Hybrid Building Occupancy Estimation using Thermal Imaging and Environmental Sensing

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***Abstract*—Estimating building occupancy is a fundamental aspect of effective building management. By predicting building occupancy over time, we may reduce energy consumption, and contribute to energy efficiency in buildings. Building Occupancy Estimation (BOE) can be useful to compute building management metrics, such as the number of users in each room during work hours or in the entire building overnight. This paper presents a Hybrid Building Occupancy Estimation (HBOE) method that uses thermal imaging and environmental sensing to deliver a qualitative occupancy metric. Results show that the chosen approach represents a cost-effective solution, delivering an indicative BOE value based on thermal imaging and environmental sensing.**

***Index Terms*—Building Occupancy Estimation, Indoor Air Quality, Carbon-Dioxide, Thermal Imaging.**

I. Introduction

Indoor air quality (IAQ) and thermal comfort are among the key factors that affect building occupants' health, productivity, and comfort. In this context, Building Occupancy Estimation (BOE) is a crucial task for building automation and control [1], allowing for efficient use of resources, energy efficiency [2], and improving the overall IAQ [3]. In recent years, various methods for occupancy estimation [4], [5] have been proposed, including thermal imaging and environmental sensing. However, these methods are often used independently, with their limitations and drawbacks [6]. In this work, we propose a novel approach that combines the strengths of both thermal imaging and environmental sensing as cost-effective way to perform Hybrid Building Occupancy Estimation (HBOE).

This paper proposes the design of a cost-effective HBOE indicative sensor, that takes advantage of both thermal imaging and environmental sensing (e.g., Carbon-Dioxide(CO_2), Total Volatile Organic Compounds(TVOC), etc.). The proposed approach aims to address efficient and intelligent decision-making with applicability to Building Management Systems, IAQ Management, Energy Efficiency improvement, or in Heating Ventilation and Air Conditioning(HVAC) control. The paper is structured as follows: II summarizes the most relevant work with regard to the impacts of CO_2 on health, the use of environmental sensing in indoor environments, and occupancy estimation techniques utilizing thermal imaging cameras; in III the experimental apparatus is presented as well as detailing how the dataset was acquired; in IV the data is analyzed and manipulated; in V results from the work are presented; finally, section VI is dedicated to conclusions and future work.

II. Related Work

Several techniques and methods have been proposed for BOE. In [1], Huang et al., provide a comprehensive review of occupancy detection using deep learning for building automation, which is a key application for building occupancy estimation. Hong and Lin, [2], review the use of machine learning for occupancy prediction in building energy management, with a focus on the benefits of accurate occupancy estimation for energy efficiency in buildings. In [5], Li et al., review occupancy detection based on environmental sensing data in buildings, which includes air quality and temperature sensors, to provide additional information about occupants' activities and behavior. Lastly, Alseddiqi et al., [6] review the use of thermal imaging for occupancy detection and classification, highlighting that it is a non-intrusive and privacy-preserving solution for BOE.

Multiple works in the literature address IAQ monitoring for BOE. For example, in [9], the authors present a method for detecting human presence using a commercially available smart weather station to monitor indoor CO_2 concentration levels. In [10], Szczurek et al., utilize an IAQ probe to measure CO_2 concentration, temperature, and humidity, and apply the k-Nearest Neighbors (k-NN) and Liner discriminant analysis (LDA) algorithms to classify the data and determine occupancy. In [8] the authors present the design and development of a low-cost Internet of Things(IoT) edge device capable of multimodal environmental sensing for BOE and discuss its potential applications in the field of smart building management. However, it is known that when using only environmental sensing for BOE, it may result in limited accuracy since environmental monitoring, namely CO_2 monitoring, may be affected by other building management actions, such as ventilation and HVAC operation.

