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# Towards Reliable Intelligent Occupancy Detection for Smart Building Applications

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***Abstract*—Occupancy detection is the core of smart lighting and smart ventilation systems with a significant role in energy cost reduction and improving occupants' comfort. Reliability and scalability are two main issues of the existing occupancy detection solutions. In this paper, we investigate the fusion of different sensing modalities to reduce false positive and false negative and hence improve the reliability. The proposed solution is being experimented for an office cubic but could be scaled up easily for the whole room. More specifically, we developed an alternative solution to passive infra-red (PIR) motion sensors so that it can only react to human presence rather than any moving object. We show that the combination of a distance sensor and $CO_2$ could work as good as a PIR motion and also reduce the false detections when all sensors combined.**

***Keywords—Intelligent occupancy detection; human vs object detection, carbon dioxide sensor, ultrasonic sensing; passive IR motion; sensor fusion.***

## I. Introduction

As green energy utilization and energy conservation initiatives become more prevalent, there is no better time to invest in technology to curb usage. The influx of devices used to gauge occupancy for the purpose of lighting and heating, ventilation, and air conditioning (HVAC) control and hence improving the comfort has skyrocketed over recent years [1,2, 3]. As buildings become "intelligent" they will rely primarily on sensors to control various tasks as well as energy consumption, with HVAC and lighting systems being the two main consumers in residential buildings. Many buildings have already made the switch to motion controlled lighting, which lowers consumption and energy costs. By utilizing occupancy detectors, we can also reduce or eliminate wasteful heating or cooling cycles. Without reliable sensors driving the controllers to make decisions, buildings will be left with inconsistent data and money on the table.

There are currently two different categories of approaches in detecting occupancy; First, well established direct approaches where the occupancy is determined through a motion sensor, for example, versus the new indirect/non-intrusive approaches where the occupancy is inferred from the state of other actuators such as position of the damper and heating valve of a Variable Air Volume (VAV) unit in the room [4]. The latter is economically more attractive but is limited to commercial buildings with central HVAC system. The former is more independent detection and scalable; however, the reliability of sensors is limited. In fact, most commercial direct occupancy sensing products rely strictly on some variation of a motion sensor; Passive Infrared (PIR) [5] or ultrasonic. Passive Infrared sensors use the change in infrared light reflected onto it from objects to determine motion of anything in its field of view. When an object which emits heat passes in front of the sensor, it detects the temperature change from room temperature to the temperature of the object. This change in temperature is what the sensor uses to signal occupancy. The disadvantage of standard motion sensors is that lack of movement results in false negatives. To combat this problem, some added sound sensors as well. This allows for more accurate results due to incorporation of different sensing techniques [6,7]. One could also add other complementary sensors such as indoor air quality such as Volatile Organic Compound (VOC) or carbon dioxide ($CO_2$) [8] that could react to human presence. The sensing mechanism of such sensors is chemical reactions with varies by length of the time their being in constant use. For such sensors, there is no direct reading of how it could accurately sense the level of particulates; hence, making it very challenging to find a reliable reading from these sensors. Among more active approaches, digital imaging [9] *and* video analytics has also been used for occupancy detection and people counting [6] but their usage being limited mainly due to privacy issue, especially with high resolution and high quality videos. Moreover, vision systems are cost prohibitive in a larger scale.

While a vast majority of today's occupancy detectors use a PIR motion sensor [8, 9], this work proposes an alternative approach, an ultrasonic distance sensor and PIR motion sensor in combination with a $CO_2$ sensor as the primary sensing modality. The advantage of the distance sensor comes from a constant measurement, whereas the PIR sensor relies on a change in environment and hence not reliable for a still human. The distance sensor detects an object within range, while the $CO_2$ sensor is used to verify if the object is human. In our experiment for cubic space occupancy detection, combination of distance sensor and $CO_2$ work similar to motion sensor but could also react when the motion sensor didn't pick up the still person. This means a proper fusion of all of these sensors could reduce both false positive and false negative. It is worth mentioning that our system could communicate wirelessly and

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uses an IoT based platform to send and visualize the date on the cloud.

The following sections will address the various components of the proposed system for occupancy detection as well as the solutions to problems faced in conceptualization. Section II will outline the system components and give a detailed look at the configuration. Section III will outline the research questions. Section IV will cover the major challenges associated with sensors readings. Section V provides the results followed by the conclusion and future directions in Section VI.

