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* **Corresponding author**.

r.lavanya@aalimec.ac.in

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Thermal Image Based Occupant Count Measurement Model using Human Body Temperature for Smart Building

R Lavanya[1]*, N R Shanker[2]

1 Department of Information Technology, Aalim Muhammed Salegh College of Engineering, Chennai, 600 055, Tamil Nadu, India
2 Department of Computer Science and Engineering, Aalim Muhammed Salegh College of Engineering, Chennai, 600 055, Tamil Nadu, India

Abstract

Objectives: The proposed Occupant Count Measurement (OCM) model aims to enhance sustainability, energy efficiency, comfort, and safety in smart buildings by accurately determining occupant count using thermal camera images and body temperature data. **Methods:** The model leverages real-time thermal camera images without the need for a pre-existing dataset. Key parameters include temperature threshold, occupant motion, size, and shape to ensure accurate occupancy estimation. The K-means algorithm identifies and clusters regions of interest (ROI) in thermal images corresponding to human body temperatures. The model also employs sensors like PIR, RGB cameras, and thermal image sensors. Manual counting serves as a benchmark for comparison. **Findings:** The K-means algorithm extracts regions with elevated temperatures related to human bodies from thermal images, partitioning them into K-clusters based on temperature ranges and assigning each pixel to one of the clusters. A temperature threshold differentiates human clusters in the thermal image, while connected component labeling refines human object segmentation by identifying blobs, which are then used for occupant counting. The model's precision is assessed using diverse image sensors and compared to the actual number of occupants. The proposed OCM model achieves an accuracy of about 90.2% compared to traditional methods. **Novelty:** This study introduces an OCM model that uses thermal images to estimate the number of occupants in a room based on their body temperature. The method focuses on detecting and counting occupants by their overall thermal body signature, providing a novel approach to occupant measurement in smart buildings.

Keywords: Thermal Images; Segmentation; Occupant Estimation; Occupant Comfort; Smart Building

1 Introduction

Smart building utilizes advanced technologies, integrated systems and enhances overall efficiency, sustainability and occupant comfort. OCM is a critical component in smart buildings, enabling better resource management, energy efficiency, safety, and overall occupant well-being. In conventional approach, occupant count measurement in smart building room is performed using sensors such as PIR, RFID, ultrasonic and CO_2 sensors[(1)] are inaccurate due to limited sensitivity, range, time consumption and scalability issues. Precise occupancy estimation is necessary for energy savings in smart buildings. In existing occupant measurement methods, occupant count is obtained using various methods such as Bluetooth Low Energy (BLE) signals[(2)], Cost effective mobile platform using ANN[(3)], Regression based indoor occupant estimation model[(4)] and IoT and machine learning based controllers[(5)]. Occupancy was forecasted using smart phone[(6)] detection and validated with real data, achieving 20% energy savings compared to traditional methods. Optical camera systems with deep learning improved localization accuracy by 9%[(7)]. Low-resolution thermal sensors, used with machine learning, estimated occupancy with 99% accuracy but were limited to detecting three occupants per area[(8)]. Occupant models developed using Genetic algorithms[(9)] and ensemble models[(10)] optimized accuracy and enhanced energy performance. Moreover, current method tracks the count of individuals within a space and never evaluates the temperature of the occupants. To address the above mentioned problem, thermal camera sensors are used in proposed OCM model for estimation of occupants. Thermal camera is used for measurement of occupant count and body temperature in the room. This work evaluates the performance of occupant count estimation through different sensor and camera images. The effectiveness of reducing energy consumption in smart energy management system is based on occupant measurement methods. Accurately differentiating between persons and other heat-emitting objects or ambient factors is a common research need in thermal camera-based occupant count models, particularly in complex interior environments with variable thermal signatures. Due to these difficulties, conventional thermal imaging-based occupancy detection techniques may experience false positives or erroneous counts.