The use of thermal imaging for BOE has also been recently addressed. Chidurala et al., [11], perform occupancy estimation using thermal cameras and machine learning. For the processing, four major blocks of estimation algorithms are used, which are active pixel and active frame detection, connected component analysis, feature extraction, and lastly classification. Kraft et al., [12], with the purpose of energy saving in smart buildings, present a solution using the low-cost and low-resolution MLX90640 and a convolution neural network architecture to estimate the occupancy density. Cokbas et al., [13], present a low-resolution overhead thermal tripwire for occupancy estimation by utilizing the Melexis MLX90640 thermal camera combined with Gaussian average-based background subtraction and k-NN classifiers to detect an event and classify it. The results showed an 80-90% accuracy in extreme scenarios (e.g., multiple people passing through at the same time) and 100% accuracy in simpler scenarios (e.g., only a single person passing). However, relying solely on thermal imaging for BOE can lead to reduced accuracy due to the limited zone of interest captured by the camera, as well as the impact of environmental factors such as temperature fluctuations, sunlight, and humidity [7].

III. Implementation and Experimental Validation

The developed prototype device aimed at using low-cost, off-the-shelf, and efficient devices capable of being installed in an office building with low complexity. As such, for the thermal camera, the choice was to utilize the FLIR Lepton 3.5 [14] coupled to the PureThermal2. This setup for the thermal imaging is capable of outputting 160×120 pixels images, with a Field-of-View (FOV) of 57° and a thermal sensitivity of (0.050°C), all this while consuming a nominally 150 mW while operating, 650 mW during the shutter event and 5 mW on standby. The PureThermal2 features a Micro-USB port, which enables easy connectivity and is capable of allowing communications via I2C, UART, and JTAG [15]. It also includes a STM32F412 [16] that allows for its firmware to be customized to perform image processing. For the CO_2 concentration analysis, we used the Adafruit breakout board with the Sensirion SGP30 [17], which is an IAQ sensor for TVOC (Total Volatile Organic Compounds) and CO_2eq measurements. The sensor specification (range, resolution, and frequency) can be seen in Table I.

TABLE I
SENSIRION SGP30 TVOC AND CO_2EQ SPECIFICATIONS

Signal	Values	Resolution	Sampling Rate
TVOC	0 ppb - 2008 ppb	1 ppb	1 Hz
	2008 ppb – 11110 ppb	6 ppb	
	11110 ppb – 60000 ppb	32 ppb	
CO_2eq	400 ppm – 1479 ppm	1 ppm	1 Hz
	1479 ppm – 5144 ppm	3 ppm	
	5144 ppm – 17597 ppm	9 ppm	
	17597 ppm – 60000 ppm	31 ppm	

Figure 1 depicts the Hybrid Building Occupancy Estimator (HBOE) block diagram with the main components identified. For the processing of the data, both from the thermal module and the CO_2 sensor, a Raspberry Pi 3B was utilized, for its low-cost, adequate computational capabilities. The thermal module was connected to the RPi by USB and the Adafruit SGP30 sensor by I^2C (Inter-Integrated Circuit) protocol. To store the data an InfluxDB database was used, the choice was made by being one of the most robust time series database available.

To develop a method to estimate occupation, first, a dataset was required to be captured. This dataset was made by capturing images and the CO_2eq readings every 10 minutes from a closed room. This room, of approximately 42 m^2, had only mechanical ventilation (e.i., air conditioning) and could only be accessed by one door, which was kept close by the whole remainder of the experiment. The subjects that were to enter or leave the room were required to register in a form the type of action (i.e., in, out, short, i.e., less than 3 minutes), day of action, time of action if the HVAC was ON or OFF if the lights were on or off (this parameter was later discarded as it had only one state by the entire experiment), and finally, an observation box to describe any event that could directly influence the reading from either the CO_2eq sensor or the thermal camera. This form would be a base for our ground truth, carefully detailing entries and exits of the room, as well

