Occupancy Based HVAC Control

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***Abstract*—HVAC systems within buildings are the major contributors for energy consumption in the world. Lack of user comprehension of the behavior of these systems is one of the main reasons for energy wastage while using them. This gives rise to the need to understand occupant behavior and adjust HVAC systems accordingly. One of the fundamental occupant information that can be utilized for controlling HVAC systems is the occupancy count. With the advantages of a camera sensor for occupancy detection, we implement an occupancy detection and counting algorithm with local image processing in a resource constrained device (Raspberry Pi), to mitigate the privacy issues of sending captured camera images to the cloud for processing. Furthermore, we evaluate the performance of the algorithm using both real-time captured image frames and downloaded images. The algorithm, in general, shows better performance for less than 10 people in the image (with an increase in accuracy by 20% over images with more than 10 people). Finally, we study the possible strategies to control the HVAC system, based on different occupancy information – occupant count and occupant activity. We succeed in determining the correct HVAC cooling rates in different scenarios, for higher energy savings and higher thermal comfort.**

Keywords—HVAC, Occupancy Detection, Occupancy Count, Energy Saving, Thermal Comfort

I. INTRODUCTION

Buildings are the major cause of energy consumption and greenhouse gas emissions around the world. In the United States, residential buildings account for 21% of energy consumption, while commercial buildings account for 18% of energy consumption, resulting in a total of 39% of total energy consumption [1]. The building energy consumption in developing countries has increased significantly over the last few decades. In China, the energy consumption due to buildings has increased by over 10% annually over the last few decades [2]. Also, the International Energy Outlook 2017 (IEO 2017) predicts that the fastest growth in building energy consumption through 2040 will occur in India, followed by China [3]. Within buildings, the largest consumers of energy are the heating, ventilation and air conditioning (HVAC) systems. In commercial buildings, HVAC accounts for 53.4% of the total energy consumption, whereas in commercial buildings, it accounts for 26.1% of total energy usage [1]. Thus, the usage of HVAC systems in buildings is the prime area to focus for energy saving.

The six driving factors of energy usage in buildings is identified as: (1) climate, (2) building envelope, (3) building energy and services systems, (4) indoor design criteria, (5) building operation and maintenance, and (6) occupant behavior [4]. Additionally, study on thermostats by Raino Vastamaki et al. [5] also indicates that both energy efficiency of a building and thermal comfort of a user is affected by a lack of user comprehension of the behavior of the building. This lack of understanding is generally characterized by users over-turning thermostat dials in response to an uncomfortable condition [1]. This results in wastage of energy and thermal discomfort due to frequent thermal oscillations. This calls for the control of HVAC systems based on the occupancy and thermal conditions of the given enclosed space.

Researchers have demonstrated that energy consumption can be reduced significantly by reducing cooling and/or heating usage when there are no occupants in the given enclosed space [6], [7]. With the emergence of Internet of Things (IoT), monitoring and automatically detecting occupants' presence are becoming a reality. Furthermore, fine-grained occupancy information, such as the number of occupants in a particular thermal zone, can also help to drive the demand-control or personalized HVAC systems, which in turn further reduces the energy consumption [8][9]. Occupancy count is the basic information for any fine-grained analysis. Hence, for this class project, one of our major tasks is to implement an algorithm that completes the task of occupancy counting.

Occupancy counting strategies can be classified into two categories: sensor-based and camera-based [10]. Sensor-based methods usually require deployment of multiple sensors. Then, the detection procedure requires coordinating multiple sensors readings, which leads to a complicated design, and, sometimes, undesirable outcomes [10]. Camera based methods rely on visual computing technologies to detect occupancy by processing an image. Given the great success of machine learning in labeling pictures, the accuracy of occupancy counting with camera-based methods is better than sensor-based methods [11]. However, installing camera can be perceived as a privacy violation, especially when images need to be uploaded to cloud for intensive computing. Considering these factors, we can conclude that solving the limitations of camera-based methods is the way forward. Thus, we develop an occupancy counting system with local image processing in a resource constrained device, so that the privacy of people captured in the frames, is preserved. Using the occupancy information, we study the different strategies for controlling HVAC systems based on the cooling load on demand and aim to optimize energy saving and thermal comfort.

The rest of the paper is divided as follows. Section II discusses about the System Overview, with details about the hardware, the occupancy detection and counting algorithm and, the decision-making model for HVAC control. Section III discusses about the experiments and evaluation of our proposed system. Here, we discuss about the general experimental setups and discuss the significance of the results obtained. This is followed by Conclusion in Section IV.

