Enhancing Occupancy Sensing in Workplaces: Integration of mmWave and PIR Sensors in a Comprehensive Sensing System

MSc Connected Environments
Centre for Advanced Spatial Analysis
University College London

Name: Yining An
Supervisor: Dr. Duncan Wilson
GitHub Repository: https://github.com/ucfnnbx/occupancy-sensing

DECLARATION

I hereby declare that the work described in this report has been done by myself and no portion of the work contained in this report has been submitted in support of any application for any other degree or qualification on this or any other university or institution of learning.

_______Yining An________

Contents

ABSTRACT

Occupancy monitoring has evolved into an important source for property insights and data-backed decision making that is enabling new possibilities for smart workplaces. Buildings account for 40% of the global energy consumption and CO_2 emissions, with commercial buildings contributing the largest proportion, which exhibits a critical need to enhance energy saving in commercial workplaces. Using real-time occupancy data to control light and HVAC systems is an effective approach to save energy. With user-friendly applications developed, occupancy monitoring also helps manage space utilization and create a more comfortable environment for employees. Besides in offices, occupancy monitoring also enables new possibilities in security monitoring, smart healthcare and smart manufacturing.

This research proposed an occupancy sensing system with an integration of an mmWave sensor and a PIR sensor. Experiments were carried out to research the multipath effect on the performance of mmWave sensor. Bringing in a PIR sensor addressed the problem that mmWave sensor may be frequently false triggered by multipath reflections or non-human moving objects. The integrated sensor had an improved sensing accuracy compared to the individual sensors. The sensing system was deployed in the Connected Environments Lab, monitoring whether there are people using workplaces including the lounges, soldering station, tables, etc. During the deployment, the effect of configuration and placement of sensor on its sensing accuracy was investigated. In addition to the sensor, a light system and an Android mobile application were developed to showcase smart light control using occupancy data and achieve real-time remote monitoring.

INTRODUCTION

The UK government states that occupancy monitoring has evolved into an important source for property insights and data-backed decision making that is enabling new possibilities for smart workplaces (Agency, 2022). Occupancy data can be useful for many applications in workplaces including energy saving, security monitoring, smart healthcare and smart manufacturing. Buildings - both residential and commercial - account for 40% of the global energy consumption and the resulting CO_2 emissions (Nejat et al., 2015). Several studies have shown that residential, commercial, or public buildings that use occupancy data to accordingly regulate artificial light and HVAC (heating, ventilation, and air conditioning) systems can reduce their energy consumption by 10%-15% (Naseer et al., 2023; Susnea et al., 2017). The lighting industry has widely acknowledged occupancy sensors are an effective energy-saving approach (DiLouie, 2017). According to Boydak (2017), among all buildings, commercial office buildings account for the highest energy consumption, which exhibits a critical need for office occupancy monitoring. Besides saving energy, it also helps manage space utilization and create a more comfortable environment for employees.

Besides energy saving, for security-related use cases, occupancy monitoring can detect intrusion or burglary (Liu & Zhang, 2021). In smart healthcare facilities, occupancy monitoring has proven invaluable for pandemic control, allowing for real-time regulation of room capacity to ensure both patient safety and effective infection prevention measures (S et al., 2022). In smart manufacturing industries, companies that implement equipment occupancy monitoring potentially benefit from increased operational efficiency, prediction, and safety associated with their equipment usage (Tarantino, 2022).

In recent years, millimeter wave (mmWave) radars have developed rapidly and attracted significant interests, leading to the emergence of mmWave sensing technology. MmWave radars that employ FMCW (Frequency Modulated Continuous Wave) modulation are the most extensively used type in sensing applications. When first introduced, mmWave FMCW radars served the purpose of obstacle detection. Later, their application expanded to SLAM (Simultaneous Localization and Mapping) (Hong et al., 2020). During the past few years, important progress in learning-based methods has resulted in a significant growth in detection and recognition applications targeting humans, objects or environments, as illustrated in Figure 1.

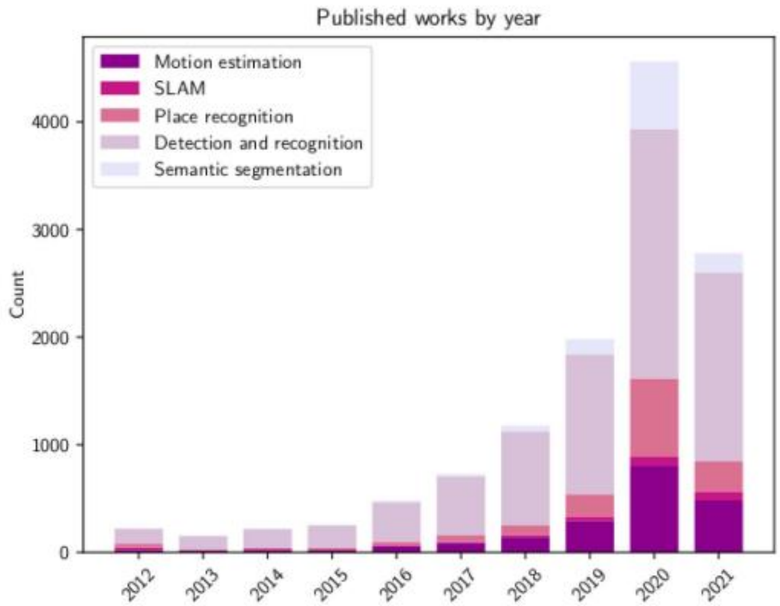

Figure 1. Works on mmWave radar by year and by number of publications. Results obtained by searching keywords “mmWave FMCW RADAR” and the corresponding application on dimensions.ai. (Venon et al., 2022)

The rapid development of mmWave sensing also benefits from its human sensing advantages over other sensing technologies (i.e., camera, Lidar, PIR sensor, ultrasonic sensor, and thermal sensor), including a wide sensing range, high resolution, directional sensing ability, and resistance to weather and illumination conditions. For building automation and lighting control, the most commonly used sensors are PIR (Passive Infrared) sensors and ultrasonic sensors (Bai et al., 2013). However, they have the drawbacks of the incapability to detect stationary human presence. Besides, PIR sensors give frequent false alarms due to high sensitivity to changes in background. Ultrasonic sensors suffer from low resolution and line-directional sensing, while mmWave sensors have a wide sensing range. Camera-based sensing methods are constrained by illumination conditions and privacy concerns in indoor monitoring cases. Moreover, the ability of a low-resolution camera to detect micro motions is compromised. Although Lidar-based sensing can detect micro movements, it has a limited sensing range compared to mmWave as well as is influenced by air conditions. Thermal sensors can perform high-precision temperature measurement to detect human presence, but they are costly and require proper temperature calibration before installation (Chuah & Teoh, 2020).

Compared to them, according to Venon et al. (2022), mmWave sensors can detect targets in moving, micro-moving, or extremely weak moving state, thus they are able to detect stationary people by minor movements such as breathing. Moreover, mmWave radars have proved to be not affected by the change of environmental conditions, including illumination conditions, temperature or dust (Ponte Müller, 2017; Yoneda et al., 2019). Table 1 compares these sensors' performances on human presence sensing, in which green blocks represent strengths while red blocks represent weaknesses. From the table, it can be intuitively found that mmWave sensors outperform other sensors in terms of a wide sensing range, the ability to detect stationary humans, low cost, resistance to environment conditions, as well as preserving privacy.

Table 1. Characteristics of human presence sensors

Sensor Type	Working principle	Sensing range	Stationary detection	Cost	Privacy
Camera	Machine vision	Projection area	Yes	High	No
Lidar	Emit a laser pulse, measure time interval between reflection	Projection area	Yes	High	Yes
Ultrasonic	Measure frequency change of reflected ultrasonic wave with a moving object	Line direction	No	Low	Yes
Thermal	Detect the infrared radiation emitted by object	Projection area	Yes	High	Yes
PIR	Detect changes in infrared radiation due to temperature difference between a moving object and its background	Projection area	No	Low	Yes
mmWave	Emits FMCW and CW radio waves, reflected by targets which are in moving, micro-moving, or extremely weak moving state	Projection area	Yes	Low	Yes

Based on the above findings, a mmWave radar sensor was used to develop an occupancy sensing system in workplaces. However, it was found that the mmWave sensor output false positives frequently in cases where they were affected by reflections and moving non-human objects. This research proposed a solution to address this problem, which was to integrate the mmWave sensor with a PIR sensor. The research focuses on investigating the question 'Can the integration of a mmWave sensor with a PIR sensor form an effective occupancy sensing system in workplaces?'. To integrate two sensors, an algorithm was developed to process two sensor data streams and output a result of occupancy with greatly improved accuracy. In addition, a light system and an Android mobile application were developed to showcase smart light control using occupancy data and achieve real-time data communication with users. Although this integration also comes with drawbacks, they can be solved by configuring and installing the sensor properly according to the use cases. The sensing system was deployed in the Connected Environments Lab, monitoring whether there are people using workplaces including the lounges, soldering station, tables, etc.

LITERATURE REVIEW

There have been some surveys summarizing works of using mmWave radars for sensing applications including localization, object detection, human activity recognition, health monitoring, etc. Abdu et al. (2021) presented a survey of deep learning algorithms for mmWave radars in an autonomous driving application. In their research, mmWave radars were evaluated to have the ability to perform well in adverse weather conditions, and the ability to measure an object's distance and radial velocity continuously. Singh et al. (2021) provided a review of non-contact vital sign (NCVS) monitoring with radar, as well as a discussion of challenges associated with hardware and signal processing algorithms. They elaborated on the future need of using mmWave radars for this application because their high frequency allows high accuracy sensing in multi-resident environments, also reduces the device size. Shastri et al. (2022) presented a survey of indoor mmWave device-based localization and device-free sensing, with an investigation of how mmWave propagation characteristics allow more accurate location estimates and higher spatial scanning resolution. Venon et al. (2022) explained algorithms and applications adapted or developed for mmWave radar sensors in automotive applications including perception, recognition and localization. They pointed out that mmWave radars require specifically tailored algorithms because of their noisy outputs, sensitivity to potential interference, and multipath rays.