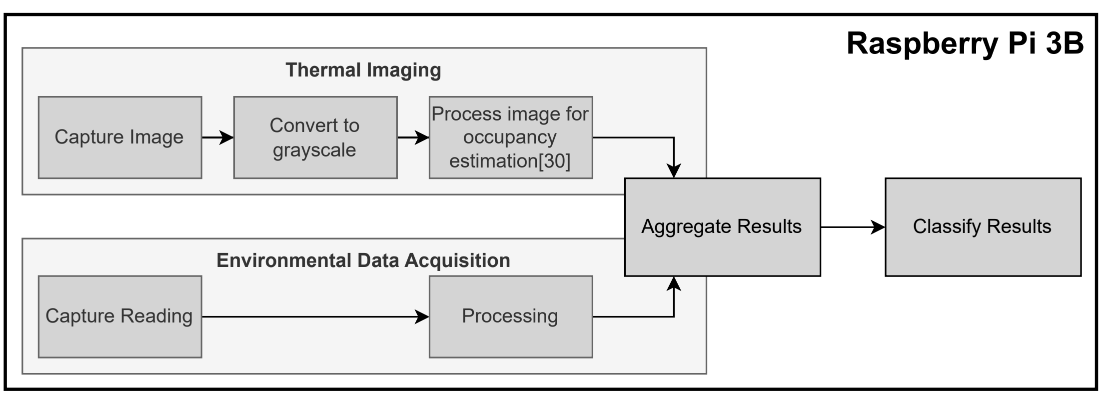

Fig. 1. Hybrid Building Occupancy Estimator (HBOE) block diagram with main components identified.

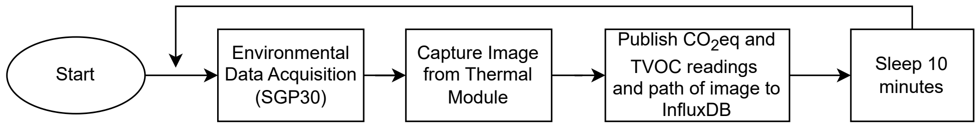

Fig. 2. Dataset acquisition process.

as the number of present persons at any given time in the room for times when the module was not capturing data. The HVAC parameter also was carefully considered as it could directly impact the CO_2eq readings as it could potentially ventilate the room. The processing of the thermal images to determine the occupation was done using a method already created and published in a previous work [18]. Figure 2 depicts the sequence of operations implemented to obtain the dataset used to evaluate the proposed system. The experiment occurred uninterruptedly from the 28th of December 2022 until the 8th of January 2023. In the end, 1527 images and CO_2eq, and TVOC readings were made. From the gathered thermal frames, 222 contained 1 or more persons, that is approximately 14,5% of all frames.

IV. Data Analysis

The results consist of the readings in for of time-series data that have been exported to a CSV file and then analyzed using Python. The file contains four columns, timestamp, CO_2, the thermal imaging-based occupancy estimation, HVAC state, and TVOC. The plotted results from the CSV file can be seen in Fig. 3 (CO_2 in parts-per-million and thermal imaging-based occupancy estimation), and Fig. 4 (TVOC in parts-per-billion and HVAC binary state). To analyze the correlation between all these time-series data, we computed all pairwise correlations among the series using the Pearson Correlation Coefficient (PCC) method. Table II presents the obtained correlation matrix among all the time-series raw data. To ensure that the dataset is in the best condition before estimating BOE, two procedures were made: 1) CO_2, TVOC and thermal imaging-based occupancy estimation time-series have been pre-processed with a moving average filter with order 10; and then 2) all time-series have been normalized. Table III depicts the correlation between all the time-series data, after filtering and normalization.

TABLE II
Correlation matrix with raw data.

	AC	CO2	TVOC	PEOPLE
AC	1	0.145435	0.050947	0.316329
CO2	0.145435	1	-0.025639	0.446152
TVOC	0.050947	-0.025639	1	0.007591
PEOPLE	0.316329	0.446152	0.007591	1

V. Results

Figures 3 and 4 show the raw data obtained, the former presents CO_2 and thermal image-based occupancy estimation,

TABLE III
Correlation matrix after filtering and normalization.

