Occupancy detection in non-residential buildings – A survey and novel privacy preserved occupancy monitoring solution

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Abstract
Buildings use approximately 40% of global energy and are responsible for almost a third of the worldwide greenhouse gas emissions. They also utilise about 60% of the world's electricity. In the last decade, stringent building regulations have led to significant improvements in the quality of the thermal characteristics of many building envelopes. However, similar considerations have not been paid to the number and activities of occupants in a building, which play an increasingly important role in energy consumption, optimisation processes, and indoor air quality. More than 50% of the energy consumption could be saved in Demand Controlled Ventilation (DCV) if accurate information about the number of occupants is readily available (Mysen et al., 2005). But due to privacy concerns, designing a precise occupancy sensing/counting system is a highly challenging task. While several studies count the number of occupants in rooms/zones for the optimisation of energy consumption, insufficient information is available on the comparison, analysis and pros and cons of these occupancy estimation techniques. This paper provides a review of occupancy measurement techniques and also discusses research trends and challenges. Additionally, a novel privacy preserved occupancy monitoring solution is also proposed in this paper. Security analyses of the proposed scheme reveal that the new occupancy monitoring system is privacy preserved compared to other traditional schemes.

Keywords Buildings, Occupancy, Energy optimization, HVAC
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1. Introduction

Primary energy is a form of energy which has not been subjected to any transformation such as crude oil, natural gas, solar energy and wind energy [2]. Globally, primary energy consumption is expected to increase at a rate of 1.4% per year [3] and as a result, the compound amount of increase for the next 20 years is about 32%. In many International Energy Agency (IEA) member countries, buildings (residential and non-residential) account for about 40% of primary energy consumption – residential (28%); non-residential (12%) [4]. For example, buildings in the United States (US) consumed 41% of primary energy, 44% more than transportation and 36% more than industrial sectors [5]. Hence even small percentage reductions in energy consumption in buildings will have a significant global impact.

Incorporating better energy consumption practices especially in new construction can contribute towards sustainable energy. However, existing buildings are considered to be very crucial as it can quickly provide the opportunities to improve efficiency over the next several decades. Replacement of old equipment and ageing infrastructure of resources can offer possibilities for energy saving. Through retrofit and other measures, low cost and efficient approaches are possible for reducing energy consumption in buildings. There are three principal approaches to reducing energy consumption in buildings:

(i) Construction with more energy efficient materials

(ii) The deployment of more energy efficient systems that are situated in the building

(iii) Adjustments to indoor conditions in proportion to the number of people in a building and their behaviour.

This paper is concerned with the latter and provides a review of measures used to count the number of people in non-residential buildings.

The term indoor conditions is often used to summarize a basket of building properties such as temperature, carbon dioxide, and humidity levels. These properties can be modified by human beings, actively through controlling some devices, e.g. opening and closing doors, turning computers, fans and lights on/off, or passively, e.g. by breathing and metabolism process. So the number of people in a building and their behaviour significantly affect the values of these properties [6–8]. The term "comfortable" indoor conditions are often used to describe a set of values for each of the properties. Typical recommended temperature ranges are between 23 °C to 26 °C and 20 °C to 24 °C for summer and winter, respectively [9,10]. Based on American Society of Heating, Refrigeration and Air-conditioning Engineers (ASHRAE) recommendation, carbon dioxide should be below than 1000 ppm and the value of humidity should be between 30% to 60% [11,12,10] for maintaining adequate Indoor Air Quality (IAQ). The term IAQ is defined as the quality of air within buildings.

Erickson et al., defined "occupancy" as the total number of people present in a defined part of a building [13] (we will use Erickson et al.'s definition in this paper). However, some authors [14] define occupancy as the "total number of present people in a space and their action (taken or not) against the indoor environment". In a non-residential large building, it is not uncommon that some spaces are unoccupied or partially occupied during a normal business day. Thus fine-grained occupancy information in a demand-driven control can lead to energy efficiency improvement and energy savings. It is outlined in [1] that fine-grained occupancy information in Demand Controlled Ventilation (DCV) systems could save more than 50% of the energy. Furthermore, in comparison to the fixed HVAC (Heating Ventilation and Air Conditioning) occupancy profile and schedule, Yang et al. showed that real-time occupancy input to HVAC system could save up to the 9% of the energy [15]. Energy saving was further increased from 9% up to 30–40% in Erickson et al. work [6]. In [16], real-time occupancy data was also used as an input to the HVAC and surprisingly energy saving was between 29% and 80%.

In principle, occupancy measurement is straightforward to conceive, but in practice, it is difficult to carry out. There are many problems including legislation about privacy, cost, social acceptability, and accuracy. This might be the reason that a significant number of non-residential buildings (such as offices and schools) still uses either fixed "occupancy" profiles and or coarse occupancy information. Several different methods and tools have been used for obtaining accurate occupancy information including camera, passive infra-red sensors, ultrasonic sensor, co2 sensor, and sensor fusion etc. Each has strengths and weaknesses.