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II. System Overview

A. Hardware

As shown in Fig.1, we use a Raspberry Pi 3, Model B, which is a single board computer that contains a System on Chip. The Raspberry Pi acts as a processing unit, which is connected to a set of sensors. The three sensors that the Raspberry Pi board is connected to are: a HC-SR04 Ultrasonic Distance Sensor, a Raspberry Pi Camera and two LEDs, colored red and green. The Raspberry Pi board further communicates with an Arduino UNO board, which is a single board microcontroller unit that acts as a controlling unit. The Arduino board is further connected to a temperature sensor and a humidity sensor. It is also connected to two actuators – a SG90 micro servo motor and an Arduino LCD module.

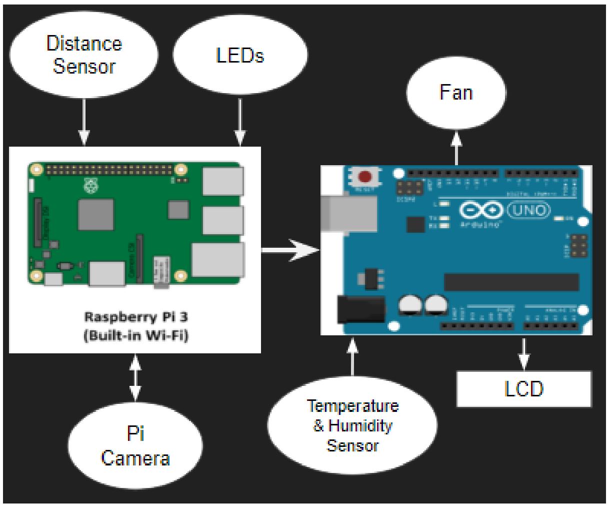

Fig. 1: Hardware Design of the proposed IoT system

The Ultrasonic Distance Sensor that is attached to the doorframe of a room, can trigger the Raspberry Pi board to capture and process frames from the real-time video whenever a person enters or exits the room through the door. The Raspberry Pi board uses the connected Pi Camera to capture multiple frames from real-time videos and then processes the captured frames to count the number of people in the frames using an occupancy count algorithm, that is discussed in the next sub-section. The red LED sensor switches ON whenever a frame is captured by the Pi camera. The green LED sensor is ON during the entire duration that the Pi board processes the captured frames for calculating the occupancy count. The Raspberry Pi board communicates the occupancy count value to the Arduino through serial communication using a USB cable. The Arduino displays the received Occupancy count value, the current temperature and humidity values that are sensed by the connected temperature and humidity sensors, in the connected LCD module. Further, depending on the occupancy count value and the current temperature, the Arduino control the connected Servo motor (which mimics a HVAC cooling unit) and displays the simulated change in temperature in the LCD module.

B. Occupancy Detection and Counting

In order to provide room occupants' information to the HVAC system, we have to tackle two challenging problems, namely, occupant detection and occupant counting. The occupant detection algorithm tries to find the regions in the image that are possibly human beings and the occupant counting algorithm tries to accumulate multiple regional information from both spatial and time domain to answer how many people are there. When we deal well with both tasks, we can then provide accurate information to the HVAC decision-making component.

Since occupant detection is not well studied as the pedestrian-detection or the human-face detection, it is quite hard to find pre-trained machine learning model or any suitable dataset to train occupant detector from the scratch. However, the HVAC systems are usually deployed indoor and the indoor camera can easily capture the details of human faces. Thus, it is plausible to assume the existence of a face in the captured image implies the existence of a person. We choose the OpenCV [12] and OpenFace [13] detection libraries as candidate algorithm and rule out OpenCV due to its sensitivity to the rotation, light condition and so on.

OpenFace is a computer vision library that aggregates most common face related applications. Besides detection of faces within an image, another benefit is that it also generates a 128-D face representation vector [14]. Using this vector, one can easily compare the similarity between two faces, such comparison is widely used in face recognition and face identification. In our HVAC system, we at first use OpenFace face-detection to crop face images, and then aggregate to get the final occupants' information using voting or clustering. The following pseudo code shows our implementation of both voting and clustering-based counting. The intuition of the clustering-based counting is that we notice that the detection algorithm failed to detect faces in some of the consecutive frames, we expect that gathering all the human faces in the video sequences and then ruling out the redundant ones would provide more accurate information.