Real-time occupancy level monitoring within a smart building with thermal cameras enables timely adjustments to resource allocation, environmental conditions, and occupancy management strategies. OCM model can distinguish between individuals and inanimate items more successfully by using human body temperature as a critical occupancy message. The proposed OCM model lowers the probability of false positives and improves occupancy detection accuracy, especially in complicated situations with fluctuating temperatures. The integration of thermal camera images and human body temperature measurements facilitates multi-modal fusion, to improve occupancy count precision by overcoming the constraints of individual sensors by utilizing complementary data streams. The main contributions of this paper are as follows:

- This paper focus on leveraging accurate occupant count data in smart buildings and creates a responsive, comfort and energy-efficient environment, lead to substantial energy savings.
- An occupant count measurement model proposed in this work uses thermal camera images, and human body temperature is used as a primary indicator of occupancy instead of just thermal signatures, with this occupants can be detected with more reliability. OCM model distinguishes human inhabitants and other sources of heat by establishing temperature limits based on metabolic norms and decrease the probability of false positives.
- K-means clustering segments thermal image based on temperature patterns separates human bodies from the background with different thermal signatures. By dividing thermal pictures into discrete clusters according to pixel intensity levels, K-means clustering can successfully isolate human bodies or other non-human items from regions of interest. The accuracy of occupancy identification is increased in this segmentation procedure, which helps separate and identify possible inhabitants within the thermal image.

The proposed model enhances occupant detection and counting in smart buildings by integrating thermal signatures for image segmentation and blob detection. This improves accuracy and reliability, making the OCM method robust for diverse indoor environments. Combining PIR sensors with thermal cameras leverages their strengths for better occupancy detection. The system enables real-time monitoring and analysis, adapting to changing patterns for energy savings. Thermal cameras capture temperature differences to distinguish occupants from objects, providing accurate counts. While machine learning algorithms are powerful, they require more resources and expertise, making them less practical for all scenarios.

2 Methodology

In the recent times, scientific and technological progresses have facilitated the creation of diverse control and optimization methodologies and attain enhanced energy efficiency in smart building. Data driven real-time tracking of occupant count measurement is performed in the proposed work. Figure 1 depicts block diagram of occupant count measurement model. OCM model integrates PIR sensors and a thermal camera for accurate occupant counting and improved building management. The HC-SR501 PIR Motion Sensor is fixed for occupant movement detection. AF-375/06 magnetic contact switch door sensor monitors the occupant movement and opening and closing of the door. NBPOWER 1080P 60 FPS RGB camera is used for occupant count measurement and HM-TJ11-3AMF-Mini1 thermal camera is used for occupant count, occupant body temperature measurement. Strategically placed within a room, the PIR sensor detects movement, triggering the thermal camera to capture images of occupants and their body temperatures. Connected to a Raspberry Pi 4B, this data is analyzed using MATLAB. The thermal camera images, processed with K-means algorithms and connected component analysis, provide real-time occupancy counts. Figure 2 shows test bed of proposed OCM system.