	AC	CO2	TVOC	PEOPLE
AC	1	0.367632	0.163742	0.744654
CO2	0.367632	1	-0.168669	0.703347
TVOC	0.163742	-0.168669	1	0.101343
PEOPLE	0.744654	0.703347	0.101343	1

and the latter TVOCs and the HVAC state, respectively. By analyzing both figures, it can be visually observed a high correlation between the thermal image-based occupation estimate and CO_2 readings. Additionally, looking at the PCC presented in Table II, what was possible to observe previously, is mathematically relevant as well. Observing the plotted values and the correlation matrix, it can be seen that there is also a lack of relation between TVOC and CO_2 readings, also, by the PCC, there is a lack of relation between the TVOC readings and the image-based occupancy estimation in the room as seen in Table II.

Results can be observed in Fig. 5, where a small relationship between TVOC and the image-based occupancy estimation, from the increase, and decrease following the image-based occupancy estimation, but, it can also be seen as a spike in values on New Year's Eve that could be caused by some anomaly on the sensor readings, or potentially, by the fallout of the New Year's Eve fireworks. The readings of CO_2 can also be influenced by the HVAC state, also seen in figure 5, wherein the first spike the CO_2 readings are lower than the second spike, although the image-based occupancy estimation in the room at the first spike was higher, because of the HVAC being turned on for a longer period of time. Computing again the pairwise correlation of the columns using the PCC shows now an increase in correlation between values, where the correlation between CO_2 and the image-based occupancy estimation increases from 44,6% to 70,3%, an approximate 63% increase in correlation. Since the goal of this work is to develop an indicative and cost-effective method for BOE, we opted to define an adaptive normalized metric that classifies occupancy in four levels, equally divided in a 0 to 100% scale, as depicted in Table IV, where level 0 represents low occupancy (green) and level 3 high occupancy (red).

Since we are working with normalized values between 1 and 0, we can create a simple formula to evaluate the level, based on the three factors, CO_2 reading, the thermal imaging-based occupancy estimation (TH), and the HVAC state. The formula is represented in 1, where HBOE will be the level

