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Carbon Dioxide Sensor Application In Building Energy Efficiency

Kasham Jummai Shamang
Department of Architecture, Faculty of Environmental Sciences, Kaduna State University, Nigeria

Miriam Ijeoma Chukwuma-Uchegbu*
Architecture Department, School of Environmental Sciences, Federal University of Technology Owerri, Nigeria

Garnvwa Jennifer Dawi
Nigerian Building and Road Research Institute, North Central Zonal office Jos, Nigeria

Allan Joseph Usman
Department of Architectural Technology, Federal Polytechnic Nasarawa, Nasarawa State, Nigeria & Department of Architecture, Abia State University, Uturu, Abia State, Nigeria

kashambiliyok@hotmail.co.uk, mimchuks@gmail.com*, garnvwajay@gmail.com, allanjosephusman71@gmail.com,

***Abstract*— Many smart home applications such as crowd activity, motion detection, and assisted living to depend on the occupancy data which heavily rely on occupant carbon dioxide. Though facial recognition using computer vision assisted by cameras can help to ensure precise occupancy details, they are expensive, disruptive, and difficult to generalize to various settings. An alternate method will accomplish the same degree of precision while addressing the concerns posed. This study illustrates the scalability of the Wireless Sensor Network-based WSNs on CO2 estimation is a viable option. This study suggested a prototype for tracking indoor daily living practices, which involved the use of humidity, CO2, and temperature sensors, as well as CO2 concentration measurements, for predicting room occupancy.**

Keywords— Smart indoor, CO2 concentration, sensor, energy efficiency

I. INTRODUCTION

As computing power and device automation become more widely accessible, there is a growing need for smart, integrated systems. End users want a smart system to enable them to anticipate their desires and react accordingly to improve their lifestyles. To face this challenge, any smart machine must be sufficiently informed about the particular action that is needed along with the state of indoor environment parameters [1]. This clear precedent must be observed and analyzed in some manner before the process can take it into account.

Technologies for smart building, crowd motion analysis, and occupant activity detection are only a few of the smart system applications that are already being developed. One feature both of these applications have in common is that they all need knowledge about where occupants are in the measurable environment. While some occupancy-based systems perform well in some of these scenarios, developing a framework that can generalize and operate in a variety of environments is challenging.

The technology used for smart office control in a large office building differs considerably from that used for smart home control. Smart security cameras may be ideal for such an office environment, but they may not be appropriate for big crowds or in an occupant home. To deal with a broader range of issues, the occupancy background should approximate the number of people present.

Therefore, a suitable solution should be able to perform anonymous and non-invasive sensing in addition to generalizing across applications. WSNs provide a feasible solution to this challenge by sensing the environmental variables, it is possible to build sensing nodes that can predict occupancy while preserving occupant confidentiality. By connecting these sensing nodes, the occupancy estimation method can generalize to a variety of applications and domains of differing sizes. Machine learning models may accompany WSN to resolve the problem of domain-specific environmental variation. Although these learned models are capable, their design space is vast and not easily constrained by the conventional design constraints of a WSN.

This section illustrates a WSN prototype that uses CO2 observations to help in node occupancy estimation. In the indoor environment, the proposed prototype was trained using estimation models. Additionally, the system accuracy is observed and the design procedure concerning the models is discussed.

This paper's structure is as follows: The second section describes the prototype modularity and training models used for occupancy estimation research. Section 3 defines the system implementation, which provides details about the planned prototype and operational requirements. Section 4 discusses machine learning models and elaborates on the architecture parameters that are of interest as well as the essence of the experiments. Section 5 summarizes and addresses the findings of these articles, and Section 6 concludes with remarks.

II. Literature Review

[2] proposed the use of ambient technology to measure indoor occupancy using indoor environmental variables. Among the indoor variables such as carbon dioxide production, indoor temperature, and relative humidity. The features are extracted from these variables using the most appropriate feature extraction techniques based on Relative Information Gain (RIG). Three machine learning techniques (MLT), namely Artificial Neural Network (ANN), Support Vector Machine (SVM), and Hidden Markov Model (HMM), were trained to estimate occupancy using the best features. For different testing days, their estimate accuracy ranged from 58 percent to 75 percent.

[3] expanded on the previous study's results by looking at the measurement precision of a certain number rather than a value. Since chosen the occupancy ranges to affect the performance of precision percent on some test days. The observations of the writers were restricted to individual bays of three to five inhabitants each, rather than the entire office where the data was gathered. Furthermore, the results of the ANN were noisy, with constant variations.

[4] used an approach similar to [5] but instead of a RIG, they used a scale of symmetric uncertainty, eventually reaching 75% prediction precision with an ANN.

