IoT”, ”Cloud Computing”, ”Smart Devices”, ”Big Data”, ”Signal Processing”, ”Crowd Sourcing”, ”Web Semantic”. The result was hundreds of articles. For the second step, we selected the most relevant articles related to smart buildings and occupant activities/behaviours detection. From the hundreds of scientific papers obtained in the first step, some of them did not correlate with smart buildings. We selected the most cited works from 2013 and some older ones that have been widely cited or represent the basis of more recent projects. To analyze and compare the selected papers, in the third step, we propose a set of criteria that describes how the energy saving and occupant comfort in smart buildings management have been considered based on the detection of occupant activities. Also, in the set of comparative criteria, it is considered the different types of data, occupant activities, and events that can be managed to implement services to ensure the minimization of energy consumption, as well as occupant’s comfort. Hence, the proposed set of comparative criteria considers the following aspects:

1. **Main goal**: This criterion is related to the proposal of the scientific article: *What is the detection of occupant activities used for? How the energy saving and occupant comfort is managed in the context of smart buildings?* According to the answers of these questions, the main goal can be focused on:
   (1) **Minimizing energy consumption** with services to reduce energy costs;
   (2) **Providing occupant comfort** in particularly during the work hours;
   (3) **Considering both aims** by offering services that focus on energy efficiency, while taking into account the comfort of occupants;
   (4) **Other goals**, such as emergency management, security services.
2. **Gathered data**: This criterion concerns the type of data gathered to detect the occupant activities in order to decide about energy management or occupant comfort. Data collected in smart buildings can be related to:
   (1) **The building itself**, such as physical features, purpose;
   (2) **The building equipment**, such as lighting, temperature, heating;

   (3) **Occupancy**, such as occupant activities, events, number of people;
   (4) **Occupants**, such as interests, preferences;
   (5) **Other information**, such as weather information.
3. **Type of detected activities/events**: According to the used technology and sensors, different activities/events can be detected inside a smartbuilding, such as:
   (1) **Binary**: represented by a boolean indicating presence of somebody in a zone;
   (2) **Numeric**: to indicate how many people are in a space (e.g., in a room);
   (3) **Atomic activity**: to identify what the people are doing in a zone that can be detected from a single read of a sensor (talking, typing, etc.);
   (4) **Complex activity**: to identify what the people are doing in a zone that can be detected from several atomic activities (e..g., making a presentation)
4. **Used technology**: This criterion describes the specific technology, both hardware and software, used in the detection of occupant activities.
5. **Additional aspects**: To consider further information related to:
   (1) **Application Scope**: it refers to the context of applicability of the technology being analyzed, in which solutions has been applied (e.g., Heating, Ventilation, and Air-Conditioning – HVAC, Electric Plug Loads Management – EPLM)
   (2) **Based on**: to describe if the technology is based on other technologies, for example Wireless Sensor Networks (WSN), signal processing, Machine Learning.

4.Sensors and Connected Devices

Sensor is originally a term referring to a component of a measuring system that is used to gather a specific data. With the advent of Internet of Things (IoT), however, sensor is now broadly referred to any physical or virtual entity capable of generating data [14]. Simple sensors can sense only a scalar value, such as air flow meter, water meter, inclinometer, velocity receiver, Radio Frequency Identification Device (RFID), Passive Infrared (PIR) sensors, infrared thermometer, motion detector; thus we call them scalar sensors. Also, sensors can be multimedia based (e.g., video, audio, image sensors) able to sense complex and multimedia data. In an orthogonal way, sensors can be integrated in a wide range of mobile devices, such as smartphones, tablets, laptops providing additional sensing perspectives. All of them are being integrated tightly in a wide range of building-related applications such as smart home automation, smart building, or smart city. In what follows, we detail several exciting approaches to observe how scalar, multimedia, and mobile sensing have been adopted to manage energy efficiency or to provide occupants' comfort.

4.1. Scalar Sensing

A traditional sensor (or actuator) can detect and measure a physical property. In this regard, we want to explore how these technologies have been adopted and used in smart buildings, since some can be added/plugged without the BMS, in order to measure energy usage and occupant's comfort. To do so, sensors can be whether used to detect/automate some actions (window/door opening/closing, human presence detection, etc.) or embedded into the HVAC or EPLM systems. In this context, many sensor manufacturers propose new advances on sensor hardware to be most cost-effective and also more competitive.

4.1.1. Application of Scalar Sensors in HVAC Systems

An HVAC system is a system that is used for controlling the indoor environmental comfort. The ultimate goal of an HVAC system is to provide occupants an ideal indoor environment (i.e., thermal comfort, acoustic comfort, visual comfort, and air quality). Several works have tried to utilize sensor networks with HVAC systems in order to monitor and reduce the overall energy consumed by the system. In such context, typically, an HVAC control system consists of two components: a monitoring system and actuators. The monitoring system is a collection of wireless sensor nodes: external and zone. External sensor nodes are used for collecting weather conditions outside the building. They usually include temperature, light, and humidity sensors. Zone sensor nodes are used for monitoring indoor thermal conditions. They usually include temperature, occupancy (e.g., infrared sensor for detecting user presence), and humidity sensors. Actuators are a collection of HVAC appliances. They react per readings provided by the monitoring system.

The work presented in [15] proposes an occupancy-based feedback control method for an HVAC system. In short, the method uses room occupancy information and sensor readings to adapt outputs of HVAC related appliances accordingly. Sensors used in this work are CO2 sensors, temperature sensors, humidity sensors, and motion sensors. The proposed method assumes that all sensor readings are gathered in a centralized database. To validate the proposed schema, the authors deployed sensor nodes and a programmable HVAC system at the Pugh Hall of Florida University (a building with 40,000 square feet of floor spaces). Five rooms were selected for the experiments, three high occupancy rate rooms and two low occupancy rate rooms. The experiments were conducted during winter period where heating energy is highly demanded. The obtained results have shown significant energy savings rate: between 29% to 80%, depending on room occupancy level, from which 50% of that total energy saving was obtained from the HVAC system.

HVACMeter [16] is a system for estimating both heating and cooling energy required within a given thermal zone. Sensors used within this system are occupancy and indoor temperature sensors. Temperature sensors and airflow volume sensors are also installed within the HVAC control units within a building. The provided system takes historical sensor readings and calculates the heating and cooling energy estimation using a mathematical model. To validate the HVACMeter system, the author deployed the system into three buildings in the University of California, San Diego campus. The experimental results have shown 44.5% average Root Mean Square Error (RMSE).

4.1.2. Application of Scalar Sensors in Demand-driven HVAC

HVAC automatic control have been a subject in the context of smart buildings from the last decade based on scalar sensors and conventional approaches. In traditional HVAC operations, the adjustment of ventilation and air conditioning is based on the occupancy during operational hours, considering only temperature and humidity inputs. This fact conduces in waste of heating energy consumption out of operational hours.