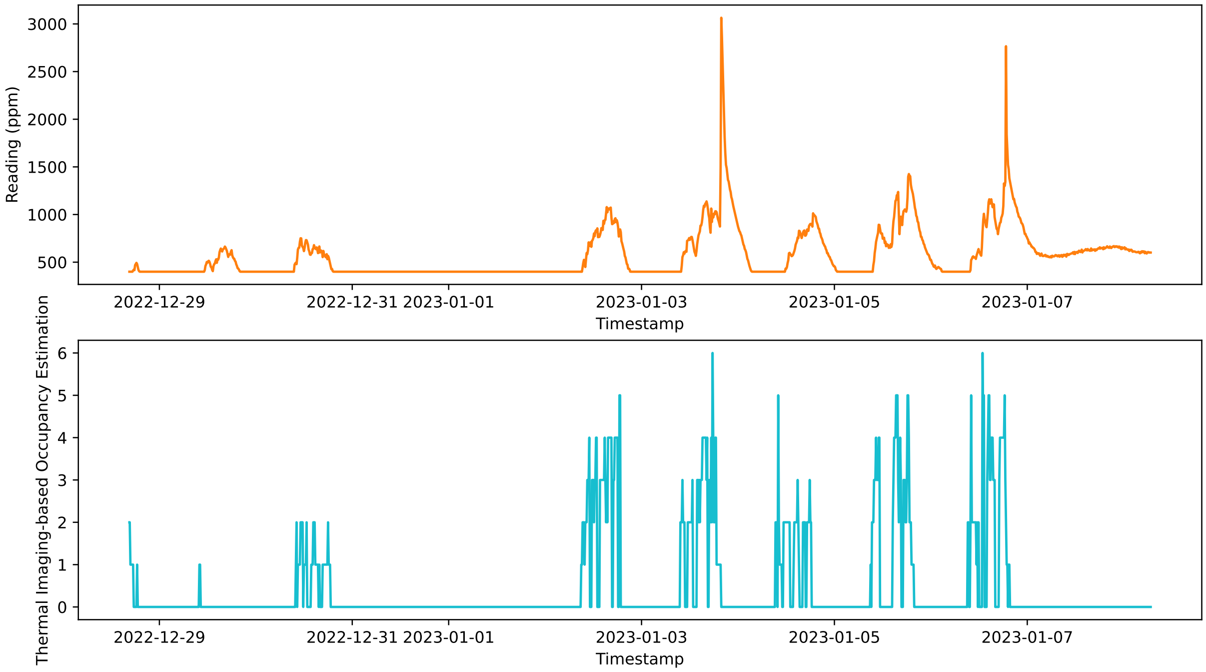

Fig. 3. CO_2 time-series data, and thermal imaging-based occupancy estimation over time.

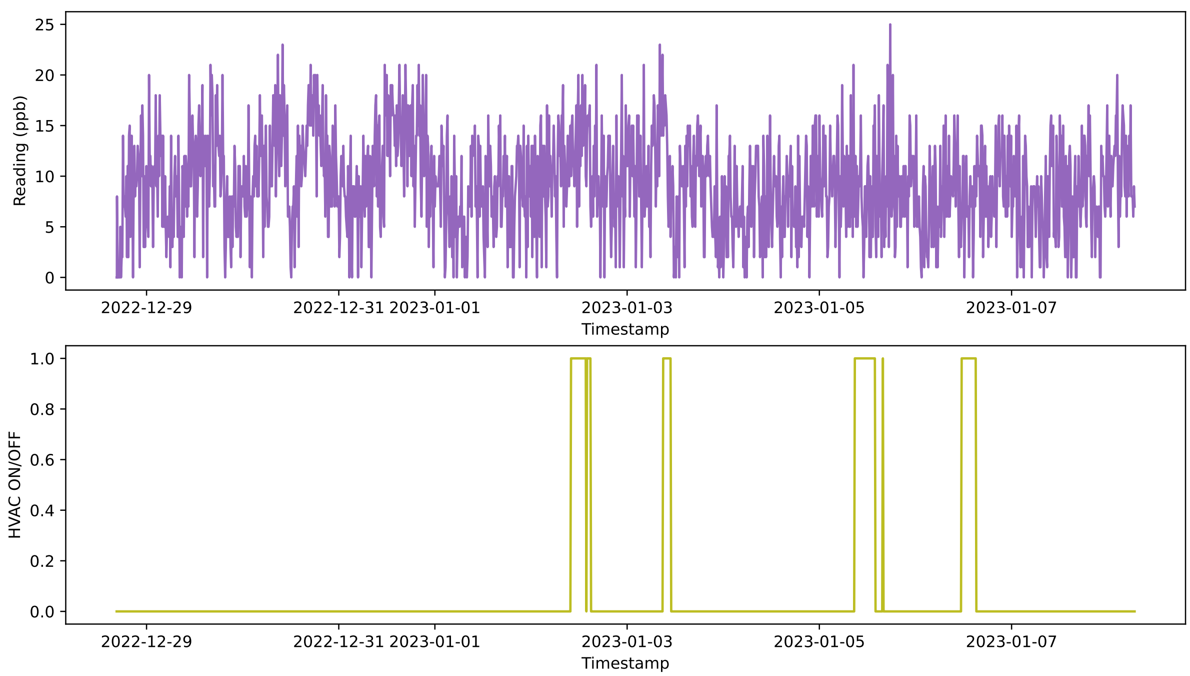

Fig. 4. TVOC time-series data, and HVAC state over time.

