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Indoor occupancy estimation using carbon dioxide concentration and neural network with random weights

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Abstract. This study presents the indoor occupancy estimation using carbon dioxide concentration and neural network with random weights (NNRW). The utilization of carbon dioxide concentration is as an alternative to overcome the limitation of existing techniques, such as dependency to favourable lighting condition and camera position. Whereas, NNRW provides a generalized and fast learning speed classification. In this study, MH-Z19 sensor is used to acquire carbon dioxide concentration and the NNRW is a multiclass estimation method. The numbers of the occupants are divided into three different classes, which are 15 occupants, 30 occupant and 50 occupant classes. Result indicates that the NNRW classifier has obtained training and testing accuracy, about 100 percent and 52 percent, respectively.

1. Introduction

Humans have been known to reside inside their shelter since the dawn ages for the reason of safety and comfort. Human comfort can be influenced by four factors, which are wind, temperature, radiation and humidity. In that term, obtaining an optimum human comfort inside a building is a paramount important for most aspect of buildings development. A mechanical ventilation system has been introduced to do so. Heating, ventilation and air conditioning (HVAC) system is a system that can provide three out of those four factors. HVAC is a system that ventilates the heating and air conditioning in a closed area. The system is important as them responsible for providing acceptable indoor air quality and thermal comfort to the occupants. Overall, it provides a condition that is comfortable for the humans inside a room. However, current system unable to operate optimally as centralized air conditioning has led to energy wasting due to its inability to operate based on the presence of people time and zone [1]. An optimum HVAC system can save energy up to 15% to 25% if it is set to respond based on indoor occupancy data [1].

Input data on predicting the indoor occupancy can be obtained by two main methods, in which 1) multi camera pattern techniques (using camera) and terminal based techniques and 2) terminal based

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techniques. Terminal based techniques rely on the human movements to the appliances such as keyboard and mouse. However, both methods are flawed in nature as the previous depended on lighting conditions and the camera location [2], while the second techniques cannot detect occupants that are not using the selected devices. Others sensors have also been used to estimate the number of occupancy including pyroelectric infrared (PIR) and ultrasound sensors. But these sensors can only detect presence of humans, but not estimate the number of humans inside the room [3]. These limitations have led to the implementation of environmental parameters such as humidity, temperature and carbon dioxide concentration. Since humans naturally exhaled carbon dioxide, the occupancy in a closed area can be obtained through carbon dioxide (CO_2) concentration [4]. It is also non-intrusive and non-terminal based, which is alternatively solved the problem encountered by existing techniques [3].

CO_2 concentration for indoor is usually between 350 to 2500 ppm [1]. In terms of CO_2 sensor, there are two types of sensor. First is chemical CO_2 sensor. The second one is Non-Dispersive Infrared (NDIR) CO_2 sensor. Chemical CO_2 sensor is noted to have a short life span and unsuitable in practical world [5]. NDIR sensor is noted to have higher accuracy and durability. The sensor in concern of the method is NDIR based. MH-Z14A PWM NDR Infrared carbon dioxide sensor [6], MQ135 sensor [7], B-530 sensor, H-550 NDIR sensor [5], K30 sensor [1, 8] and MH-Z16 NDIR sensor [9] have all been tested by recent research and have the ability to correctly monitor CO_2 concentration in indoor setting. Several occupancy prediction methods were used to predict the number of occupants. Extreme Learning Machine [3], Artificial Neuron Network [10], and Decision Tree [11] have all been tested by recent researchers.

In this study, carbon dioxide sensor, MH-Z19, is used to measure the concentration of carbon dioxide in a closed area. Next, NNRW classifier is implemented to estimate the number of occupants in a closed area in between three groups (15,30, and 50 occupants). This information, in future, can be used in controlling regulating HVAC system in a closed area. This will lead to a more efficient energy usage.

2. Methodology

2.1. Electrical schematic

The MH-Z19 carbon dioxide sensor will be connected to the Arduino Nano. The Arduino Nano will then be powered by USB connection with laptop. The connection of the sensor with the Arduino is as in Table 1 and Figure 1.

Table 1. MH-Z19 carbon dioxide sensor connection with Arduino Nano.