The main contributions of this paper are:

1. A detailed literature review of the state-of-art of people counting and detection in large non-residential buildings.
2. Critical analysis of occupancy monitoring methods i.e. advantages, limitations, and comparisons of occupancy measurements techniques are outlined.
3. Proposal of a novel camera-based occupancy monitoring system.
4. Tangent Delay Ellipse Reflecting Cavity Map System (TD-ERCS) based pixels shuffling and diffusion for individuals privacy. This paper is organized as follows:

Literature review on different methodologies for occupancy estimation is given in Section 2. Advantages and limitation of these techniques are discussed in Section 3. Furthermore, in Section 3, we also summarized the occupancy techniques from building/zone size, the maximum number of people estimation, privacy issues, sample time and accuracies. A novel privacy preserved occupancy monitoring system is presented in Section 4. Conclusion is given in Section 5.

As shown in Figure 1, energy consumption can be minimised through different methods, i.e., improving building material, replacing the outdated heating/cooling system and providing occupancy information to smart HVAC system. However, the focus of this research article is on measurement techniques for obtaining occupancy information (total number of people in a space). Nevertheless, it is not simple to gather the number of people information inside buildings. For example, in non-residential buildings, diversity in occupancy and privacy concerns pose a bigger challenge in the occupancy detection and counting process. To solve the aforementioned issues and achieving fine-grained occupancy information, many solutions have been proposed in the literature. This article reviews the counting and detection

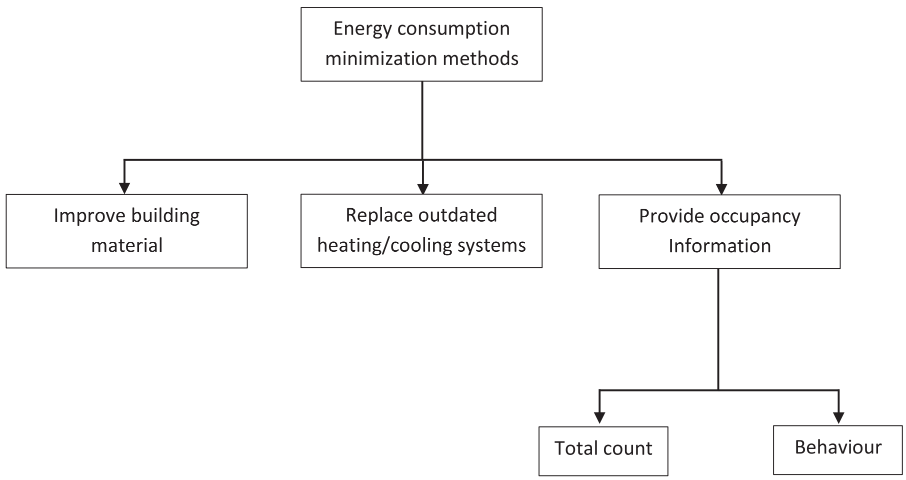


Figure 1.
Energy consumption minimization methods.

acquisition methodologies from a plethora of literature. This study further outlines the advantages and limitations of different occupancy acquisition systems. In the last part of this paper, a secured camera-based occupancy monitoring system is proposed. Different security metrics such as correlation coefficient, entropy, contrast, number of pixels change rate and unified average change intensity etc., proves the security of the proposed occupancy system.

2. Occupancy detection techniques

Melfi et al. developed the concept of presence across three dimension as shown in Figure 2 [17]. These three dimensions are the occupant, spatial and temporal resolutions. In occupant resolution, when resolution increases, accuracy and detail knowledge about occupancy and their behaviour increases. However, in HVAC energy optimisation process, the total number of occupants information (occupant) is sufficient [18]. In the literature, many measurement techniques are available. This section highlights some occupancy measurement techniques. The term 'occupancy' in the rest of paper is used to for people count/detection.

2.1 Occupancy measurement via camera

Through mounting a camera inside a room, not only number of people can be counted but their location can also be determined. A high-resolution camera network [19,20] can detect and count the number of people which can be further utilized in energy optimization processes. In order to save building energy, BODE project at the University of California dealt with occupancy measurement [21,22]. A distributed smart cameras object position estimation system known as SCOPE was developed which tracked the number of users and their motions [21,22]. The occupancy information obtained via camera is deployed in HVAC and lighting systems which reduced energy consumption [6]. Power-efficient Occupancy based Energy Measurement (POEM) comprises of wireless cameras called OPTNet for real-time occupancy measurement [23]. The occupancy measured data was used as an input to HVAC system for optimum conditioning [23]. The method proposed in [23] saved approximately