Algorithm 1: Voting based counting

Result: Number of people in the room

$counts \leftarrow \{\}$;
while $img \leftarrow Raspberry.capture()$ **do**
  $faces \leftarrow OpenFace.detect(img)$;
  $counts[faces.length]$+=1;
end
$result \leftarrow -1$;
$maxVote \leftarrow 0$;
for $i \leftarrow 0$ **to** $counts.length$ **do**
  if $maxVote \leq counts[i]$ **then**
    $maxVote \leftarrow counts[i]$;
    $result \leftarrow i$;
  end
end
return $result$;

Algorithm 2: Clustering based counting

```
Result: Number of people in the room
distinctFaces ← [];
while img ← Raspberry.capture() do
    faces ← OpenFace.detect(img);
    foreach face ∈ faces do
        faceFeature ← OpenFace.Extract(face);
        found ← False;
        foreach feature ∈ distinctFaces do
            if Distance(faceFeature, feature) < threshold then
                found ← True;
                break;
            end
        end
        if found == False then
            distinctFaces.push(faceFeature);
        end
    end
end
return distinctFaces.length;
```

C. Decision Making

The cooling load of a HVAC system is the amount of heat energy to be removed from a room to maintain the room at the indoor design temperature range [15]. Some of the factors that influence the cooling load are general features of the building, like exterior wall, roof, foundation slab, lights [16], people in the building, indoor and outdoor temperature and so on [15]. For simplicity, we assume that the room is insulated and the only factors influencing the cooling load of a HVAC system are the people present in the room and the current temperature of the room.

The human heat gain or the "people load" is usually measured by the metabolic rate of the human body during an activity. The metabolic rate "determines the amount of heat gain by the person in the zone under design conditions" [17]. The human metabolic heat gain is further divided into sensible and latent heat gain. Sensible heat gain is due to convection and radiation, while latent heat gain is due to evaporation from the human body [18]. Furthermore, from [19], we can see that the thermal insulation of clothes of an occupant does not have a significant change in the net metabolic rate of the person. So, we ignore it for our experiments. Assuming that the average weight of an adult male human is 70 kg [20], the average specific heat capacity of an average human body is 3470 J/(kg °C) [21], and using the average metabolic rates of an adult male for different activities, based on ASHRAE and ISO standards [18], we calculate the change in temperature due to human heat gain by the equation (1), taken from the First Law of Thermodynamics, as shown below:

$$\Delta Q = mc\Delta T \tag{1}$$

Since we assume that only the current internal room temperature and the people present in the room influence the cooling load, so the value of ΔT that we get from equation (1) is equivalent to the change in temperature of the room due to the metabolic rate of a person, depending on his level of activity. Based on the cooling load, the HVAC system chooses a cooling rate to keep the temperature within the indoor design temperature range. The effective change in temperature is calculated by equations (2) and (3) shown below:

$$T_t = T_{t-1} - (F_{t-1} * \upsilon) + (O_{t-1} * \sigma) \tag{2}$$

$$\begin{aligned} F_t &= 1, if\ T_t + O_t * \sigma > \theta_u \\ &= 0\ if\ O_t = 0\ or\ T_t + O_t * \sigma \leq \theta_u \end{aligned} \tag{3}$$

In equations (2) and (3), T_t represents the temperature at time t, F_t signifies if the HVAC is switched ON (value = 1) or OFF (value = 0), O_t equals the occupancy count at time t, υ represents the cooling rate of the HVAC and σ represents the rate of temperature change due to the presence of one human body. The aim is to find the correct cooling rate that would be suitable for a given room, ensuring high energy savings and high thermal comfort.

As shown in [1], the energy saving of a HVAC cooling system is linearly proportional to the average temperature of the room. Similarly, as stated in [1], frequent thermal oscillations cause thermal discomfort. Moreover, when the temperature is outside the indoor design temperature range, it can be inferred that an occupant will tend to feel thermal discomfort. So, we can define Energy Saving and Thermal Comfort by equations (4) and (5).

$$Energy\ Saving \propto T_{avg} \tag{4}$$

$$Thermal\ Comfort \propto \frac{f_{T,Range}}{\delta_T} \tag{5}$$

Equation (4) states that the energy saving is directly proportional to the average temperature T_{avg} of the room over the duration of the experiment on HVAC control. Moreover, equation (5) states that the thermal comfort of the users is directly proportional to the percentage $f_{T,Range}$ of times that the temperature has been within the indoor temperature design range divided by the standard deviation δ_T of room temperatures over the entire duration of the experiment.