Currently, the new tendency is on demand-driven HVAC operations, whose demand is based on real-time sensing of the environment. This trend relies on the possibility of simultaneously detecting and tracking in multiple spaces, stationary and mobile occupants, which in turns allows to determine the heating and cooling loads at operational hours, as well as off-hours. Thus, occupancy information ensures the occupant's comfort and minimizes energy consumption, by timely reacting to changing HVAC demands [3]. Occupants are detected in each room by sensors and may wirelessly communicate to a zonal compiler that determines zonal occupancy. The zonal occupancy count is transmitted to an interface relay that adjusts the intensity and rate of the specific utility. In order to provide effective occupancy detection in thermal zones for demand-driven HVAC systems, the most recent works are based on detecting CO2 concentration, sensing movement of occupants with PIR sensors, and detecting occupant location and activities with RFID.

Works based on the use of CO2 sensors [17, 18] offer the capability to provide the number of occupants and indoor air quality information. However, these approaches present drawbacks related to the inexact count of occupants based on estimates, the considerable time to produce results, and the impact of external conditions (e.g., variations in wind speed, opening and closing of windows/doors) on the CO2 concentration. All these constrains limit their use for demand-driven HVAC, as well as works based on PIR sensors provided to develop occupancy detection systems [19]. More recent studies include users' thermal preferences to propose preference-based demand-driven control of HVAC [20, 21]. However, the improvements reached by these studies are up to 29% of user's thermal comfort and 4% to 25% of energy saving. Since the limitations of all these approaches, solutions must combine several of them, considering the balance between accuracy and cost/effectivity.

4.1.3. Application of Traditional Sensors in a Lighting System

Lighting system is considered as one of the most important within a building. In fact, there exist an International Standard (IEC 62386) to manage digital lighting control systems, called the Digital Addressable Lighting Interface (DALI). Sensor networks can be applied to monitor and optimize the usage of such systems, whether they are DALI-based or not. Several related studies have tried to provide intelligent light control within a building.

The study presented in [22] is one of the earliest that focused on the intelligent light control system within a building. A strategy to light up necessary zones automatically when required and when external daylight is not bright enough, is proposed in that work. To do so, light and motion sensors are deployed within a building. To validate the system, an experiment was carried out in a physical testbed, composed by a room that contained 10 dimmable lamps, each one with a light sensor. The sensor readings were sent to a control unit, which evaluated all the readings and sent commands back to each sensor node to adjust the luminosity of each lamp according to the daylight harvesting strategy. The result showed a 25% energy reduction total energy usage.

Authors of [23] propose a smart LED light control system based on a WSN solution. A LED bulb consumes in general less energy than a normal light bulb. Hence, lots of current buildings choose to change all the bulbs into LED ones. Thus, existing light control systems need to be updated accordingly to provide better support for LED bulb features (mainly tunable brightness level). The work in [23] is one of the latest that focuses on intelligent LED light control system in a building. It assigns WSN nodes to every LED bulb within a building in the aim of observing current brightness level and motion within the rooms. A technique is provided to prioritize external daylight in the same manner of [22]. It is designed specifically to LED bulbs, thus it also allows the adjustment of brightness level of each bulb for further energy saving. The work has been validated in a building under a real-life scenario usage. Wireless sensor nodes are attached to every indoor LED light bulb of the VerdeLED company office. Results have shown the reduction of 55% energy consumption over 6-month span.

In the context of demand driven lighting control systems, PIR sensors are particularly used in occupancy detection [3, 19, 24]. Although PIR sensors provide accurate occupancy information on user presence and location, their application in buildings is limited to be applied for lighting control systems based on occupant presence. Their binary output [3, 24] makes them inappropriate to provide information on count, which is an essential property required for other applications (such as demand controlled ventilation). Additionally, PIR sensors can report false output, due to the presence of heat currents from HVAC systems or when having continuous motion.

4.1.4. Application of Traditional Sensors in EPLM Systems

Plug load refers to the energy that a given electronic appliance consumes through an electric plug within a building. One of the possible strategies for optimizing energy usage is to decide which plug to distribute electricity. To do so, sensor networks are commonly applied to detect room occupancies and related activities in a way to determine whether the electric should be distributed in a given room or not.

Some works, such as [25, 26] propose to monitor the electric energy consumption for each electric appliance. To do so, electric consumption sensors are developed to monitor and record the electric energy consumption data. Sensors serve as intermediates between electric appliances and electric plugs. The electric consumption usage data are monitored; thus, according the energy consumption, occupancy can be inferred.

4.2. Multimedia Sensing

A Multimedia Sensor Network (MSN) refers to a network of interconnected sensors able to capture/generate multimedia data (e.g., video, image, audio). In essence, MSNs have emerged in recent years, along with the improvement of sensor devices' capabilities. They provide several advantages over traditional scalar sensor networks, such as providing more detailed information and precision of a given event and detecting complex events through collected data. However, they demand more storage and processing capacities, which need to be considered when designing the sensor network. In buildings, MSNs have been adopted in two main applications: (i) *Building Automation Systems (BAS)*, to accurately detect events that occur within a building in order to provide suitable controlling features and thus assist occupants in their concerned activities; and (ii) *Building Occupancy Detection (BOD)*: for improving room occupancy detection.

Multimedia sensors could indeed provide better information for detecting events, particularly complex ones. However, there are some other important aspects or challenges to be considered and solved before deeming the superiority of using multimedia sensors, in comparison with scalar sensors, in a smart building environment.

4.2.1. Application of Multimedia Sensors in BASs

Some studies have integrated MSNs in a BAS [27, 28]. The Sweet Home project [27] focuses on the development of a Home Automation System (HAS). Its goal is twofold: (i) detect activities and events that occur within a home using audio sensors; and (ii) allow users to communicate with the HAS using voice commands; for instance, *Turning the light on/off*, *Call Mr.* or *Call ambulance*; all the voice commands are recorded in French language. The sensors adopted in [27] are *Multimedia Sensors* (video, cameras, and microphones) and *Scalar Sensors* (PIR, door/window contact, temperature, CO2, power usage, and water usage sensors). Using such sensors, the following events can be detected: *Sleeping, Resting, Eating, Hygiene, Using Toilet, Dress/Undress*, and *Phoning*. Authors do not propose a real-time or near-real time detection technique for a live deployment setting. Instead, they use a pre-recorded data corpus gathered from an experimental apartment. The corpus is called the *Sweet Home*. To detect the aforementioned events, they use a Support Vector Machine (SVM) to classify user activities via extracted voices and indoor spatio-temporal positions. The results have shown that user's event can be detected with an average accuracy of 86.8%. It is important to note that this study presents several advantages. First, sensors used in it are diverse which is very common in most of the smart home cases. The Sweet Home corpus, developed by the authors, can also be used for various building applications. For instance, it can be used for developing an energy optimizing system since power usage and water usage are also recorded within the corpus.

The work presented in [28] consists of detecting the following events within audio data to predict energy consumption: *Announcement/Alert, Cough, Drawer opening/closing, Keyboard/mouse usage, Table knocking, Laughing, Turing pages (of books or paper report), Pen drop, Telephoning, Printing, Speaking*, and *switches (e.g., light switch)*. To do so, the proposed approach extracts the dominant frequency and Mel Frequency Cepstral Coefficient (MFCC) features of each audio event and trains them by using an SVM learner. The results have shown that the accuracy of detecting each of the aforementioned events is high, approximating 72%. The only problem of this study is that it does not consider any aspect related to real-time or near-real-time processing deployment.