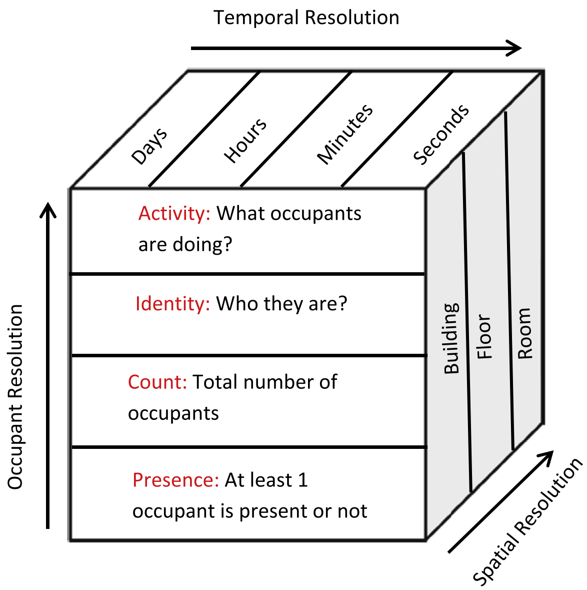


Figure 2.
Occupancy, temporal and spatial resolution [17].

30% of energy. A high accurate occupant estimator, based on multiple vision sensor has been proposed in [24]. In this work [24], Liu et al. presented a dynamic Bayesian network-based method via the data obtained from multiple cameras. A variety of image detection systems in buildings demand driven control is available, however, due to various reasons, application of such systems are limited: (a) Installing a camera causes serious privacy concerns; (b) Expensive hardware for advanced signals processing and number of counting is required; (c) Image detection systems must be Line of Sight (LOS) so that it faces least or minimal obstructions. The same difficulties are also reported in [23]. Due to aforementioned reasons, the number of occupant via a camera or image sensors is not easy to measure. The most important is that a camera should be placed in a way that it should not violate the privacy of the occupants. In literature, alternatives are available through which one can find/estimate the number of occupant. These alternatives are Passive Infra-red and other environmental sensors which are discussed in the later part of this paper.

2.2 Occupancy measurement via passive infra-red (PIR) sensor

All objects i.e., human or animal body emits heat energy in a form of infra-red radiation. A PIR sensor is an electronic device which is able to detect radiations at a wavelength of around 10 microns (the peak wavelength of the heat energy emitted by humans) [25]. The term passive means that the sensor is not using any energy for detecting purpose, it just works by detecting the energy emitted by other objects [26]. Due to the ease of implementation and cost effectiveness [27], PIR is very common for occupancy measurement and wide applications are found in Demand Control Ventilation (DCV) [28]. Using Bayesian probability theory, Dodier et al. presented a novel network of PIR sensors for correct occupancy detection [29]. This research used three PIR sensor at occupied areas in the workspace at The University of Nebraska's is located in Omaha, Nebraska [29]. The authors in [28] used PIR sensors for residential buildings and proposed a predictive control method for controlling home thermostat. In [28] Hidden Markov Model (HMM) was the base for predictive control strategy. A research group named LightWiSe (Lighting evaluation through Wireless Sensors) in The University College Dublin, used only PIR sensor for people presence [30]. The control strategy proposed in [30] activates the lighting system when PIR detects motion within its view. The decision of people presence/absence is solely based on the data obtained from PIR sensors [30]. The main drawback of such type sensor is that it is mostly prone due to 'False-off' errors, i.e. the lights are switched off even occupants are present. These types of errors usually occur due to the working principle of the PIR sensor. All PIR sensors have a field of vision which detect such occupant whose are within its range and hence vulnerable to 'False-off' errors. Moreover, a PIR sensor is unable to detect multiple persons passing through the line of sight.

2.3 Occupancy via ultrasonic sensor

Due to the cost-effectiveness and ease of implementation, both PIR and ultrasonic sensor are very well-known occupancy sensing technology. An ultrasonic sensor works on the three physical principles [31]: (a) Time Of Flight (TOF), (b) Doppler effect, and (c) attenuation of sound waves. In past, ultrasound sensors have been used for occupant detection [32–34]. Over long distances, the reliability of ultrasonic sensor for detection of occupants has been proven in [33]. These past methods are based on a single element sensor i.e., either Doppler effect or TOF. As a result, the output of past methods was only binary information about the occupant. Accurate localization and occupant presence information capability were increased when deploying ultrasound array sensor [35]. However, due to complex signal processing steps involved in obtaining the location of occupants make such scheme impractical [35]. Oliver et al. analysed the time and frequency response over the ultrasonic chirp bandwidth and proposed a new method for occupancy [36]. As compared to the traditional ultrasonic-based occupancy detection, Oliver et al. estimated number of people rather than binary information [36]. Some of the drawbacks of Oliver et al. scheme is that for large spaces multiple transducers suffer from cross-talk. When space increases, estimation of the exact number of occupants diminishes. Ultrasound used in this research is still detectable by animals and further investigation would be required to work on such sensors. Ultrasonic sensors are highly suitable for spaces in which a line of sight is not possible, such as partitioned spaces. However, sometime ultrasonic-based occupancy detection results in 'False on'. It is due to the fact that imminent movements coming from other activities other than occupant movements cause 'False on'. Sometimes just air turbulence of office air conditioners triggers ultrasonic sensor and hence prone to 'False-on' errors.

