Human Occupancy Recognition with Multivariate Ambient Sensors

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***Abstract*—With advancement in sensors and Internet of Things, gathering spatiotemporal information from one's surroundings has become easier, to an extent that we can start to use sensor data to infer indoor occupancy patterns. This paper aims to identify which ambient sensor is the most dominant in recognising human presence. Four different types of off-the-shelf sensors from two manufacturers were deployed to ensure that we could collect the following data reliably: illumination, temperature, humidity, levels of carbon dioxide, pressure and sound from within one staff office. Motion, power consumption, door opening and closing data and annotations from a self-developed mobile app were also collected as ground truth. We present our methods to preprocess the data and compute the number of people in the room with different classifiers, and identify sensors with strong and weak correlations. We explain our methodology for integrating large amounts of sensor data, discuss our experiments and findings in relation to the binary occupancy of a single person office, providing a baseline for recognising human occupancy.**

I. Introduction

Data obtained from U.S. Department of Energy indicates that the average cost of Heating, Ventilation, and Air Conditioning (HVAC) [1] accounts for 35% - 45% of the total maintenance costs within a building. Due to this factor, there are substantial investments to automate the temperature control system of a building, and any kinds of methodology to improve this area are heavily sought after. Reducing HVAC usage will massively reduce overall energy consumption. One way to improve this is to recognise human occupancy inside each particular space so a Building Management System (BMS) can intelligently adjust the HVAC.

The majority of buildings (especially older ones) do not have an adequate infrastructure to accurately sense people and locate where they are within a building, which makes it difficult to have an accurate occupancy data. Due to this fact, getting a precise ground truth value for analysis purposes will be challenging. Ambient sensors are readily available in most buildings with BMS, but have been under-utilised for occupancy recognition.

Ambient intelligence is a vision where technology blends naturally with our everyday life [2]. This area has become more important in recent years as more people are aware of their surroundings and want to know more about them. One approach to obtain information about the ambient environment is by using sensor data. With the latest technology, sensor devices are becoming more accurate and economical. In this paper, we propose a way of extracting sensor data and correlating this information with the number of occupants. Our research contributions are:

1) Feature engineering and selection method to determine top three dominant feature sets extracted from raw data and using statistical features.
2) With regression and correlation analysis, we determine the most dominant ambient sensor channel for detecting occupancy.

II. Related Work

Occupancy detection analysis has existed for some time and the biggest challenge is to do this without using image recognition. By using cameras [3], human occupancy detection can be accurate however this method raises privacy issues. Research communities have been doing their best to propose various methods to detect human occupancy.

As occupancy usually relies on motion detection, some researchers [4], [5] focus on measuring movement. One study used microwave motion sensoring to detect motion and then controls lighting with time delay to reduce electricity consumption [4]. Other research took advantage of ultra wideband radar to detect people because radar can work beyond the line of sight [5]. However, the cost to implement radars for occupancy detection is expensive. The most popular method for indoor occupancy detection is by using Passive Infrared (PIR) sensors [6], [7], [8], [9], [10], [11] as they are cheap and can detect motion easily. Some of them combine PIR sensors with magnetic reed switches and install the sensors on the doorjamb to detect when the door is opened or closed [6], [10], [12]. A combination of PIR sensor and magnetic reed switches has been used and implemented for many researches and it has become an unofficial standard to detect indoor human occupancy. SPOT+ uses Microsoft Kinect sensor, Arduino Microcontroller and an infrared sensor to detect and track the location of user [13].

In the last few years, Wi-Fi technology has been used to locate and count the number of occupants. Jiang et al. [14]

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developed ARIEL, a room localisation system that automatically learns room fingerprints based on occupants' indoor movement. Khan et al. [15] used only smartphones' acoustic, locomotive and location sensors with zero-configuration to infer the number of people present at one location. In their research, they required people to keep their smartphones in the pocket or in the hand which might not be an ideal in some cases. Recent work of Depatla et al. [16] in device-free area used only Wi-Fi signals to estimate human occupancy up to 9 people, however the accuracy was dropped significantly when the experiment was conducted indoors. Wi-Fi based localisation generally requires people to log in to the network or carry the device. There is another Wi-Fi based localisation techniques that does not require users to carry any device however it also only works for a limited number of occupants [17].