4.2.2. Application of Multimedia Sensors in BOD

The usage of multimedia sensors within a smart building to solve issues related to energy management has not yet been widely adopted. Multimedia sensors are not suitable in a residential building because they are too intrusive for users' privacy [12]. However, it is easily accepted nowadays in non-residential buildings (e.g., commercial building, university building) to adopt them since buildings and rooms are commonly equipped with a network of surveillance sensors (e.g., cameras).

In [29], it is presented an occupancy-based system for efficient reduction of HVAC energy, called OBSERVE. From a network of video cameras, OBSERVE is able to detect the following events: *area occupied, area unoccupied, user moves to another area, number of users within a given area* and adapts the HVAC control system accordingly. OBSERVE manages 16 wireless camera nodes that are used for capturing a mobility pattern of users and constructing a floor plan from such information. The energy saving potential of OBSERVE in optimizing the HVAC system has been evaluated by means of simulation. The obtained results have shown that the annual energy saving can reach the average of 42%. It is to be noted nonetheless, that the energy saving could be improved since a wireless camera used in OBSERVE consumes a lot of electric power. Thus, it is hard to operate these sensors with batteries. The significant accuracy improvement is also questionable when comparing with scalar sensor based system that may provide less accurate detection but can work better under low power condition.

In [30], it is described the POEM (Power Efficient Occupancy Based Energy Management) system, aimed to further improve the energy management proposed in OBSERVE [29], to detect the events *area occupied, area unoccupied, user moves to another area*, and *number of users within a given area.* POEM uses OPtical Turnstile NETwork (OPTNET) system, which employs a fast lightweight human motion detection and area transition technique. The movement trajectories of users are represented as a vector. In order to detect and predict the occupancies level within a building, this vector is compared to known labelled data by using a k-Nearest Neighbours (KNN) algorithm. The scalar sensor network used in the POEM is called BONET (Binary Occupancy Network), which is a wireless PIR sensor network for detecting users' presence. The energy optimizing strategy of the POEM is to program the HVAC system to match the arrival of users. The detection from both OPTNET and BONET is combined to determine actual occupancy information within a building. The results of POEM have shown that: (i) OPTNET alone can predict building occupancy with 94% accuracy; and (ii) by combining OPTNET with BONET, the accuracy can be improved even further. The occupancy amount estimation error when combining both OPTNET and BONET together is reduced to only an average of 1.83 persons. This has been validated on actual test-bed and the energy saving estimation was annually approximately to 30%. However, similar to OBSERVE, the energy required for operating a wireless camera sensor network is still a disadvantage.

Image-base and audio-based signal processing algorithms have been used nowadays to count and estimate occupants in building spaces, due to the rapid advances of technologies to process images and speech. The idea is to measure the sound waves produced by occupants, using microphones or ultrasonic sensors within the building and to process images captured by cameras installed in building spaces. A performance comparison of two methods for occupancy estimation and prediction is presented in [31]. One method is based on data gathered from common sensors (temperature, CO2, and PIR sensors) and supported by an indoor climate model. The second method is based on data collected from several 3D cameras and image processing algorithms. Results demonstrate that the image based approaches overcome the accuracy in occupancy estimation, while occupancy prediction is better performed in applications based on standard sensors. The main problem with image based applications is the privacy intrusiveness that they represent. In [32, 33], the idea is to capture the changes of the acoustic properties in a room, supported by ultrasonic sensors. Then, it is possible to detect occupants' location and presence. Indeed, techniques for sound measurement, captured from ultrasonic sensors, can substitute passive PIR sensors, since they do not require continuous movement and sight lines. However, they are susceptible to false ON, when vibrations not produced by occupants are detected (e.g., air turbulence, outdoor noise) and false OFF, when quiet occupants are in the spaces [33].

Several works try to overcome these limitations [34, 35]. The approach presented in [34] proposes to measure the variations in ultrasonic chirp emanated from a wide-band transmitter and to record how the signal is dissipated over the time. To count occupants in a room, the proposed algorithm extrapolates (by using a regression model) the response frequency over the chirp's bandwidth. The work presented in [35] takes into consideration the outdoor noise. An audio-processing algorithm able to cancel background and outdoor noise is proposed. The algorithm is applied to the raw audio data to clean up the acoustic signals, then based in Short-Time Energy (STE), the number of occupants is estimated. Experiments in several noisy environments (e.g., airport, cafeteria, train station, factory) were done. Reported results demonstrate accuracy improvements up to 16%. In presence of outdoor noise, these works report that the accuracy of results is impacted. It is to be noted that, recently, the trend in occupancy detection is based on non-intrusive techniques, mainly based on infrared cameras, in particular to provide thermal comfort [36, 37, 38].

4.3. Mobile Sensing

The performance of building subsystems (e.g., lighting, HVAC) and facility building management (e.g., safety and security systems) can be improved if grain fine occupant information is considered. As mentioned previously, scalar sensors have limitations to provide such required granularity, even though they provide other accurate building data, such as temperature, lighting level, and humidity. Multimedia sensors (e.g., video and audio sensors) currently provide a high capacity to detect and count occupants in a building. Unfortunately, their drawbacks are related to the high requirement of communication, processing, and storage capacities, as well as their high cost and privacy intrusiveness.

In order to overcome some of the limitations of scalar and multimedia sensors, sensing using mobile devices has emerged and has been more and more adopted. The analysis of electromagnetic signals from wearable and mobile devices (supported by WiFi, Bluetooth, RFID) is another approach for occupancy detection commonly used in commercial buildings. In such systems, the signal transmitter is usually carried by the occupant, while the signal receiver is usually static. Hence, it is possible to measure, in the receiving node, the energy and the response echo time of a transmitted signal to count and detect occupants. These sensing means are not privacy invasive and are able to collect other necessary data, that provide reliable occupancy information. Hence, to do that in an effective way, mobile sensing devices generally produce processed data, after doing on-board the analysis of the collected raw data. The data analytics is normally based in object tracking and deep learning algorithms that are tunned to be effectively executed on low power processors.

4.3.1. Wearable Smart Devices

A wearable device refers to an electronic technology that is incorporated into items of clothing and accessories during the realization of daily tasks inside the building. There are several types of wearable devices (e.g., watch, wristband, chest straps), which are characterized according to some relevant criteria, such as: (i) Software/Hardware openness to allow open and extensible frameworks; (ii) *Occupant Comfort*, the more comfortable the device is, the more the occupant is engaged to wear it; (iii) *Accuracy* that represents the quality of measurements, that directly affects the quality of the signal analysis; it highly depends on the type of sensor, which can be red infrared light sensor, optical, or contact sensors, and on the part of the body, where the sensor must be worn, which can be chest straps, arm, and finger; (iv) *Periodicity of monitoring*, data analysis requires a minimum set of data in order to guarantee the validity of the analysis; (v) *Privacy*, it is a must to provide the occupant with a solution that guarantees and secures his/her privacy. This should consider different parameters (age, culture, gender, activities, etc.).