TABLE IV
LEVEL WITH OCCUPANCY CLASSIFIER

Level	0	1	2	3
Occupancy	0% - 25%	25% - 50%	50% - 75%	75% - 100%

value between 0 and 1, following the scale of 0-100%, in the sample n, and CO_2 will represent the reading in the sample n as well, the same for TH that is the thermal imaging-based occupancy estimation and HVAC state.

$$\mathrm{HBOE}_n = \frac{\mathrm{CO}_{2_n} + \mathrm{TH}_n + \mathrm{HVAC}_n}{3}, \quad \text{with n=0,1,2,...} \quad (1)$$

where, CO_2 represents the time series regarding carbon dioxide concentration, TH represents the thermal imaging-based occupancy estimation, and HVAC represents the air conditioning state, i.e. ON or OFF. For every sample, computing it into the Eq. 1 leads to the results depicted in Fig. 6, where it can be seen the corresponding level in regard to the parameters given. Comparing the results obtained from Eq. 1 to the ground truth obtained from the form described in Section III, it is possible to observe that the proposed system shows a good and reactive performance, when compared with the effective room occupancy, cf. Fig. 7 ground-truth). Note that, the values presented in Fig. 7 are filtered using a moving average filter (N=10), and then are normalized. Another observation that can also be made is that, in the first spike between sample 200 and 400, although the image-based occupancy estimation appears high, it only got to a maximum of 3 people in the room and a

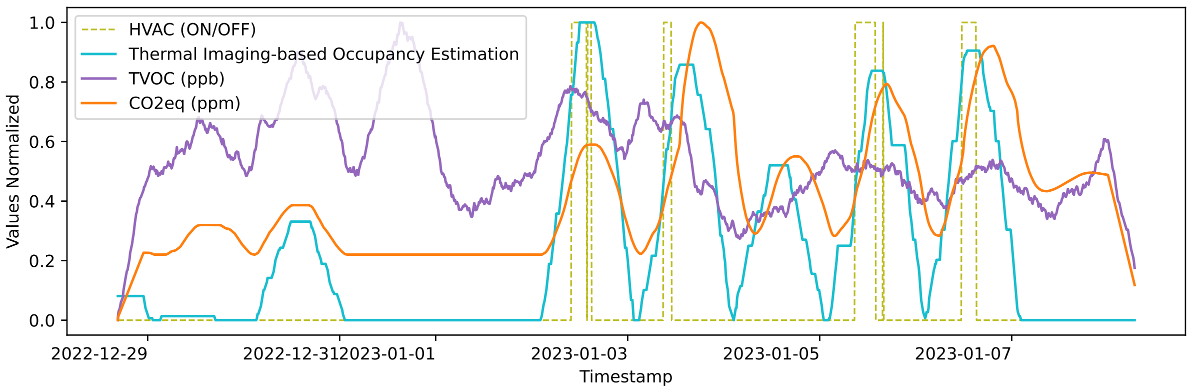

Fig. 5. Time-series data filtered with a moving average filter with order 10, and then normalized.