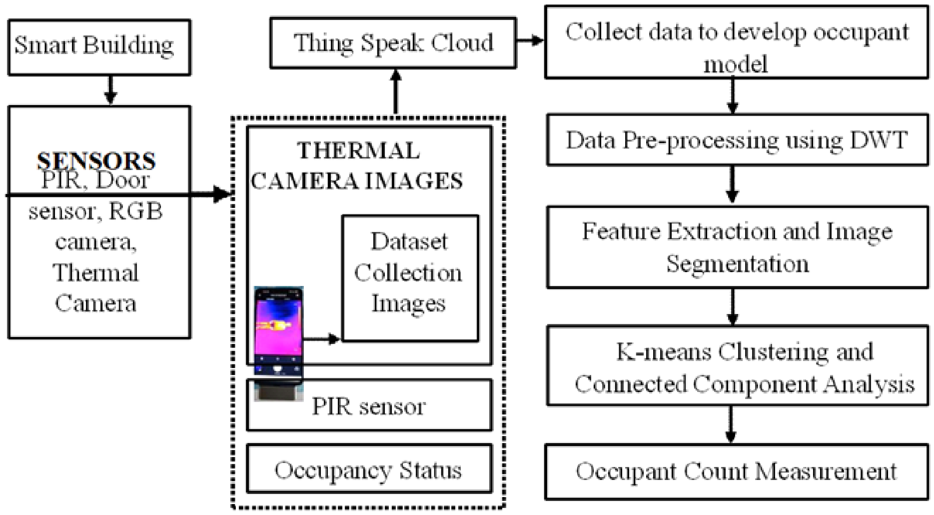

Fig 1. Block diagram of occupant count measurement model

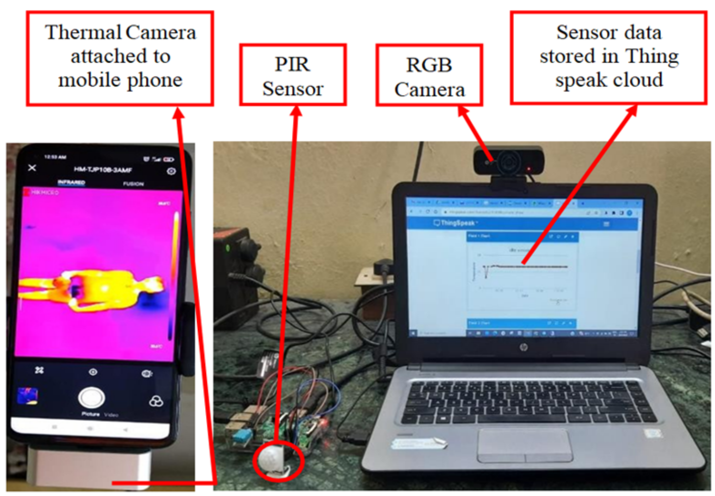

Fig 2. Test bed of proposed OCM model

The proposed OCM system uses a PIR sensor to detect occupant motion, a door sensor, and both RGB and thermal cameras to estimate occupant count. Data from these devices are continuously monitored through a thermal camera accessed via an IP webcam app. The dataset includes PIR sensor data and thermal images, which are processed by a Raspberry Pi 4B to measure occupancy. Information is stored in Thingspeak every minute, with preprocessing to eliminate redundant data. The Raspberry Pi handles feature extraction, image segmentation, and occupant count estimation. The system was tested in an experimental room at the college's IT building, involving faculty participants. Manual logging and various test conditions validated the OCM model's accuracy and effectiveness, demonstrating high reliability across different scenarios.

3 Results and Discussion

3.1 PIR and Door Sensor

In the first testing scenario, occupant count measurement was performed using combination of passive infrared and door sensors. This approach allowed for a comprehensive assessment of OCM performance more accurately and determines the number of occupants within the room. PIR sensor is utilized for identification of human motions and door sensor registers the events of door close and open within the room. PIR sensor strategically positioned and monitors the persons in room and detects the difference in infrared radiation induced by human movements [(11)]. Simultaneously, door sensor is affixed in the entrance of experimental room, determines the close or open of the door. The acquired sensor data is transmitted to the Raspberry- Pi 4B, where a programmed algorithm is implemented and tracks the occupant entries and exits. However, system faces challenges when several individuals enter the room simultaneously, as software considers single occupant count. Conversely, if an occupant enters and leaves concurrently, the system may inaccurately measure the occupant count, leads to errors [(12)]. The overall accuracy of the OCM model, using PIR along with door sensor, is about 72.8%. Occupant estimation using PIR and door sensors never reliable for scenarios involving simultaneous entries and exits. Figure 3 presents a side-by-side comparison of the occupant count estimated by PIR and door sensor with the manually measured actual number of occupants.