MH-Z19	Arduino Nano
PWM	*D05*
GND	*GND*
Vin	*5V*

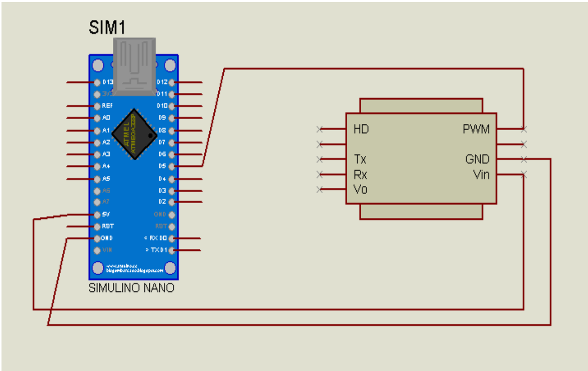

Figure 1.MH-Z19 carbon dioxide sensor connection with Arduino Nano.

2.2. Data collection

The data collection was done inside a classroom sized 6.75 meter times 9.00 meters. The data collection will be done during the class is occupied and when it is vacant. The time for data collection is shown in Table 2. Student count is done through observing. There will be three different numbers of students, which are 15 students, 30 students and 50 students. The sensor will be put at the back of the room to minimise interruption for the occupants learning process. The windows of the class are locked down to minimise air flow going in and out of the classroom. The classroom door was also closed. The air conditioner and air ventilating were ensuring to be in functioning during the data collecting. The data collection will occur for every second for at least 30 minutes.At least three set of data were obtained for each classes to ensure consistent reading. However, the effect of students going in and out of the classroom and the best sensor position for occupancy prediction is out of scope for this experiment. In theory, human occupancy should affect the reading of the sensor.

Table 2. Data collection schedule.

Time	Day	Number of occupants
8.00 AM – 10.00 AM	Monday	15
8.00 AM – 10.00 AM	Tuesday	15
2.00 PM – 4.00 PM	Tuesday	30
8.00 AM – 10.00 AM	Thursday	30
2.00 AM – 4.00 PM	Thursday	50

Figure 2. Classroom where the study conducted

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2.3. Sorting of the data
The raw data is obtained from the Arduino Serial Monitor. The data is copied manually and then sorted in Microsoft Excel in ascending order. A graph will be plotted from the data with PPM reading as y-axis and seconds as x-axis. Another Microsoft Excel file is created in order to sort the data again. This time divided into three part, number of data, data sample and class. There will be 300 rows with 50 data per row, representing 50 input. The row will be labelled into three different classes (class 0 for 15 occupants, class 1 for 30 occupants, and class 2 for more than 30 occupants/50 occupants). Each class will have 100 rows of data, totalling 15,000 of datasets. The file will then be analysed and saved.

Two m.file will be created. One m.file will be detailing and setup the NNRW. Another m.file will execute the training and predicting the result. The Excel file will then be link with MATLAB for training purposes. The hidden neuron will be set to 800 while the activation function is set as manipulated variable. 225 datasets will be used for training purposes while another 75 will be used for predicting purposes. The NNRW will predict whether the dataset is in class 0, class 1 or class 2. This is illustrated in Figure 3. The result will be displayed after running ended on the Command Window. The step was repeated with changing the number of hidden nodes (200, 400, 600, 800) for each activation function (Sigmoid, Sine, Hardlim, Triangular basis and Radial).

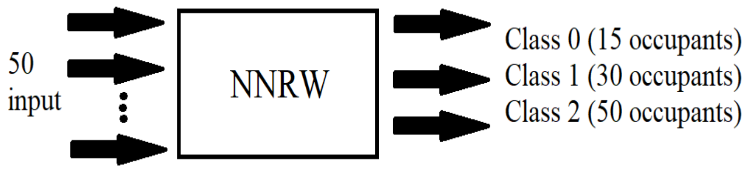

Figure 3. Sorting of the data.