Several types of wearable devices are used to monitor health (heart rate, blood pressure, occupant activities, etc.). Wearable devices that allow to monitor and sense people activities, are the most relevant in the context of smart building. They usually incorporate contact type sensors or optical sensors, connected to the body through a lightweight smart fabric strap, located at the chest, wrist, or arm, from which it is possible to obtain physiological and behavioral data of users. Some measurements supplied by these devices are Heart Rate, Breathing Rate, Skin Temperature, User Activity (steps counter, floors rises, calories, and sleep monitoring), Posture, Skin Conductance, Speed, Distance, Peak Acceleration, R-R Interval, Stress Level. They normally transmit data by Bluetooth or by Java Android API with direct methods to get measured data. Some of them also allow to record data in their internal memory or in a continuous way published or stored as needed by third parties applications. The accuracy of the data is high, however, some of them require some constraints in humidity, positioning, pressure, etc. Some recent works have demonstrated the utility of wearable devices to detect occupant activities in intelligent buildings, in order to mostly provide occupant thermal comfort [39, 40], to reduce the CO2 concentration [41], and even some work, besides, include energy saving [42, 43].

4.3.2. Smartphones

Nowadays, mobile technologies, particularly smartphones, are powerful and offer a wide range of possibilities to use their embedded capabilities. There are about 2 billion people with smartphones, which represents one-quarter of the global population in the world, and the tendency is to increase [44]. It is therefore possible to ensure that most occupants of an office building have a smartphone. Some recent works have realized this potentiality to be used in BOD systems. Most approaches in this concern are based on existing IT infrastructure common to many office buildings (e.g., already deployed WiFi routers). The idea is to eliminate the need of buying explicit sensors to detect building occupancy.

The study performed in [45] shows the effects of controlling users' devices based on the gathered information. The study also shows a comparison of the results obtained using implicit and explicit sensing methods. As the explicit sensor, a PIR sensor was connected to the monitor of the PC facing the user's seat. The implicit sensor data was the lease logs of the DHCP server for the building - i.e., WiFi users' smartphones as implicit sensing signal to detect occupancy. The results showed that the PIR sensor's accuracy was higher. However, it was prone to false positives produced by other occupants entering the area. On the other hand, implicit sensors yielded to false negatives when the occupants were at their desk but not using the computer. This suggest that sensor redundancy may be necessary for more accurate measurement.

In [46], authors describe the Non-Intrusive Occupant Load Monitoring (NIOLM) framework, which evaluates WiFi connection/disconnection events within a commercial building to estimate starting and ending of individual occupants' energy-consuming behaviours.

The analysis is based on monitoring the WiFi packets from occupants' smartphones, under the supposition that occupancy sensing and energy consuming data are directly related. The study also shows that occupants of office buildings tend to present similar behaviour patterns on a daily basis. This regularity allows to be confident on the predictions of energy consumption of occupants over time. Authors concluded that NIOLM can be a valid cheap alternative to predict occupants energy consumption based on their start and end WiFi smartphone connections. Individual plug-load meters installed at each point of interest may perform better; however, they require a large capital investment.

A proposal based on stationary WiFi TX/RX to determine the number of people in indoor and outdoor areas is presented in [47]. The work consists on measuring the received signal power and feeding a mathematical motion model to predict number of people between the TX and RX. To validate the proposal, authors performed experiments in indoor and outdoor areas with up to nine people. Results show that this approach can estimate the number of people with an error up to two persons.

The work presented in [48] defines a case-study that accurately estimates occupancy using WiFi networks instead of CO2 sensors, commonly used for demand-controlled HVAC systems. More specifically, the study tests the ability of WiFi counts to predict occupancy patterns in the Engineering and Information Technology Complex (EITC) at University of Manitoba Fort Garry in Canada campus, whose occupants are mainly professors and students. Data analysis showed that WiFi connections counting allow to predict actual occupancy levels more accurately than CO2 concentration levels, thus validating the use of this technology to track occupancy. This study uses both CO2 concentration and WiFi counts simultaneously as indicators for occupancy. It suggests that building managers do not need to install expensive CO2 sensors in order to predict building occupancy. However, this suggestion is only valid for building whose occupants have the same behaviour as the one in the study. Building with users that make more WiFi connections could predict a higher occupancy rate, causing waste of energy, while building whose users make fewer connections will predict a lower occupancy rate causing occupant discomfort.

WinOSS is a non-intrusive sensing system [49] based on the building's WiFi infrastructure to obtain occupancy information (i.e., occupancy detection, counting, and tracking), by counting WiFi-enabled smartphones of occupants. This occupant information is used by a centralized lighting control system, called WinLigth [50], able to reduce energy consumption and occupants lighting comfort. WinLight controls the brightness of each lamp, which contains a local controller integrated, while considering occupants luminance preferences, who also can control nearby lamps through a mobile application. WinOSS and WinLight were implemented in a 1500 m2 office building environment in Singapore. Experiments performed with WinOSS reported an accuracy of 98.85% for occupancy detection when occupants remain stationary, while results obtained with WinLight revealed 93.09% and 80.27% energy savings compared to a PIR sensor based lighting control system and a static scheduling lighting control system.

A system that estimates the location of the people within a building and predicts where occupants will go next is described in [51]. To do the study, the data were collected using a combination of two different networks: WiFi and Bluetooth networks. By using this hybrid network, building managers can reduce the deployment cost required to estimate occupants locations. These locations are estimated using a k-nearest neighbour algorithm whose input is the signal strength of the devices. These estimations are then used to predict the next location using a stochastic random walk algorithm. Experimental results show that the model can effectively detect the spatial distribution of occupants and track their movement. Although the algorithm yields to some physical constraint due to the lack of reference signals, the algorithm sufficiently provides the basis for separate zone control mechanisms. The use of a simple metric allows the positioning algorithm to respond much faster and to provide higher data streaming speed without compromising accuracy. The error development test suggests that the performance of the positioning algorithm is stable and deteriorates slowly with the accumulation of error, which suggests that it is practical for long-term deployment. Such occupancy information has a great potential to serve as the basis for more intelligent and responsible control, reshaping the operation mechanisms in modern buildings and improving building energy performance.

A methodology for building energy performance simulation based on accurate estimates of building occupancy data was proposed in [52]. Estimation is done by using location data obtained from an Internet company. The occupancy information collected in this pilot case study was tracked under supervision of the Internet company and only used for the presented building energy simulation research. This approach defines two main steps: firstly, an initial model using the traditional way is created: a calibration is conducted only using the history data (the electricity consumption of lighting and equipment) from the BAS. This model is used to perform the simulation to get preliminary results. The acquired results are compared to the BAS measured data to evaluate how good this initial model is. Second, if the data obtained from the model presents high discrepancy with the real data, a further calibration is then performed by replacing the code-based occupancy information with the mobile-internet-based occupancy information. A clear advantage of this approach is that it does not require the acquisition and deployment of expensive sensors to detect building occupancy data as state of the art approaches do. The proposed method takes advantages of the already-built mobile Internet system and can potentially monitor and update the occupancy information of every single building. However, this approach presents some serious disadvantages, related to the need of users to turn on location services on their smartphones to provide the data to Internet providers, and depending on the local laws and regulations, this data source may not be available in some countries and regions. In fact, for this approach to be used, it needs to be integrated an extensive cyber-security and privacy research.