III. Experiments and Evaluation

A. CPU Usage

We assume that the energy consumption for person detection and counting algorithms is proportional to the CPU usage. Thus, we report the CPU usage using the Linux "*top*" command and plot it over the CPU usage reading sequences, to quantitatively analyze the energy consumption. We compare our triggering strategy using the distance sensor to the baseline strategy that periodically activates the image processing algorithm. For the periodical activation baseline method, we set the period to be 30 seconds, that is, the image processing module detects and counts the number of people in the room every 30 seconds. For our distance sensor triggering strategy, the image processing module is activated after a few seconds once the distance sensor detects someone passing through.

In Fig. 2a, the CPU utilization of using distance sensor triggering is low (mean = 3.26) compared to periodic detection (mean = 19.63) because it was a "nearly passive" or a less busy interval. In Fig. 2b, we show a "busy time" or an "active interval" scenario for our proposed method in Fig. 2b. In this case, the mean CPU utilization is 19.63 for periodic detection compared to 15.61 for detection using distance sensor. Thus, from our experiments, we can state that by using the distance sensor-based activation, we reduced the energy consumption on the Raspberry Pi.

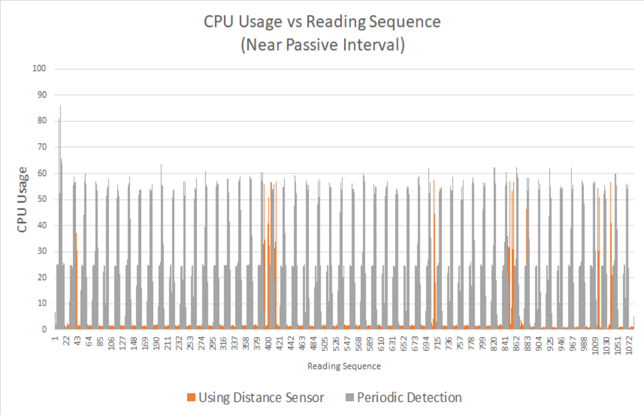

Fig. 2a

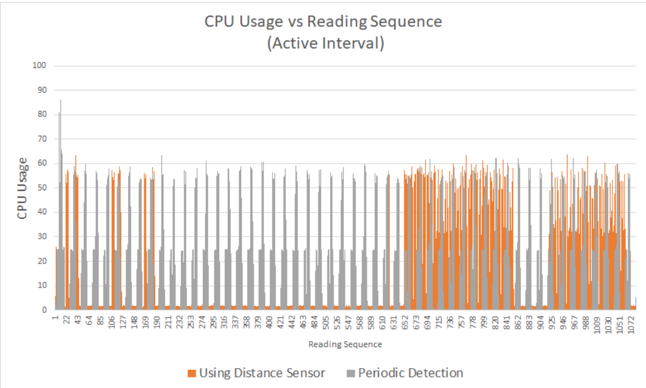

Fig 2b

Fig. 2: Comparison of CPU Usage due to periodic detection and distance sensor trigger in (a) nearly passive interval and (b) active interval

The CPU usage of periodic detection can however, be reduced by setting a higher value of periodic interval. However, a very big value of periodic interval will be counter-productive because the system might miss detection and count of new occupants who arrived and left within the sleep period of the system.

B. Occupancy Detection & Counting – Website Images

In the real-time scenario, the office room setup for experiment has a maximum of three occupants within the range of the camera. It is difficult to setup the experiment in a larger classroom, since it requires permissions from all the involved students in advance, adjustment of camera angles, setup of experiment equipment without interfering regular class, etc. To complement the limited number of occupants in the real-time scenario, we download images from different websites to evaluate the performance with more occupants.

To conduct a fair comparison, we setup the camera facing a laptop, in which the downloaded image is displayed. As such, we mimic a real-time scenario. The setup environment is illustrated in Fig. 3 below.