2.4 Occupancy measurement via radio frequency (RF) signals

In some commercial office buildings, indoor occupancy and localization have been demonstrated in the form of Wireless Fidelity (WIFI) or Radio Frequency (RF) based devices [37]. All Radio Frequency Identification Tags (RFID) based system consists of the transceiver, transponder and typical antenna. Two different methods knowns as active and passive modes in RFID based localization and occupancy can be applied. In case of active mode [38], the antenna is installed at the target location and information about their occupancy and location is transmitted to the central location. Active RFID can be used for occupant density and profiling. It can also be used for localization of occupants based on the Received Signal Strength Indication (RSSI), which varies based on the distance of the occupants (tags) from the reader. The received RSSI may be affected by other factors such as diffraction, reflection and transmission of radio waves. To counter such type of shortcomings, Zhang et al. [39] reduced the probability of error in localization by proposing the use of multiple readers instead of one reader. The method proposed by Zhang et al. [39] was proved to be 93% accurate in localization. In [40], it has been discussed that Global Positioning System (GPS) can estimate occupancy and localization. However, due to precision issues, such solutions are impractical. As a solution to the aforementioned problem, Tesoriero et al. [40] proposed the concept of passive localization mode. In passive mode, coordinates of an entity are determined using reference tag coordinates [40]. However, a serious drawback such as larger distance from the target causes incorrect occupancy which is highlighted in research [41]. Despite such inaccuracies, studies on passive mode RFID are found in [42,43]. In [44], Manzoor et al. changed occupant detection mechanism by replacing PIR with passive RFID. The 'False-off' error caused by PIR sensor was reduced using the data from RFID system.

Tracking based on GPS is an attractive option in an outdoor environment. However, application of such systems in the indoor environment need a clear LOS and hence alternative solution need to be presented [45]. In [45], the performance of three different localization method for dynamic indoor user position tracking has been reported. It is outlined in [45] that these three techniques require a complex and complete station for advanced signal processing. Fine-grained occupancy information can be obtained via an RFID based occupancy estimation system, however, other indoor electromagnetic conditions may strongly affect such RFID-based systems. RFID systems also raise privacy issues as occupants have to carry the RFID tags.

2.5 Occupancy measurement via sensors fusion

In past, occupant activities and changes in indoor environmental conditions are measured via some basic sensors such as PIR and CO_2 sensors. However, relying on a single sensor data causes significant errors [46]. Due to different applications and targeting higher accuracy, a fusion of multiple sensors is used in occupancy detection and estimation [47].

Wang et al. [48,49], found a strong relation between indoor CO_2 concentration and occupancy. In [48–50], occupancy were estimated which was solely based on exhausted CO_2 data. The problem in CO_2 based occupancy is that it cannot granularly count people in cubicle areas and the response of CO_2 sensors are very slow. A single motion detection sensor can only detect an occupant and cannot count the number of people [51]. Furthermore, the motion detector fails in an office environment where people are relatively still. Such scenarios can lead to false negative signals. Recently, the integration of multiple sensors such as light, acoustic, temperature, motion, CO_2, humidity and PIR sensors are suggested for accurate occupancy detection. A new method [46] introduced as SUN (sensor-utility-network) utilises a number of sensor measured data which reduced error from 70 to 11% as compared to such method which uses solely one sensor output. The occupancy was measured via distributed sensor measures such as CO_2, PIR, video, sound and badge counters [46]. Ebaddat et al. [52], used three different sensors data i.e., CO_2, ventilation actuation signals and temperature to build a dynamic model for occupancy. However, it has been pointed out in a research [53] that temperature parameter contains less information gain for occupancy modelling.