The maximum number of people who could be in the house was limited to eleven. They also failed to account for the indoor climate's ambient pressure levels, which the occupants can influence. [6] . For seven days, carbon dioxide, light, vibration, power consumption, and motion sensors were tested in an office environment. They did not use the data to assess occupancy; rather, they used it to predict the presence or absence of occupancy. They used decision trees to pick the functions. Based on the weighted function incidence of the random forest the features extracted from occupant carbon dioxide data. This contrasts with the vast majority of other occupancy measurement studies, which rank carbon dioxide near the top of their feature selection algorithms.

The feature selection in [7]; [8] the correlation measure was created using a filter model system, which means that it is independent of the classification algorithm. As a consequence, there is no certainty that the features chosen would have the most trustworthy calculation. A different approach is to use a wrapper process of extracting features that involve initial and final feature classification by the same MLT. As a result, the function collection is adapted to the machine learning technique in use, resulting in increased precision. [9] & [10] used sensor networks to estimate an open office's occupancy testbed using CO2, CO, total pollutants, PM2.5, sound systems, lighting, rotation, temperature, and humidity. First-order deviation and 20-minute incremental conductance were extracted as simple statistical functions. The most important features were then chosen using knowledge gain theory. MLT such as SVM, ANN, and HMM was employed and applied an ELM-based wrapper approach for feature extraction and compared it to an information gain filter-based feature ranking system. Experiments proved that the solution they proposed was successful.

[11] investigated different combinations of sensors, such as motion, vibration, indoor, temperature, humidity, CO2, illumination, and light intensity, to predict occupancy using six data-driven approaches. The approach used raw data from sensors for features gathering. It's worth noting that the writers used a vast range of sensors to ensure that their system works properly. The information gain hypothesis was used to evaluate each sensor's contribution (feature). The three most informative variables were discovered to be CO2, door state, and light levels.

A CO2, temperature, humidity, and light level-based occupancy detection system was recently presented [12]. They used raw sensory data as features same as applied to the recent study conducted by [13]. To measure and predict occupancy the presence, statistical models were used. They experimented with different feature combinations and mathematical models before deciding on the most appropriate feature selection model. Finally, the study chose the SVM technique for the feature selection and learning algorithms that would lead to good results.

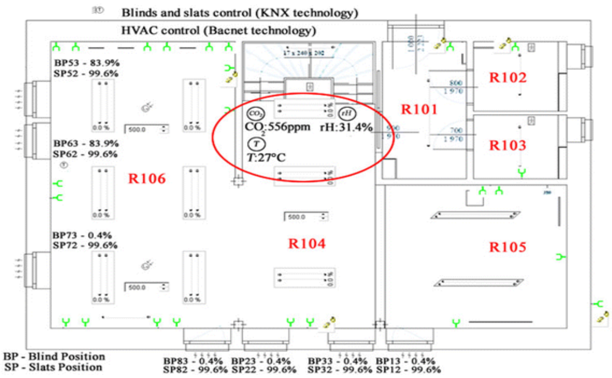
A CO2, temperature, humidity, and light level-based occupancy detection system was recently presented [13]. They used raw sensory data as features, as proposed in [14]. To predict the occupancy presence. They experimented with different feature combinations and mathematical models before deciding on the best feature set and model. Finally, they concluded that proper feature selection and learning algorithms would lead to good results.

III. Proposed Approaches

Filter model function selection has been used in previous studies on occupant prediction. Supervised learning has little influence on the filter model's feature collection, due to the trade between approximation performance and time performance. The feature extraction for wrapper model uses linear regression function for feature extraction, which is a better solution that guarantees higher prediction performance.

Using the ANN's recent study will be computationally prohibitive. Since the Extreme Learning Machine (ELM) is even faster than traditional neural networks, the feature selection wrapper model can be used. Sensor data in its raw form would be inefficient due to the inclusion of obsolete and redundant components. As a consequence, it is important to remove valuable functionality from data and pick the most suitable ones. Figure 1 illustrates how ANN can be used to calculate CO2 levels in various building areas.

Figure 1: Carbon dioxide monitoring in a different zone of the building



Monitoring CO2 Concentrations in occupied rooms can be used to efficiently control operational-technical functions like energy usage, lighting, comfort, and indirect monitoring of seniors' daily activities to avoid potentially dangerous situations.

1. *3.1 System Implementation*

This section defines the components used in developing the prototype, preceded by the software implementation and data collection exercise.

Hardware components

Figure 2 represents the prototype configuration consisting of Arduino UNO, CO2 sensor, temperature, and humidity sensor.

The sensing hub must have the ability to communicate with installed, collect the sensors reading data, and pass it to a centralized location for pre-processing.