MmWave sensing technology also has a few drawbacks. According to Akyildiz et al. (2018), mmWave signals experience significant attenuation due to their extremely high frequency, as a result, mmWave can hardly be used for long-distance sensing applications. Hemadeh et al. (2018) and Wang et al. (2018) stated that mmWave signals suffer great penetration loss through solid materials such as concrete. When used in outdoor applications, raindrops can induce considerable signal attenuation because their sizes are comparable to mmWave wavelengths.

The above literature provides a general review of the abilities and limitations of mmWave radars in sensing applications. Their focus is rather on developing learning-based algorithms to process 3D point cloud data for different applications. However, this paper discovered that besides built-in algorithms in mmWave radars, the sensor performance also heavily depends on practical factors at deployment stage, such as interferences and the choice of installation locations. This research used an mmWave sensor that already has a built-in algorithm for human presence sensing, and explored practical factors that will affect its performance during deployments. Despite the research focuses are different, above literature acknowledged that mmWave radars are adequately capable of sensing humans, objects, and environments for a variety of applications, due to their high accuracy, high sensitivity, small size, and resistance to adverse weather and illumination conditions. Although it might need tailored algorithms to remove noise and offset potential interferences, they are still highly suitable for performing sensing tasks, especially in indoor scenarios.

There are also mmWave radars applications focusing on occupancy sensing. Hsu et al. (2023) proposed an on-line indoor occupancy counting system using mmWave FMCW radar. They gave a review of existing algorithms to process the 3-D radar point cloud data, and proposed a feature extraction algorithm that can correctly distinguish multiple occupants. Gross et al. (2020) conducted an overview and evaluation across a wide variety of existing approaches for occupancy detection with the goal of increasing energy efficiency and safety within buildings, including PIR, temperature/humidity/CO_2, video camera, LIDAR, etc. They comprehensively evaluated these sensors using a Pugh matrix approach on their abilities to fulfill functional requirements (i.e., accuracy, detection range, resolution, delay, computational resources) and non-functional requirements (i.e., privacy, social acceptability, ease of implementation, ease of installation, cost). Their result is shown in Figure 2, with PIR-Matrix and the mmWave sensor evaluated as the two most suitable approaches for indoor occupancy detection.

	Requirements	Weight	PIR	FIR / PIR - Matrix	Temp/Humidity/CO2 (+PIR)	Video Camera	Blurred Video camera	Structured Light	LIDAR	Ultrasound / Ultrasonic	mmWave 2D/3D antennas	Microphone array	Counting people at doors (break beam / handles / pressure mat)	Floor Pressure sensor	Footstep vibration detection	WiFi (Deep learning)	Mobile Radio Frequency	Visual Light Detection	Network Packets	Electricity consumption data
Functional	Accuracy	8	-1	0	-1	1	1	0	1	0	0	0	0	1	0	0	-1	0	-1	-1
	Count range	7	-1	0	0	1	0	1	1	-1	1	0	-1	0	0	0	0	-1	0	0
	Resolution/Spatial	2	0	0	0	0	0	0	-1	0	1	0	-1	0	0	-1	0	0	0	1
	Delay	7	1	0	-1	1	0	1	1	1	1	-1	1	1	1	0	1	1	0	0
	Computational Resources	5	1	1	1	-1	-1	0	0	1	0	1	1	1	0	-1	0	1	1	1
Non-Functional	Privacy	10	1	1	1	-1	0	0	0	1	1	-1	1	1	1	0	0	1	-1	0
	Social Acceptability	4	1	1	1	-1	0	0	1	0	1	-1	1	1	1	1	-1	1	0	0
	Ease of implementation	4	1	1	0	0	0	0	0	1	0	0	1	-1	-1	0	-1	1	1	0
	Ease of installation	4	1	1	0	1	0	1	0	1	0	1	0	-1	-1	-1	0	0	1	0
	Cost	4	1	1	1	0	0	0	-1	0	0	1	1	-1	0	1	0	1	1	0
	Sum		5	6	2	1	0	3	2	4	5	0	4	2	1	-1	-2	5	2	1
	Weighted Sum		23	31	8	7	3	18	20	23	30	-8	25	22	13	-3	-9	27	-1	-1

Figure 2. Pugh matrix comparing different approaches for occupancy detection (Gross et al., 2020)

Then, Gross et al. (2020) further carried out experiments to test the accuracy of two approaches in a meeting room scenario. They used algorithms including averaging, thresholding, clustering and low pass filtering to reduce noise in the signal and obtain occupancy results. As a result of their experiment, mmWave sensor could detect the occupancy with a 50% accuracy, and PIR matrix sensor gave a slightly lower accuracy of 45%. They have identified the error was majorly caused by multipath propagation of the mmWaves and limited resolution of PIR sensor, which was the in-built defects of sensors and could not be solved with noise removing algorithms. Concluding from their work, PIR matrix and mmWave sensor are evaluated the most promising among all occupancy sensing approaches. However, they did not achieve good accuracy due to separate limitations of two kinds of sensors. In the work of this paper, the same problem caused by multipath propagation of mmWaves was encountered. To solve it, these two most promising sensors were integrated to complement their respective drawbacks and combine their advantages. An algorithm was developed to process two data streams and deliver the final occupancy decision with higher accuracy.

There are currently few literatures focused on solving the reflection problem of mmWave sensor due to multipath propagation, although there are works stating this problem. Subrt et al. (2010) introduced an approach to model diffuse reflection and scattering of mmWaves in indoor environments. They used the model to measure the reflection degree of mmWaves on different indoor furniture such as concrete walls, floor, ceiling, wooden wardrobe, table and door. The result was that reflections from furniture contribute to a significant part of the received mmWaves besides the direct transmitted mmWaves. Therefore, indoor furniture does have an impact on mmWave propagation, yet there are few works to investigate its decrease in sensing accuracy or using an integration of mmWave and PIR sensors address this problem.

In terms of communicating the sensor data, Berlo et al. (2021) pointed out that mmWave sensing infrastructures have a future trend to collaborate with other sensing and communication infrastructures. For example, Alloulah & Huang (2019) investigated that through the integration of mmWave radar sensing and special communication access points, the application domains can be expanded from in-home digital health monitoring to new approaches for building analytics. For the occupancy sensing system developed in this paper, effort was also made to enable effective communication of real-time occupancy data with people, including a smart light system and an Android mobile application.

METHODOLOGY

System Overview

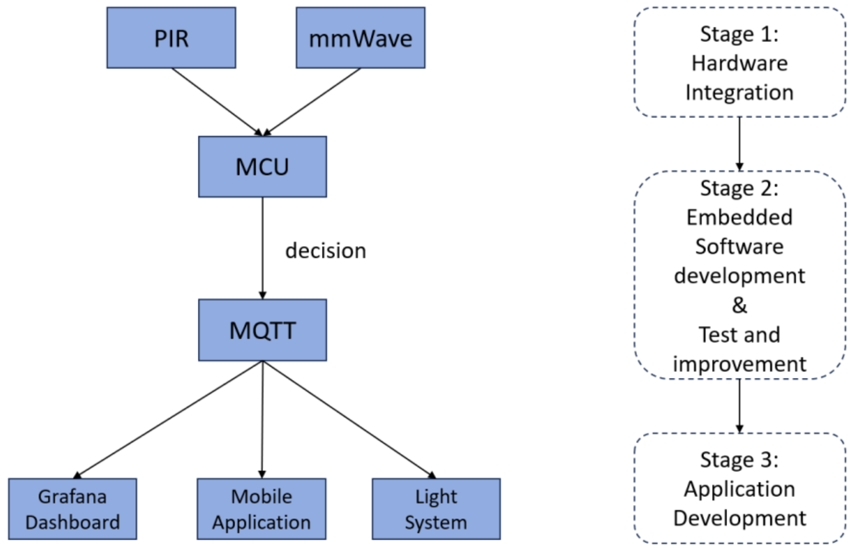

Figure 3. Occupancy sensing system overview

The microcontroller in this system is Wemos ESP8266 Mini, which collects real-time data from two sensors, makes decisions on the occupancy status, and uploads it to MQTT for later application development. This microcontroller allows Wi-Fi connection so that it can publish data to an MQTT server. MQTT is a lightweight communication protocol that enables stable transmission of data over devices and networks. Both sensors output data to MQTT at a frequency of 1 Hz. A Raspberry Pi 4 model B was set up as a gateway to transmit data to the online database, with tools InfluxDB, Telegraf, and Grafana installed. Telegraf is a time-series data collector for the open-source database InfluxDB. It is configured to collect data from the MQTT topic that data is published to. Grafana pulls data from InfluxDB and creates dashboards to visualize the data. Viewing the time-series sensor data on dashboards greatly helps develop algorithms to process data as well as helps administrators to view the occupancy data intuitively.

MQTT is also used as the data feed for applications in this sensing system, including a light displayer driven by Adafruit Feather HUZZAH ESP8266 and an Android mobile application developed in Flutter.

Sensor Characteristics

MmWave Radar

The mmWave radar sensor used was DFRobot SEN0395 shown in Figure 4. The radar emits radio waves at 24 GHz with a wavelength of 1 to 10 mm, which allows it to perform high resolution sensing. The radar employs Frequency Modulation Continuous Wave (FMCW) and Continuous-Wave (CW) multi-mode modulation and has separated transmitter and receiver antenna structure. In the CW transceiver, narrow bandwidth signal is continuously transmitted and received. In FMCW modulation, the radar emits a frequency modulated continuous radio wave, which is reflected by all targets that are in moving, micro-moving, or extremely weak moving state and received back by the receiver antenna with a time delay and frequency shift. They will be processed with embedded algorithms to solve out the target information regarding human presence. The sensor outputs a binary result through serial port or I/O port, with '1' representing a positive human presence and '0' representing no human presence within the detection range.

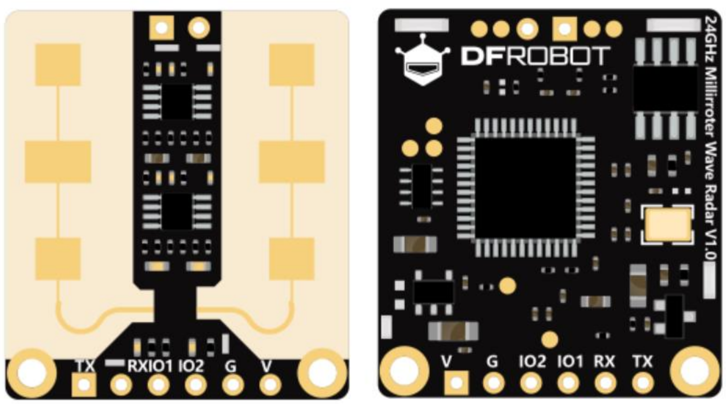

Figure 4. Board overview of mmWave sensor DFRobot SEN0395.