Given that occupancy recognition does not require users to be tracked, which would rely on the use of vision-based or wireless-based technology, we ask the following research question '*Is it possible to detect indoor occupancy using the proliferation of sensor devices that are already widely available in buildings and installed for other purposes so that we can leverage the functionality of these devices?*' Building-Level Energy Management Systems (BLEMS) project in University of Southern California [18] has thought about this possibility and decided to do it using several ambient sensors such as indoor temperature, relative humidity, illumination, carbon dioxide and sound sensors. The limitation of their research is that they did not use cross-validation to optimise the result and a limited types of sensors were utilised.

With regards to the location used in occupancy detection experiments, there are a few studies that focused on residential house [10], [12], [19]. Most research is usually related to user profiling for the purpose of reducing energy consumption. Other research focuses more on single person office room [4], [11], as it is a more controlled environment, and supervised learning could be implemented with fewer people engaged.

This research focuses on using contact-free, device-free approach of occupancy recognition using ambient sensors. With ambient sensors, users privacy are protected and they are widely available in existing buildings with HVAC systems installed [20], [21].

III. Methodology

A. Feature Engineering

For feature extraction, several types of sensors were used as our main features. The overall set of features are:

- Time: the time information in minutes as the lowest granularity.
- Segment of the Day: the daily event was divided into 4 equal subsections: morning, afternoon, evening and night (only for experiment 3).
- Indoor temperature (T): the room temperature, in Celsius, which is recorded by the sensor.
- Relative humidity (H): the ratio of the partial pressure of water vapour to the equilibrium vapour pressure of water recorded by the sensor.
- CO_2 rate (CO_2): the carbon dioxide content in ppm recorded by the sensor.
- Sound rate (S): the level of noise within a room in decibels recorded by the sensor.
- Atmospheric pressure (P): the value of pressure exerted by the weight of air recorded by the barometer.
- Illumination (L): the level of brightness within a room in lux recorded by the sensor.

To ensure the ground-truth data (the number of people who were staying in the room at that time) several other sensors and a web-based app were used as listed below:

- Door state: all opening and closing events are recorded.
- Power consumption: the monitor power usage is monitored.
- Motion sensor: detects and stores data if there is a motion within the range of the sensor.
- Occupancy App: Our own custom-built web-based app to gather ground truth data. The room owner stores data about times when people enter and leave the room and record the number of people in the room as it changes.

Door state, power consumption, motion sensor data are for ground truth and are not to be used as features for the data mining analysis.

Other than normalised raw data analysis, there are several derived features such as:

1) Ten minutes time segment
   a) Ten minutes time window with maximum value
   b) Ten minutes time window with minimum value
   c) Ten minutes time window with mean (μ) value
   d) Ten minutes time window with variance (σ) value
2) Part of the day segment: We divide the data into part of the day segments (morning, afternoon, evening and night). Below is the detail of the temporal segments division:
   - Morning is from 6AM to 12PM
   - Afternoon is from 12PM to 6PM
   - Evening is from 6PM to 12AM
   - Night is from 12AM to 6AM

To summarise, there are 8 main features that are used in our experiment.

B. Machine Learning Algorithm

In this paper, we used multi-layer perceptron, Gaussian processes with Radial Basis Function (RBF) as core, Support Vector Machine (SVM), Random Forest and Naïve Bayes to recognise the level of accuracy.

To identify the most dominant sensor, we fit our data to Linear Regression in equation (1) and perform regression analysis on it.

$$\hat{O} = \alpha T + \beta H + \gamma CO_2 + \delta S + \varepsilon P + \zeta L + \eta \tag{1}$$

where $\ddot{O}$ is the number of occupants, T is Temperature, H is Humidity, CO_2 is the level of CO_2, S is Sound, P is Pressure and L is Light (illumination). Our formula provides a straight-forward but effective way to identify the dominant sensors for human occupancy as they will have higher coefficients compared to the coefficients of the other sensors.