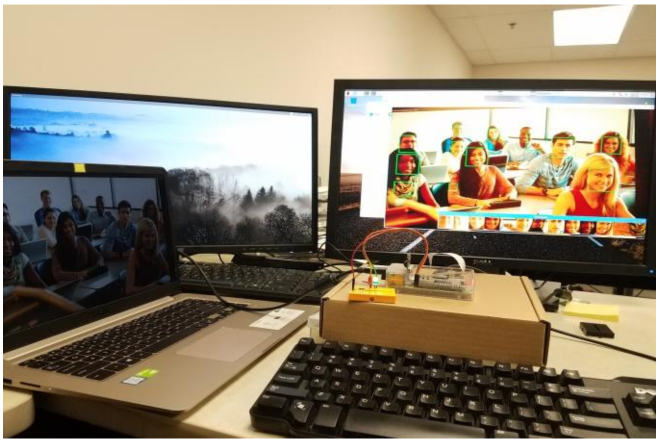

Fig. 3: Experiment setup – Website Images

Initially, we test with 10 downloaded images. After the detection phase, the performance of both clustering and majority vote methods were tested. As shown in Table I, the accuracy of both the methods is quite low. Although the overall performance is poor, we see that the majority vote method performs better than Clustering with lower Root Mean Square Error (RMSE) and higher accuracy. Overall, the algorithms suffer to count the correct number of faces from a downloaded image. However, this is not highly surprising because, in images with higher number of people, it is difficult to even manually set the ground truth with the naked eye.

The small sample size may be another factor that hurts the results. Hence, we included 50 more downloaded images to enlarge the testing dataset. These 50 images are grouped into two classes, according to the number of people in each image – less than 10 people and 10 people or more. There are 25 images in each group. Average number of people in each group is 6.76 and 17.12, respectively.

TABLE I. WEBSITE IMAGES - INITIAL RESULT

Method	**Website Images**	
	Accuracy	***RMSE***
Majority Vote	12.5%	3.37
Clustering	0	4.14

Table II presents the result of testing 50 images. Accuracy for the class of less than 10 people is improved significantly without much increase in the value of RMSE. However, for the group of more than 10 people, the accuracy is poorer, with worse RMSE value. Addressing the limitations of the trained Occupancy detection model is beyond the scope of this project.

TABLE II. WEBSITE IMAGES – RESULT WITH 50 IMAGES

No. of People	**Website Images**	
	Accuracy	***RMSE***
< 10	32%	3.43
>= 10	12%	10.09

C. Occupancy Detection & Counting – Real-time Scenario

To evaluate the developed system in real-time scenario, we set up the experiment in SENSQ 6410. Distance sensor is attached to the door frame, so that any person passing through the door will trigger the camera. As shown in the demo video, the camera only faces half of the office, due to the limited angle of view of the camera. Experiments were conducted for two days, within three periods of time: day 1: 10:00 – 11:30am: day 2, 11:00am – 1:00pm, day 3: 7:00 – 9:00 pm. Ground truth was recorded manually every time when the camera was triggered. We try to make the testing periods as diverse as we can, changing the levels of occupancy at times of the day. Although the two morning periods on day 1 and day 2 were similar in terms of occupancy, on day 1 there was a visitor in the office. The frequent communication between the visitor and occupants inside the camera range caused movement of people, which complicates the scenario. The implemented system achieves 36.11% accuracy with RMSE of 1.1. We use the majority vote method in this scenario because of its relatively better performance for downloaded images, as shown in Table I.