The detection distance of this mmWave sensor can be configured from 0 to 9 meters. Although the configuration file specifies that the detection distance can be set to be a combination of separated distances such as from 1.5 to 3 m and from 3 to 4.5 m, this couldn't be achieved during the practical tests. The sensor only allows setting a distance that starts from 0 (i.e., starts from the sensor position). The beam angle of sensor is 100° × 40°. Figure 5 illustrates the detection range of a wall-mounted sensor from side view and top view.

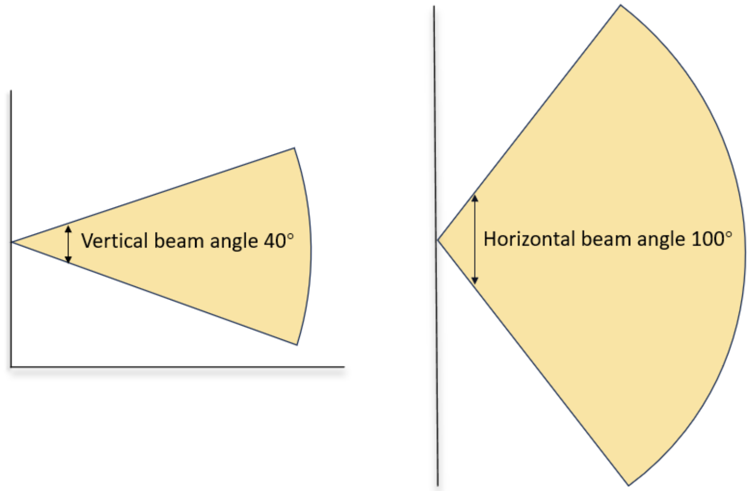

Figure 5. Beam angle illustration of a wall-mounted sensor, from the side view (left) and top view (right).

PIR Sensor

HC-SR501 PIR Sensor was used, as shown in Figure 6. PIR sensors detect human presence by detecting changes in infrared radiation between a moving object and its background. Compared to mmWave sensor, it needs bigger movements to trigger. Similar to mmWave sensor, it outputs a binary result to represent human presence, 1 for positive human presence and 0 for negative human presence. However, its output will return to 0 if the person is not in a major movement continuously.

A PIR sensor has two parameters that can be configured - sensitivity and off delay time. Both parameters were tuned to be the smallest, because increasing either of them will result in the sensor being triggered for more than 10 seconds even when there is no human presence. The sensor has a beam angle of 120° × 120° and detection distance of 7 meters. Although PIR sensor's detection distance cannot be changed, the detection distance of integrated sensor can be limited by mmWave sensor. Also, the coincident beam angle of two sensors would be the beam angle of mmWave sensor 100° × 40°.

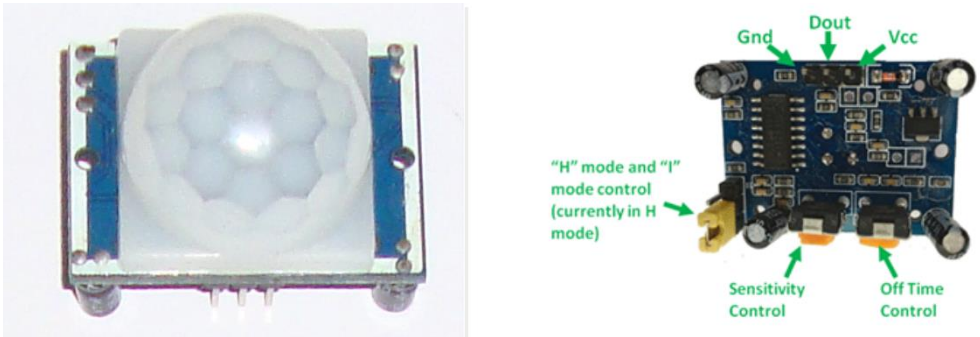

Figure 6. HC-SR501 PIR sensor and its pinout

Reasons for Integrating Two Sensors

Multipath Effect of MmWave Sensor

The influence of multipath effect on mmWave sensors performance was investigated. Figure 7 is an illustration of multipath effect of mmWave radar, with three propagation patterns of a radio wave pulse between the radar and an assumed target that is within the detection range. The red path means a direct propagation between radar and target. In the yellow path, the wave propagates through a reflection in the peripheral area besides at the target. The blue path represents two reflections in the peripheral area. In the first case, the signal received by radar only contains information about one target that is within the set detection range. In the second and third cases, the reflection points might fall outside the configured detection range. If the reflection point is a moving object, the signal will contain moving information and will output a positive human presence even though it is not within the sensing range.

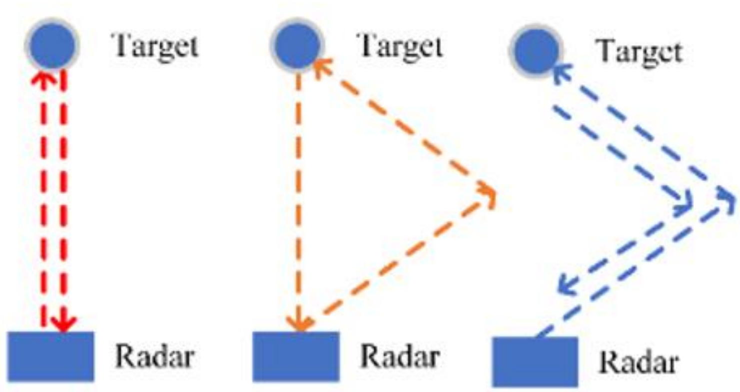

Figure 7. Multipath effect of mmWave radar (Hao et al., 2022)

The reason that might cause mmWaves to propagate outside the configured detection area is explained below. MmWaves are essentially electromagnetic waves. According to

Kaiser (2006), electromagnetic waves are reflected by highly conductive metals like copper, silver, and brass. To investigate the influence of metal material on mmWave radar performance, an experiment was conducted as shown in Figure 8. A metal cylinder was placed in front of the mmWave sensor. The detection area of mmWave sensor was configured to be the blue triangle area. To test if the mmWaves were reflected outside the detection area (the red lines), a person was walking behind the radar. The output of mmWave sensor is shown in Figure 9, which is viewed in a Grafana dashboard. X-axis is the time and y-axis is the binary output of sensor, with 1 representing positive human presence and 0 representing negative human presence. The experiment ensured no humans were in the detection area. When there was a person behind the sensor, the sensor output high discontinuously. When there was no human both in the detection area and in the behind, the sensor output low constantly. From this experiment it can be inferenced that metal material in the detection range will cause mmWaves reflected to unwanted area and potentially enlarge the detection area. Also, the detection in the enlarged area is not stable because it may not be fully covered by mmWaves. Therefore, if there is metal material in the detection area, it will induce unreliable outputs of mmWave sensors.

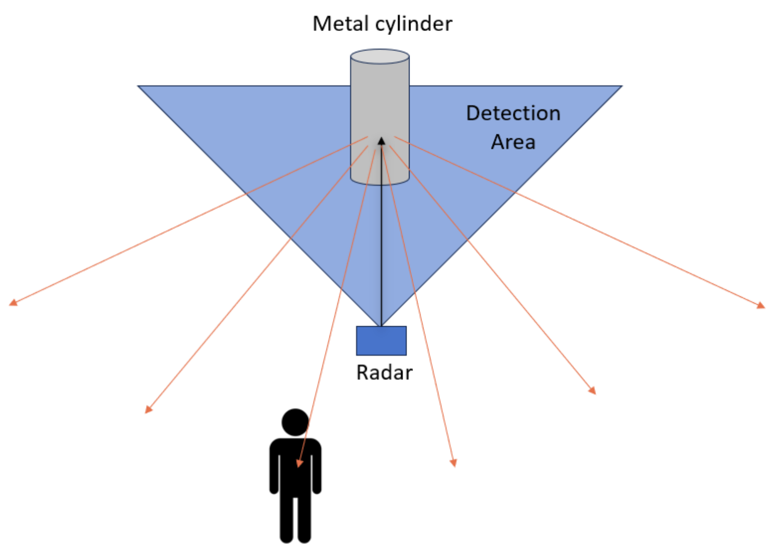

Figure 8. Experiment on mmWaves reflection on metal.

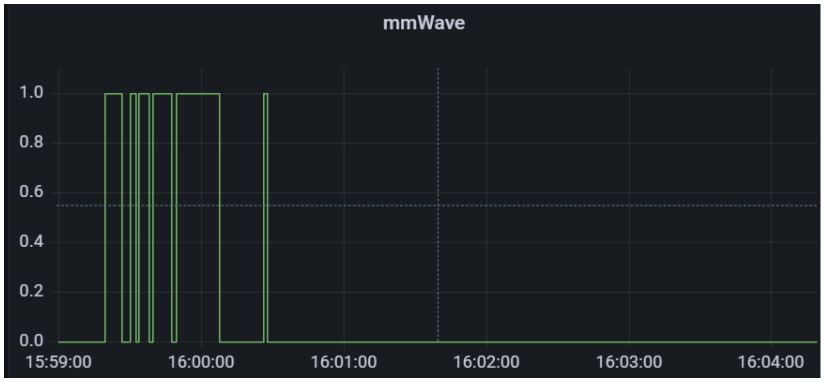

Figure 9. MmWave sensor outputs in the experiment on mmWaves reflection on metal.

Moving Non-human Objects

Another reason for integrating PIR and mmWave sensor is that the used mmWave sensor was not able to distinguish movements of human or non-human objects. A turned-on rotary fan was placed in the detection range of mmWave sensor while there was no human presence. The output result is shown in Figure 10, which is constantly positive. Therefore, this mmWave sensor will recognize moving objects as humans, which means using this sensor alone for occupancy sensing is not reliable.