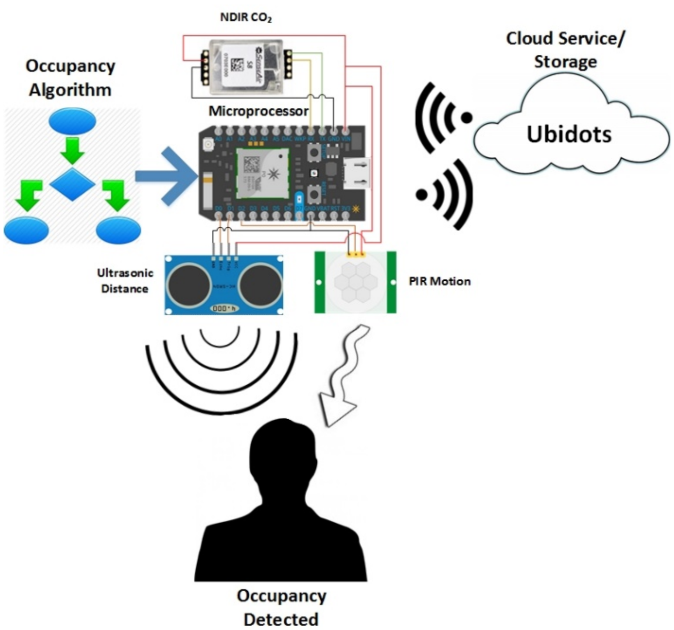


Fig. 1: Block diagram of the proposed occupancy detection system.

## II. System Outline

In this section we describe different components of the proposed occupancy detection.

### A. Occupancy Parameters

The current test scenario involves the prototype to be placed on a desk, in front of the occupant, measuring $CO_2$, distance and motion. While an object is measured within 100 centimeters of the sensor, located at the back of the desk, it is assumed that an individual is sitting at the desk. After the distance sensor is triggered, the $CO_2$ level is compared to the ambient $CO_2$ level. If the $CO_2$ Parts per Million (PPM) has increased from initial trigger, then we can determine that the object within distance is a human. In addition, temperature and humidity are also measured as an index of ventilation system performance compared to the number of occupants. Our hypothesis is that the fusion of different sensing modalities allows for consistent and accurate occupancy detection results. Table 1 provides the model number of the sensors we used in our experiment.

TABLE 1: SENSING MODALITIES

| Model Number | Sensor Type |
|---|---|
| S-8 | NDIR $CO_2$ Sensor |
| HC-SR04 | Ultrasonic Distance Sensor |
| HC-SR501 | PIR Motion Sensor |

### B. Microcontroller

We used the Particle Photon as the brain of the system which is a miniature Wi-Fi enabled controller with cloud access and the ability to utilize different libraries. As it stands, the Particle Photon has the ability to publish data to Particle servers, this action allows other Photons connected to the same account to subscribe to the published data. With the expansion of the research, multiple sensors will be able to communicate through the Photons, allowing for the integration of data and decision making.

### C. Occupancy Detection

We can assume occupancy of a cubicle when there is an object closes enough to the desk. $CO_2$ measurement will then determine if the object is indeed a person. Motion sensor could also be fused to utilize both redundant and complementary response of different sensor. Equation (1) describes the occupancy detection using fusion of different sensing modalities in which $w_i$ is the weight/role of the sensor $X_i$. In a general setting, $w_i$ is a spatio-temporal value that automatically will be learn though a probabilistic classifier with training samples.

$$Occupancy = \sum_{i=1}^{n} w_i X_i \tag{1}$$

### D. Cloud Storage

For the current experiments, the ability to store large amounts of data is pivotal. The cloud storage solution chosen is Ubidots as it directly integrates with the microprocessor and provides live graphing and data analytics.

## III. Methodology

While typical occupancy detection relies solely on PIR motion sensors, which are only active when an occupant is moving, our goal was to develop a system to accurately and efficiently detect occupants using multiple sensors which will allow for more consistent data. Primarily, motion sensors are used for occupancy detection. For most applications this appears to work well, although it does not take into account any time between motion events. This can lead to false negatives as the occupant may not be moving or false positives since the delay of the system could keep an active signal. The ultrasonic distance sensor used in this work has a constant signal input with adjustable distance triggers. The trigger for this experiment is set to 100 cm. Once the distance sensor is triggered, the carbon dioxide value is measured and a previously determined $CO_2$ threshold. If the current value goes up in comparison to the ambient value, then it is perceived that the object which was detected is a person.