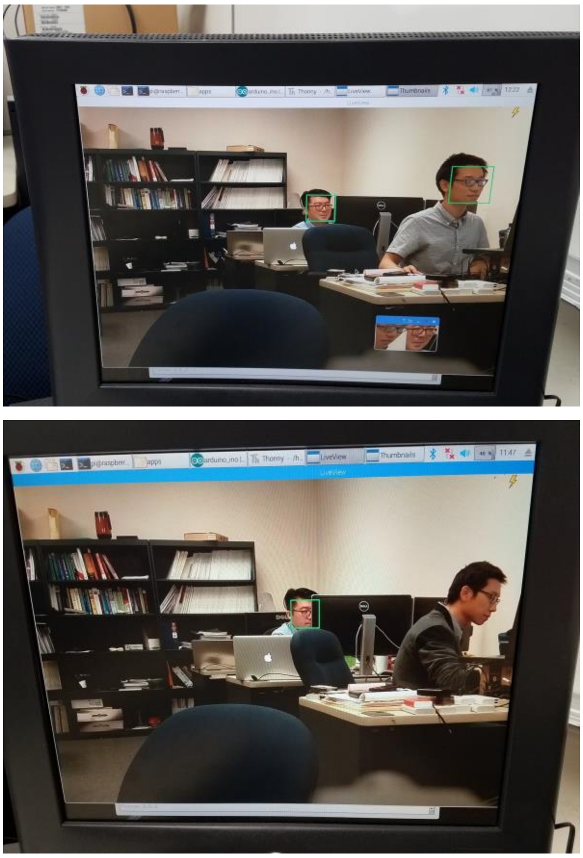

Fig. 4: Testing example from real-time scenario experiment

A real-time detection example is shown in Fig. 4. In the first figure, the two occupants' faces were successfully detected. However, one occupant is missed in the second image. Side face detection is a challenging problem for face detection. The model implemented in our system is mostly trained by front faces. Hence, the detection error is not surprising. Adjusting camera angles, field of view and setup may solve the problem, but could raise the cost.

D. Decision Making

As specified in the ASHRAE thermal guidelines [21], the rate of change of cooling of an HVAC cooling system ranges from 5°C/hr to 20°C/hr. The indoor temperature design range is 18°C - 30°C. Since, we are using a servo motor as an actuator that simulates the HVAC system, so we are not able to change the actual temperature of the room based on the occupancy of the room. So, we simulate hourly occupancy count values over a 24-hour period on a common weekday in our office, SENSQ 6410. The average number of occupants in the simulated data is 2.6 persons per hour, with an average of 6 persons per hour during the peak period from 11 am to 6 pm. We implemented the thermal model on the simulated occupancy data using equations (2) and (3). Further, we compare the thermal comfort and energy savings using equations (4) and (5) for different cooling rates of HVAC.

As shown in Fig. 5 and Fig. 6, we evaluate our model using Cooling rates of 5°C/hr, 10 °C/hr, 15°C/hr, 20°C/hr and determine the appropriate cooling rate to be applied by the HVAC cooling system, depending on thermal comfort and energy savings. Since we evaluate our IoT system for occupancy detection and counting in our office, the type of activity for which we study the effects of different cooling rates in details is light activity (like working on a computer) because it is most applicable for our office. From ASHRAE and ISO standards of metabolic rates [18], we get the average metabolic rate for light activity as 120 W. With an initial temperature of 28°C and using equation (1), we calculate the average rate of change of temperature due to one adult male as 1.78°C/hr. Referring to Fig. 5 and Table III, we can see that among all the fixed cooling rates, for the cooling rate of 10°C/hr, the standard deviation of the average temperature is the lowest, the percentage of times that the temperature has been within the indoor temperature design range is the highest. So, by using equation (5), we find that thermal comfort is the highest for cooling rate of 10°C/hr among all the fixed cooling rates. Moreover, the average temperature is higher than the cooling rates of 15°C/hr and 20°C/hr. So, using equation (4), the energy saving is higher than that of rates 15°C/hr and 20°C/hr. Although the average temperature is higher for cooling rate of 5°C/hr, yet we do not choose it because of lower thermal comfort in this cooling rate.

However, if the HVAC system is capable of applying variable cooling rates depending on the "people load", then, as shown in Table III, the results are even better, with an increase in thermal comfort by 16.85% and an increase in energy savings of 2.35%.

TABLE III. EFFECT OF HVAC COOLING RATES ON ROOM TEMPERATURE FOR LIGHT ACTIVITY OF OCCUPANTS

Cooling Rate (°C/hr)	Light Activity		
	Avg Temperature (T_{avg} °C)	*Std. Deviation (δ_T)*	*Temp. In Range % ($f_{T,Range}$)*
5	43.42	17.86	50.00
10	26.75	3.12	95.83
15	24.05	5.44	83.33
20	22.59	7.14	66.67
Variable	27.38	2.67	95.83

For maintaining generality, we study the variance of room temperature for two other types of activity – Sleep and moderate activity. The rates of change of temperature calculated due to human metabolic rate are 1.2°C/hr and 2.4°C/hr respectively for sleep and moderate activity respectively. As shown in Fig. 6a, the fixed cooling rate that we should choose for sleep activity based on the calculations using equations (4) and (5) is the cooling rate of 10°C/hr (T_{avg} = 25.67°C, δ_T = 3.47, $f_{T,Range}$ = 100). For a moderate activity level of occupants (as shown in Fig. 6b), the fixed cooling rate that should be chosen is 15°C/hr (T_{avg} = 23.13°C, δ_T = 6.84, $f_{T,Range}$ = 41.67).