2.4. Classification of the data
Neural Network with Random Weight (NNRW) is a non-iterative algorithm that have high convergence rate, fast training speed and produce certain model, difference than the traditional ANN, such as BP-based method. It was first proposed in 1992. One of the biggest differences between NNRW and BP-based method is the fact that its output weight is obtained analytically while the hidden weights are randomly selected. [12] have proposed a generalized version of NNRW, called ELM. ELM is proven to have universal approximation capability and have the ability to approximate any continuous target function with probability one under certain condition. It also has allowed nonlinear piecewise continues random hidden nodes to be used. This includes but is not limited to Sigmoid nodes, Wavelet and etc.

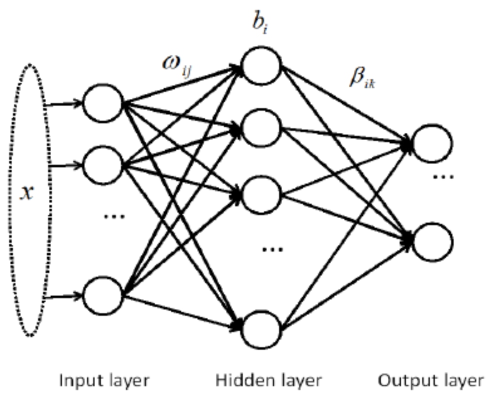

Figure 4. NNRW structure. Source: [13]

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As an overview, NNRW, such as in Figure 4, consists of three layer, input layer, hidden layer and output layer. ωmean the weight between the input layer and hidden layer. $b$mean the threshold of hidden nodes, while β represent the output weights. There is an activation function in the hidden layer which performs nonlinear transformation. That activation includes but is not limited to Sigmoid, Sine, Hardlim, Triangular basis and Radial basis function. It is basically Equation 1;

$$H\beta = T \tag{1}$$

Which means;
H= Hidden layer output matrix of the neural network
B = L*m matrix of the output weights
T= N*m matrix of target
m = The number of output neurons

NNRW classifier of a given unknown sample, x will produce output function which is:

$$fc(x)=hc(x)\beta \tag{2}$$

3. Result and discussion

3.1. Carbon dioxide reading inside an occupant area

Figure 5 shows that there is a stark difference in term of reading for indoor area that is packed with 15, 30 and 50 occupants. On average, one person will increase the reading by 26 PPM. On average, 15 occupants will have 1000 PPM reading, 30 occupants will have 1400 PPM reading and 50 occupants having 1500 PPM reading.

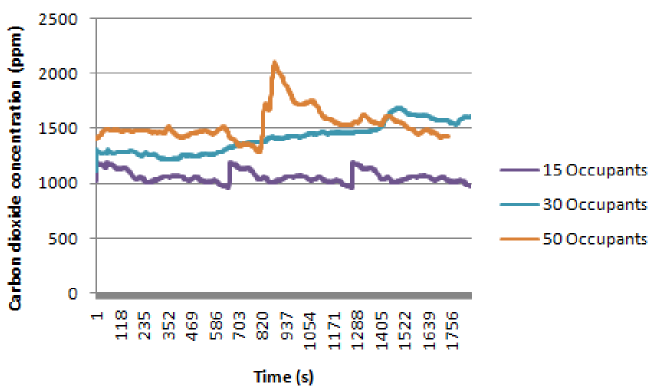

Figure 5. MH-Z19 reading comparison in indoor area.

3.2. Pattern of the data

The data collected were divided into three different classes, class 1 for 15 occupants, class 2 for 30 occupants, and class 3 for 50 occupants. Pattern of average, mode, median, standard deviation, minimum value (Min) and maximum value (Max) were tabulated on Table 3 and Figure 6. Based on the table, the minimum value is 567 PPM and the highest reading is 1706 PPM. The mode for class 0 is 698 PPM, 1251 PPM for class 1, and 1482 for class 2. On average, class 0 will have reading at 699.8706 PPM, class 1 at 1199.6910 PPM while class 2 have average reading at 1452.1320 PPM. Mode for class 0 is 698.0000 PPM, class 1 is 1251.0000 PPM while class 2 at 1482.0000 PPM. Median for class 0 is 698.0000 PPM, class 1 is 1219.0000 PPM and class 2 is 1462.0000 PPM. The standard deviation for class 0 is 34.8844, class 1 is 117.9111 while class 2 is 81.1304.