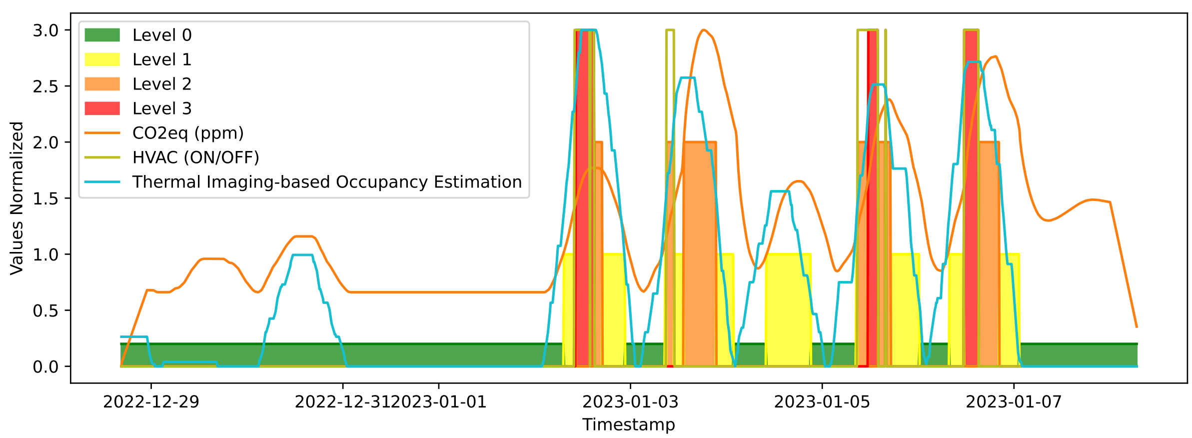

Fig. 6. Values normalized and plotted with regard to level of IAQ

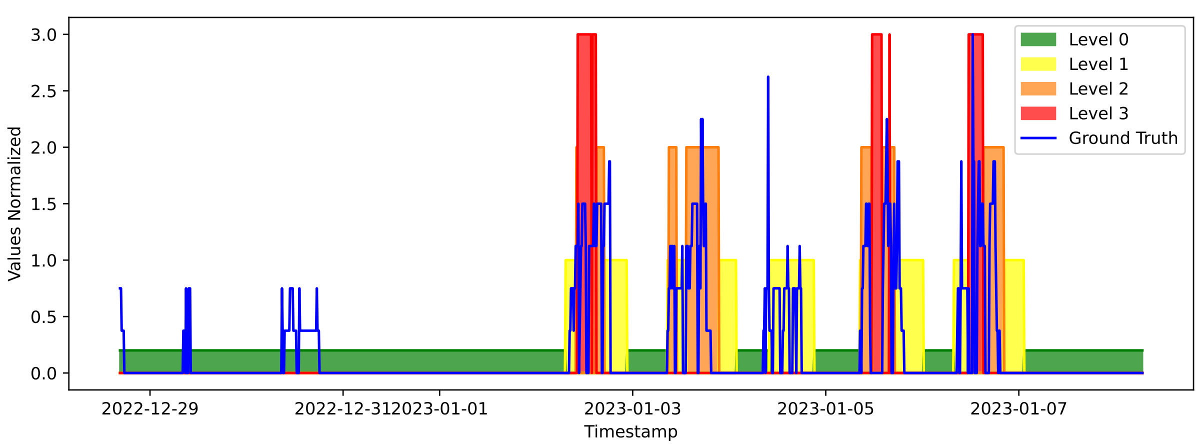

Fig. 7. Values normalized and plotted with real number of people in the room

CO_2 reading of approximately 800 ppm. The estimates from the thermal camera were not off from what could be observed, but, the positioning of the camera resulted in some blind spots that usually were only used in small moments of time (e.g., SCRUM meetings). The monitoring of the HVAC state also proved to be important as it showed to have an impact on the readings and also, during, the validation of the results. Not taking the HVAC state into consideration showed to have an impact on the final estimates, as it made the results show a less overall occupancy level.

VI. Conclusions

This paper described a hybrid approach to environmental sensing for building occupancy estimation by utilizing a thermal camera and a gas sensor, that could be implemented in a room or office building to estimate the occupancy based on levels of occupancy. This qualitative approach allows for more flexibility in terms of assessing the occupancy and at the same time the quality of the room's air. The prototype, with an overall cost of approximately 200 euros, shows a great compromise between performance, in terms of computational capabilities as well as hardware features. The use of a thermal imaging camera also makes for a great solution as it is only sensitive to heat sources does not suffer from the normal problems of RGB cameras (e.g., low light, artifacts, etc.). The proposal could also be easily implemented in a microcontroller, such as an ESP32, reducing the cost of the hardware but not compromising the performance as it could easily perform both the CO_2 readings and the estimation of occupancy [18]. An advantage of using the hybrid approach is the reduction of sensitivity to noise and interference, when compared to what the methods could result when used separately. With the work completed some future work can already be planned, as the dataset of 1527 images will be later used to train a machine learning algorithm to be implemented in a microcontroller (e.g., ESP32) making use of TinyML. Also, with the CO_2 reading, TVOCs, and HVAC state can be later used as well to train an ML model to predict the occupancy of the room based on these three features.

VII. Acknowledgments

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