For each dominant sensor, we fit a fourth order polynomial and perform a logistic regression analysis to check the goodness of fit and R^2, a statistical measure of how close the data are to the fitted regression line. For our final evaluation, we compute the Pearson product-moment correlation coefficient to check the correlation between each sensor and the occupancy data.

IV. Data Collection and Preprocessing

A. Type of Sensor Devices

For this experiment, we deployed one Z-Wave Aeon Multi Sensor, one SmartThings SmartSense Open/Closed Sensor, one SmartThings SmartPower Outlet and one Netatmo Urban Weather Station shown in Fig. 1. We ran the experiment for two weeks continuously and gathered the data for indoor temperature, relative humidity, the rate of carbon dioxide (CO_2), sound level, atmospheric pressure, level of illumination, whether the door was open or closed, power consumption of the monitor and the motion within the room.

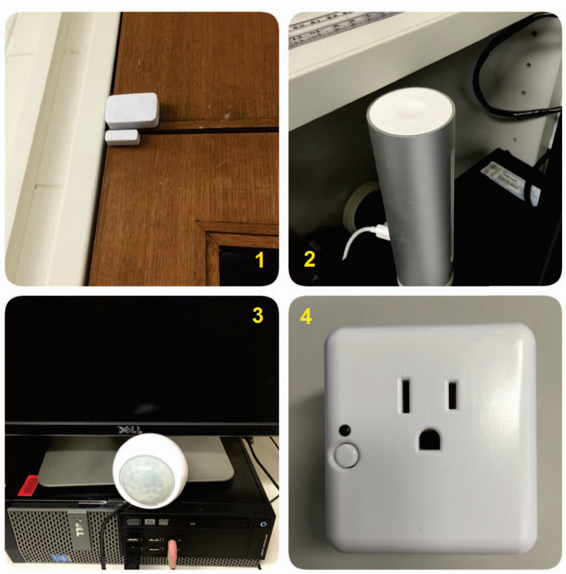

Fig. 1. (1) SmartThings SmartSense Open/Closed Sensor; (2) Netatmo Urban Weather Station; (3) Z-Wave Aeon Multi Sensors; and (4) SmartThings SmartPower Outlet

For SmartSense Open/Closed Sensor, we deployed it on the door to detect the opening or closing of the door. The Urban Weather Station consists of multivariable sensors that can detect indoor temperature, relative humidity, atmospheric pressure, rate of CO_2 in air and sound level. For the SmartPower Outlet, we combined it with a step-down converter due to the difference in voltage between the device's country of origin (U.S.A.) and our country voltage (Australia), and it is installed to the monitor. The last device is Multi Sensors which is the combination of the four sensors (indoor temperature, relative humidity, illumination level and motion sensor). We deployed this device in front of the user, below the monitor so it would detect the user motion every time the user sits in front of the PC.

B. Occupancy Web-based Application

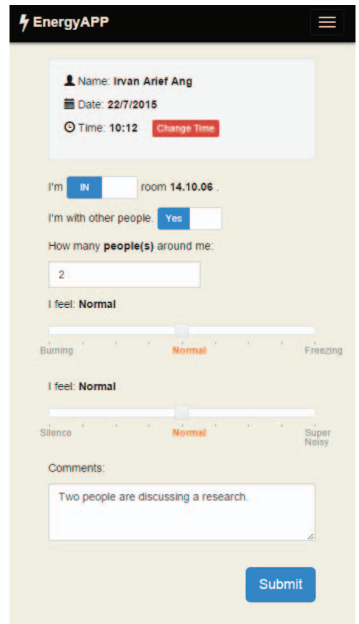

Fig. 2. Occupancy web-based application

We developed an occupancy application to collect user annotations of their room's actual occupancy. This is a web-based application for the room owner to fill every time an event happens with the door where event means there is person comes in or out. The interface of this application is shown in Fig. 2.

C. Data Preprocessing

To be able to recognise indoor human occupancy and correlate it with ambient sensor data, the ground truth about the number of people within a room at specific time is required. On the other hand, privacy must be respected and therefore the use of cameras was not an option. Thus, multiple methods are applied to secure a solid ground truth.