Zhang et al. concluded in their research [53] that the correlation between the number of occupants and each individual environmental variable temperature, relative humidity, CO_2 and acoustic ranks approximately 11.98%, 32.49%, 35.70% and 48.05%, respectively. For the demand-driven application such as HVAC, Yang et al. [54] presented a multi-sensor based occupancy estimation model. The novel [54] which can estimate the number of people using the combination of indoor temperature, humidity, CO_2 concentration, light, sound and motion. To measure the aforementioned parameters, sensors are deployed to estimate the number of people. Another implicit method for occupancy was proposed via the data obtained from (1) physical sensors: temperature sensor, relative humidity sensor, light levels sensor; and (2) software sensors: computer power consumption [55]. In [55], it was found in experiments that the average peak occupancy rate is less than 40% and the daily occupancy profile varies among different weekdays. In our previous work, Random Neural Network (RNN) based occupancy was estimated from four sensors: (1) environmental CO_2 sensor (2) Air inlet CO_2 sensor (3) room temperature sensor and (4) Air inlet temperature [56]. The occupancy information is further utilized in the HVAC system and the accuracy of the smart controller was 94.87%, 98.39%, and 99.27% for heating, cooling, and ventilation, respectively. Occupancy estimation time in [56] was slower due to CO_2 sensor which is improved via a Hybrid RNN based occupancy estimation and PIR and magnetic reed switches [57]. Detection of a single occupant through the data obtained from room temperature, inlet air temperature, inlet CO_2 concentration, indoor CO_2 levels, and inlet air actuation signal is proposed in [58]. The accuracy of the estimation proposed in [58] was 92.48%. A novel multiple sensor based technique for correct occupancy estimation is recently proposed by [59]. Motion detection, power consumption, CO_2 concentration sensors, microphone and door/window positions were the main sensors in [59]. This research used feature selection via information gain strategy and concluded that indoor environment temperature has a very low role in occupancy detection. Acoustic sensors were the main feature in the proposed occupancy detection algorithm. Candanedo et al. proposed [60] a model for occupancy detection via light, humidity, CO_2, and temperature measurements using Classification and Regression Trees (CART), Random Forest (RF) and Linear Discriminant Analysis (LDA). However, the work outlined in [60] is limited to occupancy detection only and cannot estimate the number of occupants. The reported accuracy of Candaneod et al. model was surprisingly 95 to 99%. Only using the temperature data [60], the accuracy was 83 to 85%.

Instead of utilizing multiple wireless sensors, Jiang et al. measured carbon dioxide concentration via CO_2 sensor for real-time indoor occupancy [61]. In [61], authors utilized Feature Scaled Extreme Learning Machine (FS-ELM) algorithm, which is a variation of the standard Extreme Learning Machine (ELM). The performance of FS-ELM is better than ELM in occupancy estimation problem [61]. The measured CO_2 concentration was suffered from serious spikes and the problem was resolved with pre-smoothing filtering. Authors in [61] found out that pre-smoothing the CO_2 data can greatly improve the estimation accuracy up to 94%. Zhao et al., used heat source and temperature information and proposed a solution for occupancy via two methods: (i) support vector regression (SVR) (ii) and recurrent neural network [62].

2.6 Occupancy measurement via WLAN, Bluetooth and WiFi

Due to the rapid advancement in the area of information and communication, latest technology such as cellular data, GPS, Wireless Local Area Network (WLAN) and Bluetooth [63] are also widely employed [41] in occupancy detection. Explicit sensing based on PIR, ultrasound or any other sensors incur the cost of installation and maintenance as compared to implicit sensing methods [64]. In [65], authors proposed a novel model for occupancy which uses existing WiFi infrastructure within commercial buildings. The accuracy of WiFi-based model [65] was 86%. The fine-grained occupancy information saved approximately 18% of energy [65]. In [66] a pair of transmitter and receiver was deployed for measuring WiFi received signal strength. The problem associated with Received Signal Strength (RSS) modelling technique for occupancy estimation is outlined by Depatala et al. [66]. The outlined problem related to RSS modelling are: lesser accuracy and (2) limited people count. A model for counting the total number of people was developed by working on two important scenarios: blocking the Line of Sight (LOS) and scattering effects [66]. Depatala et al. studied the impact of blocking the LOS and scattering effects and an efficient mathematical expression for people estimation were derived [66]. The IP and MAC addresses in WiFi access points were used by Christensen et al. and proposed an algorithm for measuring the total number of occupants [64]. Some problems in WiFi only method have been reported by Rana et al. [67]. These problems include inaccurate estimation of people and existence of different locations with the same signatures. Occupancy detection via iBeacon on Android devices for effective and better building management is proposed in [68]. The solution proposed in [68] is a novel idea as it is different from the previous techniques. This technique uses the maximum advantage of Bluetooth low energy standard, which as a result provides lower power consumption. However, such occupancy measurement may result in false negative/positive detection for a large scale building as well as large occupancy in an institutional building [41].

3. Discussion and summary of review

As outlined in Figure 3, initially raw data about occupancy is obtained and then this data is analysed via an occupancy algorithm for occupancy estimation. It can be seen from Figure 3 that occupancy can be measured through different ways and they can be utilised in smart controllers. Additionally, these smart controllers can utilise the obtained occupancy information for energy efficiency. Therefore, occupancy has a key role in energy optimisation processes. Each occupancy method has their advantages and disadvantages. For an example a 2×2 diagram shown in Figure 4 highlight the cost of each method against the quality of data.