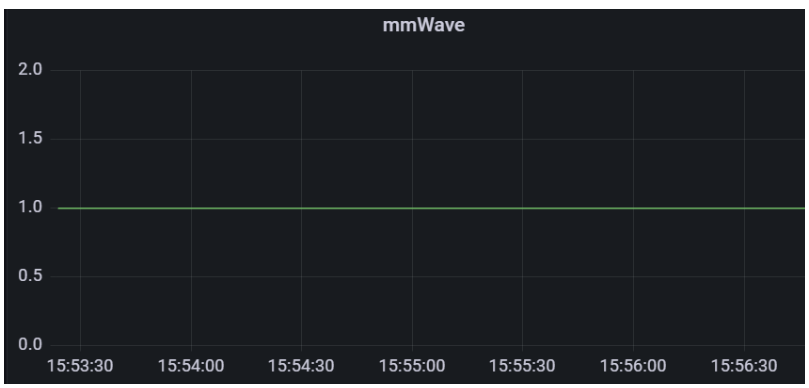

Figure 10. MmWave sensor outputs when there was a fan in the detection area.

Integrating MmWave and PIR sensors

PIR sensors detect human presence by changes in infrared radiation due to temperature differences. Therefore, they are not affected by metal materials or non-human objects. Integrating PIR and mmWaves sensors together helps correct the wrong outputs of mmWave sensor due to multipath effect or false trigger by non-human objects.

The algorithm embedded in the microcontroller processes data streams from two sensors, and outputs a result that represents human presence to MQTT. The fundamental logic of the algorithm is shown in Figure 11. If the current occupancy state is negative, it will turn to positive when both sensors output positive. In this way, the final outputs are ensured to be triggered by a moving human in the detection area. If the current occupancy state is positive, it will turn to negative when mmWave sensor outputs negative. This is because a PIR sensor cannot detect stationary human while a mmWave sensor can.

```
if (final == 0) {
  if ((pir == 1) & (mmwave == 1)) {
    final = 1;
  }
} else {
  if (mmwave == 0) {
    final = 0;
  }
}
```

Figure 11. Fundamental logic of the integrated sensor, where ‘final’ represents final occupancy state, ‘pir’ is PIR sensor output, ‘mmWave’ is mmWave sensor output.

Algorithm Improvements

Based on the fundamental logic in Figure 11, the algorithm was improved during testing to ensure better sensing accuracy.

Filter PIR Output Noises

The PIR sensor was observed to be frequently triggered for 1 second when there was no human presence. This may be caused by PIR sensor’s high sensitivity to changes in background. To improve this, only the positive PIR signals that last more than 2 seconds will be considered as a true positive. The comparison of before and after implementing this algorithm is shown in Figure 12 and 13. All the 1-second interferences were effectively filtered out, only leaving true positives.

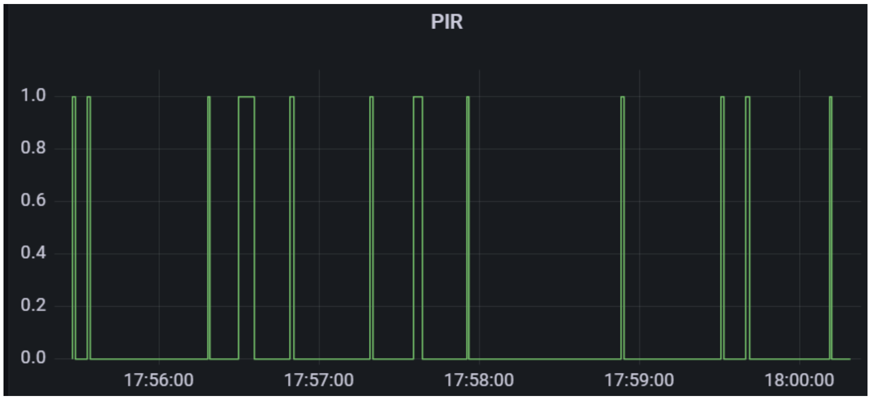

Figure 12. Outputs of PIR sensor before implementing 2-second filter

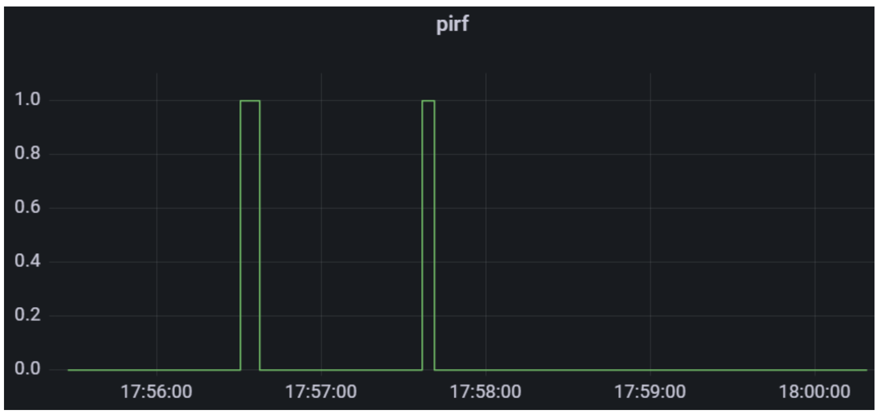

Figure 13. Outputs of PIR sensor after implementing 2-second filter

Extend PIR Positive Duration

One common workplace scenario is a person walks to the workplace, sits down and starts to work. In this case, the PIR sensor was observed to only output a high signal for 2 to 3 seconds and then return to low signal. This is because the person can only trigger the PIR sensor for a short period of time when he enters the workplace (i.e., walking, sitting down), and then goes into a relatively steady state when the person starts to work.

The problem is that sometimes there is a time difference between the output of two sensors. If the mmWave sensor turns positive after PIR has returned to negative, the sensors are not triggered together and will result in a wrong result. To solve this, the positive output of PIR sensor is extended to 5 seconds to ensure the output of two sensors align with each other. In the ESP8266 code, this was achieved by using a dynamic array to store the past five PIR outputs. If any two adjacent data in the array are ‘1’, then the final PIR output will be ‘1’, based on the previous 2-second filter for PIR output.

By extending the PIR positive duration, it also solved another performance bug of mmWave sensors used in this research. It happens occasionally that the mmWave sensor returned to ‘0’ for 1 second right after being triggered, then performed normally afterwards, as shown in Figure 14. With the extended PIR output duration, this error will not cause the final output to change.

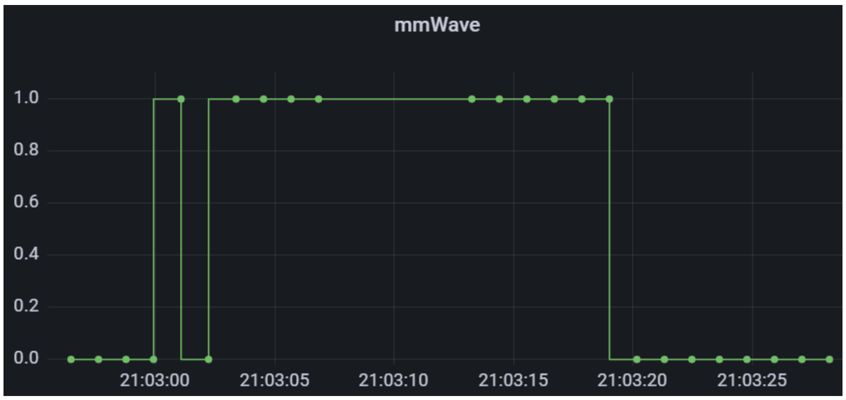

Figure 14. MmWave sensor performance bug.

Hardware Integration

The circuit that connects microcontroller and two sensors was soldered onto a PCB to enhance robustness, shown in Figure 15.

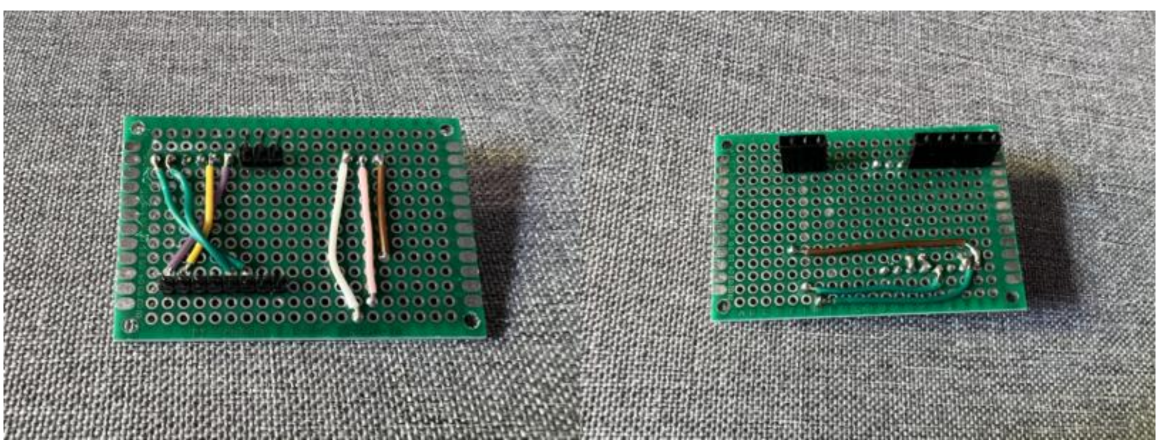

Figure 15. Two sides of soldered PCB, with sockets for MCU, PIR and mmWave sensors.

A box-shaped enclosure was designed in Fusion 360 and 3D printed. The design ensures the PCB is tightly fixed inside and does not move around. The whole size is optimized as small as possible (4 cm by 6 cm by 4 cm) to make the sensor device compact and unobtrusive. The top and base are snap fit which makes the box easy to open. Also, the components will be easy to replace by unplugging them off the PCB.

Figure 16. 3D-printed enclosure base, with support inside to fix PCB.