Human occupancy ground truth data is collected from a web-based application that provides a form which needs to be filled in by the resident every time anybody enters and leaves the room. As ground truth data from human input may be unreliable, we put three more ground truth validation layers to ensure high quality ground truth data. The first validation layer is power consumption sensor that connects to the monitor. If the power consumption goes up

TABLE I

LIST OF COEFFICIENTS FOR EACH PARAMETER FOR LINEAR REGRESSION FORMULA (IN PERCENTAGE)

Experiment	Temp (α)	Humidity (β)	CO2 (γ)	Sound (δ)	Pressure (ε)	Illumination (ζ)	Coefficient (η)
Exp. 1	-29.55	-6.2	**144.8**	54.98	-12.15	83.59	-0.06
Exp. 2 - Max	-26.96	-6.9	**137.66**	51.82	-12.32	83	-0.48
Exp. 2 - Min	-40.5	-5.11	**132.09**	49.12	-15.81	74.82	6.43
Exp. 2 - Avg	-31.59	-6.23	**128.85**	55.03	-13.28	82.4	1.57
Exp. 2 - Var	26.39	0	53.79	159.23	68.86	**213.29**	5.98
Exp. 3	0	0	0	**96.57**	0	64.46	-6.28

after a while, it is best to assume that there is a person in the room. The second validation layer is motion sensor and the last ground truth assurance is the door open and close sensor. Every time the door is opened and closed, there is a possibility that the number of human inside changes. With those three more validation layers of ground truth, we have developed a rigorous evaluation method to get an accurate number of indoor human occupancy without using a camera. For data collection, we set up background devices to gather the data from various different sensors. As we gather the data using a variety of devices, data integration is challenging. Some sensors' data (temperature, humidity, illumination, CO_2, sound and pressure) are continuous data. On the other hand, door open/close and web-based app data are events based discrete data. We use the timestamp to integrate the data and generate the missing data using the interpolation method.

Algorithm 1 Fixing missing occupancy value Algorithm

```
procedure MISSING_OCCUPANCY(SensorData[t])
    Occ[t] ← 0                          ▷ Occ[t]: Occupancy
    PC[t] ← low                         ▷ PC[t]: Power Consumption
    M[t] ← low                          ▷ M[t]: Motion
    DS[t] ← 0                           ▷ DS[t]: Door State
    for each node i ∈ SensorData[t] do
        if (Occ[i] = 1) AND (PC[i] = high) then
            if (M[i] = high) AND (DS[i] = 1) then
                SensorData[i].Occupancy ← 1
            end if
        end if
    end for
end procedure
```

Each sensor data was normalised between 0-1 to ensure consistency. The normalisation process was conducted for each type of sensor. All indoor human occupancy data from the web-based app input was converted to binary occupancy and was integrated with normalised sensor data using timestamp as the joint key.

V. EXPERIMENT, RESULT AND ASSUMPTION

In this paper, we present three experiments with the data. The first experiment used the normalised raw data with the pre-processing method which was explained in the previous section. We used each of the data mining algorithms mentioned previously to determine the most accurate algorithm. In the second experiment, the normalised raw data was aggregated at ten minute intervals. Several statistical features such as maximum value (max), minimum value (min), average value (μ) and variance (σ) were used for analysis. We adopted the same data mining algorithms for each feature to see if the result differs from the first experiment. The third experiment the data is segmented into four temporal segments (morning, afternoon, evening, night) before using each data mining algorithms. The reason behind this is that every temporal segment has a different context which may indicate the difference in occupancy number (i.e.: night time has less people) so this is a reasonable segmentation. We compared all three results and find out which condition generates the highest level of accuracy. Table I result shows coefficients result for equation (1).