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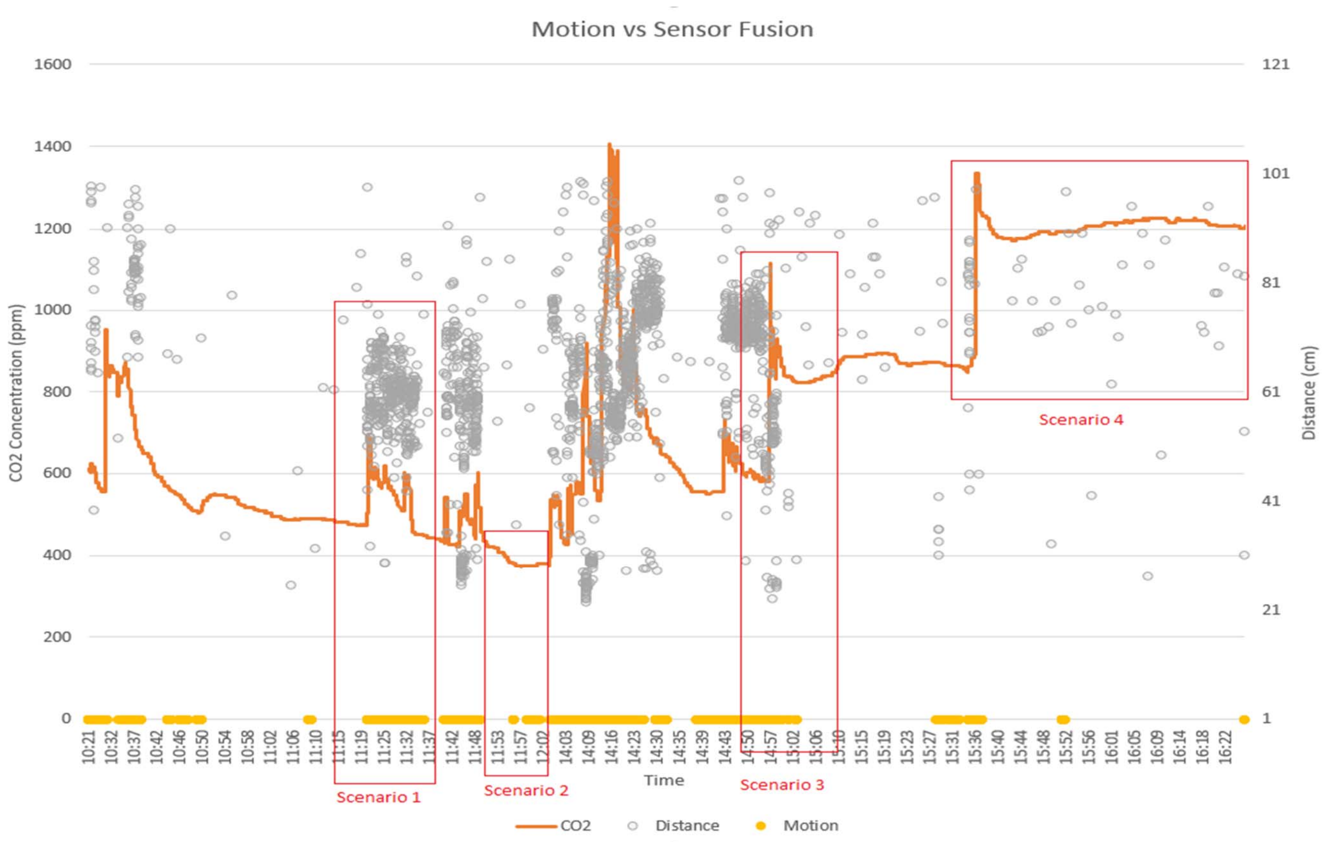


Fig. 2: Experimental results of occupancy detection

When selecting the sensors, occupancy deduction method should be considered first. Accuracy, price and ease of use are other parameters to consider. When these experiments began, the chosen sensors were chemical $CO_2$ sensors which use a chemical reaction to give an output for the level of carbon dioxide in its vicinity. This small voltage in combination with a given formula gives you the $CO_2$ level.