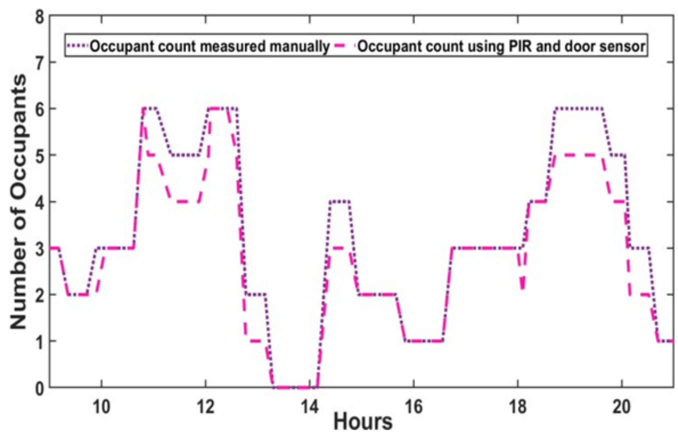

Fig 3. Occupant count measurement utilizing PIR and door sensor

3.2 RGB Camera

In the second testing scenario, an RGB image camera is utilized to assess the occupant count. This camera captures background images without individuals to establish a reference point for occupant count measurement. The system employs an image capture mechanism activated by PIR sensor. When motion of human objects detected, RGB camera system captures frames, Raspberry-Pi 4B performs preprocessing of image and feature extraction, and identifies occupants within the room through image segmentation. The image segmentation process employs a k-means algorithm for improving color space representation during image segmentation [(13)], while blob extraction is utilized and identifies distinct "blob" regions within the thermal image. In this context, each identified blob corresponds to a human presence, and count of these blobs directly provides the number of occupants within the room. This method ensures a precise and efficient means of occupant estimation based on the distinct features extracted from the segmented image. RGB camera counting systems performs in ambient lighting conditions. In low-light environment, occupants identification are challenging and leads to reduced accuracy [(14)]. Using an RGB image camera for occupant estimation never suitable under these circumstances. Figure 4 shows occupant count measurement using RGB images. The average occupant estimation accuracy is about 79.50%.

3.3 Thermal Camera

In the third testing scenario, the thermal camera establishes a connection with the Raspberry-Pi 4B through Wi-Fi and the internet protocol web camera application (IP webcam app), enables seamless communication and data transfer. Figure 5, depicts the framework of OCM model, showcases the various stages involved in the number of occupant count measurement using thermal images. The IP web camera application is set up and configured to establish a connection with the thermal camera,

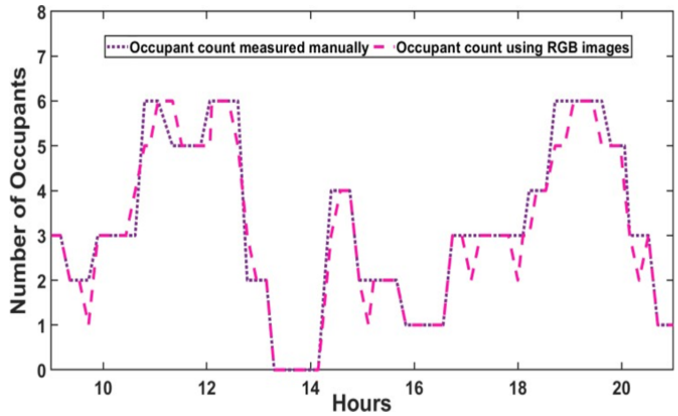

Fig 4. Occupant count measurement utilizing RGB images

facilitates the retrieval and access of thermal images. The thermal camera captures images, which identifies the human objects in the room based on their respective body temperatures[15] and measures the number of occupants inside the room.