Table 1: Sensor Technologies in Smart Buildings Comparison: Scalar Sensor

Ref.	Main Goal	Gathered Data	Type of Activities	Used Technology (type of sensors)	Additional Aspects	
					Scope	Based on
[15]	Energy s.	Equipment Occupancy Occupancy feedback	Binary Numeric	Temperature CO2,Motion Humidity	HVAC	WSN Main controller
[16]	Energy s.	Equipment Occupancy	Binary	Temperature Presence, Air flow volume	HVAC	Historical data Energy consump. prediction
[17, 18]	Energy s. Comfort	Equipment Occupancy	Binary Numeric	CO2, PIR RFID	On-demand HVAC	Main controller
[20, 21]	Energy s. Comfort	Equipment Occupancy Occupancy feedback Weather	Binary Numeric	CO2, Motion Temperature Humidity	On-demand HVAC	Main controller Machine Learning
[22, 23]	Energy s. Comfort	Equipment External daylight	Binary	Light Motion	Lighting control	WSN Main controller
[3, 19] [24]	Energy s. Comfort	Equipment Occupancy External daylight	Binary	PIR	Demand Lighting System	WSN
[25, 26]	Energy s. Comfort	Equipment	Numeric	Electric consumption	EPLM Systems	

4.4. Discussion

Table 1, Table 3, and Table 4 summarize the comparison of the reviewed works respectively related to scalar, multimedia, and mobile sensors, in terms of the proposed criteria.

Beyond providing better energy consumption and occupants comfort, some works based on multimedia and mobile sensors consider other aims such as images monitoring, user mobility prediction, and thermal prediction. In general, the gathered data in all of these works come from the equipment or building subsystems (e.g., HVAC, lighting) and form the occupancy; other works consider data from the building infrastructure, such as plans of some zones, and other data sources like weather and external daylight. Also, some of these works consider feedback from the occupants to consider their preferences.

From scalar sensors, most detected activities are binary and numeric, while atomic and complex events can also be detected with multimedia and mobile sensors. Detecting complex events (a person is eating, people are walking, etc.), is precious when dealing with occupant comfort and energy consumption reduction. However, it is not always possible with scalar sensors. It is also worth noting that with scalar sensors most solutions are centralized, with multimedia and mobile sensors the machine learning techniques are commonly used to provide better results on prediction and events detection. It is true that multimedia and mobile sensors could provide better information for detecting events, particularly complex ones. However, there are some other important challenges to be considered before deeming the superiority of using multimedia or mobile sensors, in comparison with scalar sensors, in a smart building environment.

To compare the features of scalar, multimedia, and mobile sensors, we suggest the following criteria: supported event type, precision, intrusiveness, price, investment, processing cost, and energy consumption. Table 2 summarizes a comparison of sensors. Briefly, PIR and contact generally are able to detect binary events, since the result of their detection is a boolean value (e.g., true or false, on or off). Temperature, CO2, power usage, and water usage sensors can identify Numeric events as they produce numerical values as an output. Concerning the precision, intrusiveness, price, energy consumption, and processing cost, all scalar sensors share the same features: high precision, low privacy intrusiveness, low price per unit but the building instrumentation could represent from medium to high investment, low data processing cost, and low energy consumption. Also, most of them are mainly connected to some equipment in the building, except PIR and contact sensors.

Multimedia sensors, such as cameras and microphones, can be used to detect different kinds of events with a various precision depending on the used multimedia algorithms. They can be connected to the building, the equipment, and the occupants. The intrusiveness can be considered as high due to the privacy concerns. The hardware cost is slightly higher than scalar sensors in general, thus the investment could result higher. Their energy consumption and processing requirements (processor, bandwidth, etc.) are also considered high, while their battery life duration is considerably shorter than scalar sensors.

Like multimedia sensors, the use of smart devices to detect occupant activities allow the detection of complex events and the precision depends on the software used to detect and predict activities. Smart devices share the same characteristics of multimedia sensors, regarding energy consumption (high), processing requirements (high), and battery life duration (low). In contrast, they are generally considered as attached to occupants, instead to building or equipment. Thus, the intrusiveness can vary from low to medium depending on the collected data, that in turn is taken directly from occupants. These data can be binary, numeric, and with multimedia content. Although the cost of these devices is higher than scalar and multimedia sensors, from the point of view of investment in the building,

Table 2: Sensor Features Evaluation

	Sensor/ Device	Supported Event	Precision	Intrusiv.	Price per Unit	Investment	Energy Cons.	Proc. Cost	Data
Scalar	PIR	Binary	High	Low	Low	Medium to High	Low	Low	Occup.
	Contact	Binary	High	Low	Low	Medium to High	Low	Low	Occup.
	Tempera- ture	Numeric	High	Low	Low	Medium to High	Low	Low	Equip.
	CO2	Numeric	High	Low	Low	Medium to High	Low	Low	Equip.
	Power Usage	Numeric	High	Low	Low	Medium to High	Low	Low	Building Equip.
	Water Usage	Numeric	High	Low	Low	Medium to High	Low	Low	Building Equip.
Multimedia	Camera	Various	Various	High	Medium	High	High	High	Building Occup.
	Micro- phone	Various	Various	High	Medium	High	High	High	Building Occup.
Mobile	Fitbit e-watch	Various	Various	Low to Medium	High	Low	Low	High	Occup.
	Smart- phones	Various	Various	Low	Medium	Low	Low Medium	Low to	Occup. Building

Table 3: Sensor Technologies in Smart Buildings Comparison: Multimedia Sensors

Ref.	Main Goal	Gathered Data	Type of Activities	Used Technology (type of sensors)	Additional Aspects Scope	Based on
[27]	Comfort	Building Occupancy	All (B, N, A, C)	PIR, Door CO2, Water Window Cameras Microphones	BAS	MSN, SVM
[28]	Predict energy consump.	Occupancy	All (B, N, A, C)	Microphones	BAS	MSN, SVM
[29, 30]	Energy s. Predict occ./ user mobility	Building Occupancy	All (B, N, A, C)	PIR Cameras	HVAC BOD	MSN, KNN Agent-based Markov
[31]	Energy s. Predict occ.	Building Occupancy	All (B, N, A, C)	3D Cameras	BOD	MSN, Image processing
[32, 33]	Energy s. Predict occ.	Building Occupancy	Numeric Complex	Ultrasonic sensors	BOD	MSN, Audio processing
[34, 35]	Energy s. Predict occ.	Building Occupancy	Numeric Complex	Ultrasonic sensors Microphones	BOD	MSN, STE Audio processing
[36]–[38]	Comfort Thermal prediction	Equipment Occupancy	All (B, N, A, C)	Scalar sensors IR Cameras	BAS BOD	MSN, SVN Lineal regression

they do not represent a limitation, since they are already in the building: most occupants have a smart device. Also, some of such smart devices are supported on open software and hardware, which allow free access to data and easy to tune the network protocols.