Detail pros and cons are outlined as:

With the recent advancement in camera technologies, it can be a good choice to mount a camera for occupant counting. Camera-based occupancy measurement is more accurate when compared to other occupancy methods. But due to privacy concerns, hardware installation cost and LOS requirements, researchers are trying to find such solutions which

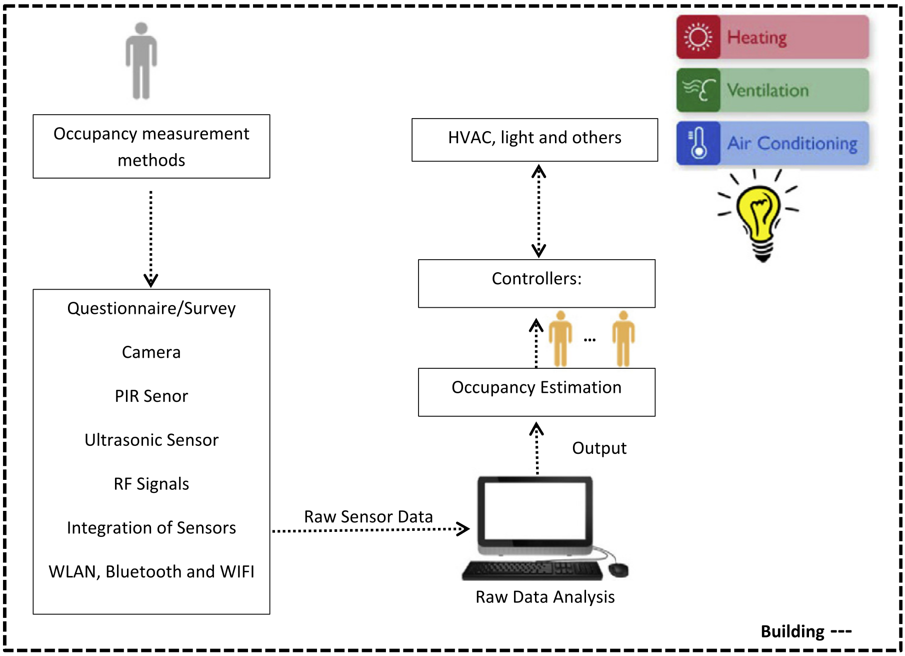


Figure 3. Occupancy measurement methods and its applications.

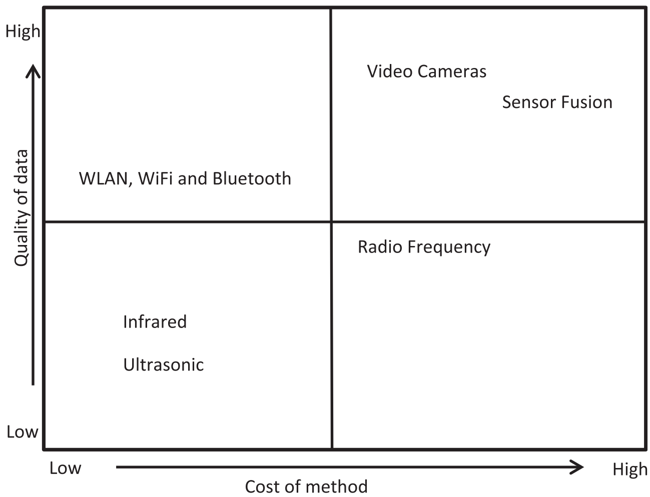


Figure 4. 2×2translation diagram indicating strength and weaknesses of occupancy measuring methods.

are least expensive and applicable in real-time applications. PIR and ultrasonic sensors are commonly known for its low cost and hence widely deployed for occupant detection. A PIR sensor can only detect the presence/absence of an occupant and cannot count the number of people. As a result, PIR output is binary. Also, PIR sensor has its field of vision, and it is susceptible to 'False off'. Due to high sensitivity, an ultrasonic sensor is prone to 'False on' error.

In order to reduce 'False off' error caused by PIR sensor, RFID based solution for occupancy were proposed. But as occupants have to carry RFID tags, it has privacy issues same as a camera. A single sensor is vulnerable to either 'False off' or 'False on' or even both; as a result, many researchers used the idea of sensor fusion. Occupancy obtained through sensors fusion is highly accurate and can be easily applied to demand driven controllers. Sensor fusion based occupancy techniques are costly and moreover, its response is prolonged. In order to use the existing infrastructure for occupancies such as WLAN, WiFi and Bluetooth, the cost of hardware installation can be reduced. But the use of such technologies is not applicable in a large building due to its high positive/negative detection of occupants. Table 1 summarise pros described above and cons information in a better way.

Occupancy methods presented in the literature are compared in Table 2. Size of buildings/zone under consideration varies from 7.4 m^2 to 13471 m^2. Surprisingly, for some studies size of buildings/zone are not mentioned in the article. Generally, those techniques which involve video camera and/or RF tags have privacy issues. Time varies from half hour to 30 ms to obtain data samples. Accuracy is one of the important parameters for occupancy, but surprisingly it is not discussed in many studies. Building type and size, the maximum number of people prediction, privacy issues, sampling time and accuracies of various occupancy methods are also outlined in Table 2.