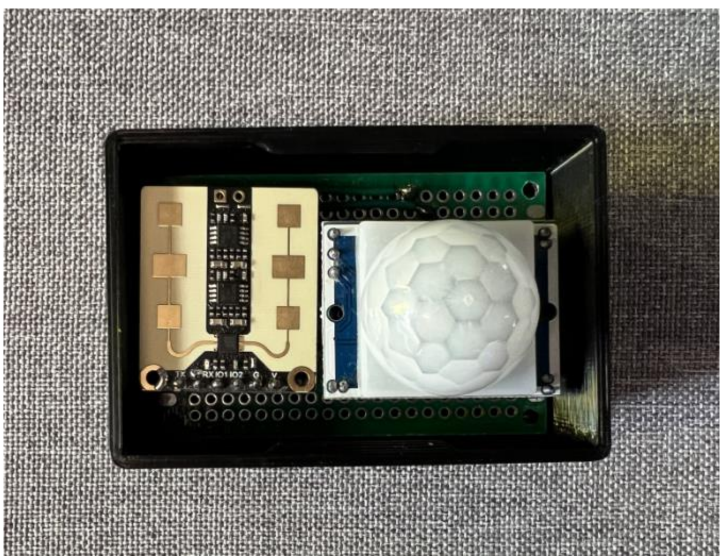

Figure 17. PCB fixed tightly within enclosure.

Figure 18. Side view of sensor box.

Figure 19. Top view of sensor box.

The hook and loop sticky pads in Figure 20 were used to stick the sensor to any surfaces, which are easy to remove or change the location.

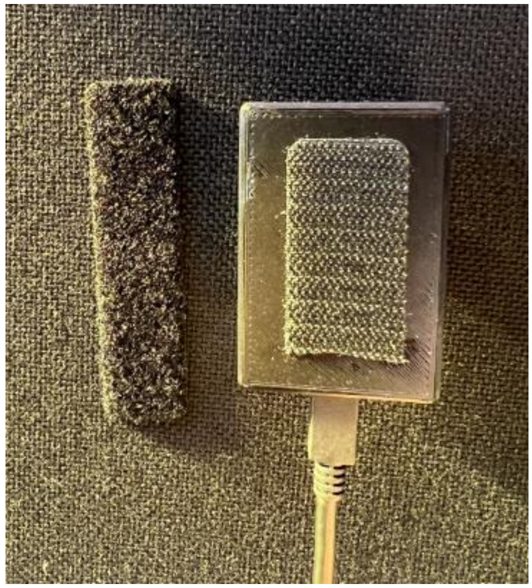

Figure 20. Way to fix sensor box on a surface.

Installation Methods

For a workplace at table scenario, ideal locations to mount the sensors are on the ceiling and by the side of the table.

Ceiling-mounted Method

The integrated sensor was deployed on the ceiling to monitor the occupancy of a lounge, as shown in Figure 21. The detection area can be calculated with the beam angle (100° × 40°) and the roof height (2.4 m). As shown in Figure 22, the detection area on the ground was calculated to be approximately an ellipse of 5.72 m by 1.74 m, which is suitable for covering this lounge.

It was found that the detection distance has a large effect on the performance of a ceiling-mounted sensor. Figure 23 is the mmWave sensor output when the detection distance was set 5 m. Figure 24 is when the detection distance was the ceiling height 2.4 m. In both cases there was no human presence. The interferences in the first case were more severe than in the second case, which might have been caused by mmWaves reflected on the floor. As a result, for ceiling-mounted sensors, the detection distance needs to not exceed the ceiling height. The result of a daylong test at this workplace is included in the Result and Discussion section.

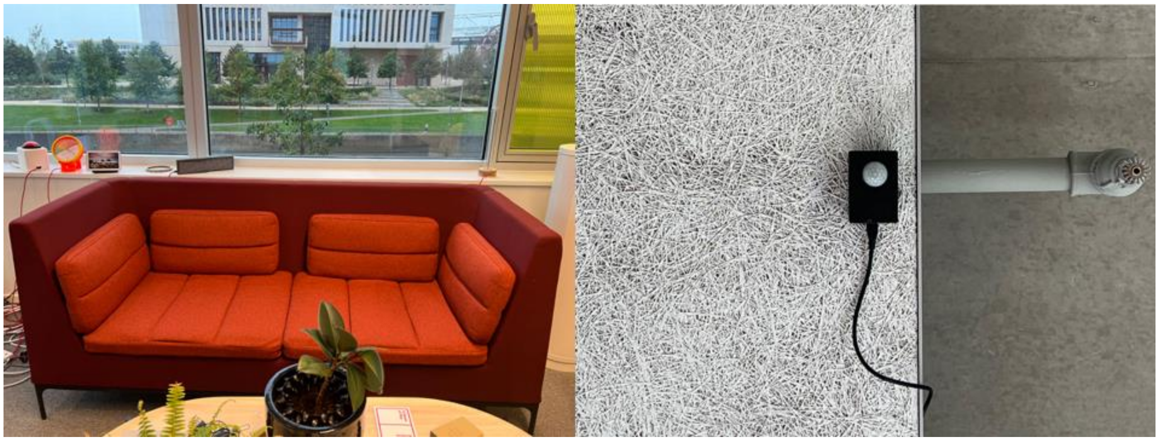

Figure 21. Ceiling-mounted sensor to monitor a lounge.

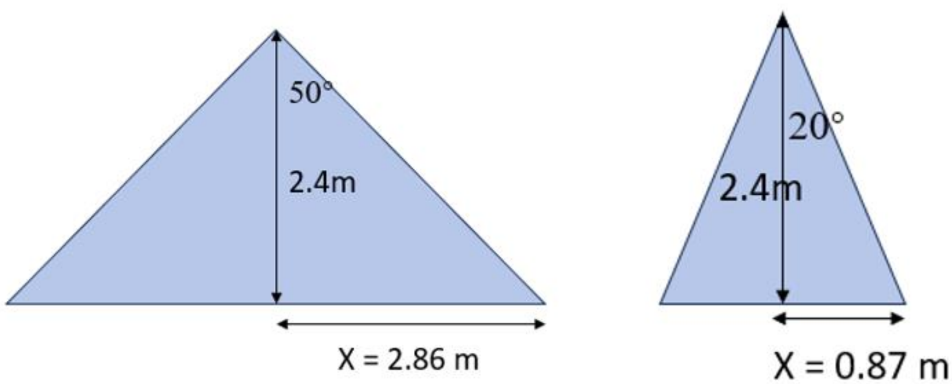

Figure 22. Calculate the detection range of a ceiling-mounted sensor.

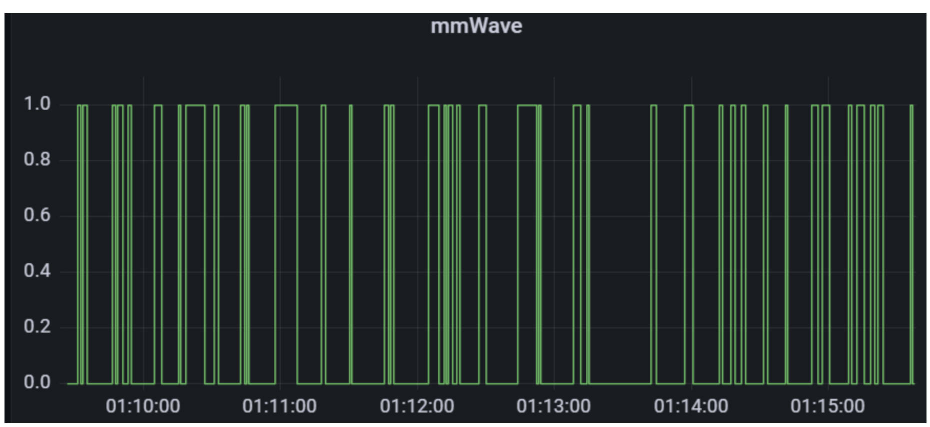

Figure 23. MmWave outputs when the detection distance is 5 m (ceiling height 2.4 m)

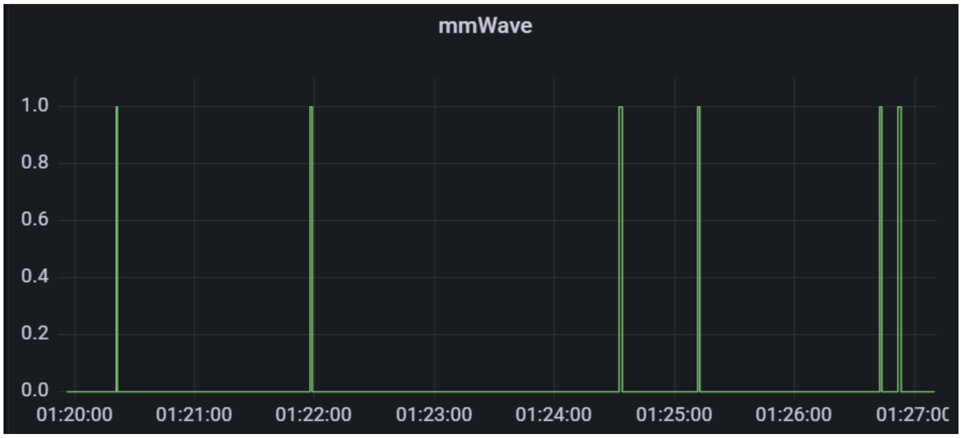

Figure 24. MmWave outputs when the detection distance is 2.4 m (ceiling height)

Wall-mounted Method

The sensor was mounted towards the occupant, which could successfully detect the occupant whether the occupant was working or sleeping at the table. To use the best of the sensor, it is better placed at the height of human's upper body. Also, the sensor shouldn't be blocked. The detection distance was set to be 0.9 m in this experiment, which could avoid other people in the back to be detected. The detection distance should be configured case by case according to the real situation.

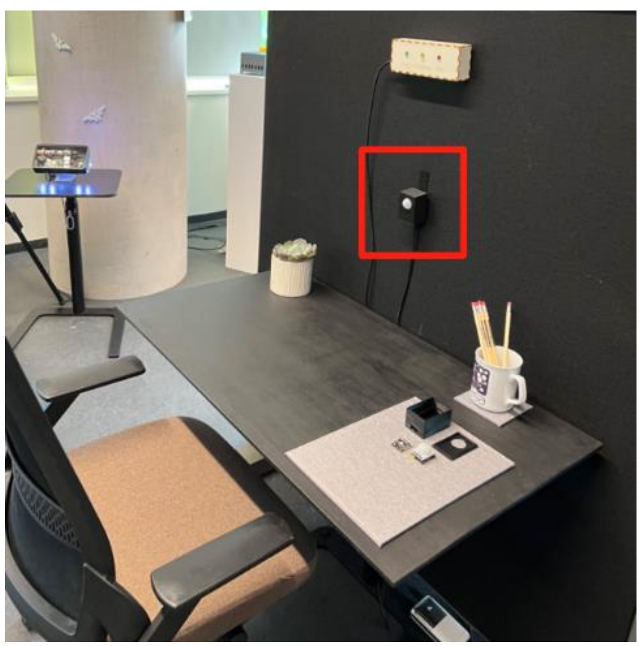

Figure 25. Wall-mounted sensor to monitor a desk.