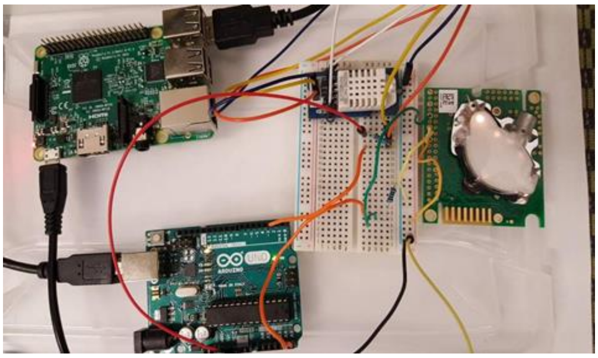
-Temperature sensor (QPA 2062) with accuracy 1K and reading within 0 - 35 °C

-Relative humidity sensor with accuracy ±5 and reading within the range of 0-100%

-CO2 sensor with an accuracy of ±50 ppm and reading with the range of 0 -2000 ppm,

-Arduino UNO WiFi Rev.2 supports IoT using the UNO family's regular form factor.

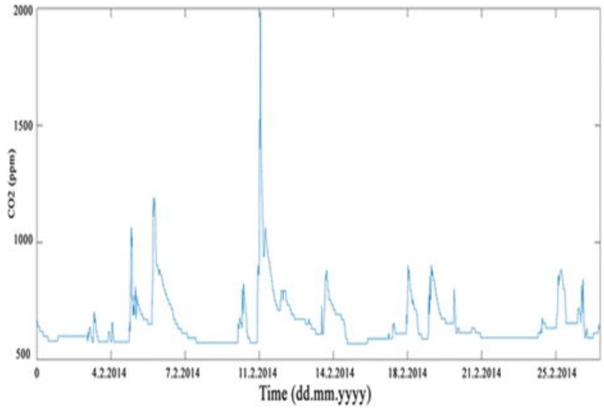
Figure 2: Prototype Setup



2. *3.2 Data collection*

CO2, relative humidity, and temperature were measured using DHT22 and K30 sensors. The Lutron MHB-382SD sensor was used to measure pressure levels. The dataset sample was collected from several sensors using one-minute intervals (see Figure 3). These readings were initially kept in the sensors' internal memory before being moved to a laptop via a USB cable. It was then run via MATLAB. The goal is to control the operation of mechanical ventilation when there are no occupants present in the room and also control the flow of the fresh air in the room.

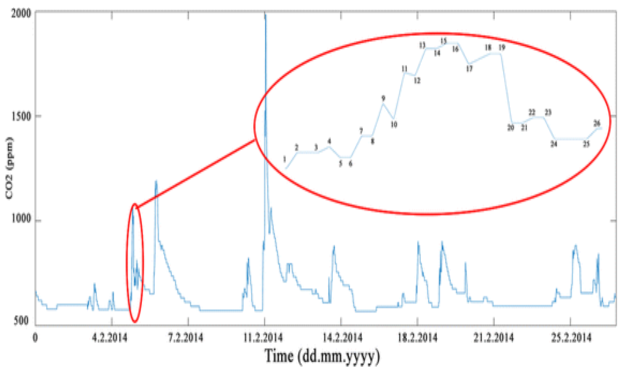
Figure 3: Carbon dioxide distribution during room occupation and departure



CO2 concentrations are the most common pollutant found in indoor environments. House interiors often have a higher concentration than the outside. When the is a greater number of occupants, the CO2 concentration tends to rise exponentially in the room primarily due to human activity. Oxygen and CO2 are exchanged during breathing. The amount of CO2 emitted is proportional to the amount of physical activity. The volume of carbon dioxide in the atmosphere is estimated in parts per million (ppm) [15].

A Time-series algorithm can be applied to calculate the arrival or departure time of the occupant to/from the controlled room using the measured CO2 concentration values (see Figure 4) in a room. This is based on the premise that if CO2 levels rise, an individual is present. When an individual leaves the monitored room, the CO2 concentration increases.

Figure 4: The pattern of carbon dioxide during occupancy present in the room



The pattern of CO_2 dispersion in the indoor environment with controlled ventilation, natural spreading of CO_2 (ppm)] can also be determined based on CO_2 concentration dispersion (see Figure 4.).

IV. DISCUSSION

Today environmental monitoring technology is deployed in the indoor to be constantly aware of the state of environmental variables. These variables offer knowledge about the quality of an indoor environment's internal climate. This detail is critical for lighting control comfort and occupancy. The cost of high-quality temperature and air humidity sensors, as well as CO_2 sensors, is not prohibitively costly. The importance of good thermal insulation for big buildings is stressed, resulting in considerable long-term energy savings. This is feasible in huge office complexes, colleges, hospitals, apartments, private houses, and apartment buildings. With increasing CO_2 concentrations and relative humidity, the internal climate of restored insulated buildings is deteriorating.

When the CO_2 concentration is too high, the indoor air quality level decrease which can affect the overall health of the occupant. To tackle this problem, a window and a door can be open or force ventilation approach in a room as part of a complex solution offered by HVAC technology (Heating, Ventilation, and Air Conditioning). To use technology in conjunction with building automation, it is important to provide CO_2 concentration measurements before the implementation of HVAC-managed technology.

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