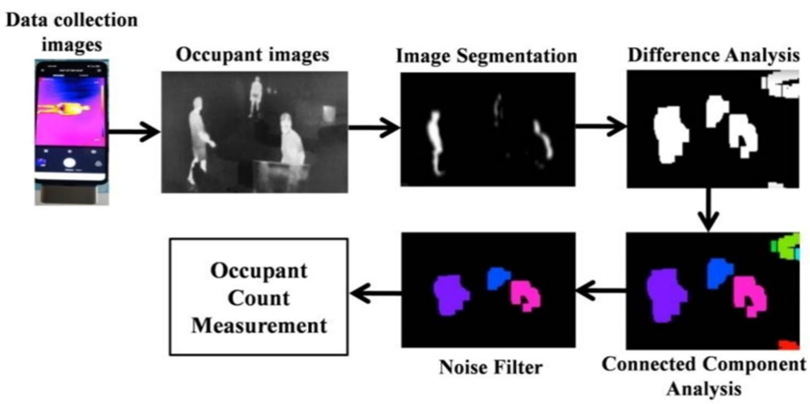

Fig 5. Framework of thermal occupant count model

Thermal analysis allows for an accurate and non-intrusive method of occupant counting. The thermal camera captures images to identify active pixels and frames with human objects. Initially, a set of 'N' background frames is collected to derive a threshold frame. Pixels in new frames are categorized as active or non-active based on this threshold. Frames with active pixels proceed to the next processing stage, while non-active frames result in an occupant count of zero ('0'). The segmented image results are presented in Table 1, shows the clusters generated through the K-Means algorithm.

Table 1. Image segmentation algorithm using K-means

K-means algorithm
Step 1: Import image data.
Step 2: Cluster size 'k' and center is initialized.
Step 3: For each pixel in thermal image, the Euclidean Distance (ED) among center and image pixel is calculated by using relation: $ED = \|\|(P(x,y) - c_k\|\|$.
Step 4: Assign pixel having the minimum distance to the nearest center, determined using ED.
Step 5: Repeat Step 4 for all pixels.
Step 6: Recalculate new position for center location using relation: $c_k = \frac{1}{k}\sum y \in c_k \sum x \in c_k P(x,y)$.
Step 7: Repeat steps 4-7 process until satisfied the error or tolerance value.
Step 8: Cluster pixels reshaped into image.

Feature extraction identifies characteristics in thermal images to distinguish human objects and shapes. The thermal camera measures heat distribution, with more high-value pixels indicating more occupants. Occupant count estimation involves the total number of active pixels per frame. Image segmentation divides an image into distinct segments using the K-Means algorithm, which partitions data into 'K' clusters based on temperature ranges. Each pixel is assigned to a cluster, and the K-Means algorithm helps differentiate the targeted area from the background [16]. The cluster associated with occupant body temperature becomes the region of interest (ROI). A temperature threshold filters out non-human elements, and a brightness threshold addresses over-segmentation due to thermal noise. This segmentation process aids in accurately identifying features and objects within the thermal image data, as depicted in Figure 6.

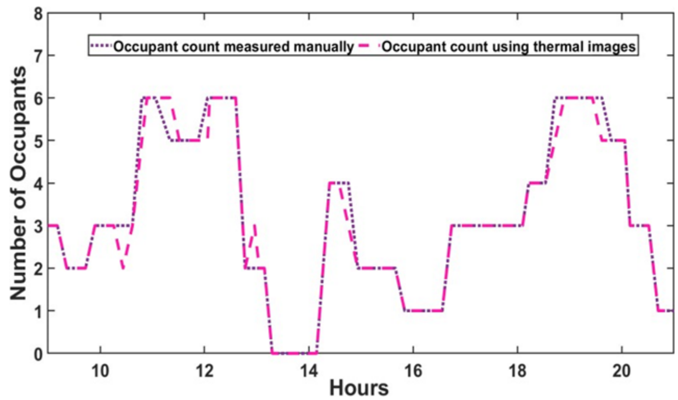

Fig 6. Occupant count measurement utilizing thermal images

A Gaussian filter refines output and mitigates thresholding effects [17]. Difference analysis identifies changes between consecutive frames, detecting individual movements. Connected component labeling assesses connectivity in thermal images, identifying regions in binary images and simulating actual movement. This labeling aids in granular blob filtering, determining the number of occupants. A noise filter removes thermal noise, enhancing occupant count accuracy to 90.20%. The OCM model shows notable improvements in accuracy. Table 2 offers a comparative analysis between the conventional and proposed OCM models, while Table 3 presents various experimental scenarios and occupant count accuracy using different sensors.