Clearly, it is necessary to find a trade-off between scalar sensors, multimedia sensors, and mobile devices to be adopted in a smart building: *Scalar sensors can provide high precision measurements. The hardware can be cheaper and consume low power. However, they provide very limited information about occupants. Multimedia sensors can detect various kinds of events and occupant activities. However, the detection accuracy can be various and the intrusiveness can be very high and problematic in some cases. The accuracy of occupancy and occupant activities detection based on mobile devices could result low, however the intrusiveness and the investment needs are negligible.*

5. Technology Trends for Occupant Activities Detection

Various recent methods have been provided in the literature to allow better description and detection of the occupant activities and more efficient solutions for BAS and BOD. Most of the works referenced in this section combine both traditional approaches (like the

Table 4: Sensor Technologies in Smart Buildings Comparison: Mobile Sensors

Ref.	Main Goal	Gathered Data	Type of Activities	Used Technology (type of sensors)	Additional Aspects Scope	Based on
[39, 40]	Comfort Thermal prediction	Occupancy Occupants feedback	Binary Numeric	Fitbit/HR, pedometer accelerometer	BAS	Bluetooth
[41]	Energy s. Comfort	Building Occupancy Occupants feedback	Binary Numeric	Scalar sensors Wearable devices	BAS	Bluetooth Machine Learning
[42, 43]	Energy s. Comfort	Equipment Occupancy Occupants feedback	Binary Numeric	Temperature Humidity Light, Fitbit e-watch	BAS	Bluetooth
[45]	Energy s. Predict occ.	Occupancy	Numeric	Smartphones	HVAC BOD	WiFi connec. counting
[46]	Energy s.	Occupancy	Numeric Atomic Complex	Smartphones	BOD	WiFi connec. counting
[47]	Predict occ.	Occupancy	Numeric	Smartphones	BOD	WiFi TX/RX power
[48]	Energy s. Predict occ.	Occupancy	Numeric	Smartphones	BOD	WiFi connec. counting Bluetooth
[49, 50]	Energy s. Comfort Crowd count	Occupancy Occupants feedback	Numeric	Smartphones	BOD, Ligh. Control	WiFi connec. counting Machine Learn.
[51]	Predict occ./ user mobility	Occupancy	Numeric Atomic Complex	Smartphones	HVAC. BOD Lighting Control	WiFi connec. counting Bluetooth
[52]	Energy consump.	Occupancy Building	Numeric Complex	Smartphones	BOD	Internet provider

ones described in Section 3) with other technologies to detect occupancy and also provide more functionalities such as indoor location. The intention is to show some tendencies on using different technologies to efficiently support smart building management.

5.1. Signal Processing for indoor localization

Indoor localization and noise detection are important facilities that should be provided by smart buildings to meet Federal Communications Commission (FCC) regulations (for 911 calls) and for occupants' safety [53]. Despite the availability of Global Navigation Satellite Systems (GNSS) and cellular-based methods, indoor positioning remains a difficult problem. Restrictions of both methods are mainly related to the building structure (e.g., producing signal impairments) and to the requirement for each person to carry some compatible device. Recent approaches are proposing to use vibration sensors for measuring occupant-generated vibrations (i.e., vibrations mainly produced by person footsteps). With this new source of information and by extending conventional localization algorithms, that allow to correct signal distortions caused by vibrations of building structures, it will be possible to locate one person [54] or multiple persons moving within a building [53, 55]. A little different work is presented in [56], which is able to tracking a person, based on the knowledge of the structural behaviour of the floor slab.

One advantage of these approaches is their possibility of supporting BAS for safety, security, and health, for example, by offering a mean to detect and locate a person who falls, which is a significant capability in hospitals, assisted living homes, and in office buildings during emergency situations. Furthermore, vibration sensors are not intrusive.

5.2. Internet of Things (IoT)

The connected devices provided by Internet of Things (IoT), can communicate with each other as well as with users, allowing for creating, processing, and delivering information that can be collected to provide rapid databases with the raw data needed to make decisions. Hence, this inter-connected devices system implies the integration of high computational resources and the possibility of generating a huge quantity of data, which generally demands (intelligent) data analytics (e.g., machine learning) to obtain meaningful information to support decisions. As such, IoT technologies represent a new opportunity to improve functionalities and provide better services for smart buildings.

Many works have realized these benefits of IoT technologies, particularly on automation of public buildings for monitoring energy consumption, pollution level, carbon dioxide level, temperature, humidity, pressure, light intensity [57, 58, 59, 60]. Most of these works combine WiFi connectivity with ambient sensors to monitor indoor environments over long periods of time. Some of them use ad-hoc WSN and protocols [57, 58], while others use traditional Zig-Bee wireless networks combined with IoT technologies [59, 60]. All of them consider a centralized database to store the remote collected data.

To ensure efficiency, one essential requirement of the IoT is an ultra-low power communication. This need can be covered with Bluetooth Low Energy (BLE) technology, which within a short distance not more than 50m, provides high throughput and low latency, while keeping low energy consumption. It has been demonstrated that this low energy consumption allows sensors and devices to communicate during two years, using only a coin cell battery [61]. In the context of smart buildings, BLE solutions can be used for Location Based Services (LBS), by using the existing BLE-supported smartphone technology. Indeed, with this BLE solutions it is possible to get much more accurate indoor positioning than solutions based on traditional WiFi, allowing to capture utilization across a space and improving reliability of user centric micro-location services. LBS have fostered the BLE technology for mobile applications: beacons. A beacon (or iBeacon for Apple) is a device able to emit BLE signals, which can be captured by mobile applications. Hence, in a smart building scenario, the use of occupants mobile devices (with BLE-based beacons technology) as a source of information represents an effective solution to accurately detect occupancy, with energy efficient methods [61, 62, 63, 64]. The work presented in [65] proposes a modification of the iBeacon protocol to change the way the beacons advertise the region associated with them. Authors in [65] adapt iBeacon to allow beacons advertise more than one region, thus every time a beacon changes the region advertised, the device will receive a notification as the ones received when it enters in a new region. In such a way, it is possible to gather and process information about the beacons movements (thus identifying and tracking them) inside the building, to realize an occupancy detection system characterized by high levels of accuracy and power efficiency.

In [66], it is presented a methodology to infer occupant activities in buildings based on energy consumption patterns. Authors use information gathered by sensors to create time-series to infer individual activities. However, their model requires explicit domain knowledge of exactly how occupant activities impact the data gathered by the sensors. The proposed strategy, based on Gaussian Mixed Model, allows to automatically analyze and differentiate the highly variable data associated with occupant presence from the less variable data associated with occupant absence. Based on these differences, their model can be used to inform energy efficient operations as well as improve building designs. The experimental results validate and demonstrate that the proposed method is able to determine individual occupancy states with a high-level of accuracy on a small control study. They also showed the merits and applicability of their approach on a case study of a real 47-person open office in San Francisco, CA, USA.

In [67], it is proposed a real-time vision-based occupant pattern recognition system for occupancy counting as well as activity level classification. The approach is divided into two parts. The first part uses an open source library based on deep learning for real-time occupancy counting and background subtraction methods in order to classify activity level from images taken by a static RGB camera. The second part utilizes a Department of Energy (DOE) reference office building model with dynamic set-point control and conventional HVAC control to identify the potential energy savings and thermal comfort. Results revealed that the vision-based system can detect occupants and classify activity level in real-time with accuracy around 90% when there are not many occlusions.

5.3. Big Data Analytics

Smart buildings are composed of systems and devices that produce a huge amount of data related to building management (e.g., temperature and relative humidity levels), access control (e.g., occupancy statistics), as well as other measurements. Once all these data are collected, they can be combined and modelled to adjust seasonality, measurement scales, and other factors that may skew the findings. In addition, data is becoming more accessible on tablets and smartphones, resulting in connectivity in real time for quick and better decisions. Hence, to support smart buildings, high-speed analytics are necessary to aggregate that information. Big data technologies enable the collection, storing, real-time analysis and visualization of massive-sized data sets, with small-sized hardware or through a cloud analytic data warehouse platform.