Through further research it was discovered that there was another, simpler sensor, Non-dispersive Infrared (NDIR) sensors, which use infrared light and a detector which is used to analyze the drop in light through a space. The $CO_2$ molecules are of the same wavelength as the light, meaning they absorb the light. The detector then reads the amount of other light striking the surface, and gives an output directly related to the amount of $CO_2$ in the chamber. The selected NDIR sensor communicated directly with the microcontroller thus no mathematical calculations were needed since a simple send-receive command meet the requirements.

## IV. Experimental setup Challenges

Over the course of these experiments the apparatus has been left running for days or weeks at a time. At certain points through the experiment, the results began to show higher than average values for $CO_2$. There was no indication that our sensor was not operating properly, other than the increasing values. After a brief shutdown of an hour or so, the values returned to normal. This is because the sensor became saturated with $CO_2$ and needed to be powered down in order to reset the value to appropriate level. For the office cubic experiments, variables such as the distance from the sensors and overall conditions can be quantified and recorded. Part of the reasoning for this testing scenario is to control the amount that $CO_2$ disperses through a room. The larger the room the less the reading will change in proportion to occupancy. This is an issue if the experiment is to accurately measure the $CO_2$ in the room, as it is a main sensor used in detecting occupancy.

The amount of $CO_2$ in outside air is approximately 400 PPM, which is the general threshold for fresh air. Inside air does not have the same properties. This change comes from not only occupancy but also the ventilation system. When working with the occupancy sensing system, the threshold for which occupancy is determined to be true must change with the ambient $CO_2$ level in the room. This complicates our system, because we must try to measure two different values from one $CO_2$ sensor and change the level at which occupancy is true based on said ambient value.

The reason for using Infrared motion sensors is their price point and ability to detect at fairly large distances. Ultrasonic sensors have a range limited to approximately 2 meters, which isn't practical for large rooms. While the motion sensor detects a change almost immediately, the $CO_2$ sensor requires a small amount of time to detect a change which slow system response.

## V. RESULTS

From the graph presented in Fig. 2, with the motion (yellow) being our reference, as the motion sensor is triggered, you can see the $CO_2$ (orange) increase as well as the distance sensor (gray) mimicking the motion sensor. Moreover, a correlation is evident between the motion sensor values and the data from $CO_2$ sensor. The graph highlights different scenarios appearing as the day went on. From scenario 1, it can be seen that all the three sensors follow the same trend, proving that with the combination of sensors, reliable results can be found. Scenario 2 shows that the motion sensor is triggered, yet the $CO_2$ actually drops slightly. It is evident that the motion sensor alone can be triggered by passing objects, giving false negatives. In scenario 3, all of the sensors trigger appropriately, with a large spike in the $CO_2$ level, this is due to a person arriving at the desk, and staying relatively still while present. While the motion sensor no longer picks up on movement, the sustained $CO_2$ level confirms that a human is still in the space. The final scenario is the most concerning, as the motion sensor and distance sensor have both not been triggered, yet the $CO_2$ level rises to quite a high level. At the time the level of $CO_2$ rises, the ventilation system has turned on; this disturbs the air in the room and introduces air into the room from the ducts. While the system is designed to provide fresh air in the room, it is not an instant change, moving air from the room disrupts the $CO_2$ sensor as well as stale air from the duct work, causing the spike in $CO_2$. This suggests that to better understand adaptive thresholding, remotely operated sensors should be placed in both the supply and return air ducts. This will provide a differential $CO_2$ level between the two ends of the HVAC system so we can actively see the increase in $CO_2$ from occupants on a large scale.

## VI. CONCLUSION

In this paper we developed an occupancy detection for an office cubicle space using combination of three different sensing modalities. We showed that for cubic space occupancy detection, combination of distance sensor and $CO_2$ work similar to motion sensor but could also react when the motion sensor didn't pick up the still person. This means a proper fusion of all of these sensors could reduce both false positive and false negative. It is worth mentioning that our system could communicate wirelessly and uses an IoT based platform to send and visualize the date on the cloud. With the addition of more sensors, the future plan is to have multiple sensor arrays to cover an entire room. The focus of this experiment will be measuring the impact of a large group of students on the $CO_2$ level in the room. In order to automatically learn the weights of fusion of different sensors (equation 1) and hence reliable occupancy detection, we are currently experimenting different classifiers including Support Vector Machine (SVM) with different linear/non-linear distance metric.

## VII. ACKNOWLEDGMENTS

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