OCM model using simple algorithms and fewer computational resources compared to training and running complex machine learning models. The labeled dataset is not required, which saves time and resources in data preparation. In proposed work, the occupants are analyzed based on body temperature, occupants are distinctly segmented from the background and other objects based on temperature differences. Thermal images lend themselves well to threshold-based methods and it is effectively utilized in this work for blob detection. The Thermal image adaptation technique used in OCM improve the efficiency of K-means image segmentation and CCL and makes it accurate for real-time monitoring and counting of occupants in smart building without requiring significant computational power.

Table 2. Comparison of v arious sensors and methods in occupant prediction

Occupancy Sensor	Objective	Methodology	Note
CO_2 and temperature sensor	Occupancy prediction for energy savings	Mathematical Model	Franco et al. [18]
Occupancy from ambient environment data and electrical consumption data	Shedule air conditioning based on occupancy	Compled rule based Scheduling Algorithm	Dorokhova et al. [19]
Occupancy sensor	Energy efficiency	Occupancy aware MPC – Non probabilistic model	Turley et al. [20]
Network of thermal sensor arrays	Control HVAC system and conditioning the rooms	Recurrent neural network and Internet of Things	Luo et al. [21]
Low-energy thermal imaging sensor	Occupancy monitoring system	Convolutional neural network	Kraft et al. [22]
Camera-based occupant count and virtual sensing WiFi device	Control HVAC operation	Statistical algorithms - Occupancy analytics	Naseer et al. [23]
Thermal camera images (assessed thermal parameters of persons)	Occupant count for efficient resource usage	Low complexity occupant count using K-means algorithm and CCL	[proposed]

Table 3. Different scenario in experimental room with occupancy sensors and occupant count estimation accuracy of OCM model

Occupancy Sensors	Room Environment	Occupant count accuracy	Average occupant count Accuracy
PIR and door sensor	HO, LL	71.7%	72.8%
	LO, OL	73.9%	
PIR and RGB Camera images	LO, OL, RI	85.6	79.50%
	HO, OL, RI	78.7	
	LO, LL, RI	79.9	
	HO, LL, RI	73.8	
PIR and Thermal Camera Images	LO, OL, TI	95.6	90.20%
	HO, OL, TI	89.8	
	HO, LL, TI	89.5	
	LO, LL, TI, TN	85.9	

HO: High Occupancy; LO: Low Occupancy, LL: Low Light; OL: Over Light; RI: RGB Camera Image; TI: Thermal Camera Image; TN: Thermal Noise

4 Conclusion

Smart buildings, while offering advanced functionalities, often consume significant energy, necessitating increased efforts for energy savings. Unlike complex machine learning models, the OCM model employs straightforward algorithms, requiring minimal computing power. Accurate occupant count estimation by the OCM model is pivotal for intelligent control of electrical appliances and optimizing energy usage. This study proposes OCM models for various rooms, utilizing different sensors: PIR and door sensors, RGB cameras, and thermal image analysis. Evaluation reveals enhanced accuracy, contributing to efficient energy management. PIR and door sensor-based models achieve 72.8% accuracy, while visual image-based models reach 79.5%. Thermal image-based models achieve 90.2% accuracy, advancing intelligent systems for energy-efficient smart buildings and urban planning. Future work could integrate deep learning techniques to further enhance accuracy by adapting to diverse environmental conditions and occupancy patterns.

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