Table 3. Pattern of the data according to the classes

Classes	**0**	**1**	**2**
Average	699.8706	1199.6910	1452.1320
Mode	698.0000	1251.0000	1482.0000
Median	698.0000	1219.0000	1462.0000
Standard Deviation	34.8844	117.9111	81.1304
Min	567.0000	969.0000	1115.0000
Max	937.0000	1452.0000	1706.0000

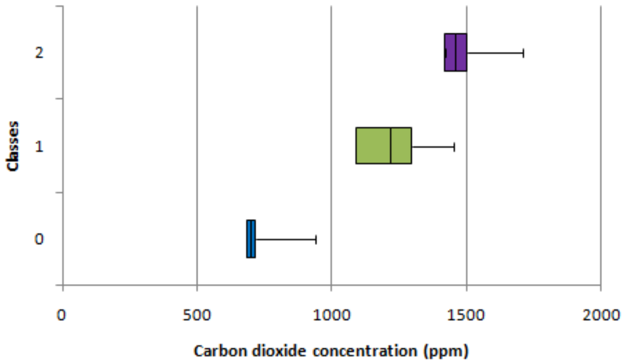

Figure 6. Pattern of the data according to the classes.

3.3. Predicting occupancy accuracy (comparison between activation function)

As illustrated on Table 4, sin activation function produces the highest accuracy, in term of training and testing. The training is higher 45.66833% compare to the second highest, Sig activation function. The testing accuracy is higher 10.50467% compare to the second highest, also Sig activation function. Tribas, on the other hand, produce the worst result in both area (36.80392% for training and 33.88235% for testing).

Table 4. Predicting accuracy (comparison between activation function)

Activation Function	**Training**	**Testing**
Sin	100.0000	52.67137
Sig	54.33167	42.16667
Hardlim	53.27538	41.52744
Tribas	36.80392	33.88235
Radbas	41.12289	34.98423

3.4. Predicting occupancy accuracy (comparison between number of hidden nodes)

Changing the number of hidden nodes gives affect the result differently for each activation function. It increases the training and testing accuracy for sig, hardlim and radbas activation function. It causes the training accuracy to fluctuate for tribas activation function. It did not give any significant differences when tested with sin activation function. This is illustrated in Table 5 till Table 9.

Table 5. Predicting accuracy for Sin activation function (comparison between number of hidden nodes)

Number of hidden nodes	Training	Testing
200	100.00000	52.42167
400	100.00000	52.57210
600	100.00000	51.70002
800	100.00000	52.67137

Table 6. Predicting accuracy for Sig activation function (comparison between number of hidden nodes)

Number of hidden nodes	Training	Testing
200	42.193460	37.416025
400	47.1565800	39.639646
600	51.4934700	40.960785
800	54.3316675	42.166666

Table 7. Predicting accuracy for Hardlim activation function (comparison between number of hidden nodes)

Number of hidden nodes	Training	Testing
200	41.96111	37.03541
400	46.49768	39.28624
600	49.99418	40.60465
800	53.27538	41.52744

Table 8. Predicting accuracy for Radbas activation function (comparison between number of hidden nodes)

Number of hidden nodes	Training	Testing
200	31.78055	30.80000
400	35.40015	32.26577
600	38.84685	34.94595
800	41.12289	34.98423

Table 9. Predicting accuracy for Tribas activation function (comparison between number of hidden nodes)

Number of hidden nodes	Training	Testing
200	34.13399	33.21421
400	36.70173	33.46135
600	35.74194	33.41577
800	36.80385	33.88235

4. Conclusion

Overall, the objective of the study managed to be achieved. The study managed to estimate the number of people in a closed area using carbon dioxide sensor by measuring the carbon dioxide concentration in a closed area. It also managed to find the best result on two parameters, activation functions and number of hidden nodes using NNRW. It was tested with sin, sig, hardlim, radbas and tribas activation functions. It was later on checked with 200, 400, 600 and 800 hidden nodes. The best result obtained when it were tested with sin activation function and 800 hidden nodes, where it achieved 100% training accuracy and 52% testing accuracy respectively. The result cannot be higher due to the fact that the testing and prediction is done using raw data.

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