4. Proposed solution to the camera based occupancy

As outlined in the previous section that camera-based occupancy has many limitations. Out of these limitations, privacy is one of the major concerns these days. Security and privacy of innocent people are seriously compromised during camera-based occupancy. An unauthorized person or intruder can access people flow information. Even in some attacks, whole video or image data are compromised. In order to secure occupancy information from attackers, image data should be in an encrypted format. In this section, we proposed a novel video frame encryption method for people privacy. Details steps of the proposed privacy preserved are discussed as:

1. Obtain image/video data from an overhead installed camera.

Technique	Benefits	Limitations
Video cameras	More precise and fine-grained data	Privacy concern and requires LOS image detection systems
Infra-red	cost effective, easy to implement and low power consuming	Prone to False-off error, binary output and not applicable in DCV applications
Ultrasonic	cost effective, easy to implement	Prone to False-on error, receiver must be LOS environmental sounds can affect results
Radio frequency	Low-cost and commercially available	Affected by other RF devices and electromagnetic conditions
Data obtained from multiple sensors; such as CO_2 and other environmental sensors	Accurate and can be applied for demand control ventilation applications	Multiple sensors cost slow response and sensitive to environment
Wireless Local Area Network (WLAN), WIFI and Bluetooth	Low power consumption and utilize only existing communication infrastructure	False negative/positive detection in large scale building

Table 1. Advantages and drawbacks of occupancy measurement techniques.

Technique/ Technology	Reference	Scope (Shape/Size)	Number of People	Privacy Issues	Sampling Time	Accuracy
Video Camera	[21]	NA	18	Yes	1 min	80%
	[22]	670.2 m^2	NA	Yes	1 min	80%
	[6]	2799.2 m^2	NA	Yes	1 min	80%
	[23]	6689 m^2	NA	Yes	NA	92.4%
	[24]	300 m^2	8	Yes	30 s	NA
	[69]	NA	6	Yes	10 min	NA
	[70]	NA	2	Yes	5 s	95.3%
	[71]	511 m^2	1	Yes	0.1 s	96%
Infra-red	[29]	36.5 m^2	1	No	30 ms	NA
	[30]	NA	1	No	NA	NA
	[72]	NA	1	No	5 min	79–98%
	[27]	NA	14	No	30 s	86%
	[73]	NA	1	No	30 s	80%
Ultrasound	[35]	13.5 m^2	2	No	30 ms	NA
	[36]	NA	150	No	NA	90%
Radio Frequency	[39]	382 m^2	1	Yes	7-9 s	93%
	[40]	4.920 cm^2	NA	Yes	100 ms	79–100%
	[42]	24 m^2	NA	Yes	7.5 s	NA
	[43]	40–55 m^2	6	Yes	1.5 s	62–88%
	[44]	31.84 m^2	32	Yes	NA	91.43%
Sensor Fusion	[46]	NA	45	Yes	10 min	79–89%
	[52]	NA	4	No	1 min	88%
	[53]	768.6 m^2	4	No	1–2 min	NA
	[54]	40 m^2	9	No	1 min	89–86%
	[55]	2422 m^2	23	No	NA	NA
	[56]	7.4 m^2	1	No	NA	83%
	[57]	7.4 m^2	3	No	1 min	88%
	[58]	8.9 m^2	3	No	1 min	92.48%
	[59]	NA	3	No	30 min	76–100%
	[74]	NA	2	No	NA	NA
WLAN, WiFi and Bluetooth	[64]	NA	70	No	NA	59–91%
	[65]	13471 m^2	41	No	20 min	86%
	[66]	70 m^2	9	No	5 min	NA
	[68]	NA	NA	No	2 s	94%
	[75]	10 m radius	NA	No	180 s	73%

Table 2.
Building type, scope, scale, privacy issues, sampling time and accuracies of various occupancy techniques.

2. Apply well-known algorithm i.e., Gaussian Mixture Model (GMM) [76] and morphological opening and closing operations on the video frame.
3. Detect the presence of person(s) through frame subtraction method.
4. Perform chaos-based (TD-ERCS map [77]) pixels shuffling and diffusion (see Figure 5) on region of interest (ROI) only i.e., detected person(s) body.
5. Track the person(s) in the encrypted domain and count the person(s) when passes a virtual line.