Collecting sensor data streams that can be analyzed in real time, offers a significant possibility to implement just-in-time services to enable insights for patterns and correlations, while low costs are maintained. Such analysis can be used to improve traditional services for smart buildings (e.g., energy savings, fault detection, automatic HVAC control, workplace optimization), and in some cases, to generate business intelligence [68, 69]. In [69], a smart building architecture is presented, which combines Big Data technology with Cloud Computing to offer an energy efficient system for collecting and managing sensor data. Authors also present a comparative analysis of several topologies and architectures for smart buildings, based on IoT and Cloud computing.

Beyond research projects on the integration of IoT and Big Data technologies in smart buildings, nowadays there exist a bench of companies that offer new related facilities. For example, MSC Corporation provides an output/outcome-based collaborative model to predict cleaning services (cleaning service is no longer executed per fixed schedules but targeted where they are most needed, without wasting time or resources). This service consists of WSN, real-time data analytics, and direct communication with field workers and end occupants through mobile applications, dashboards, and kiosks. Collected data is related to occupancy, reservations, weather conditions, measurements of cleaning results (output-based information) as well as previous cleaning results, impact on occupants, and occupant satisfaction tracking (outcome-based information). By correlating these data, predictive cleaning is possible, bringing to building managers facilities to deploy resources most effectively and to cleaners facilities to provide most efficient services.

5.4. Ontologies and Semantic Web

To address the diversity and heterogeneity of sensor data (scalar and multimedia) and occupant activities modelling, some approaches have based the occupant activities recognition in the semantic web, by proposing domain specific and general ontologies.

An ontology to model activities and contextual information, in the context of buildings, is proposed in [70]. The main classes of the proposed ontology are: `Scenario` to represent an activity being executed; `Action` to model the different actions comprised in an activity; `Artifact`, representing the objects in the environment that are monitored; `Space`, represents the space in which the artifact is located; `Occupant`, modelling the person that use the artifact; and `WasteType`, that are relevant to the artifacts.

More generic knowledge-based models for BAS are proposed in [71, 72, 73, 74]. In [71], an ontology called BACS (Building Automation and Control System), is proposed to model information related to BASs (such as control behaviours, physical devices and their locations, smart appliances, and logical topologies of BASs). Another ontology, called OntoH2G, is proposed in [72] to store building information under a common vocabulary and consequently to enable fine-grained vision of buildings with their equipment and occupants. OntoH2G describes building infrastructure, including physical and digital entities, as well as user-building interactions not only in the form of activities but also comfort requirements, user preferences, and other aspects that motivate users to interact with the building. Both BACS and OntoH2G, align and extend various well-known and standard ontologies, such as Industry Foundation Classes (ifcOWL) and Semantic Sensor Network Ontology (SSN) In contrast in [73], a new ontology, called Brick, is proposed to model sensors, resources, subsystems, and locations. Authors provide automatic transformation of data represented in ifcOWL and Haystack schemes into the scheme of Brick, instead of aligning or integrating them.

In [74], a generic ontology to represent sensor network information, called MSSN-Onto, is proposed. MSSN-Onto allows the modelling of the infrastructure of the sensor network, the characteristics of individual sensors, and the data gathered from sensors (scalar and multimedia data), as well as information related to atomic and complex events (e.g., activities of occupants in a building), that can be detected from the gathered data. MSSN-Onto can be aligned with application domain knowledge. It extends the SSN ontology and was integrated into OntoH2G, the ontology of the HIT2GAP European project.

5.5. Crowd-sourcing/sensing

Crowd-sourcing/sensing is an evolving approach to collect massively environmental or behavioural data from a population, emerged along with the rapid emergence of mobile devices. A big and disperse group of participants are involved in the task of gathering reliable data from the environment, that can be used in several applications, such as urban mobility, environmental monitoring (e.g., air or noise pollution, carbon emission monitoring, controlling of water levels and observing widlife habitats), traffic congestion detection and dynamic road planning, parking availability checking and outages of public works detection (fire hydrants, traffic lights), social and health networking [75], natural disasters monitoring [76], and the study of sociocultural attitudes [77].

In the context of smart buildings, this technology starts to gain attention for indoor localization [45], for emergency managing [78], and energy saving [79]. A quite good survey of works related to indoor location based on crowd-sensing is presented in [80]. In [78], a system to detect and manage emergencies in smart buildings, called Danger-System, is presented. Danger-System collects information during a crisis, benefiting from existing building management systems that are based on mobile crowd sensing. It is able to detect false alarms and to provide context-dependent notifications.

5.6. Discussion

Table 5 summarizes the comparison of these technology trends according to the set of criteria proposed in Section 3. As we pointed before, the tendency is to combine classical approaches, like the ones described in Section 4, with more recent technologies, such as signal processing, BLE, IoT, Big Data analytics, and Semantic Web.

Signal processing techniques, supported by different types of sensors (e.g., ultrasonic sensors, wearable devices, scalar and multimedia sensors), have been effectively used for demand driven applications to obtain fine-grained information related to occupant location, presence, count, identity, and track. However, despite their effectiveness, such occupancy

Table 5: Technology Trends in Smart Buildings Comparison

Ref.	Main Goal	Gathered Data	Type of Activities	Used Technology (type of sensors)	Additional Aspects Scope	Based on
[53]–[55]	Energy s. Indoor loc.	Building Occupancy	Binary Numeric	Vibration sensors	BAS	Footstep vibration Signal process.
[56]	Indoor loc. Occup. track.	Building Occupancy	All (B,N,A,C)	Vibration sensors	BAS	Footstep vibrat. Signal process.
[57]–[60]	Energy s.	Equipment Occupancy	All (B,N,A,C)	Scalar/ Multimedia Mobile dev.	BAS	IoT, WiFi Zig-Bee Main control
[61]–[64]	Energy s. Indoor loc.	Occupancy	Binary Numeric	Scalar/ Multimedia Mobile dev.	BAS	IoT, BLE
[65]	Indoor loc. Occup. track.	Occupancy	All (B,N,A,C)	Mobile dev.	BAS	IoT, BLE iBeacon
[66]	Indoor loc.	Occupancy	Numeric	Scalar/ Multimedia Wi-Fi firmw.	BAS	IoT, Classif. Signal process.
[67]	Indoor loc. Energy s.	Occupancy	Numeric	Scalar/ Multimedia	BAS	IoT
[68, 69]	Energy s. Comfort	Building Equipment Occupancy	All (B,N,A,C)	Scalar/ Multimedia Mobile dev.	BAS BI	Big Data Cloud Computing
[70]–[74]	Energy s. Comfort	Building Equipment Occupancy Occupant feedback	All (B,N,A,C)	Scalar/ Multimedia	BAS	General Ontology
[45][78]	Indoor loc.	Occupancy	Binary Numeric	Mobile dev.	Emergency situations	Crowd sensing
[79]	Energy s. Comfort	Building Occupancy Occupants feedback	Binary Numeric	Scalar Mobile dev.	HVAC	Crowd sensing

detection systems present limitations related to the need of specialized devices connected or associated to occupants (for the case of wearable devices) and the requirement of complex and advanced signal processing algorithms that demand powerful processing stations. However, footstep vibration analysis is becoming a real alternative for indoor localization and tracking, since it represents a non-intrusive approach.