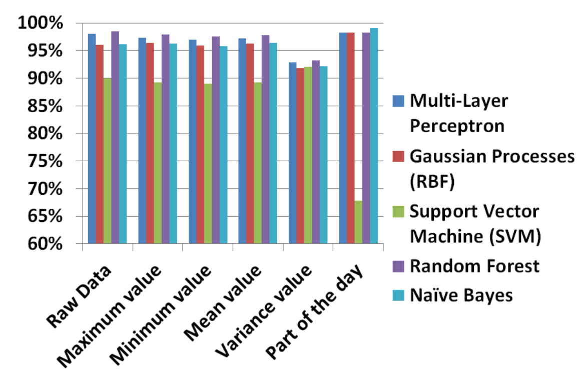

Fig. 3. Accuracy result of various machine learning algorithms

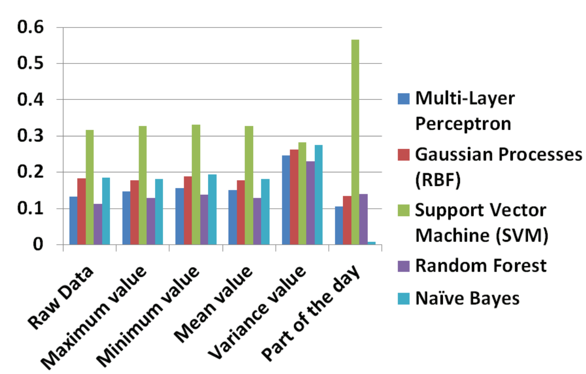

Fig. 4. RMSE result of various machine learning algorithms

A. Experiment 1 (Normalised raw data)

This experiment utilised a total of 32,152 normalised raw data points that were collected from one single person office room. Table I shows that CO_2, light and sound are three dominant features to be considered for human occupancy recognition. As can be seen in Fig. 3, Random Forest has the highest accuracy result and has a more stable performance across different feature sets in comparison to other machine learning algorithms. Fig. 4 shows that most machine learning algorithms have low RMSE except SVM. With this finding, the accuracy result can be trusted.

B. Experiment 2 (Ten minutes time segments)

For ten minutes time segments, four sets of features are extracted: data analysis with maximum value (max), minimum value (min), average value (μ) and variance (σ). For the first three experiments in maximum, minimum and mean (μ) value, the result are similar with Experiment 1 (refer to Table I, Fig. 3 and Fig. 4). However last experiment with variance (σ) value resulted differently. Table I shows the relative humidity is ignored. The top three dominant features are the same (light, sound and CO_2) albeit different order compared to the previous ones. Fig. 4 shows that Root Mean Square Error (RMSE) value is between 0.2 to 0.3. As the degree of error is quite high, accuracy result for each machine learning algorithm could not be trusted.

C. Experiment 3 (Part of the day segments)

From Fig. 3, the level of accuracy for majority of machine learning algorithms are generally higher than the raw data. This result is acceptable as aggregate data by part of the day make the data more congested. There are two outputs that need to be highlighted. First, the accuracy of SVM classifier significantly dropped (<70%), however Naïve Bayes classifier achieves very high accuracy level (>99%) with very low RMSE.

D. Most Dominant Sensor in Determining Human Presence

Based on the result of all the experiments in Table I, we conclude that the top three dominant sensors to recognising indoor human occupancy are CO_2 rate, illumination level and sound rate sensor. Table II contains both R^2 value and Pearson correlation r value for top three sensors mentioned above.

1) CO_2 rate vs indoor human occupancy: Fig. 5 shows that CO_2 correlated well with number of occupancy. Once the carbon dioxide exceed 600 ppm, there is a high change (>0.7) that there is at least one person inside the room. The logistic regression model is good and it has a very strong R^2 value (0.9272). In Table II, Pearson's r value is high and it shows a very strong correlation between CO_2 rate and the indoor human occupation recognition.