Another location to mount the sensor was below the table (i.e., under the desktop). However, the sensing result was not reliable because mmWave sensors need to detect breaths when human is in stationary, while the legs sometimes have no movements and the mmWave sensor output will turn to zero. Figure 26 is the mmWave sensor output when there was a constant human presence.

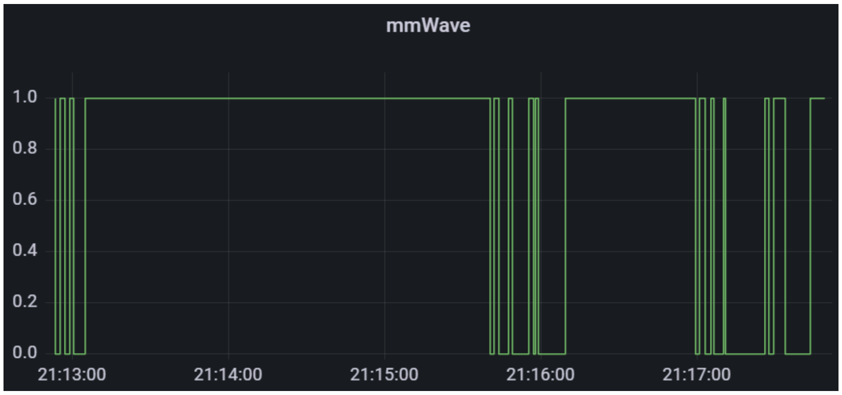

Figure 26. MmWave sensor outputs when mounted below the table.

Performance of the Integrated Sensor

The integrated sensor could detect and output a positive human presence with a delay of less than 2 seconds. However, for an output change from positive to negative, it had a 10-second delay because of mmWave sensors off delay which could not be configured. For applications that use MQTT network to obtain the data, this normally introduced a further 6 seconds delay for the application to receive data.

Performance on Multipath Effect

This experiment was same as the one carried out in Figure 8, with a metal cylinder placed in detection area and people walking behind the sensor. The final output and the individual sensor output were as shown in Figure 27-29. The integrated sensor could successfully remove the errors due to reflection.

Figure 27. Integrated sensor outputs when there is metal reflection.

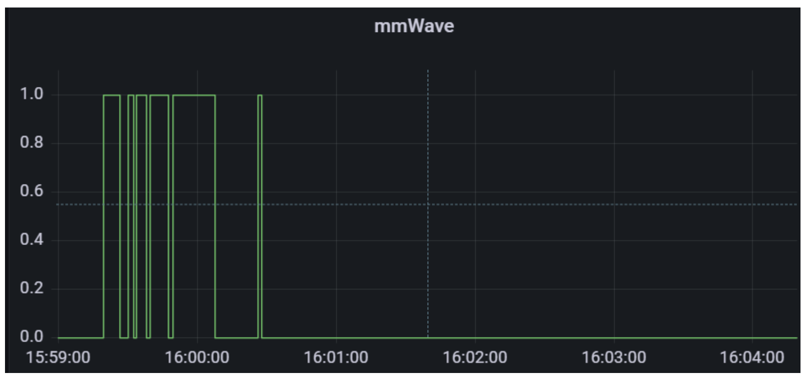

Figure 28. MmWave sensor outputs when there is metal reflection.

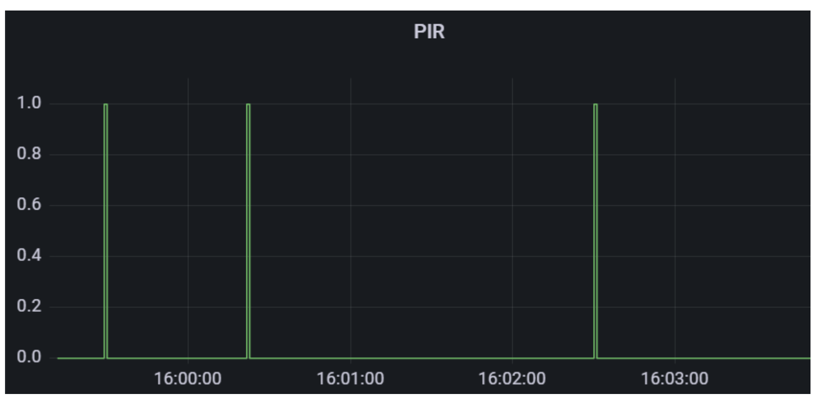

Figure 29. PIR sensor outputs when there is metal reflection.

Performance on Non-human Moving Objects

The same rotating fan experiment was carried out. The integrated sensor could also successfully remove the influence of non-human moving objects.

Figure 30. Integrated sensor outputs when there are non-human moving objects.

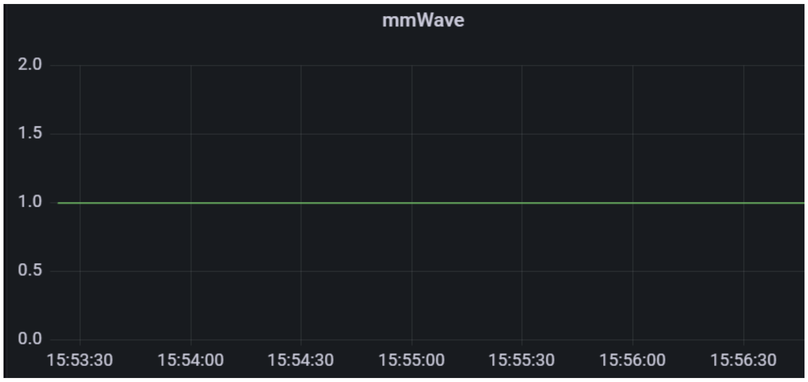

Figure 31. MmWave sensor outputs when there are non-human moving objects.

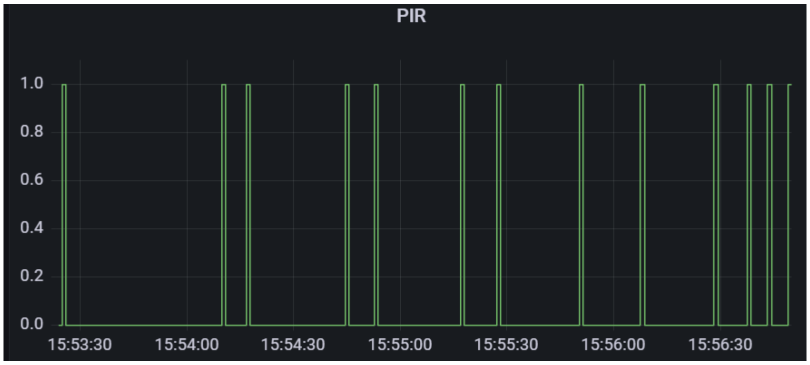

Figure 32. PIR sensor outputs when there are non-human moving objects.

Applications Based on the Sensing System

Mobile Application

An Android mobile application was developed in Flutter to communicate real-time occupancy data with people. Its data feed is from the MQTT server. The user can check the occupancy status (available or occupied) of the workplace remotely if the phone has an internet connection. Figure 33 shows that the user can switch between list view and grid view of the workplaces and bookmark their favorite places.

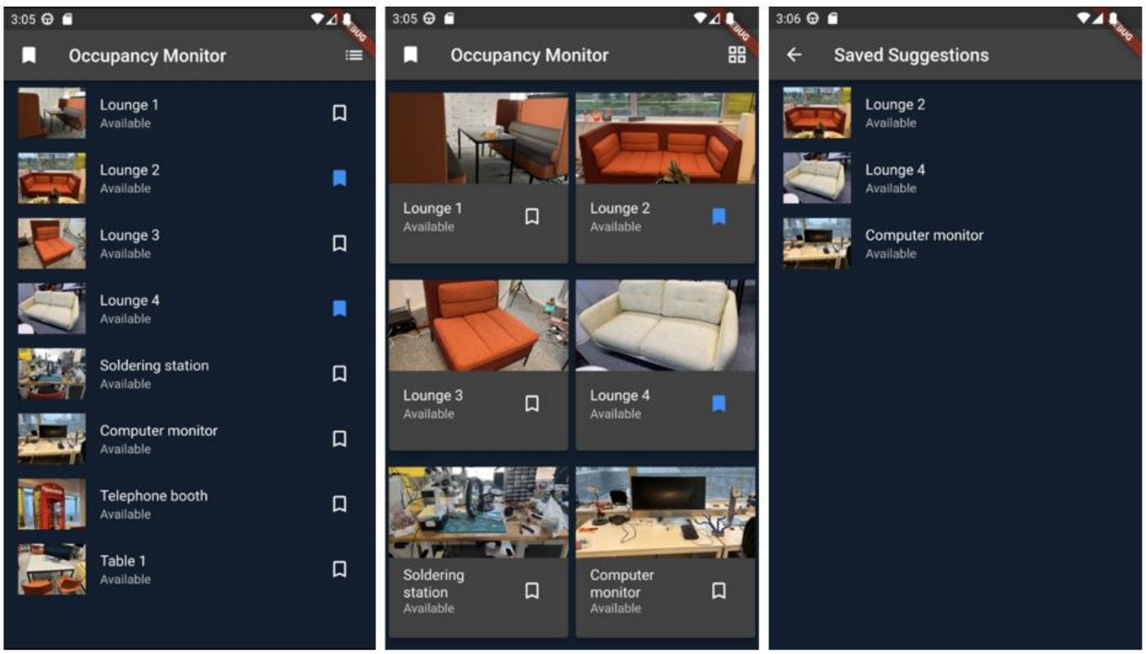

Figure 33. Screenshots of mobile application (home page)

Figure 34 is the detail page after users click into a workplace. It plots real-time data in the last one minute and guide users to find the sensor. If the users want to view all the past data, they can use the Grafana dashboards.