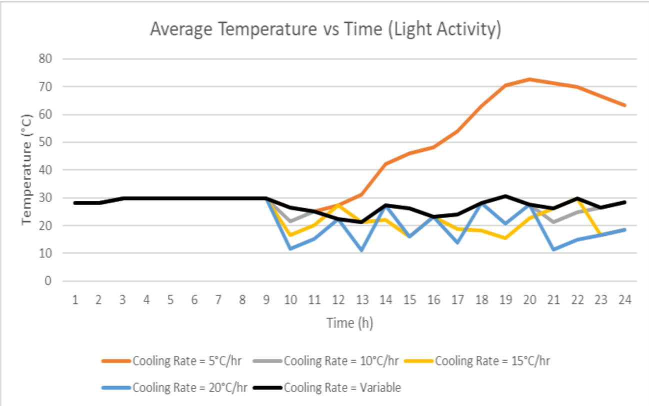

Fig. 5: Average Room Temperature vs Time for Light Activity

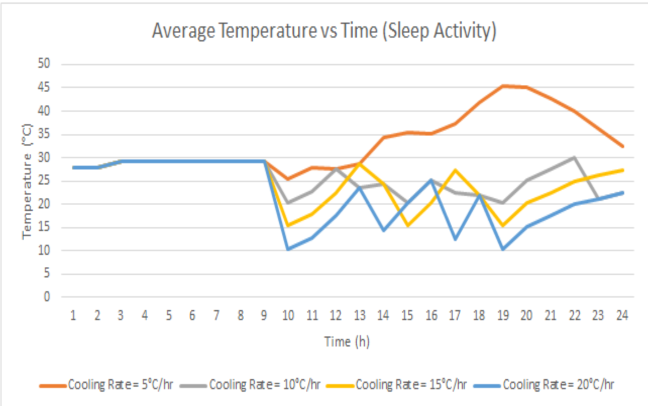

Fig. 6a

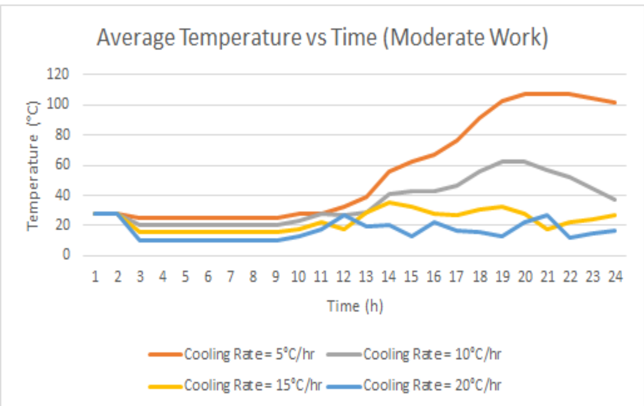

Fig. 6b

Fig. 6: Average Room Temperature vs Time for (a) Sleep activity (b) Moderate Activity (like hair dressing)

IV. Conclusion

In this paper, we have proposed an IoT system model that is capable of controlling HVAC systems based on occupancy. For occupancy detection and counting, the algorithm performs better for smaller number of people in the processed image frame (improvement in accuracy by 20% for less than 10 people compared to images with more than 10 people). Some of the obvious limiting factors that hinders the algorithm's performance for larger number of people, are limited angle of view of the camera, clarity of images and high dependence on the front face of the person for detection. Also, due to a better performance of the majority vote method (compared to clustering method) downloaded images, we apply it for experiment on real-time scenario.

Furthermore, for HVAC control, due to lack of the set of equipment to originally change the room temperature, we simulate the change in temperature based on the change in simulated occupancy numbers over time. We find that for an environment similar to our university office, SENSQ 6410, where ideal activity type is light computer work, the optimal fixed HVAC cooling rate is 10°C/hr. However, if the HVAC is capable of variable cooling rates, depending on the occupancy heat load, then the applying variable cooling rate performs better than the fixed rate of 10°C/hr in terms of thermal comfort and energy saving. Similarly, we estimate the ideal cooling rate for an activity of sleeping and for moderate activity.

One of the possible future works includes improving the accuracy of the occupancy detection and counting algorithms. Also, another future scope is to study the HVAC control strategies based on other additional parameters like building parameters, outdoor temperature, humidity and so on. Finally, the thermal comfort of the occupants can be further improved upon by taking actual thermal comfort feedbacks from the occupants.

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