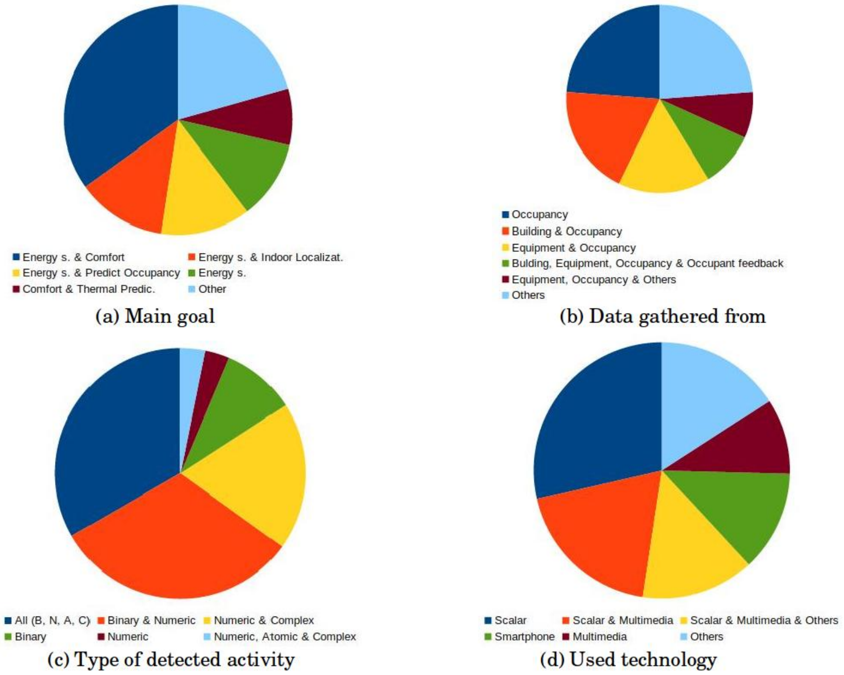
IoT-based smart systems allow long period of observations, remote data gathering, reactive ambient analysis, and further processing of historical data. Most of these works combine IoT techniques with other well-known technologies such as: Wireless Sensor Networks (e.g., temperature and relative humidity sensors, light sensors, microcontrollers, wireless transceivers, BLE), custom and adapted algorithms to collect and aggregate data (e.g., voting algorithms, information systems), database systems (e.g., MySQL, Postgres, Data Warehouses), reasoning and context awareness to make decisions, and mobile applications to monitor data remotely (e.g., Android applications, smartphones applications). Furthermore, there is a clear trend of combining Big Data analytics with well developed technologies in data management, such as IoT and Cloud computing as sources and storage of data and information. The ability of real-time processing data represents actual solutions to offer just-in-time services for better building management, that are currently applied in research and commercial applications. Thus, it is possible to develop more complex, but efficient and effective BAS.

Another complementary approach is the Semantic Web. Nowadays, there is a clear trend on proposing ontologies that extend, align, and integrate existing ontologies in the domain of smart building, such as ifcOWL and SSN ontologies. Many of these general and specif domain ontologies, allow the representation of physical resources (e.g., sensors, locations, subsystems, appliances), as well as information related to occupancy, occupant activities, context, and user preferences and constrains. In such a way, it is possible to have context-aware and user-centric BAS. It is important to note that, in the context of crowd-based technologies for smart buildings, the state-of-the-art is still in an early stage of development and lacks reusable solutions for secure collection of data and exploiting crowd activity traces. Moreover, the big challenges of these applications are related to privacy, security, energy save, and heterogeneity of mobile platforms.

To summarize, Figure 1 shows the statistics regarding the number of considered studies in terms of four aspects, Main Goal, Gathered Data, Type of detected activities, and Type of Used Technology, presented in Section 3. Because the number of criteria used is quite large, aspects with low number of works were grouped into one category called *Others*. Figure 1(a) classifies papers based on their main goals. Obviously, *Energy Saving* and *Comfort* are the focus of most researches. However, under the category *Others*, we can find also combinations with other goals, such as *Indoor Localization, Occupancy Prediction, User Mobility, Occupant Tracking.* Figure 1(b) classifies papers based on the source from which the data is collected. Most works considered data that reflect *Occupancy* in the building spaces, as well as data taken from the *Building* and its *Equipment.* Less works consider data from Occupant such as *Preferences* and *Feedback*, classified in the category *Others.* Figure 1(c) classifies papers based on the type of activity able to be recognized. It shows that *Binary* and *Numeric* activities are detected in almost all studies. However, since the use of combination of technologies (traditional sensor networks and advanced methods), *Atomic* and *Complex* events are also possible to be easily detected. Figure 1(d) classifies papers based on type of technology they are based on. Traditional technologies are still highly used, i.e., *Scalar* and *Multimedia* sensors. However, *Mobile Devices* and *Trends Technologies* (reflected in *Others*) are being increasingly considered. Despite the limitations that these new technologies present, the combination of several approaches becomes a powerful strategy to go beyond BAS focused only in *Energy Saving* and occupants' *Comfort*; other aspects, such as *Emergency Situations Management, Health, Security*, and even *Business Intelligence* (BI) can be addressed. Since the occupant activity detection involves complex large scaled systems, many faults and adversaries can inevitably impact this activity; therefore, another issue to approach in this regard is related to the robustness against failures; if sensor networks are modelled by directed graphs, consensus protocols can be applied, such as the one proposed in [81].

6. Conclusions

Reducing the energy consumption in buildings is a key requirement to ensure a sustainable lifestyle, to lead to significant cost savings, and to use resources in an efficient manner. This task implies a continuous monitoring of environmental parameters inside and outside the building, through the multiple sensors and actuators, coexisting in different locations. However, it has been demonstrated that to improve energy efficiency, it is also important to monitor occupants activities. Existing solutions attempt to reduce the energy consumed by different building's equipment, such as HVAC, lighting, and office appliances. However, if these different subsystems cooperate and occupant activities and events are monitored, energy consumption can be more reduced. In this survey, we study different exiting solutions provided to monitor building equipment (HVAC, lighting, etc.) through conventional sensors and actuators. Also, we investigated solutions related to multimedia sensors able to monitor in a better way the occupant's behaviour. Besides, we examined the limitations of non-dedicated sensors (conventional and multimedia). Further, we showed how mobile and smart sensors are emerging to complement occupant activities detection in a building. Finally, we presented several modern methods, such as Big Data



(a) Main goal (b) Data gathered from (c) Type of detected activity (d) Used technology

Figure 1: Summary of revised studies

analysis, social sensing, IoT, and Semantic Web. We showed also that several existing solutions could cope with the smart building's requirements associated with occupant's behaviour and activity detection.

However, there are several main issues and perspectives to be explored in the future: (i) how to deploy sensors and sensor networks in a building in order to detect all the requested events and activities?; (ii) what are the events and activities that should be detected in a building which can play a significant role in energy optimization?; moreover, how to make these events evolve with the building's life-cycle?; and (iii) how to cope with the privacy of occupants while looking for more precision in event detection?

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