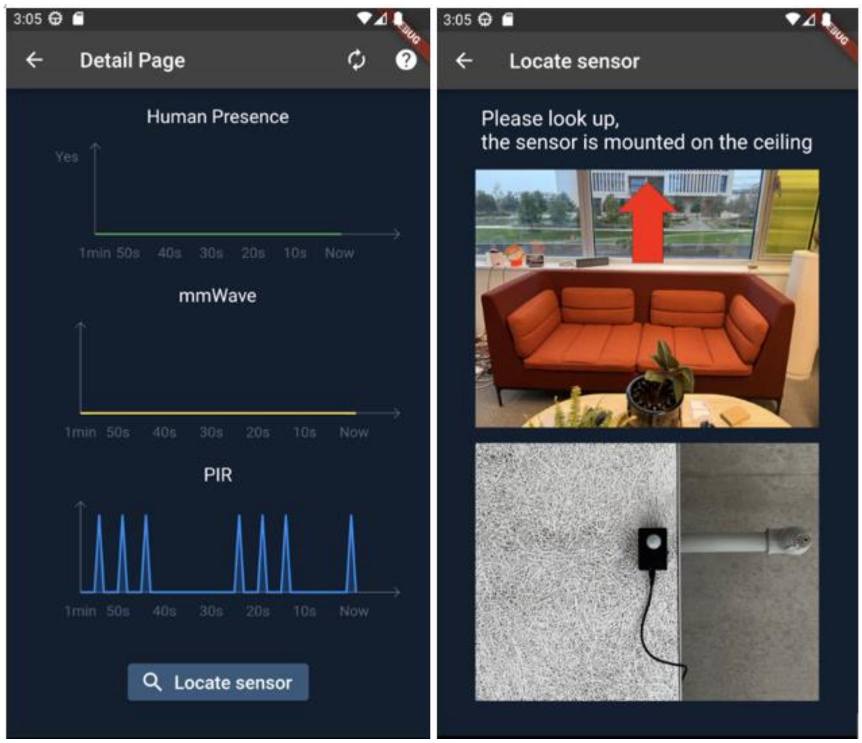

Figure 34. Screenshots of mobile application (detail page)

Light Displayer

An LED light displayer was developed as a simple model to showcase the smart lighting applications controlled by real-time occupancy data. Three LED lights are controlled by ESP8266 which receives data from MQTT, representing the integrated sensor output, mmWave sensor output and PIR sensor output. The lights will turn on when there is a positive sensor output and turn off when there is not. Moreover, the reason for including the lights representing individual sensor outputs is to help people intuitively understand how the integrated sensor improves accuracy compared to either sensor alone.

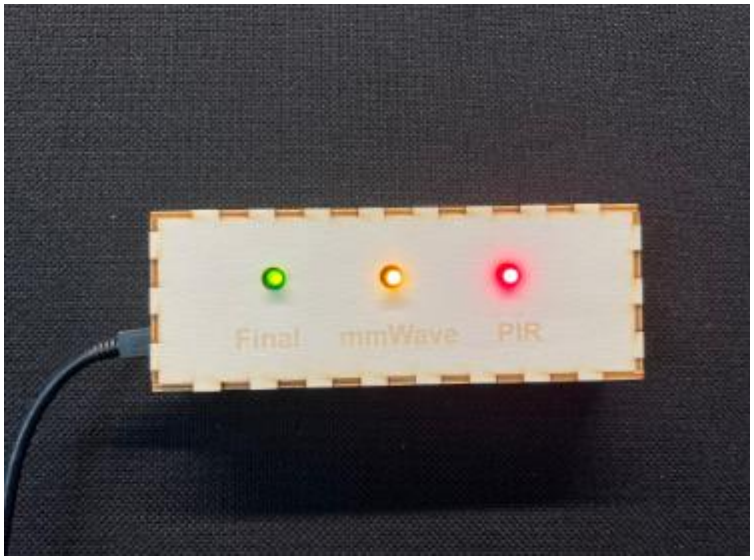

Figure 35. LED light displayer.

RESULTS AND DISCUSSION

Result of Tests

Table 2 is the result of a daylong test on a ceiling-mounted sensor monitoring the lounge shown in Figure 21. The first column is manually observed occupancy time period and is compared to the result measured by sensor.

Table 2. Result of test on a ceiling-mounted sensor

Observed occupancy	Sensor-measured occupancy	Findings
10:02 to 10:28	10:02 to 10:28	Correct measurement
11:12 to 11:56	11:12 to 11:40	Missing detection from 11:40 to 11:56 due to a sudden change of mmWave signal to zero
13:10 to 13:45	13:10 to 13:45	Correct measurement
13:55 to 14:13	13:55 to 14:13	Correct measurement
14:33 to 15:24	14:33 to 15:24	Correct measurement
No human presence	2 seconds at 15:47	False triggered, can be improved by algorithms
16:00 to 17:43	16:00 to 17:43	Correct measurement, proved the sensor's ability to continuously detect people

The cause of wrong detections was discovered by viewing dashboards in Grafana. During 11:12 to 11:56, mmWave output had a 2-second sudden change to zero at 11:40 when there was constant human presence, which caused the final sensor output change. It could not be triggered again because of PIR sensor while the person was stationary, therefore occupancy from 11:40 to 11:56 was not detected. To avoid future errors like this, in the algorithm an mmWave negative output of less than 3 seconds will be ignored if it has been positive for more than a minute. Despite this could be a random error because it has only occurred once in all the experiments carried out, it should not be ignored. Although this algorithm will induce an off delay to the sensor, the sensing accuracy can be largely improved.

For the false positive at 15:47, the mmWave sensor was experiencing severe interferences caused by reflection, because its detection distance was bigger than the ceiling height. By setting the distance to be the ceiling height, this could be improved.

Figure 36. Integrated sensor outputs during the error at 11:40.

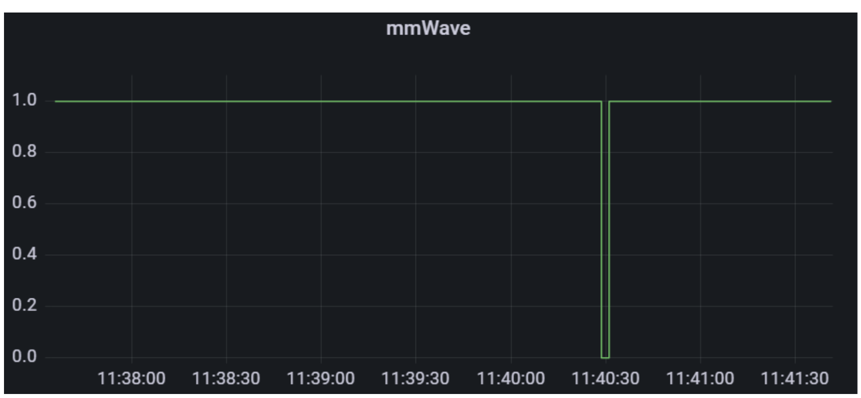

Figure 37. A sudden change in mmWave sensor outputs at 11:40.

The improved algorithm was tested with the same installation in later experiments, and no wrong detections were found. This proves that commissioning the sensor before use and improving the algorithm can effectively increase the sensing accuracy.

Discussion on Effects of Bringing In a PIR Sensor

A PIR sensor can correct the false positives of mmWave sensor due to reflections, non-human moving objects, or random interferences. During a nightlong measurement, where the sensor was installed on the ceiling with no people in the room, the integrated sensor detected no human presence while mmWave sensor was frequently triggered, as shown in Figure 38. In this measurement, the accuracy of detecting a negative occupancy status was improved by 31.2% with the PIR-integrated sensor. In cases with different reflection situations, this number might be different, but there is no doubt that PIR sensors can effectively remove the false trigger of mmWave sensors.

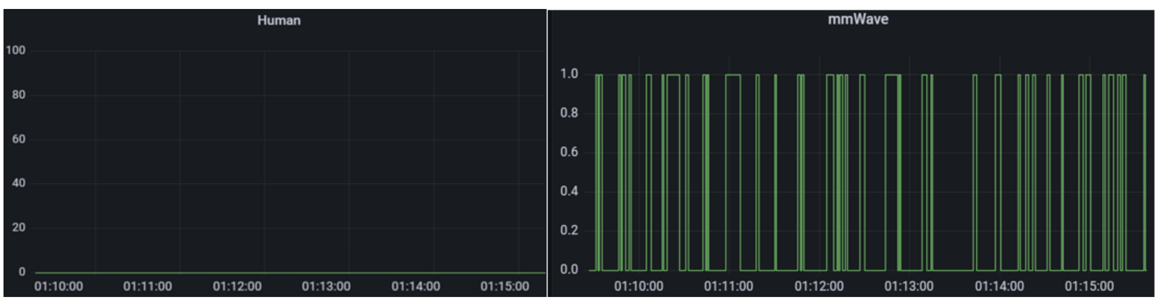

Figure 38. Sensor output after (left) and before (right) bringing in a PIR sensor.

Bringing in a PIR sensor also has disadvantages. For example, the integrated sensor does not possess the mmWave sensor's ability to penetrate through non-metal materials, which means it cannot sense properly if being blocked. Furthermore, PIR sensor makes the integrated sensor need a bigger movement to trigger than mmWave sensor. Nevertheless, in the vast majority of cases this can be satisfied because when a person enters a workplace, he/she has movements big enough to trigger the PIR sensor. Together with the algorithm to extend the PIR positive output duration, the successful trigger of the sensor is more guaranteed.

Overall, bringing in a PIR sensor could greatly improve the sensing accuracy in cases where mmWave sensor may be frequently false triggered due to reflections or non-human objects. The defects such as effected by blockage can be solved through proper installation. The integrated sensor has a reliable performance on workplace occupancy sensing. This finding aligns well with the opinion of Hao et al. (2022), which is the use of multiple sensing devices can improve performance because a larger volume of raw data can deliver improved accuracy or reproducibility or enable the determination of properties that the sensors is not able to detect individually.

Limitations & Future improvements

In this study, the communication between sensor and light displayer is through MQTT. A delay of approximately 6 seconds is observed of the light response. For applications that require rapid response, low latency networks could be used.

Besides, the DFRobot mmWave sensor has a 10-second off delay time which could not be configured shorter. It means the output will change to zero 10 seconds after the sensor detects no human presence. This can only be improved by using other mmWave sensor modules.

This sensor device currently does not support remote configuration of parameters such as detection distance, which means people need to take it off to configure it. For future improvements, remote configuration can be achieved with ESPHome, which is a system to control ESP8266 remotely by configuration files.