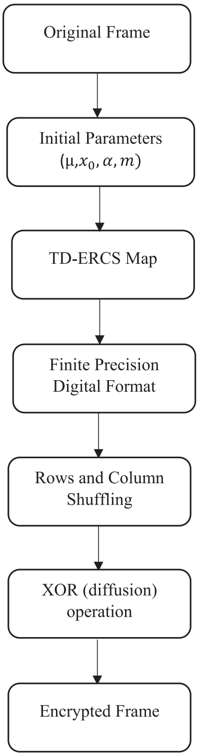
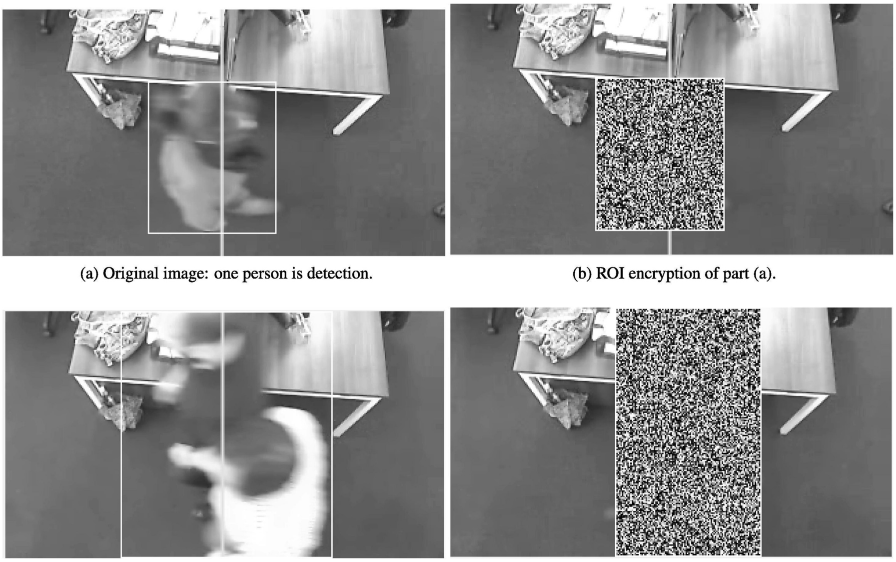


Figure 5.
Choas-based frame encryption.

Results of the proposed novel camera-based motioning is shown in Figure 6. The original frames are shown in Figure 6(a) and (c) highlights that the privacy of people is compromised with traditional camera-based monitoring and counting system. However, the proposed chaos-based novel scheme, hides and encrypt the ROI and hence preserve the privacy of an individual during monitoring and counting process. In order to test the robustness and security of the proposed monitoring system, we have applied various security parameters [77]. Interested readers can find the details and mathematical definition of these security parameters in [77]. Results of these parameters highlighted in Table 3 shows that the proposed solution hides original content and the image data is secure as compared to traditional camera-based occupancy. The encryption step increases the computation overhead but the occupancy monitoring system will be secured from attackers, eavesdroppers and unauthorized access. Without encryption, the execution time of each frame is 2 ms but when the encryption step is included in the monitoring process, the execution times slightly increases to a value of 3 ms (scheme tested using MATLAB R2017b on a PC with 3.3 GHz CPU, and 8 GB memory). In camera-based occupancy monitoring, whenever privacy is requested, the proposed scheme can protect an individual privacy with a slight computational overhead. In the proposed system, chaos-based encryption is carried out during occupancy monitoring. The accuracy of system is dependent on Gaussian Mixture Model (GMM), morphological operations (opening/closing), image subtraction and tracking (via Kalman filter) etc. The encryption step was just included for privacy protection. The accuracy of the counting process in an encrypted domain and without encryption is same.



(a) Original image: one person is detection.

(b) ROI encryption of part (a).

(c) Original image: two persons are detection.

(d) ROI encryption of part (c).

Figure 6.
ROI based Image encryption and counting number of person.

Table 3.
Security assessment of the proposed scheme: One person detected in frame.

Security metric	Original Frame	Encrypted Frame
H_{CC}	0.8962	0.5315
V_{CC}	0.9180	0.5805
D_{CC}	0.8231	0.4626
Entropy	6.6776	6.9647
Contrast	0.4274	2.8591
Energy	0.9011	0.1992
NPCR	NA	67.0225
UACI	NA	8.9078

5. Conclusion

Occupants affect building energy consumption through active and passive actions, and hence they are considered to be the real drivers of energy consumption. In addition to energy consumption, indoor air quality is also a very prominent factor that is profoundly influenced by occupants. In such scenarios, building occupancy plays a crucial role in energy optimisation techniques. In order to reduce the energy consumption, occupancy is used as an input in the HVAC system. However, occupancy measurement is not easy as it involves legislation about privacy and accuracy. Through literature review, no single method or sensor is identified that best estimate and solve the problem of occupancy information. In future, simplified, secure, and highly accurate methods are expected from the research community. In the last part of this paper, a novel secure occupancy monitoring and counting scheme is also presented. The proposed occupancy scheme is tested against various security parameter and all results reveal that the proposed occupancy monitoring scheme is secure and resistant against many statistical attacks.

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