TABLE II
R^2 VALUE AND PEARSON CORRELATION R VALUE FOR THREE MOST DOMINANT SENSORS TO RECOGNISING INDOOR HUMAN OCCUPANCY

	R^2	Pearson correlation r
CO_2 rate	0.9272	0.882469
Illumination level	0.7665	0.288449
Sound rate	0.9317	0.897066

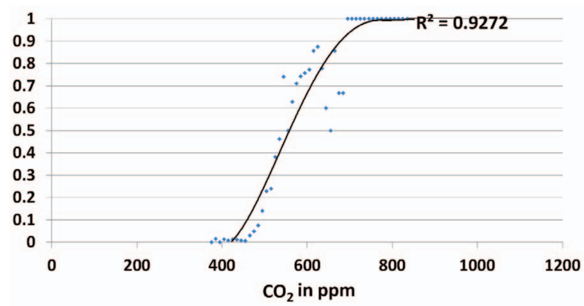

Fig. 5. Occupancy recognition probability over CO_2 level

2) Illumination level vs indoor human occupancy: Fig. 6 shows that illumination level is not highly correlated to number of occupant. R^2 value (0.7665) is not really high as well. Our conclusion is once the value of illumination level is above 10 lux, there is a high change that inside the room there is at least one person (>0.8). Regardless of whether the room getting brighter or not afterwards, it is indifferent for the occupancy recognition.

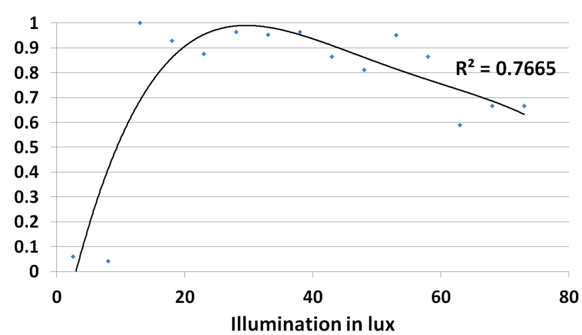

Fig. 6. Occupancy recognition probability over illumination level

The Pearson's r value in Table II shows that it has a weak correlation. An external factor such as window placement in the room complicates the number as the sun will make the room brighter during midday compared to night time. This reasoning is the main cause of why there is lux >70 however occupancy recognition probability is only close to 0.7.

3) Sound rate vs indoor human occupancy: In Fig. 7, there is a strong correlation between sound rate and number of occupant. Below 40 dB, the probability of the human inside a room is 0. Once the value reaches 53 dB and above, we discover that there is at least one person inside the room. The logistic regression model also fit perfectly with a high goodness of fit value (R^2 = 0.9317) so we can safely assume that this regression fitting line have a great correlation with the sound rate aggregate data.

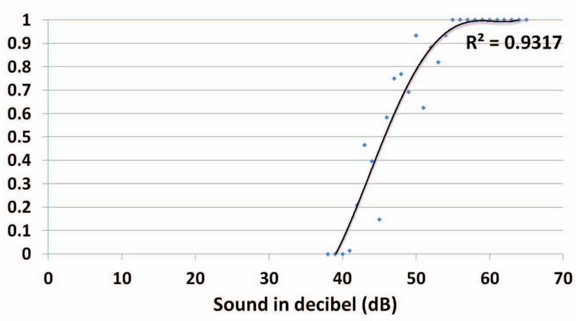

Fig. 7. Occupancy recognition probability over sound sensor rate

Based on Pearson's r value in Table II, it has a very strong correlation between sound rate and the indoor human occupation recognition.

VI. Conclusion, Limitation and Future Work

By using only non-intrusive ambient sensor data, we have shown that it can be used to recognise indoor human occupancy accurately. With Random Forest data mining classifier on normalised raw data and aggregated data using various methods of statistic, we managed to achieve an accuracy level as high as 98%. With the right treatment of data aggregation, Naïve Bayes can achieve 99% accuracy. This level of accuracy is higher than any other similar studies before. We also proved that CO_2 rate, illumination level and sound rate are the top three most dominant features to detect indoor human occupancy and the most dominant one is CO_2 rate. This result is encouraging because when there are more people inside one room, the rate of CO_2 in that room gradually increases.

As our research was only conducted in one location, we plan to expand this research to many locations. The research that has been done above is based on off-line learning. For future work, real-time on-line learning can be adapted to this problem. Future work also includes the use of CO_2 data alone to estimate the number of occupants in different rooms with varying configurations and usage patterns.

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