Discussion on Integrated Sensing System Overall Performance

According to Hao et al. (2022), poor performance of occupancy sensors usually results from multiple causes – ranging from fundamental limitations of the sensor technology to misconfiguration, to poor placement in the room or space. In this research, these factors were all investigated. Firstly, by integrating PIR and mmWave sensors, their fundamental limitations were complemented. Secondly, how to configure the detection distance to give a better sensing accuracy was investigated.

Thirdly, in terms of sensor placements, Feagin Jr. et al. (2020) pointed out that occupants sometimes remove or bypass occupancy sensors that hinder their work or otherwise do not perform as expected. Therefore, it is crucial to place the sensor right. In this research, multiple sensor installation methods were experimented including ceiling-mounting, wall-mounting and below the table. Wall-mounted installation could give reliable results if not blocked and placed at an appropriate height to detect breathing activities. However, in the real case where people normally work with computers and other office utilities, it can be hard to keep the sensor unblocked. Ceiling mounting is considered the most suitable method to keep the sensor unblocked, unobtrusive, while giving a high measuring accuracy. However, ceiling-mounting is not ideal if the workplaces are intensive and close to each other because a 2.4 m high ceiling gives a 5.7 m by 1.7 m detection area on the ground.

According to Feagin Jr. et al. (2020), a barrier to the commercial success of new occupancy-sensor products has been delivering reproducible results across different implementations. The sensing system produced in this research was deployed in sufficiently different cases. Through those experiments, the algorithm was improved to produce high accuracy results across different implementations. Also, the advantages of this device including privacy-preserving and unobtrusive would make it easily accepted by people. Although the sensor will need human resources for commissioning before use to ensure sensing accuracy, it will greatly benefit the sensor's performance in real cases.

In addition, occupancy data measured by this sensor system was proved useful by applications in smart lighting and remote monitoring through a mobile application. The sensing system and applications have the potential to enhance workplace management in terms of optimizing energy efficiency, space utilization and creating a more convenient environment for workers.

Overall, the research question can be answered positively. The integration of a mmWave sensor with a PIR sensor can form an effective occupancy sensing system in workplaces.

CONCLUSION

In this study, an occupancy sensing system was developed by integrating basic PIR and mmWave sensor modules and was deployed in workplace scenarios. Occupancy data was utilized by a lighting system and a mobile application for remote monitoring, which has the potential to improve energy efficiency and space utilization management in workplaces. Compared to using a mmWave sensor alone, bringing in a PIR sensor could greatly improve the sensing accuracy in cases where mmWave sensor may be frequently false triggered due to reflections or non-human objects. This integration could compensate for their respective drawbacks and combine their strengths. Results showed that the integrated sensor will not be affected by reflections, movements of non-human objects, and could detect continuous stationary human presence. The sensing system was tested with different deployments to ensure it can deliver reproducible results across different implementations.

Different installation methods for the sensor were investigated. Ceiling mounting was considered the most suitable method because it keeps the sensor unblocked and unobtrusive, while giving a high measuring accuracy. Wall mounting is more suitable for intensive workplaces, but the sensor may be easily blocked or removed by people. Also, it was found that mmWaves sensors detect a sitting person's presence mainly by the movements of upper human body. Therefore, for a sitting workplace scenario, mounting the sensor at a place where it can detect upper body movements of occupants would be necessary.

Future improvements could focus on improving the user experience of the sensing system such as enabling remote configurations through ESPHome and decreasing the response latency of applications by using low-latency protocols other than MQTT.

REFERENCES

Abdu, F.J. *et al.* (2021) 'Application of deep learning on Millimeter-Wave Radar Signals: A Review', *Sensors*, 21(6), p. 1951. doi:10.3390/s21061951.

Agency, G.P. (2022) *Occupancy monitoring: Watching you, or supporting you?*, *GOV.UK*. Available at: https://www.gov.uk/government/news/occupancy-monitoring-watching-you-or-supporting-you (Accessed: 10 August 2023).

Akyildiz, I.F., Han, C. and Nie, S. (2018) 'Combating the distance problem in the millimeter wave and terahertz frequency bands', *IEEE Communications Magazine*, 56(6), pp. 102–108. doi:10.1109/mcom.2018.1700928.

Alloulah, M. and Huang, H. (2019) 'Future millimeter-wave indoor systems: A blueprint for joint communication and Sensing', *Computer*, 52(7), pp. 16–24. doi:10.1109/mc.2019.2914018.

Bai, Y., Cheng, C. and Xie, Z. (2013) 'Use of ultrasonic signal coding and PIR sensors to enhance the sensing reliability of an embedded surveillance system', *2013 IEEE International Systems Conference (SysCon)* [Preprint]. doi:10.1109/syscon.2013.6549895.

Berlo, B. *et al.* (2021) 'Millimeter Wave Sensing: A Review of Application Pipelines and building blocks', *IEEE Sensors Journal*, 21(9), pp. 10332–10368. doi:10.1109/jsen.2021.3057450.

Boydak (2017) 'Commercial Buildings Energy Consumption Survey (CBECS) and its comparison with Turkey applications', *Journal of Clean Energy Technologies*, 5(1), pp. 69–72. doi:10.18178/jocet.2017.5.1.346.

Chuah, F.K. and Teoh, S.S. (2020) 'Thermal sensor based human presence detection for smart home application', *2020 10th IEEE International Conference on Control System, Computing and Engineering (ICCSCE)* [Preprint]. doi:10.1109/iccsce50387.2020.9204940.

DiLouie, C. (2017) *Estimating energy savings with lighting controls*, *Lighting Controls Association*. Available at: http://lightingcontrolsassociation.org/2013/09/16/estimating-energy-savings-with-lighting-controls/ (Accessed: 04 August 2023).

Feagin Jr., B., Poplawski, M. and Day, J. (2020) *A review of existing test methods for occupancy sensors* [Preprint]. doi:10.2172/1668746.

Gross, C. *et al.* (2020) 'Towards an occupancy count functionality for smart buildings - an industrial perspective', *2020 2nd IEEE International Conference on Industrial*

Electronics for Sustainable Energy Systems (IESES) [Preprint]. doi:10.1109/ieses45645.2020.9210641.

Hao, Z. *et al.* (2022) ‘Millimeter-wave radar localization using indoor multipath effect’, *Sensors*, 22(15), p. 5671. doi:10.3390/s22155671.

Hemadeh, I.A. *et al.* (2018) ‘Millimeter-wave communications: Physical Channel models, design considerations, antenna constructions, and link-budget’, *IEEE Communications Surveys & Tutorials*, 20(2), pp. 870–913. doi:10.1109/comst.2017.2783541.

Hong, Z., Petillot, Y. and Wang, S. (2020) ‘RadarSLAM: Radar based large-scale slam in all Weathers’, *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* [Preprint]. doi:10.1109/iros45743.2020.9341287.

Hsu, P. *et al.* (2023) ‘Novel robust on-line indoor occupancy counting system using mmwave Radar’, *IEEE Sensors Journal*, 23(11), pp. 12159–12170. doi:10.1109/jsen.2023.3266450.

Kaiser, K.L. (2006) *Electromagnetic shielding*. Boca Raton: CRC/Taylor & Francis.

Liu, C. and Zhang, Y. (2021) ‘An intrusion detection model combining signature-based recognition and two-round immune-based recognition’, *2021 17th International Conference on Computational Intelligence and Security (CIS)* [Preprint]. doi:10.1109/cis54983.2021.00109.

Nejat, P. *et al.* (2015) ‘A Global Review of energy consumption, CO 2 emissions and policy in the residential sector (with an overview of the top ten CO 2 emitting countries)’, *Renewable and Sustainable Energy Reviews*, 43, pp. 843–862. doi:10.1016/j.rser.2014.11.066.

Naseer, A. *et al.* (2023) ‘Occupancy detection via thermal sensors for energy consumption reduction’, *Multimedia Tools and Applications* [Preprint]. doi:10.1007/s11042-023-15553-0.

Ponte Müller, F. (2017) ‘Survey on ranging sensors and cooperative techniques for relative positioning of vehicles’, *Sensors*, 17(2), p. 271. doi:10.3390/s17020271.

Shastri, A. *et al.* (2022) ‘A review of millimeter wave device-based localization and device-free sensing technologies and applications’, *IEEE Communications Surveys & Tutorials*, 24(3), pp. 1708–1749. doi:10.1109/comst.2022.3177305.

Singh, A. *et al.* (2021) ‘Multi-resident non-contact vital sign monitoring using radar: A Review’, *IEEE Sensors Journal*, 21(4), pp. 4061–4084. doi:10.1109/jsen.2020.3036039.

S, J.M. *et al.* (2022) ‘Smart Health Care Monitoring and indoor occupancy control system using Arduino’, *2022 6th International Conference on Electronics, Communication and Aerospace Technology* [Preprint]. doi:10.1109/iceca55336.2022.10009584.

Subrt, L., Pechac, P. and Zvanovec, S. (2010) ‘New approach to modeling of diffuse reflection and scattering for millimeter-wave systems in indoor scenarios’, *PIERS Online*, 6(8), pp. 719–722. doi:10.2529/piers091219071256.

Susnea, I. *et al.* (2017) ‘Improved occupancy-based solutions for energy saving in buildings’, *2017 5th International Symposium on Electrical and Electronics Engineering (ISEEE)* [Preprint]. doi:10.1109/iseee.2017.8170641.

Tarantino, A. (2022) “Introduction to industry 4.0 and Smart Manufacturing,” *Smart Manufacturing*, pp. 1–19. Available at: https://doi.org/10.1002/9781119846642.ch1.

Venon, A. *et al.* (2022) ‘Millimeter wave FMCW radars for perception, recognition and localization in Automotive Applications: A survey’, *IEEE Transactions on Intelligent Vehicles*, 7(3), pp. 533–555. doi:10.1109/tiv.2022.3167733.

Wang, X. *et al.* (2018) ‘Millimeter Wave Communication: A comprehensive survey’, *IEEE Communications Surveys & Tutorials*, 20(3), pp. 1616–1653. doi:10.1109/comst.2018.2844322.

Yoneda, K. *et al.* (2019) ‘Automated Driving Recognition Technologies for adverse weather conditions’, *IATSS Research*, 43(4), pp. 253–262. doi:10.1016/j.iatssr.2019.11.005.